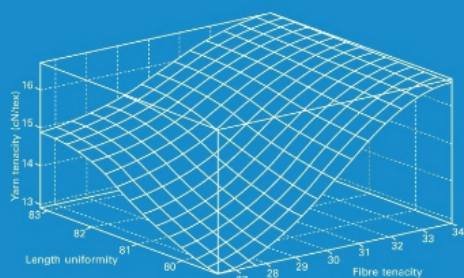


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Soft computing in textile engineering

Edited by A. Majumdar



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Introduction to soft computing techniques: artificial neural networks, fuzzy logic and genetic algorithms

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Abstract: This chapter gives an overview of different ‘soft computing’ (also known as ‘computational intelligence’) techniques that attempt to mimic imprecision and understanding of natural phenomena for algorithm development. It gives a detailed account of some of the popular evolutionary computing algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO) and artificial immune systems (AIS). The paradigm of fuzzy sets is introduced and two inferencing methods, the Mamdani model and the Takagi–Sugeno–Kang (TSK) model, are discussed. The genesis of brain modelling and its approximation so as to develop neural networks that can learn are also discussed. Two very popular computational intelligence techniques, support vector machines (SVMs) and rough sets, are introduced. The notions of hybridization that have aroused interest in developing new algorithms by using the better features of different techniques are mentioned. Each section contains applications of the respective technique in diverse domains.

Key words: evolutionary algorithms, fuzzy sets, neural networks, support vector machines, rough sets, hybridization.

1.1 Introduction: traditional computing and soft computing

Given some inputs and a well laid-out procedure of calculation, traditional computing meant application of procedural steps to generate results. It ensured precision and certainty of results and also reduced rigour in manual effort. This is known as ‘hard computing’ as it always led to precise and unique results given the same input. But the real world is replete with imprecision and uncertainty, and computation, reasoning and decision making should have a mechanism to consider the imprecision, vagueness and ambiguousness of expression. In fact, such reasoning from ambiguous expression is a part of day-to-day life as it is possible to make something out of the handwriting of different persons, to recognize and classify images, to drive vehicles using our own reflexes and intuition, and to make rational decisions at every moment of our life. The challenge lies in representing imprecision, understanding natural instincts and deriving some end result from them. It should lead to an

acceptable, low-cost solution to real-life problems. This has led to the notion of 'soft computing' that includes mimicking imprecision and understanding natural phenomena for algorithm development to generate improved results. Of late, it has been bestowed with another name, 'computational intelligence', to accommodate several recent techniques under its fold.

Traditional hard computing is often violated in day-to-day life. For example, the regulation of a domestic fan is always guided by the ambient temperature, humidity and other atmospheric conditions and also varies between individuals. On a certain day a person may decide to run the fan at 'medium speed'. Since a fan can only be run at some fixed settings, the notion of 'medium' varies with the individual. Running the fan using traditional 'hard' computing would involve regulation using set rules such as 'If the temperature is 20°C, run the fan at the second setting', 'If the temperature is 30°C, run the fan at the third setting', etc. A question naturally arises, at what speed should the fan be run if the temperature is 19.9°C on a certain day? Decision making under this circumstance is difficult using traditional 'hard' computing. But human beings always make approximate decisions in such situations, though decisions vary from individual to individual. Providing such a methodology to reason from approximation is the hallmark of soft computing.

The rest of the chapter is organized as follows. Section 1.2 introduces the subject of evolutionary algorithms and discusses in detail some of its different variants such as genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO) and artificial immune systems (AIS). Section 1.3 introduces the notion of fuzzy logic, and discusses the different fuzzy set operations and inferencing using Mamdani's model and the Takagi–Sugeno–Kang (TSK) model. Section 1.4 discusses the modelling approaches to describe a biological neuron and to derive its artificial variant. Various activation functions, a multilayer network structure, neural network training, types of neural networks, and neural network applications are discussed. Two very recently proposed computational intelligence paradigms, support vector machines (SVM) and rough sets, are discussed in Section 1.5. In Section 1.6, various hybridization approaches that take the best features of different computational intelligence techniques are discussed. Section 1.7 contains concluding remarks.

1.2 Evolutionary algorithms

Evolutionary algorithms are a class of algorithms that are related in some respects to living organisms. These algorithms are an attempt to mimic the genetic improvement of human beings or the natural behaviour of animals to provide realistic, low-cost solutions to complex problems that are hitherto unsolvable by conventional means. Some widely prevalent evolutionary algorithms are described in this section.

1.2.1 Genetic algorithms

Genetic algorithms (GA) are a method of optimization involving iterative search procedures based on an analogy with the process of natural selection (Darwinism) and evolutionary genetics. Professor John Holland of the University of Michigan, Ann Arbor, envisaged the concept of these algorithms in the mid-sixties and published his seminal work [1]. Later, Goldberg [2] made valuable contributions in this area.

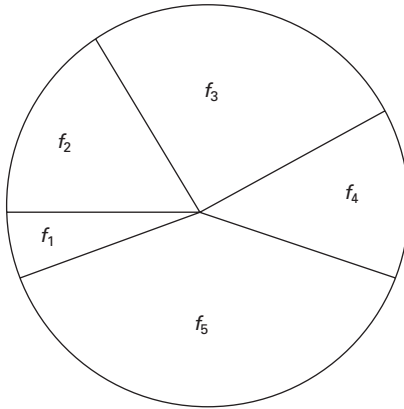
Genetic algorithms aim to optimize (maximize) some user-defined function of the input variables called the ‘fitness function’. Unlike conventional derivative-based optimization that requires differentiability of the optimizing function as a prerequisite, this approach can handle functions with discontinuities or piecewise segments. To perform the optimization task, GA maintains a population of points called ‘individuals’ each of which is a potential solution to the optimization problem. Typically, a GA performs the following steps:

- It evaluates the fitness score of each individual of the old population. Suppose that for an optimization problem, for a fixed number of inputs the task is to achieve a desired function value g . In GA, each individual i of a population will represent a set of inputs with an associated function value g_i . A GA may be designed to finally obtain a set of inputs whose function value is close to the desired value g . The approach thus requires one to minimize the error between g and the g_i ’s. Since GA is a maximizing procedure, a fitness value for the i th individual may be

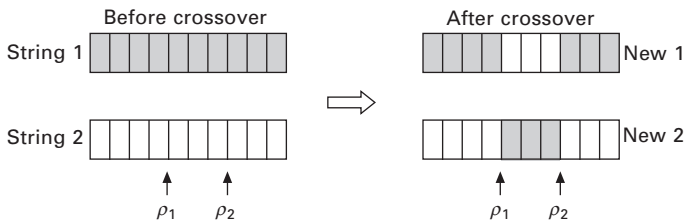
$$f_i = \frac{1}{1 + |g - g_i|} \quad 1.1$$

which can be considered as a fitness function. This choice of fitness function is not unique and a given task has to be formulated as a maximizing function.

- It selects individuals on the basis of their fitness score by the process called ‘reproduction’, often algorithmically implemented like a ‘roulette wheel selection’. In this method, each individual is assigned a slice of a wheel proportional to its fitness value. If the wheel is rotated several times and observed from a point, the individuals having a high value of fitness will have the greatest chances of selection. Figure 1.1 shows the selection of five individuals by the ‘roulette wheel’ method. Based on their sector areas, the chances of occurrence of the individuals in decreasing order are f_5, f_3, f_2, f_4 and f_1 .
- It combines these selected individuals using ‘genetic operators’ [3] such as crossover and mutation, both having an associated probability, which algorithmically can be viewed as a means to change the current solutions



1.1 Roulette wheel selection.



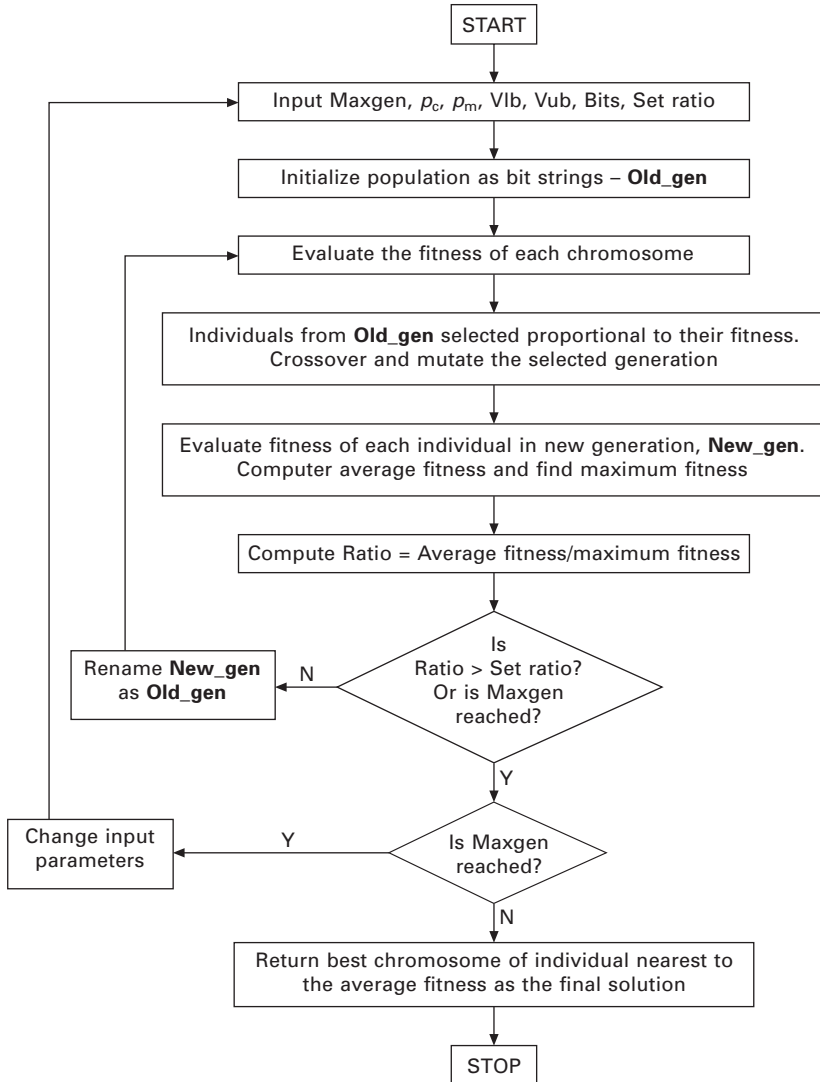
1.2 Multi-point crossover.

locally and to combine them. Typical values of crossover probability p_c lie in the range 0.6–0.8 while mutation occurs with a very low probability (p_m) typically in the range 0.01–0.001. The mechanism of multi-point crossover of two sample strings is depicted in Fig. 1.2.

- The algorithm is supposed to provide improved solutions over the ‘generations’ that algorithmically are equivalent to iterations.
- The programs are terminated either by the maximum number of generations or by some termination criterion that is an indicator of improvement in performance. A realistic termination criterion may be if the ratio of the average fitness to the maximum fitness in a generation crosses a predefined ‘threshold’. Variables encoded in the best string of the final generation are the solution to the given optimization problem. GA thus has the potential to provide globally optimum solutions as it explores over a population of the search space.

The following symbols are used to describe the algorithm in Fig. 1.3:

- Maxgen: Maximum number of generations allowed
- p_c : Probability of crossover
- p_m : Probability of mutation



1.3 Basic genetic algorithm flowchart.

- **Vlb**: Array containing lower bound of the variables
- **Vub**: Array containing upper bound of the variables
- **Bits**: Array containing bit allocation for each variable
- **Set ratio**: Termination condition for computed value of the ratio
- **Old_gen**: Old generation
- **New_gen**: New generation.

The notion of GA was later extended to problems where multiple objectives

needed to be satisfied. Deb [4] has introduced the concept of pareto-optimality for problems requiring satisfaction of multiple objectives.

1.2.2 Particle swarm optimization

Particle swarm optimization (PSO) [5] is an algorithm which derives its inspiration from the social behaviour and dynamics of insects, birds and fish and has performance comparable to GAs. These animals optimize their adaptation to their environment for protection from predators, seeking food and mates, etc. If they are left in an initialized situation randomly, they adjust automatically so as to optimize to their surroundings. This leads to the stochastic character of the PSO.

In analogy to birds, for example, here a number of agents are considered, each being given a particle number i and each possessing a position defined by coordinates in n - dimensional space. These particles/agents also possess an imaginary velocity which in turn reflects their proximity to the optimal position. The initialization is random and thereafter a number of iterations are carried out with the particle velocity (v) and position (x) updated at the end of each iteration, as follows:

$$\text{Position: } x^i(k+1) = x^i(k) + v^i(k+1) \quad 1.2$$

$$\text{Velocity: } v^i(k+1) = w^i v^i(k) + c_1 r_1 (x_{\text{best}}^i - x^i(k)) + c_2 r_2 (x_{\text{gbest}} - x^i(k)) \quad 1.3$$

where:

w^i = inertia possessed by each agent

x_{best}^i = most promising location of the agent

x_{gbest} = most promising location amongst the agents of the whole swarm

c_1 = cognitive weight which represents the private thinking of the particle itself; it is assigned to particle best x_{best}^i

c_2 = social weight assigned to swarm best x_{gbest} which represents the collaboration among the particles

r_1, r_2 = random values in the range [0, 1].

1.2.3 Ant colony optimization (ACO)

Ant colony optimization (ACO) methodology [6] is based on the ant's capability of finding the shortest path from the nest to a food source. An ant repeatedly hops from one location to another to ultimately reach the destination (food). Each arc (i, j) of the graph $G = (N, A)$ has an associated variable τ_{ij} called the pheromone trail. Ants deposit an organic compound called pheromones while tracing a path. The intensity of the pheromone is an indicator of the utility of that arc to build better solutions. At each node,

stochastic decisions are taken by the ant to decide on the next node. Initially, a constant amount of pheromone (i.e., $\tau_{ij} = 1, \forall (i, j) \in A$) is allocated to all the arcs. The probability of the k th ant at node i choosing node j using the pheromone trail τ_{ij} is given by

$$p_{ij}(k) = \begin{cases} \frac{\tau_{ij}^\alpha}{\sum_{l \in N_i^k} \tau_{il}^\alpha} & \text{if } j \in N_i^k \\ 0 & \text{if } j \notin N_i^k \end{cases} \quad 1.4$$

where N_i^k is the neighbourhood of ant k when sitting at the i th node. The neighbourhood of the i th node contains all nodes directly connected to it excepting the predecessor node. This ensures unidirectional movement of the ants. As an exception for the destination node, where N_i^k should be null, the predecessor of node i is included. Using this decision policy, ants hop from the source to the destination.

The pheromone level at each iteration is updated by

$$\tau_{ij}(k+1) = \rho \tau_{ij}(k) + \Delta \tau_{ij}(k) \quad 1.5$$

where $0 \leq \rho < 1$ and $1 - \rho$ represent the pheromone evaporation rate, and $\Delta \tau_{ij}$ is related to the performance of each ant.

1.2.4 Artificial immune systems

Artificial immune system (AIS) is a newly emerging bio-inspired technique that mimics the principle and concepts of modern immunology. The current AISs observe and adopt immune functions, models and mechanisms, and apply them to solve various problems like optimization, data classification and system identification. The four forms of AIS algorithm reported in the literature are the immune network model, negative selection, clonal selection and danger theory. The more popular clonal selection algorithm is similar to GA with slight exceptions.

- *Initial population*: A binary string which corresponds to a immune cell is initialized to represent a parameter vector, and N such vectors are taken as the initial population, each of which represents a probable solution.
- *Fitness evaluation*: The fitness of the population set is evaluated to measure the potential of each individual solution.
- *Selection*: The parameter vector (corresponding cells) for which the objective function value is a minimum is selected.
- *Clone*: The parameter vector (corresponding cells) which yields the best fitness value is duplicated.
- *Mutation*: The mutation operation introduces variations into the immune

cells. The low probability of mutation p_m indicates that the operation occurs only occasionally. Here the fitness as well as the affinity of the antibodies is changed towards the optimum value.

The best-fit population (known as memory cells) obtained by the above process replaces the initial population and the cycle continues till the objective is achieved.

Different evolutionary computing algorithms and their variants are being applied in diverse domains [7, 8], including mathematics, biology, computer science, engineering and operations research, physical sciences, social sciences and financial systems.

1.3 Fuzzy sets and fuzzy logic

The real world is complex, and complexity generally arises from uncertainty in the form of ambiguity. Most of the expressions of natural language are vague and imprecise, yet it is a powerful medium of communication and information exchange. To person A, a 'tall' person is anybody over 5 feet 11 inches, while for another person B, a 'tall' person is 6 feet 3 inches or over. Fuzzy set theory [9–12], originally proposed by Lotfi Zadeh, provides a means to capture uncertainty. The underlying power of fuzzy set theory is that it uses 'linguistic' variables rather than quantitative variables to represent imprecise concepts. It is very promising in its representation of complex models and processes where decision making with human reasoning is involved. It is used widely in applications that do not require precision but depend on intuition, like parking a car, backing a trailer, vehicle navigation, traffic control, etc.

All objects of the universe are subject to set membership. In binary decision making, if 'tall' is defined as a set of individuals having height greater than 6 feet, a person having a height of 5 feet 11.99 inches does not belong to this set even though he may possess comparable attributes to the 6-foot person. In such crisp set-theoretic considerations, the membership of an element x in a set A can be denoted by the indicator function,

$$\chi_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases} \quad 1.6$$

To an element, by assigning various 'degrees of membership' on the real continuous interval $[0, 1]$, a fuzzy set tries to model the uncertainty regarding the inclusion of the element in a set. The degree of membership of an element in the fuzzy set $\underline{A}$ is given by

$$\mu_{\underline{A}}(x) \in [0, 1] \quad 1.7$$

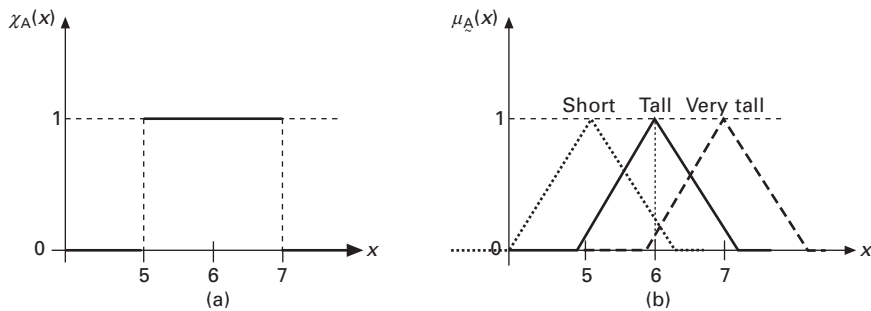
Figure 1.4(a) shows the representation of a crisp set A and how it can be represented by indicator function values for an element, $5 \leq x \leq 7$. Figure 1.4(b) shows the membership functions of a fuzzy set $\underline{A}$ having maximum membership at $x = 6$. This may be named as the membership function for 'tall'. Another membership function having maximum membership at $x = 7$ could be named 'very tall', while a membership function having maximum membership at $x = 5$ may be named 'short' as shown in Fig. 1.4(b). These are linguistic terms that are used daily by human beings. Fuzzy logic attempts to provide a mathematical framework to such linguistic statements for further reasoning. When the universe of x is a continuous interval, a fuzzy set is represented as $A = \left\{ \int \frac{\mu_A(x)}{x} \right\}$, where the integral operator indicates continuous function-theoretic union; the horizontal demarcating line separates the membership values and the corresponding points and is in no way related to division. When the universe is a collection of a finite number of ordered discrete points, the corresponding fuzzy set may be represented by

$$A = \left\{ \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \dots + \frac{\mu_A(x_n)}{x_n} \right\} = \left\{ \sum_{i=1}^n \frac{\mu_A(x_i)}{x_i} \right\}$$

where the summation indicates aggregation of elements.

Basic operations related to fuzzy subsets $\underline{A}$ and $\underline{B}$ of X having membership values $\mu_A(x)$ and $\mu_B(x)$ are

- $\underline{A}$ is equal to $\underline{B} \Rightarrow \mu_A(x) = \mu_B(x) \forall x \in X$
- $\underline{A}$ is a complement of $\underline{B} \Rightarrow \mu_A(x) = \mu_{\bar{B}}(x) = 1 - \mu_B(x) \forall x \in X$
- $\underline{A}$ is contained in $\underline{B}$ ($\underline{A} \subseteq \underline{B}$) $\Rightarrow \mu_A(x) \leq \mu_B(x) \forall x \in X$
- The union of $\underline{A}$ and $\underline{B}$ ($\underline{A} \cup \underline{B}$) $\Rightarrow \mu_{\underline{A} \cup \underline{B}}(x) = \vee (\mu_A(x), \mu_B(x)) \forall x \in X$, where $\vee$ denotes maximum



1.4 (a) Membership representation for crisp sets; (b) degree of membership representation for fuzzy sets.

- The intersection $\underline{A}$ and $\underline{B}$ ($\underline{A} \cap \underline{B}$) $\Rightarrow \mu_{\underline{A} \cap \underline{B}}(x) = \wedge (\mu_{\underline{A}}(x), \mu_{\underline{B}}(x))$
 $\forall x \in X$, where $\wedge$ denotes minimum.

Fuzzy sets obey all the properties of classical sets, excepting the excluded middle laws, i.e., the union and intersection of a fuzzy set and its complement are not equal to the universe and null set respectively. They support modifiers or linguistic hedges like *very*, *very very*, *plus*, *slightly*, *minus*, etc. If ‘tall’

is represented by the fuzzy set $\underline{A} = \left\{ \int \frac{\mu_{\underline{A}}(x)}{x} \right\}$, ‘very tall’ can be derived

from it as $\int \frac{[\mu_{\underline{A}}(x)]^2}{x}$, while ‘slightly tall’ may be derived as $\int \frac{[\mu_{\underline{A}}(x)]^{0.5}}{x}$, by carrying out the exponentiation of the membership values at each point of the original fuzzy set.

In the real world, knowledge is often represented as a set of ‘IF premise (antecedent), THEN conclusion (consequent)’ type rules. Fuzzy inferencing is performed based on the fuzzy representation of the antecedents and consequents. Two popular fuzzy inferencing methods are the Mamdani model and the Takagi–Sugeno–Kang (TSK) model.

1.3.1 Mamdani’s fuzzy model

A typical rule in Mamdani’s method of inferencing having n conjunctive antecedents has the structure below:

R_r : IF x_1 is A_{r1} AND x_2 is A_{r2} AND ... AND x_n is A_{rn} ,
 THEN y is B_r . ($r = 1, 2, \dots, m$)

For a given input, $[x_1 \ x_2 \ \dots \ x_n]$, using a max–min type of implication, the output is generated by firing all the rules and taking their aggregation considering the maximum membership value at each point as shown in eqn 1.8:

$$\mu_{B_r}(y) = \vee [\wedge \{\mu_{A_{r1}}(x_1), \mu_{A_{r2}}(x_2), \dots, \mu_{A_{rn}}(x_n)\}], \quad r = 1, 2, \dots, m$$

1.8

The crisp output is obtained by defuzzification of the resultant output membership function profile by any of the defuzzification methods such as the max-membership principle, the centroid method, the weighted average method, mean–max membership, etc. [9–12].

1.3.2 Takagi–Sugeno–Kang (TSK) fuzzy model

In this model of inferencing, the output generated by each rule is a linear combination of the inputs, thereby having a structure as shown below:

R_r : IF x_1 is A_{r1} AND x_2 is A_{r2} AND ... AND x_n is A_{rn} ,
 THEN $y_r = a_{r0} + a_{r1}x_1 + \dots + a_{rn}x_n$. ($r = 1, 2, \dots, m$)

For a given input, $[x_1 \ x_2 \ \dots \ x_n]$, the crisp output after firing all the rules is given by

$$y = \frac{\sum_{i=1}^m \tau_i y_i}{\sum_{j=1}^m \tau_j} = \frac{\sum_{i=1}^m \tau_i (a_{i0} + a_{i1}x_1 + \dots + a_{in}x_n)}{\sum_{j=1}^m \tau_j} \quad 1.9$$

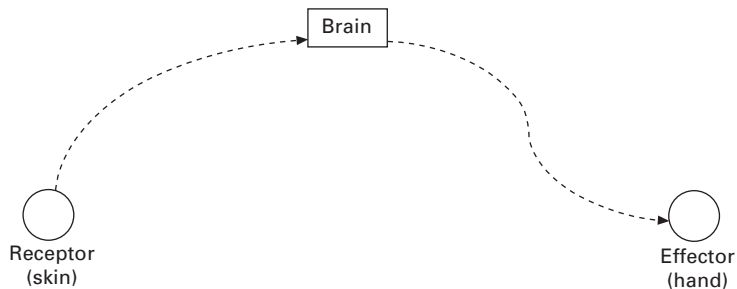
where $\tau_i = \wedge [\mu_{A_{i1}}(x_1) \ \mu_{A_{i2}}(x_2) \ \dots \ \mu_{A_{in}}(x_n)]$.

Fuzzy logic techniques are increasingly being used in various applications [10–12] like classification and clustering, control, system identification, cognitive mapping, etc.

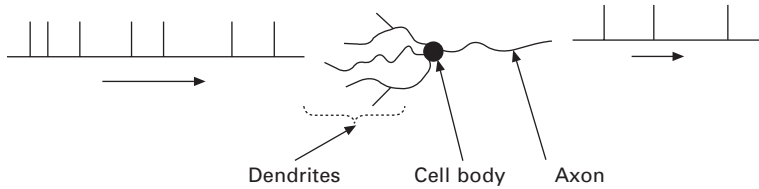
1.4 Neural networks

The human brain has a mass of about 30 lb and a volume of 90 cubic inches, and consists of about 90 billion cells. Neurons, numbering about 10 billion, are a special category of cells that conduct electrical signals. The brain is made up of a vast network of neurons that are coupled with receptor and effector cells as shown in Fig. 1.5. It is characterized by a massively parallel structure of neurons with a high degree of connection complexity and trainability. It consists of several sub-networks performing different functions. Neurons interact with each other by generating impulses (spikes) as shown in Fig. 1.6.

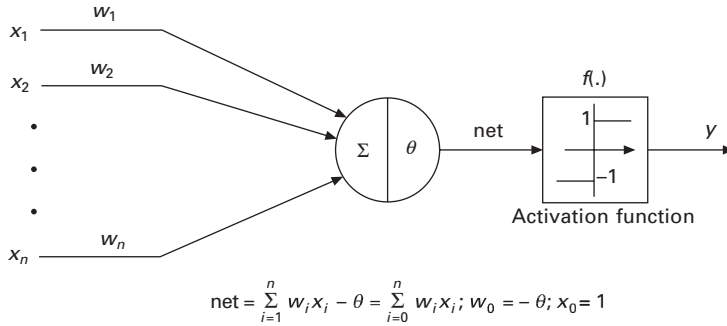
The spiking behaviour of neurons has received increasing attention in the last few years. Neuro-scientists have attempted to model the spiking behaviour of neurons [13–15] with the hope of deciphering the functioning of the brain to build intelligent machines. A neuron receives inputs in the form of impulses



1.5 Connection between brain, receptor and effectors.



1.6 Structure of a neuron.

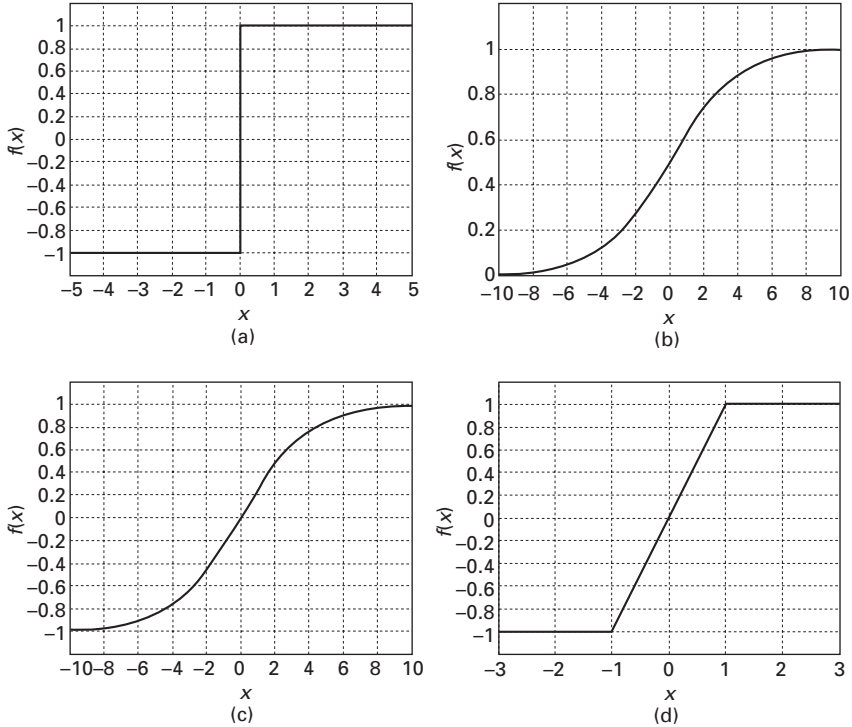


1.7 A simple neuron model.

from its pre-synaptic neuron through dendrites and transmits impulses to its post-synaptic neurons through synapses. Such functional behaviour is well suited for hardware implementations, in the digital as well as the analogue domain rather than by conventional programming. Some of the approaches to modelling the spiking behaviour of a neuron are the Hodgkin–Huxley model, the integrate and fire model, the spike response model and the multi-compartment integrate and fire model [13, 14]. Neuro-scientists differ in describing the activity of neurons. The rate of spike generation over time, and the average rate of spike generation over several runs, are some of the measures used to describe the spiking activity of neurons.

The spiking behaviour of neurons can only be realized in hardware. For computational purposes, a neuron is identified by the rate at which it generates the spikes. This is the assumption made in artificial neural networks (ANN). In a simple neuron, the input $X = [x_1 \ x_2 \ \dots \ x_n]^T$ is weighted and compared with a threshold θ before passing through some activation function to generate its output. In Fig. 1.7, the hard limiter activation function has been used to generate the output. Some of the most commonly used activation functions such as the threshold logic unit, logsigmoid, tansigmoid and the saturated linear activation function are shown in Fig. 1.8.

A simple neuron can easily distinguish a linearly separable dataset but is incapable of learning a linearly inseparable dataset. This requires a multilayered structure of neurons. Kolmogorov's theorem states that any continuous



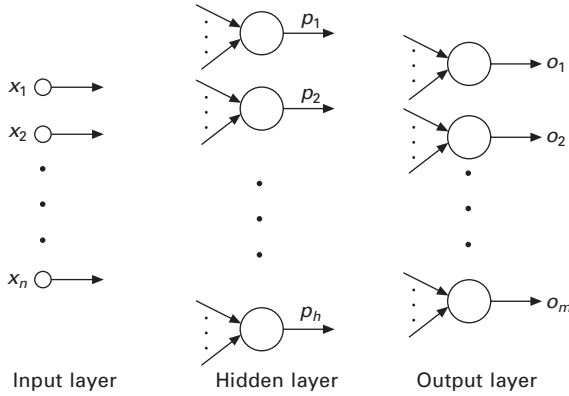
1.8 Different activation functions: (a) threshold logic unit; (b) logsigmoid; (c) tansigmoid; (d) saturated linear.

function $f(x_1, x_2, \dots, x_n)$ of n variables $x_1, x_2, \dots, x_n$ can be represented in the form

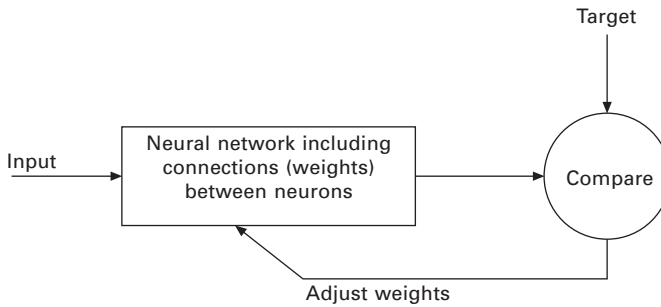
$$f(x_1, x_2, \dots, x_n) = \sum_{j=1}^{2n+1} h_j \left(\sum_{i=1}^n g_{ij}(x_i) \right) \quad 1.10$$

where h_j and g_{ij} are continuous functions of one variable and the g_{ij} 's are fixed monotone increasing functions. Kolmogorov's theorem basically gives an intuition that by using several simple neurons that basically mimic a function, any function can be approximated. It results in a multilayered structure (Fig. 1.9) that is capable of function approximation. Commonly, neural networks are adjusted or trained so that a particular input leads to a specific target output. Typically, many such input/target pairs are used to train a network. Learning tasks where input/target pairs are provided is known as supervised learning. Supervised learning problems can be categorized as classification problems and the regression problem.

- **Classification problem:** In an M -ary classification problem, the task is



1.9 Multilayered neural network architecture.



1.10 Neural network training.

to learn a data set S containing the input–output tuples $S = \{(X^i, y^i), X^i \in \mathfrak{R}^n, y^i \in \{1, 2, \dots, M\}, i = 1, 2, \dots, N\}$. If $y^i \in \{1, -1\}$, it is known as a binary classification problem.

- **Regression problem:** In a regression problem, the task is to learn a data set S containing the input–output tuples $S = \{(X^i, y^i), X^i \in \mathfrak{R}^n, y^i \in \mathfrak{R}^m, i = 1, 2, \dots, N\}$.

1.4.1 Neural network training

Training of neural networks takes place by updating its weights in an iterative manner as shown in Fig. 1.10. Given the training data set $S = \{(X^i, y^i), X^i \in \mathfrak{R}^n, y^i \in \mathfrak{R}^m, i = 1, 2, \dots, N\}$ let the actual output due to the k th pattern be $\mathbf{o}^k$. The sum squared error over all the output units for the k th pattern is

$$E^k = \frac{1}{2} \sum_{j=1}^n (o_j^k - y_j^k)^2 \quad 1.11$$

The total error over the N patterns is

$$E_T = \sum_{k=1}^N E^k \quad 1.12$$

A typical weight update rule [15–20] is designed so as to reduce the error in the direction of negative gradient as in eqn 1.13:

$$\mathbf{w}(i+1) = \mathbf{w}(i) - \eta \frac{\partial E_T}{\partial \mathbf{w}(i)} \quad 1.13$$

where η is the learning rate.

Another weight update algorithm that represents the history of earlier weight updates is known as ‘weight update with momentum’ (1.14):

$$\mathbf{w}(i+1) = \mathbf{w}(i) - \left[\eta \frac{\partial E_T}{\partial \mathbf{w}(i)} + \beta \mathbf{w}(i-1) \right] \quad 1.14$$

where β is the momentum parameter. In batch training the entire set of inputs are presented and the network is trained, while in incremental training the weights and biases are updated after presentation of each individual input.

In training by the backpropagation method [15–20], the error at the output of a multilayer network is propagated backwards to each of the nodes and the weights are updated. This continues till the error at the output reaches a predefined tolerance limit. Many types of neural networks, such as the RBF network, the time delay neural network, the ‘Winner Takes All’ network, self-organizing maps, etc. [15–20], are widely used. There is another class of neural networks known as Hopfield networks that have feedback connections from the output towards the input [15–20]. Here weights are updated by minimizing some energy function. Hopfield networks are capable of learning data to implement auto-associative memory, bidirectional associative memory, etc.

Neural networks are being used in various pattern recognition applications, control and system identification, finance, medical diagnosis, etc. Neural network functionalities are increasingly being synthesized in analogue electronic and digital hardware.

1.5 Other approaches

There are several other approaches that are more and more being considered under the newly coined area of ‘computational intelligence’. Two such powerful techniques known as support vector machines and rough sets are discussed here.

1.5.1 Support vector machines

Support vector machines (SVM) [21–23] have been proposed as a powerful pattern classification technique which aims at maximizing the margin between two disjoint half spaces: the original input spaces for a linear classification problem or the higher dimensional feature space for a nonlinear classification problem. The maximal margin classifier represents the classification problem as a convex optimization problem: minimizing a quadratic function under linear inequality constraints. Given a linearly separable training set $\{S = (x^i, y^i), x^i \in \mathfrak{R}^n, y^i \in \{-1, 1\}, i \in I, \text{card}(I) = N\}$ the hyperplane w that solves the optimization problem

$$(\text{QPP}) = \min_{w, b} \langle w \cdot w \rangle \quad 1.15$$

subject to

$$y^i (\langle w \cdot x^i \rangle + b) \geq 1; i = 1, 2, \dots, N \quad 1.16$$

realizes the maximum margin hyperplane [21–23] with geometric margin $\gamma = \frac{1}{\|w\|_2}$. The solution to the optimization problem (eqns 1.15, 1.16) is obtained by solving its dual, given by

$$\max \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N y^i y^j \alpha^i \alpha^j \langle x^i \cdot x^j \rangle \quad 1.17$$

subject to

$$\sum_{i=1}^N y^i \alpha^i = 0 \quad 1.18$$

$$\alpha^i \geq 0, i = 1, 2, \dots, N \quad 1.19$$

If the parameter α^* is the solution of the above optimization problem, then the weight vector $w^* = \sum_{i=1}^N y^i \alpha^{i*} x^i$ realizes the maximal margin hyperplane with geometric margin $\gamma = 1/\|w^*\|_2$. As b does not appear in the dual formulation, the value of b^* is found from the primal constraints:

$$b^* = - \frac{\max_{y^i=-1} (\langle w^* \cdot x^i \rangle) + \min_{y^i=1} (\langle w^* \cdot x^i \rangle)}{2} \quad 1.20$$

The optimal hyperplane can be expressed in the dual representation in terms of the subset of parameters:

$$\begin{aligned}
 f(x, \alpha^*, b^*) &= \sum_{i=1}^N y^i \alpha^{i*} \langle x^i \cdot x \rangle + b^* \\
 &= \sum_{i \in SV} y^i \alpha^{i*} \langle x^i \cdot x \rangle + b^*
 \end{aligned}
 \tag{1.21}$$

The value of the Lagrangian multiplier α^{i*} associated with sample x^i signifies the importance of the sample in the final solution. Samples having substantial non-zero value of the Lagrangian multiplier constitute the support vectors for the two classes. A support vector classifier for separating a linearly separable data set is shown in Fig. 1.11.

If data set S is linearly separable in the feature space implicitly defined by the kernel $K(x, z)$, to realize the maximal margin hyperplane in the feature space the following modified quadratic optimization problem needs to be solved:

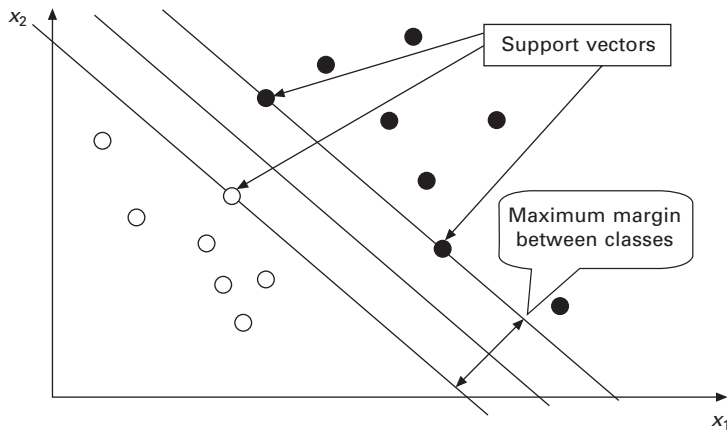
$$\max \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N y^i y^j \alpha^i \alpha^j K(x^i \cdot x^j)
 \tag{1.22}$$

subject to eqns 1.18 and 1.19.

The maximal margin hyperplane in the feature space obtained by solving eqns 1.18, 1.19 and 1.22 can be expressed in the dual representation as

$$f(x, \alpha^*, b^*) = \sum_{i=1}^N y^i \alpha^{i*} K(x^i, x) + b^*
 \tag{1.23}$$

The performance of a SVM depends to a great extent on the *a priori* choice of the kernel function to transform data from input space to a higher-



1.11 Support vector classifier.

dimensional feature space [21–23]. For a given data set the performance of different kernel functions varies. Some commonly used kernel functions are mentioned in Table 1.1.

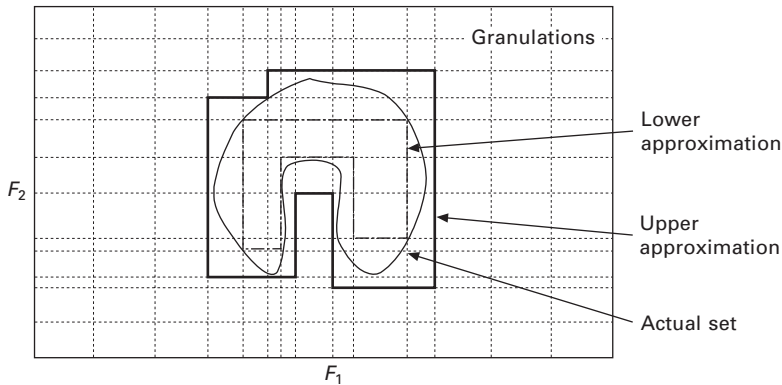
Recently, some alternative SVMs have been suggested that attempt to overcome some of the limitations of the original SVM proposed by Vapnik. In least squares support vector machines (LSSVM) [24], the optimal values of the Lagrangian multipliers are obtained by solving a set of $N + 1$ linear equations, thus reducing computational complexity in obtaining the final hyperplane. In proximal support vector machines [25], the final hyperplane is obtained by inverting a matrix of dimension $(n + 1) \times (n + 1)$. The value of the bias needed in the final hyperplane is also obtained from this solution. The potential support vector machine [26] gives a hyperplane that is invariant to scaling of the data. The twin SVM [27] determines two non-parallel planes for solving two SVM-type problems. SVMs are now being used for various applications of classification and regression.

1.5.2 Rough sets

The theory of rough sets has been proposed to take care of uncertainty arising from granularity in the universe of discourse, i.e., from the difficulty of judging between objects in the set. Here it is attempted to define a rough (imprecise) concept in the universe of discourse by two exact concepts known as the lower and upper approximations. The lower approximation is the set of objects that completely belong to the vague concept, whereas the upper approximation is the set of objects that possibly belong to the vague concept. Discernibility matrices, discernibility functions, reducts and dependency factors that are widely used in knowledge reduction are defined using the approximations. A schematic diagram of rough sets is shown in Fig. 1.12. Analytical details of the theory can be found in [28–30]. Its efficacy has been proved in areas of reasoning with vague knowledge, data classification, clustering and knowledge discovery [29].

Table 1.1 Some kernel functions

Kernel	Kernel function	Parameters
Linear kernel	$K(x^i, x^j) = \langle x^i \cdot x^j \rangle$	
Multilayer perceptron kernel	$K(x^i, x^j) = \tanh(s \langle x^i \cdot x^j \rangle + t^2)$	t : bias s : scale parameter
Polynomial kernel	$K(x^i, x^j) = (\langle x^i \cdot x^j \rangle + t)^d$	t : intercept d : degree of the polynomial
Gaussian kernel	$K(x^i, x^j) = e^{(\langle x^i - x^j \rangle \langle x^i - x^j \rangle) / \sigma^2}$	σ^2 : variance



1.12 Lower and upper approximations in a rough set.

1.6 Hybrid techniques

By adopting the good features of different soft computing techniques, several hybrid approaches have been devised. The capability of fuzzy logic to represent knowledge in the form of IF–THEN rules has been utilized to develop controllers for nonlinear systems. Following hybrid approaches to design these controllers, different evolutionary computation techniques have been used to simultaneously design the structure of membership function, rule set, normalizing and de-normalizing factors of fuzzy logic controllers [31–39]. Incorporating the better interpretation and understandability of fuzzy sets and the decision making and aggregation capability of neural networks, fuzzy neural networks [40] and neuro-fuzzy techniques [41] have been proposed and their performance validated on different pattern recognition problems. Hybrids of support vector machines, fuzzy systems and neural networks [42–50] have been used for various pattern classification tasks. Combination of SVM and neural network where each neuron is an SVM classifier has been used to solve the binary classification problem [51] and further to act as a ‘critic’ in the control framework [52]. The rough-neuro-fuzzy synergism [53, 54] has been used to construct knowledge-based systems, rough sets being utilized for extracting domain knowledge.

1.7 Conclusion

This chapter gives a brief overview of the different ‘computational intelligence’ techniques, traditionally known as ‘soft computing’ techniques. The basics of the topics on evolutionary algorithms, fuzzy logic, neural networks, SVMs, rough sets and their hybridization have been discussed with their applications. More details concerning their theory and implementation aspects can be found in the references provided. The different techniques discussed create

the background for applying ‘soft computing’ in various textile engineering applications as discussed in the rest of this book.

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Artificial neural networks in materials modelling

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Abstract: This chapter discusses the development of artificial neural networks (ANNs) and presents various models as illustration. The importance of uncertainty is introduced, and its application, along with that of neural networks in materials science, are described. Finally, the future of neural network applications is discussed.

Key words: artificial neural networks (ANNs), data modelling techniques, least squares method.

2.1 Introduction

Data modelling has been a textbook exercise since the school days. The most evident of the data modelling techniques, which is widely known and used, is the method of least squares. In this method a best fit is obtained for given data. The best fit, between modelled data and observed data, in its least-squares sense, is an instance of the model for which the sum of squared residuals has its least value, where a residual is the difference between an observed value and the value provided by the model. The method was first described by Carl Friedrich Gauss around 1794 (Bretscher, 1995). The limitation of this method lies in the fact that the relationship so obtained through the exercise is applied across the entire domain of the data. This may be unreasonable as the data may not have a single trend. This is true in cases where there are many variables controlling the output.

With increasing complexity in a system, the understanding of the parameters becomes extremely difficult, nay impossible. Each parameter controlling a process adds to one dimension. If there are seven variables controlling a process, say, then this amounts to a seven-dimensional problem. Note the term ‘variables’ which means these are controllable parameters that could influence a process significantly. With such complex problems, scientists are more drawn towards tools that can enable better understanding. Hence, artificial intelligence tools are gaining more attention.

Artificial intelligence tools such as neural networks, genetic algorithms, support vector machines, etc., have been extensively used by researchers for more than two decades to solve complex problems. The scope of this chapter is restricted to neural networks.

Neural networks have their basis in biological neurons and their functioning. Though the term originates from biological systems, neural networks do not replicate the latter in full since they are very simplified representations. Neural networks, commonly known as artificial neural networks (ANN), are mostly associated with statistical estimation, optimization and control theory. They have been successfully used in speech recognition, image analysis and adaptive control mechanisms through software agents. ANN also has found application in robots where learning forms a core necessity. Thus mechatronics has a large domain that concentrates on artificial intelligence based tools.

2.2 Evolution of neural networks

The development of artificial neural networks has an interesting history. Since it is beyond the scope of this chapter to cover the history in depth, only major milestones have been highlighted. This glimpse should provide the reader with an appreciation of how contributions to the field have led to its development over the years.

The year 1943 is often considered the initial year in the development of artificial neural systems. McCulloch and Pitts (1943) outlined the first formal model of an elementary computing neuron. The model included all necessary elements to perform logic operations, and thus it could function as an arithmetic logic computing element. The implementation of its compact electronic model, however, was not technologically feasible during the era of bulky vacuum tubes. The formal neural model was not widely adopted for the vacuum tube computing hardware description, and the model never became technically significant. However, the McCulloch and Pitts neuron model laid the groundwork for further developments.

Donald Hebb (Hebb, 1949), a Canadian neuropsychologist, first proposed a learning scheme for updating neuron connections that we now refer to as the *Hebbian learning rule*. He stated that the information can be stored in connections, and postulated the learning technique that had a profound impact on future developments in this field. Hebb's learning rule made primary contributions to neural network theory.

During the 1950s, the first neurocomputers were built and tested (Minsky, 1954). They adapted connections automatically. During this stage, the neuron-like element called a *perceptron* was invented by Frank Rosenblatt in 1958. It was a trainable machine capable of learning to classify certain patterns by modifying connections to the threshold elements (Rosenblatt, 1958). The idea caught the imagination of engineers and scientists and laid the groundwork for the basic machine learning algorithms that we still use today.

In the early 1960s a device called *ADALINE* (for ADaptive LINEar

combiner) was introduced, and a new, powerful learning rule called the *Widrow–Hoff learning rule* was developed by Bernard Widrow and Marcian Hoff (Widrow and Hoff, 1960). The rule minimized the summed square error during training involving pattern classification. Early applications of ADALINE and its extensions to MADALINE (for Many ADALINES) include pattern recognition, weather forecasting and adaptive controls. The monograph on learning machines by Nils Nilsson (Nilsson, 1965) clearly summarized many of the developments of that time. That book also formulates inherent limitations of learning machines with modifiable connections.

The final episode of this era was the publication of a book by Marvin Minsky and Seymour Papert (Minsky and Papert, 1969) that gave more doubt as to the potential of layered learning networks. The stated limitations of the perceptron-class of networks were made public; however, the challenge was not answered until the mid-1980s. The discovery of successful extensions of neural network knowledge had to wait until 1986. Meanwhile, the mainstream of research flowed towards other areas, and research activity in the neural network field, called at that time *cybernetics*, had sharply decreased. The artificial intelligence area emerged as a dominant and promising research field, which took over, among others, many of the tasks that neural networks of that day could not solve.

During the period from 1965 to 1984, further pioneering work was accomplished by a handful of researchers. The study of learning in networks of threshold elements and the mathematical theory of neural networks was pursued by Sun-Ichi Amari (Amari, 1972, 1977). Also in Japan, Kuniyiko Fukushima developed a class of neural network architectures known as *neocognitrons* (Fukushima, 1980). The neocognitron is a model for visual pattern recognition and is concerned with biological plausibility. The network emulates the retinal images and processes them using two-dimensional layers of neurons.

Associative memory research has been pursued by, among others, Tuevo Kohonen in Finland (Kohonen, 1977, 1982, 1984, 1988) and James Anderson (Anderson, 1977). Unsupervised learning networks were developed for feature mapping into regular arrays of neurons (Kohonen, 1982). Stephen Grossberg and Gail Carpenter have introduced a number of neural architectures and theories and developed the theory of adaptive resonance networks (Grossberg, 1977, 1982; Grossberg and Carpenter, 1991).

During the period from 1982 until 1986, several seminal publications were published that significantly furthered the potential of neural networks. The era of renaissance started with John Hopfield (Hopfield, 1982, 1984) introducing a recurrent neural network architecture for associative memories. His papers formulated computational properties of a fully connected network of units.

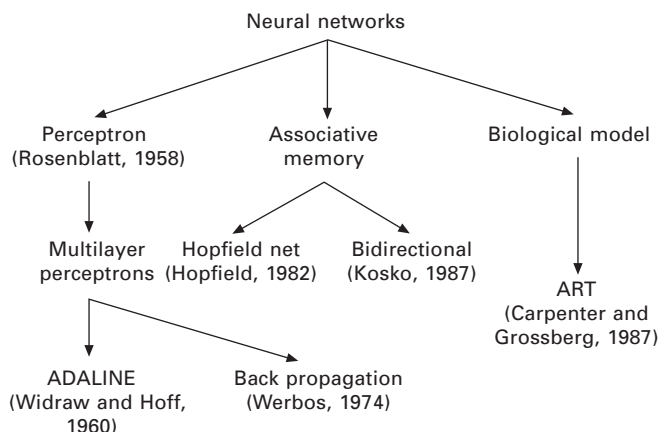
Another revitalization of the field came from the publications in 1986 of

two volumes on parallel distributed processing, edited by James McClelland and David Rumelhart (McClelland and Rumelhart, 1986). The new learning rules and other concepts introduced in this work have removed one of the most essential network training barriers that grounded the mainstream efforts of the 1960s. Many researchers have worked on the training scheme of layered networks. The reader is referred to Dreyfus (1962, 1990), Bryson and Ho (1969) and Werbos (1974).

Figure 2.1 shows the three branches and some leading researchers associated with each branch. The perceptron branch, associated with Rosenblatt, is the oldest (late 1950s) and most developed. Currently, most neural networks (NNs) are perceptrons of one form or another. The associative memory branch is the source of the current revival in NNs. Many researchers trace this revival to John Hopfield's 1982 paper. The biological model branch, associated with Steve Grossberg and Gail Carpenter, is the fastest developing and might have the greatest long-term impact.

2.3 Neural network models

Neural network models in artificial intelligence are also commonly known as artificial neural network (ANN) models. The models are essentially simple mathematical constructs of the kind $f: X \rightarrow Y$. The word network defines $f(x)$ as a function of $g(x)$ which again can be a function of $h(x)$. Hence, there is a network of functions which are dependent on the previous layer of functions.



2.1 A simplified depiction of the major neural network schools. Perceptron, associative memory and the biological model are three categories of neural networks that overlap but differ in their emphasis on modelling, applications and mathematics. The principles are the same for all schools.

This can be represented as a network structure, with arrows depicting the dependencies between variables as shown in Fig. 2.2.

A commonly used representation is that of the non-linear weighted sum as:

$$f(x) = K\left(\sum_i w_i g_i(x)\right)$$

where K is a predefined function and is commonly referred to as the activation function, such as the hyperbolic tangent. In linear regression the general form of the equation is generally a sum of inputs x_i each of which is multiplied by a corresponding weight w_i , and a constant θ : $y = \sum_i x_i w_i + \theta$.

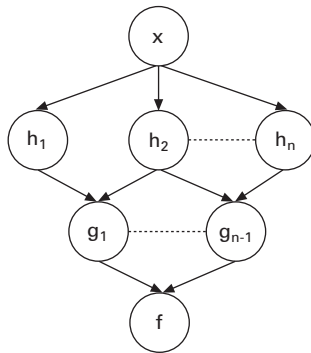
Similar to linear regression, the input variable x_i is multiplied by weight w_{ij} , but the sum of all these products forms an argument of another transfer function. The transfer function could take the form of a Gaussian or a sigmoid in most cases. The final output is, however, defined as a linear function of hidden nodes and a constant. Mathematically, this could be represented as follows:

$$y = w_i^{(2)} h_i + \theta^{(2)}$$

where

$$h_i = \tanh\left(\sum_j x_j w_{ij}^{(1)} + \theta^{(1)}\right)$$

Figure 2.2 represents the decomposition of the functions as in ANN, with dependencies between variables indicated by arrows. There can be two interpretations for this, the first being functional and the second probabilistic. In the functional interpretation, the input x is transformed into a three-

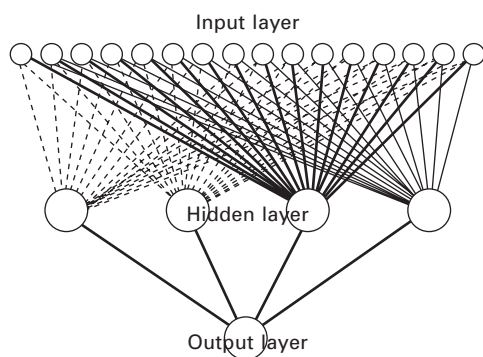


2.2 A simplified representation of function dependency as in a network.

dimensional vector h , which is then transformed into a two-dimensional vector g , which is finally transformed into f . In the probabilistic interpretation the random variable $F = f(G)$ depends upon the random variable $G = g(H)$, which depends upon $H = h(x)$, which depends upon the random variable X . The functional interpretation is more accepted in the context of optimization, whereas the probabilistic interpretation is more accepted in the context of graphical models.

As observed in Fig. 2.2, each layer feeds its output to the next layer until the final output of the network is arrived at f . This kind of network is known as a *feed-forward network*. A much more general representation of such a network is shown in Fig. 2.3. Each neuron in the input layer is connected to every neuron in the hidden layer. In the hidden layer, each neuron is connected to the next layer. There could be any number of hidden layers, but usually one hidden layer would suffice for most problems. Every neuron in the hidden layer is further connected to the output layer. In Fig. 2.3, only one output is shown in the output layer, but there could be more than one output.

Once the neural network with the appropriate inputs in the input layer, the hidden layer and the output layer is created, it has to be trained to decipher an impression of the pattern existing in the data. This pattern is expressed in terms of a function with appropriate weights and biases. The weights are normally selected through the randomization process. The weights so selected are fitted in the function to observe whether the necessary output has been arrived at; otherwise the weight adjustment continues. This is essentially an optimization exercise where the appropriate weights and biases are obtained. The training is complete when the weights and biases are appropriately adjusted to obtain the required output. In such a training process the network is given with the inputs and the output through a database from which the



2.3 General representation of a network in ANN feed-forward systems.

learning can happen. Hence this learning process is termed *supervised learning* and the data that are fed from the database are the *training set*. There are many ways to adjust the weights, the most common way being through *backpropagation* of the error. The backpropagation algorithm will not be discussed in this chapter as it is beyond the scope.

Although the weights and biases are optimized to find a function to fit the data by the neural network training process, there is every possibility that one function may not be able to represent all the data points in the database. Hence, there is a need to assess the uncertainty that is introduced through models that can fit various patterns in the data. The next section highlights the importance of this uncertainty.

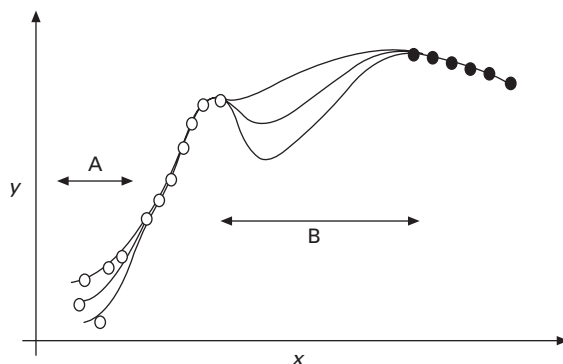
2.4 Importance of uncertainty

A series of experimental outcomes with similar settings (or inputs) result in a standard deviation from the mean. This is the reason why any experiment is performed at least three times to assess the consistency. Noise gets introduced even at the stage of experimentation, hence the database, constructed from experiments has this noise as its component.

The database thus consisting of several data points could be fitted by several different functions. There can be more than one function to represent a dataset accurately. However, all functions or models may not extrapolate in a similar manner. Hence, a function can be correct if its extrapolation makes physical sense and incorrect otherwise. In cases where the science has not yet evolved to decipher the physical sense, all models may be considered appropriate. There is now uncertainty existing: any of the models could be correct. Hence, all models that correctly fit the experimental data need to be considered. The band of uncertainty thus increases from the known region to the unknown regions of the input space. In the known region all models predict in a similar manner and hence the uncertainty remains less, whereas in the unknown regions of the input space each model behaves differently thus contributing to a large uncertainty.

This can be explained using Fig. 2.4. Region A, which has a scatter in the database, results in more than one model representing the space. Hence, the uncertainty is higher. Region B, where there is no prior information in the database, results in models extrapolating into different zones, thus leading to larger uncertainty. The regions between A and B and those represented by closed circles are accurately represented by all the models and hence the uncertainty remains low.

Larger uncertainty warns of insufficient information to decipher the knowledge. This also paves the way for experimental exploration to get more insight into the physical reality and thus validation to choose the appropriate models or functions.



2.4 Plot showing uncertainty in prediction depending upon the input space.

Following this introduction, the next section highlights the application of neural networks in alloy design.

2.5 Application of neural networks in materials science

ANN finds application in many fields, more importantly electronics due to the large amount of data required to be processed. In the last decade, application of ANN has also been extended to the field of materials science. Applications include alloy design, iron and steel making, hot working, extrusion, foundry metallurgy, powder metallurgy, nano materials and welding metallurgy. The next few subsections highlight some of these applications.

2.5.1 Non-destructive testing

Non-destructive testing (NDT) consists of a gamut of non-invasive techniques to determine the integrity of a material, component or structure or quantitatively to measure some characteristic of an object. In contrast to destructive testing, NDT does not harm, stress or destroy the test object. The destruction of the test object usually makes destructive testing more costly and is also inappropriate in many circumstances. Many methods are used for flaw detection in steel slabs using NDT techniques of which ultrasonic testing is the most widely used industrial practice. In this test process, waves of ultrasound are passed into the steel slabs to check for discontinuities within the slabs (Baosteel). Coarser grain sizes in steel act as scattering centres and form randomly distributed background noise, obstructing the recognition of flaw echoes. Flaws in steels consist mainly of inclusions, bubbles and cracks and all three affect the quality of steels in their own way, so flaw detection

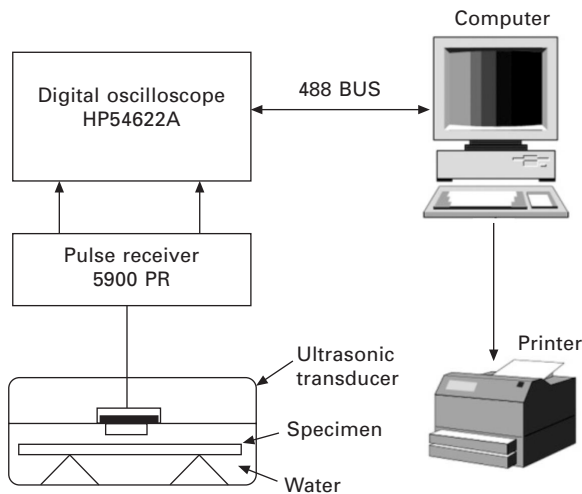
in steels is becoming more and more significant and urgent, especially when the quality of the steel is compromised.

Neural networks have been largely employed in the field of pattern recognition and data compression. Some of the commonly used networks are learning vector quantization networks, probabilistic neural networks and self-organizing maps (Baker and Windsor, 1989; Santos and Perdigão, 2001) which have been reported for signal classification works. Ultrasonic signals containing different defect echoes are decomposed by wavelet transform methods (which process the signals with localized core function and have excellent resolution either with time or with frequency) and analysed by multi-resolution techniques (which can provide detailed location feature and frequency information at any given decomposition level, focusing on any part of the signal details). These defect signals are used as the dataset.

The test setup, shown in Fig. 2.5, that was used to capture the data comprised a 20 MHz transducer (Panametrics V116-RM, 3 mm diameter), a 200 MHz HP54622A digital oscilloscope, a Panametrics 5900PR ultrasonic pulse-receiver analyser, and a personal computer. The detected result was displayed in A-type ultrasonic scanning mode. Flaw detection was carried out by immersing the specimen and the probe perpendicularly into the water so as to avoid the influence of the near-field of the energy transducer.

The following procedure was adopted for testing the specimen:

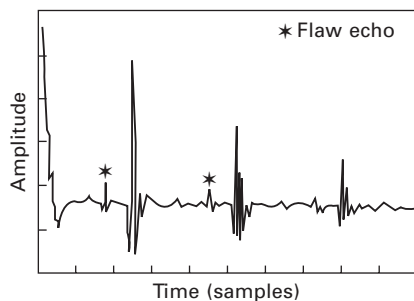
1. Inspection of the specimen by the immersion mode
2. Signal process and character data extraction
3. Checking ultrasonic test results by metallographic examination
4. Classification of the character waveform data



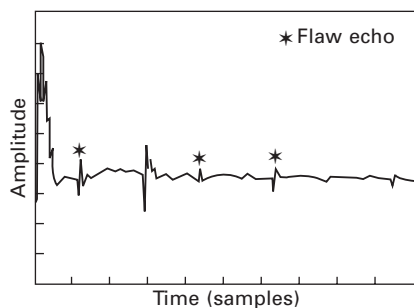
2.5 Experimental ultrasonic setup.

5. Selection of the neural network architecture
6. Training the neural networks
7. Testing the neural networks.

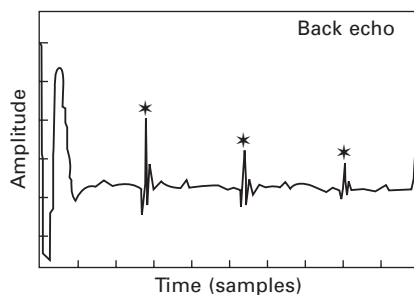
Figures 2.6, 2.7 and 2.8 represent the specimen with defects such as bubbles and inclusions and a non-defective specimen respectively. In all three, back wall echoes are plotted from the first water specimen interface to the third back wall echo of the specimen. The flaw echo is randomly located between these back wall echoes. The back wall reflection echoes had high frequency



2.6 Specimen with bubble.



2.7 Specimen with inclusions.



2.8 Non-defective specimen.

levels when compared to the flaw echoes which were of lower frequency. These higher frequency signals were filtered and all the flaw signals were compiled into a dataset for the neural networks. The dataset consisted of 120 discrete flaw signals. For the current work, 42 data points were collected, namely 13 bubble flaws, nine artificial slots and 20 inclusions, all taken from the first ultrasonic cycle in the specimen, after the disturbance of the probe near-field had been eliminated. Signal analysis revealed that the echo amplitude was comparatively higher than in other later cycles. Based on these results, 32 data points were randomly collected for the training set; the remaining 10 signals were used as the testing set, named set I, and testing set II was 10 data chains randomly chosen from the training set. The flaws were classified using the following neural networks.

Learning vector quantization (LVQ) networks are composed of a competitive layer and a linear layer. The competitive layer is responsible for classification of the input vectors, and the linear layer then transforms the competitive layer's classes into predefined target classifications. The number of neurons in the linear layer is less than that in the competitive layer (Baker and Windsor, 1989).

Probabilistic neural networks (PNN) can be used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a *complete* transfer function on the output of the second layer picks the maximum of these probabilities, and produces a '1' for that class and a '0' for the other classes (<http://www.dtreg.com/pnn.htm>).

The architecture of self-organizing maps (SOM) is based on simulation of the human cortex. These are also called self-organizing feature maps (SOFM) and are a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (generally two-dimensional) discretized representation of input space of the training samples, called a map. The neurons in the layer of an SOFM are arranged originally in physical positions according to a topological function, and these layers of neurons are used for network construction. SOM networks produce different responses with differed input vectors (http://en.wikipedia.org/wiki/Self-organizing_map). This makes them useful for visualizing low-dimensional views of high-dimensional data, akin to multi-dimensional scaling.

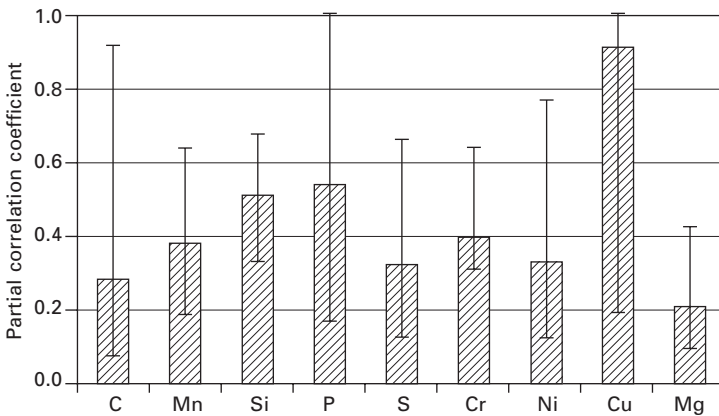
2.5.2 Foundry processes

There are many sectors in foundry processes where ANN can be used effectively. One such application is to predict the Brinell hardness, tensile

strength and elongation of ductile cast iron, based on industrial analysis of the chemical composition of the cast iron and other input parameters. Models have been developed for the above output parameters and checked with the input parameters collected from other foundries. It was also found from Fig. 2.9 that copper plays a significant role in the strength of ductile cast iron, as it improves the austemperability. The height of the bars in Fig. 2.9 gives the averaged results of the trained dataset and the black lines denote their scatter in the trained dataset.

A similar process was carried out for austempered ductile cast iron, which is one of the most advanced structural cast iron materials. The input parameters were the heat treatment time and temperature, the chemical composition of the cast iron, the amount and shape of graphite precipitations, and the geometry and casting conditions of the casting. The parameters were fed to the network against the output variable strength and the predictions were found to be within their standard limits. Apart from the strength predictions, casting defects can also be identified. During the casting process, different parameters influence the occurrence of defects, such as operating conditions, environmental conditions, sand permeability, vapour pressure in the mould, time from moulding to pouring, and air humidity. Analysis from the models has led to a conclusion that the direct cause of gas porosity was water vapour pressure in the vicinity of the mould cavity.

Neural networks have been used as an aid for decision making regarding the new additives to bentonite moulding sand. ANN also find wide use in other foundry applications such as the breakout forecasting system for continuous casting, control of cupola and arc furnace melting, power input control in the foundry, design of castings and their rigging systems, design of vents in core boxes, green moulding sand control, predicting material



2.9 Significance of the composition of ductile iron on the mechanical properties.

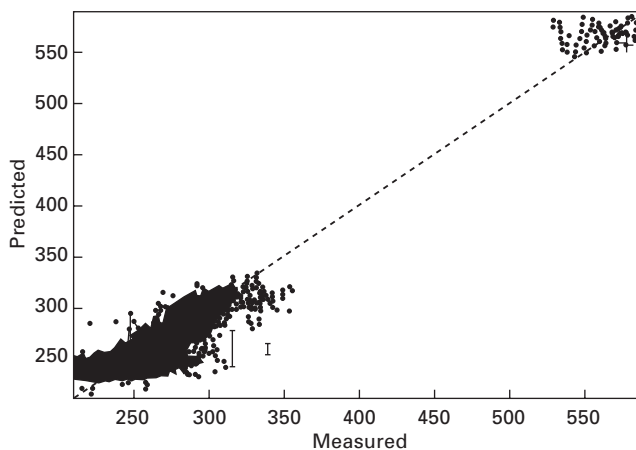
properties in castings, the determination of pressure die casting parameters (Perzyk, 2005).

2.5.3 Complex applications

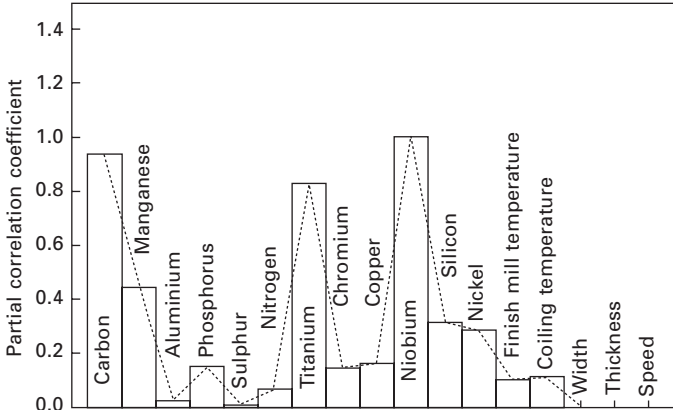
Apart from solving simple problems, ANNs are also used to solve complex industrial problems such as those found in steel plants. One such application that was carried out for the ladle furnace at V&M do, Brazil, was used to predict the steel temperatures in the ladle furnace (Sampaio *et al.*, n.d.). The models were used as a tool to support the production process by making the steel temperature behaviour visible. Some of the gains from these models were reduction in electric power consumption and reduction of the number of temperature measurements.

The rolling process in the production of steel plates involves a very large number of variables, including chemical composition, processing parameters, temperature of the slab in the furnace, temperature at the entry and exit of the mill, and coiling temperatures. In this case, neural network models were developed to calculate the mechanical properties (lower yield strength, tensile strength and elongation) of the steel strips, which included 18 input variables. The neural network output for a mechanical property (yield strength) is shown in Fig. 2.10, which plots the measured experimental strength against that predicted by the neural network.

These models are also capable of capturing the inner science possessed by the input data. This can be explained using the significance charts shown in Fig. 2.11, which measure the strength of association between the dependent variable (output) and one independent variable (input) when the effects of all



2.10 Experimental vs predicted yield strength plot.



2.11 Significance chart for yield strength.

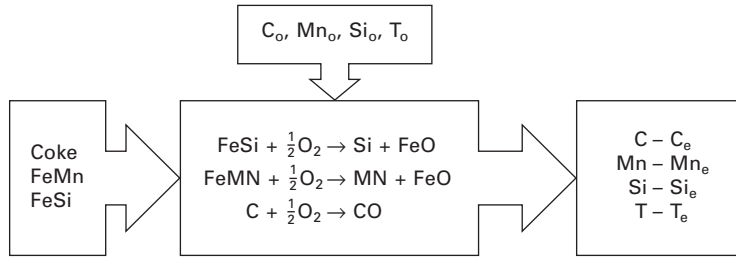
other independent variables are removed. It is an excellent achievement that these models are also used for online predictions of the properties at a hot strip mill. It is obvious that the analysis using neural networks is complex and nonlinear, which means that unexpected and elegant relationships may emerge which sometimes may not be obtained through experimental routes.

The ladle metallurgical refining process is another area which involves complex relations between process variables. The main chemical reactions are the oxidation of iron and the augmentation of manganese, silicon and carbon in liquid steel. These reactions are complex and depend particularly on the thermodynamic parameters. Models were developed to predict the liquid steel temperature variation and the variation of chemical composition (C, Mn, Si), the input parameters being the additions of different raw materials (coke, FeMn, FeSi), the thermodynamic parameters (initial steel temperature) and the initial chemical composition of liquid steel (C, Mn, Si) (Bouhouche *et al.*, 2004). All the chemical reactions are controlled by temperature and pressure, but in this work the pressure was considered to be a constant. Figure 2.12 gives a schematic view of different reactions that take place in a ladle.

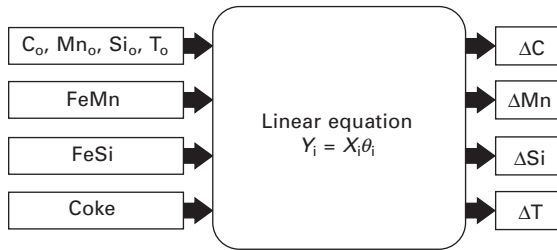
A study comparing the linear approach obtained by the iterative least-squares algorithm and the nonlinear approach based on the backpropagation learning algorithm was carried out by Bouhouche *et al.* (2004). The structures of the linear and neural network models are shown in Figs 2.13 and 2.14. Where X is the set of input variables,

$$X = [C_0, Mn_0, Si_0, T_0, FeSi, FeMn, Coke]$$

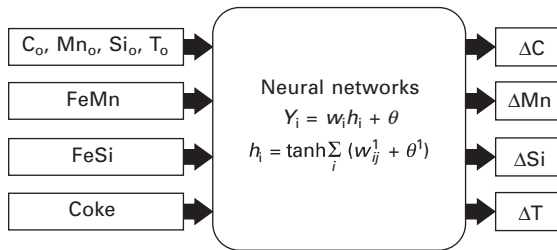
and Θ_i is the estimated parameter vector for each output i



2.12 Input/output reactions.



2.13 Structure of linear model.



2.14 Structure of neural network model.

$$\Theta_i = [aC_{0i}, aMn_{0i}, aSi_{0i}, aT_0, bFeSi_i, bFeMn_i, bCoke_i]$$

the output is given by

$$y_i = [\Delta C, \Delta Mn, \Delta Si, \Delta T]$$

where T_0 is the initial temperature of the steel. The result from the two different models after testing with unseen data (the data which the model has not confronted during the training process) concluded that the output predictions from the neural network models were better than those of the linear model. Because the cast cycle which was used was long, and the learning process was easily realized between the actual and the next cast, the prediction ability using neural networks improves the prediction capacity.

2.5.4 Alloy design

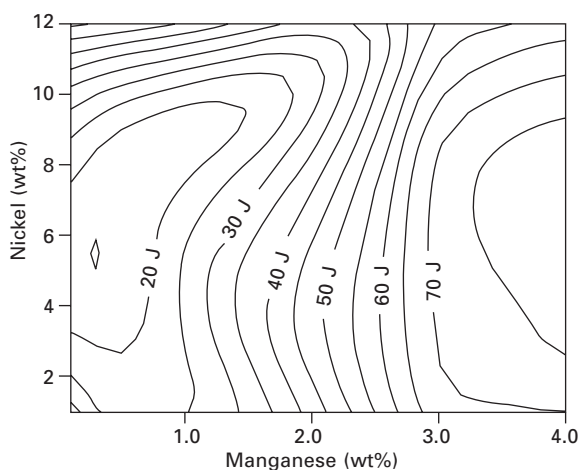
Welding is an established process, which originated many years ago when man first became proficient in the manufacture of wrought iron. Thereafter, the use of this process multiplied rapidly and today this method of joining is the dominant feature in modern metalworking. It has been proven that neural networks can be used to discover better alloys for demanding applications like welding. One such is the evolution of coalesced bainite, which was the outcome of research work on high nickel-ferritic welds carried out by Muruganath and colleagues (Muruganath, 2002; Muruganath *et al.*, 2002).

Coalesced bainite occurs when the transformation temperatures are suppressed by alloying such that there is only a small difference between the bainitic and martensitic start temperatures (Bhadeshia, 2009). The nickel and manganese concentrations in these steel welds were adjusted in order to achieve better toughness. Using neural networks, it was discovered that at large concentrations, nickel is only effective in increasing toughness when manganese concentration is small. The effect of nickel and manganese concentrations on toughness is shown in Figs 2.15 and 2.16.

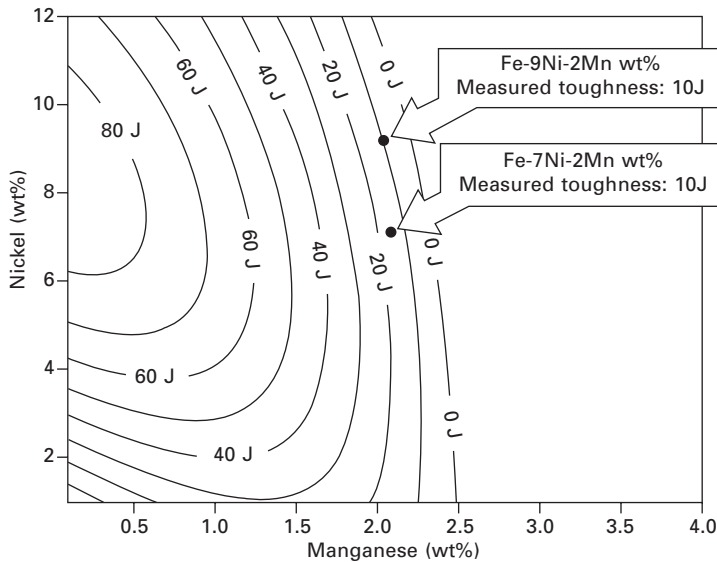
In this context, neural networks do not of course indicate the mechanism for the degradation of toughness when both the nickel and manganese concentrations are high. The discovery of coalesced bainite in weld metals is a direct and unexpected consequence of neural network modelling.

2.6 Future trends

Apart from the applications listed above neural networks find extensive application in other areas such as robust pattern detection, signal filtering, virtual reality, data segmentation, text mining, artificial life, optimization



2.15 Predictions of toughness within $\pm 1\sigma$ uncertainty.



2.16 Predicted effect of Mn and Ni concentrations on toughness as predicted using neural networks.

and scheduling, adaptive control and many more. The applications are ever growing, and others of importance also include financial analysis (stock prediction), signature analysis, process control oversight, direct marketing, etc.

The future of neural networks is wide open. There is much to be discovered in the behaviour of nature. Research is being undertaken into the development of conscious machines that have their base engine functioning on neural networks. There have also been debates on whether neural networks can pave the way to finding answers about intelligence. Though neural networks are considered as statistical models, will enough information lead to learning that is akin to intelligence? There is a long way to go before neural networks can provide the answers. Nevertheless, intelligence in conscious beings and statistical models like ANN stand way apart in their functioning. Neuro-fuzzy models have been used to observe whether models could represent nature more realistically.

In conclusion, there are no limits on what neural networks could achieve. But the highest one could achieve is replication of nature itself.

2.7 Acknowledgements

I would like to thank Tata Steel, Jamshedpur, for all their support. Thanks are due to my research associate Mr R Thyagarajan for his support in drafting this chapter.

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Abstract: Methods for building empirical models may be broadly divided into three categories: linear statistical methods, neural networks and nonlinear multivariate statistical methods. This chapter demonstrates the basic principles of empirical model building and surveys the criteria for parameter estimation. The development of regression-type models, including techniques for exploratory data analysis and reducing dimensionality, is described. Typical empirical models for linear and nonlinear situations are discussed, along with evaluation of model quality based on degree of fit, prediction ability and other criteria. The main techniques for building empirical models are compared. The second part of the chapter describes some variants of neural networks. Radial basis function (RBF) networks are described in detail. The application of RBF networks in modeling univariate and multivariate regression problems is discussed. Finally, the application of neural networks in color difference formulae and drape prediction is presented.

Key words: empirical model building, parametric regression, nonparametric regression, special regression models, neural networks.

Make the model as simple as possible, but not simpler! *A. Einstein*

3.1 Introduction

There is a wide variety of methods for empirical model building. These methods may be broadly classified into three categories: linear multivariate statistical methods, neural networks, and nonlinear multivariate statistical methods. Selecting the appropriate empirical modeling method is an art, since it involves the use of *ad hoc*, subjective criteria. Strictly speaking, neural and statistical modeling methods have several complementary properties. Linear and nonlinear statistical methods are usually more open to physical interpretation and are often based on theoretical arguments which facilitate model selection, estimation of parameters and validation of results [1]. Neural networks are especially well suited for large-scale computation, recursive modeling and continuous adaptation, but are ‘black box’ in nature and often require a large amount of training data to obtain acceptable results [15].

The first part of this chapter describes the basic principles of empirical model building. Techniques for empirical model building are surveyed and typical models for linear and nonlinear situations are compared. The estimation

procedures based on the normality of error distribution are derived and the evaluation of model quality based on the degree of fit, prediction ability and other criteria is discussed.

In the second part, selected neural networks are discussed. Radial basic functions (RBF) networks are described in detail. The application of RBF for modeling univariate regression problems (the Cui–Hovis function for color difference formula), and multivariate regression problems (drape prediction from Kawabata fabric parameters), are discussed. The MATLAB system is used for all computations. The MATLAB package NETLAB [20] and MATLAB functions for radial basic function – RBF2 toolbox [21] are used for neural network computations.

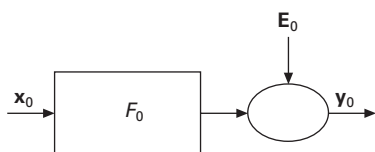
The final part of the chapter provides a brief survey of the application of selected neural networks in textiles.

3.2 Empirical model building

Building an empirical model is a relatively specific discipline capable of solving many of the practical problems associated with constructing nonlinear models $f(\mathbf{x}, \boldsymbol{\beta})$ based mainly on data behavior. In this chapter, basic information about models, different types of models, and techniques of model building are summarized.

3.2.1 Models of systems

The role of a model is to generalize information about a given system. Let us take system F_0 transforming causes (inputs) $\mathbf{x}_0$ to the effect (output) $\mathbf{y}_0$. Due to various types of disturbances, $\mathbf{E}_0$ (errors) are outputs and $\mathbf{y}_0$ are random variables. The main source of error is often measurements (see Fig. 3.1). *Modeling* is a way of describing some of the features of an investigated system (original) by using a (physical, abstract) model and defined criteria. Instead of the inputs $\mathbf{x}_0$, a subset of explanatory variables $\mathbf{x}$ is used and outputs $\mathbf{y}_0$ are replaced by scalar response y . The unknown functions F_0 transforming inputs into outputs are replaced by model $f(\mathbf{x}, \boldsymbol{\beta})$. Disturbances $\mathbf{E}_0$ are characterized by errors ε_i (errors due to measurement). The selection of the best model form is the main goal of modeling.



3.1 Deterministic system with stochastic disturbances.

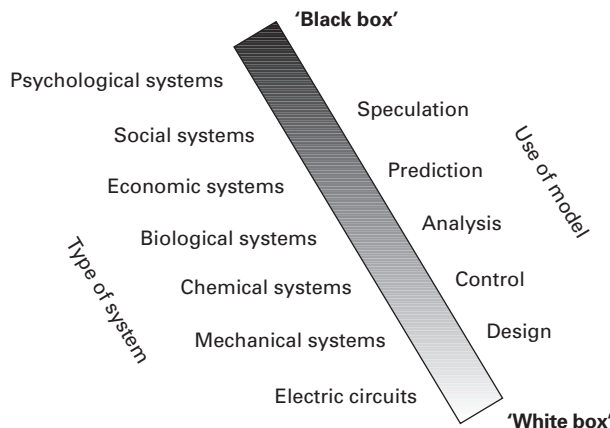
In some disciplines (e.g. physics and chemistry) systems are simple and well organized. Models thus have a physical background and are dependent on a small number of interpretable parameters. The creation of models is based on hypothesis and theories, the scientific approach. However, this modeling style is very knowledge-intensive, and the lack of expertise is an ever-increasing problem. The larger the system, the more probable it is that a model will not be suited for real use.

In other disciplines (e.g. economics, medicine and sociology) systems are huge and badly organized. There are many variables and no identifiable influences. Plenty of inexact data are collected and modelers attempt to find the relevant system properties underlying the measurements. Instead of being knowledge-intensive, these models are data-oriented.

In the technical sciences, we typically find the partially disorganized, diffusion-type systems. Physical processes are involved, but unknown or partially known factors and connections also have an influence. Empirical models are constructed with regards to prediction ability or model fit (data approximation), prognostic ability (forecasting) and model structure (agreement with theories and facts).

Empirical model building is becoming more and more common and the systems being modeled are becoming more complicated and less structured (see Fig. 3.2). There are three main ways in which empirical models are utilized:

- *Calibration models*, where the measured response variable y is a nonlinear function of the exploratory (adjustable) variables x
- *Mechanistic models*, which describe the mechanisms of processes or transformation of input variables x to output y (examples are chemical



3.2 Systems and models [4].

reactions and equilibriums or the dynamic processes in liquids and solids)

- General *empirical models* based on a study of the nonlinear dependence between the response variable y and explanatory variables x .

Empirical models are often used for exploring product properties P using the properties of materials and process variables x_j , for instance:

- Identification of links between explanatory variables $x_i = 1, \dots, m$ for removing multicollinearity and elimination of parasite variables
- Selection of dependencies between response P and explanatory variables x to modify and improve model $P(x)$ (including interaction and nonlinearities)
- Data quality examination from the point of view of limited range (e.g. the number of chemical elements is limited on both sides), presence of influential points (outliers, extremes), and non-normality of data distribution.

Data-based multiple linear and nonlinear model building is generally the most complex in practice. In many cases, it is not possible to construct a mathematical model based on the available information about the system under investigation. In these cases, an interactive approach to empirical model building could be attractive. Classical tasks solved by empirical model building in textiles include:

- Describing the dependence between fiber properties and the properties of fibrous structures
- Quantifying the influence of process parameters on the structural parameters and properties of fabrics
- Predicting non-measurable properties of textiles from some that are directly measurable (e.g. hand or comfort prediction), known as multiple calibration
- Optimizing technological processes based on appropriate models, such as Taylor expansion models (the experimental design approach).

In all these examples, there are very complex interdependencies and therefore data-based models with good predictive capability are required.

Building an empirical model can be divided into the following steps [1]:

1. Task definition (aims)
2. Model construction (selection of provisional model)
3. Realization of experiments
4. Analysis of assumptions about model, data and estimation methods used (model diagnostic)
5. Model adjustment (parameter estimation)

6. Extension and modification of model, data and estimation method
7. Testing model validity, prediction capability, etc., based on experiment, hypotheses, and assumptions.

The practical realization of these steps is described in [1].

In order to find the proper criterion for model adjustment and to make a statistical analysis, the distribution of the response quantities y_i must be determined. This distribution is closely related to the distribution of errors ε_i given by the probability density function $p_\varepsilon(\varepsilon)$. This function depends on distribution parameters such as variance σ^2 , etc. The error distribution is assumed to be unimodal and symmetrical, with the maximum at $E(\varepsilon) = 0$. It is often assumed that the measurement errors ε_i are mutually independent. The joint probability density function $p_\varepsilon(\varepsilon_i)$ is then given by the product of the *marginal* densities $p_\varepsilon(\varepsilon_i)$. Several distributions, including normal, rectangular, Laplace and trapezoidal, may be expressed by the probability density function

$$p_\varepsilon(\varepsilon_i) = Q_N \exp(-|\varepsilon_i|^p/\alpha) \quad 3.1$$

where Q_N is the normalizing constant and α is a parameter proportional to the variance. If $p = 1$, the resulting distribution is Laplace. When $p = 2$, the distribution is normal, and when $p \rightarrow \infty$ it is rectangular. For the additive model of measurements (see Eq. (3.13) in Section 3.2.3), the following relation results:

$$p(y_i) = p_\varepsilon(y_i - f(x_i, \beta)) \quad 3.2$$

Hence, it may be concluded that the additive model does not cause any deformation of the distribution of the measured quantities with regard to the error distribution. For the vector of response (measured) values $\mathbf{y} = (y_1, \dots, y_n)^T$, the joint probability density function is denoted by the likelihood function $L(\theta)$. This function depends on the vector of parameters, θ , which contains the model parameters, β , and distribution parameters, σ . The maximum likelihood estimates of parameters, $\hat{\theta}$, are determined by maximization of the logarithm of the function [1]:

$$\ln L(\hat{\theta}) = \ln p(\mathbf{y}) = \sum_{i=1}^n \ln p(y_i) \quad 3.3$$

For maximum likelihood estimates, some important properties may be derived [1]:

- The estimates $\hat{\theta}$ are asymptotically ($n \rightarrow \infty$) unbiased. For a finite sample size n , the estimates $\hat{\theta}$ are biased and the magnitude of bias depends on the degree of nonlinearity of the regression model.
- The estimates $\hat{\theta}$ are asymptotically efficient and the variance of estimates

is minimal for all unbiased estimates. For finite samples, this property is generally not fulfilled.

- The random vector $\sqrt{n}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})$ has, asymptotically, the normal distribution $N(0, \mathbf{I}^{-1})$ with zero mean and variance equal to the inverse of the Fisher information matrix [1]. When the error distribution is approximately normal, the normality of estimates is valid for finite samples.

For sufficiently large sample sizes, many interesting properties of the estimates $\hat{\boldsymbol{\theta}}$ may be used. For finite sample sizes, some difficulties arise from the biased estimates $\hat{\boldsymbol{\theta}}$. If the probability density function $p(\mathbf{y})$ is known, the maximum likelihood estimates or a criterion for their determination (the *regression criterion*) may be found.

When measurement errors are independent, with zero mean, constant variance, and distribution defined by Eq. (3.1), and assuming the additive model of measurement errors (see Eq. (3.6) in Section 3.2.2), maximum likelihood estimates computed by minimizing of the criterion are

$$U(\boldsymbol{\beta}) = \sum_{i=1}^n (y_i - f_i)^p \quad 3.4$$

For a normal distribution of errors $N(0, \sigma^2 \mathbf{E})$ with $p = 2$, from Eq. (3.4) the criterion of the *least-squares* (LS) or the residual sum of squares of deviations results, denoted as $S(\boldsymbol{\beta})$. For geometric interpretation, the least-squares criterion $S(\boldsymbol{\beta})$ is rewritten in vector notation as

$$S(\boldsymbol{\beta}) = \|\mathbf{y} - \mathbf{f}\|^2$$

where $\mathbf{y} = (y_1, \dots, y_n)^T$, $\mathbf{f} = (f(x_1, \boldsymbol{\beta}), \dots, f(x_n, \boldsymbol{\beta}))^T$ and the symbol $\|\mathbf{x}\| = \sqrt{\mathbf{x}^T \mathbf{x}}$ means the Euclidean norm. Examination of the shape of the criterion function $S(\boldsymbol{\beta})$ in the space of the estimators helps to explain why the search for the function minimum is so difficult. In this $(m + 1)$ -dimensional space, values of criterion $S(\boldsymbol{\beta})$ are plotted against the parameters $\beta_1, \dots, \beta_m$.

For linear regression models, the criterion function $S(\boldsymbol{\beta})$ is an elliptic hyperparaboloid with its center at $[\mathbf{b}, S(\mathbf{b})]$, the point where $S(\boldsymbol{\beta})$ reaches a minimum.

The modeling problem is generally formulated with regard to a triplet:

- The training data set
- A proposed model
- A criterion for estimation of model parameters.

The problem consists of a search for the best model $f(\mathbf{x}, \boldsymbol{\beta})$ based on the data set $(y_i, x_i), i = 1, \dots, n$, such that the model sufficiently fulfills the given criterion.

In the interactive strategy of empirical model building [1] used here,

graphically oriented methods for estimating model accuracy and identifying spurious data are used. These methods are based on special projections enabling partial dependencies of response on the selected exploratory variable to be investigated. Classical ones are partial regression plots or partial residual graphs. Nonlinear or special patterns in these graphs can be used to extend the original model and include nonlinear terms or interactions. The analysis of influential points can also be used to identify spurious data. To evaluate model quality, characteristics derived from predictive capability are used. Some statistical tools for these techniques are described in [1].

3.2.2 Hard and soft models

Models for industrial processes are frequently created using the classical methods of experimental design. This approach, while it enables experimental conditions to be optimized, often leads in practice to incorrect models containing too many parameters [1].

The approach to building the model $f(\mathbf{x}, \boldsymbol{\beta})$ is chosen according to the type of task. The model $f(\mathbf{x}, \boldsymbol{\beta})$ is a function of a vector of explanatory variables $\mathbf{x}$ and of a vector of unknown parameters $\boldsymbol{\beta}$ of dimension $(m \times 1)$, $\boldsymbol{\beta} = (\beta_1, \dots, \beta_m)^T$. For adjustment of nonlinear models, the set of points, $(y_i, \mathbf{x}_i^T)$, $i = 1, \dots, n$ (the training set), where y represents the response (dependent) variable, is used. The dimension of vector $\mathbf{x}_i$ does not directly affect the dimension of vector $\boldsymbol{\beta}$.

For the so-called *hard models*, the main aim is to select the appropriate function $f(\mathbf{x}, \boldsymbol{\beta})$. This function is typically in the explicit form and is used instead of the original.

Soft models are used for approximation of unknown functions given by a table of values $(\mathbf{x}_i, y_i)$, $i = 1, \dots, n$. Function $f(\mathbf{x}, \boldsymbol{\beta})$ is often replaced by a linear combination of some elementary functions $h_j(\mathbf{x})$. Final function forms are often too complex to be expressed in the explicit form and are typically applied jointly with data using computers. Typical elementary functions $h_j(x)$ are polynomials x^{j-1} , rational functions such as the ratios of polynomials, trigonometric functions, exponential functions, kernel functions (in the form of symmetric unimodal probability density function), etc. The choice of approximate function depends on the application, and affects the quality of the approximation; that is, the distance between the soft model and the discrete values y_i .

The application of continuous elementary functions $h_j(x)$ on the whole real axis has many disadvantages. The resulting models, often of higher degree, may have many local minima, maxima, and inflections that do not correspond to the data (x_i, y_i) , $i = 1, \dots, n$ trends. In modeling physical data, the behavior in a particular interval may differ significantly from that in adjoining intervals. These relationships are said to be non-associative in

nature. Therefore, for modeling purposes, it is more convenient to select locally defined functions that are continuous in functional value and the values of the derivatives at the connecting points (i.e. the knots).

Model functions are composed of polynomial segments, and belong to the class $C^m[a, b]$. Generally a $C^m[a, b]$ function is continuous, in the interval $\langle a, b \rangle$ in functional values, and in the first m derivatives [1]. For functions of class C^m , the m th derivative is a piecewise linear function, the $(m + 1)$ th derivative is piecewise constant and the $(m + 2)$ th derivative is piecewise zero, and is not defined at the knots ξ_i .

By using these properties of $C^m[a, b]$ functions we can define a general polynomial spline $S_m(x)$ with knots $a = \xi_1 < \xi_2 < \xi_3 < \dots < \xi_n = b$. In each interval $[\xi_j, \xi_{j+1}]$, $j = 1, \dots, n - 1$, this spline is represented by a polynomial of, at most, m th degree. If at any point x_i some derivative $S_m^{(1)}(\xi_i)$ is non-continuous, we have a *defect spline*. The properties of spline $S_m(\xi_i)$ depend on the following [17, 18]:

- The degree m of the polynomial (a cubic spline $m = 3$ is usually chosen)
- The number and positions of knots $\xi_1 < \xi_2 < \dots < \xi_n$
- The defects in the knots.

Classical splines with minimal defect equal to $k = 1$ are from the class $C^{m-1}[a, b]$. To create a model function based on the splines, it is simple to use truncated polynomials

$$S_m(x) = \sum_{j=0}^m a_j x^j + \sum_{i=1}^n b_j (x - \xi_j)_+^m \quad 3.5$$

where

$$(x)_+ = \begin{cases} x & \text{for } x > 0 \\ 0 & \text{for } x \leq 0 \end{cases} \quad 3.6$$

The corresponding model is linear in the parameters **a** and **b**, and contains in total $(n + m + 1)$ parameters. When the number and position of knots are estimated, the corresponding model is nonlinear [17, 18]. Truncated polynomials are used in the multivariate adaptive regression splines (MARS) introduced by Friedman [19]. This can be seen as an extension of linear models that automatically add nonlinearities and interactions. MARS is a generalization of recursive partitioning that allows the model to better handle complex data sets.

Soft models $g(x)$ should usually be sufficiently smooth and continuous for a selected number of derivatives. Let us restrict ourselves to a common case, where $g(x)$ is twice differentiable (i.e. from class $C^2[a, b]$ where

$a = x_1$ and $b = x_n$). The criterion of smoothness can be described by the integral

$$I(g) = \int_a^b [g^{(2)}(x)]^2 dx \quad 3.7$$

where $g^{(2)}(x)$ is the second derivative of the smoothing function. The integral $I(g)$ is called the *smoothness measure* in the curvature of function $g(x)$. The corresponding least-squares criterion has the form

$$U(g) = \sum_{i=1}^n w_i [y_i - g(x_i)]^2 \quad 3.8$$

where w_i denotes the weight of individual points; this depends only on their ‘precision’ or scatter.

The goal is to find a function $g(x)$ with a sufficiently small value of $U(g)$, i.e. it should be close to the experimental data, and have a small value of $I(g)$. Finding the best smoothing function $g(x)$ leads to the minimization of the modified sum of squares

$$K_1 = U(g) + \alpha I(g) \quad 3.9$$

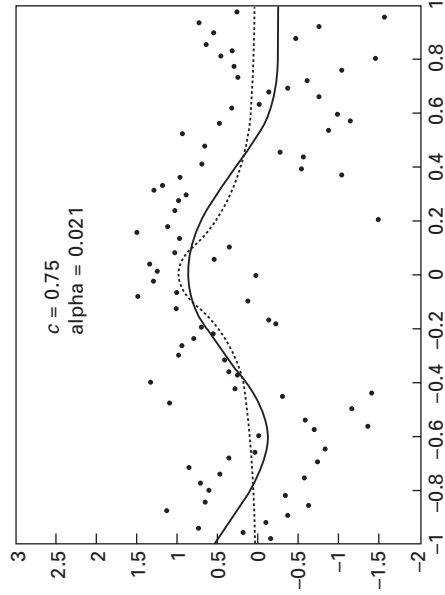
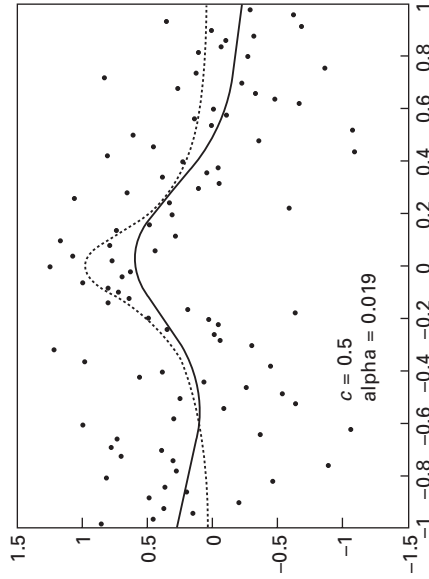
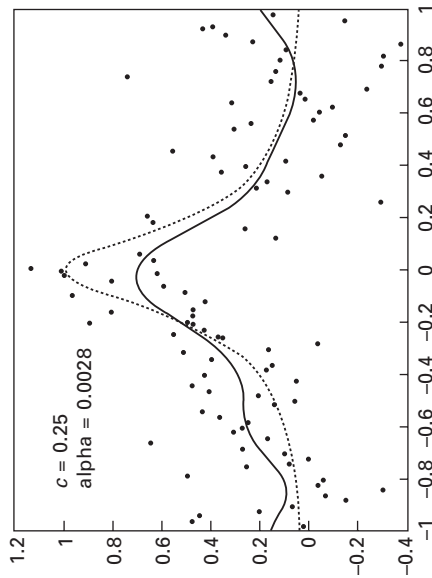
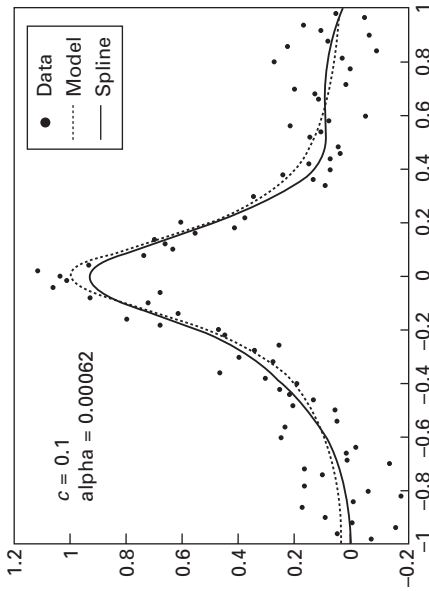
where $0 \leq \alpha \leq \infty$ is a smoothing parameter which ‘controls’ the ratio between the smoothness $g(x)$ and its closeness to the experimental points. All functions satisfying these conditions are cubic splines $S_3(x)$ with knots x_i . For known α , the smoothing cubic spline results [1]. To determine parameter α , the mean quadratic error of prediction $MEP(\alpha)$ is often used.

Cubic spline smoothing with optimal α to minimize $MEP(\alpha)$ was used to create a soft model for a univariate case. The 101 points in interval $[-1, 1]$ were generated from the corrupted Runge function

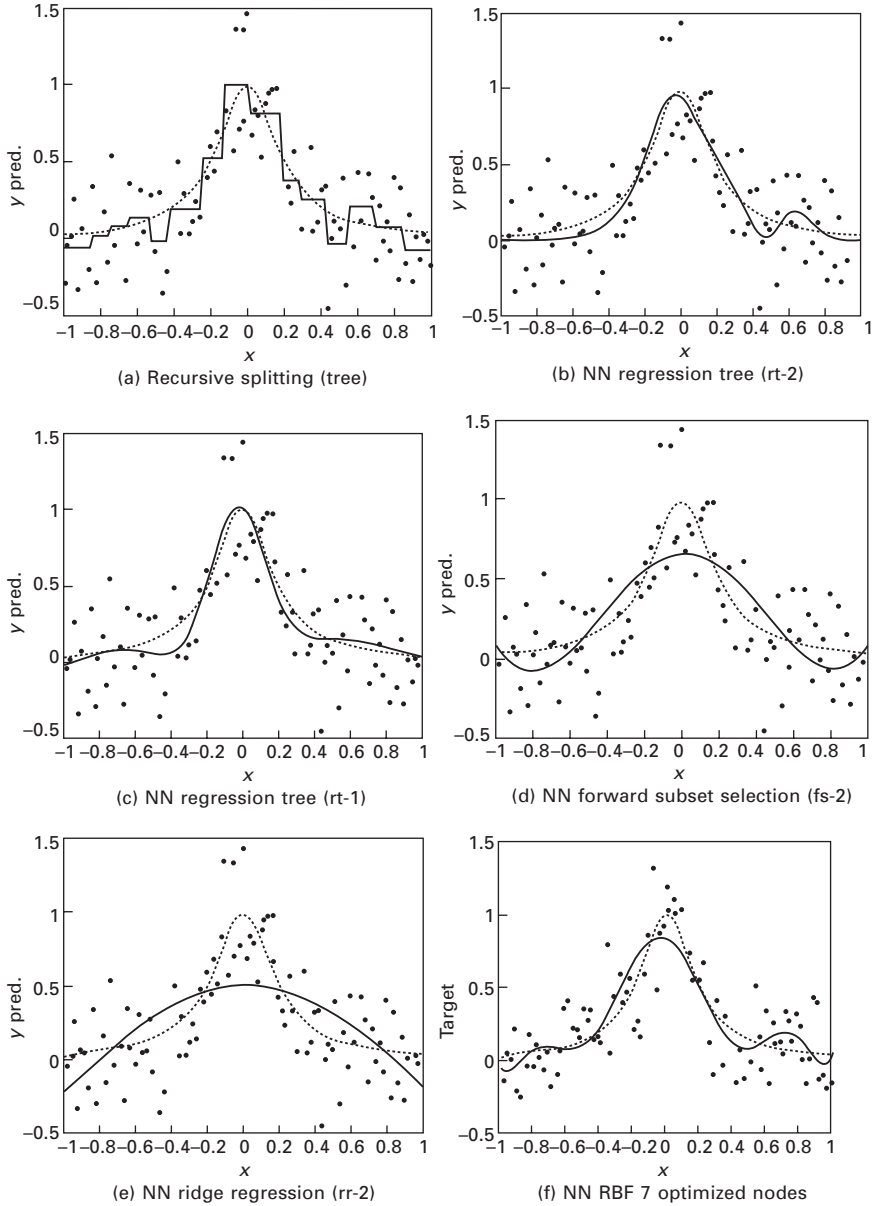
$$y = \frac{1}{1 + 25x^2} + N(0, c^2) \quad 3.10$$

where $N(0, c^2)$ is a random number generated from a normal distribution with variance c^2 . The influence of c on the cubic smoothing spline (soft model) is shown in Fig. 3.3. It is clear that the cubic smoothing splines reconstruct the Runge function form from relatively scattered data as well. Other types of smoothing and nonparametric regression soft models are summarized in [1].

The results of some neural network (RBF) methods for the same function and standard deviation $c = 0.2$ are given in Fig. 3.4 and for standard deviation $c = 0.5$ in Fig. 3.5. RBF neural network regressions lead to very different model curves, far from the Runge function form for relatively scattered data.



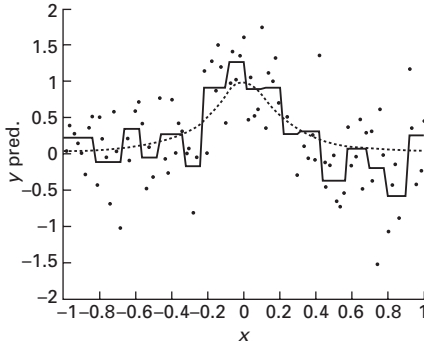
3.3 Cubic spline
 smoothing for
 Runge model
 with various
 level of noise
 (c); alpha is
 computed
 optimal
 smoothing
 parameter.



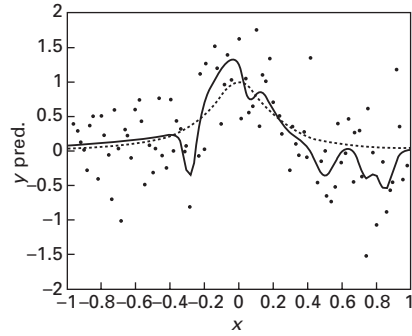
3.4 Results of various RBF neural network regressions for Runge model with noise level $c = 0.2$.

3.2.3 Model types

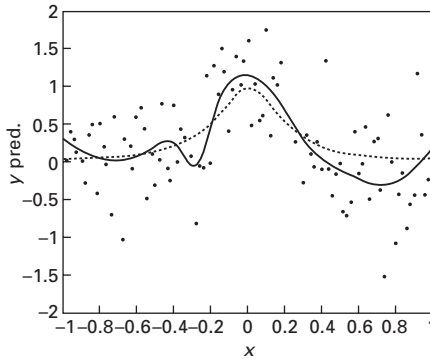
Empirical model building aims to find a relationship between the response (output) variable y and the controllable (independent) variables x . There are three possible scenarios:



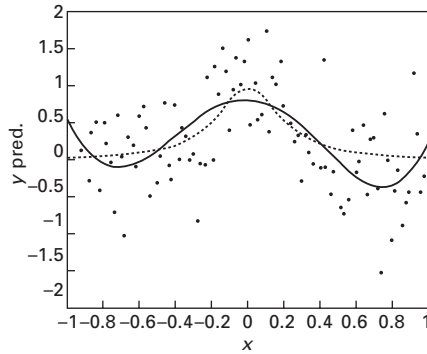
(a) Recursive splitting (tree)



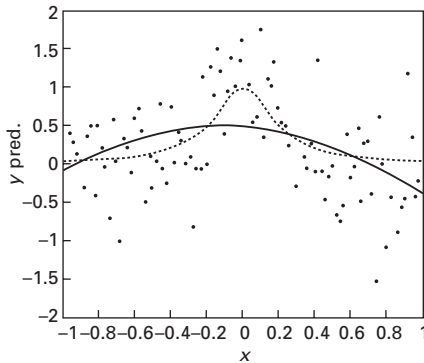
(b) NN regression tree (rt-2)



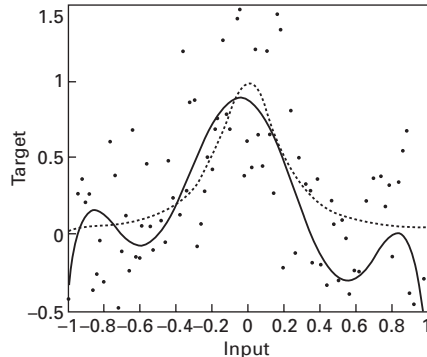
(c) NN regression tree (rt-1)



(d) NN forward subset selection (fs-2)



(e) NN ridge regression (rr-2)



(f) NN RBF 7 optimized nodes

3.5 Results of various RBF neural network regressions for Runge model with noise level $c = 0.5$.

1. Variables y and x have no random errors. The function $y = f(x, \beta)$ contains a vector of unknown parameters β of dimension $(m \times 1)$. To estimate them, at least $n = m$ measurements y_i , $i = 1, \dots, n$, at adjusted values x_i are necessary to solve a set of n equations of the form

$$y_i = f(\mathbf{x}_i, \boldsymbol{\beta}) \quad 3.11$$

with regard to unknown parameters $\boldsymbol{\beta}$. The measured variables y_i are assumed to be measured completely precisely, without any experimental errors. The model function $f(\mathbf{x}, \boldsymbol{\beta})$ is assumed to be correct and to correspond to data y . In the laboratory, none of these assumptions are usually fulfilled.

2. Variable y is subject to random errors, but variables $\mathbf{x}$ are controllable. This case is the *regression model*, for which the conditional mean of the random variable y at a point $\mathbf{x}$ is given by

$$E(y/\mathbf{x}) = f(\mathbf{x}, \boldsymbol{\beta}) \quad 3.12$$

The method of estimation of parameters $\boldsymbol{\beta}$ depends on the distribution of the random variable y . The *additive model of measurement errors* is usually assumed:

$$y_i = f(\mathbf{x}_i, \boldsymbol{\beta}) + \varepsilon_i \quad 3.13$$

where ε_i is a random variable containing the measurement errors $\varepsilon_{M,i}$ and the model errors $\varepsilon_{T,i}$ coming from an approximate model which does not correspond to the true theoretical model $f_T(\mathbf{x}_i, \boldsymbol{\beta})$. Empirical model building by regression analysis starts usually with the choice of a linear model

$$f(\mathbf{x}, \boldsymbol{\beta}) = \sum_{j=1}^m \beta_j g_j(\mathbf{x}) \quad 3.14$$

which can either be an approximation of the unknown theoretical function f_T or be derived from a knowledge of the system being investigated. In Eq. (3.14), instead of functions which do not contain parameters $\boldsymbol{\beta}$, the individual variables x_j are often used. Parameter estimates of model (3.14) may be determined, on the assumption that Eq. (3.13) is valid, either by the *method of maximum likelihood* or by the *method of least squares* [1].

3. Variables $y, \mathbf{x}$ are a sample from the random vector (η, ξ^T) with $m + 1$ components. Regression is a conditioned mean value (see Eq. (3.12)). The vector $\mathbf{x}$ represents an actual realization of the random vector ξ . Unlike regression models, in these ‘correlation models’ the regression function can be derived from a simultaneous probability density function $p(y, \mathbf{x})$ and a conditional probability density function $p(y/\mathbf{x})$.

For either correlation or regression models, the same expressions are valid, although they differ significantly in meaning. In many cases, the model $f(\mathbf{x}, \boldsymbol{\beta})$ is known, so the model building problem consists of searching for the best estimates of the unknown parameters $\boldsymbol{\beta}$. In contrast to linear regression

models, in nonlinear models the parameters β play a very important role. In linear regression models, the regression parameters usually have no physical meaning, whereas the parameters in a nonlinear model have often a specific physical meaning. Examples are equilibrium constants (dissociation constants, stability constants, solubility products) of reactions, or rate constants in kinetic models. In the interpretation of estimates of model parameters, it must be remembered that they are *random variables* which have variance, and which are often strongly correlated.

A *linear* (regression) model is a model which is formed by a linear combination of model parameters. This means that linear models can, with reference to the shape of the model functions, be nonlinear. For example, the model $f(x, \beta) = \beta_1 + \beta_2 \sin x$ is sinusoidal, but with regards to parameters it is a linear model. For linear models, the following condition is valid:

$$g_j = \frac{\partial f(x, \beta)}{\partial \beta_j} = \text{constant}, \quad j = 1, \dots, m \quad 3.15$$

If for any parameter β_j the partial derivative is not a constant, we say that the regression model is nonlinear. Nonlinear regression models may be divided into the following groups:

- *Non-separable models*, when condition (3.15) is not valid for any parameter. An example is the model $f(x, \beta) = \exp(\beta_1 x) + \exp(\beta_2 x)$.
- *Separable models*, when condition (3.15) is valid for at least one model parameter. For example, the model $f(x, \beta) = \beta_1 + \beta_2 \exp(\beta_3 x)$ is nonlinear only with regard to the parameter β_3 .
- *Intrinsically linear models* are nonlinear, but by using a correct transformation they can be transformed into linear models. For example, the model $f(x, \beta) = \beta^2 x$ is nonlinear in parameter β , but the shape of the model is a straight line. With the use of the reparameterization $\gamma = \beta^2$ the nonlinear model is transformed into a linear one.

Reparameterization means transformation of parameters β into parameters γ which are related to the original ones by a function

$$\gamma = g(\beta) \quad 3.16$$

By reparameterization, many numerical and statistical difficulties of regression may be avoided or removed, and non-separable models transformed into separable models. The Arrhenius model

$$f(x, \beta) = \beta_1 \exp(\beta_2/x) \quad 3.17$$

is separable, i.e. linear with regard to β_1 , and using the reparameterization $f(x, \gamma) = \exp(\gamma_1 + \gamma_2/x)$ is transformed into a non-separable model, where $\gamma_1 = \ln \beta_1$ and $\gamma_2 = \beta_2$. Each regression model may be reparameterized in many ways.

In empirical model building, we often distinguish models that are linearly transformable, i.e. those which can, by use of an appropriate transformation, be transformed into linear regression models. For example, the Arrhenius model (3.17) may be transformed into the form (if random errors ε are neglected) $\ln y = \gamma_1 + \gamma_2 z$ where $\gamma_1 = \ln \beta_1$, $\gamma_2 = \beta_2$ and $z = 1/x$. The resulting model is a linear model with respect to z . For finite errors ε , however, this transformation is not correct, and causes heteroscedasticity. When the measured rate constants k_i have constant variance $\sigma^2(k_i)$, then the quantities $\ln k_i$ have non-constant variance $\sigma^2(\ln k) = \sigma^2(k_i)/(k_i)^2$, i.e. constant relative error. The linear transformation is useful for simplifying the search for parameters, but it leads to biased estimates and is therefore used only to guess initial estimates of unknown parameters.

The derivatives g_j in Eq. (3.15) are *sensitivity measures* of parameter β_j in model $f(\mathbf{x}, \boldsymbol{\beta})$. From the sensitivity measures of individual parameters, a preliminary analysis of nonlinear models can be made, classifying their quality and identifying any redundancy caused by an excessive number of parameters. A model should not contain excessive parameters and its parameters may be unambiguously estimated if the sensitivity measures, g_j , for given data are found to be linearly independent. This means that it is not possible to determine non-zero coefficients $v_j, j = 1, \dots, m$, such that Eq. (3.18) is fulfilled:

$$\sum_{j=1}^m g_j v_j = 0 \quad 3.18$$

However, if at least one non-zero coefficient, $v_j \neq 0$, exists for which Eq. (3.18) is fulfilled, the regression model is redundant and should be simplified by *excluding* some parameters. If Eq. (3.18) is valid, all parameters may not be individually estimable.

Ill-conditioned nonlinear models cause problems when Eq. (3.18) is only approximately fulfilled. This is typical for neural network models and is analogous to multicollinearity in linear regression models [1]. Although parameter estimates may be found when $\mathbf{J}^T \mathbf{J}$ is ill-conditioned, some numerical difficulties appear during its inversion. The matrix $\mathbf{J}$ of dimension $(n \times m)$ is called the *Jacobian matrix*. Elements of this matrix correspond to the first derivative of the regression model in terms of the individual parameters at a given point. These elements have the form

$$J_{ik} = \frac{\partial f(x_i, \boldsymbol{\beta})}{\partial \beta_k}, i = 1, \dots, n, k = 1, \dots, m \quad 3.19$$

If we know the approximate magnitude of the parameter estimates $\mathbf{b}^{(0)}$, we may construct the matrix $\mathbf{L} = n^{-1}(\mathbf{J}^T \mathbf{J})$ with elements

$$L_{jk} = \frac{1}{n} \sum_{i=1}^n \frac{\partial f(x_i, \mathbf{\beta})}{\partial \beta_j} \frac{\partial f(x_i, \mathbf{\beta})}{\partial \beta_k} \bigg|_{\mathbf{\beta}=\mathbf{b}^{(0)}} \quad 3.20$$

Matrix $\mathbf{L}$ corresponds to the matrix $(1/n) \mathbf{X}^T \mathbf{X}$ for linear regression models. To estimate the ill-conditioning, matrix $\mathbf{L}$ is transformed into the standardized form $\mathbf{L}^*$ with elements

$$L_{ij}^* = \frac{L_{ij}}{\sqrt{L_{ii} L_{jj}}} \quad 3.21$$

The conditioning of matrix $\mathbf{L}^*$ guides the conditioning of parameters $\mathbf{b}^{(0)}$ in a given model for a given experimental data set.

A simple measure of ill-conditioning is the determinant of matrix $\mathbf{L}^*$, $\det(\mathbf{L}^*)$. When the determinant is less than 0.01, i.e. $\det(\mathbf{L}^*) < 0.01$, the nonlinear model is ill-conditioned and hence has to be simplified [1].

In many computer programs, the inversion of matrix $(\mathbf{J}^T \mathbf{J})$ involves its eigenvalues, $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_m$. (An indication of redundancy is the zero value of some eigenvalues.) For a measure of ill-conditioning, the ratio $\lambda_p = \lambda_1 / \lambda_m$ may be used. If $\lambda_p > 900$, the corresponding model is ill-conditioned [5]. Ill-conditioned models are typical for neural networks, especially in cases where the number of neurons (nodes) and their locations are not optimized.

3.2.4 Model building approaches

Methods of empirical model building may be classified into three broad categories:

- Linear statistical methods (use of linear models)
- Neural networks (use of separable nonlinear models)
- Nonlinear multivariate statistical methods (use of separable nonlinear models).

Selecting the appropriate empirical modeling method is still based on the user's subjective interpretation [15]. There are three basic groups of methods:

1. Linear multivariate statistical methods using linear models in the form of Eq. (3.14). For parameter estimation, ordinary least squares (OLS), principal component analysis (PCA), principal component regression (PCR), partial least squares (PLS), and ridge regression (RR) are extremely popular and successful. These techniques are used for multivariate regression model building in almost all branches of science [13] including, e.g., analytical chemistry [1] and process engineering [11, 12]. The linear model is physically interpretable, and may provide useful insights into the system being modeled, such as the relative importance of each variable in predicting the output.

2. Neural network modeling is inspired by artificial intelligence research, and has become a popular technique for nonlinear empirical modeling of technical systems. The corresponding model has the form of the weighted sum of basis functions $h_j(\mathbf{x})$ [15]:

$$f(\mathbf{x}, \boldsymbol{\beta}, \boldsymbol{\alpha}, k) = \sum_{j=1}^k \beta_j h_j(g_j(\mathbf{x}, \boldsymbol{\alpha})) \quad 3.22$$

where k is the number of basis or activation functions (neurons), g_j represents the input transformation, β_j is the output weight or regression coefficient relating the j th basis function, and $\boldsymbol{\alpha}$ is the vector of basis function parameters. Specific empirical modeling methods may be derived from Eq. (3.22) depending on decisions about the nature of activation or basis functions, neural network topology, and optimization criteria. Neural networks have found wide application in process engineering [7, 9], signal processing [6], fault detection and process control [8], and business forecasting [10]. The appeal of neural networks lies in their universal approximation ability [14, 20], parallel processing, and recurrent dynamic modeling, but the models developed by neural networks are usually ‘black box’ in character, often require a large ratio of training data to input variables, and are computationally expensive due to network construction being based on simultaneous computation of all the model parameters.

3. Many properties of linear statistical methods have been extended to nonlinear modeling by nonlinear multivariate statistical methods such as nonlinear least squares (NLS), nonlinear principal component regression (NLPCR), nonlinear partial least squares regression (NLPLS), projection pursuit regression (PPR), classification and regression trees (CART) [16], and multivariate adaptive regression splines – MARS (see [15]). Application of some soft nonlinear statistical methods is relatively limited [15]. Like neural networks, nonlinear statistical methods are also universal approximating models, and like linear statistical methods, the model is often physically interpretable. These methods often perform well with a relatively small amount of training data.

Selecting the best technique requires the user to have a deep understanding of all the modeling techniques with their advantages and disadvantages, and significant insight into the nature of the measured data and the process being modeled. Unfortunately, this combination of expertise is hard to find.

It can be easily established that neural and statistical modeling methods are complementary in nature. Greater understanding of empirical modeling methods has also led to some cross-fertilization between various methods. The benefits of these methods indicate that similar hybridization of other different empirical modeling properties may be desirable. Combining empirical

modeling methods requires deep insight into the properties, similarities and differences between methods [15].

3.3 Linear regression models

A *linear* regression model is formed by a linear combination of explanatory variables $\mathbf{x}$ or their functions. A linear model generally means linear according to the model parameters. The analysis of linear models can be extended to nonlinear models using the linear approximation (see Eq. (3.24)). This analysis is in fact valid for all types of model where the least-squares criterion is used for model adjustments. Examples are neural networks, regression splines, piecewise regression models etc. [1].

3.3.1 Linear regression basics

For additive modeling of measurement errors, the simple linear regression model (linear combination of $\mathbf{x}$) has the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad 3.23$$

In Eq. (3.23) the $(n \times m)$ matrix $\mathbf{X}$ contains the values of m explanatory (predictor) variables at each of n observations, $\boldsymbol{\beta}$ is the $(m \times 1)$ vector of regression parameters and $\boldsymbol{\varepsilon}$ is the $(n \times 1)$ vector of experimental errors. The $\mathbf{y}$ is the $(n \times 1)$ vector of observed values of the dependent variable (response).

The analysis described below can be applied to nonlinear models as well. With the use of a Taylor series expansion, the function $f(x_i, \boldsymbol{\beta})$ in the vicinity of the point $\boldsymbol{\beta}_j$ may be linearized as

$$f(x_i, \boldsymbol{\beta}) = f(x_i, \boldsymbol{\beta}_j) + \mathbf{J}_i(\boldsymbol{\beta} - \boldsymbol{\beta}_j) \quad 3.24$$

The $\mathbf{J}_i$ is the i th row of the *Jacobian matrix* with elements defined by Eq. (3.19). For linear models, the Jacobian matrix $\mathbf{J}$ is equal to the matrix $\mathbf{X}$, and analysis valid for linear models can then be used for nonlinear models in the vicinity of the optimal solution $\mathbf{b}$.

Columns $\mathbf{x}_j$, i.e. individual explanatory variables, define geometrically the m -dimensional coordinate system or the hyperplane L in n -dimensional Euclidean space E^n . The vector $\mathbf{y}$ does not usually have to lie in this hyperplane L . Least-squares is the most frequently used method in regression analysis. For a linear regression, the parameter estimates $\mathbf{b}$ may be found by minimizing the distance between vector $\mathbf{y}$ and hyperplane L . This is equivalent to finding the minimal length of the residual vector $\mathbf{e} = \mathbf{y} - \mathbf{y}_p$, where $\mathbf{y}_p = \mathbf{X}\mathbf{b}$ is the *predictor* vector. In Euclidean space, the length of the residual vector is expressed as

$$d = \sqrt{\sum_{i=1}^n e_i^2}$$

The geometry of linear least-squares is shown in Fig. 3.6. The classical least-squares method is based on the following assumptions [1]:

- Regression parameters β are not restricted
- The regression model is linear in parameters and the additive model of measurements is valid
- The design matrix X has a rank equal to m
- Errors ε_i are independent and identically distributed random variables with zero mean $E(\varepsilon_i) = 0$ and diagonal covariance matrix $D(\varepsilon) = \sigma^2 E$, where $\sigma^2 < \infty$.

For testing purposes, it is assumed that errors ε_i have normal distribution $N(0, \sigma^2)$. When these four assumptions are valid, the parameter estimates $\mathbf{b}$ found by minimization of the least-squares criterion

$$S(\mathbf{\beta}) = \sum_{i=1}^n \left[y_i - \sum_{j=1}^m x_{ij} \beta_j \right]^2 \quad 3.25$$

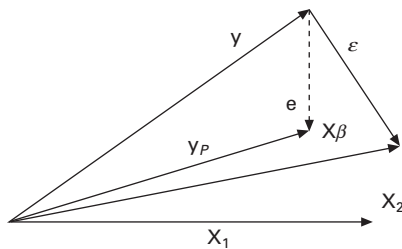
are called best linear unbiased estimators (BLUE). The conventional least-squares estimator $\mathbf{b}$ has the form

$$\mathbf{b} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \quad 3.26$$

The symbol $\mathbf{A}^{-1}$ denotes inversion of matrix $\mathbf{A}$.

The term *best* estimates $\mathbf{b}$ means that any linear combination of these estimates has the smallest variance of all linear unbiased estimates. That is, the variance of the individual estimates $D(b_j)$ is the smallest of all possible linear unbiased estimates (Gauss–Markov theorem). The term *linear* estimates means that they can be written as a linear combination of measurements $\mathbf{y}$ with weights Q_{ij} which depend only on the location of variables $\mathbf{x}_j$, $j = 1, \dots, m$, and $\mathbf{Q} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T$ for the weight matrix. We can then say

$$b_j = \sum_{i=1}^n Q_{ij} y_i$$



3.6 Geometry of linear least squares for case of two explanatory variables.

Each estimate b_j is the weighted sum of all measurements. Also, the estimates $\mathbf{b}$ have an asymptotic multivariate normal distribution with covariance matrix

$$D(\mathbf{b}) = \sigma^2 (\mathbf{X}^T \mathbf{X})^{-1} \quad 3.27$$

The term *unbiased* estimates means that $E(\mathbf{\beta} - \mathbf{b}) = 0$ and the mean value of an estimate vector $E(\mathbf{b})$ is equal to a vector of regression parameters $\mathbf{\beta}$. It should be noted that there are *biased estimates*, the variance of which can be smaller than the variance of estimates $D(b_j)$ [22].

The perpendicular projection of $\mathbf{y}$ into hyperplane L can be made using projection matrix $\mathbf{H}$ and may be expressed as

$$\mathbf{y}_p = \mathbf{X}^T \mathbf{b} = \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} = \mathbf{H} \mathbf{y} \quad 3.28$$

where $\mathbf{H}$ is the projection matrix. Residual vector $\mathbf{e} = \mathbf{y} - \mathbf{y}_p$ is orthogonal to subspace L and has the minimal length, the variance matrix corresponding to prediction vector $\mathbf{y}_p$ has the form $D(\mathbf{y}_p) = \sigma^2 \mathbf{H}$ and the variance matrix for residuals is $D(\mathbf{e}) = \sigma^2 (\mathbf{E} - \mathbf{H})$. The residual sum of squares has the form

$$\text{RSC} = S(\mathbf{b}) = \mathbf{e}^T \mathbf{e} = \mathbf{y}^T (\mathbf{E} - \mathbf{H}) \mathbf{y} = \mathbf{y}^T \mathbf{P} \mathbf{y}$$

and its mean value is $E(\text{RSC}) = \sigma^2(n - m)$. An unbiased estimate of the measurement variance σ^2 is given by:

$$s^2 = \frac{S(\mathbf{b})}{n - m} = \frac{\mathbf{e}^T \mathbf{e}}{n - m} \quad 3.29$$

Statistical analysis related to least squares is based on normality of estimates $\mathbf{b}$.

The quality of regression is often (not quite correctly) described by the multiple correlation coefficients R defined by the relation

$$R^2 = 1 - \frac{\text{RSC}}{\sum (y_i - \sum y_i/n)^2} \quad 3.30$$

The quantity $100 \times R^2$ is called the *coefficient of determination*. For model building, the multiple correlation coefficient is not suitable. It is a non-decreasing function of the number of predictors and therefore results in an over-parameterized model [1].

The predictive ability of a regression model can be characterized by the quadratic error of prediction (MEP) defined for linear models by the relation

$$\text{MEP} = \sum_{i=1}^n (y_i - x_i^T \mathbf{b}_{(i)})^2 / n \quad 3.31$$

where $\mathbf{b}_{(i)}$ is the estimate of regression model parameters when all points

except the i th are used (see Fig. 3.7). The statistics MEP for linear models uses the prediction $y_{Pi} = \mathbf{x}_i^T \mathbf{b}_{(i)}$ which was constructed without the information about the i th point. The estimate $\mathbf{b}_{(i)}$ can be computed from least-squares estimate $\mathbf{b}$:

$$\mathbf{b}_{(i)} = \mathbf{b} - [(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}_i e_i] / [1 - H_{ii}] \quad 3.32$$

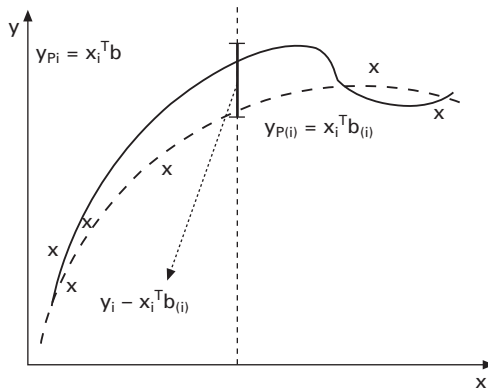
where H_{ii} is a diagonal element of the projection matrix $\mathbf{H}$. The optimal model has minimal value of MEP. The MEP can be used to define the predicted multiple correlation coefficient PR [1]:

$$\text{PR}^2 = 1 - \frac{n \times \text{MEP}}{\sum (y_i - \sum y_i/n)^2} \quad 3.33$$

The quantity $100 \times \text{PR}^2$ is called the *predicted coefficient of determination*. PR is especially attractive for empirical model building because it is not dependent on the number of regression parameters. For over-parameterized models, PR is low.

Analyzing various types of regression residuals, or some transformation of the residuals, is very useful for detecting inadequacies in the model, creating more powerful models and indicating problems in data. The true errors in the regression model $\boldsymbol{\varepsilon}$ are assumed to be normally and independently distributed random variables with zero mean and common (i.e. constant) variance, i.e. $N(\mathbf{0}, \mathbf{I}\sigma^2)$.

Classical residuals e_i are defined by the expression $e_i = y_i - \mathbf{x}_i^T \mathbf{b}$, where $\mathbf{x}_i$ is the i th row of matrix $\mathbf{X}$. Classical analysis is based on the wrong assumption that residuals are good estimates of errors ε_i . Reality is more complex, the residuals $\mathbf{e}$ are a projection of vector $\mathbf{y}$ into a subspace of dimension $(n - m)$,



3.7 Principle of MEP construction.

$$\mathbf{e} = \mathbf{Py} = \mathbf{P}(\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}) = \mathbf{P}\boldsymbol{\varepsilon} = (\mathbf{E} - \mathbf{H})\boldsymbol{\varepsilon} \quad 3.34$$

and therefore, for the i th residual, the following is valid:

$$e_i = (1 - H_{ii}) y_i - \sum_{j \neq i}^n H_{ij} y_j = (1 - H_{ii}) \varepsilon_i - \sum_{j \neq i}^n H_{ij} \varepsilon_j \quad 3.35$$

Each residual e_i is a linear combination of all errors ε_j . The distribution of residuals depends on the following:

- The error distribution
- The elements of the projection matrix $\mathbf{H}$
- The sample size n .

Because the residual e_i represents a sum of random quantities with bounded variance, the *supernormality effect* appears when the sample size is small. Even when the errors ε do not have a normal distribution, the distribution of residuals is close to normal. In small samples, the elements of the projection matrix $\mathbf{H}$ are larger and the main role of an actual point is to influence the sum of terms $H_{ii} \varepsilon_i$. The distribution of this sum is closer to a normal one than the distribution of errors ε . For a large sample size, where $1/n$ approaches 0, we find that $e_i \rightarrow \varepsilon_i$ and analysis of the residual distribution gives direct information about the distribution of errors. Classical residuals are always associated with non-constant variance; they sum to be more normal and may not indicate strongly deviant points. The common practice is to use residuals for investigation of model quality and for identification of nonlinearities. As has been shown above for small and moderate sample sizes, the classical residuals are not good for diagnostics or identifying model quality. Better properties have *jackknife residuals* defined as

$$e_{J,i} = e_{S,i} \sqrt{\frac{n-m-1}{n-m-e_{S,i}^2}} \quad 3.36$$

The jackknife residual is also called the *fully Studentized residual*. It is distributed as Student t with $(n-m-1)$ degrees of freedom when normality of errors ε holds [2]. The residuals $e_{J,i}$ are often used for identification of outliers. The *standardized residuals* $e_{S,i}$ exhibit constant unit variance and their statistical properties are the same as those of classical residuals:

$$e_{S,i} = e_i / (s \sqrt{1 - H_{ii}}) \quad 3.37$$

The jackknife residuals use a standard deviation estimate that is independent of the residual for standardization. This is accomplished by using, as the estimate of σ^2 for the i th residual, the residual mean square from an analysis where that observation has been omitted. This variance is labeled $s_{(i)}^2$, where the subscript in parentheses indicates that the i th observation has been omitted

for the estimate of σ^2 . As with e_i and $e_{s,i}$, residuals $e_{J,i}$ are not independent of each other.

One of the main problems is the quality of data used for parameter estimation and model building. The term regression diagnostics has been introduced for a collection of methods for identifying influential points and multicollinearity [2], including exploratory data analysis, analyzing influential points, and identifying violations of the assumptions of least-squares. In other words, regression diagnostics represent procedures for identification of the following [1, 68]:

- Data quality for a proposed model
- Model quality for a given set of data
- Fulfillment of all least-squares assumptions.

The detection, assessment and understanding of influential points are major areas of interest in regression model building. They are rapidly gaining recognition and acceptance by practitioners as supplements to the traditional analysis of residuals. Numerous influence measures have been proposed, and several books on the subject are available [1, 2, 22]. The commonly used graphical approaches in regression diagnostics, seen for example in [23], are useful for distinguishing between ‘normal’ and ‘extreme’, ‘outlying’ and ‘non-outlying’ observations.

3.3.2 Numerical problems of least squares

If a regression model $f(\mathbf{x}, \boldsymbol{\beta})$ is nonlinear in at least one model parameter β_r , substitution into the criterion function (Eq. (3.3)) leads to a task of *nonlinear maximization*. The application of any regression criterion leads to the problem of finding an extreme, where the regression parameters $\boldsymbol{\beta}$ are ‘variables’.

This task can be solved by using general optimization methods to search for a free extreme if no restrictions are placed on the regression parameters, or for a constrained extreme if the regression parameters are subject to restrictions.

Owing to the great variability of regression models, regression criteria and data, ideal algorithms that can achieve convergence to a global extreme sufficiently fast cannot be found. Most algorithms for many numerical methods often fail, i.e. they converge very slowly or diverge. The more complicated procedures for complex problems are rather slow and require a large amount of computer memory.

The problem of model parameter β estimation by the least-squares criterion (see Eq. (3.4) for $p = 2$) is the minimization of criterion function $S(\boldsymbol{\beta})$. This task can be solved using a specific method due to the local quadratic nature of least-squares near optimal point $\mathbf{b}$.

Quantitative information on the local behavior of the criterion function

$S(\boldsymbol{\beta})$ in the vicinity of any point $\boldsymbol{\beta}_j$ may be obtained from a Taylor series expansion up to quadratic terms:

$$S^*(\boldsymbol{\beta}) \approx S(\boldsymbol{\beta}_j) + \Delta\boldsymbol{\beta}_j^T \mathbf{g}_j + \frac{1}{2} \Delta\boldsymbol{\beta}_j^T \mathbf{H} \Delta\boldsymbol{\beta}_j \quad 3.38$$

where $\Delta\boldsymbol{\beta}_j = \boldsymbol{\beta} - \boldsymbol{\beta}_j$ and $\mathbf{g}_j$ is the gradient vector of a criterion function containing the components

$$\mathbf{g}_k = \frac{\partial S(\boldsymbol{\beta})}{\partial \beta_k}, \quad k = 1, \dots, m \quad 3.39$$

The matrix $\mathbf{H}_j$ of dimension $(m \times m)$ is the symmetric *Hessian matrix* defined by the second derivative of the criterion function $S(\boldsymbol{\beta})$ with components

$$H_{lk} = \frac{\partial^2 S(\boldsymbol{\beta})}{\partial \beta_l \partial \beta_k}, \quad l, k = 1, \dots, m \quad 3.40$$

The criterion function $S^*(\boldsymbol{\beta})$ expressed by Eq. (3.38) is a quadratic function of increment $\Delta\boldsymbol{\beta}_j$ and therefore it is possible to obtain the optimal increment by analytic differentiation:

$$\frac{\partial S^*(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} = \mathbf{g}_j + \mathbf{H} \Delta\boldsymbol{\beta}_j^* = 0 \text{ and then } \Delta\boldsymbol{\beta}_j^* = -\mathbf{H}^{-1} \mathbf{g}_j \quad 3.41$$

In the vicinity of local minima $\mathbf{b}$, the gradient $\mathbf{g}$ is approximately equal to zero. This means that:

- The error vector $\hat{\mathbf{e}}$ is perpendicular to the columns of a matrix $\mathbf{J}$ in m -dimensional space.
- The criterion function $S(\boldsymbol{\beta})$ is proportional to the quadratic form $\Delta\boldsymbol{\beta}_i^T \mathbf{H}_i \Delta\boldsymbol{\beta}_i$.

The type of local extreme is distinguished by a matrix $\mathbf{H}$. For practical calculation, it is necessary that $\mathbf{H}$ is a positive-definite regular matrix, with rank m and all eigenvalues positive [1].

In the least-squares method, the gradient of the criterion function $S(\boldsymbol{\beta})$ from Eq. (3.39) has the form

$$\mathbf{g}_j = -2\mathbf{J}^T \mathbf{e} \quad 3.42$$

where $\mathbf{e}$ is the difference vector with elements $e_i = y_i - f(x_i, \boldsymbol{\beta})$, $i = 1, \dots, m$. The *Jacobian matrix* $\mathbf{J}$ ($n \times m$) has elements corresponding to the first derivative of the regression model in terms of the individual parameters at given points (see Eq. (3.19)). A similar relationship involving the Hessian matrix may be derived:

$$\mathbf{H}_j = 2[\mathbf{J}^T \mathbf{J} + \mathbf{B}] \quad 3.43$$

where $\mathbf{B}$ is a matrix containing the second derivatives of the regression function with elements

$$B_{kj} = \sum_{i=1}^n e_i \frac{\partial^2 f(x_i, \boldsymbol{\beta})}{\partial \beta_k \partial \beta_j}, \quad k, j = 1, \dots, m \quad 3.44$$

For small error values e_i the matrix $\mathbf{B}$ may be neglected, and the Hessian matrix then has the form

$$\mathbf{H}_j = 2\mathbf{J}^T \mathbf{J} \quad 3.45$$

After substitution into Eq. (3.41), the optimal increment for the least-squares criterion has the form

$$\Delta \boldsymbol{\beta}_j^* = -(\mathbf{J}^T \mathbf{J})^{-1} \mathbf{J}^T \mathbf{e} \quad 3.46$$

The iterative solution of Eq. (3.46) leads to the selection of optimal solution $\mathbf{b}$ (for details see [1]). For the linear model, Eq. (3.46) is the same as Eq. (3.26) and the optimum vector $\mathbf{b}$ is obtained in one step.

Many problems with numerical and statistical analysis of least-squares (LS) estimates are caused by strong multicollinearity [24]. Multicollinearity in multiple linear regression (MLR) analysis is defined as approximate linear dependencies among the explanatory variables, i.e. the columns of matrix $\mathbf{X}$. The multicollinearity problem arises when at least one linear combination of the independent variables with non-zero weights is very nearly equal to zero, but the term collinear is often applied to the linear combination of two variables. It is known that given strong multicollinearity, the parameter estimates and hypotheses tests are affected more by the linear links between independent variables than by the regression model itself. The classical t -test of significance is highly inflated owing to the large variances of regression parameter estimates, and the results of statistical analysis are often unacceptable.

The problem of multicollinearity has been addressed by means of variable transformation, several biased regression methods, Stein shrinkage [25], ridge regression [26, 27], and principal component regression and its variations [29–32]; for a brief review, see, for example, Wold *et al.* [33]. The continuum regression is one example of combining various biased estimators. Belsey [34], Bradley and Srivastava [35], and Seber [36], among others, have discussed the problems that can be caused by multicollinearity in polynomial regression, and have suggested certain approaches to reduce the undesirable effects of multicollinearity. Although ridge regression has received the greatest acceptance, other methods have been used with apparent success. Biased regression methods address the multicollinearity problem by computationally suppressing the effects of collinearity, but should be used with caution [37, 38]. While ridge regression does this by reducing

the apparent magnitude of the correlations, principal component regression attacks the problem by regressing y on the important component variables to the original variables. Our approach to biased estimation is described below.

Modern software tools solve least-squares problems very efficiently in cases where the system of equations is ill-conditioned. For example, in MATLAB it is possible to use procedure 'Inv' to solve a relatively ill-conditioned system arising in polynomial regression of higher degree. Safer is the method of singular value decomposition (SVD), where the input matrix $\mathbf{X}$ ($n \times m$) is decomposed as $\mathbf{X} = \mathbf{U} * \mathbf{S} * \mathbf{V}^T$. In MATLAB software with `svd(x, 0)`, it is possible to obtain a shorter SVD, which is used here (for this modification of SVD the dimensions of matrix $\mathbf{U}$ and $\mathbf{S}$ are changed). For the shorter SVD, matrix $\mathbf{S}$ ($m \times m$) is diagonal, having singular values of the $\mathbf{X}$ matrix on the diagonal. There are r positive singular numbers $S_{11} \geq S_{22} \geq S_{33} \geq \dots \geq S_{rr}$ for the case where the matrix $\mathbf{X}$ has rank r (i.e. has r linearly independent columns only), and matrices $\mathbf{U}$ ($n \times m$) and $\mathbf{V}$ ($m \times m$) are orthogonal and normalized and therefore $\mathbf{U}^T \mathbf{U} = \mathbf{E}$ and $\mathbf{V}^T \mathbf{V} = \mathbf{E}$, where $\mathbf{E}$ is the identity matrix.

The shorter SVD has positive singular values of square roots from eigenvalues of the matrix $\mathbf{X}^T \mathbf{X}$ (and $\mathbf{X} \mathbf{X}^T$ matrix also); the columns of matrix $\mathbf{U}$ are eigenvectors of matrix $\mathbf{X} \mathbf{X}^T$ and the columns of matrix $\mathbf{V}^T$ are eigenvectors of matrix $\mathbf{X}^T \mathbf{X}$. The linear regression model (3.4) can be expressed as

$$\mathbf{y} = \mathbf{U} * \mathbf{S} * \mathbf{V}^T \boldsymbol{\beta} + \boldsymbol{\varepsilon} \text{ or } \mathbf{y} = \mathbf{U} * \boldsymbol{\omega} + \boldsymbol{\varepsilon} \text{ where } \boldsymbol{\omega} = \mathbf{S} * \mathbf{V}^T \boldsymbol{\beta} \quad 3.47$$

Vector $\boldsymbol{\omega}$ has the same dimension as vector $\boldsymbol{\beta}$. Due to the orthogonality of matrix $\mathbf{U}$, it is possible to obtain least-squares estimates $\mathbf{o}$ of parameters $\boldsymbol{\omega}$ after substitution into Eq. (3.6), in the form

$$\mathbf{o} = (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \mathbf{y} \text{ or } \mathbf{o} = \mathbf{U}^T \mathbf{y} \quad 3.48$$

Because the vector of estimates is equal to $\mathbf{o} = \mathbf{S} * \mathbf{V}^T \mathbf{b}$, estimated parameters $\mathbf{b}$ can be computed from the relation

$$\mathbf{b} = (\mathbf{V}^T)^{-1} \mathbf{S}^{-1} \mathbf{o} \text{ respectively } \mathbf{b} = \mathbf{V} \mathbf{S}^{-1} \mathbf{U}^T \mathbf{y} \quad 3.49$$

Inverse matrix $\mathbf{S}^{-1}$ is also diagonal, with elements $S_{ii}^{-1} = 1/S_{ii}$ on the main diagonal. If the columns of matrix $\mathbf{U}$ are $\mathbf{u}_j$ and the rows of matrix $\mathbf{V}^T$ are $\mathbf{v}_j$, then the solution of the linear regression task is in the simple form

$$b = \sum_{j=1}^r \frac{1}{S_{jj}} * \mathbf{u}_j * \mathbf{v}_j * \mathbf{y} \quad 3.50$$

If $r = m$, the classical least-squares estimates result. For integer $r < m$, the principal component regression (PCR) occurs. For real r , the so-called

generalized principal component regression (GPCR) results. The GPCR is described in detail below.

Common practice is to decompose matrix $\mathbf{X}^T\mathbf{X}$ to eigenvalues and eigenvectors. This decomposition is often used in GPCR. For ill-conditioned regressions, which are common in polynomial regressions and neural networks, the use of SVD and GPCR leads to different results depending on the selection criteria. In some cases, method selection is based on the length of the confidence interval for each regression coefficient. For predictive models, criteria based on the mean error of prediction, MEP, are suitable.

3.3.3 Generalized principal component regression

As the OLS estimators of the regression parameters are the best linear and unbiased estimates (of those possible estimators that are both linear functions of the data and unbiased for the parameters being estimated), the LS estimators have the smallest variance. In the presence of collinearity, however, this minimum variance may be unacceptably large. *Biased regression* refers to that class of regression methods that do not require unbiased estimators. Principal component regression (PCR) attacks the problem by regressing $\mathbf{y}$ on the important principal components and then parceling out the effect of the principal component variables to the original variables [26, 27].

GPCR approaches the collinearity problem from the point of view of eliminating from considerations those dimensions of the X -space that are causing the collinearity problem. This is similar in concept to dropping an independent variable from the model when there is insufficient dispersion in that variable to contribute meaningful information on $\mathbf{y}$. However, in GPCR the dimension dropped from consideration is defined by a linear combination of the variables rather than by a single independent variable.

GPCR builds a matrix of centered and standardized independent variables. In the scaled form, $\mathbf{X}^T\mathbf{X} = \mathbf{R}$ where $\mathbf{R}$ is the correlation matrix for variables $\mathbf{X}$, and $\mathbf{X}^T\mathbf{y} = \mathbf{r}$ where $\mathbf{r}$ is the correlation vector between $\mathbf{y}$ and $\mathbf{X}$ variables. To detect ill-conditioning of $\mathbf{X}^T\mathbf{X}$, the matrices are decomposed into eigenvalues and eigenvectors. Since the matrix $\mathbf{X}^T\mathbf{X}$ is symmetrical, the eigenvalues are ordered so that $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \dots \geq \lambda_m$, and the corresponding eigenvectors $\mathbf{J}_j$, $j = 1, \dots, m$, are in the form of the sum

$$\mathbf{R} = \sum_{j=1}^m \lambda_j \mathbf{J}_j \mathbf{J}_j^T \quad 3.51$$

The inverse matrix $\mathbf{R}^{-1}$ may be expressed in the form

$$\mathbf{R}^{-1} = \sum_{j=1}^m \lambda_j^{-1} \mathbf{J}_j \mathbf{J}_j^T \quad 3.52$$

and therefore the relation for the parameter estimate $\mathbf{b}_N$ may be rewritten in the form

$$\mathbf{b}_N = \sum_{j=\omega}^m [\lambda_j^{-1} \mathbf{J}_j \mathbf{J}_j^T] \mathbf{r} \quad 3.53$$

and the covariance matrix of normalized estimates $\mathbf{b}_N$ may be rewritten in the form

$$D(\mathbf{b}_N) = \sigma_N^2 \sum_{j=\omega}^m \lambda_j^{-1} \mathbf{J}_j \mathbf{J}_j^T \quad 3.54$$

From both equations, it follows that the estimates $\mathbf{b}_N$ and their variances are rather high when the eigenvalues λ_i are small. Regression problems can be divided into three groups according to the magnitude of the eigenvalues λ_i :

1. All eigenvalues are significantly higher than zero. The use of the least-squares method (OLS) does not cause any problems.
2. Some eigenvalues are close to zero. This is a typical example of multicollinearity, when some common methods fail.
3. Some eigenvalues are equal to zero: the matrix $\mathbf{X}^T \mathbf{X}$ or $\mathbf{R}$ is singular and cannot be inverted.

One way of avoiding difficulties with groups 2 and 3 is by the use of principal component regression (PCR) [28]. Here, the terms with small eigenvalues λ_i are neglected. The main shortcoming of PCR is that it neglects the whole terms that are unacceptable in the case of higher differences between λ_i ; a better strategy would be to choose a cut-off value that is part-way between two PCs. For example, the presence of λ_i leads to unacceptably high *variances of parameters* (small *t*-test) and avoiding PCs leads to an unacceptably high *bias of parameters* and small correlation coefficient (i.e. degree of fit). A solution to the dilemma of classical PCR is generalized principal component regression, GPCR. Here only parts of terms corresponding to λ_i are neglected and therefore the results of regression are continuously changed according to a parameter P which we call *precision*. Eigenvalue ω is retained, for which

$$\frac{\sum_{j=1}^{\omega} \lambda_j}{\sum_{j=1}^m \lambda_j} \geq P \quad 3.55$$

where P can be selected by the user as discussed below but is usually about 10^{-5} . Here m equals the total number of principal components in the datasets: note that the smallest eigenvalue is numbered 1, and the largest m . If

$$\frac{\sum_{j=1}^{\omega} \lambda_j}{\sum_{j=1}^m \lambda_j} \geq P \quad \text{and} \quad \frac{\sum_{j=1}^{\omega-1} \lambda_j}{\sum_{j=1}^m \lambda_j} \leq P \quad 3.56$$

then only part of eigenvalue $\omega - 1$ is retained; eigenvalues from $\omega - 2$ onwards are rejected. Therefore, the length of estimates $\mathbf{b}_N$ with their variances may be continuously decreased as a function of increasing precision P . However, this is followed by an increase in the estimate bias and a decrease in the multiple correlation coefficients. The bias of estimates is due to neglecting some terms in matrix inverse creation. It has been suggested [39] that the squared bias $h_V^2(b_N) = [\beta - E(b)]^2$ achieved by the method of GPCR is equal to

$$h_V^2(b_N) = \beta_N^T \left[\sum_{j=1}^{\omega} J_j J_j^T \right] \beta_N \quad 3.57$$

The optimum magnitude of P may be determined by finding a minimum of the *mean quadratic error of prediction (MEP)* defined by Eq. (3.31). In our GPCR, optimal P is selected as a value corresponding to minimal MEP with minimal bias [40]. A suitable P corresponds therefore to the first local minimum of dependence $MEP_i = f(P_i)$. The calculated P does not correspond generally to a global minimum, but parameter estimates and the statistical characteristics are greatly improved and good predictive ability is achieved.

3.3.4 Graphical aids for model creation

Preparing the data used in building empirical models is a very important step. Adequate representation and preprocessing (cleaning, dimension reduction, scaling, etc.) of input data can have a dramatic influence on the success of neural network models [88].

Information visualization and visual data analysis can help to deal with the flood of information. The advantage of visual data exploration is that the user is directly involved in the data analysis process. Visual data exploration is usually faster, and often provides more interesting results, especially in cases where automatic algorithms fail. While visualization is quite a powerful tool, there are two fundamental limitations: the human ability to distinguish image details and memorize them, and available computing power. The three distinct goals of visualization are:

1. *Explorative data analysis*: where the visualization of data or data objects provides hypotheses about the data [51].
2. *Confirmative data analysis*: where the visualization of data provides confirmation for existing hypotheses [52].

3. *Presentation of data*: where *a priori* fixed facts are being visualized [49, 50].

One of the main features of multivariate data is their dimension, which is the main source of complications for statistical analysis [56]. It is often necessary to reduce the amount of data, which is acceptable in either of the following cases:

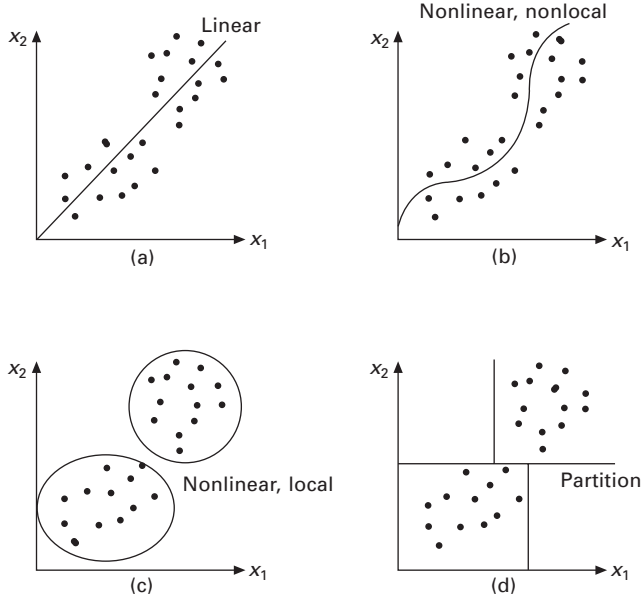
- The scatter of some variables is at the noise level and therefore they are not informative.
- There are strong linear dependencies (correlations between columns of matrix $\mathbf{X}$ given by redundant variables or as the result of inherent dependencies between variables. These variables can be replaced by a smaller number of new variables, or replaced by artificial ones without loss of precision).

The main reason for dimension reduction is the curse of dimensionality [53], i.e. the fact that the number of points required to achieve the same precision of estimators grows exponentially with the number of variables. For higher numbers of variables, e.g. multivariate regression, this leads to the parameter estimates having confidence intervals that are too wide, imprecise correlation coefficients, etc.

Neural network techniques often transform inputs into latent variables which capture the relationship between the inputs but are fewer in number. Such dimensionality reduction is usually accomplished by exploiting the relationship between inputs, distributing training data in the input space, or weighting the relevance of input variables for predicting the output. There are three categories according to the input transformation [57]:

- Methods based on linear projection exploit the linear relationship among inputs by projecting them on a linear hyperplane, before applying the basis function (Fig. 3.8(a)). Thus, the inputs are transformed by combination as a linear weighted sum to form the latent variables.
- Methods based on nonlinear projection exploit the nonlinear relationship between the inputs by projecting them on a nonlinear hypersurface, resulting in latent variables that are nonlinear functions of the inputs, as shown in Fig. 3.8(b) and (c). If the inputs are projected on a localized hypersurface, then the basis functions are local, as shown in Fig. 3.8(c). Otherwise, the basis functions are non-local in nature.
- Partition-based methods fight the curse of dimensionality by selecting the input variables that are most relevant to efficient empirical modeling. The input space is partitioned by hyperplanes that are perpendicular to at least one of the input axes (Fig. 3.8(d)).

One of the simplest techniques for reducing dimensions is principal



3.8 Input transformation in (a) methods based on linear projection, (b) and (c) methods based on nonlinear projection, non-local and local transformation respectively, and (d) partition-based methods [57].

component analysis (PCA), which is a linear projection method [54]. The main aim of PCA is linear transformation of the original variables $x_j = 1, \dots, m$, into a smaller group of latent variables (principal components) y_j . Latent variables are uncorrelated, explore much of the data variability, and are often far fewer in number. Latent variables are commonly known as principal components. The first principal component y_1 is a linear combination of the original variables and describes as much of the overall data variability as possible. The second principal component y_2 is perpendicular to y_1 and describes as much of the variability not contained in the first principal component as possible. Further principal components are generated in the same way [54].

As well as linear projection methods such as PCA, there are many nonlinear projection methods [55]. Among the more widely known are the Kohonen self-organizing map (SOM), nonlinear PCA [56] and topographical mapping. The principle behind the SOM algorithms is projection to a smaller dimension space while preserving approximately the distances between points. When d_{ij}^* are distances between pairs of points in the original space and d_{ij} are distances in the reduced space, the target function E (reaching minimum during solution) is in the form

$$E = \frac{1}{\sum_{i < j} d_{ij}^*} \sum_{i < j} \frac{(d_{ij}^* - d_{ij})^2}{d_{ij}^*} \quad 3.58$$

Minimization of the E function is realized using Newton's method or by heuristic searching. The simple projection technique is a robust version of PCA where the covariance matrix S is replaced by robust variant S_R . In this projection, it is simpler to identify point clusters or outliers [1, 54]. The Scree plot and contribution plot are used here to evaluate principal components replacing fabric construction parameters.

In multiple regression, one usually starts with the assumption that response y is linearly related to each of the predictors. The aim of graphical analysis is to evaluate the type of nonlinearity due to the predictors that describes the experimental data. A power-type function for the predictors is suitable when the relationship is monotone. Several diagnostic plots have been proposed for detecting the curve between y and x_j [2, 3]. Partial regression plots (PRP) are very useful for experiments without marked collinearities. PRP uses the residuals from the regression of y on the predictor x_j , graphed against the residuals from the regression of x_j on the other predictors. This graph is now a standard part of modern statistical packages and can be constructed without recalculating the least squares. To discuss the properties of PRP, let us assume the regression model in the matrix notation

$$y = X_{(j)} \beta^* + x_j c + \varepsilon_i \quad 3.59$$

Here $X_{(j)}$ is the matrix formed by leaving out the j th column x_j from matrix X , β^* is the $(m-1) \times 1$ parameter vector and c is the regression parameter corresponding to the j th variable x_j . For investigating partial linearity between y and the j th variable x_j , the projection into subspace L orthogonal to the space defined by columns of matrix $X_{(j)}$ is used. The corresponding projection matrix into space L has the form $P_{(j)} = E - X_{(j)} (X_{(j)}^T X_{(j)})^{-1} X_{(j)}^T$.

Using this projection on both sides of Eq. (3.59), the following relation results:

$$P_{(j)} y = P_{(j)} x_j c + P_{(j)} \varepsilon \quad 3.60$$

The product $P_{(j)} X_{(j)} \beta^*$ is equal to zero because the space spanned by $X_{(j)}$ is orthogonal to the residual space. The term $v_j = P_{(j)} x_j$ is the residual vector of regression of variable x_j on the other variables that form columns of the matrix $X_{(j)}$, and the term $u_j = P_{(j)} y$ is the residual vector of regression of variable y on the other variables that form columns of the matrix $X_{(j)}$. The partial regression graph is then the dependence of vector u_j on vector v_j . If the term x_j is correctly specified, the partial regression graph forms a straight line. Systematic nonlinearity indicates incorrect specification of x_j . A random pattern shows the unimportance of x_j for explaining the variability of y .

The partial regression plot (PRP) has the following properties [1]:

- Slope c in PRP is identical with the estimate b_j in a full model.
- The correlation coefficient in PRP is equal to the partial correlation coefficient R_{xyj} .
- Residuals in PRP are identical with residuals for the full model.
- The influential points, nonlinearities and violations of least-squares assumptions are clearly visualized.

Therefore PRPs are useful for investigating data and model quality. The correct transformation or selection of nonlinear functions of explanatory variables can be deduced from the nonlinearities in the PRP graph. The application of PRP in empirical model building is described in Section 3.5.

3.4 Neural networks

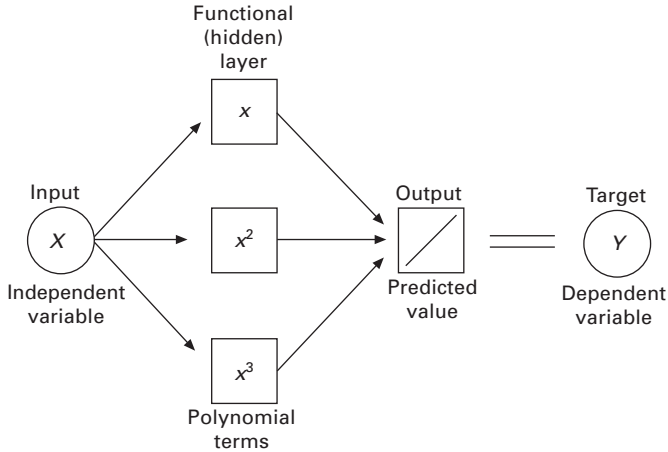
Neural networks (NN) have recently been widely applied in many fields where statistical methods were traditionally employed [45]. From a statistical point of view, NN comprise a wide class of flexible nonlinear regression and discriminant models, data reduction models, and nonlinear dynamic systems models [47]. The terminology used in the neural networks literature is quite different from that in statistics. Typical differences are given in Table 3.1.

NN methodology uses special graphical structures for describing models. The same structural elements can be used for other empirical models as well. The cubic regression model structure is shown in Fig. 3.9. The meaning of the boxes is clear because this model has the analytic form $Y = a_1x + a_2x^2 + a_3x^3$.

Neural networks can be applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns, performing general mapping from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems [69, 70].

Table 3.1 Differences between statistical and neural networks terms

Statistics	Neural networks
Model	Network
Variables	Features
Independent variables	Inputs
Predicted values	Outputs
Dependent variables	Targets, training values
Residuals	Errors
Estimation	Training, learning, adaptation, self-organization
Estimation criterion	Error function, cost function
Observations	Patterns, training pairs
Parameter estimates	(Synaptic) weights



3.9 Structure of cubic regression model.

3.4.1 Basic ideas

Artificial NN have been developed as generalizations of mathematical models of human cognition or neural biology, based on the following assumptions [67]:

- Information processing occurs at many simple elements called neurons.
- Signals are passed between neurons over connection links.
- Each connection link has an associated weight, which multiplies the signal transmitted in a typical neural net.
- Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

A neural network is characterized by:

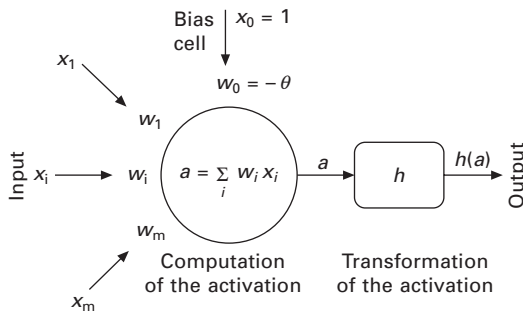
- A pattern of connections between neurons (called its architecture)
- The method used to determine the weightings of the connections (called its training, or learning, algorithm)
- Its activation function.

The use of neural networks offers the following useful properties and capabilities:

1. *Nonlinearity.* A neuron is basically a nonlinear device. Consequently, a neural network made up of interconnected neurons is itself nonlinear. Moreover, the nonlinearity is of a special kind in the sense that it is distributed throughout the network. Nonlinearity is a highly important property, particularly if the underlying physical mechanism responsible

- for the generation of the input signal (e.g. speech signal) is inherently nonlinear.
2. *Input–output mapping.* A popular paradigm of learning called supervised learning involves the modification of the synaptic weights of a neural network by applying a set of task examples. Each example consists of a unique input signal and the corresponding desired response. The network is presented with an example picked at random from the set, and the synaptic weights (free parameters) of the network are modified so as to minimize the difference between the desired response and the actual response of the network produced by the input signal in accordance with an appropriate statistical criterion. Training the network is repeated for many examples in the set until the network reaches a steady state, where there are no further significant changes in the synaptic weights.
 3. *Adaptivity.* Neural networks have a built-in ability to adapt their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retrained to deal with minor environmental changes in operating conditions.
 4. *Uniformity of analysis and design.* Neural networks enjoy universality as information processors. Neurons, in one form or another, represent an ingredient common to all neural networks. This commonality makes it possible to share theories and learning algorithms in different neural network applications. Modular networks can be built through a seamless integration of modules.

Neural networks are made of basic units (neurons, see Fig. 3.10) arranged in layers. A unit collects information provided by other units to which it is connected with weighted connections called synapses. These weights, called synaptic weights, multiply (i.e., amplify or attenuate) the input information. A positive weight is considered excitatory, a negative weight inhibitory.



3.10 The basic neural unit (neuron) [70].

Each of these units transforms input information into an output response. This transformation involves two steps:

1. Activation of the neuron, computed as the weighted sum of all inputs
2. Transforming the activation into a response by using a transfer function.

Formally, if each input is denoted x_i , and each weight w_i , then the activation is equal to the sum

$$a = \sum_{i=1}^m x_i w_i \quad 3.61$$

and the output is obtained as $h(a)$. Any function whose domain is the real interval can be used as a transfer function. A transfer function maps any real input into a usually bounded range, often from 0 to 1 or from -1 to 1 . Bounded activation functions are often called squashing functions. Some common transfer functions are [70]:

- linear or identity: $h(a) = a$
- hyperbolic tangent: $h(a) = \tanh(a)$
- logistic: $h(a) = (1 + \exp(-a))^{-1} = (\tanh(a/2) + 1)/2$
- threshold (step function): $h(a) = 0$ if $x < 0$, and 1 otherwise
- Gaussian: $h(a) = \exp(-a^2/2)$

The architecture (i.e., the pattern of connectivity) of the network, along with the transfer functions used by the neurons and the synaptic weights, specify the behavior of the network completely.

A neural network consists of a large number of neurons or nodes. Each neuron is connected to other neurons by means of directed communication links, each with an associated weight. The weights represent information being used by the net to solve a problem. Each neuron has an internal state, called its activation level, which is a function of the inputs it has received. Typically, a neuron sends its activation as a signal to several other neurons. It is important to note that a neuron can send only one signal at a time, although that signal is broadcast to several other neurons.

For example, consider a neuron x_j which receives inputs from neurons $x_1, x_2, \dots, x_m$. Input to this neuron is created as a weighted sum of signals from other neurons. This input is transformed into the scalar output o_i . The classical McCulloch and Pitts neuron is a threshold unit having adjustable threshold μ_j . The output is then defined as

$$o_i = h \left(\sum_{j=1}^m w_{ij} x_j - \mu_i \right) \quad 3.62$$

$$h(x) = 1 \text{ for } x \geq 0$$

$$h(x) = 0 \text{ for } x \leq 0$$

One of the most popular architectures in neural networks is the multi-layer perceptron (see Fig. 3.11).

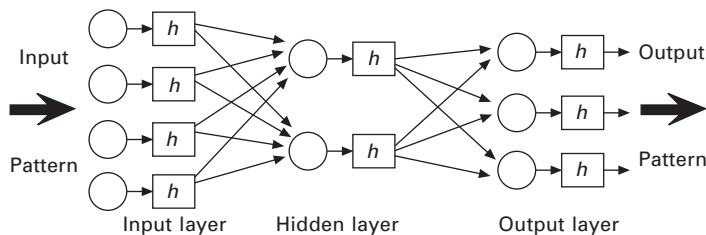
Most of the networks with this architecture use the Widrow–Hoff rule as their learning algorithm, and the logistic function as the transfer function for the units of the hidden layer (the transfer function is in general nonlinear for these neurons) [70]. These networks are very popular because they can approximate any multivariate function relating the input to the output. In a statistical framework, these networks are used for multivariate nonlinear regression. When the input patterns are the same as the output patterns, these networks are called auto-associative. They are closely related to linear (if the hidden units are linear) or nonlinear (if not) principal component analysis and other statistical techniques linked to the general linear model [70], such as discriminant analysis and correspondence analysis.

The standard three-layer neural network structure has an input layer, an output layer and one hidden layer. The signals go through the layers in one direction. After a set of inputs has passed through the network, the difference between true or desired output and computed output represents an error. The sum of squared errors, ESS, is a direct measure of the performance of the network in mapping inputs to desired outputs. By minimizing ESS, it is possible to obtain the optimal weights and parameters of activation function $h(a)$.

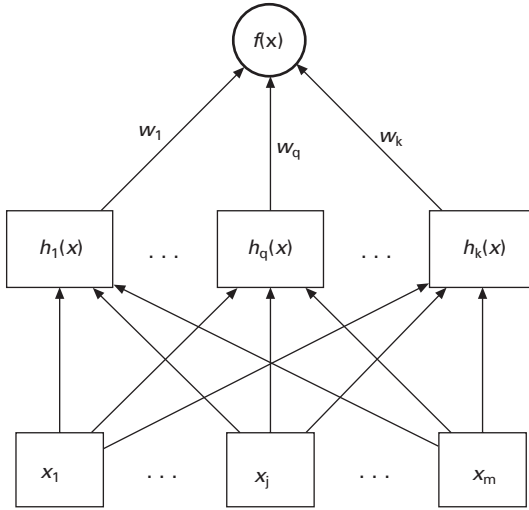
3.4.2 Radial basis function network

Radial basis function networks (RBFN) are a variant of the three-layer feedforward neural networks [48]. They contain a pass-through input layer, a hidden layer and an output layer (see Fig. 3.12).

The transfer function in the hidden layer is called a radial basis function (RBF). The RBF networks divide the input space into hyperspheres, and utilize a special kind of neuron transfer function in the form



3.11 A multi-layer perceptron network [70].



3.12 The traditional radial basis function network.

$$h(\mathbf{x}) = g(\|\mathbf{x} - \mathbf{c}\|^2) \quad 3.63$$

where $\|\mathbf{d}\|^2$ is the distance function from a prescribed center (squared Euclidean norm). Radial basis functions come from the field of approximation theory [66]. The most simple are the multi-quadratic RBFs defined by the relation [69]

$$h(x) = \sqrt{(d^2 + c^2)} \quad 3.64$$

and the thin plate spline function

$$h(x) = d^2 \ln(d) \quad 3.65$$

The popular Gaussian RBF has the form

$$h(x) = \exp(-d^2/2) \quad 3.66$$

A typical Gaussian RBF for the j th neuron (node) in the univariate case (one input) has the form

$$h_j(x) = \exp\left(-\frac{(x_j - c_j)^2}{r_j^2}\right) \quad 3.67$$

where c_j is the center and r_j is the radius. The center, the distance scale and the precise shape of radial functions are adjustable parameters. Radial basis functions are frequently used to create neural networks for regression-type problems. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point.

A traditional single-layer network with k neurons can be expressed by the model [67]

$$f(x) = \sum_{j=1}^k w_j h_j(x) \quad 3.68$$

where w_j are weights. For the training set $y_i, \mathbf{x}_i, i = 1, \dots, n$, weights $\mathbf{w}$ are evaluated based on the minimization of least-squares criterion

$$S = \sum_{i=1}^n (y_i - f_i(\mathbf{w}, \mathbf{x}_i))^2 \quad 3.69$$

If a weight penalty term is added to the sum of squared errors, the ridge regression criterion occurs:

$$C = \sum_{i=1}^n (y_i - f_i(\mathbf{w}, \mathbf{x}_i))^2 + \sum_{j=1}^m \lambda_j w_j^2 \quad 3.70$$

where λ_j are regularization parameters. For fixed parameters of functions $h(x)$, weight estimation is typically a linear regression task solved by the standard or modern methods (see Sections 3.2 and 3.3). MATLAB functions for the radial basis function – RBF2 toolbox [21] – contain four algorithms for neural network modeling:

1. *Algorithm fs-2 (regularized forward selection)* implements regularized forward selection with additional optimization of the overall RBF scale. Candidates are selected and added to the network one at a time, while keeping track of the estimated prediction error. At each step, the candidate which most decreases the sum of squared errors and has not already been selected is chosen to be added to the network. As an additional safeguard against overfitting, the method uses ridge regression (see the criterion defined by Eq. (3.70)).
2. *Algorithm rr-2 (ridge regression)* is based on ridge regression combined with optimization of the overall RBF scale. The locations of the RBFs in the network are determined by the inputs of the training set, so there are as many hidden units as there are cases. This and the previous algorithm depend on the training set inputs to determine RBF center locations and restrict the RBFs to the same width in each dimension.
3. *Algorithm rt-1 (regression tree and ordered selection)* determines both RBF locations and widths from the positions and sizes of the hyper-rectangular subdivisions imposed on the input space by a regression tree [16]. The regression tree is only used to generate potential RBF centers and its size. Each collection of RBFs forms a set of candidate RBFs from which a subset is selected to create a network. The selection algorithm depends on the concept of an active list of nodes. The special

subset selection scheme is based on intuition rather than any theoretical principle and its success can only be judged on empirical results.

4. *Algorithm rt-2 (regression tree and forward selection)* performs exactly the same steps as rbf-rt-1 except that the subset selection algorithm is plain forward selection.

The performance of these algorithms is dependent on the choices for their parameters. The default parameters are here used for simplicity (see Figs 3.4 and 3.5). It is evident that the results of neural network modeling are strongly dependent on the algorithm used.

A multidimensional Gaussian RBF may be obtained by multiplying univariate Gaussian RBFs. For this case, Eq. (3.68) is replaced by

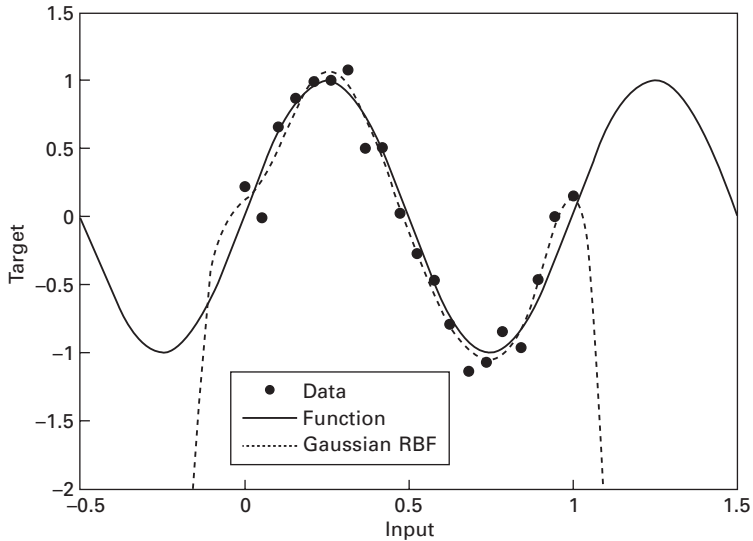
$$f(x) = \sum_{j=1}^k w_j \exp \left(\sum_{q=1}^m \frac{1}{r_{qj}^2} (x_q - c_{qj})^2 \right) \quad 3.71$$

The most popular method for modeling using RBFN involves separate steps for determining the basis function parameters, r_{qj} and c_{qj} , and the regression coefficients, w_j . The RBF parameters are determined without considering the behavior of the outputs by k -means clustering and the nearest neighbors heuristic. The regression parameters that minimize the output mean-squares error of approximation are then determined. Due to the known disadvantages of computing the basis function parameters based on input space only, various approaches have been suggested for incorporating information about the output error in determining the basis function parameters [20]. The NETLAB system uses the EM algorithm and then the pseudoinverse for least-squares estimation of weights w [20] for basis functions parameter estimation. The number of neurons k is defined.

The NETLAB results for approximating the sine function $\sin(x)$ corrupted by normally distributed noise with standard deviation 0.2 for the number of neurons $k = 7$ are shown in Fig. 3.13. The quality of approximation in the range of data is excellent, but outside this range approximation precision drops very quickly. Therefore this model is not useful for forecasting purposes.

Broomhead and Lowe [71] pointed out that a crucial problem is the choice of centers, which then determines the number of free parameters in the model. Too few centers and the network may not be capable of generating a good approximation to the target function, too many centers and it may fit misleading variations due to imprecise or noisy data. This is a consequence of the model complexity common for all methods of nonparametric regression [72]. The number of hidden nodes k can be estimated from an empirical formula [75]

$$k = 0.51 + \sqrt{0.43m_1m_2 + 0.12m_2^2 + 2.54m_1 + 0.77m_2 + 0.35} \quad 3.72$$



3.13 Approximation of sine function by Gaussian RBF – NETLAB (optimized positions of seven hidden nodes).

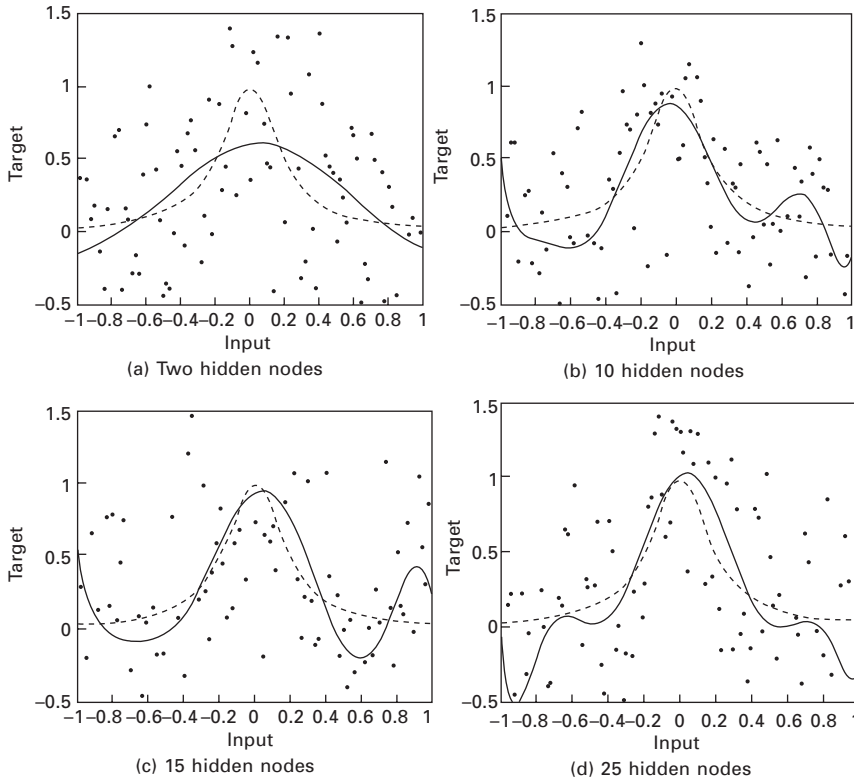
where m_1 and m_2 are the number of input and output neurons, respectively. In the RBFN there is only one neuron in the output layer, so $m_2 = 1$ and the number of input neurons is equal to m (number of input variables).

The influence of the number of nodes on the approximation of the Runge model (Eq. 3.10) corrupted by normally distributed errors with standard deviation $c = 0.2$ is shown in Fig. 3.14, which demonstrates that increasing the number of nodes leads to a better fit but the comparison with the true function is worse.

3.4.3 Peculiarities of neural networks

Neural network models are generally very flexible in adapting their behavior to new and changing environments. They are also easy to maintain and can improve their own performance by learning from experience. The need for preliminary analysis in modeling is reduced and discovery of interactions and nonlinear relationships becomes automatic [65]. It is simple to tune the degree of fit by, e.g., adjusting the number of nodes. Since neural networks are data dependent, their performance will be improved as sample size increases.

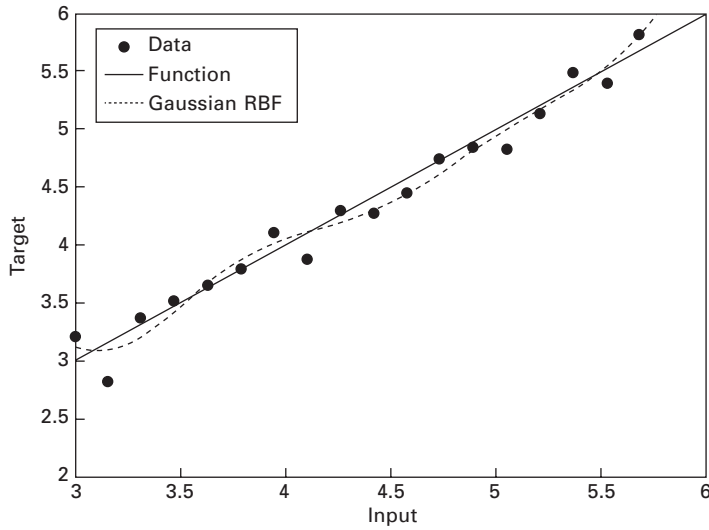
On the other hand, the use of neural network models has serious disadvantages. The main problem is the impossibility of preserving shape and limiting behavior, typical for simple shapes such as lines. Approximation by neural network is not acceptable for these cases because the shapes are



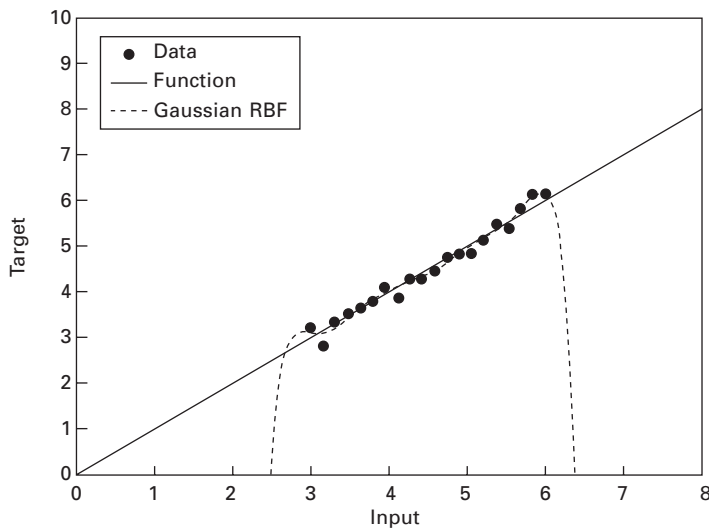
3.14 Results of optimized RBF neural network regression (NETLAB) for Runge model with noise level $c = 0.5$.

different and predictive ability is very bad. This is illustrated in Figs 3.15 (seven nodes) and 3.16 (three nodes). Here, the approximation of line $y = x$ corrupted by normally distributed errors with standard deviation 0.2 is shown. It is clear that approximation by a neural network in the range of data is different from the original line, and forecasting outside the data range is not acceptable. Generally, it is hard to interpret the individual effects of each predictor variable on the response.

The programs for neural networks are filled with settings, which must be input. The results are very sensitive to the algorithm used and small differences in parameter setting can lead to huge differences in neural network model forms (see, e.g., Figs 3.4 and 3.5). The estimated connection weights usually do not have obvious interpretations. Neural networks do not produce an *explicit model* even though new cases can be fed into them and new results obtained.



(a) Original range

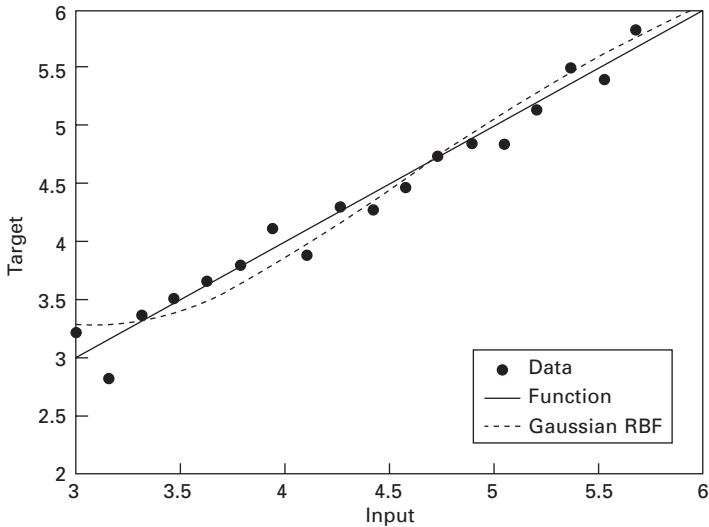


(b) Extended range

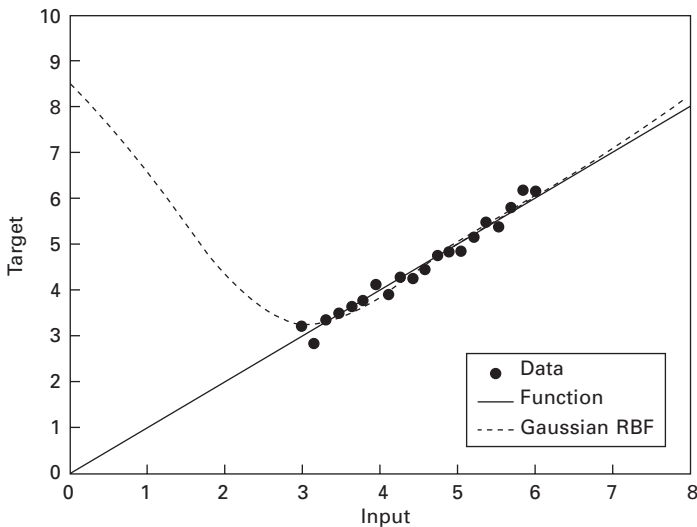
3.15 Approximation of scattered line $y = x$ by Gaussian RBF – NETLAB (optimized positions of seven hidden nodes).

3.5 Selected applications of neural networks

Selected applications of neural networks in the textile field are described in [46]. The back-propagation algorithm with a single hidden layer has been widely applied to solving textile processing problems [76–82, 84]. The neural



(a) Original range



(b) Extended range

3.16 Approximation of scattered line $y = x$ by Gaussian RBF – NETLAB (optimized positions of three hidden nodes).

network model for predicting pilling propensity of pure wool knitted fabrics from fiber, yarn and fabric properties is described in [83]. Implementing the Kalman filter algorithm to training a neural network to evaluate the grade of wrinkled fabrics using the angular second moment, contrast, correlation, entropy, and fractal dimension obtained by image analysis is described in [73].

The neural network classifier for cotton color using a two-step classification that identifies major and sub-color categories separately is presented in [74]. Neural network modeling was successfully applied to creating the relationship between the scanner device-dependent color space and the device-independent CIE color space [85].

3.5.1 Color recipes and color difference formula

The standard techniques for color recipe prediction are based on the well-known Kubelka–Munk (K–M) theory. This so-called *relative two-constant* approach is possible because the reflectance R of an opaque colorant layer is related to the *ratio* of the K and S coefficients by

$$K/S = (1 - R)^2/(2R) \quad 3.73$$

and the inverse relationship

$$R = 1 + K/S - ((1 + K/S)^2 - 1)^{0.5} \quad 3.74$$

The coefficients $K_i(\lambda)$ and $S_i(\lambda)$ are obtained normalized for unit concentration and unit film thickness for each colorant i and at each wavelength λ . A single estimate of $K_i(\lambda)$ and $S_i(\lambda)$ is made using two opaque samples (a mass tone and a mixture with white) for each colorant. The coefficients are assumed to be linearly related to colorant concentration so that, for a colorant mixture or recipe $\mathbf{c}$ (where $\mathbf{c}$ is a vector of colorant concentrations), the ratio K/S can be computed at each wavelength and Eq. (3.73) used to predict reflectance $\mathbf{r}$. In fact, the K–M theory does not account for reflections that take place at the interface between the colorant layer and air, and therefore appropriate corrections need to be applied.

An alternative approach is based on the radiative transfer theory. A simple approach avoiding these mathematical complexities is based on the application of artificial neural networks. The neural network can be used in place of Kubelka–Munk theory to relate reflectance values to colorant concentrations [58, 59] and, more generally, for transformation between color spaces [61, 62].

The use of several nets of different topologies trained by means of the Kubelka–Munk equation is described in the work of Wölker *et al.* [60]. The calculations here were based on reflection and not on color space, and the number of colorants was extended considerably. The network training errors fell considerably with increasing number of colorants. An RBFN was used in combination with a genetic algorithm for computer color matching [86]. The dye concentration was the neural network input value and the color coordinates L a b of the textile were the output. The use of different transformed reflectance functions as input for a fixed, genetically optimized, neural network match prediction system is described in [87].

There is a strong desire among industrialists for a single reliable color difference equation suitable for a wide range of industries. All the advanced formulae have a common feature: they were derived by modifying the CIELAB equation. A generic formula given in Eq. (3.75) represents all these formulae [63]:

$$\Delta E = \sqrt{\left(\frac{\Delta L^*}{k_L S_L}\right)^2 + \left(\frac{\Delta C^*}{k_C S_C}\right)^2 + \left(\frac{\Delta H^*}{k_H S_H}\right)^2} + \Delta R \quad 3.75$$

where

$$\Delta R = R_T f(\Delta C^* \Delta H^*)$$

and where ΔL^* , ΔC^* and ΔH^* are the CIELAB metric lightness, chroma and hue differences respectively, calculated between the standard and sample in a pair, ΔR is an interactive term between chroma and hue differences, and S_L , S_C and S_H are the *weighting functions* for the lightness, chroma and hue components, respectively.

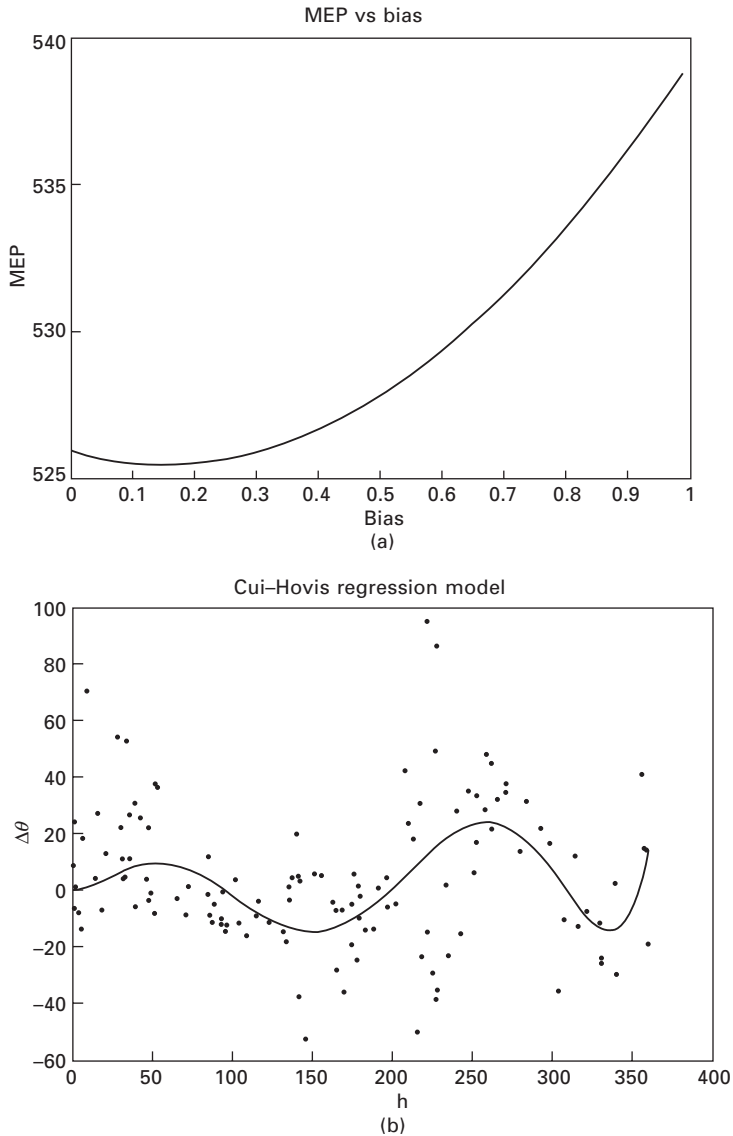
Cui and Hovis [64] used a ninth-degree polynomial function of hue angle h for approximation of $S_H = f(h)$. Due to strong multicollinearity, the parameter estimates obtained using classical least squares are incorrect.

To improve the Cui and Hovis approximation for the S_H function, the seventh-degree polynomial was selected, leading to the maximal predicted multiple correlation coefficient and minimal length on individual confidence interval. An algorithm based on GPCR was used. The dependence of MEP on P for the seventh-degree polynomial is shown in Fig. 3.17(a). Optimal $P = 0.154$ and corresponding $\text{MEP} = 525.47$ were found. For this P , the course of the regression polynomial is shown in Fig. 3.17(b).

There is no information about the shape of the function $S_H = f(h)$ and therefore neural network models are useful. NETLAB software was used for neural network model creation. The results of optimized neural network regression for Gaussian RBF for Clovis data are shown in Fig. 3.18 [64]. The differences between Fig. 3.18(a) and 3.18(b) are due to variation in the number of hidden nodes. The number of hidden nodes increases the degree of fit. Selecting more than 12 hidden nodes leads to the stabilization of the neural network curve. Compared with the seventh-degree polynomial (Fig. 3.17), the neural network model in Fig. 3.18(b) has a slightly better degree of fit, but the number of parameters is very high.

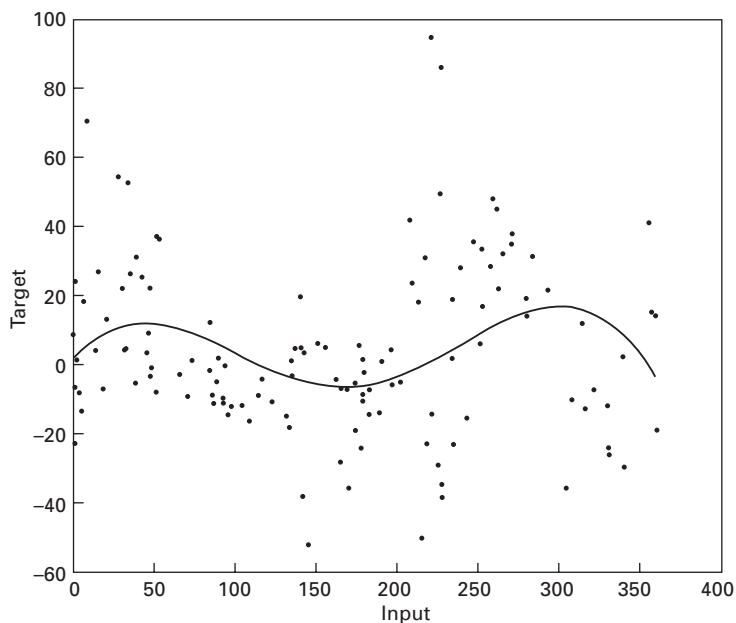
3.5.2 Prediction of fabric drape

Drape behavior is mechanically very complex and depends on fabric weight and various characteristics such as bending rigidity and shear resistance. Some empirical models based on the one-third rule have been applied to

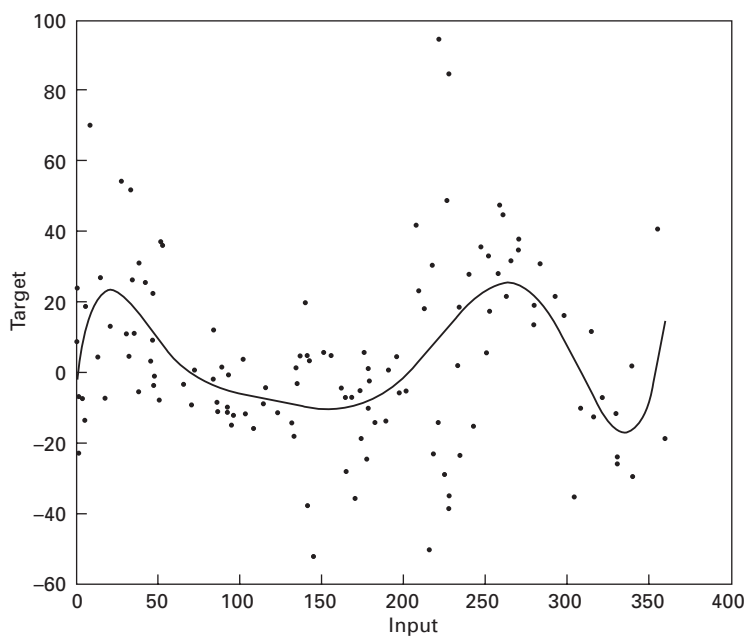


3.17 (a) Selection of optimal bias P for seventh-degree polynomial; (b) corresponding regression model.

bending and shear [42]. The main aim is to be able to predict the drape coefficient from the mechanical characteristics of woven fabrics. Measurements of Cusick's drape coefficient DC (from draped fabric images) [43] and mechanical characteristics measured on KES apparatus [44] are used for model evaluation. The area weight of the fabrics in this study varied from



(a) Three hidden nodes



(b) 12 hidden nodes

3.18 Results of optimized RBF neural network regression (NETLAB) for Clovis data [64].

55 to 350 g/m² and fabric sett was in the range 100–900 (1/10 cm). Plain, twill, satin and derived weaves were used. Material composition included pure cotton, polyester, viscose, wool and two component blends. The majority of fabrics were dyed and finished. To test model predictions, set II (see below), 12 gray fabrics not used for creating the model were used. Data sets are presented in [41].

Based on preliminary knowledge from testing and dimensional analysis, four potential variables were chosen. These variables are given in Table 3.2.

The prediction ability of a regression model is characterized by predicted multiple correlation coefficients PR. The three main variables $x_1 = B/W$, $x_2 = G/W$ and $x_3 = RT/W$ (see Table 3.2) were selected. The corresponding linear regression has the form

$$DC = b_0 + b_1x_1 + b_2x_2 + b_3x_3 \quad 3.76$$

The predicted correlation coefficient, 59.6%, is moderate but the dependence between measured and predicted drape DC is curved and highly scattered (see Fig. 3.19).

In the second run, the modified regression model

$$DC = b_0 + b_1\sqrt[3]{x_1} + b_2\sqrt[3]{x_2} + b_3x_3 \quad 3.77$$

was selected. The predicted correlation coefficient 80.6% is relatively high but the dependence between measured and predicted drape DC is slightly curved and scattered (see Fig. 3.20). The partial regression graphs in Fig. 3.21 show nonlinearity in all variables.

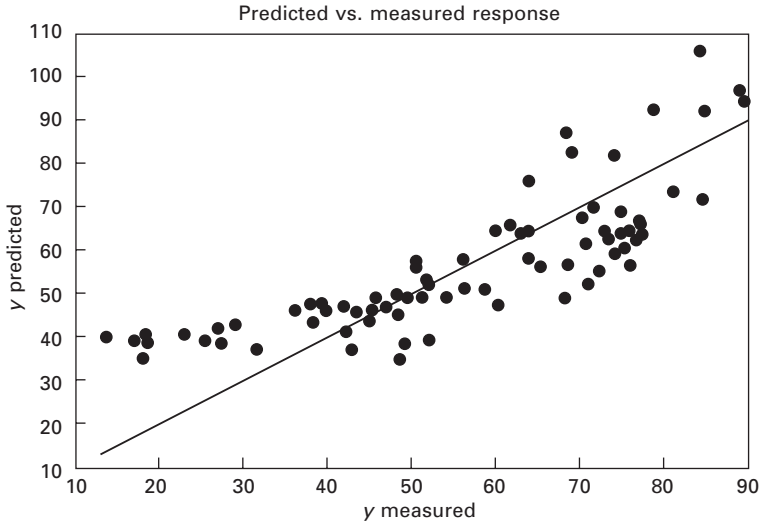
An optimal regression model was created using transformation of these variables, leading to the maximum degree of linearity in the partial regression plot (PRP). The optimal model has the form

$$DC = 111.98 - 25.5 \sqrt{\frac{W}{B}} + 14.8 \ln \left(\frac{G}{W} \right) - 40.57 \sqrt[4]{\frac{RT}{W}} \quad 3.78$$

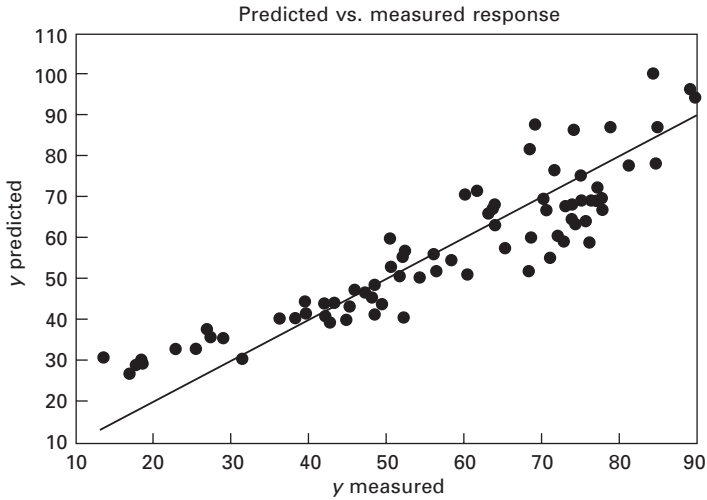
The corresponding predicted correlation coefficient was 89.4%. The relation between predicted and measured drape for this model is shown in Fig. 3.22.

Table 3.2 Basic variables for drape prediction

Symbol	Characteristic name
RT	Tensile resilience
B	Bending rigidity
G	Shear stiffness
W	Weight per unit area

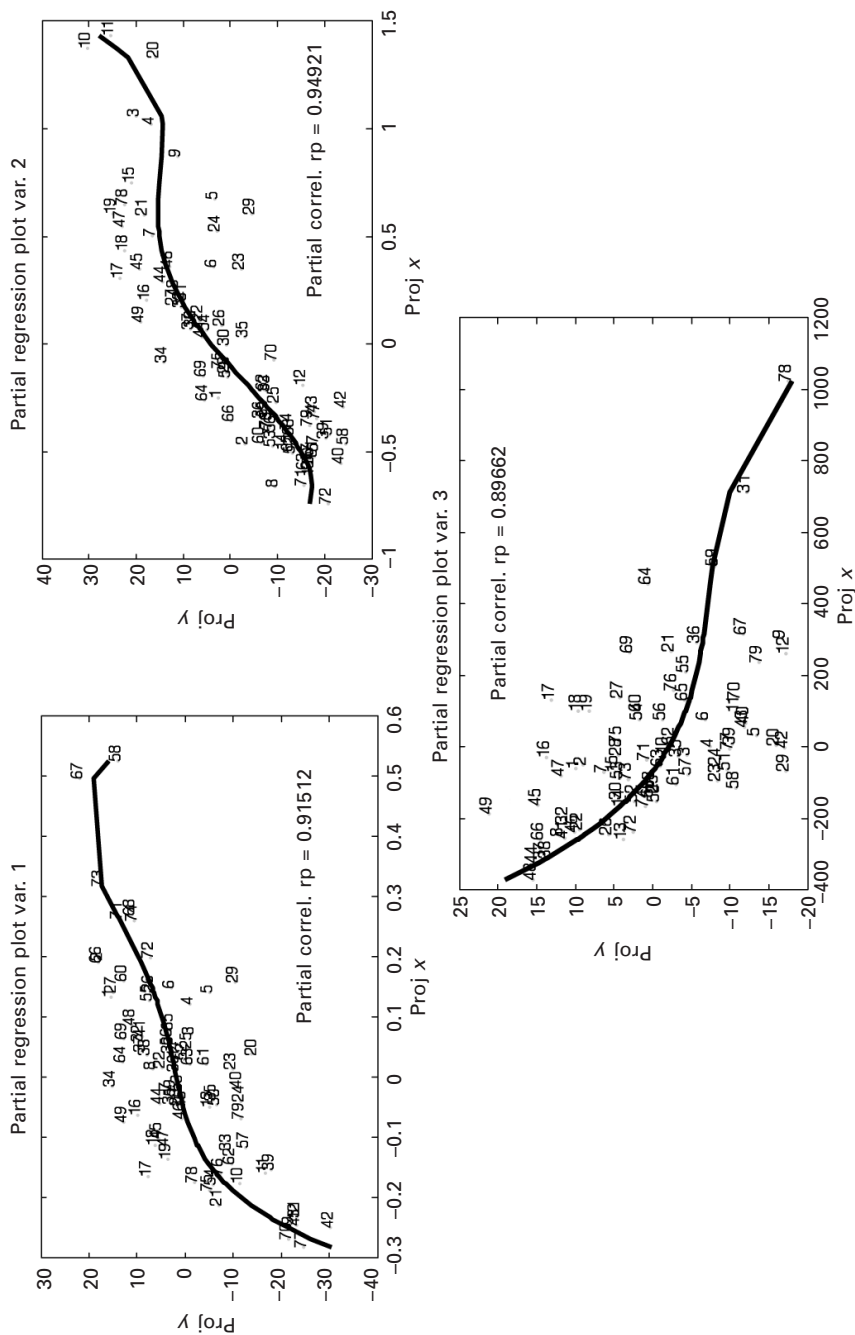


3.19 Relation between measured and predicted drape for model (Eq. (3.76)).

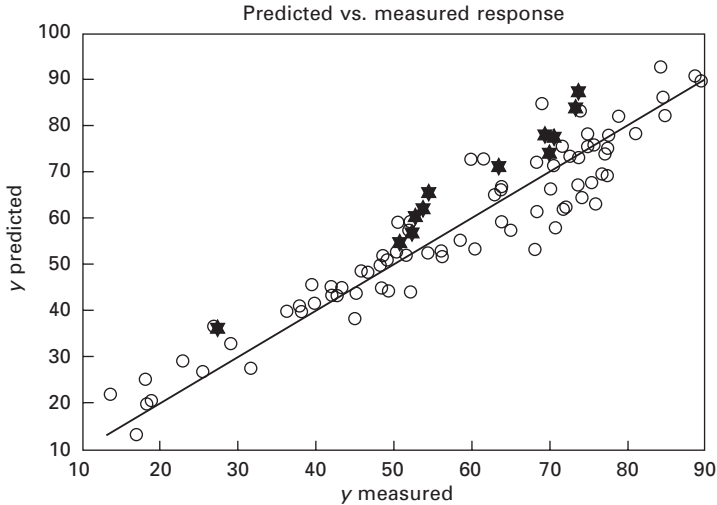


3.20 Relation between measured and predicted drape for model (Eq. (3.77)).

The RBF neural network (MATLAB functions for radial basis function – RBF2 toolbox) was used to predict drape coefficient DC from the four main variables $x_1 = B$, $x_2 = G$, $x_3 = RT$ and $x_4 = W$. Set I was used as the training set, and set II was used to test model quality. The best algorithm ‘regression tree 2’ selected 15 nodes as optimum. The centers and radii of



3.21 Partial regression graphs for model (Eq. (3.7)).

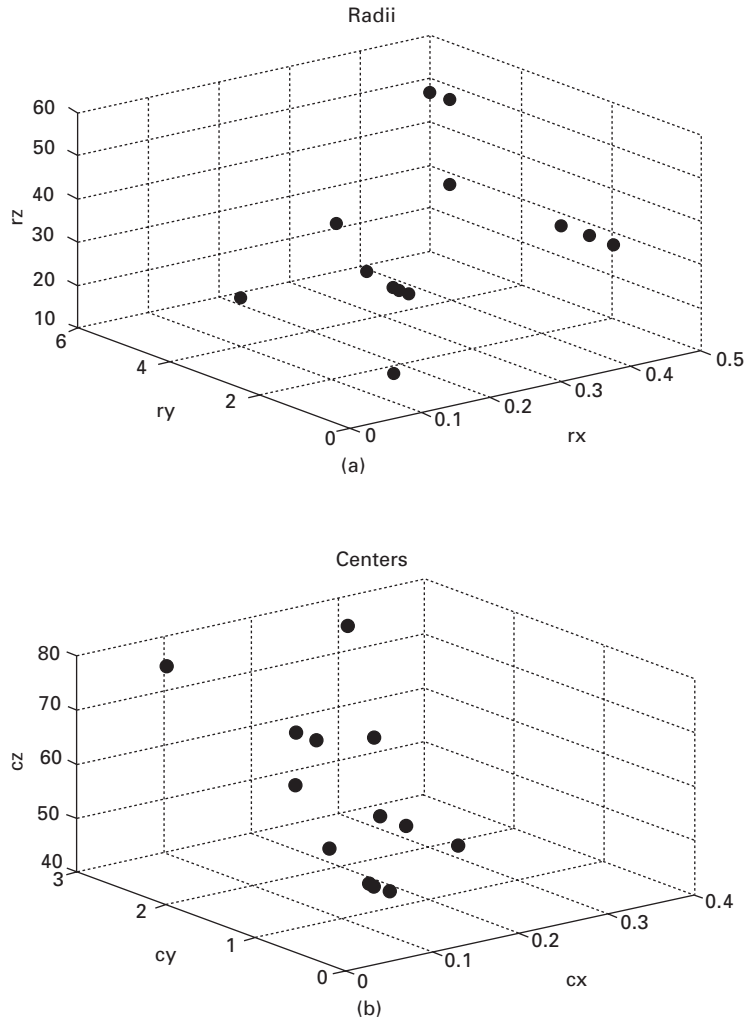


3.22 Relation between measured and predicted drupe for optimal model (Eq. (3.78)). Stars are data not used for model creation.

these nodes are shown in Fig. 3.23. Optimal weights are 63.0489, -11.4070 , 23.3772, -30.6885 , -100.0251 , -20.3704 , -76.879 , -95.02 , 28.33, 40.08, -102.79 , -38.93 , 183.68, 319.06 and -244.72 . The mean relative error of prediction, 14.65%, is the lowest of all the strategies used in the RBF2 toolbox. The quality of prediction is shown in Fig. 3.24. The systematic shift is clearly visible. The better prediction ability of the regression model is clearly visible from direct comparison of Figs 3.22 and 3.24. When the variables used in RBF neural network regression are selected by regression model building (see Eq. (3.78)) instead of from Table 3.2, the mean relative error is about 12.4% and prediction is much better (the optimal number of nodes is eight). The nonparametric regression model based on RBF has a worse fit in comparison with the optimized regression model. The number of parameters in RBF greatly exceeds that for optimized linear regression. The use of neural networks for practical computation is typically computer assisted because the number of estimated parameters (total 24) is so high.

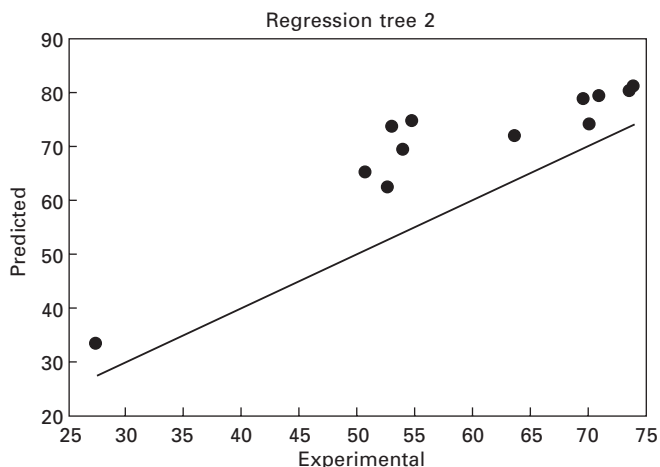
3.6 Conclusion

Using partial regression graphs to build empirical models is very useful for creating statistical models based on experimental data. These nonlinear models are often very simple and are attractive to use, especially for selecting optimal technological process conditions. The use of neural network models is probably acceptable when there is insufficient time to build regression



3.23 (a) Optimal radii and (b) centers for RBF functions.

models interactively with the help of computers, or in cases where multimodal model shape and limits are undefined. Neural networks are very useful when the functional relationship between dependent and independent variables is not known.



3.24 Relation between predicted and measured drape for optimal RBF model and data set II not used for model creation.

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Artificial neural networks in yarn property modeling

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Abstract: Modeling yarn properties from fiber parameters has been a theme of research for many years. Mechanistic and statistical approaches have been dominating the area. The limitations and strengths of both approaches have been appreciated and presently neural networks, fuzzy logic, and computer simulations are being explored. The use of artificial neural networks for predicting yarn properties from fiber parameters is discussed in this chapter.

Key words: yarn engineering, yarn property modeling, neural networks in textiles.

4.1 Introduction

The industrial relevance of the topic of yarn property modeling is obvious. Predicting product performance and its properties from raw material characteristics has been a theme of research in many areas including textiles. The outcome of a process in the textile industry could be a fiber, yarn, fabric or garment. Manufacturing each product is an industry by itself. The yarn manufacturing industry involves a large number of processes such as opening, cleaning, carding, drawing, combing, roving preparation and spinning that lead to the production of yarns of various counts and blends. Knowing what is expected from a raw material is important to both the supplier of raw material and the purchaser. For example, a cotton grower would like to know what sort of yarn quality can be produced from his crop so that he can claim the right price for his produce. The buyer, a spinning mill, would be interested in knowing whether it is possible to attain the desired yarn properties from a particular variety of cotton it intends to buy. The user of the yarn, either a knitter or a weaver, will be interested in knowing the performance of the yarn from its physical and mechanical properties. Hence, there is a need for a reliable method for predicting yarn properties from fiber characteristics and relevant yarn parameters. Many of these parameters are statistical in nature and follow distributions of their own. Some of them such as fiber length, fineness, strength, elongation, yarn uniformity, thin places, and twist can be estimated by modern instrumentation. It is very difficult to establish a definite relationship between fiber, process and yarn parameters as their

exact relationship is yet to be established, since they are highly nonlinear, complex and interactive. Hence there is a need to follow a non-traditional approach to model them.

4.2 Review of the literature

The literature suggests mainly three approaches for yarn property modeling, namely mechanistic, statistical and neural network. The mechanistic models proposed by authors such as Bogdan (1956, 1967), Hearle *et al.*, (1969), Subramanian *et al.* (1974), Linhart (1975), Pitt and Phoenix (1981), Lucas (1983), Zurek and Krucinska (1984), Kim and El-Shiekh (1984a, 1984b), Zurek *et al.* (1987), Zeidman *et al.* (1990), Frydrych (1992), Pan (1992, 1993a, 1993b), Önder and Baser (1996), Van Langenhove (1997a, 1997b, 1997c), Rajamanickam *et al.* (1998a, 1998b, 1998c) and Morris *et al.* (1999) overtly simplify the process to make the equations manageable, leading to limited accuracy. Statistical models based on regression equations (El Sourady *et al.*, 1974; Ethridge *et al.*, 1982; Smith and Waters, 1985; El Mogahzy, 1988; Hunter, 1988) have also shown their limitations in use – not least their sensitivity to rogue data – and are rarely used in any textile industry as a decision-making tool. Mechanistic approaches coupled with statistical tools, e.g. regression analysis (Neelakantan and Subramaniam, 1976; Hafez, 1978; Aggarwal, 1989a, 1989b; DeLuca *et al.*, 1990) have shown limited successes.

An artificial neural network is a promising step in this direction. ‘Learning from examples’ is the principle that has inspired the development of artificial neural networks (ANNs) which has been used by many researchers (Ramesh *et al.*, 1995; Cheng and Adams, 1995; Pynckels *et al.*, 1997; Rajamanickam *et al.*, 1997) and is being used in process control, identification diagnostics, character recognition, robot vision and financial forecasting.

4.3 Comparison of different models

There are four types of model used for predicting yarn properties. These are the mechanistic model, empirical model, computer simulation model and artificial neural network model. Each model has its own attributes which favors its application in certain areas (Table 4.1). The artificial neural network model will now be discussed.

4.4 Artificial neural networks

Artificial neural networks were developed in an attempt to imitate the functional principles of the human brain. In order to design a computer that can emulate the properties of a human brain, it is necessary to define a

Table 4.1 Comparison of attributes of various models

Model	Attributes
Mechanistic models	1. Based on certain assumptions and mechanics based on first principles 2. Can be used to explain the reason for the relationship between the different parameters that determine strength 3. Predictive power depends upon the assumptions used 4. Can be used as design tools for engineering yarns.
Empirical models	1. Based on statistical regression equations 2. Easy to use and have good predictive power if the R^2 value of the model is high 3. Do not provide deep understanding of the relationship between different parameters or variables 4. Should not be used for predicting yarn strength outside the range of levels of independent variables 5. Good for routine process planning to predict the effect of different process and material variables on product properties.
Computer simulation models	1. Mathematical model is the basis of computer simulation model 2. Can model the structural parameters of the yarn which are inherently random 3. Large simulation can be set up to study the second and higher order interactions 4. Can be used as design tools for engineering yarns 5. Less time-consuming than the experimental approach.
ANN models	1. Characterized by a large number of simple neuron-like processing elements and a large number of weighted connections between them which can accurately capture the nonlinear relationship between different process and material parameters 2. Have good predictive power 3. Require fewer data sets than conventional regression analysis 4. The neural net can be easily updated with both old and new data 5. Cannot be reliably used to predict the parameter outside the range of data 6. Do not provide any insight about the mechanics of the relationship between the parameters.

Source: Rajamanickam *et al.* (1997)

simple unit or function (i.e. an artificial neuron), join a number of such units through connections or weights, and allow these weights to decide the manner in which data is transferred from one unit to another. The whole system is allowed to learn from examples where a set of input and corresponding output data are fed and weights are adjusted iteratively to match the output from a

given set of input. The weight adjustment is called training and, once trained, the system becomes capable of delivering an output for a given set of input parameters. It is therefore an information processing mechanism consisting of a large number of interconnected simple computational elements.

A neural net is characterized by

- A large number of simple neuron-like processing elements
- A large number of weighted connections between elements: the weights of these connections contain the knowledge of the network
- Highly parallel and distributed control.

A neural network is specified by its topology, node characteristics and training rules.

4.4.1 Artificial neuron

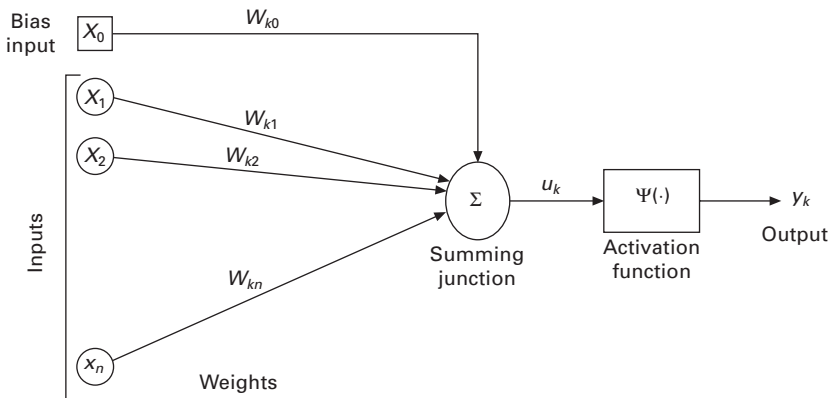
An artificial neuron attempts to capture the functional principles of a biological neuron. The schematic representation of the ANN model of McCulloch and Pitts is shown in Fig. 4.1.

There are n inputs to the neuron (x_1 to x_n). They are multiplied by weights w_{k1} to w_{kn} respectively. The weighted sum of the inputs, which is denoted by u_k , is given by

$$u_k = \sum_{j=0}^n w_{kj} x_j \quad 4.1$$

u_k now becomes the input to the activation function and gets modified according to the nature of the activation function. The output y_k is given by

$$y_k = \psi(u_k) \quad 4.2$$



4.1 Artificial neuron.

where ψ is a function of u_k and is termed an *activation function*. In practice, the actual data set is often pre-scaled to lie within a certain range (e.g. 0 to 1 or -1 to $+1$). After training the neural network with this data, the results need to be scaled back to the original range.

For an output to lie between 0 and 1, popular choices of the activation function include the following:

1. Threshold function

$$\psi(u) = \begin{cases} 1 & \text{if } u \geq 0 \\ 0 & \text{if } u < 0 \end{cases} \quad 4.3$$

2. Piecewise linear function

$$\psi(u) = \begin{cases} 1 & \text{if } u \geq +\frac{1}{2} \\ u + \frac{1}{2} & \text{if } +\frac{1}{2} > u > -\frac{1}{2} \\ 0 & \text{if } u \leq -\frac{1}{2} \end{cases} \quad 4.4$$

3. Sigmoid function (e.g. logistic function)

$$\psi(u) = \frac{1}{1 + e^{-au}} \quad 4.5$$

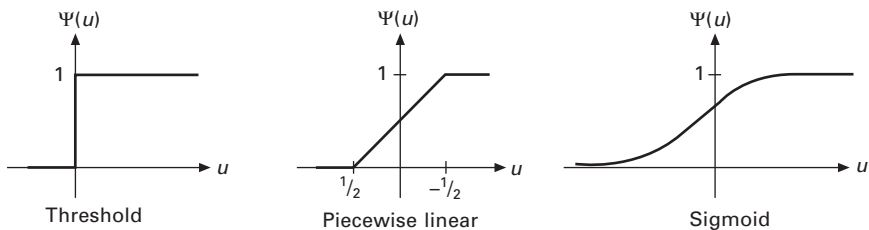
This is a very commonly used activation function.

The three functions are plotted over the most commonly used ranges in Fig. 4.2.

When y_k ranges from -1 to $+1$, the activation function is normally one of the following:

1. Threshold function

$$\psi(u) = \begin{cases} +1 & \text{if } u > 0 \\ 0 & \text{if } u = 0 \\ -1 & \text{if } u < 0 \end{cases} \quad 4.6$$



4.2 Three activation functions to give an output between 0 and 1.

2. Sigmoid function (e.g. hyperbolic tangent function)

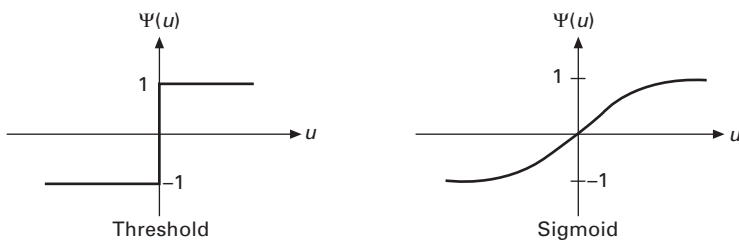
$$\psi(u) = \tanh(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}} \quad 4.7$$

The two functions are plotted over the most commonly used ranges in Fig. 4.3.

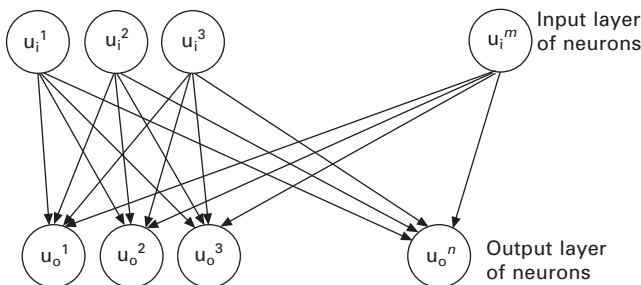
The simplest ANNs consist of two layers of neurons (Fig. 4.4). Introduction of another layer of neurons (known as the hidden layer) between the input and output layers results in a multi (three)-layer network (Fig. 4.5). Though a single-layer network can perform many simple logical operations, some are left out and introduction of a hidden layer aids in solving such problems. According to Kolmogorov's theorem, networks with a single hidden layer should be capable of approximating any function to any degree of accuracy.

4.4.2 Learning rule: back-propagation algorithm

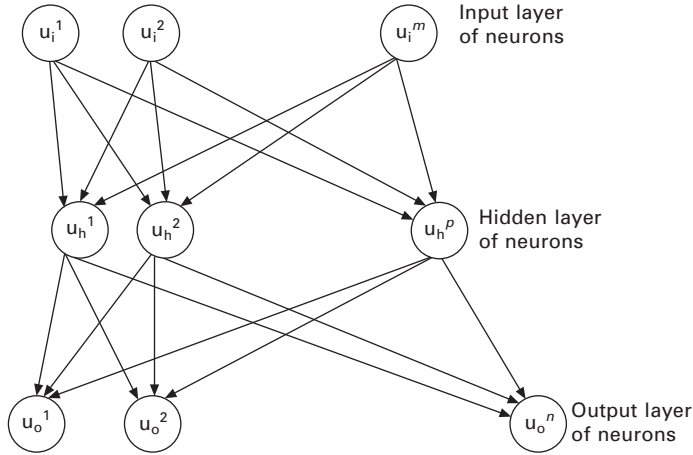
For the determination of the weights, a multilayer neural network needs to be trained with the back-propagation algorithm (Rumelhart *et al.*, 1986; Parker, 1985). The learning procedure involves the presentation of a set of pairs of input–output patterns to the network. The network first uses the input vector



4.3 Two activation functions to give an output between – 1 and +1.



4.4 A neural network without any hidden layer.



4.5 A neural network with one hidden layer.

to produce its own output vector and then compares this with the desired output or target vector. Based on the difference, the weights are changed in such a manner that the difference is reduced. The rule for changing weights following the presentation of an input–output pair p is given by

$$\Delta_p w_{ji} = \eta \delta_{pj} i_{pi} \quad 4.8$$

where

$\Delta_p w_{ji}$ is the change to be made to the weight connecting the i th and j th units following presentation of pattern p

η = a constant known as the learning rate

δ_{pj} = the error signal

i_{pi} = the value of the i th element of the input pattern.

Computation of the error signal is different depending on whether the unit is an output unit or whether it is a hidden unit. For output units, the error signal is given by

$$\delta_{pj} = (t_{pj} - o_{pj}) f'_j(\text{net}_{pj}) \quad 4.9$$

where,

t_{pj} = target output for the j th component of the output pattern p

o_{pj} = j th component of the output pattern produced by the trained ANN on presentation of the input pattern p

$f'_j(\text{net}_{pj})$ = derivative of the activation function with respect to net_{pj}

net_{pj} = net input to unit j .

For hidden units, the error signal is given by

$$\delta_{pj} = f'_j(\text{net}_{pj}) \sum_k \delta_{pk} w_{kj} \quad 4.10$$

This is known as the generalized delta rule. For applying this rule, the activation function has to be such that the output of a unit is a non-decreasing and differentiable function of the net input to that unit. The application involves two phases. During the first phase, the input is presented and propagated forward through the network to compute the output value o_{pj} for each unit. The output is then compared with the targets, resulting in an error signal δ_{pj} for each output unit. The second phase involves a backward pass through the network (analogous to the initial forward pass) during which the error signal is passed to each unit of the network and the appropriate weight changes are made. The backward pass allows the recursive computation of δ (error) as indicated above. The first step is to compute δ for each of the output units. This is simply the difference between the actual and desired output values multiplied by the derivative of the activation function. One can then compute weight changes for all connections that feed into the final layer. After this is done, one should compute the values of δ for all the units in the penultimate layer. This propagates the errors back one layer, and the same process can be repeated for every layer. The backward pass has the same computational complexity as the forward pass, so it is not unduly expensive.

True gradient descent requires that the weights be changed in infinitesimally small steps, i.e. the learning rate η be very small. However, a small learning rate leads to very slow learning. For practical purposes, the learning rate is chosen to be as large as possible without leading to oscillation. This offers the most rapid learning. One way to increase the learning rate without leading to oscillation is to modify the generalized delta rule to include a 'momentum' term as follows:

$$\Delta w_{ji}(n+1) = \eta \delta_{pj} i_{pi} + \alpha \Delta w_{ji}(n) \quad 4.11$$

where

$\Delta w_{ji}(n+1)$ = weight change in the $(n+1)$ th iteration

$\Delta w_{ji}(n)$ = weight change in the n th iteration

α = momentum term.

The momentum term is a constant which determines the effect of past weight changes on the current direction of movement in weight space. This provides a kind of momentum in weight space that effectively filters out high frequency variations of the error surface in the weight space. The advantages of neural networks are:

1. Neural networks require little human expertise: the same neural net algorithm will work for many different systems.
2. Neural networks have nonlinear dependence on parameters, allowing a nonlinear and more realistic model.
3. Neural networks can save manpower by moving most of the work to computers.

4. Neural networks typically work better than traditional rule-based expert systems for modeling complex processes because important rules and relations are difficult to know or numbers of rules are overwhelming.
5. The trained neural net can be used for sensitivity analysis to identify important process or material variables.

4.5 Design methodology

Bose (1997) has suggested the following methodology for designing a neural network:

1. Select feed-forward network if possible.
2. Select input and output nodes equal to the number of input and output signals.
3. Select appropriate input and output scale factors for normalization and denormalization of input and output signals.
4. Create input–output training data based on experimental results.
5. Set up network topology assuming it to be a three-layer network. Select hidden layer nodes equal to average of input and output layer nodes. Select transfer function.
6. Select an acceptable training error. Initialize the network with random positive and negative weights.
7. Select an input–output data pattern from the training data set and change the weights of the network following the back-propagation training principle.
8. After the acceptable error is reached, select another pattern and repeat the procedure until all the data pattern is completed.
9. If a network fails to converge to an acceptable error, increase the hidden layers neurons or increase the number of hidden layers as one may feel necessary. Usually problems are solved by having three hidden layers at most.
10. After successful training, test the network's performance with some intermediate data input.

4.6 Artificial neural network model for yarn

The problem of trying to predict yarn properties from fiber properties and process parameters can be viewed as one of function approximation. The yarn property is an unknown function of fiber properties and yarn parameters reflecting the arrangement of fibers within the yarn, and the goal is to approximate that function from a set of measurements, i.e. yarn property = f (fiber properties, fiber configuration and their arrangement, yarn count, yarn twist).

Fiber configuration and their arrangement in a way is a reflection of the dynamics of the process. If the process remains constant then it may be considered to be a black box and the yarn property then becomes a function of fiber properties and yarn count. Examples of inputs used by some researchers to the model are shown in Table 4.2.

4.6.1 Network selection

Feed-forward neural networks have been widely used for a variety of function approximation tasks. A feed-forward neural network can be created using

- several units in the input layer (corresponding to the experimentally determined input variables),
- hidden layers, and
- one unit in the output layer (corresponding to each yarn property).

First the network needs to be trained with the help of the back-propagation algorithm on the data sets. To accomplish this one needs to optimize various network parameters such as the number of hidden layers, the number of

Table 4.2 Fiber properties used as input to ANN model

No.	Researchers	Reference	Input fiber properties	Output yarn properties
1	Cheng and Adams (1995)	<i>Text. Res. J.</i> , 65(9), 495–500	Upper half mean length, uniformity index, short fiber %, strength, fineness, maturity, grayness, yellowness	Count strength product (CSP)
2	Ramesh <i>et al.</i> (1995)	<i>J. Text. Inst.</i> , 86(3), 459–469	Percentage polyester in blend, yarn count, first and second nozzle pressure	Breaking load, breaking elongation
3	Zhu and Ethridge (1996)	<i>J. Text. Inst.</i> , 87, 509–512	Upper quartile length, mean fiber length, % short fibers, diameter, neps, total trash	Yarn irregularity
4	Rajamanickam <i>et al.</i> (1997)	<i>Text. Res. J.</i> , 67(1), 37–44	Blend ratio, yarn count, first and second nozzle pressure	Yarn tenacity
5	Chattopadhyay <i>et al.</i> (2004)	<i>J. Appl. Polym. Sci.</i> , 91, 1746–1751	2.5% span length uniformity ratio, fiber fineness, bundle strength, trash content, nominal yarn count	Lea strength, CSP, yarn unevenness, total imperfection

units in the hidden layer, the type of activation function, the learning rate and the number of training cycles (also known as epochs). The procedure is described in the following section.

4.6.2 Optimizing network parameters

Number of hidden layers

Multilayer networks can handle complex nonlinear relationships easily. It is known that a feed-forward neural network with only one hidden layer can approximate any function to an arbitrary degree of accuracy. It is possible to have two or more hidden layers. However, a greater number of hidden layers increases the computation time exponentially. Therefore, a neural network with one hidden layer is better for yarn property modeling.

Number of units in the hidden layer

The number of hidden units is key to the success of the model. As stated by Cheng and Adams (1995) too few may starve the network of the resources it needs for solving the problem, whereas too many may increase the training time and may lead to over-fitting. The number of units in the hidden layer is to be decided by conducting an exercise with each set of data. In each case, the first neural network to be tried out is the one in which the number of hidden layer units satisfies the relation

$$n_{\text{hidden}} > 2 \times [\max(\text{input units, output units})] \quad 4.12$$

The initial values of weights are randomly chosen in the range -0.1 to $+0.1$. The learning rate is chosen by trial and error. Starting from an initial value of 0.1 , various values are to be tried out in the range of 0.001 to 0.5 and finally the one that gives the least mean squared error for the training set is to be accepted. A typical case (Table 4.3) shows how the mean squared error of the training set changes with the learning rate.

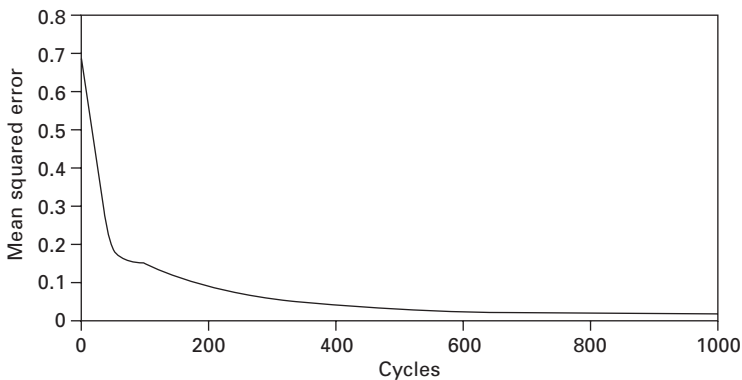
Training cycle

A typical training cycle obtained with a learning rate of 0.1 is shown in Fig. 4.6. It refers to one of the more easily trained networks in which the training error reduces very quickly in the initial stages and stabilizes to a low value. It changes marginally thereafter. In many cases, reduction of the training error may not be so drastic in the initial stages. In many cases $10,000$ cycles are needed and in some extreme cases $100,000$ cycles are necessary before the network stabilizes. The criterion for network stabilization is:

$$\frac{\varepsilon_i - \varepsilon_{i+5000}}{\varepsilon_i} < 0.1 \quad 4.13$$

Table 4.3 Mean squared error versus learning rate

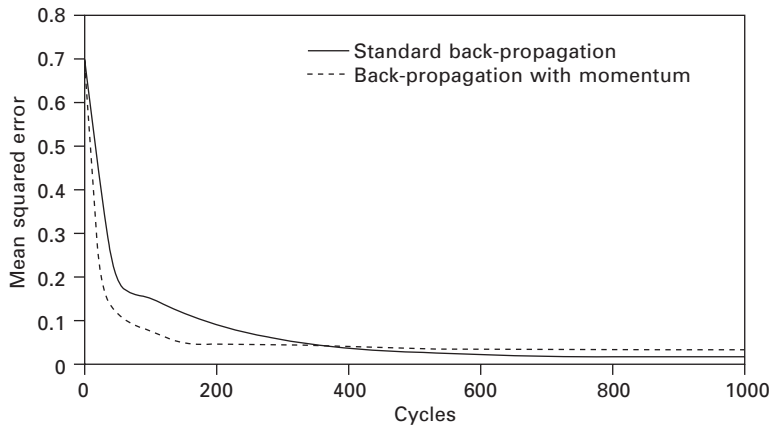
Learning rate	Mean squared error
0.001	0.0082
0.005	0.0065
0.010	0.0026
0.025	0.0009
0.050	0.0004
0.075	0.0004
0.100	0.0003
0.200	0.0008
0.300	0.0021
0.400	0.0138
0.500	0.0927



4.6 Mean squared error as a function of the number of training cycles.

where ε_i is the mean squared error of the training set after the i th iteration. A majority of networks stabilize with a mean squared error less than 0.0001. Changing the training algorithm from ‘standard back-propagation’ to ‘back-propagation with a momentum term’ causes a change in the way initial training progresses. In some cases the training error reduces faster initially but the asymptotic error value is never lower than that obtained with standard back-propagation. ‘Standard back propagation’ as opposed to the back-propagation with momentum term is shown in Fig. 4.7.

It may be observed that network training is much better if the data are normalized. Property-wise normalization of the data caused a drastic reduction in training error. Since the hyperbolic tangent (tanh) function was used as the activation function, each property was normalized to lie between 0 and 0.8. This is done by using the formula



4.7 Comparison of two training algorithms.

$$x' = \left(\frac{x - \min}{\max - \min} \right) \times 2 - 1 \quad 4.14$$

where

x' = the normalized data

x = the original data

min = value lower than the minimum value observed in x

max = value higher than the maximum value observed in x .

After training the network with this normalized data using the training set, the test data set – also comprising normalized data – was fed to the trained network. The network outputs were then renormalized by the formula

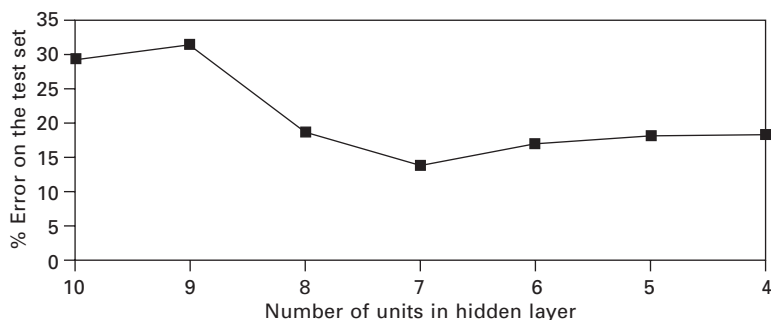
$$x = \frac{(x' + 1)(\max - \min)}{2} + \min \quad 4.15$$

The number of hidden units was then reduced one at a time and the error on the test set was noted for each case. The network with the minimum test set error was used for further analysis. A plot of the test set error as a function of the number of hidden units for a typical network is depicted in Fig. 4.8.

4.7 Modeling tensile properties

4.7.1 Data collection

The performance of a neural network is highly dependent on the quality of data used as an input to the model. Hence, the availability of quality data is extremely important. In the present case, all the relevant data were collected from a reputed industry. Lot-wise data pertaining to fiber and corresponding



4.8 Test set error as a function of the number of hidden units.

yarn properties were obtained. The five fiber properties were 2.5% span length, uniformity ratio, fineness, bundle strength and trash content. The yarn properties noted were yarn count, lea strength, count strength product (CSP), coefficient of variation (CV) of count, CV of lea strength, yarn unevenness (CV) and total imperfections per kilometer. Twenty distinct lots were spun over the four-month period during which data were collected and, thus, 20 sets of data were obtained. The details are shown in Table 4.4.

4.7.2 Model architecture

A feed-forward neural network was constructed with six input units, five corresponding to the fiber properties and one to the yarn count. The network had one hidden layer. Two types of architecture were chosen:

- A network with one output unit corresponding to one of the other six yarn properties at a time (Fig. 4.9)
- A network with six output units corresponding to six yarn properties as depicted in Fig. 4.10.

The number of units in the hidden layer was varied between 20 and 2. It was trained with the help of a back-propagation algorithm on the same 11 data sets. The values were all scaled to lie between -1 and $+1$ and the hyperbolic tangent (tanh) function was used as the activation function for all the units. The number of units in the hidden layer was decided by gradually reducing the number of units and observing their effect on the error of the test set.

4.7.3 Results

6-1 Network architecture

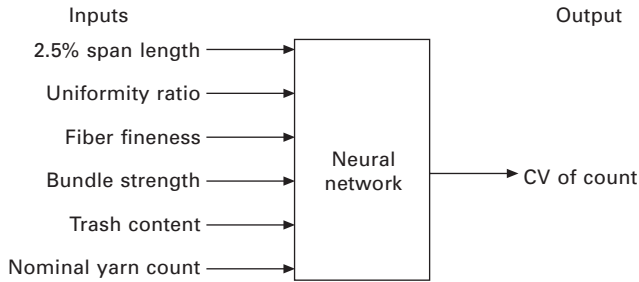
The results are summarized in Table 4.5 for the yarn properties for 6-1 network architecture. It can be seen that the yarn unevenness (CV%) shows

Table 4.4 Ring yarn related data obtained from industry

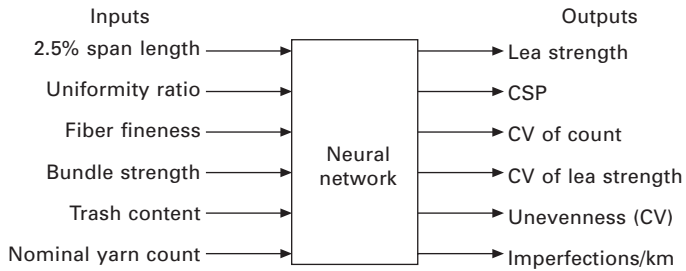
Sl. no.	Fiber properties				Yarn properties							
	2.5% span length (mm)	UR (%) [†]	Fineness (μg/inch)	Bundle strength (cN/tex)	Trash content (%)	Count (tex)	Lea strength (kg)	CSP	CV% of count	CV% of strength	Unevenness (CV)	Total imperfections per km
1	28.32	49.6	4.18	22.25	5.32	36.91	82.56	2879	1.19	4.08	14.19	347
2*	27.98	49.6	3.80	21.84	5.60	36.91	83.46	2956	2.15	3.53	13.97	342
3	28.53	48.0	4.50	22.17	6.30	36.91	85.73	3011	1.43	4.93	13.88	303
4	29.58	50.0	4.24	22.17	5.38	36.91	79.38	2747	2.25	5.47	13.94	178
5*	29.20	50.5	4.25	22.27	5.30	36.91	76.66	2701	2.40	5.50	14.24	168
6	27.67	49.0	4.42	21.71	5.73	36.91	75.30	2643	2.12	4.84	14.46	213
7	27.94	48.8	3.90	21.46	5.48	29.53	63.96	2760	1.37	3.92	15.58	484
8	28.32	49.6	4.18	22.25	5.32	29.53	68.04	2905	2.00	4.36	14.95	331
9*	27.98	49.6	3.80	21.84	5.60	29.53	63.50	2844	1.74	4.61	14.69	434
10	28.53	48.0	4.50	22.17	6.30	29.53	57.61	2556	2.39	6.00	14.77	390
11*	27.67	49.0	4.42	20.73	5.73	29.53	56.70	2483	1.35	4.16	14.94	342
12	28.32	50.2	4.44	20.44	5.52	29.53	58.51	2587	1.87	4.16	14.97	370
13	25.40	48.0	5.44	15.36	14.20	28.80	41.73	1829	2.39	5.35	18.01	748
14	24.67	47.3	5.50	15.70	14.40	28.80	44.00	1841	1.90	5.19	18.34	752
15*	25.20	46.0	5.00	14.72	13.87	28.80	41.73	1848	2.03	4.66	18.19	765
16	25.48	48.0	5.48	15.63	13.75	28.80	43.09	1916	2.13	4.38	17.92	750
17	25.40	48.0	5.44	15.36	14.20	28.80	44.00	1919	2.35	4.26	17.88	680
18*	25.05	47.5	5.25	15.19	13.18	28.80	42.18	1933	1.96	4.61	17.88	762
19	24.17	46.3	5.10	14.65	14.40	28.80	42.64	1919	1.82	4.90	18.79	729
20	22.40	45.5	5.40	15.25	14.40	28.80	43.09	1910	2.46	5.17	18.18	739

*Indicates test data.

[†]UR: uniformity ratio.



4.9 Network architecture.



4.10 6-6 Network architecture.

Table 4.5 Test set errors (%) for ring yarn

	Test sample number						Average error (%)
	1	2	3	4	5	6	
Lea strength	8.0	2.1	18.0	3.4	7.4	3.5	7.1
Count strength product	9.3	5.7	4.7	5.4	6.0	5.7	6.1
CV% of count	21.1	20.3	6.2	43.5	7.3	14.2	18.8
CV% of lea strength	33.4	2.1	16.9	3.7	5.6	2.9	10.8
Unevenness (CV%)	2.8	0.3	0	5.1	1.7	4.6	2.4
Total imperfections per km	34.0	13.4	12.3	39.0	3.4	8.1	18.4
Average error (%)	18.1	7.3	9.7	16.7	5.3	6.5	10.6

a high degree of predictability (giving an average error of 2.4%) by the neural network followed by CSP and lea strength. Total imperfections and CV% of yarn count, giving more than 18% errors, are not well predicted. The overall error was 10.6%. Out of six samples, the average error was less than 10% in four cases.

6-6 Network architecture

Out of the 20 data sets available, 14 were randomly chosen for training the network and the remaining six were used as the test set. The trained

network was able to predict the training set with almost 100% accuracy. The average errors on the test set are shown in Table 4.6. It can be seen that lea strength, count strength product, CV of strength and unevenness (CV) are very well predicted while total imperfections per kilometer and CV of count are not. The average error is 7.5%. The high error in the case of CV of count and total imperfection could be due to insufficient data used for training, absence of process-related information in the training set data, or network complexity.

4.7.4 Error reduction

One way of reducing the error is to reduce the complexity of the network by reducing the number of inputs. Since cotton properties are known to be correlated, there exists an opportunity to reduce the number of fiber properties used as input. Therefore the correlation coefficients between fiber properties were determined (Table 4.7).

It can be seen that the magnitudes of the correlation coefficients lie between 0.73 and 0.98. Except for two, all were 0.8 or more. Therefore it can be presumed that using only one of these five properties may cause an improvement in the network's performance. This is expected because the information lost by neglecting the other four properties might be more than offset by the reduction in network size and subsequent reduction in network

Table 4.6 Average error (%) of test set for predicting properties of ring yarn

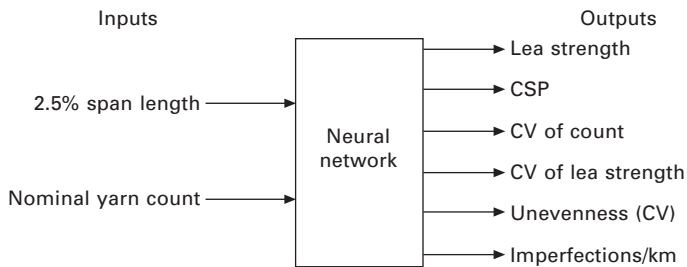
Predicted property	Error (%) for 6-6 architecture	Error (%) for 6-1 architecture
Lea strength	3.9	7.1
Count strength product	2.7	6.1
CV% of count	19.1	18.8
CV% of strength	3.4	10.8
Unevenness (CV%)	2.4	2.4
Total imperfections per km	13.6	18.4
Average error (%)	7.5	10.6

Table 4.7 Correlation coefficients amongst properties of fibers

	2.5% span length	Uniformity ratio	Fiber fineness	Bundle strength	Trash content
2.5% span length	1	0.8738	-0.8365	0.9287	-0.9289
Uniformity ratio	0.8738	1	-0.7341	0.7998	-0.8249
Fiber fineness	-0.8365	-0.7341	1	-0.9079	0.9337
Bundle strength	0.9287	0.7998	-0.9079	1	-0.9837
Trash content	-0.9289	-0.8249	0.9337	-0.9837	1

complexity. The fiber property to be retained as input to the network is made on the basis of correlation coefficients by a high volume instrument (HVI). It can be seen that in the case of the uniformity ratio, the correlation coefficients between it and the fiber fineness and bundle strength are less than 0.8. Only span length and trash content have correlation coefficients with the rest of the other properties of 0.8 or above. So the choice narrowed down to 2.5% span length and trash content. HVI measures trash content by optically scanning the surface of a fiber tuft and comparing the image with previously stored standard images from its database. This method can hardly be called very reliable. Besides, trash content is not an intrinsic property of the fiber. Hence, 2.5% span length was selected as the fiber property to be used to carry out the exercise.

A feed-forward neural network (Fig. 4.11) was trained with the same 14 data sets used earlier but by using only 2.5% span length and yarn count as inputs. The errors of the test set are shown in Table 4.8. It can be seen from Table 4.8 that prediction of all the yarn properties except lea strength deteriorated for the network with two inputs. In most cases, the deterioration was quite small except for CV of strength and total imperfections per kilometer. Nevertheless, the overall performance deteriorated from 7.5% to 9.2%. This indicated that this approach at reducing network complexity was not capable of delivering the desired result.



4.11 Structure of the truncated network.

Table 4.8 Comparison of error % of test set for networks with six and two inputs

Predicted property	Error % of networks with	
	Six inputs	Two inputs
Lea strength	3.9	3.4
Count strength product	2.7	4.0
CV% of count	19.1	20.0
CV% of strength	3.4	7.8
Unevenness (CV%)	2.4	3.4
Total imperfections per km	13.6	16.6
Average error (%)	7.5	9.2

4.8 Conclusion

- In all the cases, neural networks could predict the training set data with almost 100% accuracy.
- For test set data, the prediction error varied from 2 % to 18%.
- The presumption that cutting down the number of inputs to a network, based on the strength of correlation coefficients, would lead to better network performance due to a reduction in network complexity was found not to work well.

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Performance evaluation and enhancement of artificial neural networks in prediction modelling

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Abstract: This chapter describes attempts to break the black box myth of neural networks. It describes two attempts to find the relative importance of inputs from a trained network. The first of these is skeletonization, a method reported for pruning neural networks, while the second is an approach based on first-order sensitivity analysis. This is followed by a description of the application of principal component analysis for analysing and improving the performance of neural networks. The methods suggested in all these sections have been explained with examples relevant to the textile industry.

Key words: neural network, skeletonization, sensitivity analysis, principal component analysis, orthogonalization.

5.1 Introduction

Neural networks were developed in an attempt to mimic the human brain. It has not been possible to unearth all the secrets of the human brain so far. However, that has not prevented the brain from being used to solve intricate problems. Similarly, even though artificial neural networks (ANNs) have been used to solve a range of complex problems, the networks have been mostly used as a black box and the structure of a trained network has been analysed by very few. The efforts of the researchers, who have applied ANNs to diverse fields, have been to design the problem so that it becomes easier for the ANN to get trained. Little attempt has been made to understand what happens to the weights and biases as the network gets trained. Such studies have been left to researchers in artificial intelligence – who have come up with better and more efficient algorithms for training ANNs. Analysis of the trained network, either to improve its performance or to extract information from it, has not been widely reported. This chapter will outline some techniques which can be used to address these issues. A specific scenario in a textile industry where such techniques can be of use (as outlined by Guha, 2002) is as follows.

The fibre purchase department of a mill spinning cotton yarn would find it useful to use neural networks to get an idea about the kind of yarn which could be spun from a particular type of fibre. Sometimes, it may be found

that all the desirable properties of the fibre for spinning a yarn as per the customer's specifications are not being met by any particular variety. Each variety is good in some aspect but is deficient in the others. When fibre with the ideal property profile is not available, one has to choose from the currently available fibre varieties which can be spun into a yarn with properties closest to those desired. To make a right decision in such a case, one needs to know the relative importance of the fibre properties with respect to specific yarn properties. This is because the mill usually has to meet some yarn property requirements very stringently and can afford to be lenient on some others. This relative importance is usually known to an experienced technologist but is not so obvious to a newcomer. In addition they may vary slightly depending on the processing conditions prevalent in the mill. Therefore, if a method exists that can quantify the relative importance of various fibre properties for specific yarn properties, it will be an invaluable tool in the hands of the fibre purchase department. It has already been shown in the previous chapter that a neural network can be trained to predict yarn properties from fibre properties. So, in one sense, the knowledge about the relative importance of the fibre properties is latent in the trained network. However, an ANN is generally thought to act like a "black box". It yields probable outputs for given inputs but does not divulge any other information about the system.

The next two sections will explore two approaches for solving this problem. The first of these discusses skeletonization, a method reported for pruning neural networks, while in the second, an approach based on first-order sensitivity analysis is described. The two succeeding sections will discuss the application of principal component analysis for analysing and improving the performance of neural networks. The methods suggested in all these sections will be explained with examples relevant to the textile industry.

5.2 Skeletonization

To judge the importance of any input on the output of a network, it is necessary to establish a quantitative measure of 'importance' (saliency) of the input unit (neuron) of a network. Very little information is found on this topic. By contrast, a number of attempts have been reported to compute the saliencies of the 'weights' in a feedforward neural network with the aim of identifying the least important weights and pruning them, thereby achieving a network with better generalizing capabilities. Le Cun *et al.* (1990), Stork and Hassibi (1993) and Levin *et al.* (1994), to name a few, have done pioneering work in this respect. Of all the pruning techniques proposed, only Mozer and Smolensky (1989) have proposed a method of evaluating the saliencies of the hidden 'units' and then pruning the least important ones. They have termed this method 'skeletonization'. The same technique can be used for

evaluating the saliencies of units in the input layer. This would allow a comparative assessment of the importance of the inputs to a network to be made. Their method is based on the following assumption:

$$\rho_i = E_{\text{without unit } i} - E_{\text{with unit } i} \quad 5.1$$

where

$$\begin{aligned} \rho_i &= \text{saliency of unit } i \\ E_{\text{without unit } i} &= \text{training error of the network without unit } i \\ E_{\text{with unit } i} &= \text{training error of the network with unit } i. \end{aligned}$$

This is computationally quite expensive. Since the objective of Mozer and Smolensky (1989) was to devise a method by which the least important units can be pruned during training, it was necessary to arrive at an approximation of this relationship which was computationally less expensive. However, since the present objective is only to analyse a trained network to calculate the saliency of the input units, high computational expense can be tolerated. So Equation 5.1 can be directly used for calculating the saliency of an input unit.

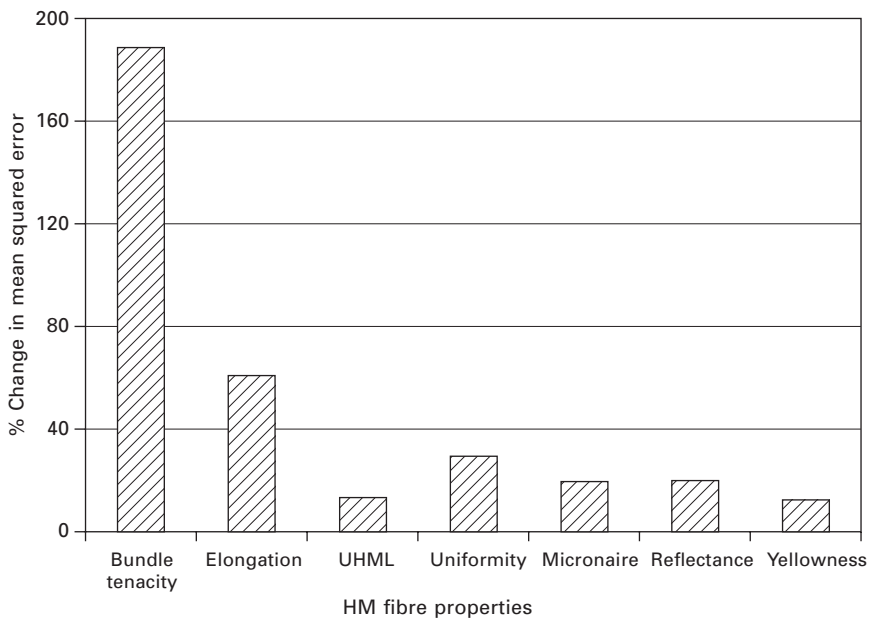
In order to use this technique for estimating the relative importance of inputs to a neural network, the 'sum squared error' of the network at the end of training needs to be noted. Then the first input unit should be removed, the network should be retrained and the final sum squared error should be noted. The difference between these two sum squared errors can be considered the saliency (importance) of the first input neuron. The saliencies of all the inputs to the original network can be obtained in a similar manner.

The method, though simple and straightforward, may fail to give the correct result. Jayadeva *et al.* (2003) describe an exercise in which neural networks were used to predict ring yarn lea strength, CSP, unevenness and imperfections from yarn count, 2.5% span length of cotton, uniformity ratio, bundle strength, fibre fineness and trash content, and then skeletonization was used to find the relative importance of the inputs for each of the yarn properties. The whole process was repeated for networks with four and six hidden units respectively (since both these types of networks gave the least errors on the test set). From the two rank values, the average ranking was found for each input parameter. However, when the results of the rankings were compared with similar rankings given in the *Uster News Bulletin* No. 38 (Uster, 1991), considerable differences were observed. Overall, the differences between the rankings derived from skeletonization and those reported by Uster were too large to consider the exercise to be a success. However, the simplicity of the technique is a temptation for one to study it for different data sets.

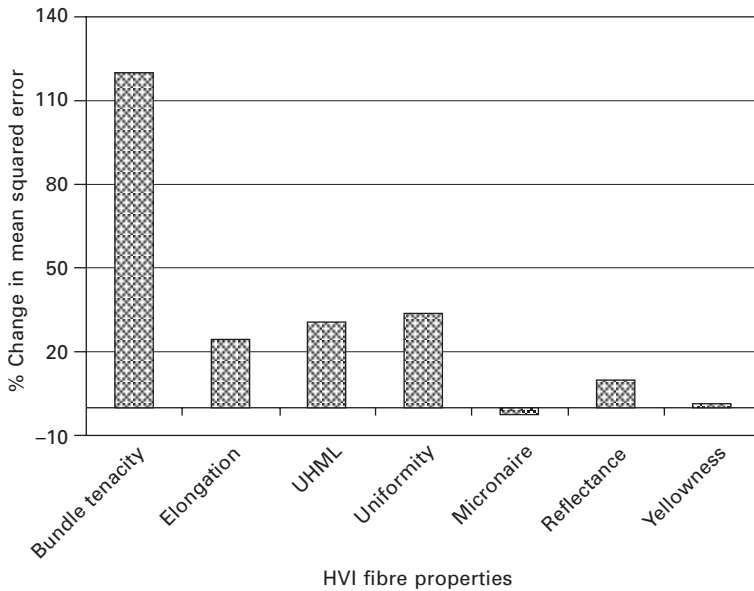
Such a study has indeed been reported by Majumdar *et al.* (2004). They have reported an exercise in which ring and rotor single yarn tenacity was predicted from seven cotton properties measured by HVI (fibre bundle tenacity,

elongation, upper half mean length, uniformity index, micronaire, reflectance degree and yellowness). Feedforward neural networks with a single hidden layer were used. The importance of an input was judged by removing that input, training the ANN for the same number of iterations and noting the percentage change in mean squared error of the training set (compared to the mean squared error for the original network). A higher change indicated greater importance. The results reported by them are shown in Figs 5.1 and 5.2.

Fibre bundle tenacity was shown to be the most important fibre property for predicting tenacity of both ring and rotor yarns. For ring spun yarns, the next two cotton properties in order of descending importance are fibre elongation and uniformity index, while for rotor spun yarns these are uniformity index and upper half mean length. Ethridge and Zhu (1996) also found fibre bundle tenacity and length uniformity to be the first and second most important contributors of rotor yarn tenacity. However, in stark contrast to these findings for ring spun yarns, Shanmugam *et al.* (2001) and Guha (2002) found the least importance of length uniformity towards yarn CSP. This apparent disparity in the ranking may be ascribed to the difference in the testing methods for CSP and single yarn tenacity. In case of single yarn tenacity measurement a solitary yarn is subjected to tensile loading. It is a well-known fact that the yarn breaks from its weakest region during tensile



5.1 Relative importance of cotton fibre properties for predicting ring yarn tenacity (Majumdar *et al.*, 2004).

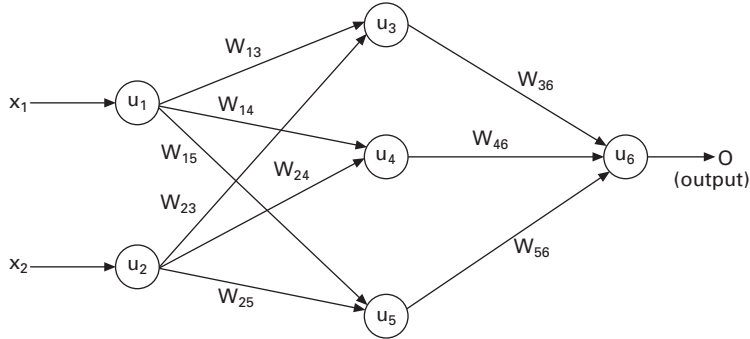


5.2 Relative importance of cotton fibre properties for predicting rotor yarn tenacity (Majumdar *et al.*, 2004).

loading. Length uniformity determines the evenness of ring spun yarns and thereby emerges as a dominant contributor to single yarn tenacity. The preponderance of uniformity index over UHML is evident for both ring and rotor spun yarns. Uniformity index is an indicator of short fibre content in cotton fibre (Ramey and Beaton, 1989). Short fibres undermine the single yarn tenacity of ring yarns by creating hairs and generating drafting waves. In rotor yarns, too long fibres have a higher propensity of wrapper formation which does not contribute to yarn tenacity (Pal and Sharma, 1989). Therefore, uniformity index probably becomes more influential than UHML. It is noteworthy that bundle tenacity, elongation and uniformity index find their place within the top four in the hierarchy of cotton properties for both ring and rotor spun yarns. Colour properties (reflectance degree and yellowness) and micronaire of cotton rank low in the list. Ethridge and Zhu (1996) and Guha (2002) gave similar ranking to micronaire in the case of rotor and ring spun yarns respectively. For a given yarn count, micronaire value generally influences the tenacity and evenness of spun yarns by determining the number of fibres present in the cross-section. However, for rotor spun yarns a huge amount of doubling occurs at the final stage of yarn formation, which makes the yarn very regular. Therefore, the influence of cotton micronaire on yarn tenacity diminishes. The influence of yarn count (N_e) on single yarn tenacity is more pronounced in the case of rotor spun yarns.

5.3 Sensitivity analysis

A second method of evaluating the relative importance of input neurons is based on an analysis of the trained network. A typical feedforward neural network with two units in the input layer, three units in a single hidden layer and one unit in the output layer is shown in Fig. 5.3. The importance of



5.3 A typical neural network.

input x_1 can be evaluated by first-order sensitivity analysis, which computes the rate of change of output with respect to the input, i.e. $\partial O / \partial x_1$. This can be estimated as follows:

$$O = f(\text{net } u_6) \quad 5.2$$

where 'net u_6 ' stands for 'net input to unit 6' and, in general, 'net u_i '; stands for 'net input to unit i ' and $f(\cdot)$ stands for activation function. Let $f'(\cdot)$ stand for the first derivative of the activation function and u_i stand for the output from 'unit i '. Then

$$\begin{aligned} \frac{\partial O}{\partial x_1} &= \frac{\partial \{f(\text{net } u_6)\}}{\partial x_1} \\ &= \frac{\partial \{f(\text{net } u_6)\}}{\partial (\text{net } u_6)} \cdot \frac{\partial (\text{net } u_6)}{\partial x_1} \\ &= f'(\text{net } u_6) \cdot \frac{\partial (u_3 w_{36} + u_4 w_{46} + u_5 w_{56})}{\partial x_1} \\ &= f'(\text{net } u_6) \left(w_{36} \frac{\partial u_3}{\partial x_1} + w_{46} \frac{\partial u_4}{\partial x_1} + w_{56} \frac{\partial u_5}{\partial x_1} \right) \\ &= f'(\text{net } u_6) \left(w_{36} \frac{\partial \{f(\text{net } u_3)\}}{\partial x_1} + w_{46} \frac{\partial \{f(\text{net } u_4)\}}{\partial x_1} \right. \\ &\quad \left. + w_{56} \frac{\partial \{f(\text{net } u_5)\}}{\partial x_1} \right) \end{aligned}$$

$$\begin{aligned}
&= f'(\text{net } u_6) \left(w_{36} \frac{\partial \{f(\text{net } u_3)\}}{\partial (\text{net } u_3)} \cdot \frac{\partial (\text{net } u_3)}{\partial x_1} \right. \\
&\quad + w_{46} \frac{\partial \{f(\text{net } u_4)\}}{\partial (\text{net } u_4)} \cdot \frac{\partial (\text{net } u_4)}{\partial x_1} \\
&\quad \left. + w_{56} \frac{\partial \{f(\text{net } u_5)\}}{\partial (\text{net } u_5)} \cdot \frac{\partial (\text{net } u_5)}{\partial x_1} \right) \\
&= f'(\text{net } u_6) \left(w_{36} f'(\text{net } u_3) \frac{\partial (u_1 w_{13} + u_2 w_{23})}{\partial u_1} \cdot \frac{\partial u_1}{\partial x_1} \right. \\
&\quad + w_{46} f'(\text{net } u_4) \frac{\partial (u_1 w_{14} + u_2 w_{24})}{\partial u_1} \cdot \frac{\partial u_1}{\partial x_1} \\
&\quad \left. + w_{56} f'(\text{net } u_5) \frac{\partial (u_1 w_{15} + u_2 w_{25})}{\partial u_1} \cdot \frac{\partial u_1}{\partial x_1} \right) \\
&= f'(\text{net } u_6) \left(w_{13} w_{36} f'(\text{net } u_3) f'(x_1) + w_{14} w_{46} f'(\text{net } u_4) f'(x_1) \right. \\
&\quad \left. + w_{15} w_{56} f'(\text{net } u_5) f'(x_1) \right) \\
&= f'(\text{net } u_6) f'(x_1) \left(w_{13} w_{36} f'(\text{net } u_3) + w_{14} w_{46} f'(\text{net } u_4) \right. \\
&\quad \left. + w_{15} w_{56} f'(\text{net } u_5) \right) \quad 5.3
\end{aligned}$$

The value of $\partial O / \partial x_1$ has to be determined for all the patterns (i.e. sets of data) and then added up. This sum can be considered to be a measure of the importance of the input x_1 .

$$\text{Saliency of } x_1 = \sum_{i=1}^n \frac{\partial O}{\partial x_1^i} \quad 5.4$$

The importance of input x_2 can be evaluated by following a similar procedure.

Jayadeva *et al.* (2003) have applied this technique to the same neural network described earlier in Section 5.2. For every yarn property, two networks were considered, one with four hidden units and one with six hidden units. The saliency of an input unit was taken to be the average of saliencies evaluated from these two networks. A positive value of saliency was taken to indicate that an increase in the numerical value of that fibre property (keeping all other factors constant) would result in an increase in the numerical value of that yarn property. The reverse holds true for a negative saliency. However, for judging the ‘importance’ of a fibre property, only the magnitude of the saliency was considered.

The saliencies of all the fibre properties are summarized in Tables 5.1 to 5.4. The ranking of the input parameters thus obtained was quite different from that obtained by the previous method (skeletonization). It is interesting

Table 5.1 Importance of fibre properties for prediction of lea strength

	Saliency from a network of		Average saliency
	Four hidden units	Six hidden units	
2.5% span length	8.6	8.3	8.45
Yarn count	-5.4	-5.4	-5.40
Bundle strength	3.7	3.7	3.70
Trash content	2.4	2.4	2.40
Uniformity ratio	-2.2	-1.9	-2.05
Fibre fineness	-0.1	-0.4	-0.5

Table 5.2 Importance of fibre properties for prediction of CSP

	Saliency from a network of		Average saliency
	Four hidden units	Six hidden units	
2.5% span length	6.4	6.9	6.65
Bundle strength	4.5	4.5	4.50
Trash content	2.2	3.4	2.80
Fibre fineness	-1.7	-3.0	-2.35
Uniformity ratio	-1.5	-0.9	-1.20
Yarn count	0.4	-0.9	-0.25

Table 5.3 Importance of fibre properties for prediction of unevenness (CV%)

	Saliency from a network of		Average saliency
	Four hidden units	Six hidden units	
2.5% span length	-11.2	-10.5	-10.85
Bundle strength	3.5	3.4	3.45
Trash content	-2.5	-2.7	-2.60
Fibre fineness	-1.7	-1.6	-1.65
Uniformity ratio	-0.8	-0.6	-0.70
Yarn count	-0.5	-0.5	-0.50

Table 5.4 Importance of fibre properties for prediction of total imperfections per kilometre

	Saliency from a network of		Average saliency
	Four hidden units	Six hidden units	
Bundle strength	-5.7	-4.1	-4.90
Fibre fineness	-5.5	-3.8	-4.65
Uniformity ratio	-4.1	-3.9	-4.00
Yarn count	1.8	2.7	2.25
Trash content	1.9	2.5	2.20
2.5% span length	-0.3	0.0	-0.15

to note that these rankings were quite close to the rankings reported in the *Uster News Bulletin* No. 38 (Uster, 1991) which is selectively reproduced in Table 5.5. For example, fibre length and bundle strength are the two most important fibre properties affecting lea strength in Table 5.1. The Uster bulletin also shows fibre length and bundle strength to be highly correlated with yarn tenacity. The bulletin also shows fibre length and fibre fineness to be highly and moderately correlated with yarn unevenness respectively. The other fibre properties are shown to be sparsely correlated. In Table 5.3, 2.5% span length and fibre fineness are indeed shown to be the two most important fibre properties affecting yarn unevenness. Yarn count is shown to be very important for predicting lea strength (Table 5.1) but not so important for predicting CSP (Table 5.2). This is more in line with what was expected in contrast to the previous method.

The only significant deviation between the rankings obtained by the sensitivity analysis and those published in the Uster bulletin is with respect to yarn imperfections. The bulletin shows the length and trash content of a fibre to be highly correlated with imperfections in the yarn; in Table 5.4, span length and trash content come last in the rankings.

Another significant anomaly was the low importance given to uniformity ratio while predicting yarn unevenness (CV%) (Table 5.3). Short fibre content is a significant factor that affects yarn unevenness (CV%) and uniformity ratio is generally accepted to be an indicator of the short fibre content. So uniformity ratio and unevenness (CV%) were expected to be closely related, which is not reflected in Table 5.3. This apparent anomaly can be explained by calling into question the hypothesis that uniformity ratio is 'always' a true indicator of short fibre content. It is indeed possible to have two different fibre arrays that have similar uniformity ratios but widely different short fibre percentages and vice versa. Smirfitt (1997) has commented at length on the incongruity of the relationship between short fibre content and uniformity ratio. It has also been reported in *Textile Topics* (1985) that short fibre content and uniformity ratio have a correlation coefficient of only 0.53 when short fibre content is measured by the array method and when uniformity ratio

Table 5.5 Correlation between fibre properties and ring yarn properties reported by Uster

Fibre	Yarn		
	Tenacity	Unevenness	Imperfections
Length	H	H	H
Bundle strength	H	L	L
Fineness	M	M	M
Trash content	L	L	H

H: High correlation; M: Medium correlation; L: Little or no correlation

is measured by the digital fibrograph (which measures span lengths in the same manner as that of an HVI).

One interesting observation is the low ranking given to 'trash content' for prediction of 'total imperfections per kilometre' in both the methods. This may be ascribed to easily extractable trash and highly efficient cleaning equipment (namely, blowroom and carding machines) in the textile industry from which data had been collected, which resulted in the removal of all significant trash particles from cotton by the time yarn was formed. Alternatively, it may be caused by the inability of the network to create a system which can properly predict yarn imperfections from fibre properties. This is further borne out by the fact that yarn imperfections was the worst predicted of these four yarn properties, giving an average error of 18.4%, compared to 7.1%, 6.1% and 2.4% for the other three yarn properties.

The existence of a high degree of correlation between fibre properties can also blur the distinction between 'important' and 'unimportant' fibre properties. This can inadvertently give high importance to an input simply because it is highly correlated with another input that is known to be very important. In order to check this assumption, correlation coefficients between all the fibre properties of the fibres used in this study were calculated. It was found that the correlation coefficients range from 0.73 to 0.98 in magnitude and, except for two, all had a magnitude higher than 0.8. This might explain the apparent anomalies in the ranking of fibre properties when studying their effect on yarn properties. For example, though uniformity ratio is shown to have the least importance for predicting yarn unevenness (CV%) (Table 5.3), it had a high correlation coefficient (0.87) with 2.5% span length, which is given the highest importance. Therefore uniformity ratio can be thought to have been given a high importance, albeit indirectly.

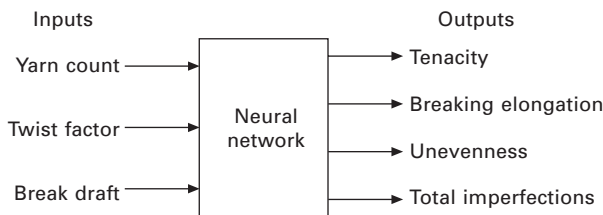
The sensitivity analysis technique can thus be considered to be useful for analysing a trained neural network to find out the relative importance of the inputs. This can be used for better understanding of processes (textile or otherwise) which have been simulated from a large database but for which a clear understanding of the underlying process is missing. However, if the input parameters are not independent and have a high correlation amongst each other, the results of sensitivity analysis may deviate from what is expected.

5.4 Use of principal component analysis for analysing failure of a neural network

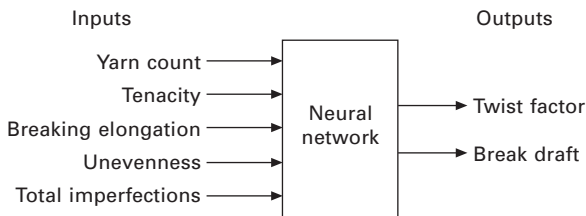
One of the useful ways in which neural networks can be used by a spinning industry is for predicting the process parameters required to spin a yarn with desired properties from a particular fibre on a given process line. In most studies, neural networks have been trained by using fibre properties or process

parameters as inputs and yarn properties as outputs. What happens when the reverse is attempted is reported by Guha (2002). A data set pertaining to ring yarns spun in the laboratory was used for this study. When the data was used to train a neural network in the usual manner – process parameters (and yarn count) as input and yarn properties as output (Fig. 5.4) – it was possible to train the network. The errors of the test set lay between 1.1% and 5.9%.

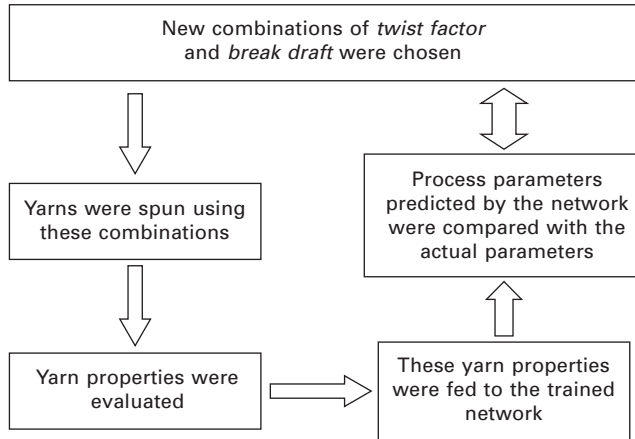
Next, the situation was reversed, i.e. the network was trained with yarn properties as inputs and process parameters as output (Fig. 5.5). There are two ways in which the performance of such a network can be tested. These are depicted pictorially in Figs 5.6 and 5.7. The first scheme resulted in test set errors of 2.9% and 5.4% for twist factor and break draft. The second scheme resulted in an average test set error of 28.1%. A detailed analysis of the cause of failure of the neural network in the second scheme was carried out. It was found that out of the seven random combinations of yarn properties which were chosen, three gave low errors and four gave very high errors. One conjecture which could have explained this was that the training set input data forms clusters in a four-dimensional space (each dimension corresponding to a yarn property). The four test set data which gave high errors perhaps lay outside these clusters. In order to prove this conjecture, it was necessary to visualize the samples as data points so that clusters, if any, could be identified. For this, it was necessary to reduce the four-dimensional



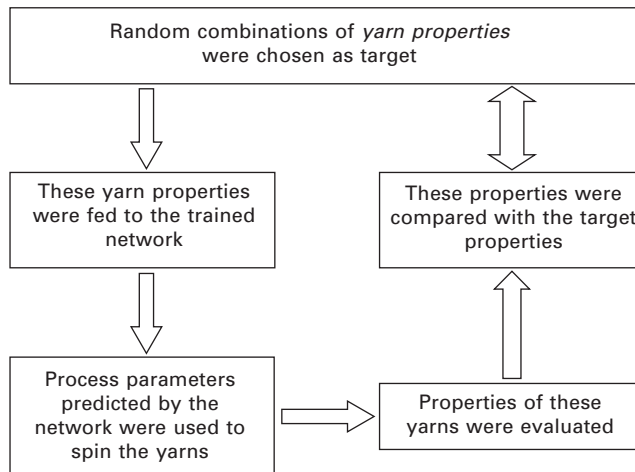
5.4 Schematic representation of network for predicting yarn properties.



5.5 Schematic representation of network for predicting process parameters.



5.6 Flow diagram for procedure adopted to predict process parameters for yarns which had already been spun (first scheme).



5.7 Flow diagram for procedure adopted to predict process parameters for yarns which had not been spun (second scheme).

data to three-dimensional data while losing the least amount of information. Principal component analysis allowed this to be done.

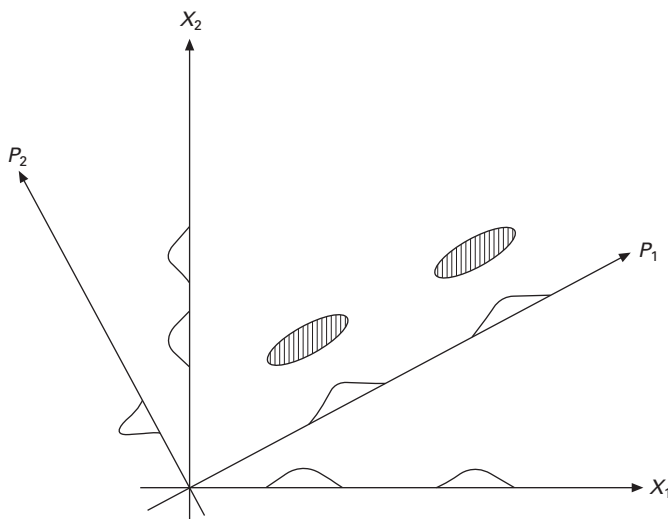
A detailed treatment of principal component analysis (PCA) is available in many references (Haykin, 1994; Hertz *et al.*, 1991). The aim of principal component analysis is the construction, out of a set of variables X_i ($i = 1, 2, \dots, k$), a new set of variables (P_i) called principal components, which are linear combinations of the X 's. These combinations are chosen so that the principal components satisfy two conditions:

1. The principal components are orthogonal to each other.
2. The first principal component accounts for the highest proportion of total variation in the set of all X 's, the second principal component accounts for the second highest proportion and so on.

Figure 5.8 shows a two-dimensional data set (plotted in the X_1 – X_2 plane) which is divided into two clusters. The variations of the data along the axes are also shown. Neither of these two axes can be termed more important than the other for describing the data. Now, the principal components P_1 and P_2 can be drawn in such a way that the highest variation of the data occurs along P_1 (the first principal component) and the next highest variance (in this case the lowest) occurs along P_2 (the second principal component). It is now obvious that P_1 is more important for describing the data than P_2 .

In the current problem, this technique needs to be applied to four-dimensional data. Once the relative importance of the four principal components is known, the projection of the data along the first three principal components will give a projected data set in three dimensions (instead of four) with least information being lost. The three-dimensional data can then be visualized and the existence of clusters in the data can be explored.

Given a set of data, the principal components are the eigenvectors of the covariance matrix sorted in decreasing order of the corresponding eigenvalues i.e. the first principal component is the eigenvector corresponding to the largest eigenvalue. Let the data be arranged in the form of a matrix with m rows and n columns, with the rows indicating the samples and the columns



5.8 Principal components.

indicating the properties. The following steps need to be performed to extract the principal components from the data.

Step 1: The data are first converted to a set of values with zero mean by subtracting the average of each column from each of the values of the column. Let any row of this zero-mean matrix be given by

$$y_1 \quad y_2 \quad \dots \quad y_n$$

Step 2: The correlation matrix corresponding to this row must be calculated as follows:

$$\begin{bmatrix} (y_1)^2 & (y_1 y_2) & \dots & (y_1 y_n) \\ (y_2 y_1) & (y_2)^2 & \dots & (y_2 y_n) \\ \dots & \dots & \dots & \dots \\ (y_n y_1) & (y_n y_2) & \dots & (y_n)^2 \end{bmatrix}$$

Step 3: The correlation matrices for all the m rows must be evaluated.

Step 4: All the correlation matrices obtained in step 3 must be added up to get the final correlation matrix.

Step 5: The eigenvalues and eigenvectors of this correlation matrix should be calculated. The eigenvectors are the principal components and the eigenvalues give their relative importance.

Step 6: The projection of the original matrix onto the principal components gives an orthogonalized data set of n dimensions. The relative importance of each dimension is given by the corresponding eigenvalue.

In this exercise, the eigenvectors were the columns of the following matrix:

$$E = \begin{bmatrix} -0.1944 & 0.8397 & 0.5063 & 0.0281 \\ -0.3206 & 0.4331 & -0.8352 & -0.1103 \\ 0.6484 & 0.2029 & -0.047 & -0.7323 \\ 0.6626 & 0.2574 & -0.2096 & 0.6714 \end{bmatrix} \quad 5.5$$

The corresponding eigenvalues were given by

$$\lambda = (24.2306, \quad 8.2492, \quad 1.2143, \quad 0.0715) \quad 5.6$$

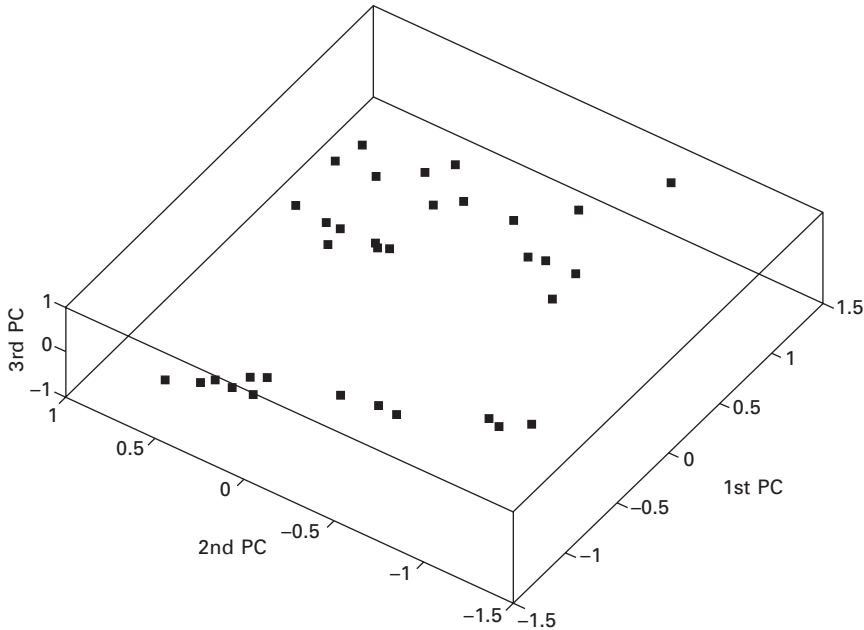
Therefore the first, second and third principal components were given by the first three columns of E . The projection of the data along these three directions yielded a three-dimensional data set which had lost very little information compared to the original data set. These projected data have

been plotted in Fig. 5.9. The clusters in the data were clearly visible. Next, the projections of the targeted yarn properties of the seven yarns spun later on the first three principal components (PCs) were taken and superimposed on the plot of the original data cluster (Fig. 5.10). It was clearly seen that the target data of those four yarn property combinations which gave very high errors lay outside the clusters formed by the original data. The other three yarn property combinations which gave low errors were a part of these clusters.

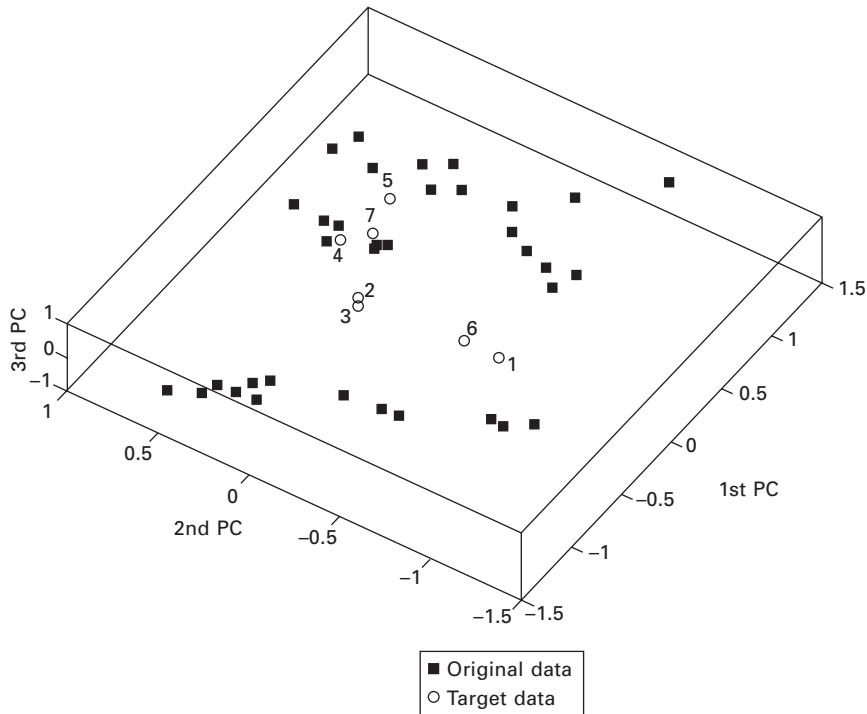
This exercise showed how principal component analysis can be used for pictorial depiction of data with more than three dimensions. This allows clusters in data to be identified. When a neural network gives a high error on test data, it would be worthwhile to use PCA to check whether the test data fall in the same cluster as the training data.

5.5 Improving the performance of a neural network

One way of reducing errors of the test set in a neural network is to reduce network complexity. Pruning of weights has been the standard way of approaching this problem. Another simple way of reducing network complexity is to use fewer inputs. However, this is feasible only if the input data is not independent but is correlated. In such a case, the data can be separated into



5.9 Plot of the data projected onto the subspace formed by the first three principal components.



5.10 Projected target data along with projected original data.

independent components by using the technique of principal component analysis discussed in the previous section. The transformed data aligned along the most important eigenvectors can be retained and the others can be deleted. Both the steps – separation of data into independent components and its truncation – have the potential of giving some improvement in test set error over the original database.

Chattopadhyay *et al.* (2004) have reported an exercise which will clarify how this can be implemented. Ring yarn data obtained from the spinning industry was used to train a neural network. Six yarn properties were predicted from five fibre properties and yarn count. The average error in the test set was 7.5%. The correlation coefficients between the five fibre properties were evaluated. The results are given in Table 5.6. It can be seen that the magnitudes of the correlation coefficients lie between 0.73 and 0.98. Except for two, all are greater than 0.8 in magnitude. Principal component analysis was carried out on the input data of five fibre properties following the procedure described in the previous section. The eigenvalues were 31.23, 1.5, 0.7, 0.26 and 0.12. The data set was transformed along the eigenvectors to obtain the orthogonalized data and only the first two were retained for obtaining the truncated data. Neural networks trained with orthogonalized

data without truncation did not give any change in the average error of the test set. When the orthogonalized and truncated data were used, the error of the test set reduced to 7.1%.

Chattopadhyay *et al.* (2004) then attempted a similar exercise on data pertaining to rotor yarns. The results were quite different from the ring yarn data. Here, orthogonalization without truncation resulted in a reduction of test set error from 17.1% to 14.7% and orthogonalization with truncation failed to achieve network training. The reason for this was found in the correlation coefficients amongst fibre properties (Table 5.7) and the eigenvalues (41.19, 12.96, 8.68, 5.05 and 2.42). It can be seen that the correlation between fibre properties is much weaker for the fibres used to spin rotor yarns than for those used to spin ring yarns. In this case, except for one value, all the correlation coefficients are lower than or equal to 0.5 in magnitude, whereas, for the ring yarn data, except for two, all were greater than 0.8 in magnitude. Because of the low degree of correlation amongst fibre properties, none of the orthogonalized components had an eigenvalue too low to be ignored. This is reflected in the spread (ratio of largest to smallest) of the eigenvalues for ring and rotor yarn data. The spread of eigenvalues of ring yarn data was 263 while that of the rotor yarn data was only 17. As a result, even the least important dimension in orthogonalized rotor yarn data contained too much information to be ignored.

Thus, if the inputs to a neural network are known to be correlated (not independent), then orthogonalization of the data may bring about an improvement in the network. If the correlations are very high, then truncation

Table 5.6 Correlation coefficients among properties of fibres used for ring spinning

	2.5% span length	Uniformity ratio	Fibre fineness	Bundle strength	Trash content
2.5% span length	1	0.8738	-0.8365	0.9287	-0.9289
Uniformity ratio	0.8738	1	-0.7341	0.7998	-0.8249
Fibre fineness	-0.8365	-0.7341	1	-0.9079	0.9337
Bundle strength	0.9287	0.7998	-0.9079	1	-0.9837
Trash content	-0.9289	-0.8249	0.9337	-0.9837	1

Table 5.7 Correlation coefficients among properties of fibres used to spin rotor yarn

	2.5% span length	Uniformity ratio	Fibre fineness	Bundle strength	Trash content
2.5% span length	1	0.1690	0.4959	0.8316	-0.4767
Uniformity ratio	0.1690	1	0.2966	0.3239	-0.1117
Fibre fineness	0.4959	0.2966	1	0.4196	-0.2723
Bundle strength	0.8316	0.3239	0.4196	1	-0.5168
Trash content	-0.4767	-0.1117	-0.2723	-0.5168	1

of the least important orthogonalized parameters would lead to a further improvement in the network's performance. Whether such a truncation can be done is indicated by a study of the spread of the eigenvalues, a high spread indicating the possibility of truncation.

Orthogonalization of input data is not the only way to improve the performance of feedforward neural networks. Mwasiagi *et al.* (2008) have reported an interesting exercise in which skeletonization (described in Section 5.2) was used to obtain the relative importance of inputs and finally optimize the performance of neural network. They identified 19 parameters which various researchers have reported as being important for predicting yarn properties. Thirteen of these were fibre properties measured in an HVI, four were ring frame machine settings and two were yarn properties. The yarn properties that they tried to predict were strength, elongation and evenness. Those parameters which had been reported as being strongly correlated with a yarn property were called class A while others were called class B. The network was trained with the class A inputs. One input was removed at a time and the relative importance of the class A inputs was determined. This process was similar to the skeletonization-related studies reported earlier (Section 5.2). Thereafter, one class B input was added at a time and the improvement (or deterioration) of mean squared error of the trained network was observed. This provided the basis for ranking the class B inputs. The final number of inputs of the optimized network was chosen by considering the importance of both class A and class B inputs. The results were compared with the original network (with only class A inputs) and a network trained with all 19 inputs. The results are summarized in Table 5.8 which shows the mean squared errors of the training sets. This exercise shows the potential of skeletonization for network optimization.

5.6 Sources of further information and future trends

This chapter has described two methods for obtaining the relative importance of input parameters of a neural network. The first of these – skeletonization

Table 5.8 Mean squared errors in network optimization by skeletonization

	Yarn properties predicted		
	Strength	Elongation	Evenness
<i>Inputs</i>			
13 class A inputs	0.004598	0.01160	0.047440
All 19 inputs	0.001194	0.00908	0.022768
14 inputs for optimized network	0.000720	0.00570	0.011960

Source: Data compiled from Mwasiagi *et al.* (2008)

– was not found to be successful in the example reported here. However, it is a very simple method and it is possible that refinements to this method will be reported in future which will be able to give a better ranking of the inputs. The second method is based on first-order sensitivity analysis and has been found to be successful.

The use of principal component analysis to visualize clusters in multidimensional data has also been described in this chapter. In the example described here, this technique has been used for analysing the cause of failure of a neural network. However, there are other applications of such techniques, and other techniques such as data mining can also be used for this purpose.

The use of principal component analysis for orthogonalizing and truncating input data with the aim of improving the performance of a neural network has been reported extensively in the domain of image processing. Application of such image processing techniques in the textile domain has mostly been in the area of fault recognition. Karras and Mertzios (2002) and Kumar (2003) reported significant improvements in network performance using these techniques. Such techniques are expected to be used more often in future because online inspections of fabric defects require a trade-off between performance and time required for network running. Use of PCA with fuzzy logic has been shown to give very good results for fabric defect recognition (Liu and Ju, 2008). The techniques reported in this chapter can be used for foreign object detection in any industrial process, as has been reported by Conde *et al.* (2007). The earliest reference to PCA being used in the textile domain for simplification of inputs to neural networks is that of Okamoto *et al.* (1992) where the shape of fabric drape was simplified using PCA. No further work has been reported in this area and this remains one of the promising areas of future research.

Since textile process simulation using neural network is a widely reported topic, it is surprising that the number of papers reporting the use of principal component analysis in conjunction with ANNs in this area is not very high. The few who have worked in this area include Chattopadhyay *et al.* (2004), Liu and Yu (2007) and Wang and Zhang (2007). Many more researchers are expected to work in this area and one looks forward to the era in which such techniques will transcend academic circles and find widespread use in the industry.

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Yarn engineering using an artificial neural network

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Abstract: Engineering yarn quality has remained a challenge for researchers and shop-floor technicians for a long time. The advent of high-speed computers has helped researchers in facing this challenge in a better manner. Attempts have been made to apply linear programming, mechanistic models and statistical models to the assessment of engineering yarn quality. Various studies have shown that an artificial neural network (ANN) can engineer yarn more accurately than those methods. In this chapter, the engineering of ring yarn and air-jet yarn is discussed. Prediction of fibre properties and process parameters from the required yarn quality can be made with acceptable accuracy using ANN.

Key words: artificial neural network, breaking elongation, hairiness index, HVI, linear programming, mechanistic model, spinning consistency index, statistical model, unevenness, yarn tenacity.

6.1 Introduction

According to the *Cambridge Advanced Learners Dictionary* (2003), the meaning of ‘to engineer’ is ‘to design and build something using scientific principles’. It is a common practice to predict the properties of yarn from the constituent fibre properties and process parameters. But it is more important to know the opposite way, i.e. what fibres should be used and what process parameters should be adopted to produce a yarn of specified quality parameters keeping the cost factor in mind, which in short can be termed yarn engineering. The increasing application of technical textiles has made yarn engineering more important. In technical textiles, the textiles are used for functional properties only, hence it is important to produce textile materials with predetermined physical and chemical properties. A technologist has to decide what fibres he should use based on the quality requirement of the output material where he generally uses his experience and acquired knowledge for decision making. The common practice in industry is to buy cotton when the price is low in the market. The cotton purchase manager is given a rough guideline for buying the cotton and he or she uses his or her skill to buy cotton at optimum price. In many cases, the cotton is purchased for three to six months, and within that period whatever order comes the

spinning technologist needs to deliver. So the literature shows that most of the work has been done for prediction of yarn properties based on the available fibre properties.

6.1.1 Early attempts using linear programming approach

Some attempts have been made earlier using linear or quadratic equations to predict the yarn properties from a set of known fibre properties. The process parameters were maintained at optimum conditions. Then those equations were used for yarn engineering. In one of SITRA's publications (Ratnam *et al.*, 2004), a guideline was provided showing which cotton fibre properties should be used to produce a yarn of a particular count strength product (CSP) or single yarn strength. For example, to produce 20s Ne cotton yarn having a CSP value of 2050, cotton fibre with the following parameters should be used: mean length 22.8 mm, bundle strength 21.0 g/tex, micronaire value 4.4. Some workers used linear programming (LP) for yarn engineering (Garde and Subramanian, 1974). They considered fibre properties required for a particular yarn as constraints. The linear programming of cotton mixings used individually four technologically important fibre properties for characterizing the quality of mixing, namely effective length, mean length, fibre bundle strength and fineness. For each quality parameter the mixing should be better than the specified value. Based on those properties, the linear programming was formulated to get the best mixing combination as shown below.

Minimize the overall mixing cost

$$c' = c'_1 p'_1 + c'_2 p'_2 + c'_3 p'_3 + \dots + c'_n p'_n \quad 6.1$$

where c'_1 and p'_1 refer to the cost per kg and the proportion of clean cotton for cotton fibre 1, respectively, and n is the total number of cottons that are available for use in the mixing.

The constraints on the mixing quality were given by

$$e_1 p'_1 + e_2 p'_2 + \dots + e_n p'_n \geq E_s \quad 6.2$$

$$m_1 p'_1 + m_2 p'_2 + \dots + m_n p'_n \geq M_s \quad 6.3$$

$$s_1 p'_1 + s_2 p'_2 + \dots + s_n p'_n \geq S_s \quad 6.4$$

$$\frac{p'_1}{f_1} + \frac{p'_2}{f_2} + \dots + \frac{p'_n}{f_n} \geq \frac{1}{F_s} \quad 6.5$$

where e , m , s and f stand for effective length, mean length, strength and fineness of cotton fibre respectively, and E_s , M_s , S_s and F_s are the required effective length, mean length, strength and fineness of the resultant mixing. As p'_1 , p'_2 , ..., are the proportions in a mixing of various cottons,

$$p'_1 + p'_2 + \dots + p'_n = 1 \quad 6.6$$

Application of computer and customized software is needed for solving the linear programming. However, when the aforesaid system was developed, the use of computers was very limited and testing of individual bales was not popular in the spinning industries. Hence the application of LP was restricted to research activities only.

6.1.2 Artificial neural networks (ANNs)

Artificial neural networks (ANNs) represent a set of very powerful mathematical techniques for modelling, control and optimization that 'learn' processes from historical data. These networks are computational models inspired by the structure and operation of the human brain. They are massively parallel systems, made up of a large number of highly interconnected, simple processing units. The most significant property of a neural network is its ability to learn from its environment and to improve its performance through learning. An ANN learns about its environment through an interactive process of adjustments. Ideally, the network becomes more knowledgeable about its environment after each iteration of the learning process. The learning process implies the following sequence of events for the neural network (Haykin, 1999):

- It is stimulated by an environment.
- It undergoes changes in its free parameters as a result of the stimulation.
- It responds in a new way to the environment because of the changes that have occurred in its internal structure.

The main feature that makes neural nets the ideal technology for yarn engineering is the non-linear regression algorithms that can model high-dimensional systems and have a very simple, uniform user interface. A neural net architecture is characterized by a large number of simple neuron-like processing elements, a large number of weighted connections between elements, highly parallel and distributed control and an emphasis on learning internal representations automatically.

A neural net can be thought of as a functional approximation that fits the input–output data with a high-dimensional surface. The major difference between conventional statistical methods and ANN is the basic functions that are used. Standard functional approximation techniques use complicated sets of orthonormal basic functions (sines, cosines, polynomials, etc.). In contrast an ANN uses very simple functions (usually sigmoids), but it combines these functions in a multilayer nested structure.

6.2 Yarn property engineering using an artificial neural network (ANN)

A number of attempts have been made to engineer yarn quality by utilizing an artificial neural network. Generally the back-propagation algorithm of ANN is employed. The steps followed are as follows (Chattopadhyay *et al.*, 2004):

1. *Initialization*: Assuming that no prior information is available, the weights and thresholds are picked from a uniform distribution whose mean is zero and whose variance is chosen to make the standard deviation of the induced local fields of the neurons lie at the transition between the linear and saturated parts of the sigmoid activation function.
2. *Presentation of training examples*: The network is presented with an epoch of training examples.
3. *Forward computation*: In the forward pass the synaptic weights remain unaltered throughout the network, and the function signals of the network are computed on a neuron-by-neuron basis.
4. *Backward computation*: The backward pass starts at the output layer by passing the error signals leftward through the network layer by layer and recursively computing the local gradient.
5. *Iteration*: Iteration is done in forward and backward computations by presenting new epochs of training examples to the network until the stopping criterion is met.

Steps involved in yarn engineering using ANN are as follows:

1. A set of yarns is produced using cotton or other fibres with known fibre and process parameters.
2. The reverse artificial neural network is trained by using the yarn parameters as the inputs and fibre and/or process parameters as outputs.
3. After the training, the testing data set is presented to the neural network and fibre and/or process parameters needed to achieve desired yarn properties are predicted.
4. Yarns are spun using the predicted combinations of fibre and/or process parameters. Association or closeness between the desired and achieved yarn properties is compared to appraise the accuracy of yarn engineering.

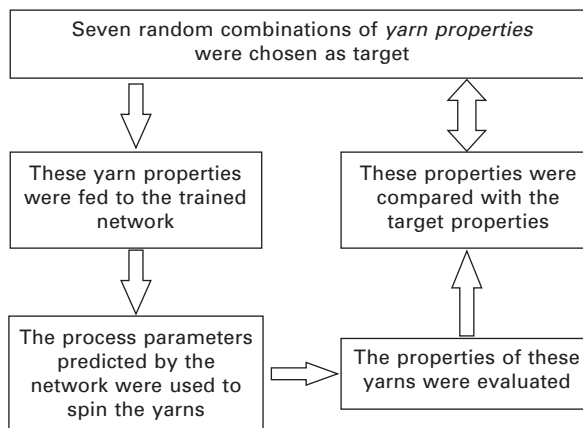
6.3 Ring spun yarn engineering

6.3.1 Process parameters

An in-depth study on yarn engineering (Guha, 2002) showed that it is possible to predict a few key process parameters from yarn properties by using ANN. In that study, yarn properties such as yarn count, tenacity, breaking

elongation, unevenness and total imperfections were used as input, and twist factor and break draft as outputs. A feed-forward neural network was trained with 35 data sets. Seven more yarns were produced as a testing data set, with different combinations of twist factor and break draft (Fig. 6.1). The yarn properties of the testing data set were then used as input to the trained ANN. The twist factor and break draft combination predicted by the ANN as output were compared with the actual parameters used to spin the yarns. It was observed that average errors were 2.9% for twist factor and 5.4% for break draft, which is within acceptable limits (Table 6.1).

As the second stage of investigation, arbitrary yarn properties were chosen which lay within the range of values obtained by actual experiments. Seven combinations of yarn count and four properties were chosen at random. The ANN which was earlier trained with the 35 data sets was used to predict



6.1 Flow diagram for procedure adopted to predict process parameters for yarns which had not been spun (source: Guha, 2002).

Table 6.1 Process parameters predicted by the network

Sl. no.	Twist factor (tpcm (tex) ^{0.5})			Break draft		
	Actual	Predicted	Error (%)	Actual	Predicted	Error (%)
1	30.14	30.41	0.9	1.28	1.27	0.9
2	32.61	30.50	6.5	1.38	1.42	3.1
3	36.55	38.13	4.3	1.28	1.49	16.7
4	36.30	35.88	1.2	1.38	1.39	1.0
5	39.60	40.07	1.2	1.38	1.27	7.8
6	44.00	43.01	2.3	1.44	1.35	6.5
7	44.53	42.59	4.4	1.28	1.26	1.9
Average			2.9			5.4

Source: Guha (2002).

twist factor and break draft. The seven unknown combinations of properties were fed to the ANN and then actual yarns were spun using the predicted values of break draft and twist factor combination. Guha observed that the target values of yarn properties and the properties of actually spun yarns were in close proximity in three cases and unacceptably far apart in the other four cases (Table 6.2). The analysis showed that due to improper choice of target values those four results did not match. One of the reasons may be the limited flexibility of raw materials and process parameters. However, these experiments showed that ANN can be used for predicting process parameters from yarn parameters provided the yarn property combinations are feasible.

6.3.2 Fibre parameters

Fibre parameters play the most dominant role in determining the properties of spun yarns. Majumdar (2005) and Majumdar *et al.* (2006) utilized ANN for prediction of fibre properties from commonly used yarn properties such as yarn tenacity, breaking elongation, unevenness and hairiness index. The outputs of the ANN model were expected to be the individual characteristics of the cotton. It was thought by Majumdar (2005) that if all the HVI properties are

Table 6.2 Properties of yarns obtained by trying to achieve the arbitrary combinations

	Sl. No.							Average error
	1	2	3	4	5	6	7	
<i>Tenacity (cN/tex)</i>								
Target	12.0	14.0	16.0	16.0	14.0	10.1	17.1	12.6
Obtained	15.09	16.43	16.27	15.03	12.79	7.39	16.75	
Error %	25.8	17.4	1.7	6.1	8.6	26.8	2.0	
<i>Break elongation(%)</i>								
Target	5.0	6.0	5.0	5.5	6.0	6.6	4.4	
Obtained	5.62	7.09	5.96	4.66	6.16	4.08	4.74	
Error %	12.4	18.2	19.2	15.3	2.7	38.2	7.7	16.2
<i>Unevenness (CV%)</i>								
Target	18.00	18.00	19.00	21.00	22.00	22.28	16.79	
Obtained	21.82	17.84	17.06	20.55	17.94	21.31	16.91	
Error %	21.2	0.9	10.2	2.1	18.5	4.4	0.7	8.3
<i>Imperfections/km</i>								
Target	2000	3000	1500	2000	3000	833	3973	
Obtained	3674	933	826	2660	2971	3048	2833	
Error %	83.7	68.9	44.9	33.0	1.0	265.9	28.7	75.2
Average error	35.8	26.3	19.0	14.1	7.7	83.8	9.8	28.1

Source: Guha (2002).

to be used in the output of ANN, then the model would be highly complex. Moreover, it would hardly be possible to form a mixing which fulfils all the properties predicted by ANN. A comprehensive quality index of cotton, namely the spinning consistency index (SCI), consisting of fibre bundle tenacity, upper half mean length, uniformity index, fibre fineness (micronaire) and colour values was used in the network to reduce the complexity (Uster, 1999). Majumdar used SCI as first priority and micronaire as second priority for selection of cottons. Twenty-five controlled samples of combed cotton yarn having linear densities ranging from 34 Ne to 90 Ne were spun. From the available 25 yarns, 20 yarns were used for the training of ANN model. Five other data sets were used for testing, i.e. for the engineering of yarns using suitable cottons. It was found that ANN with six nodes in the hidden layer showed the best prediction results after 5000 iterations. The prediction errors were below 10% in most cases (Table 6.3). The correlation coefficient between the actual and predicted values was 0.876 and 0.981 for SCI and micronaire, respectively.

While yarn engineering, Majumdar (2005) also used linear programming to control the cost of the yarns as recommended by Garde and Subramanian (1974). They optimized the proportion of various cotton lots required to fulfil the average SCI and micronaire value of the mix considering cost minimization. Table 6.3 shows that the predicted values of SCI and micronaire for 50 Ne yarn were 155 and 4.14, respectively. The SCI values of the two cotton lots (A and C) available for the spinning of this particular yarn were 160 and 155. For the micronaire the corresponding values of lot A and lot C were 4.01 and 4.2. The cost of the cotton lots A and C were Rs 65/kg and Rs 59/kg. Therefore, for 50 Ne yarn, a linear programming problem of the following form was created:

$$\text{Minimize } Z = 65P_A + 59P_C$$

$$160P_A + 154P_C \geq 155$$

Table 6.3 Prediction results of SCI and micronaire in testing dataset

Testing sample no.	Actual combination		Predicted combination		Error (%)	
	SCI	Micronaire	SCI	Micronaire	SCI	Micronaire
1	130	4.00	139	4.19	6.92	4.75
2	165	4.20	147	4.16	10.91	0.95
3	154	4.14	155	4.14	0.65	0.00
4	188	3.10	192	3.16	2.13	1.94
5	155	4.08	157	4.16	1.29	1.96
Mean					4.38	1.92

Source: Majumdar (2005).

$$\frac{1}{4.01} P_A + \frac{1}{4.20} P_C \geq \frac{1}{4.14}$$

$$P_A + P_C = 1, P_A \geq 0, P_C \geq 0$$

The solution of the above linear programming problem shows that cotton A and cotton C have to be mixed in the ratio of 30:70. This will give the resultant SCI value of the mix of 155.8 which is higher than the required SCI value of 155. Besides, this mix will also ensure that the resultant micronaire becomes 4.14 which is just equal to the requirement. A similar linear programming problem was formulated for 40 Ne and 60 Ne yarns also. Finally, three yarns (40 Ne, 50 Ne and 60 Ne) were produced using the cotton mix having predicted SCI and micronaire values. Table 6.4 shows the important properties of three target yarns and the corresponding engineered yarns. It can be seen from Table 6.4 that the tenacity and evenness values of target and engineered yarns show reasonably good agreement. However, yarn elongation and hairiness values do not show such good agreement, which may be due to non-consideration of fibre breaking elongation and short fibre content.

Chattopadhyay *et al.* (2004) made an attempt to develop an inverse model, which can predict the process variables in ring spinning that will yield a given set of yarn properties. The input for the inverse models was fibre properties and certain yarn characteristics such as yarn hairiness and breaking elongation percent. The output was process parameters such as comber noil extraction and ring frame spindle speed (with appropriate traveller weight). Thirty-six pairs of data were used to train the network. After training, for a specified fibre mixing, process parameters were predicted for particular

Table 6.4 Properties of target and engineered yarns

Testing sample no.	Yarn count (Ne)	Target yarn properties			
		Tenacity (g/tex)	Elongation (%)	U.CV (%)	Hairiness
1	40	18.70	3.30	9.43	4.67
3	50	20.51	3.64	10.16	3.62
5	60	21.80	3.10	10.90	3.85
Testing sample no.	Yarn count (Ne)	Achieved yarn properties			
		Tenacity (g/tex)	Elongation (%)	U.CV (%)	Hairiness
1	40	19.21	3.35	9.80	5.22
3	50	21.23	3.66	10.14	3.70
5	60	21.15	2.67	10.61	4.06

Source: Majumdar (2005).

values of yarn hairiness and breaking elongation. To assess the efficiency of the predictions, yarns were produced using those process parameters. The experimentally determined values were compared with targeted values. The difference between targeted and experimentally determined values was found to be less than 3% in the case of yarn hairiness and less than 5% in the case of breaking elongation. Considering the natural variation observed in these properties, these deviations can be considered as acceptable.

The above-mentioned experiments show that ANN can be utilized for engineering ring yarn with some boundary conditions. Both fibre characteristics and process parameters play important roles in determining the properties of yarns. Hence if a set of fibre characteristics or process parameters change significantly as compared to the training set, the artificial neural network needs to be retrained to engineer the yarn properties.

For yarn engineering, ideally the fibre properties and process parameters should be predicted. It has been observed that generally this becomes very difficult for cotton. The properties of cotton, being a natural fibre, vary in nature, though it is expected that for a particular variety of cotton, major fibre properties such as fibre length, strength and fineness will be within a certain range. Other properties such as extension at break, maturity and fibre-to-fibre friction can also modify the yarn properties. Hence getting an ideal cotton fibre as per the predicted fibre parameters is much more difficult in practice. Using the spinning consistency index or the fibre quality index (FQI) as a predicted value has its own limitations. A short and fine fibre and a long and thick fibre can show the same FQI values, whereas ring spinning is more biased towards length of fibre. Similarly, immature fibres, due to their lower micronaire value, can boost the FQI value. Yarn engineering using man-made fibres should be easier as the properties of the yarn are less variable and some properties can be engineered as per the requirement.

6.4 Air-jet yarn engineering

A number of studies have been conducted into the use of computer simulation methods to predict various air-jet yarn properties (Rajamanickam *et al.*, 1997; Basu *et al.*, 2002a, 2002b) from fibre properties, yarn structural parameters and process parameters. An inverse ANN model which can predict the process variables that will yield a given set of yarn properties was used by Basu *et al.* (2002a). The yarn property used as input was flexural rigidity. The process variables obtained as output from the ANN were delivery speed, main draft ratio, first nozzle pressure, feed ratio and distance between front roller and first nozzle. Eighty-one pairs of data were used to train the net for the inverse ANN model. After training, for three particular values of flexural rigidity, the process parameters were predicted as shown in Table 6.5.

It can be seen from the table that the predicted values of process parameters

Table 6.5 Yarn properties (input variables) and predicted values of process variables

Input variables (yarn properties)		Predicted values of process variables					
Yarn linear density (tex)	Flexural rigidity ($\times 10^{-3}$ cN.cm ² /tex)	Delivery speed (m/min)	Main draft ratio	Nozzle pressure, (kg/cm ²) (N ₁)	Nozzle pressure (kg/cm ²) (N ₂)	N ₁ front roller distance (mm)	Feed ratio
19.68	0.38	179.8	41.44	2.54	3.66	39.25	0.979
14.76	0.29	179.4	43.06	2.52	3.69	39.38	0.975
9.84	0.23	179.8	42.29	2.53	3.68	39.15	0.977

Table 6.6 Targeted and experimentally determined values of flexural rigidity

Yarn linear density, tex	Flexural rigidity ($\times 10^{-3}$ cN.cm ² /tex)		Standard error of experimental value ($\times 10^{-3}$)	Control limits, ($\times 10^{-3}$ cN.cm ² /tex)*		Does target value lie between control limits?
	Targeted value	Experimentally determined value		Lower	Upper	
19.68	0.38	0.363	0.013	0.321	0.405	Yes
14.76	0.29	0.295	0.015	0.246	0.344	Yes
9.84	0.23	0.217	0.009	0.188	0.244	Yes

*Control limits were calculated assuming normal distribution for flexural rigidity of yarns.

are more or less the same in all three cases. They suggest that at a given level of process variable, in air-jet spinning, yarns of different linear density will have varying levels of flexural rigidity. Using the predicted values of process variables yarns were produced and their actual flexural rigidity was compared with the predicted values in Table 6.6. The difference between targeted and experimentally determined values of yarn properties was well within statistical limits. Similarly yarns with other engineered properties can be produced using ANN efficiently.

In another study Basu *et al.* (2002b) deduced required yarn properties from fabric properties and engineered those yarns by varying the process parameters. By using the predicted values of yarn properties as input variables, process parameters in air-jet spinning were taken as output. The flexural rigidity and compressional energy and hairiness of the yarns were considered as input variables, and process parameters such as delivery speed, first nozzle pressure, second nozzle pressure, main draft ratio and feed ratio were considered as output to be variables. Yarns were spun using those process parameters and the fabrics made of those yarns were assessed. The results were found to be within acceptable limits in most cases. The applications of ANN for

engineering yarns produced by other unconventional spinning systems such as rotor spinning, friction spinning, etc., are limited.

6.5 Advantages and limitations

Application of artificial neural networks has a big advantage over the experimental route in yarn engineering, as ANN is less time-consuming. Larger simulations can be set up to study second- or higher-order interactions between several factors, which are nearly impossible to find using the experimental approach. Use of ANN also reduces waste of raw material and machine time considerably. It has been reported by various workers that the prediction or engineering by using ANN is more accurate as compared to mechanistic and statistical models. Guha *et al.* (2001) observed that cotton ring yarn tenacity prediction error was only 6.9% as against 9.3% and 9.9% for mechanistic and statistical models, respectively. Similarly for polyester ring yarn the prediction error was 1.1%, 8.0% and 2.2% for neural network, mechanistic and statistical model, respectively.

Like all models, ANN has some limitations. One of the important drawbacks is that it cannot be reliably used outside the range of the dataset over which it is trained. It does not provide any understanding of why an input set of materials and process parameters result in the predicted level of yarn properties or vice versa. The prediction of process parameters and required fibre properties for a particular set of yarn properties is very difficult due to the highly variable nature of the natural fibres and the spinning process.

6.6 Conclusions

Although some efforts have been made in the area of engineering yarn, their application in commercial factories is very limited. The acceptability of this technique is not so popular as fabric engineering, because engineering the properties of end products is more acceptable than engineering intermediate products. Chemical processing or fabric formation processes can change the properties of the fabrics so efficiently that many prefer to use those processes to engineer fabric or end product. The yarn properties play very important role in determining fabric properties. Hence yarn engineering will be able to help the industry to achieve the desired results with minimum cost. More work needs to be carried out on an industrial level to make yarn engineering acceptable commercially.

6.7 Sources of further information and advice

A number of studies have been undertaken by researchers into the application of ANN in engineering various textile products such as fibre, yarn, fabric, etc.

A detailed review has been presented by Chattopadhyay and his co-authors in a volume of *Textile Progress*. The details are as follows:

Chattopadhyay, R. and Guha, A. (2004), Artificial neural networks: applications to textiles, *Textile Progress*, Vol. 35, No. 1.

6.8 References

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Adaptive neuro-fuzzy systems in yarn modelling

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Abstract: This chapter presents the scope of application of hybrid neuro-fuzzy inference systems for the prediction of yarn properties. The chapter begins with a brief introduction to artificial neural networks (ANNs) and fuzzy logic. This is followed by a description of adaptive neuro-fuzzy inference systems which amalgamates the advantages of both the ANN and fuzzy logic. Finally, application of an adaptive neuro-fuzzy system is demonstrated to predict the tenacity and unevenness of spun yarns using the cotton fibre properties as the input variables. The prediction accuracy of the hybrid neuro-fuzzy model is compared with those of the statistical regression model and virgin ANN models. The linguistic rules extracted by the neuro-fuzzy model give better understanding about the spinning process by revealing some important information about the role of input variables on yarn properties.

Key words: artificial neural network, fuzzy logic, neuro-fuzzy system, ANFIS, yarn property.

7.1 Introduction

In recent years, modelling of structure–property relationships using intelligent techniques has become an attractive area of research for materials scientists and engineers. In the domain of textile research, artificial neural networks (ANNs) have received a lot of attention from researchers to predict yarn properties from the fibre properties and process parameters. Cheng and Adams (1995), Ramesh *et al.* (1995), Zhu and Ethridge (1996, 1997), Ethridge and Zhu (1996), Pynckels *et al.* (1997), Chattopadhyay *et al.* (2004) and Majumdar *et al.* (2004) have successfully employed ANN models for the prediction of various yarn properties. All the researchers have appreciated the high prediction accuracy of the ANN models. Rajamanickam *et al.* (1997) compared the efficacy of mathematical, statistical, computer simulation and ANN models for the prediction of air-jet yarn strength. They found that the performance of the ANN model is much better than that of the other three approaches. Various modelling methodologies for yarn property prediction have also been compared by Guha *et al.* (2001) and Majumdar and Majumdar (2004). In both researches, ANN was found to be outperforming the mathematical and statistical approaches.

ANN provides a ‘black box’ model, which simply connects inputs and outputs without giving a clear insight about the process. This limitation could be partially eliminated by integrating the ANN with fuzzy logic. Fuzzy logic, which is an extension of classical crisp logic, can deal with situations involving imprecision and ambiguity by using linguistic rules. It functions by mapping the input space into the output space by using membership functions and linguistic rules. Since ANN and fuzzy logic are two complementary facets of artificial intelligence, their hybridization or amalgamation can enhance the accuracy and insight given by the prediction model. Hybrid neuro-fuzzy systems have been used in most engineering and management fields to solve complex modelling problems. In textile engineering, neuro-fuzzy systems have been used by Huang and Chen (2001) and Huang and Yu (2001) to classify fabric and dyeing defects, respectively. Fan *et al.* (2001) and Ucar and Ertuguel (2002) have employed neuro-fuzzy systems for the prediction of garment drape and forecasting circular knitting machine parameters, respectively. This chapter discusses applications of neuro-fuzzy systems to model spun yarn properties from the properties of constituent cotton fibres. The prediction accuracy of the neuro-fuzzy model has been compared with those of other models. The process information yielded from the developed linguistic rules has also been analysed.

7.2 Artificial neural network and fuzzy logic

7.2.1 Artificial neural network

The artificial neural network (ANN) is a potent data-modelling tool that is able to capture and represent any kind of input–output relationships. Here one or more hidden layers, which consist of a certain number of neurons or nodes, are sandwiched between the input and output layers. The number of hidden layers and the number of neurons in each hidden layer vary depending on the intricacy of the problem. Each neuron receives a signal from the neurons of the previous layer and these signals are multiplied by separate synaptic weights. The weighted inputs are then summed up and passed through a transfer function (usually a sigmoid), which converts the output to a fixed range of values. The output of the transfer function is then transmitted to the neurons of the next layer. Finally the output is produced at the neurons of the output layer.

Although the prediction performance of ANN is generally very good, it does not reveal much information about the process. It is often said that the functioning of ANN mimics that of a ‘black box’. The user cannot easily understand how the ANN is producing the output or making a decision. Although input significance testing (Guha, 2002; Majumdar *et al.*, 2004) and trend analysis are conducted to understand the role of input parameters

in the model, the problem is still to be completely solved. Hybridization of ANN with other intelligent techniques can provide some solutions in this respect.

7.2.2 Fuzzy logic

The foundation of fuzzy logic was laid by Professor Zadeh (1965) at the University of California at Berkeley, USA. In crisp logic, such as binary logic, variables are either true or false, black or white, 1 or 0. If the set under investigation is A , testing of an element x using the characteristic function χ is expressed as follows:

$$\chi_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases}$$

In fuzzy logic, a fuzzy set contains elements with only partial membership ranging from 0 to 1 to define uncertainty of classes that do not have clearly defined boundaries. For each input and output variable of a fuzzy inference system (FIS), the fuzzy sets are created by dividing the universe of discourse into a number of sub-regions, named in linguistic terms *high*, *medium*, *low*, etc. If X is the universe of discourse and its elements are denoted by x , then a fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{x, \mu_A(x) | x \in X\}$$

where $\mu_A(x)$ is the membership function of x in A .

All properties of the crisp set are also applicable for fuzzy sets except for the excluded-middle laws. In fuzzy set theory, the union of a fuzzy set with its complement does not yield the universe and the intersection of a fuzzy set and its complement is not the null set. This difference is shown symbolically below:

$$\left. \begin{aligned} A \cup A^c &= X \\ A \cap A^c &= \emptyset \end{aligned} \right\} \text{Crisp sets}$$

$$\left. \begin{aligned} A \cup A^c &\neq X \\ A \cap A^c &\neq \emptyset \end{aligned} \right\} \text{Fuzzy sets}$$

Membership functions and fuzzification

Once the fuzzy sets are chosen, a membership function for each set is created. A membership function is a typical curve that converts the numerical value of input within the range of 0 to 1, indicating the belongingness of the input to a fuzzy set. This step is known as ‘fuzzification’. A membership

function can have various forms, such as triangle, trapezoid, Gaussian and bell-shaped. Some of the membership function forms are shown in Fig. 7.1. A triangular membership function is the simplest and is a collection of three points forming a triangle as shown below:

$$\mu_A(x) = \begin{cases} \frac{x-L}{m-L} & \text{for } L < x < m \\ \frac{R-x}{R-m} & \text{for } m < x < R \\ 0 & \text{otherwise} \end{cases}$$

where m is the most promising value, and L and R are the left and right spread (the smallest and largest values that x can take).

The trapezoidal membership curve has a flat top and looks like a truncated triangle producing $\mu_A(x) = 1$ in large regions of the universe of discourse. The trapezoidal curve is a function of a vector x and depends on four scalar parameters a , b , c and d , as shown below:

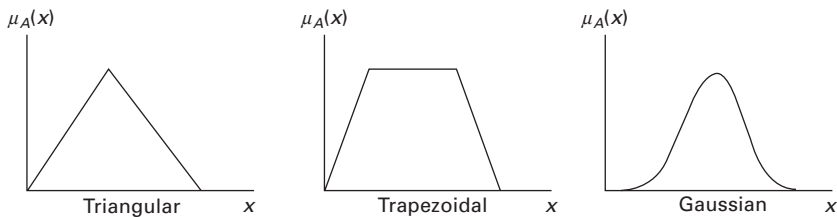
$$\mu_A(x) = \begin{cases} 0 & \text{for } x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a} & \text{for } a \leq x \leq b \\ 1 & \text{for } b \leq x \leq c \\ \frac{d-x}{d-c} & \text{for } c \leq x \leq d \end{cases}$$

The Gaussian membership function depends on two parameters, namely standard deviation (σ), and mean (μ), and is represented as shown below:

$$\mu_A(x) = e^{-(x-\mu)^2/2\sigma^2}$$

The general bell-shaped membership function is defined by three parameters (a , b and c) as shown below:

$$\mu_A(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}}$$



7.1 Different forms of membership function graphs.

Fuzzy linguistic rules

Fuzzy linguistic rules provide quantitative reasoning that relates input fuzzy sets with output fuzzy sets. A fuzzy rule base consists of a number of fuzzy if-then rules. For example, in the case of a two-input and single-output fuzzy system, it can be expressed as:

If x is *high* and y is *medium* then z is *low*

where x and y are two input variables, z is an output variable, and *high*, *medium* and *low* are the fuzzy sets of x , y and z , respectively.

Defuzzification

The output of each rule is also a fuzzy set. Output fuzzy sets are then aggregated into a single fuzzy set. This step is known as ‘aggregation’. Finally, the resulting set is resolved to a single crisp number by ‘defuzzification’. There are several methods of defuzzification, such as centroid, centre of sums, mean of maxima and left-right maxima. However, the centroid method of defuzzification is used in most cases, which is shown below:

$$x^* = \frac{\int \mu_A(x)x dx}{\int \mu_A(x) dx}$$

where x^* is the defuzzified output and $\mu_A(x)$ is the output fuzzy set after aggregation of individual implication results.

Mamdani and Sugeno type fuzzy inference system

In terms of inference process there are two main types of fuzzy inference system (FIS), namely the Mamdani type and the TSK (Takagi, Sugeno and Kang) type. In the case of Mamdani FIS the consequent membership functions are also fuzzy in nature. Mamdani FIS is more popularly used, largely because it provides reasonably good results with a relatively simple structure. Besides, the intuitive and interpretable nature of the rule base makes it more appealing. Since the consequent membership functions in a TSK FIS are not fuzzy (either linear or constant), the interpretability is lacking. Moreover, in the TSK FIS, the consequent membership functions can have as many parameters per rule as input variables, which translates into more degrees of freedom in the design as compared to Mamdani FIS, thus providing more flexibility in the design of the system. Mamdani FIS can be used directly for MISO systems (multiple input, single output) and MIMO systems (multiple input, multiple output), while the TSK FIS can only be used in the case of the former. Mamdani FIS can be seen as a function that

maps the input space into its output space and ensures that there exists a TSK FIS that can approximate any given Mamdani FIS with some arbitrary level of accuracy. Some advantages of TSK FIS over Mamdani FIS are listed below:

- The TSK FIS is more apt for functional analysis than the Mamdani FIS.
- In computational terms, the TSK FIS is more effective because the complex defuzzification process of the Mamdani FIS is supplanted with the weighted average method.
- The TSK FIS is more flexible than the Mamdani FIS because the former allows more parameters in the output and since the output is a function of the inputs it expresses a more explicit relation among them.

7.2.3 Similarities and differences between ANN and fuzzy logic

From the ongoing discussion, the following points can be listed about the similarities and differences between the ANN and fuzzy logic:

Similarities:

- ANN and fuzzy logic are universal estimators.
- Both approaches are numerical in nature.
- Both systems have been successfully used for a wide variety of real-world systems.

Differences:

- ANN has a large number of interconnected processing elements (neurons or nodes) and thus demonstrates ability of learning and generalization. Fuzzy systems arrive at decisions based on the linguistic rules.
- ANN models are good at prediction and pattern recognition. However, they are not good at explaining how they reach the decisions. Fuzzy systems are good at explaining their decisions with the aid of linguistic rules but they cannot automatically acquire the rules.

The limitations of individual systems have been the driving force behind the creation of hybrid intelligent systems where two or more techniques are combined in a manner that overcomes the limitations of the individual technique. Neural-fuzzy hybrids, neural-genetic hybrids and fuzzy-genetic hybrids are some of the examples of hybrid intelligent systems. The hybrid systems which amalgamate ANN and fuzzy logic can be classified into two groups:

- Fuzzy neural networks
- Neuro-fuzzy systems.

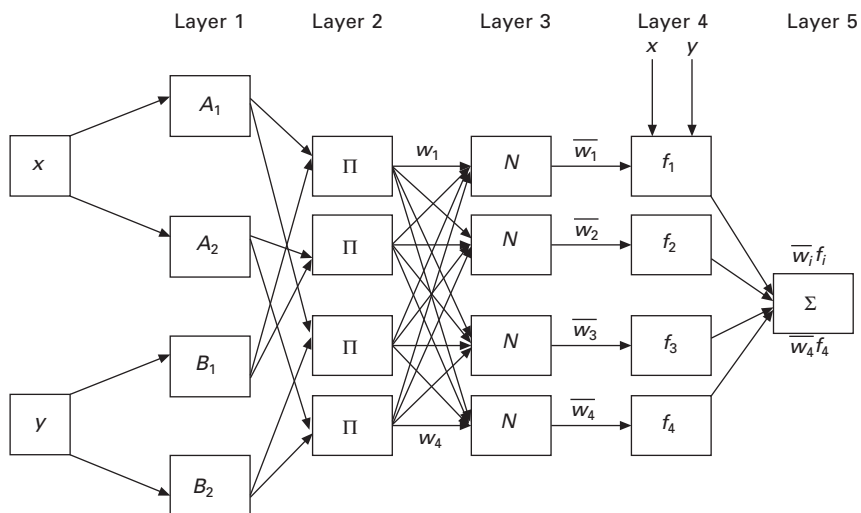
A fuzzy neural network is basically a neural network where the inputs as well as the connection weights are fuzzy numbers. On the other hand, a neuro-fuzzy system is basically a FIS where the learning capability of ANN is used.

7.3 Neuro-fuzzy system and adaptive neural network based fuzzy inference system (ANFIS)

A neuro-fuzzy system combines the fuzzification technique of fuzzy logic with the learning capability of ANN. Therefore, it possesses the merits of both approaches and can fit the training data more accurately. Neural network techniques aid the fuzzy modelling procedure in learning information about the data set and compute the membership function parameters that best allow the associated FIS to track the given input–output data. ANFIS (adaptive neural network based fuzzy inference system) is a class of adaptive network that is functionally equivalent to FIS (Jang, 1993). Using the given input–output data, ANFIS constructs a FIS whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm or a hybrid learning algorithm (a combination of back-propagation and the least-squares method). Figure 7.2 illustrates the architecture of ANFIS having five layers assuming that there are two inputs x and y and only one output z . A common rule set with four fuzzy if–then rules is shown below:

Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2 and y is B_1 then $f_2 = p_2x + q_2y + r_2$



7.2 ANFIS architecture.

Rule 3: if x is A_1 and y is B_2 then $f_3 = p_3x + q_3y + r_3$

Rule 4: if x is A_2 and y is B_2 then $f_4 = p_4x + q_4y + r_4$

where A_1 and A_2 are the fuzzy sets for the variable x and B_1 and B_2 are the fuzzy sets for the variable y .

Layer 1: Every node in this layer is an adaptive node with a node function as shown below:

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i = 1, 2 \text{ or } O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3, 4$$

where x and y are the input to node i and A_i and B_i are a linguistic level such as long or short associated with this node. $O_{1,i}$ is the membership grade of a fuzzy set A ($= A_1, A_2$).

Layer 2: Every node in this layer is a fixed node labelled Π , whose output is the product of all the incoming signals:

$$O_{2,i} = \mu_A(x)\mu_B(y) = w_i \text{ for } i = 1, 2, 3, 4$$

Each node output represents the firing strength (w_i) of a rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labelled N . The i th node calculates the ratio of the i th rule's firing strength to the sum of all rules' firing strengths. The output of this layer is called the normalized firing strength:

$$O_{3,i} = \frac{w_i}{w_1 + w_2 + w_3 + w_4} = \bar{w}_i$$

Layer 4: Every node in this layer is an adaptive node with a node function as shown below:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i)$$

where $\bar{w}_i$ is the normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labelled Σ , which computes the overall output as the summation of all incoming signals:

$$\text{Overall output} = O_{5,i} = \sum \frac{\bar{w}_i f_i}{\sum \bar{w}_i}$$

7.3.1 ANFIS parameters

Selection of the proper combination of inputs and determination of the number of membership functions for each of the inputs is very important

for ANFIS since they determine the number of rules to be trained. If m is the number of membership functions for each input and n is the number of inputs, then there are m^n rules to be trained. Table 7.1 shows the number of nodes and the number of parameters in various layers of ANFIS considering three parameter membership functions for the input variables.

The learning scheme for ANFIS is represented in Table 7.2. In the forward pass, the consequent parameters (p , q and r) are optimized by the least-squares method. In the backward pass, the premise parameters (non-linear parameters such as a , b and c for bell-shaped membership forms) are optimized by the gradient descent algorithm.

7.4 Applications of adaptive neural network based fuzzy inference system (ANFIS) in yarn property modelling

7.4.1 Modelling of yarn tenacity

Majumdar *et al.* (2005) reported the prediction of ring and rotor yarn tenacity using ANFIS. They also compared the prediction performance of ANFIS against those of ANN and linear regression models. For ANN and linear regression models, seven cotton fibre properties measured by high volume instrument (bundle tenacity, elongation, upper half mean length, uniformity index, micronaire, yellowness and reflectance degree) and yarn count were used as inputs. An ANN model having a single hidden layer was used. The transfer function in the hidden and output layers was log-sigmoid. The number of neurons in the hidden layer was varied from six to 14 with an increment of two in each step. ANN structures with six and eight neurons

Table 7.1 Number of ANFIS parameters

Layer number	Layer type	Number of nodes	Number of parameters
0	Inputs	n	0
1	Fuzzification	mn	$3mn$
2	Rules	m^n	0
3	Normalization	m^n	0
4	Linear functions	m^n	$(n + 1) m^n$
5	Summation	1	0

Table 7.2 Hybrid learning for ANFIS

	Forward pass	Backward pass
Premise parameters (nonlinear)	Fixed	Gradient descent
Consequent parameters (linear)	Least-squares	Fixed
Signals	Node outputs	Error signals

in the hidden layer were found to be the best predictors for ring and rotor spun yarns, respectively.

As the number of fuzzy rules to be trained and the number of parameters to be optimized depend on the number of input variables (n) and the number of membership functions for each variable (m), an input selection scheme was employed to elicit the best combination of inputs. Different combinations of input parameters were tried in the input selection scheme. It was found that a combination of yarn count, fibre bundle tenacity and length uniformity index was optimal for neuro-fuzzy modelling. Triangular, trapezoidal, sigmoid and Gaussian-type membership functions were tried and it was found that the Gaussian form with two membership functions for each input gives the best prediction accuracy. Therefore, the total number of linguistic rules to be developed was eight in this case. For ring and rotor spun yarns 72 and 88 data sets were used, respectively, for the training of models. The numbers of test set data were 15 and 20 for ring and rotor spun yarns, respectively.

Prediction performance of different models

The accuracy of the prediction models was evaluated by their performance in the unseen test data, which were not used for the training. The results are shown in Table 7.3. It is evident that, irrespective of yarn type, the performance of the neuro-fuzzy and ANN models is better than that of the linear regression model. The mean absolute error of prediction for both the ANN and neuro-fuzzy models is less than 5% for ring yarns and around 2% or even less for rotor yarns. In contrast, the regression model exhibits a mean absolute error of prediction higher than 5% and 2% for ring and rotor yarns, respectively. Moreover, the maximum error of prediction of the regression model is also much higher than those of the ANN and neuro-fuzzy models. The reason behind the superior accuracy of the ANN and

Table 7.3 Prediction performance in test data of yarn tenacity

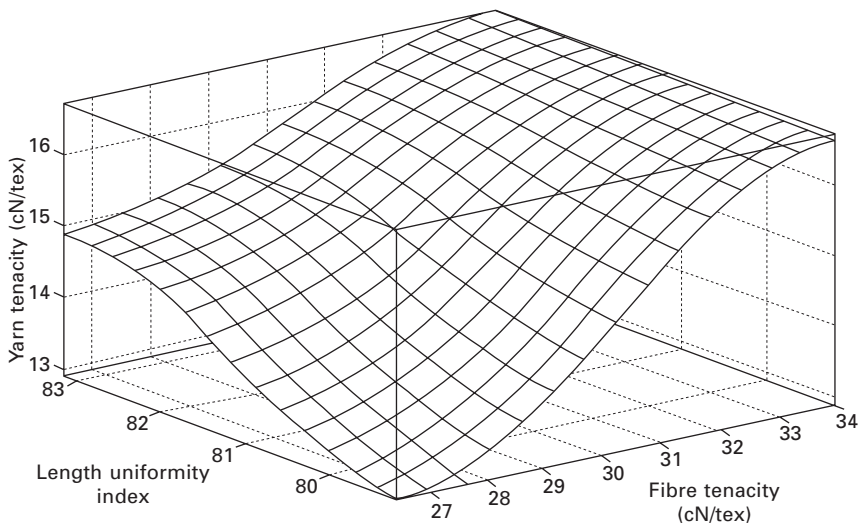
Yarn type	Statistical parameter	Prediction models		
		Regression	ANN	Neuro-fuzzy
Ring	Correlation coefficient	0.717	0.738	0.802
	Mean absolute error %	5.36	4.92	4.72
	Maximum error %	12.10	9.32	10.44
Rotor	Correlation coefficient	0.933	0.964	0.959
	Mean absolute error %	2.34	1.59	2.03
	Maximum error %	7.43	6.69	4.47

Source: Majumdar *et al.* (2005).

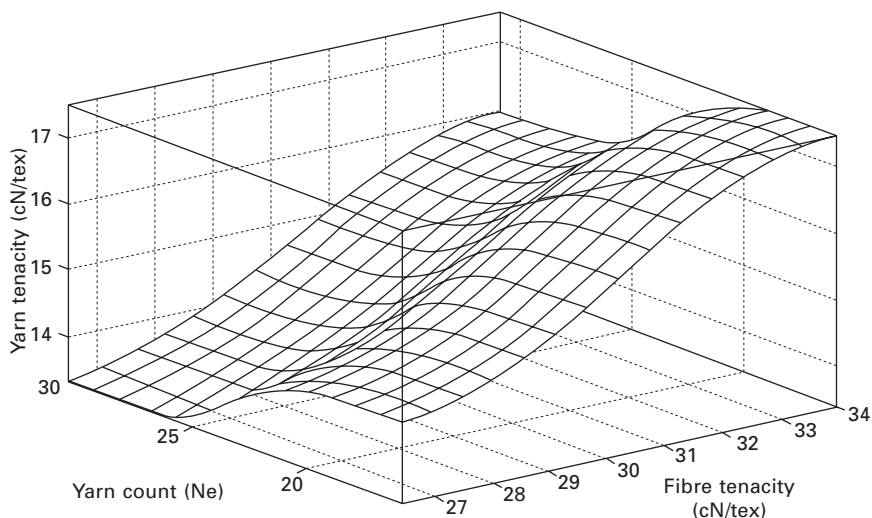
neuro-fuzzy models may be attributed to their aptness to handle the nonlinear relationship prevailing between fibre and yarn properties. In the case of ring spun yarns, the performance of the neuro-fuzzy system ($R = 0.802$, mean absolute error = 4.72%) seems to be better than that of the ANN model ($R = 0.738$, mean absolute error = 4.92%) whereas it is the reverse in the case of rotor spun yarns. However, it must be considered that only three input parameters were used in the neuro-fuzzy model as against eight in the ANN and regression models. In spite of this difference, the prediction accuracy of the neuro-fuzzy model is comparable with or even better than that of the ANN model. Adequate training of an increased number of fuzzy rules may lead to much better performance of the neuro-fuzzy model. However, training of an increased number of fuzzy rules using a limited amount of data may actually undermine the performance of the neuro-fuzzy system, and therefore a tradeoff is needed when selecting the number of input variables and the number of membership functions for each variable.

Effect of input parameters on yarn tenacity

The advantage of the neuro-fuzzy system over the virgin ANN lies in the fact that the former can unearth some physical information about the process in the form of fuzzy linguistic rules. This makes the model more understandable and the effect of various input parameters on yarn tenacity becomes transparent. Figures 7.3 and 7.4 depict the relationships among



7.3 Effect of fibre tenacity and length uniformity on ring yarn tenacity (source: Majumdar *et al.*, 2005).



7.4 Effect of fibre tenacity and yarn count on ring yarn tenacity. (source: Majumdar *et al.*, 2005).

fibre tenacity, length uniformity, yarn count and yarn tenacity. From Fig. 7.3, it is observed that as the fibre tenacity increases there is a concomitant increase in the yarn tenacity. The length uniformity also exhibits a similar influence on yarn tenacity. These findings are well in agreement with the established perception. For both the ring and rotor spun yarns, the effect of length uniformity is more pronounced when the fibre tenacity is low. However, when the fibre tenacity reaches its apex the influence of length uniformity becomes almost negligible. The effect of yarn count and fibre tenacity on yarn tenacity is shown in Fig. 7.4. As the yarn becomes finer the yarn tenacity reduces. This is attributed to the higher unevenness of finer yarns as compared to their coarser counterpart.

7.4.2 Modelling of yarn unevenness

Majumdar *et al.* (2008) also reported the use of the ANFIS for the prediction of ring spun yarn unevenness using the cotton fibre properties measured by the advanced fibre information system (AFIS) and yarn count as inputs. ANN and linear regression models were also developed for the comparative evaluation of prediction performance. In the ANN model, the number of input nodes was eight as there were eight input parameters (mean length, short fibre content, maturity, fineness, neps, seed coat neps, trash and yarn count). Only one output node was kept for predicting yarn unevenness. The transfer function in the hidden and output layers was log-sigmoid. It was found that 10 nodes in the single hidden layer yields the best prediction

performance in the test set data. For the ANFIS model, it was found that the combination of mean length, short fibre content and yarn count (Ne) with the triangular form of membership function and two levels for each input produces the best prediction accuracy.

Linear regression model

The complete linear regression model was developed for predicting ring yarn unevenness using all eight input parameters. The equation is shown below:

$$\text{Unevenness} = 28.495 - 11.949ML + 0.379SFC - 7.244Maturity - 0.012FF - 0.003Neps + 0.025Seed\ neps - 0.002Trash + 0.321Yarn\ count\ (Ne) \quad (R^2 = 0.848)$$

where *ML* is the mean length of cotton fibre in inches, *SFC* is short fibre content (%) and *FF* is fibre fineness in millitex.

From the R^2 value, it can be said that the equation is able to explain 85% of the total variability of yarn unevenness. It was found that the mean length, short fibre content and yarn count (Ne) are the only three input variables, which are statistically significant at the 99% level. This supports the findings of the input selection scheme of ANFIS model. The contribution of maturity, fibre fineness, neps and seed coat neps was found to be statistically insignificant at the 95% level. To remove the insignificant inputs from the regression model, a forward stepwise regression equation was also developed, which is shown below:

$$\text{Unevenness} = 17.578 - 9.886ML + 0.422SFC - 0.002Trash + 0.317Yarn\ count\ (Ne) \quad (R^2 = 0.837)$$

The above equation can explain about 84% of the variability of yarn unevenness, which is almost the same as with the complete regression equation. For a given yarn count, fibre fineness determines the number of fibres in the yarn cross-section and thereby fibre fineness is expected to be a significant parameter influencing yarn unevenness. However, correlation analysis of cotton fibre parameters showed that fibre fineness is significantly correlated with short fibre content (correlation coefficient $R = -0.638$) and trash content (correlation coefficient $R = 0.652$). The intercorrelation among cotton properties might have made the contribution of fibre fineness insignificant.

Prediction performance of different models

The prediction performance of linear regression, ANN and neuro-fuzzy models was evaluated separately for the 72 training data as well as the 15 unseen testing data. The results for the training data sets are summarized in

Table 7.4 Prediction performance in training data of yarn unevenness

Statistical parameter	Prediction models		
	Regression	ANN	Neuro-fuzzy
Correlation coefficient	0.921	0.925	0.918
Mean absolute error %	3.783	3.528	3.496

Source: Majumdar *et al.* (2008).

Table 7.5 Prediction performance in test data of yarn unevenness

Statistical parameter	Prediction models		
	Regression	ANN	Neuro-fuzzy
Correlation coefficient	0.960	0.959	0.970
Mean absolute error %	3.073	2.794	2.367
Samples with more than 5% error	4	1	1

Source: Majumdar *et al.* (2008).

Table 7.4. It is observed that the correlation coefficient between the actual and predicted values is around 0.92 for all three prediction models. However, the mean absolute error of prediction was maximum for the regression model (3.783%), closely followed by the ANN model (3.528%) and the neuro-fuzzy model (3.496%).

Table 7.5 summarizes the prediction results in the testing data sets, from which it is observed that the correlation coefficients between the actual and predicted values were very high (higher than 0.95) for all three models. However, as with the training data, the mean absolute error of the prediction was maximum for the linear regression model (3.073%), followed by the ANN model (2.794%) and the neuro-fuzzy model (2.367%). Table 7.6 shows the prediction results for 15 individual testing samples. It is observed that for the regression model, four test samples had more than 5% prediction error. In contrast, the ANN and neuro-fuzzy models had only one test sample in each case where the prediction error was higher than 5%. Therefore, it can be inferred that both of the soft computing models are better predictors of yarn unevenness than the linear regression model. Although the prediction performance of ANFIS is marginally better than that of the ANN, the former provides a much simpler model as it has been developed with only three input parameters as against eight in the case of the latter.

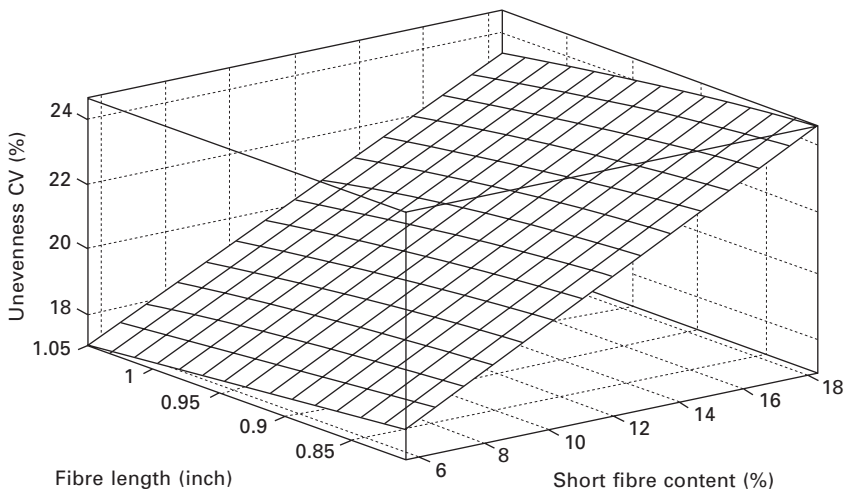
Effect of input parameters on yarn unevenness

Figure 7.5 depicts the effect of mean fibre length and short fibre content on yarn unevenness in accordance with the ANFIS rules, keeping the third input

Table 7.6 Detailed prediction performance in test data of yarn unevenness

Test sample no.	Actual	Regression		ANN		Neuro-fuzzy	
		Predicted	Error %	Predicted	Error %	Predicted	Error %
1	23.32	23.96	2.744	24.32	4.288	24.7	5.918
2	18.01	16.96	5.830	17.51	2.776	17.2	4.498
3	17.82	16.68	6.397	17.39	2.413	17.1	4.040
4	23.34	23.28	0.257	23.50	0.686	23.3	0.171
5	19.92	20.32	2.008	20.25	1.657	20	0.402
6	22.34	22.82	2.149	23.21	3.894	22.5	0.716
7	20.41	20.81	1.960	20.15	1.274	20.3	0.539
8	18.68	18.99	1.660	18.52	0.857	18.6	0.428
9	20.72	21.16	2.124	20.99	1.303	21.1	1.834
10	22.49	23.11	2.757	23.44	4.224	23.2	3.157
11	22.97	22.37	2.612	22.82	0.653	22.4	2.481
12	19.22	20.31	5.671	19.96	3.850	19.8	3.018
13	20.49	19.25	6.052	18.95	7.516	19.9	2.879
14	16.61	16.26	2.107	17.49	5.298	17.2	3.552
15	19.77	20.12	1.770	19.53	1.214	19.4	1.872

Source: Majumdar *et al.* (2008).



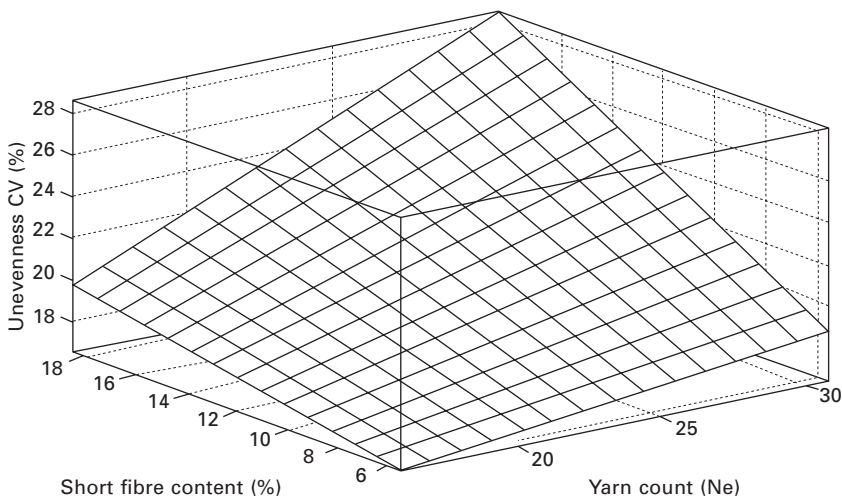
7.5 Effect of fibre length and short fibre content on ring yarn unevenness (source: Majumdar *et al.*, 2008).

variable (yarn count) constant at the mid-level (23.4 Ne). It is observed that as the fibre length increases there is consistent reduction in yarn unevenness, although the effect is not very pronounced. It is also noted that the increase in short fibre content in cotton leads to a drastic increase in yarn unevenness. During roller drafting, short fibres float in between the front and back roller nip and their velocity is totally uncertain. Thus, the short fibres generate

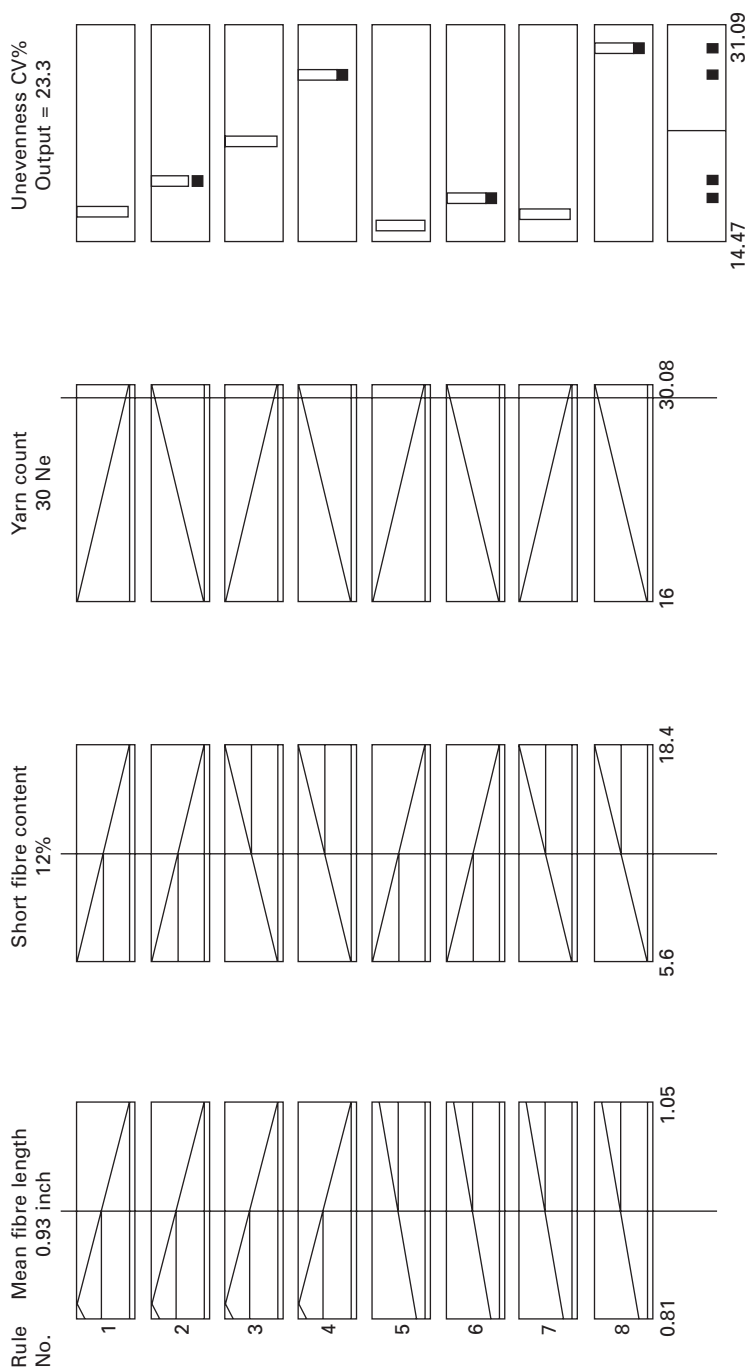
drafting waves and increase the unevenness of the fibre strand. Figure 7.6 shows the impact of yarn count and short fibre content on yarn unevenness, keeping fibre length constant at mid-level (0.93 inch). In general, finer yarns exhibit higher unevenness, as expected. The effect of short fibre content on unevenness is very gradual for coarser yarns and radical for finer yarns. In the case of finer yarns, there are fewer fibres in the yarn cross-section and thus the generation of drafting wave causes increase of irregularity by a greater extent as compared to coarser yarns. Therefore, short fibre content should be given more importance when selecting the cotton fibres for finer counts.

Linguistic rules of ANFIS

Figure 7.7 shows the eight ANFIS rules which linguistically relate the three input variables (mean length, short fibre content and yarn count) with the output variable (yarn unevenness). The membership function of each input variable has two levels, namely low and high. The output variable (yarn unevenness) has eight levels of membership function. From rules 1 and 2, it can be inferred that if yarn is made finer, keeping the mean fibre length and short fibre content constant, then yarn unevenness will increase. Similarly, comparing rules 1 and 3, it can be inferred that increase in short fibre content increases the yarn unevenness rather drastically. Rule 5 depicts that minimum yarn unevenness is expected when fibre length is high, short fibre content is low and yarn count is coarse. These linguistic rules are in agreement with the established perceptions of spinning technology. Figure 7.7 also shows



7.6 Effect of yarn count and short fibre content on ring yarn unevenness (source: Majumdar *et al.*, 2008).



7.7 ANFIS rules showing the effect of input parameters on yarn unevenness (source: Majumdar *et al.*, 2008).

that when mean fibre length is 0.93 inch, short fibre content is 12% and yarn count is 30 Ne, four fuzzy rules (rules 2, 4, 6 and 8) become active with different firing strength and produce output (yarn unevenness). These four output membership functions are defuzzified using the weighted average method to produce the unevenness CV% of 23.3, as shown in the lowest block of the extreme right column of Fig. 7.7. Therefore, the mechanism of producing a particular output value can easily be understood by analysing the linguistic fuzzy rules. Thus the neuro-fuzzy system provides a better understanding of the process than the ANN model.

7.5 Limitations of adaptive neural network based fuzzy inference system (ANFIS)

- All the output membership functions must be of the same type and either linear or constant.
- ANFIS does not allow any rule sharing. Different rules cannot share the same output membership functions. In practice this means that two different combinations of input parameters cannot result in the same value of the output parameter.
- The number of output membership functions must be equal to the number of rules.

7.6 Conclusions

This chapter outlines the theory and applications of a neuro-fuzzy system (ANFIS) with reference to yarn property modelling. The predictive power of ANFIS is better than that of the linear regression model and comparable with the ANN model. However, the developed fuzzy rules provide clear understanding about the influence of input parameters on yarn properties. Moreover the human expert can further extend the linguistically interpretable rule base by incorporating process parameters like twist as additional inputs to the model. In a complex problem where the formation of rules is difficult, ANFIS can provide useful solutions by automatically extracting the rules using the available data.

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Woven fabric engineering by mathematical modeling and soft computing methods

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Abstract: The engineering design of woven fabric has traditionally been an iterative process of trial-and-error, based on the designer's intuitions, skills and creativity. There have been attempts to partially design fabrics by devising experiments, using statistical techniques, mathematical modeling and neural network modeling, and by assuming ideal structures of fabrics to model the properties of fabrics. But in real-world applications, these methods have been found to be wanting in terms of accuracy or conditions of application. Soft computing suggests a new computing methodology that is both flexible and easy. Three major branches of soft computing, namely fuzzy logic, neural networks, and genetic algorithms, are discussed with respect to their applications in solving a variety of textile problems ranging from fiber classification, color grading, yarn and fabric property prediction, to the optimization of products and processes and even searching for a pleasing garment design.

Key words: fabric engineering, structure–property relationship, theoretical modeling, soft computing, fuzzy logic, neural network, genetic algorithm, hybrid modeling, prediction, optimization.

8.1 Introduction

The complexity in defining the fabric design process arises from the ill-defined nature of engineering problems, i.e. specific functional and aesthetic properties to be imparted to the fabric. The problem is often internally inconsistent and there is no definitive formulation of the problem. Thus engineering design has traditionally been an iterative process of trial-and-error, based on the designer's intuitions, skills and creativity. There have been attempts to partially design fabrics by devising experiments using statistical techniques and by assuming ideal structures of fabrics to model the properties of fabrics. But in real-world applications, these methods have been found to be wanting in terms of accuracy or conditions of application.

Attempts to solve design problems by application of conventional types of expert systems have not succeeded, because there are only a few highly experienced experts in the industry who know rule-of-thumb principles and methods of complex structural synthesis under performance constraints. Acquisition of domain-specific knowledge is the major challenge in building

knowledge-based expert systems. Efforts to make such expert systems in general have run into a number of problems. As the complexity of the system increases, the system simply demands too much computing resources and becomes too slow. Validation and verification of the system are slow and difficult. Maintenance and up-grading of the system also become difficult. Under this situation expert systems could be feasible only when narrowly confined.

The challenge is to solve the technical difficulties of fabric engineering, using various neural network architectures to find solutions to the optimum fabric structure and properties to produce quality fabric. This could be achieved by embedding a trained artificial neural network to execute structure–property relationships of the fabric in an expert system in order to engineer woven fabrics with the desired mechanical and physical properties.

Soft computing suggests a new computing methodology that is both flexible and easy. Three major branches of soft computing, namely fuzzy logic, neural networks, and genetic algorithms, are discussed with respect to their applications in solving a variety of textile problems ranging from fiber classification, color grading, yarn and fabric property prediction, to the optimization of products and processes, and even the search for a pleasing garment design. These tools of soft computing are complementary rather than competitive. A number of prediction models of ‘hybrid type’ are being developed combining the merits of each of these techniques. These hybrid models could very well result in a system that is more intelligent and effective in problem solving.

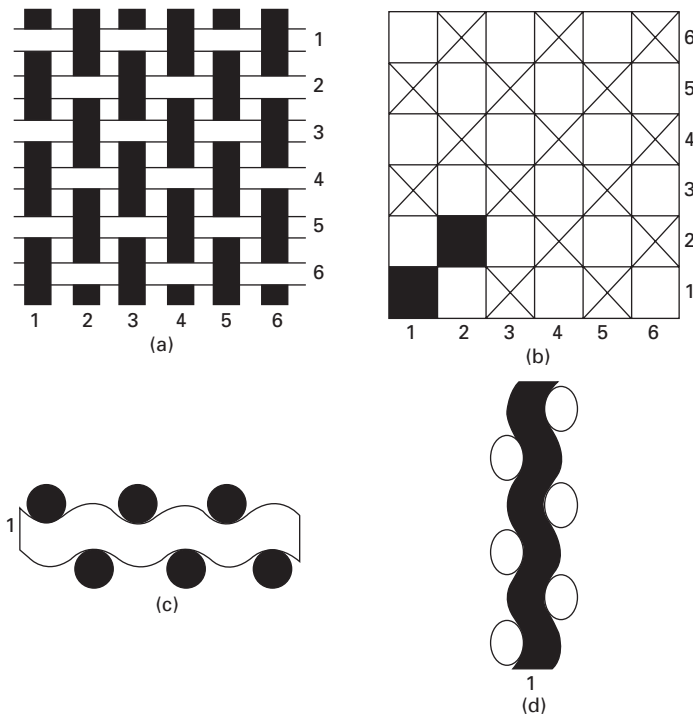
8.2 Fundamentals of woven construction

There are many ways of making fabrics from textile fibers. The most common and most complex category comprises fabrics made from interlaced yarns. The most common form of interlacing is weaving [1]. A woven fabric is produced by interlacing two sets of yarns, the warp and the weft, which are at right angles to each other in the plane of the cloth. The warp is along the length and the weft along the width of the fabric. Individual warp and weft yarns are called ends and picks. The interlacement of ends and picks with each other produces a coherent and stable structure. The yarns are held in place due to the inter-yarn friction [2]. The repeating unit of interlacement is called the weave. In this fabric formation process, there is a great scope in choosing fibers with particular properties, arranging fibers in the yarn in several ways and organizing in multiple ways interlaced yarns within the fabric. This gives the textile designer great freedom and variation for controlling and modifying the fabric structure. The woven structures provide a combination of strength with flexibility. The flexibility at small strains is achieved by yarn crimp due to freedom of yarn movement, whereas at

high strains the threads take the load together, giving high strength. Figure 8.1 shows plain weave in plan view and in cross-section along warp and weft. The weave representation is shown by a grid in which vertical lines represent warp and horizontal lines represent weft. Each square represents the crossing of an end and a pick. A mark in a square indicates that the end is over the pick at the corresponding place in the fabric that is warp-up. A blank square indicates that the pick is over the end that is weft-up. One repeat of the weave is indicated by filled squares and the rest by crosses. The plain weave repeats on two ends and two picks.

8.3 Elements of woven structure

The properties of the fabric, for given yarns, depend on the fabric structure. The formal structure of a woven fabric is defined by weave, thread density, crimp and yarn count. The interrelation between fabric parameters can be obtained by considering a geometrical model of the fabric. The geometrical model is mainly concerned with the shape taken up by the yarn in the warp or



8.1 (a) Plan, (b) weave representation, (c) cross-sectional view along weft, and (d) cross-sectional view along warp of a plain woven structure.

weft cross-section of the fabric. Mathematical deductions obtained from simple geometrical form and physical characteristics of yarn combined together help in understanding various phenomena in fabrics. The basic model of Pierce's [3] analysis is shown in Fig. 8.2. It represents a unit cell interlacement in which the yarns are considered inextensible and flexible. The yarns have circular cross-section and consist of straight and curved segments. The main advantages in considering this simple geometry are as follows:

- It helps to establish the relationship between various geometrical parameters.
- It enables the calculation of the resistance of the cloth to mechanical deformation such as initial extension, bending and shear in terms of the resistance to deformation of individual fibers.
- It provides information on the relative resistance of the cloth to the passage of air, water or light.
- It provides a guide to the maximum density of yarn packing possible in the cloth.

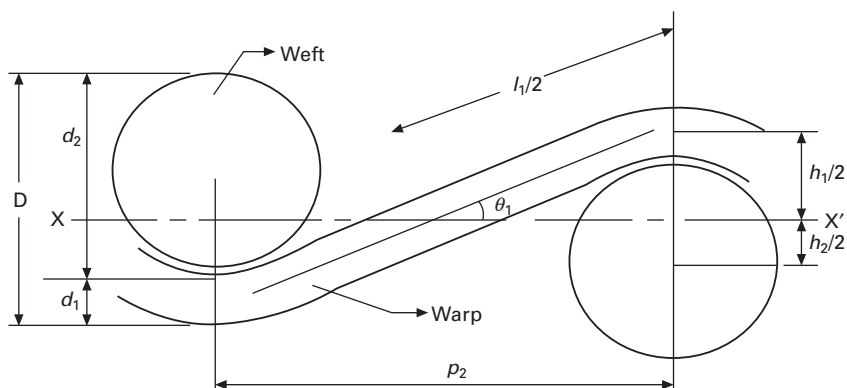
From the two-dimensional unit cell of a plain woven fabric, geometrical parameters such as thread spacing, weave angle, crimp and fabric thickness are related by deriving a set of equations. The symbols used to denote these parameters are listed below:

d = diameter of thread

p = thread spacing

h = maximum displacement of thread axis normal to the plane of the cloth (crimp height)

θ = angle of thread axis to the plane of the cloth (weave angle in radians)



8.2 Peirce model of plain weave.

l = length of thread axis between the planes through the axes of consecutive cross-threads (modular length)

c = crimp (fractional)

$D = d_1 + d_2$

Suffixes 1 and 2 to the above parameters represent warp and weft threads, respectively.

In Fig. 8.2, projection of the yarn axis parallel and normal to the cloth plane gives the following equations:

$$c_1 = \frac{l_1}{p_2} - 1 \quad 8.1$$

$$p_2 = (l_1 - D\theta_1) \cos\theta_1 + D\sin\theta_1 \quad 8.2$$

$$p_1 = (l_1 - D\theta_1) \sin\theta_1 + D(1 - \cos\theta_1) \quad 8.3$$

Three similar equations are obtained for the weft direction by interchanging suffixes 1 and 2 and vice-versa as follows:

$$c_2 = \frac{l_2}{p_1} - 1 \quad 8.4$$

$$p_1 = (l_2 - D\theta_2) \cos\theta_2 + D\sin\theta_2 \quad 8.5$$

$$h_2 = (l_2 - D\theta_2) \sin\theta_2 + D(1 - \cos\theta_2) \quad 8.6$$

Also,

$$d_1 + d_2 = h_1 + h_2 = D \quad 8.7$$

In all there are seven equations connecting 11 variables. If any four variables are known then the equations can be solved and the remaining variables can be determined. Unfortunately, these equations are difficult to solve. Researchers have tried to solve these equations using various mathematical means to find new relationships and also some simplified useful equations.

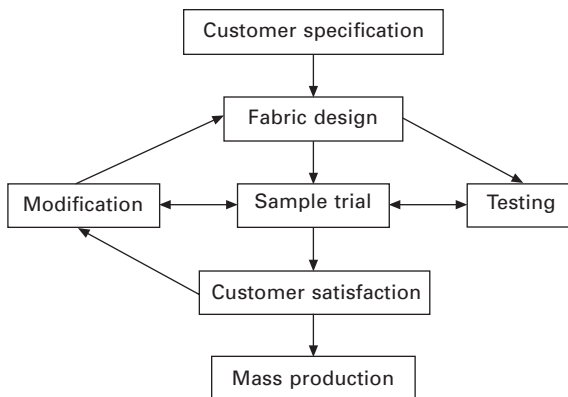
8.4 Fundamentals of design engineering

Design is the process of delineating a product to meet the functional and the aesthetic performance criteria with efficient use of resources. The design process should satisfy certain criteria such as simplicity, testability, manufacturability and reusability. Engineering is an applied science dealing with relationships between the raw material, the fabric and the finished product. Therefore, the design engineer has to engineer fabric construction for predetermined properties that fit specific applications with quick response. Design of textile-related products has been carried out for thousands of years in a traditional and intuitive way. However, in the last few decades the

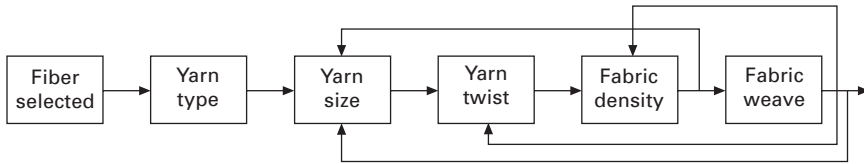
importance of design has increased due to the growing needs of the industry and the consumer for complex and specific requirements of functionality. This has called for a system of engineered manufacturing of textile products in place of traditional experience-oriented manufacturing. The design process itself may be subjected to certain restrictions such as time, manpower, cost, etc. Nevertheless, no standard procedure or logic is available or followed as far as textile product design is concerned. The design is usually carried out manually, based on experience and trial-and-error. In recent years, increasingly inexpensive computers have made the designing of textile products more popular. Also, simulation and other technologies are brought into use to design and develop numerous quality products.

8.5 Traditional designing

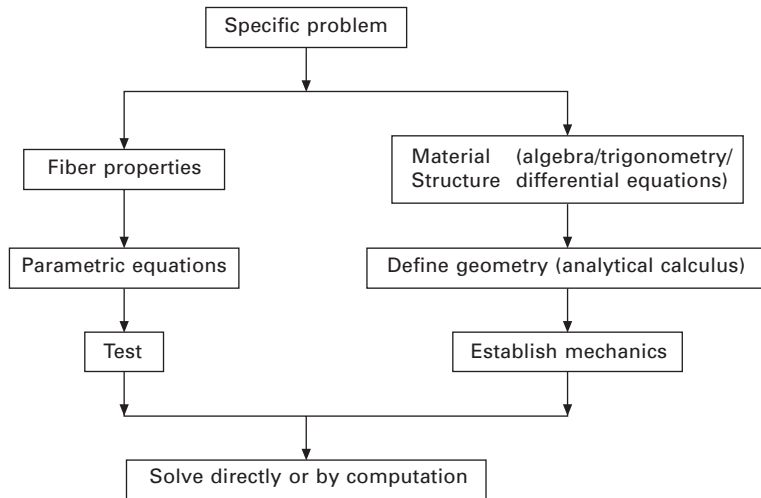
In the traditional designing method [4], as shown in Fig. 8.3, the market expert formulates the rough concept of fabric requirements; thereafter the fabric designer in consultation with the experts from various departments such as marketing, production, quality assurance, costing and others, prepares a detailed description of the fabric design. With this derived design, a sample fabric is woven and tested, and undergoes the whole process until the customer is satisfied; then the fabric is taken for mass production. This cyclical process of fabric design depends on experience, heuristic reasoning, and intuition. The basic problem related to this process is the amount of expert knowledge available and its consistency and also the fact that no single expert is usually available for a group of domains. Further development introduced in the fabric design process is known as manual design procedure. The typical manual design procedure [5] for industrial fabrics is illustrated in Fig. 8.4. This is a rough procedure for synthesizing a fabric structure through several



8.3 Traditional fabric design cycle.



8.4 Manual design procedure for industrial fabrics.



8.5 Mechanics of textile structure: traditional route.

sub-tasks from top-down resolution of the overall design task. At first, for a set of property constraints, the designer chooses the fiber type for interlacing yarns governed by its cost, physical properties, etc., along with the type of yarn and its strength. The yarn linear density with the strength of individual yarn components is then determined. At this point, the fabric tensile strength is specified, and fine adjustment of yarn properties is made by using yarn twist followed by consideration of yarn density. The fabric weave is then selected, depending on the tearing strength, thickness, fluid permeability, etc. The manual design procedure for other types of textile materials is almost the same, with the only difference being in the properties required, depending on end-use applications.

8.6 Traditional designing with structural mechanics approach

The stages of the traditional approach based on mathematical and physical principles are depicted in Fig. 8.5 [6]. The approach is strongly mathematical

with computations brought in at the end in order to solve the equations. Fiber properties are specified by the parameters of the linear or nonlinear equations. The geometry can be defined by algebraic and trigonometric equations, and the mechanics can be analyzed by differential or integral calculus.

8.7 Designing of textile products

Overall, the major areas of designing textile products can be broadly classified into color or pattern and material design. Figure 8.6 depicts the difference in an artistic and engineering design approach. The color or pattern design deals with the visual appearance and fashion of the products that includes the motif [7–10], color [11–17], pattern preparation [18–30], etc. This involves creating infinite combinations of motifs and arriving at an arrangement that may be aesthetically pleasing to the consumer.

In artistic design, traditionally the main process is accomplished through ‘pencil and paper’ sketching. To begin with, the creative idea is expressed by freehand sketching. If the design is thought to have commercial potential, it is then processed by the designer or design technicians from the sketch onto special design paper. At this stage, the design is modified according to the process for which it is intended, that is knitting, weaving, printing, etc. [31–33]. Then, this design paper bears an enhanced sketch with additional information. With the advent of computing, the creative idea of designers is translated into the computer environment for design purposes. Large amounts of innovative work have been carried out in the area of color and pattern designing [34] by using computer-aided design (CAD). In fact, the application of color graphics technology for color pattern design is becoming ever more popular because of its effectiveness.

Material design can be defined broadly as design that deals with the structural, aesthetic and functional behavior of the material based on product type [35]. The logic of material design involves mapping a specified function onto a realizable structure [36]. A correct material design is one whose basic structure correctly sets up the specified function or effect. In this system, material behavior mediates function and structure. On the other hand, the color or pattern and material design has a common region that is the surface or texture appearance caused by the material effect. Both will overlap effectively in producing a product. Although a considerable amount

CAD for artistic design	CAD for engineering design
Colour	Thread count
Pattern	Thread density
Weave	Weave
Motif	Areal density, etc.

8.6 CAD: artistic design versus engineering design for woven fabric.

of research has been carried out on color or pattern designing related to fabric appearance and fashion, the material design technology for textile products is still at the development stage. In fact there are no standard procedures available so far for carrying out the material design process. Compared to other fields of engineering, textiles may be the field that takes longer to realize the potential of CAD [37] for innovation and creativity in product design. This is primarily attributed to the constraint of material characteristics.

CAD for material technology to design textile products needs more integrated versatile knowledge and expertise to handle a large number of variables. Since many parameters related to functional, structural and manufacturing method and cost need to be considered simultaneously, it necessitates more scientific solutions. But only a few experts are available to cope with this situation. Therefore, CAD is surely a feasible tool to handle such problems as discussed earlier. The general requirements for CAD in the perspective of material design to suit industrial needs comprise the necessity of an integrated system, information as a basis for structural mechanics calculations, data availability of functions and structures suitable for the computer environment, a well-defined structure of target products, etc.

8.8 Design engineering by theoretical modeling

8.8.1 Model

A model is a description or an analogy used to help visualize something that cannot be directly observed. It can be a system of postulates, data and inferences presented as a mathematical description of an entity or state of affairs. Modeling is an activity in which we think about and make models to describe how the objects of interest behave. There are several ways by which objects and their behavior can be described. We can use words, drawings, physical models, computer programs or mathematical formulae. In designing an engineered product, normally mathematical equations and/or logical concepts are used to simulate and predict real events and processes while making models. Mathematical models represent the behavior of objects in mathematical terms. In modeling it is important to know how to generate mathematical representations (equations) and how to validate them. It is also important to know how model equations are used and their limitations. Before analyzing these issues, it is worth explaining why we do mathematical modeling.

8.8.2 Theoretical modeling

A theoretical model describes a type of object or system by attributing to it what might be called an internal structure, a composition or mechanism that, when taken as a reference, will explain various properties of that object or

system. A theoretical model, therefore, analyzes a phenomenon that exhibits certain known regularities by reducing it to more basic components, and not simply by expressing those regularities in quantitative terms or by relating the known properties to those of different objects or systems. A theoretical model is considered as an approximation that is useful for certain purposes. It can be used for explanation, prediction, calculation, systematization, derivation of principles, and so on. The most important characteristic of a theoretical model is that it consists of a set of assumptions about the concept or system. The models provide explanations; but these explanations are based on assumptions that may be simplified, and this condition must be borne in mind when one compares them with theories. However, a theoretical model is often formulated and developed and sometimes even named on the basis of an analogy between the object or system that it describes. Models simulate the behavior or activity of systems, processes, or phenomena. They include the use of mathematical equations, computers, and other electronic equipment.

8.8.3 Need for theoretical modeling

Modeling methodologies for predicting fabric properties are essential to design fabrics as per the specifications desired by the customer. If the relationships between different parameters that determine the specific fabric property are known, they can be handled to optimize that particular property for different end-use applications. Predictive modeling methodologies can also be used to identify different levels of combinations of process parameters and material variables that yield the desired fabric property. From this, a specific combination of process and material variables resulting in maximum savings in cost and time can be selected.

8.8.4 Mathematical modeling and scientific method

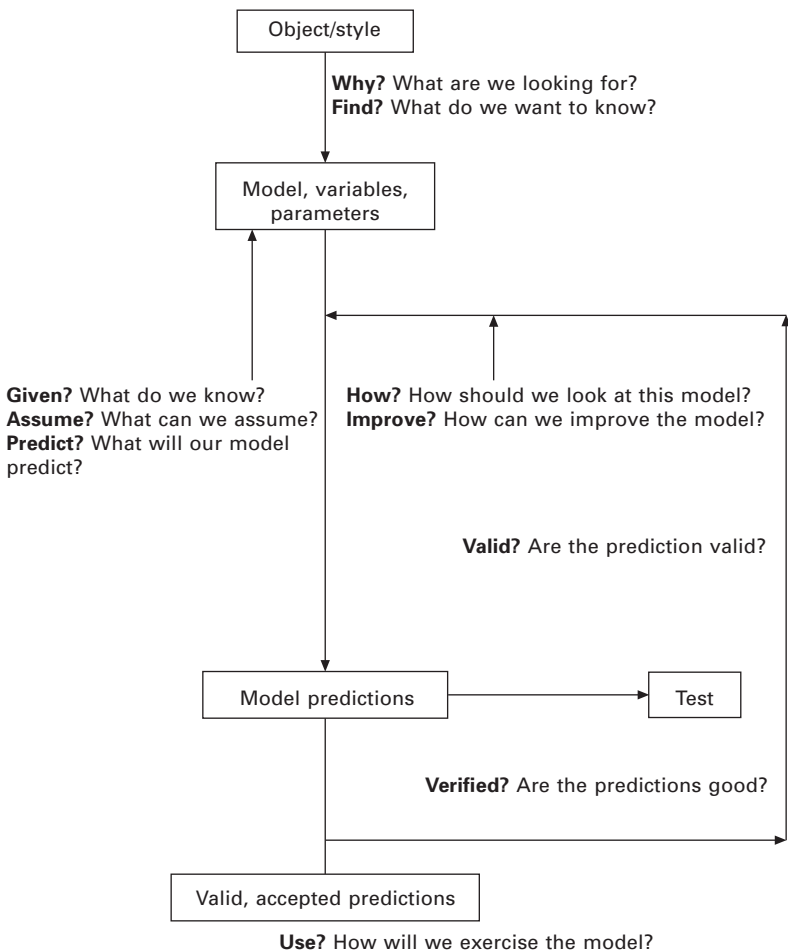
Scientific methods help to identify the real world and the conceptual world. In the real world we observe various phenomena and behaviors which could be either natural or produced by artifacts. The conceptual world is the world of the mind. The conceptual world has three stages: observation, modeling and prediction. In observation part of the scientific method we measure what is happening in the real world. Here we gather empirical evidence and facts on the ground. The modeling is concerned with analyzing the above observations for at least one of the three reasons. The model describes the behavior or results observed and the models allow us to predict future behaviors that are yet unseen or unmeasured. In the prediction of a scientific method, we use models to tell us what will happen in a future experiment or in an anticipated set of events in the real world. These predictions are

followed by observations that serve either to validate the model or to suggest reasons for an inadequate model. Scientific method and engineering design have much in common, but there are differences in motivation and approach. In the practices of science and engineering design, models are often applied to predict what will happen in a future situation.

Mathematical modeling is formulated using certain principles. The basic philosophical approach to formulate a model is shown in Figure 8.7.

8.9 Modeling methodologies

Over the years, many attempts have been made to develop predictive models for textile properties using different modeling methodologies. These are



8.7 Philosophy of mathematical modeling.

essentially of two kinds: deterministic and non-deterministic. Mathematical models, empirical models, and computer simulation models such as finite element analysis are deterministic models, whereas models based on genetic methods, neural networks, chaos theory and soft logic are non-deterministic. Each method has its own merits and demerits. Nowadays more and more processes and systems are modeled and optimized using non-deterministic approaches. This is due to the high degree of complexity of systems, and consequently the inability to study them efficiently with conventional methods only. In the non-deterministic approach, there are no precise, strict mathematical rules. No assumptions regarding the form, size and complexity of models are made in advance. Hence this approach offers a flexible means to provide solutions to a wide variety of textile problems with reasonable prediction accuracy [38]. A brief overview of various computing tools is given in this chapter. For a detailed explanation on these modeling methodologies and other soft computing tools, one can refer to the standard texts available [39–41].

8.10 Deterministic models

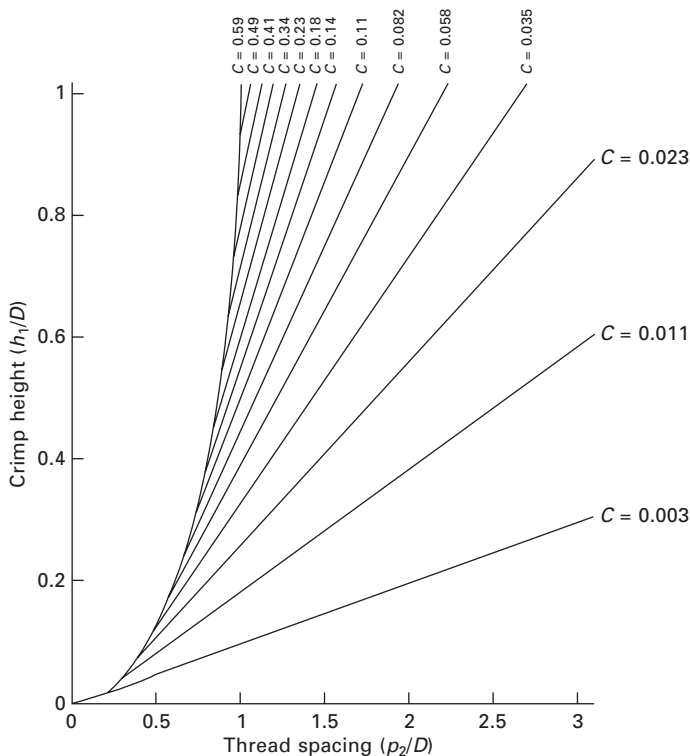
8.10.1 Pure geometrical model

Fabric properties are greatly affected by the choice of fabric parameters. The choice of fabric parameters influences the structure. The behavior of and relationship between the fabric parameters is a precursor to the optimal solution for fabric engineering problems. Many features of cloth are essentially dependent on geometrical relationships. The geometrical model of fabric provides some simplified formulae to facilitate calculations and specific constants which are of value for fabric engineering, problems of structure and mechanical properties [38]. These fabric parameters are a tool for an innovative fabric designer to create fabrics for diverse applications. The theoretical relationships between the fabric parameters enable the fabric designer to play with different fibers, yarn linear densities, thread densities and weaves to vary texture and fabric properties.

It is possible to predict the fabric parameters and their effect on the fabric properties by simple computing. This information is helpful in taking a decision regarding specific buyers' needs. A simplified algorithm is used to solve fabric geometry equations and relationships are obtained between useful fabric parameters such as thread spacing and crimp, fabric cover and crimp, warp and weft cover, etc. Such relationships help in guiding the direction for moderating fabric parameters. For example the parameters of a fabric requiring a certain crimp in warp and weft even in a jammed state can be calculated. It may be desirable to make a non-jammed fabric with a certain amount of warp and weft. Even fabrics with maximum crimp in either the

warp or weft direction can be estimated. In this chapter only a few relations are graphically demonstrated to optimize engineering attributes of a plain weave fabric.

Needless to mention that the pioneering work of Peirce on geometrical modeling provides a basic platform for fabric engineering. Many basic fabric dimensional parameters can be worked out from the geometrical model by use of modern computing methods. Fabric parameters for any relationship between warp and weft cover can be evaluated. Last but not least, the relationship between fabric mass and fabric cover can also be evaluated. This is the strength of the computing method which cannot be achieved by any other means such as the graphical or nomogram method. The basic equations derived from the geometrical model given in Eq. 8.1–8.7 are taken as a basis to work out many derived relationships. For example, the solution of p_2/D and h_1/D is obtained for different values of θ_1 (warp crimp angle) ranging from 0.1 to $\pi/2$ radians. Such a relationship is shown in Fig. 8.8. It is a very useful relationship between fabric parameters for engineering desired fabric constructions. One can see its utility for jammed structures,



8.8 Relation between thread spacing and crimp height.

non-jammed fabrics and even for some special cases in which cross-threads are straight. For jammed structures, Fig. 8.8 shows a non-linear relationship between the two fabric parameters p and h on the extreme left. In fact, this curve is for jamming in the warp direction. It can be seen that the jamming curve shows different values of p_2/D for increasing crimp. Interestingly this curve is a part of circle and its equation is:

$$\left(\frac{p_2}{D}\right)^2 + \left(\frac{h_1}{D} - 1\right)^2 = 1 \quad 8.8$$

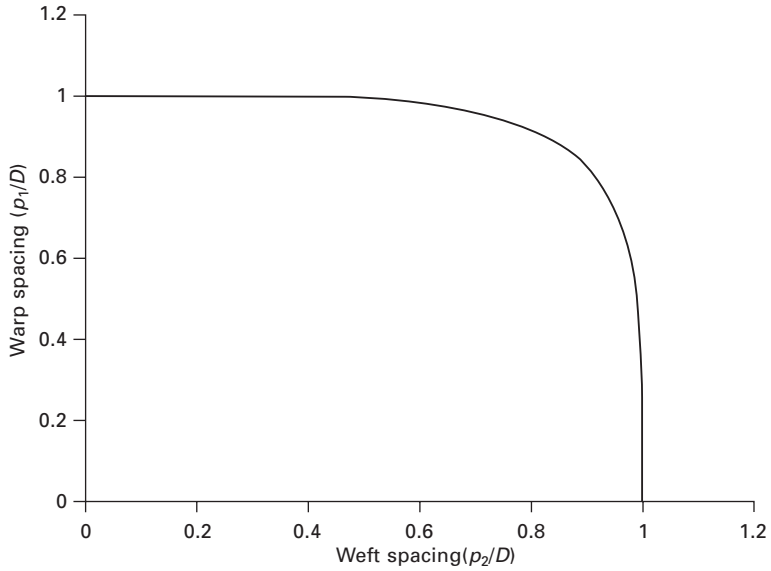
with center at (0, 1) and radius equal to 1. For jamming in the warp direction of the fabric the parameters p_2/D and the corresponding h_1/D can be obtained either from Fig. 8.8 or from the above equation. The relationship between the fabric parameters over the whole domain of the structure being jammed in both directions can be obtained by developing a suitable algorithm for computation using the following derived equations:

$$\begin{aligned} p_2 &= D \sin \theta_1 = D \sin \frac{l_1}{D} \\ h_1 &= D(1 - \cos \theta_1) = D \left(1 - \cos \frac{l_1}{D}\right) \end{aligned} \quad 8.9$$

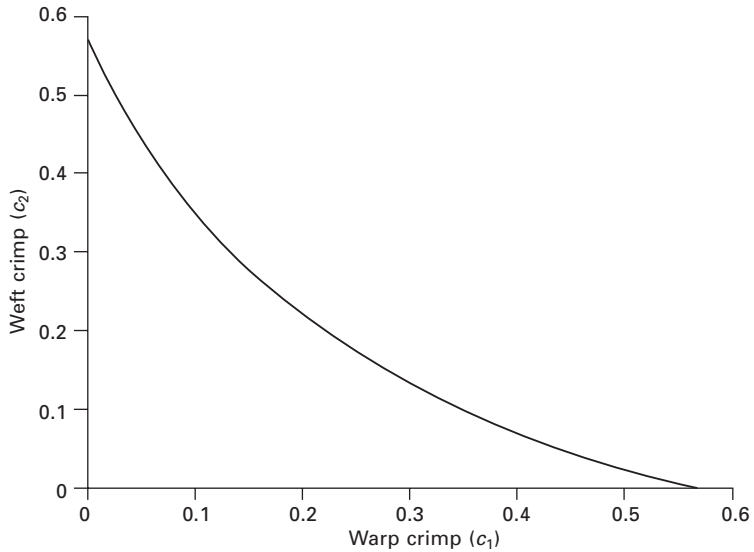
$$\begin{aligned} \frac{h_2}{D} &= 1 - \frac{h_1}{D} \\ p_1 &= D \sin \theta_2 = D \sin \frac{l_2}{D} \\ h_2 &= D(1 - \cos \theta_2) = D \left(1 - \cos \frac{l_2}{D}\right) \end{aligned} \quad 8.10$$

From the computation, the relationships between different useful fabric parameters are obtained and are given in Figs 8.9 to 8.13. Figure 8.9 gives the relationship between p_2/D and p_1/D . This figure shows that the relationship between these parameters is less sensitive at the two extreme ends. The relationship is sensitive in a p/D range closer to 1. In fact this sensitive range corresponds to maximum crimp in one direction only. Scope for change in both p_2 and p_1 lies in the range 0.6 to 0.9. Beyond this range, change in thread spacing is possible only in one direction.

A useful relationship between the crimps in the two directions is shown in Fig. 8.10. It indicates an inverse non-linear relationship between c_1 and c_2 . The intercepts on the axis give maximum crimp values with zero crimp in the cross-direction. This is a fabric configuration in which the cross-threads are straight and all the bending is done by the intersecting threads. It may be concluded here that at either end a small change of crimp in one direction can permit a large change in crimp in the other direction.

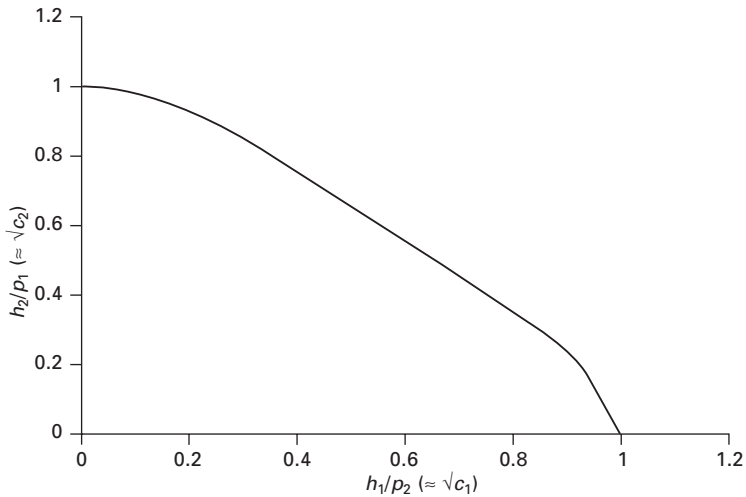


8.9 Relation between warp and weft thread spacing for jammed fabric.

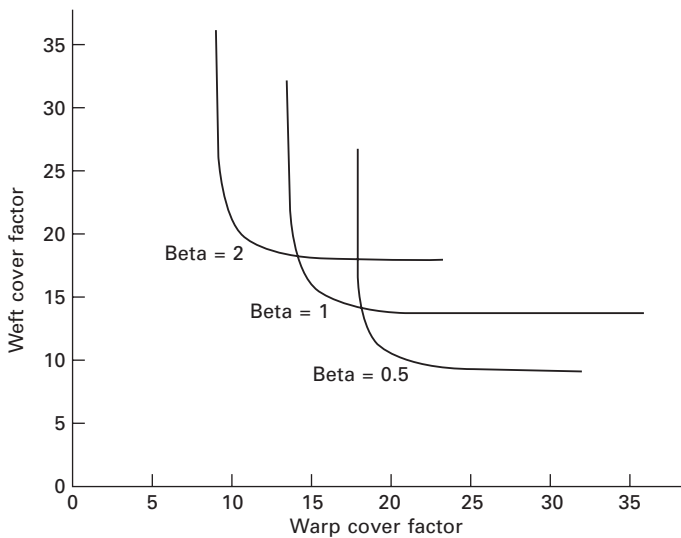


8.10 Relation between fraction warp and weft crimp for jammed fabric.

Figure 8.11 shows the relation between h_1/p_2 and h_2/p_1 . This shows linearity between them except at the two extremes. The behavior is in fact a relationship between the square root of crimp in two directions and the



8.11 Relation between $\sqrt{c_1}$ and $\sqrt{c_2}$ for jammed fabric.



8.12 Relation between warp and weft cover factor for different values of β for jammed fabric.

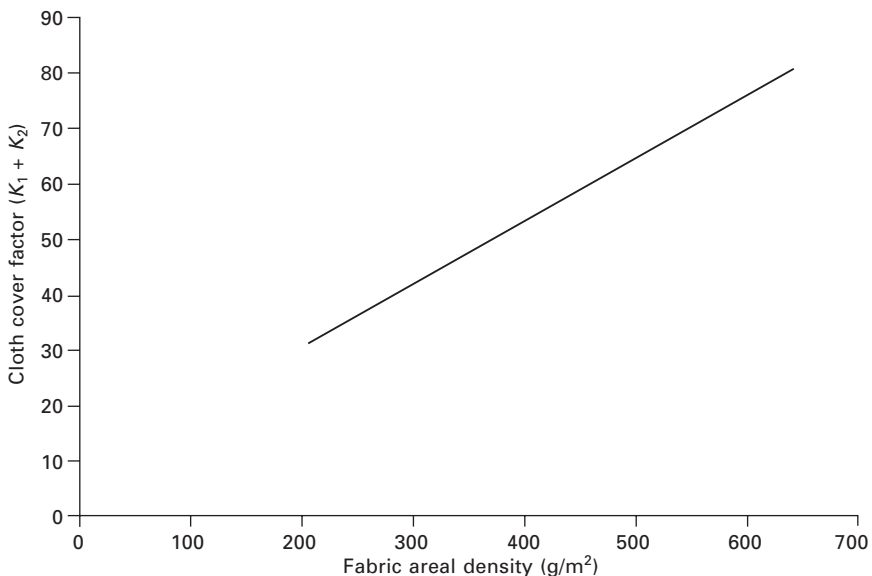
constant is fixed for any jammed fabric. Other practical relations are obtained between warp and weft cover factor and between cloth cover factor and fabric mass (gsm).

Figure 8.12 gives the relation between warp and weft cover factor for different ratios of weft to warp yarn diameters (β). The relation between the

cover factors in the two directions is sensitive only in a narrow range for all values of β . The relations between the cover factors in the two directions are interdependent for jammed structures. Maximum threads in warp/weft direction depend on yarn count and weave. Maximum threads in one direction of the fabric will give unique maximum threads in the cross-directions. The change in the value of β causes a distinct shift in the curve. A comparatively coarse yarn in one direction with respect to the other direction helps to increase the cover factor. For $\beta = 0.5$, the warp yarn is coarser than the weft, this causing an increase in warp cover factor and a decrease in weft cover factor. A similar effect can be noticed for $\beta = 2$, in which the weft yarn is coarser than the warp yarn.

The relation between fabric mass in gsm and cloth cover ($K_1 + K_2$) is positively linear as shown in Fig. 8.13. The trend may appear to be self-explanatory. In practice, an increase in fabric mass and cloth cover factor for jammed fabrics can be achieved in several ways, such as zero crimp in the warp direction and maximum crimp in the weft direction, zero crimp in the weft direction and maximum crimp in the warp direction, equal crimp in both directions, and dissimilar crimp in both directions. This explanation can be understood by referring to the non-linear part of the curve in Fig. 8.8.

Similarly in the case of a non-jammed structure, it can be seen that the relation between p_2/D and the corresponding h_1/D is linear for different values of crimp. This relationship is useful for engineering non-jammed structures



8.13 Relation between fabric cover factor and fabric areal density for jammed structure.

for a range of values of crimp. The fabric parameters can be calculated from the above non-jammed linear relation between p_2/D and h_1/D for any desired value of warp crimp. Then h_2/D can be obtained from $(1 - h_1/D)$ and for this value of h_2/D one can obtain the value of p_1/D for the desired value of weft crimp. Thus all fabric parameters can be obtained for desired values of p_2/D , picks/cm, warp and weft yarn tex, and warp and weft crimp. One can choose any other four parameters to get all fabric parameters. The algorithm mentioned in Fig. 8.1 can be used to get several solutions for the non-jammed fabric.

Considering a fabric in which cross-threads are straight, it may further be realized from Fig. 8.8 that the intersection of the horizontal line corresponding to $h_1/D = 1$ gives all possible structures ranging from relatively open to jammed configuration. In this case $h_2 = 0$, $h_1 = D$. The fabric designer gets the options to choose the possible fabric constructions. These options include jamming and other loose constructions. Using the above logic it is also possible to get fabric parameters for a fabric jammed in both directions, a fabric with maximum crimp in one direction and cross-threads being straight, and a fabric which is neither jammed nor has zero crimp in the cross-threads.

Applications of geometrical models

In the weaving and processing industry computer and mathematical models of fabric can facilitate rapid development of required products without the need to produce many fabric samples. Geometrical modeling can be used as a tool to achieve the desired functionality in the case of industrial fabric production. The model and analysis system would make it possible to realistically model the fabric structure and predict its performance before it is used or even manufactured, thereby saving both time and energy. Examples of some properties for specific industrial applications are discussed below:

- *Weavability and maximum sett*: This is helpful in realizing maximum areal density of the fabric and the suitability of the fabric for applications like waterproof fabrics and airproof fabrics. A very close value of end and pick densities can be found, thereby reducing the extent of experimentation.
- *Fabric design and engineering*: The fabric can be engineered and designed for specific applications by using structural parameters such as crimp, thickness, cover factor, etc. For example, filter fabrics where the thickness of the fabric plays an important role can be accurately designed.
- *Manipulation of the fabric shape and structure*: This is possible in some specific applications like stentering and calendering (the geometrical model is very much applicable here because of the type of forces in action) in which the width or length of the fabric is changed under the

application of force. The final length and width of the fabric can be predicted using the computation method embedded in the algorithm. It may be mentioned here that the geometrical model can predict only the structural parameters of the fabric and therefore is of very little use for predicting the mechanical properties of the fabric.

8.10.2 Mathematical models

Mathematical models are derived from first principles. These models are very appealing because they have their basis in applied physics. They can be used to explain the reasons that determine structure–property relationships. The main purpose for carrying out these structural analyses is to provide tools to enable the designer to design textile structures to meet various end-use specifications.

Limitations of mathematical modeling

Mathematical modeling has certain limitations. The development of theory is cumbersome and requires many years to yield results. The models are normally problem specific and any change in the system requires a new analysis and new programs to solve the equations. It often produces large prediction errors and the procedures are not user-friendly.

8.10.3 Empirical modeling

The most common approach has been to develop predictive models for fabric properties and performance through experimental investigations. In this case, a large number of experiments are made under controlled conditions and statistical techniques are used to derive empirical models. Data generated from experimental results are used to develop regression models to predict desired property parameters. The empirical equations are used based on the regression technique. In the statistical method of modeling, a multilinear regression equation between fabric properties and constructional parameters is applied to the same data, to find the predictability of the statistical method. The coefficient of multiple determination (R^2) which defines the fraction of variability in the dependent variable explained by the regression model, is taken as a guiding parameter. If the R^2 value of the model is high, it suggests that the empirical model fits the data reasonably well.

Limitations of empirical modeling

Empirical models can have limited applications for two reasons. First, the size of the experiments is generally limited due to cost and time factors,

therefore selection of materials and processes can be considered in a narrow range only. Secondly, the existing tools and techniques are inadequate for accurately modeling and optimizing complex non-linear processes like woven fabric manufacturing. Hence, there is a need for models that can accurately predict process and product design for woven fabrics.

8.10.4 Finite element modeling

The finite element method is a powerful tool for the numerical solution of a wide range of engineering problems. Application of FEM ranges from deformation and stress analysis of automotive, aircraft, building, and bridge structures to field analysis of heat flux, fluid flow, magnetic flux and other flow problems. In recent years, finite element analysis has also been applied to flexible materials like textile fabrics for modeling and simulation. In this method of analysis, a complex region defining a continuum is discretized into simple geometric shapes called finite elements. The material properties and the governing relationships are considered over these elements and expressed in terms of unknown values at element corners. An assembly process, duly considering the loading and constraints, results in a set of equations. Solution of these equations gives the approximate behavior of the continuum.

FEM is considered useful for textiles because the complexity of the structure, the anisotropic properties of yarns and fabrics, and the interaction phenomena between yarns at the contact areas preclude the use of analytical methods. With FEM-based calculation models, processes can be understood with regard to the physical phenomena in depth and it is possible to change important parameters in a short time in order to improve textile-based constructions and also to generate new products [42]. From a structural point of view, woven fabrics are discontinuous in microstructure and therefore do not satisfy the continuity requirement in solid mechanics. However, discontinuity in the fabric is small in comparison to the finite element mesh size, and therefore fabric continuity is a reasonable assumption to make. Several research works have been reported during recent years on the application of FEM analysis for prediction of fabric mechanical properties which can be used for engineering of woven constructions [43–46].

8.11 Non-deterministic models

Models based on genetic methods, neural networks, chaos theory and soft logic are non-deterministic models and are known as soft computing methods according to convention for predicting properties and performance. Soft computing is a collection of methodologies which aim to exploit tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost. It is unlike conventional (hard)

computing in that it is tolerant of imprecision, uncertainty, partial truth, and approximation. The soul of soft computing is to make computers as soft as the human brain, and capable of carrying out both quantitative and qualitative computing. Along this direction, fuzzy logic has been developed to handle qualitative information, and in this sense it is called fuzzy computing. A neural network is a kind of soft computing technology as it provides a relatively easy way for acquiring the information about a system through learning. The inclusion of neural computing and genetic computing in soft computing came at a later stage. There are a number of publications in this field of computing covering a wide range of application domains including that of textiles. Notable ones are a book on soft computing in textile sciences by Sztandera and Pastore [47], a textile institute monograph on artificial neural network applications in textiles by Chattopadhyay and Guha [48], and research work carried out by Behera and Muttagi [76–82] on the development of ANN-embedded expert systems for woven fabric engineering.

8.11.1 Fuzzy logic

Knowledge representation and processing are the keys to any intelligent system. In logic, knowledge is represented by propositions and is processed through reasoning by the application of various laws of logic, including an appropriate rule of inference. Fuzzy logic uses the fuzzy set theory and approximate reasoning to deal with imprecision and ambiguity in decision making. A crisp set is defined by the characteristic function that can assume only the two values $\{0, 1\}$, whereas a fuzzy set is defined by a ‘membership function’ that can assume an infinite number of values, i.e. any real number in the closed interval $[0, 1]$. The idea of fuzzy logic was introduced by Lofti A. Zadeh (1965) in his paper on fuzzy sets [49].

Consider a universe of discourse X with x representing its generic element. A fuzzy set $\tilde{A}$ in X has the membership function $\mu_{\tilde{A}}(x)$ which maps the elements of the universe onto numerical values in the interval $[0, 1]$:

$$\mu_{\tilde{A}}(x): X \rightarrow [0, 1] \quad 8.11$$

Every element x in X has a membership function $\mu_{\tilde{A}}(x) \in [0, 1]$. $\tilde{A}$ is then defined by the set of ordered pairs:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X, \mu_{\tilde{A}}(x) \in [0, 1]\} \quad 8.12$$

A membership value of zero implies that the corresponding element is definitely not an element of the fuzzy set $\tilde{A}$. A membership value of unity means that the corresponding element is definitely an element of fuzzy set $\tilde{A}$. A grade of membership greater than zero and less than unity corresponds to a non-crisp (or fuzzy) membership of the fuzzy set $\tilde{A}$. Classical sets can be considered as special cases of fuzzy sets with all membership grades

equal to unity. Membership functions characterize the fuzziness in a fuzzy set [50].

Models designed based on fuzzy logic usually consist of a number of fuzzy if-then rules expressing the relationship between inputs and desired output. For instance, in the case of two-input single-output systems, it is expressed as:

$$R_i: \text{IF } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ THEN } z \text{ is } C_i \quad 8.13$$

where R_i is a fuzzy relation representing the i th fuzzy rule; x , y , z are linguistic variables representing two inputs and the output; and A_i , B_i , C_i are linguistic values of x , y , z , respectively. In these models, inputs are fuzzified, membership functions are created, association between inputs and outputs are defined in a fuzzy rule base, and fuzzy outputs are restated as crisp values. Fuzzy modeling can be categorized into two categories: subjective modeling and objective modeling. In the subjective modeling approach, it is assumed that *a priori* knowledge about the system is available and that this knowledge can be directly solicited from experts. By contrast, in the objective modeling, it is assumed that either there is no knowledge about the system, or the expert's knowledge is not trustworthy enough. Therefore, instead of any *a priori* interpretation of the system, raw input and output data is used to augment human knowledge or even generate new knowledge about the system. This approach was initially proposed by Takagi-Sugeno-Kang in 1985 and called TSK fuzzy modeling.

Applications of fuzzy logic

Fuzzy logic has been used in several areas of textiles which include color grading of cotton into different classes, prediction of tensile strength and yarn count of melt spun fibers, an intelligent diagnosis system for fabric inspection and automatic recognition of fabric weave pattern. Raheel and Liu [51] used a fuzzy comprehensive evaluation technique to calculate fabric handle of lightweight dress fabrics. Thickness, weight, flexural rigidity, wrinkle recovery, and 45° filling elongation were used to describe the hand of light weight fabrics. In order to obtain the fuzzy transformation matrix R , five membership functions corresponding to the five properties were selected. A decreasing half-Cauchy distribution was used to describe the membership degrees of fabric weight, fabric thickness, fabric flexural rigidity and 45° filling elongation. For wrinkle recovery, a linear membership function was used. From a survey of judges, the importance of each property selected was ascertained and expressed as a weighted vector. By using the weighted vector and the fuzzy transformation matrix, fabric handle was calculated. The same approach was followed by Park and Hwang [52] for predicting total hand value from selected mechanical properties of double weft knitted

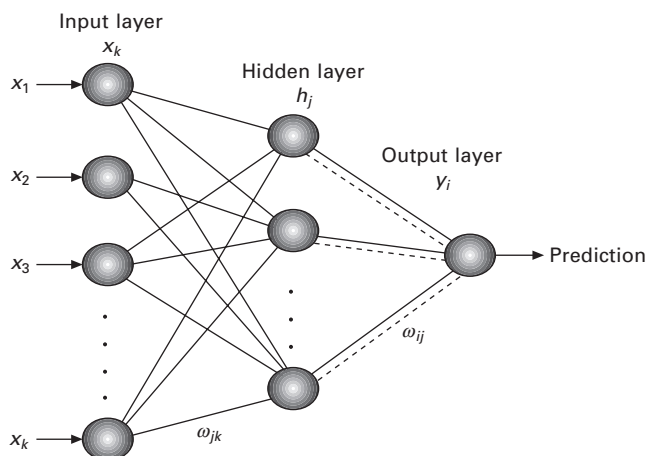
fabrics and by Chen *et al.* [53] for grading softness of 100% cotton and cotton/polyester blended fabrics.

8.11.2 Artificial neural networks

The term neural network is used to describe a number of different models intended to imitate some of the functions of the human brain, using certain of its basic structures. The development and use of neural networks are part of an area of multidisciplinary study that is commonly called neural computing, but is also known as connectionism, parallel distributed processing and computational neuroscience. ANN is a powerful data modeling tool that is able to capture and represent each kind of input–output relationship. A neural network is composed of simple elements called neurons or processing elements operating in parallel, which are inspired by biological neuron systems. As in nature, the network function is determined largely by weighted connections between the processing elements. The weights of the connections contain the knowledge of the network.

Applications of ANN

Image processing analysis and neural networks have been widely used for fabric defect detection. The basic principles underlying this technique along with numerous applications are detailed by Behera in *Textile Progress* [83]. Lin [54] used feed-forward back-propagation neural nets to find the relationships between the shrinkage of yarns and the cover factors of yarns and fabrics. A typical multilayer feed-forward network is shown in Fig. 8.14.



8.14 Multilayer feed-forward network.

Beltran *et al.* also studied the use of MLP-BP neural networks to model the multilinear relationships between fiber, yarn and fabric properties and their effect on the pilling propensity of pure wool knitted fabrics as reviewed by Guruprasad and Behera [55]. Behera and Muttagi [56] predicted the low-stress mechanical, dimensional, and tensile properties of woven suiting fabrics using a back-propagation network (BPN) and a radial basis function neural network (RBFN). Fiber, yarn, and fabric constructional parameters of wool and wool–polyester blended fabrics were given as input variables. Radial basis function neural networks were found to have better predictability and are faster to train and easier to design than back-propagation neural networks. A reverse engineering approach is also reported for prediction of constructional particulars from the fabric properties.

Hui *et al.* [57] predicted sensory fabric hand from fabric properties using a resilient back-propagation (RBP) neural network. Shyr *et al.* [58, 59] studied the use of neural networks for discriminating the generic hand of cotton, linen, wool, and silk woven fabrics. They established translational equations for the total hand value of fabrics using back-propagation nets. Wong *et al.* [60] investigated the predictability of clothing sensory comfort from psychological perceptions by using a feed-forward back-propagation network. The ANN-based prediction of fabric appearance index by Behera and Mishra [84, 85] can be used as an objective method of fabric engineering to achieve desired aesthetic performance. This work provides measurement of an integrated fabric appearance index (FAI) as given in equation 8.14 using image processing and the neural network computation method:

$$FAI = \sum_{i=1}^n A_i W_i \quad 8.14$$

where n is the total number of properties, A_i is the grade of the i th property obtained by digital image processing, and W_i is the weighting of the i th property. Properties such as drape, texture, wrinkle, and pilling are used to access the aesthetic appearance of an apparel fabric.

8.11.3 Genetic algorithms

A relatively new area of study in artificial intelligence is that of genetic algorithms (GAs). GAs are a powerful set of stochastic global search techniques that have been shown to produce very good results for a wide class of problems. GAs can find good solutions to nonlinear problems by simultaneously exploring multiple regions of the solution space and exponentially exploiting promising areas through mutation, crossover and selection operations [61]. GAs are programs that attempt to find optimal solutions to problems when one can specify the criteria that can be used to evaluate the optimal solution.

They are useful when a problem has multiple solutions, some of which are better than others. Unlike deterministic, linear and nonlinear optimization models, GAs test a variety of solutions and, through an evolving process, attempt to find the best solution through processes that parallel the metaphors of survival of the fittest, genetic crossover, mutation and natural selection. Evolutionary algorithms differ substantially from more traditional search and optimization methods. The most significant differences are:

- GAs work with a coding of the parameter set, not the parameters themselves.
- GAs search from a population of designs, not a single design.
- GAs use objective function information, not derivatives or other auxiliary knowledge.
- GAs use probabilistic transition from design to design; they do not use deterministic rules.
- Evolutionary algorithms can provide a number of potential solutions to a given problem. The final choice is left to the user.

In building a genetic algorithm, six fundamental issues that affect the performance of the GA must be addressed: chromosome representation, genetic operators, selection strategy, initialization of the population, termination criteria, and evaluation measures. The initial population is randomly generated, which is the most common method, while the GA was run for a specified number of generations as its termination criteria. For any GA, a chromosome representation is needed to describe each individual in the population of interest. The representation scheme determines how the problem is structured in the GA and also determines the genetic operators that are used. The operators are used to create new solutions based on existing solutions in the population. There are two basic types of operators: crossover (recombination) and mutation. Mutation operators tend to make small random changes in one parent to form one child in an attempt to explore all regions of the state space. Mutation serves the crucial role of preventing the system from being stuck in the local optimum. Crossover operators combine information from two parents to form two offspring such that the two children contain a 'likeness' (a set of building blocks) from each parent. The application of these two basic types of operators and their derivatives depends on the chromosome representation used.

The selection of individuals to produce successive generations plays an extremely important role in a genetic algorithm. A probabilistic selection is performed based upon the individual's fitness such that the better individuals have an increased chance of being selected. However, all of the individuals in the population have a chance of being selected to reproduce into the next generation. Evaluation functions of many forms can be used in a GA, subject to the minimal requirement that the function can map the population into a

totally ordered set. The evaluation function is independent of the GA (i.e. stochastic decision rules) [62].

The basic procedure of genetic algorithms can be explained as follows. Let $P(g)$ and $C(g)$ be parents and offspring, respectively in the existing generation g . Then

```

for
  g: = 0;
  initialize population  $P(g)$ ;
  evaluate  $P(g)$ ;
for
  recombine  $P(g)$  to generate  $C(g)$ ;
  evaluate  $C(g)$ ;
  select  $P(g + 1)$  from  $P(g)$  and  $C(g)$ ;
  g: = g + 1
end
end

```

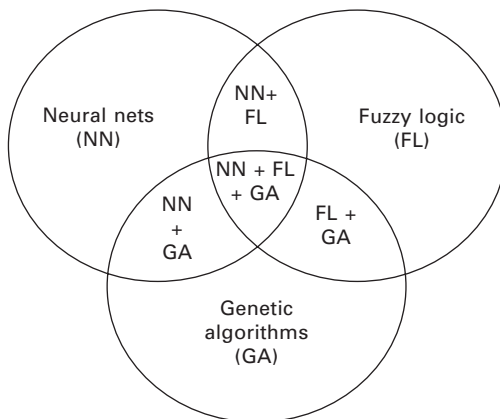
Applications of genetic algorithms

Genetic algorithms are being used to solve a wide variety of problems in textiles right from production of fibers to apparel design and manufacturing. Amin *et al.* [63] reported detection of the spinning fault source from spectrograms by using a genetic algorithm technique. Blaga and Draghici [64] reported the application of genetic algorithms in knitting technology. Lin [65] investigated the use of GA for searching weaving parameters for woven fabrics. A searching mechanism was developed to find the best combinations of warp and weft counts and yarn densities for fabric manufacturing, considering costs. This helps the designer to select appropriate combinations of these parameters to achieve the required weight of fabric at a pre-controlled cost. Grundler and Rolich [66] developed software based on an evolutionary algorithm for creating different weave patterns. Only the weave and yarn color were considered as attributes for fabric appearance, and different patterns can be created by various combinations of weave and color of warp and weft threads. Jasper *et al.* [62] investigated fabric defect detection using a genetic algorithm tuned wavelet filter. Patrick *et al.* [67] studied the application of GA on the roll planning of fabric spreading in apparel manufacturing. It was demonstrated that use of GAs to optimize roll planning will result in reduced wastage in cutting and hence can reduce the cost of apparel production. Keith *et al.* [68] investigated the problem of handling the assembly line balancing in the clothing industry. Inui [69] presented a computer-aided system using a genetic algorithm applied to apparel design. In this study, a computer technique that helps consumers to take part in apparel design was presented.

An interactive computer-aided system for designing was constructed on the basis of the GA search method.

8.11.4 Hybrid modeling

A trend that is growing in visibility relates to the use of fuzzy logic in combination with neurocomputing and genetic algorithms as shown in Fig. 8.15. The marriage of fuzzy logic with computational neural networks has a sound technical basis, because these two approaches generally attack the design of intelligent systems from quite different angles. Neural networks are essentially low-level, computational algorithms that offer good performance in dealing with large quantities of data often required in pattern recognition and control. Fuzzy methods often deal with issues such as reasoning on a higher (i.e., on a semantic or linguistic) level than do neural networks. Consequently, the two technologies often complement each other: neural networks supply the brute force necessary to accommodate and interpret large amounts of data, and fuzzy logic provides a structural framework that utilizes and exploits these low-level results. Neural networks (NNs) are known for their ability to perform complex, nonlinear mapping of input–output data. But it is difficult to decide which input data, network structure and learning parameters to utilize. The genetic algorithms can be applied as an optimization search to determine the optimal neural network structure design including input data combination optimization, network structure optimization, learning rate and momentum optimization. In this way, computational complexity and the time required to design the NN are reduced [70, 71].



8.15 Hybrid models using soft computing tools.

Applications of hybrid modeling

Hybrid modeling has been used in several cases of prediction of fiber, yarn and fabric properties. The prediction accuracy of the neuro-fuzzy system has been found to be superior to that of a conventional multiple regression model and comparable with an artificial neural network model. Wong *et al.* [72] predicted clothing sensory comfort from fabric physical properties by building eight different hybrid models combining statistics, fuzzy logic, and neural network methodologies. Results showed that a TS-TS-NN-FL model has the highest ability to predict overall comfort performance, followed by a TS-TS-NN-NN model (TS, NN and FL refer to statistical, neural network, and fuzzy logic, respectively). The data reduction and information summation ability of statistics, the self-learning ability of neural nets and the fuzzy reasoning ability of fuzzy logic were exploited to develop these hybrid models.

8.12 Authentication and testing of models

While building mathematical models, it is immanent that one has to use numbers derived from experimental or empirical data, or from analytical or computer-based calculations. Errors are thus produced due to data reading or data manipulation. Normally researchers use statistics to deal with error. Error is defined as the difference between a measured or calculated value and its true or exact value. Error is immanent but how much error is present depends on how skillfully the data are read or manipulated. Therefore, error analysis is an integral part of the modeling process. There are two types of error, systematic error and random error. Systematic error occurs when an observed or calculated value deviates from the true value in a consistent way. This error occurs in experiments when instruments are improperly calibrated. Random errors do not occur due to chance. They arise mainly in experimental work because unpredictable things happen due to ignorance or by accident. There is one absolute error which is defined as the difference between the true or experimental value and the measured value. The true value may be known or it may have an expected value based on a calculation or some other data source. For example, in the case of a neural network modeling of woven fabric engineering, the ability of the model to predict the fabric structure–property relationships can be judged from the percentage error in the prediction of fabric properties for given set of input fiber, yarn and fabric constructional parameters. In such cases, the network is trained on fabric constructional parameters such as weave float, thread density, thread resultant tex, yarn crimp, fabric mass, and fabric cover as inputs to the network, and fabric shrinkage, hygral expansion, extension, bending rigidity, formability, shear rigidity, thickness, breaking strength and elongation as network outputs.

Table 8.1 shows the percentage prediction error as the average of the test data set for each fabric property predicted by the neural network. The overall absolute prediction error is 13.02%:

$$\text{Error}\% = \left(\frac{P - E}{E} \right) \times 100$$

where *Error%* = absolute error %, *P* = value predicted by the network, and *E* = experimental value.

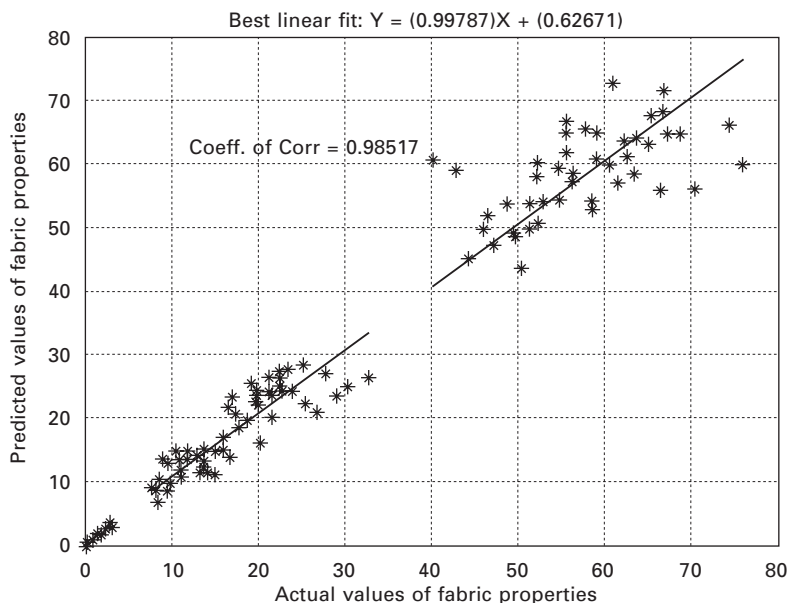
The ability of the network to model the fabric structure-property relationships can best be judged from the network's response to the influence of constructional parameters on fabric properties. This can be further authenticated by plotting the relationship between actual values and predicted values of fabric properties. Figure 8.16 shows the correlation between actual values and values predicted by the network and demonstrates a very good correlation between the actual and the predicted values ($r = 0.985$) in this example.

8.13 Reverse engineering

Reverse engineering is the process of discovering the technological principles of a device, object or system through analysis of its structure, function and operation. It often involves taking something apart and analyzing its workings in detail; it is used in maintenance or making a new device or program that does the same thing without copying anything from the original [4]. The purpose is to deduce design decisions from end products with little or no additional knowledge about the procedures involved in the original production. Reverse

Table 8.1 Prediction performance of the radial basis function neural network

Fabric properties	Absolute prediction error %
Warp extension %	12.3
Weft extension %	13.2
Warp bending rigidity, $\mu\text{N.m}$	14.8
Weft bending rigidity, $\mu\text{N.m}$	13.9
Warp formability, mm^2	14.9
Weft formability, mm^2	14.3
Shear rigidity, N/m	12.6
Warp-way breaking strength, N	10.3
Weft-way breaking strength, N	4.1
Warp-way breaking elongation %	16.2
Weft-way breaking elongation %	16.5
Average prediction error %	13.02



8.16 Actual values of fabric properties vs values predicted by neural network.

engineering is carried out under several circumstances like lost documentation (the documentation of a particular device has been lost or was never written and the person who built it is no longer available), product analysis (to examine how a product works, what components it consists of, to estimate costs, to identify potential), security auditing, removal of copy protection, circumvention of access restrictions, creation of unlicensed and unapproved duplicates and also for academic learning purposes. Reverse engineering is taking apart an object to see how it works in order to duplicate or enhance the object. Someone doing reverse engineering on software may use several tools to disassemble a program. The term forward engineering is sometimes used in contrast to reverse engineering in various literature.

8.14 Future trends in non-conventional methods of design engineering

8.14.1 Knowledge-based systems

The engineering design of woven textile structures is a complex task and makes extensive use of empirical knowledge accumulated over time. Only a few, highly experienced experts in the industry know rule-of-thumb principles and methods of complex structural synthesis under performance constraints. Therefore, if the knowledge and expertise of the experts in the field and from

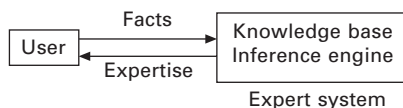
the literature is used to develop a scientific database, then computer software can be prepared with such acquired knowledge, which in turn will provide expert advice on the problem. Such a knowledge-based system is called an expert system. It is a system that has been engineered to simulate a human expert. Expert systems are well suited to database manipulations, symbolic reasoning and decision-making. They have conflict resolution principles so that mutually antagonistic requirements are satisfied to the greatest extent possible and with minimal compromise. Expert systems permit the use of different design knowledge representational modes such as heuristic, procedural and factual knowledge and the reasoning methods working with each of these representational modes.

The technology of artificial intelligence (AI) and expert systems (ESs) enables computers to be applied to less deterministic design tasks that require symbolic manipulation and reasoning rather than routine number processing. ESs can be used to diagnose, repair, monitor, analyze, interpret, consult, plan, design, instruct, explain, learn and conceptualize problems. ESs are powerful tools for solving problems like design, which is used for taking decisions. Designing is typically a decision-making process, so the application of knowledge engineering and ES is suitable for it. ESs are very suitable for database manipulation and decision making. The modularity of ESs enables them to accommodate changes or modifications easily by changing or adding merely the facts and rules in the knowledge [73–75].

In order to construct a successful ES, the problem domain must be well defined, and there must be at least one human expert acknowledged to perform well within the application area; however, additional knowledge relevant to the problem domain can be obtained from other sources. Experts must have special knowledge, judgment and experience and must be able to explain and justify their special knowledge and experience and the methods used to apply them to particular problems. Further, there must also be adequate programming tools, ideally a set of ES software building tools; specific high-level programming languages such as LISP and PROLOG are often considered to be languages of ES development.

8.14.2 Basic structure of an expert system

The basic structure of an expert system is shown in Fig. 8.17. The various components of an ES are listed below:



8.17 Basic structure of expert system.

- The knowledge base consists of the domain facts and heuristics associated with the problem area, which must be well bounded and narrow.
- The inference engine is the control structure or strategy for utilizing the knowledge base in the solution of the problem.
- The dynamic and global database is the working memory for keeping track of the problem status, the input data for the particular problem, and the relevant history of what has been done.
- A user-friendly interface facilitates interaction of the system with the user and provides a human window to its operations, preferably a natural language framework; additionally, an explanation module should be included to allow the user to make queries and to explain the reasoning process underlying the system's answers.
- The knowledge acquisition module facilitates the transfer and transformation of problem solving expertise from the knowledge source to the knowledge base. Since knowledge is central to intelligence, the performance of ES is primarily a function of the size and quality of the knowledge base it possesses. The facts constitute a body of information that is widely shared, publicly available, and generally agreed upon by experts in the field. The heuristics are mostly private, little discussed rules of good judgment or guessing that characterize expert-level decision making in the field. The knowledge must be represented or organized into a suitable form so that the inference engine can readily access it. In order to create a knowledge base for a given problem, the expert's knowledge must be formulated according to the knowledge representation scheme employed by the ES shell. The latter, with a debugging facility, represents the knowledge acquisition module. The difference between ES and conventional computer programming can be understood from the following representation:

Data + Algorithm $\rightarrow$ Program

Knowledge + Inference $\rightarrow$ ES

8.15 Conclusion

With globalization, there is increased need to reduce product lead times. Activities must be performed in parallel (integrated product development), to ensure that sufficient attention is paid to market needs and manufacturing technologies during the design process for successful product development. Designing of textile products is still based on traditional techniques, experience and intuition. This leads to (a) a limited number of experts and their expertise; (b) difficulty in finding a systematic approach for an optimum solution; and (c) increased time and cost. Compared to modeling from first principles and other techniques, computation methods can be a powerful tool

to model the nonlinearities and complexities involved in predictions of fabric properties. A system has to be developed to provide scientific databases, overall structure–function relationships, optimization procedures, suitable computer algorithms and standardization of these algorithms. The various successful applications of soft computing indicate that its impact will be felt increasingly in coming years. The employment of soft computing techniques leads to systems which have a high MIQ (machine intelligence quotient).

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Soft computing applications in knitting technology

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Abstract: This chapter deals with the research work done so far on the applications of soft computing techniques in knitted fabric engineering. At the beginning of the chapter, some basic information about the knitting process as a complex system based on interactions between yarn properties, knitted fabric attributes and process parameters is given. Soft computing techniques, such as artificial neural network, fuzzy logic and genetic algorithm, have been used for knitted fabrics modelling, manufacturing, quality control and marketing. Soft computing applications for knitted fabric defect identification in static and dynamic conditions, fabric classification, fabric engineering, knitting machine control and optimization are discussed. Some applications of soft computing methods in the prediction of fabric characteristics (hand, thermal conductivity, bursting strength, pilling, spirality) are also provided. The potential future research trends are included in the concluding section.

Key words: knitting process parameters, knitted fabric properties, artificial intelligence, neural networks, fuzzy logic, genetic algorithms, prediction, classification, optimization.

9.1 Introduction

Knitting is a fabric forming process by intermeshing of loops of yarn. Various structures can be produced by modifying the sequence of loop formation. Basically, two types of knitting techniques are popularly used, namely weft and warp knitting. In weft knitting, loops are formed by needles knitting the yarn across the width of the fabric. The needles knit in sequence for each yarn. In warp knitting, loops are formed by needles knitting a series of warp threads fed parallel to the direction of fabric formation. All needles knit simultaneously for all yarns.

Weft knitted fabrics can be produced on different types of knitting machines. The machines used for the manufacturing of knitwear can be divided into machines with individually driven needles and needle bar machines. Circular or flat bar machines, having a latch or compound needle, can produce both fabrics and whole knitted garments on the so-called 'whole garment technology' (Shima Seiki Ltd, Japan) and 'knit and wear technology' (Stoll GmbH, Germany). Straight bar or circular machines using a bearded needle

can produce fully fashioned knitwear products. By using various yarns with different properties or made of different materials, one may produce 3-D fabrics with different properties at each layer or each side (Potluri and Needham, 2005).

Warp knitted fabrics can be produced on different types of knitting machine. Raschel machines using a latch or compound needle are specialized for laces, nets, curtains and other industrial products like pile upholstery, furnishing and packing fabrics. Tricot machines using a bearded or compound needle produce mostly underwear and sports fabrics.

In both weft and warp knitting, a great variety of fabrics can be made by laying in additional yarns, which are trapped by the knit structure but not incorporated in the loops. Various forms of knitted fabrics can be produced on these machines, from rectangular flat panels to fully fashioned pieces and 3-D shaped forms. Spacer yarns can be inserted between the front and the back fabric, thus creating a complex three-layer structure.

Knitted fabrics are used worldwide in a range of apparel, domestic and industrial uses, apparel uses being most frequent among these. Some properties of weft knitted fabrics which make them suitable mostly for the apparel and domestic area are (Shaikh, 2004):

- Moulding properties
- Wrinkle resistance characteristics
- Excellent stretch and shape
- Recovery abilities
- Comfort properties.

During the last few years, as well as maintaining a permanent modest role in the apparel industry, warp knitting has been used increasingly for technical applications. The main characteristics of warp knit fabrics can be summarized as follows (Kovar, 2002):

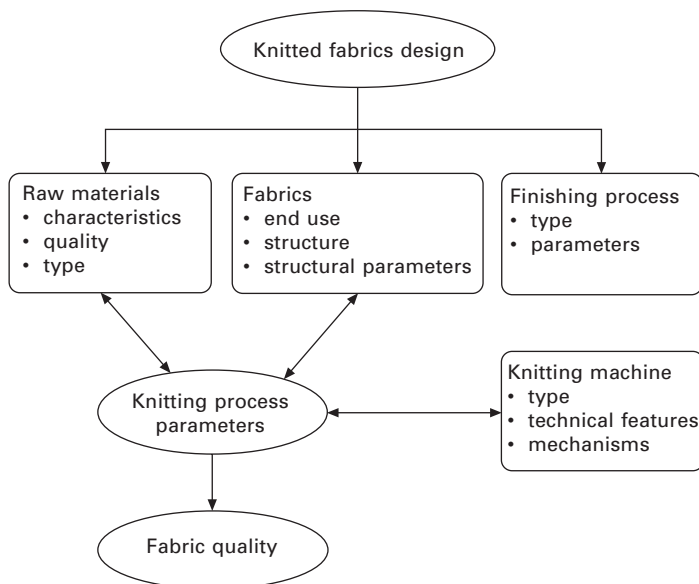
- Good dimensional stability
- Good strength
- Extremely versatile in pattern effects with yarn
- Variable thickness
- Controlled elasticity
- Good comfort properties, especially air and water permeability.

Since knit fabrics are produced on different machines with various knit stitches and conditions to create different patterns and fabric types, it is expected that they will have different qualities. Knitwear quality is determined by the physical and mechanical properties of yarns and the stress developed in the yarns during the knitting action. The level of yarn stress during knitting depends on the knitting process parameters. The quality and serviceability of knitted fabrics depend on the type of knitting used, the fibre, the fineness and

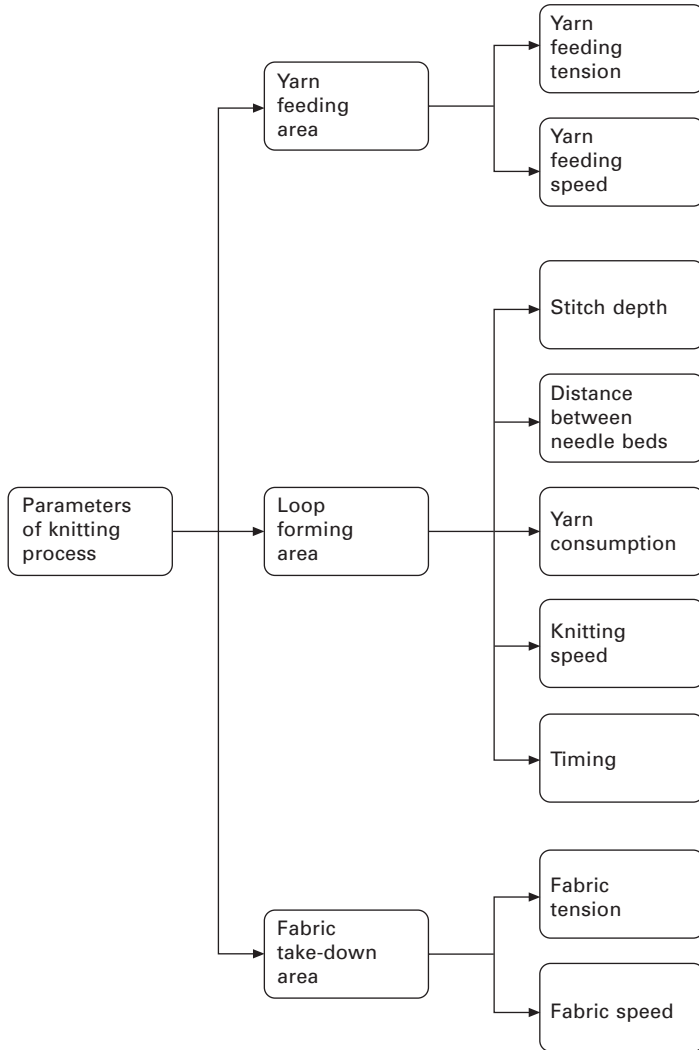
evenness of the yarn, the tightness of the fabric and the dimensional stability of the finished fabric (Shaikh, 2004). Consequently, in the design stage of knitted fabrics the following three factors must be in perfect correlation: raw materials, fabric characteristics and finishing process (Fig. 9.1).

A key action of the fabric quality assurance is the good adjustment of the knitting parameters according to the raw material and fabric features, while constantly monitoring the knitting process. Considering the main knitting machine components, this can be divided into three areas of the technological parameters adjustment and control (Budulan, 1999; Macovei, 1999) as shown in Fig. 9.2.

1. Feeding area. It is important that two parameters are monitored so that they induce a low and constant tension of the yarn, a reduced number of machine stops, a high uniformity level and good dimensional stability of the fabric. The two parameters are:
 - Yarn feeding tension (cN), which is the axial force in the yarn during its feeding to the needle
 - Yarn feeding speed (m/min), which is defined as the yarn length fed to the needles per unit time.
2. Loop forming area. This is the most important area of the knitting process, with a decisive influence on the fabric quality and appearance. Here one can define the following parameters:
 - Stitch depth (mm), which refers to the distance between the needle



9.1 Knitting process design.



9.2 Parameters of knitting process.

head and the edge of the trick-plate or sinkers, during their descent for loop formation

- The distance between needle beds (mm), which is measured in the case of a knitting machine with two needle beds, can have a constant value (flat weft knitting machines) or an adjustable one (circular weft knitting machines and flat warp knitting machines)
- Yarn consumption or yarn run-in (mm), defined as the amount of yarn used for all knit loops in one course of the knitted fabric

- Timing – the relative movement between two sets of needles, or needles and sinkers (Smith, 2004).
3. Fabric take-down area. This influences the elasticity of the knitted fabric, the dimensional stability, and the behaviour of the fabric during the finishing and make-up processes. In this area, the adjustment and control actions should be performed according to the following two parameters:
- Fabric take-down tension (cN/wale) which is the force existing in each wale during the take-down action
 - Fabric take-down speed (m/min), defined as the length of the tight fabric drawn by the loop-forming mechanism per unit time.

9.2 Scope of soft computing applications in knitting

It is evident from the above discussion that great consideration should be given to knitting technology as a complex process, which involves fibres and yarns, knitted fabrics parameters, knitting process monitoring, and the interactions between these features.

Soft computing is different from traditional or hard computing in its tolerance for imprecision, uncertainty and partial truth. Hard computing techniques are predominantly based on mathematical approaches and therefore require a high degree of precision and accuracy. On the other hand, soft computing techniques mimic the functioning of biological systems and present efficient solutions for even difficult inverse problems. Artificial neural networks (ANNs), fuzzy logic (FL) and genetic algorithms (GAs) are the major components of soft computing and have different application domains in various engineering fields, including textiles. These tools were employed to help reach the main goal of clothing manufacturers, i.e. engineered fabrics and fault-free clothing. These goals can be achieved by tackling issues like the modelling of the complex mechanical behaviour of textile fabrics, objective evaluation of the drape, handle and comfort properties of fabrics as clothing material, and online classification of fabric defects (Majumdar *et al.*, 2009).

Generally, in knitting technology, these techniques have been applied in order to foresee the global quality of the knitted fabric by close observation of the fibre, yarn, knitting process parameters and knitted fabric properties.

ANN is a prediction and classification system inspired and designed according to the behaviour of biological neural networks. The powerful modelling and prediction capability of ANN has been successfully applied for predicting knitted fabric properties, garment comfort evaluation, and detection and classification of defects in knitted fabrics.

FL systems operate with rule based systems that use flexible definitions

of fuzzy sets, being particularly useful for control systems. FL systems have been applied to identify fabric defects such as neps, slubs and composite defects.

GA is an unorthodox search method based on natural selection, which aims to solve complicated optimization problems. GA repeatedly modifies several individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population ('parents') and uses them to produce 'children' for the next generation, that will struggle to survive (Chipperfield and Fleming, 2003). Over successive generations, the population 'evolves' towards an optimal solution. GA can be applied to solve a variety of optimization problems where the objective function is discontinuous, non-differentiable, stochastic or highly nonlinear.

9.3 Applications in knitted fabrics

9.3.1 Fabric inspection and fault classification

Textile quality control is a key factor for increasing the competitiveness of companies. Textile manufacturers have to monitor the quality of their products in order to maintain the high-quality standards established for the garment industry. Fabric defect is one of the biggest problems that the textile industry has to deal with. Most defects arising in the production of textile products are still detected by the human inspection method (Abou-Taleb and Sallam, 2006; Shady, 2006; El-Kateb *et al.*, 2006), which has obvious limitations concerning identification rate and effectiveness. The attractive alternative to the conventional human inspection method is image-based inspection which includes image capturing, image processing and soft computing applications for fault diagnosis.

Various kinds of defects can arise in knitted fabrics. This may be due to poor yarn quality, yarn count, fabric structure, knitting machine parameters and finishing processes (Semnani and Sheikhzadeh, 2007). Still, there are some defined categories of defects in knitted fabrics, mainly linked to yarn quality, fabric structures, finishing processes and knitting elements, as seen in Table 9.1 (El-Kateb *et al.* 2006; Smith, 2004).

Circular knitting technology is considered to be one of the easiest and fastest ways of producing garments, socks and gloves. Fabric defects or faults are responsible for nearly 85% of the defects found by the knitted garment industry. An automated defect detection and identification system enhances the product quality and improves productivity both to meet customer demands and to reduce the costs associated with off-quality (Abou-Taleb and Sallam, 2008).

Saedi Ghazi *et al.* (2005) suggested an approach for the online detection of knitted fabric defects using the Gabor transform. They built up an image acquisition system for a single-jersey mini-jacquard knitting machine,

Table 9.1 Main knitted fabric defects

Knitted fabric defect	Appearance	Technical reasons
Horizontal stripes	Horizontal bands following courses, appear as unevenness in the courses	• Yarn fed variations (counts, tension, faults, oiling) • Malfunctioning of the feeders • Different stitch settings • Yarn fragments in the cam systems • Faulty cam settings • Faulty take-down system • Machine vibration
Vertical stripes	Longitudinal gaps, following the wales up the length of the fabric	• Broken/wrong needles or parts of the needles • Worn or dirty tricks • Oil lines • Improper setting of yarn guides • Improper settings of take-down
Holes	Breakdown in the fabric where one or more adjacent loops are severed	• Yarn quality (breakage, strength, elongation) • Too high yarn tension • Improper yarn size for gauge • Knots • Feeder problems (wrong setting, tight, rough places) • Fabric pulling down too strongly
Dropped stitches	Appear within one course, in which the yarn has not been transformed into a stitch	• Yarn feeder problems (improper setting, obstructed) • Too low yarn tension • Bad needle (bent latch, hook) • Wrong setting of take-down tension
Stitch runs	Random or continuous	• Yarn tension too high • Yarn snagging or snarling • Too high machine starting speed • Incorrect feeding of the yarn • Defective needle, sinker • Improper take-down tension
Thick places	Thick place having a diameter higher than the normal yarn	• Irregular yarn • Improper machine cleaning

Source: El-Kateb *et al.* (2006), Smith (2004).

producing plain knitted fabrics from viscose/polyester yarn. The machine was run at different speeds, and different fabric faults such as vertical stripe, vertical soil stripe, horizontal stripe, holes, nep or slub were created. To classify faults, a three-layer perceptron neural network with a feed-forward, back-propagation algorithm was applied. Thereafter, the whole process of image capturing, defect detection and classification was performed online. The results of the developed system were compared with those from visual

categorization and the success rate of the machine vision system was calculated. The overall success rate of the proposed approach was discovered to be 96.57% with a location accuracy of 2 mm and a false alarm rate of 1.4%.

Shady *et al.* (2006) developed a method for knitted fabric defect detection and classification using image analysis and neural network. A group of single jersey samples were produced on a circular, 12-inch diameter knitting machine, from 100% cotton open-end yarn, with a count of 24/1 Ne. Fabric defects were artificially introduced to the fabric, in order to create broken needle, fly, hole, barré, thick and thin yarn defects. The image acquisition system consisted of a CCD camera as the input device, a lighting service and a PC as the image analysis device. The system allowed quick and precise data acquisition and easy statistical result analysis. For image processing, the IMAQ software was chosen, since it was considered appropriate for the flexible nature of the knit structures analysis. Thirty different colour images were captured of each defect and 25 images were taken of the fabrics free of defects, as control samples.

The feature extraction stage seeks to identify characteristics which are used to describe the object, prior to the task of classification. Two approaches were used to extract image features, the statistical procedure and the Fourier transform. In the statistical approach all images were converted to black-and-white images and were represented by a matrix of binary values, 0 or 1. The column and row vectors contain the added values in rows and columns. The standard deviation, range, maximum-median and mean values were calculated for each column and row vector. The Fourier transform was applied as the image processing tool, in order to generate the image in the Fourier or frequency domain. The range of different defect images in the frequency domain was marked and shows spatial frequency changes with spatial periodicity of fabric defects. Two neural networks were trained and tested for each features extraction approach. The first was made of seven neurons in the first layer corresponding to the seven features of the statistical approach, and seven neurons in the output layer representing the six different defects and the free defect sample. The overall success rate of the classification of the features extracted using the statistical method ranged from 60% (barré defect) to 100% (broken needle, hole, thick and thin yarn).

Six neurons were used in the input layer of the second neural network, which is the equivalent of the feature number and seven neurons in the output layer, for the six different defects and the defect-free sample. The success rate list for the classification using Fourier transform indicates the 100% success of the neural network in detecting all the defect-free samples in both the training and testing phases and in classifying all four defects (broken needle, fly, hole, and thin yarn). The lowest success rate of 63.3% was obtained for the barré defect, which was mistaken for a thick yarn defect.

The opinion of knitting industry experts was taken into account in order to identify the defects in some fabric images. The major problem consisted of the samples containing the barré defect, where the success rate was 60%. On average, the automatic defect identification and classification were more successful than the experts' opinion in identifying the various types of defects.

9.3.2 Fabric property prediction

The modelling and prediction of knitted fabric properties are very complex tasks as they involve interaction between yarn properties, knitting machine variables and knitted structures. Traditional mathematical and statistical modelling techniques have inherent limitations, which could be overcome by means of soft computing applications. Researchers have successfully used artificial neural network and fuzzy systems for the prediction of handle and comfort properties, bursting strength, pilling propensity and spirality of knitted fabrics, which will be discussed in the subsequent sections.

Prediction of knitted fabric hand and comfort

Fabric hand has been considered as one of the most important properties of textiles intended for garment use. However, the modelling of fabric hand is a highly intricate task since fibre properties, yarn properties, fabric constructional properties and the finishing process play a decisive role in determining the fabric hand.

Park *et al.* (2001) used the ANN model for predicting the hand values of warp (two bar, three bar and four bar) and weft (single and double) knitted fabrics using the mechanical properties measured by the Kawabata Evaluation System (KES-FB) as the inputs. The mechanical properties and total hand value of 47 knitted fabrics were evaluated using KES-FB. The handle value of the fabrics was also subjectively evaluated by a panel of 30 Korean evaluators, who gave ratings ranging from 0 to 5 based on their perception of usefulness of the fabrics in fall or winter outerwear.

The number of input neurons or nodes in the ANN model was seven, which is equal to the number of input parameters, which are compression recovery, tensile recovery, maximum elongation, shear hysteresis, bending rigidity, surface roughness and weight. There was only one output neuron for predicting the handle value. The number of hidden layers was optimized by the trial and error method. Growth of the hidden layer number beyond three did not reduce the prediction error but the time of training became longer than for the two-hidden-layer construction. However, one hidden layer was not able to yield the desired prediction accuracy level, although the training time was shorter. The authors found that the ANN structure of

7-6-4-1 gave the best results. The predicted fabric hand values, for the nine test samples, obtained from the trained ANN were in close agreement with the subjective assessment given by the evaluators. In contrast, the total hand value given by the KES-FB system was far removed from the subjective assessment given by the evaluators. The authors suggested that the fabric hand perception changes from country to country. As the total hand value given by the KES-FB represents the perception of the Japanese, it is expected that it will differ from the evaluation made by the Korean experts. Therefore, the ANN model could be successfully used for the prediction of the total hand value of the fabric, keeping in mind the climatic conditions and the perception of the people of a particular country.

Hwang *et al.* (1998) reported the use of a fuzzy-logic-based system for the hand evaluation of warp and double weft knitted fabrics, respectively. Mathematically, the process of fuzzy transformation can be represented as follows:

$$A \cdot R = B \quad 9.1$$

where A is a weight vector of various fabric properties, expressed as follows:

$$A = [a_1, a_2, \dots, a_n], \quad a_i \geq 0 \text{ and } \sum_{i=1}^n a_i = 1 \quad 9.2$$

R is a fuzzy transformation matrix expressed as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1m} \\ r_{21} & r_{22} & \dots & r_{2m} \\ \dots & \dots & \dots & \dots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{bmatrix} \quad 9.3$$

where r_{ij} is the membership value of the j th fabric in the i th criterion, and B is the comprehensive grading vector expressed as follows:

$$B = [b_1, b_2, \dots, b_m], \quad b_j = \sum_{i=1}^n a_i r_{ij} \text{ for } j = 1, 2, \dots, m \quad 9.4$$

The authors used seven physical and mechanical properties, namely weight, compression resilience, tensile elongation, tensile resilience, shear hysteresis, bending rigidity and surface roughness measured by the KES for the fuzzy modelling of fabric hand. As can be seen below, the decreasing half-Cauchy function was used as a membership function for fabric weight and surface roughness:

$$\begin{aligned}
 \mu_w(x) &= 1 & 0 \leq x \leq A \\
 \mu_w(x) &= 0.5 - 0.5 \sin\left(\frac{\pi}{B-A}\right)\left(x - \frac{A+B}{2}\right) & A < x < B \\
 \mu_w(x) &= 0 & B \leq x
 \end{aligned} \tag{9.5}$$

where $\mu_w(x)$ is the membership value of fabric weight, and A and B are the minimum and maximum weight values.

The membership functions for tensile resilience and bending rigidity are increasing linear types whereas the compression resilience and shear hysteresis are decreasing linear types. The weights or the relative importance of fabric properties, with respect to fabric hand, were 0.16, 0.17, 0.22, 0.15, 0.16 and 0.14 for weight, compression resilience, tensile elongation-resilience, shear hysteresis, bending rigidity and surface roughness, respectively. These weights were calculated based on the rating given by the 30 experts. The nine fabric samples were tested using KES-FB and their measured properties were converted to membership values using the specified membership functions. The final hand value of the fabrics was calculated using the fuzzy transformation matrix. A similar approach was also used by Hwang *et al.* (1998) who reported that the total hand value of fabrics given by the fuzzy system differs from that obtained using KES-FB. The subsequent wear trial revealed that the total hand value yielded by the fuzzy system, rather than that given by the KES-FB, was more consistent with the rating given by the wearer.

Park *et al.* (2000) also reported the use of hybrid fuzzy ANN for the hand evaluation of warp and weft knitted fabrics.

One major aim of the comfort-oriented research is to find the optimal heat exchange between wearers and the clothing system. This property is related to the thermal conductivity of the fabric.

Fayala *et al.* (2008) used an ANN approach to predict the thermal conductivity of the knitted structure as a function of porosity, air permeability, yarn conductivity, and weight per unit area. The 81 knitwear fabrics considered for this research were produced from different raw materials: cotton, cotton/polyester, wool/acrylic and wool/polyamide. Yarn counts ranged from 18 to 306 tex, and the yarns were manufactured on knitting machines with E5, E7, E12, E20 and E24 gauge. The input parameter values were determined in the laboratory, according to the standards. The output parameter, i.e. the thermal conductivity of the samples, was measured by using an experimental device.

The developed model is based on four input parameters (yarn conductivity, weight per unit area, porosity, and air permeability) and one output parameter (fabric thermal conductivity). Input and output variables were normalized to have values between -1 and $+1$. A sigmoid transfer function was used in the hidden layer and a linear function for the output neuron. Training of the

ANN was based on the Levenberg–Marquardt algorithm, and after the trial the number of hidden neurons was fixed at five. Once trained, the neural network calculates the output values from the given input values and therefore acts as a prediction model. The correlation coefficient between the experimental and neural network-predicted values of thermal conductivity was 0.913 which is considered to be satisfactory. The authors recommend the system for industrial purposes as well, in order to improve the fabric property.

Prediction of knitted fabric bursting strength

The bursting strength is one of the most important mechanical properties of knitted fabrics and is difficult to predict before performing bursting strength tests. Ertugrul and Ucar (2000) considered fabric weight, yarn breaking strength and yarn breaking elongation as the major parameters that affect the bursting strength of plain knitted fabrics. Moreover, these three parameters could be available from the manufacturer before knitting operations. Therefore, they were employed as inputs to train the multi-layer feed-forward neural networks using the Levenberg–Marquardt back-propagation learning algorithm to predict the fabric bursting strength.

The research is based on the 62 data sets of cotton fabrics which were used for training and testing the ANN. After some trial runs, the best neural network configuration was optimized through two hidden layers with 12 and eight neurons, respectively, with tan-sigmoid activation functions. After rescaling the outputs to their original values, training errors for three different convergence cases were calculated and found to be low. The ANN converged to an error goal of 0.001 in 71, 57 and 43 epochs. A second application of this research was the design of an adaptive network-based fuzzy interference system (ANFIS), as a prediction tool for the bursting strength of plain knitted fabrics, based on the same three parameters as inputs. A system based on three inputs, one output and two membership functions was employed for each input. The number of membership functions for each input is especially important since it determines the number of rules to be trained. The results confirmed two membership functions for each input, which generate eight rules that give a better generalization capability. The linguistic rules developed by the ANFIS system explained the role of input variables and their interaction on the output variable. The entire research proved the applicability of both intelligent techniques in predicting the bursting strength of cotton plain knit fabrics, using known yarn properties.

Prediction of knitted fabric pilling

Fabric pilling is one of the biggest quality problems for the clothing industry, particularly for wool knitted fabrics. With the development of

ANN, the opportunity to predict the pilling propensity with high accuracy has become a reality. Beltran *et al.* (2005) designed an ANN to predict the pilling performance of knitted wool fabrics using fibre, yarn and fabric properties as inputs and corresponding pilling intensities as output. Two different wool knitted structures namely 1/1 rib and single jersey, each of them with two variations in the cover factor, manufactured with 8, 10, 12, 14 and 18 machine gauge were used in this research. Parameters such as fibre properties (diameter, CV_D , diameter $>30\text{ }\mu\text{m}$ and curvature), top properties (Hauteur, CV_H , short fibre $<30\text{ mm}$, bundle strength and strain), and yarn specifications (count, hairiness, thin and thick places, twist factor, folding twist ratio) along with fabric cover factor were used as inputs. These data served as quantitative inputs to the neural network model and were bounded within the range of 1 and 0, in order to eliminate any possible influence of measuring units of these parameters.

Moreover, input parameters like fabric shrink proofing treatment and fold twist were included in the model and encoded as 0 or 1, depending on the input class membership. The network consisted of a single hidden-layer perceptron trained with the back-propagation algorithm and the number of neurons in the hidden layer was established at nine. Simulation learning and cross-validation error curves were obtained by executing 150 epochs over the training set. It was found that the learning error decreases to a minimum mean squared error (MSE) value of 0.008 after 150 epochs, and the cross-validation error reaches a minimum MSE value of 0.007 after 70 epochs, beyond which the cross-validation error rises. The ANN predicted results were compared with the ratings made by the four observers and demonstrated the ability of the model for predictions based on the current inputs provided.

The sensitivity of the ANN model was assessed through the variation of normalized input values. Five inputs (cover factor, fibre diameter, curvature, hairiness and twist factor) were varied one at a time while other inputs were kept constant. It has been proved that increasing the value of cover factor, fibre diameter, curvature and twist and reducing yarn hairiness results in one grade improvement in pilling performance. By changing the values of various input parameters, the network output values were altered according to the expected trends known from previous observations on pilling.

Prediction of knitted fabric spirality

Knitted fabric spirality is a complex phenomenon that affects the aesthetics and quality of the final product. It is influenced by such factors as fibre fineness, yarn fineness, yarn twist level, fabric tightness, and the relaxation technique. Murrells *et al.* (2009) reported the use of an ANN model to predict the degree of spirality of fully relaxed single jersey fabrics made from 100% cotton ring spun yarns (conventional, low torque and plied). Eight

parameters, namely yarn linear density, yarn type, twist liveliness, fabric tightness factor, piece dyeing, number of feeders, rotational direction and gauge of the knitting machine, were considered in this work as influencing parameters. Rotational direction and piece dyeing were represented by binary coding (1 or 0) in the input vector. The 66 experimental samples were divided into three groups. The training, validation and testing set consisted of 60%, 20% and 20% of the experimental data, respectively. Two different ANN models were developed using three and eight input parameters and 14 and six nodes in the hidden layers, respectively. For the purpose of comparison, a linear regression model, as shown below, was also developed for predicting the angle of spirality:

$$\text{Spirality} = 56.58 + 0.172T - 4.14TF - 0.44C \quad 9.6$$

where T , TF and C indicate the twist liveliness (turns/25 cm), tightness factor and yarn linear density (tex), respectively.

The correlation coefficient between the experimental and the actual values of the spirality angle obtained from different methods is shown in Table 9.2. The neural network with all eight input parameters shows the best prediction for the spirality angle, as evidenced by the higher values of the correlation coefficient (0.967 and 0.976) and by the lower values of the mean absolute error. The ANN model with only three input parameters shows not only the lowest value of the correlation coefficient (0.915) but also the maximum mean absolute error of prediction in the test set data. This shows that the ANN structure with three inputs and 14 hidden nodes was not able to achieve the desired generalization.

For the determination of the relative importance of input parameters, the authors also conducted an input saliency test by eliminating one designated input from the optimized ANN model at a time. The training of the ANN was done again. The percentage increase in the MSE value in the testing set with respect to that of the optimized ANN model was considered as the indicator of importance of the eliminated input. A higher percentage change in the MSE signifies higher importance or saliency of the eliminated input and vice versa. The yarn twist liveliness was found to be the most dominant parameter influencing the knitted fabric spirality, followed by yarn linear density, tightness factor and number of feeders. Relatively good agreement

Table 9.2 Correlation coefficient of knitted fabric spirality prediction

Prediction method	Training data	Testing data
Linear regression	0.959	0.970
ANN (3 inputs)	0.963	0.915
ANN (8 inputs)	0.967	0.976

between the predicted and the actual measured values of fabric spirality was achieved.

9.4 Applications in knitting machines

9.4.1 Knitting machine parameter prediction

The properties of knitted fabrics are determined by several factors such as the nature of the raw material, the type of knitted structure, the parameters of the knitted structure, the parameters of the knitting machine, and the parameters of the finishing operations. The main concern of producers in providing high quality knitted fabrics is to choose the optimum combinations of all these parameters.

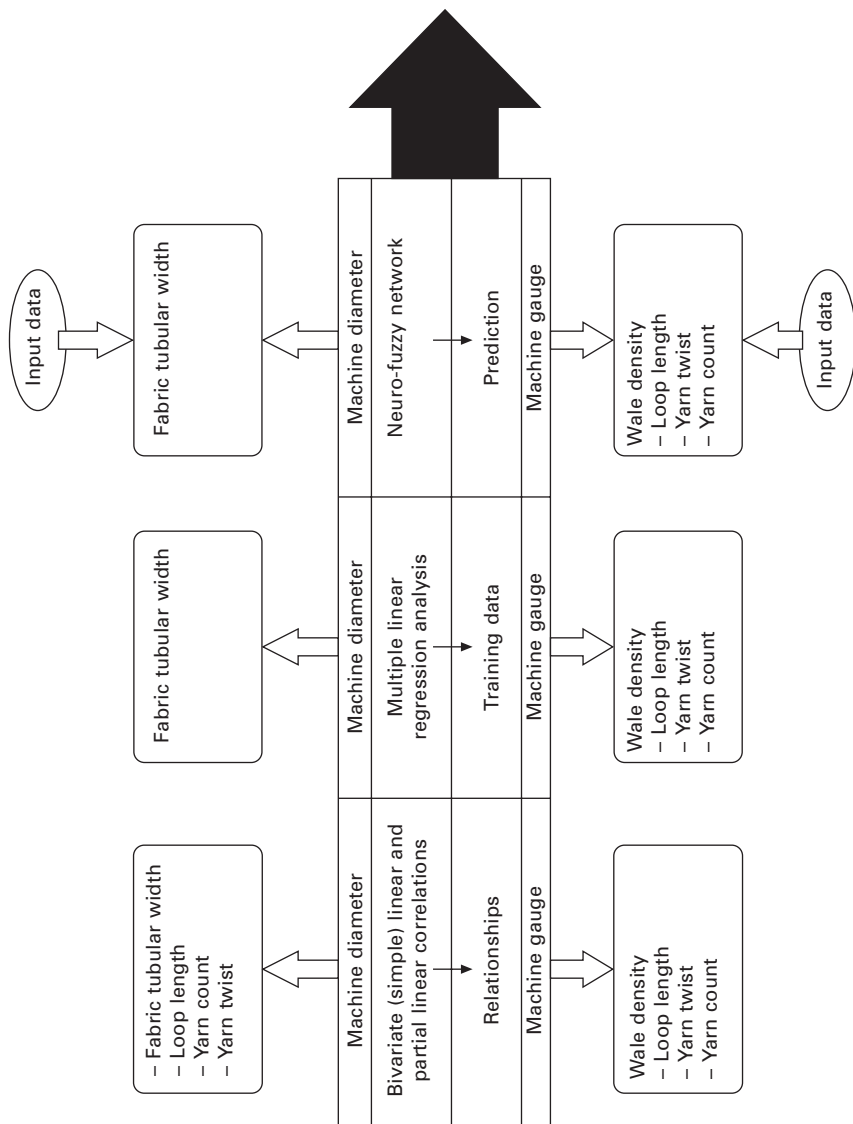
When producing fabrics on circular knitting machines, one problem that needs to be solved is the choice of the right machine gauge and diameter in connection with the desired product. This is usually done through the worker's experience. It is a known phenomenon that the width of the fabric reduces when it is removed from the machine due to the removal of stress. Therefore, it is not possible to predict the machine gauge and diameter using loop dimensions and fabric width (Ucar and Ertugrul, 2002). There are relations between machine diameter and fabric tubular width and between machine gauge and fabric wale density. A highly accurate prediction of the machine gauge and diameter requires the inclusion of other fabric and yarn parameters that affect fabric width and number of wales per unit length. Ucar and Ertugrul included the loop length, yarn count and yarn twist in their study concerning this subject. According to the research scheme presented in Fig. 9.3, bivariate correlation analysis was used to establish the strong relationships between machine diameter and fabric tubular width (significant at 1% level). Similarly, the relationship between machine gauge and wale density, loop length, yarn twist and yarn count was proved (significant at 1% level). Based on the bivariate correlation analysis results, by means of a multiple linear regression analysis and equations 9.7–9.9, one can predict the machine diameter and machine gauge.

$$MD = 17.47 + 0.644FTW \quad r = 0.901 \quad 9.7$$

$$MG = 5.950 - 6.662LL - 0.0000766YT + 0.111YC + 0.237WD \quad r = 0.820 \quad 9.8$$

$$MG = 2.599 + 0.111YC + 0.336WD \quad r = 0.810 \quad 9.9$$

where MD = machine diameter (cm), MG = machine gauge (needle/cm), FTW = fabric tubular width (cm), LL = loop length (cm), YT = yarn twist (turn/m), YC = yarn count (Ne), WD = wale density (wale/cm), and r = correlation coefficient.



9.3 Research scheme of knitting machine parameter prediction.

All the correlation coefficients are very high and the F value is greater than F – critical value (single-tailed test at 5% level) so there is a strong relationship between the dependent and independent variables. Based on the regression analysis results, two different ANFISs (adaptive network based fuzzy interference systems) were developed to predict the machine diameter and machine gauge. ANFIS is capable of learning the training data and the resulting errors are smaller than those from equations 9.7 and 9.9 obtained using a multiple linear regression. This study enables the prediction of machine parameters whenever data of plain knitted fabrics are available, without any knowledge of the machine on which they were produced. Both multiple linear regression and neuro-fuzzy systems can be effectively used for this purpose.

9.4.2 Knitting machine control

A high degree of accuracy in textile inspection can be achieved by using the newly developed computer vision systems. These systems are designed to act either as offline systems which identify and classify defects after the fabric production or as online systems which detect fabric defects during production itself. The latter system extends the possibility of exerting control measures in the knitting operations.

One of the most serious faults in knitted fabrics is the irregularity of stitches which leads to poor quality of the product. Adjusting and controlling the loop length during knitting, using computer vision systems, can improve the uniformity of the fabric surface. Semnani and Sheikhzadeh (2007) developed an image analysis based method suitable for every type of knitted fabric and presented a fuzzy control system to adjust a suitable loop length for better regularity of stitches.

The experiment has been performed on large-diameter circular knitting machines. Four samples of various yarn types were prepared: PES/cotton ring spun yarn of 15 and 30 Ne blended in 70/30, PES/cotton ring spun yarn of 15 and 30 Ne blended in 30/70, and PES/cotton rotor spun yarn of 15 and 30 Ne blended in 30/70. From each sample three types of fabric were knitted, i.e. plain, cross-miss and plain pique fabrics containing knit, knit/miss and knit/tuck, respectively. Sixteen categories of various yarn samples were analysed by an image analysis technique and were assigned to fuzzy classes according to the stitch deformation index (D). The deformation index D is defined through the equation for n knitting tools (cam systems):

$$D(t) = \frac{|p(t)|}{\alpha} \times 100 \quad k = 1, 2, \dots, n - 1 \quad 9.10$$

where $p(t)$ represents the variation of degree between stitches of consecutive knitting tools in lag time t , where one of the tools has more yarn tension

during the knitting process, and α is the angle of the majority of stitch directions.

The regularity of stitches is given by a zero value of $p(t)$, in which case the deformation index D will be zero. More differences between stitch angles in consecutive course cause more irregularity in the appearance of the fabric. Considering the irregularity as a fuzzy sense in human vision, fuzzy correlations between D and stitch regularity have been proposed (Table 9.3).

The main conclusion that can be drawn from this research concerns the capability of this method for online assessment of stitch deformation in various knitted fabrics, expanding the readjusting system of the loop length cam to enhance knitted fabric quality during the knitting process. The experimental work showed that there is an interaction between the type of yarns used and the fabric structure on the cam setting.

9.4.3 Optimization of knitting machine cam profile

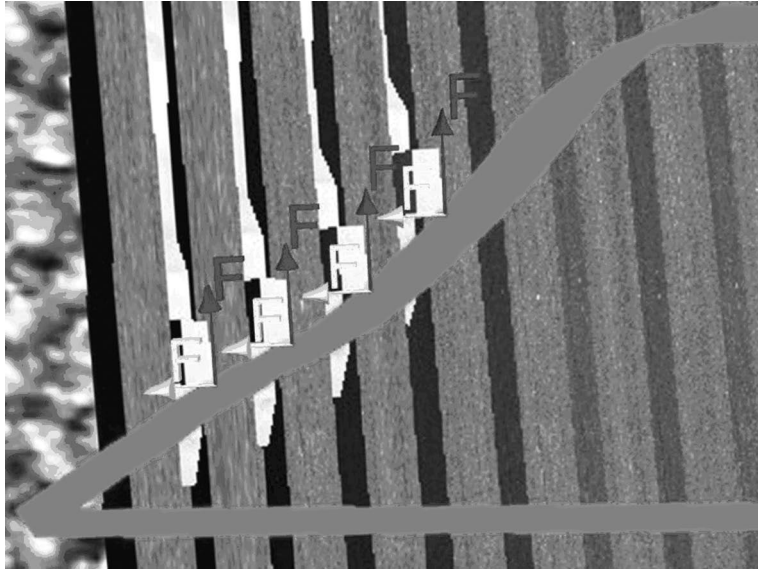
Flatbed knitting machines are generally well known for their great versatility in loop structure and pattern because the machine cams can be changed after every course and they are able to knit one or both beds easily. Weft knitting machines with a latch needle are especially suitable because their individually tricked and butted elements offer the possibility of independent movement (Spencer, 2001). The latch needle, because of its controlled knitting action, is capable of being lifted to one of three stitch positions to produce either a miss, a tuck or a knit stitch. A carriage with cam boxes travels along the beds, forcing the needle butts in its way to follow the curved shape of the cam (Raz, 1991).

The impact point between needle and raising cam is a very critical position. Cams are rigid objects fixed in their supports and needles are considered as elastic objects, so the needle butts will bend under the initial force. The first contact between needle and cam profile generates a force with two components, horizontal and vertical, as shown in Fig. 9.4 (Blaga

Table 9.3 Relation between stitch deformation index (D) and fuzzy definition of stitch deformation

D	Description	Stitch deformation class
0–2	No change	A
2–5	Low change	B
5–10	Risk of change	C
10–25	Need to readjust tools	D
25–45	Need to readjust tools/readjust delivery	E
> 45	Machine stop	F

Source: Semnani and Sheikhzadeh, 2007.



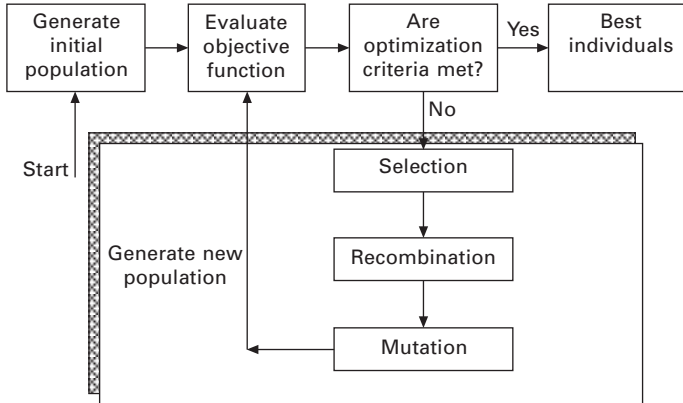
9.4 Forces at the impact between needle butt and cam (source: Blaga and Drăghici, 2005).

and Drăghici, 2005). The knitting cam profile optimization study, described below, opens up the possibility of minimizing the initial impact between the cam and the needle butt and minimizing variations of the horizontal force.

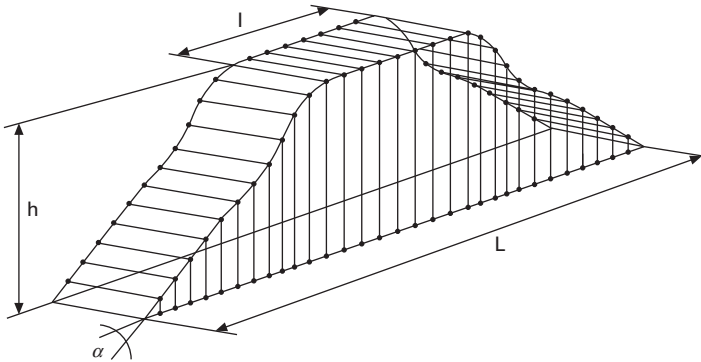
The Knitting Machine Simulator (KMS) – Cams Generator Module is a software developed to design a knitting machine's cam profiles. The program applies a genetic algorithm over a real-time knitting machine simulation in order to test the generated cam profiles. Evolutionary algorithms such as genetic algorithms can mimic natural evolution processes such as selection, recombination, mutation and migration. Figure 9.5 shows the schematic operations of a simple genetic algorithm (Chipperfield and Fleming, 2003). The KMS program uses the genetic algorithm approach for optimizing the knitting machine's raising cam profile. The first raising cam should be designed according to its geometrical characteristics (Fig. 9.6): the height (h), the bottom length (L) and the top length of the cam (l). The difference between the top and bottom length will determine its angle (α). When shaping the cam, the algorithm will not change its profile beyond these initial dimensions.

Generation of an initial population

In order to obtain the profile optimization, the program generates an initial population, named 'chromosomes'.



9.5 Structure of a simple genetic algorithm (source: Chipperfield and Fleming, 2003).



9.6 Cam generated by gene information (source: adapted from Blaga and Drăghici, 2005).

Each chromosome is represented by a binary string. Each bit in the string represents characteristics of the profile of a cam (base length, top length, height and width), using genes. The number of genes is the same for all individuals of the same population. The user has the possibility of choosing the number of genes from a chromosome and the number of chromosomes from the same population.

To describe a cam profile using genes, the height of the cam is divided by the number of genes in the chromosome. Each cam will receive a value which will describe the height of the cam for each gene (see Fig. 9.6). The first cam is generated starting from the user-specified characteristics and will have a linear profile. The others will be obtained by applying the mutation operator upon the linear profile cam. A cam will be generated until the number of chromosomes specified by the user is reached.

Evaluation of the population

The evaluation of the population has the purpose of attributing a mark to each individual from the current population. The mark is given depending on the horizontal force on the butt of the needle (see Fig. 9.4). For the evaluation of this force, each cam undergoes a simulated working test, consisting of one run of the cam. During its movement, the impact between the needle butts and the cam is detected, and the forces that appear at the collision point are calculated. After the test, the maximum, average and dispersion of the recorded horizontal forces will be calculated.

The evaluation of the population is based on the fitness function, which in this case consists of the optimization of the maximum value of the horizontal force and optimization of the dispersion values. Depending on these values, the chromosome with the characteristics of the tested cam will receive a final score. The algorithm seeks the optimization of this score. The optimization of the maximum value of the horizontal force leads to a reduction in the initial impact between the cam and the needle butt. The optimization of the average and dispersion values ensures the search for a cam profile that is as uniform as possible and with the least variations of the horizontal force.

Selection of chromosomes

The selection of chromosomes takes place in order to eliminate the specimens that have weak results. The program utilizes a selection algorithm based on sorting which utilizes selection pressure. The selection pressure will determine the number of descendents of each chromosome, depending on its hierarchical position. This way, a uniform selection is ensured, undisturbed by the big differences between the cam marks. The utilized pressure has an average value in order to help establish a slow evolution to the optimal solution, so it will perform a wide search. The ecological niche criterion was added to the algorithm to ensure the survival of several cams, with different profiles, within the same tested population. The final mark of the cam depends on the family to which it belongs. This is decided through the calculation of the distance between the chromosomes using the Hamming method, which establishes the number of genes in which two chromosomes differ, or by the Levenstein method, which calculates the sum of the modules of the gene differences. This criterion allows searching within a wider range of solutions and ensures the selection of the optimal profile.

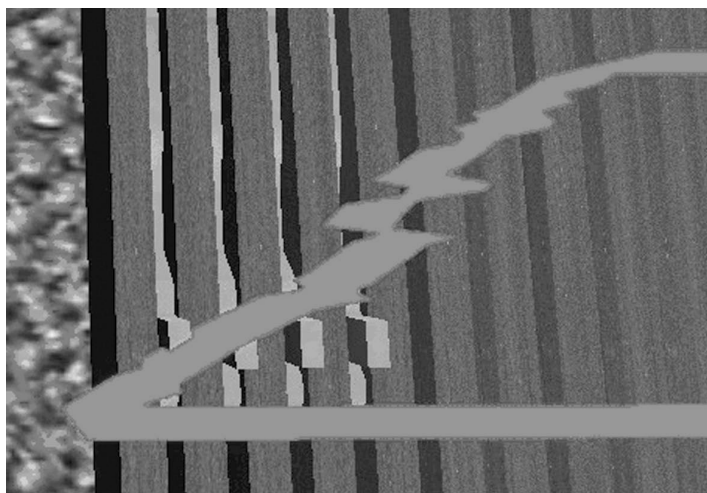
Generation of a new population

In the new population, only the chromosomes with the best scores will be copied, according to the elitist strategy, to keep the good characteristics in

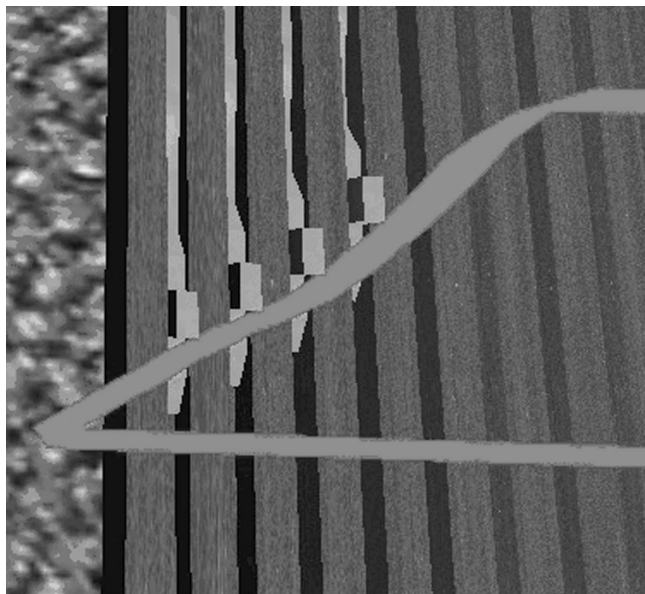
the future generation. For crossover of two chromosomes, the method with a variable number of cutting points was used. From the crossover of two parents, two children with characteristics that are similar to those of their parents' will result. The mutation ensures the evolution of in-depth search. The mutation stage will affect the chromosomes that were selected for the mutation. The mutation operator converts 0 to 1 and vice versa in the selected positions of the chromosome. After the crossing and mutation, cams with wrong profiles can be obtained (Fig. 9.7) and they are excluded from the next family as they will get lower scores in the evaluation process. The cam with a profile that is better (Fig. 9.8) than that of the previous generation will have more descendants. After the evaluation of a new population of chromosomes, the algorithm is restarted from the 'population evaluation' step.

Brief presentation of knitting machine simulator

The program was created in Visual C++, based on a user-friendly interface using Direct X technology (Fig. 9.9). To ensure compatibility with the different computer configurations or video cards, different aspects regarding the rendition process such as the adaptor type, the rendering device, the settings of the rendered image output, and the vertex rendering type may be modified in the 'Direct3D Settings' window (Fig. 9.10). The user has the possibility of configuring the mouse and keyboard to change the point of view during the rendition process (Fig. 9.11). Therefore, the user has the option to watch the evolution of the algorithm and the movement of the cam and the needles during the evaluation of the population stage.



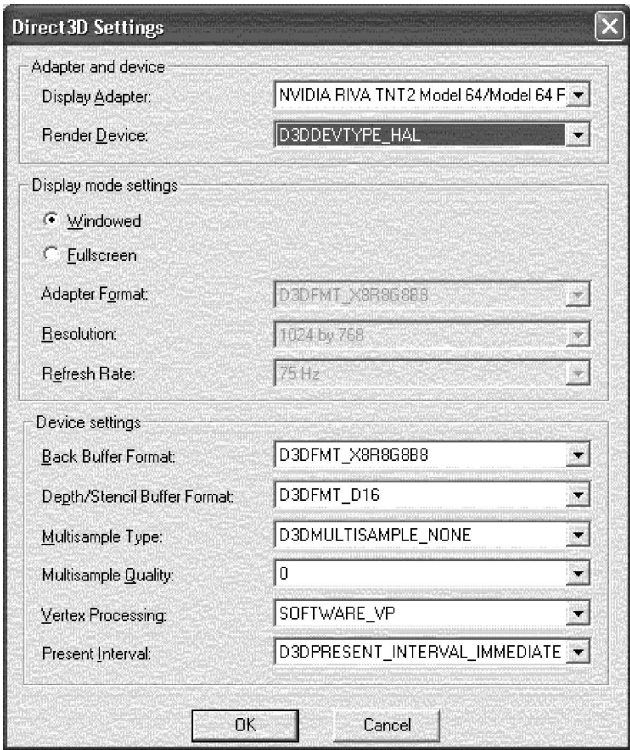
9.7 Cam with wrong profile (source: Blaga and Drăghici, 2005).



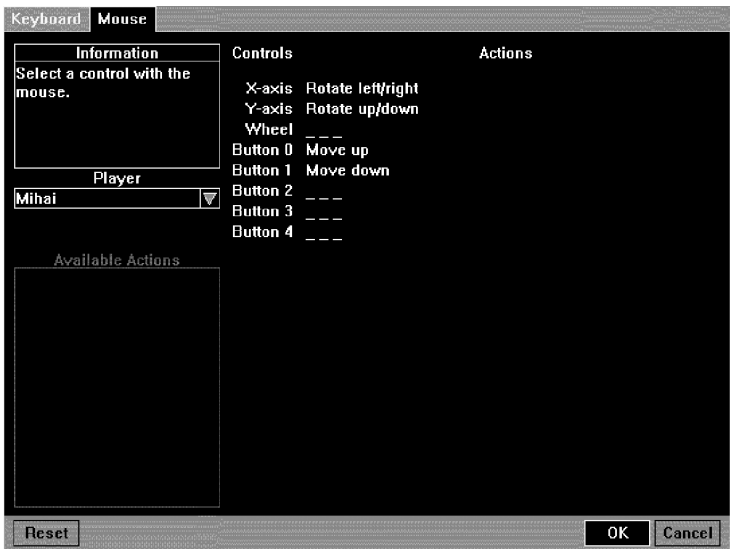
9.8 Cam with improved profile (source: Blaga and Drăghici, 2005).



9.9 The main menu of the KMS (source: Blaga and Drăghici, 2005).



9.10 'Direct3D Settings' window.



9.11 'Rendering objects options' window.

The program records every action that is taken and the cam profiles in separate files on the hard disk. Each generation is stored in a separate folder and the last two populations are always saved. This way, the program can be restored from the last step. If the final position is not acceptable, the program returns to the generation before last. To start a new search, the 'Genetic Algorithm' window is used (Fig. 9.12). The information required is related to the test name, the number of genes and chromosomes in the current test, together with data regarding the cam to be generated: base length, top length, height and width of the cam.

The 'Select Machine/Simulations Settings' window (Fig. 9.13) sets different machine configurations, such as the number of needle beds and the needle number of the test, the angle and the distance between the needle beds, the knock-over depth, the knitting speed and the knitting cycles during which the test of the cam will be carried out.

Figure 9.14 represents the KMS Cams Generator in the cam-setting stage. The software contains a routine that allows the visualization of the scores obtained by the chromosomes of a population and the visualization of a two-dimensional image of the cam profile, named the 'KMS-Mesh Profile Viewer' (Fig. 9.15). The utilization of KMS software in knitting machine cam design reduces the time required for the design process by about 25%, leading to lower costs for this stage as well.

9.5 Future trends

It is obvious that soft computing techniques have been applied in almost every sphere of textile manufacturing. The GA optimization methodology has been

Genetic Algorithm:

Algorithm :

Test Name: t1326

Test Location: HartDate

Number of Genes: 44

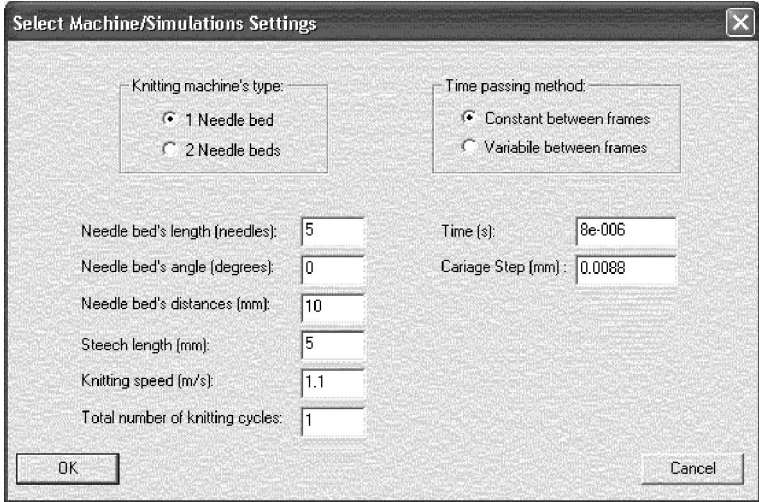
Number of Chromozoms: 20

Cam :

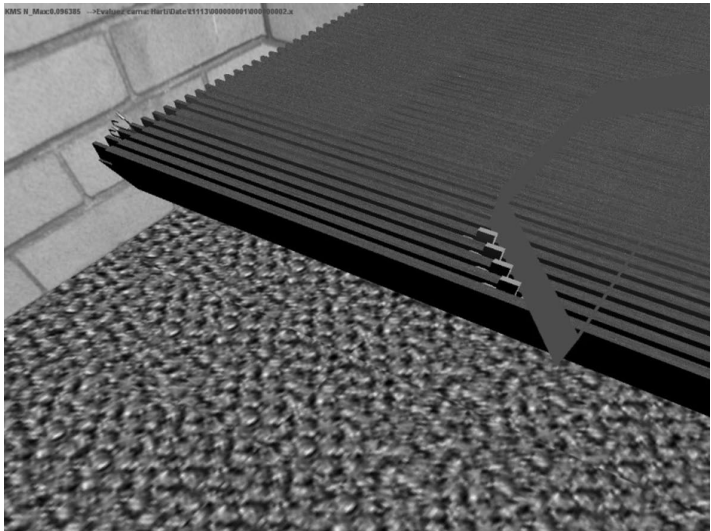
Bottom length (mm) : 47.7 Top length (mm) : 22.2

Height (mm) : 22 Width (mm) : 10.5

9.12 'Genetic Algorithm' window.

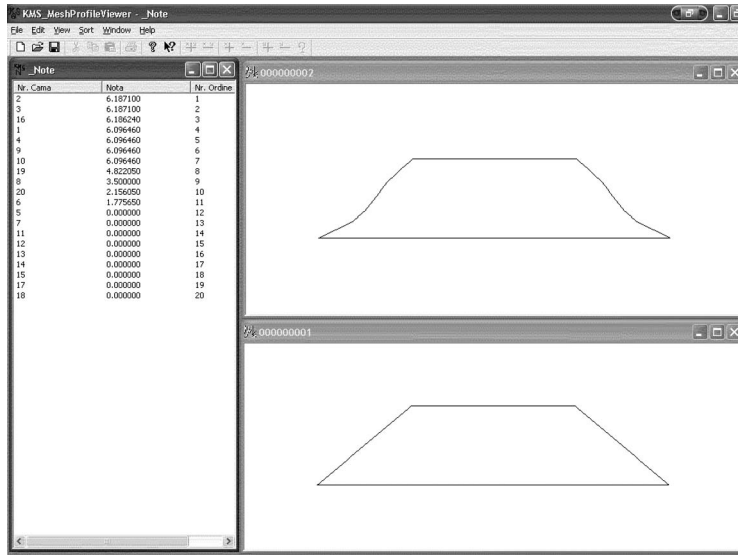


9.13 'Select Machine/Simulations Settings' window (source: Blaga and Drăghici, 2005).



9.14 'KMS_CamGenerator' – cam setting stage.

tested in the complex spinning production process and gave excellent results in optimizing the input parameters for obtaining the best yarns (Sette *et al.*, 1996). The use of these techniques has made several actions possible: to model complex fabric behaviour, to evaluate sensory properties objectively, to identify fabric defects even in dynamic cloth inspection, to classify fabrics,



9.15 KMS_MeshProfileViewer.

to engineer fabrics and to control the machine performance (Majumdar *et al.*, 2009). There is also ample scope for further research to improve the performance and online implementation of soft computing systems. Choosing the best process parameters related to knitting production and the properties of the fibres and yarns is an area of future research, taking into account the great diversity of raw materials, knitting machines and product end uses.

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Modelling nonwovens using artificial neural networks

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Abstract: This chapter deals with the application of artificial neural network modelling in the field of nonwovens. It covers various artificial neural network models applicable to different manufacturing processes in predicting different properties of nonwovens. Different manufacturing processes covered are needle-punching, melt blowing, spun bonding, thermal and chemical bonding. Different predicted properties are tensile strength, modulus, elongation, compression, water permeability, air permeability and filtration. Some of the other predictions include fibre diameter, blend ratio and classifications of defects in the nonwovens. Deficiencies and future directions are also highlighted.

Key words: artificial neural network, modelling, nonwoven.

10.1 Introduction

This chapter discusses the application of artificial neural network (ANN) modelling in the nonwoven manufacturing processes in predicting different properties. A brief background about how different manufacturing process parameters affect some of the important properties of nonwovens is also discussed. The desired properties of the final nonwoven product depend upon the raw material and processing parameters used in different manufacturing processes. For example in needle-punching, the selection of process parameters like feeding speed of the web, web area density, depth of needle penetration, punch density and stroke frequency will play a significant role in the desired properties of the product. Also the fibre properties will play a role in the final properties of the product. Similarly in the melt blowing process, extruder temperature, die temperature, melt flow rate, air temperature and pressure at die and die-to-collector distance will affect the final diameter of the fibre or filaments of the nonwoven web. This diameter is very important for a range of applications of melt blown nonwovens.

The above two nonwoven manufacturing processes involve a considerable amount of complexity due to nonlinearity in the processes and presence of noisy data. ANN is a useful tool in handling ‘noisy’ data and predicting a

nonlinear relationship between input and output parameters or variables. So the application of ANN in the above-mentioned nonwoven manufacturing processes and other processes will be helpful in understanding some of the complexity of the process in predicting different properties. Some of the other important nonwoven manufacturing processes covered are spun bonding, thermal and chemical bonding. ANN modelling was used to predict mechanical, structural, functional and fluid handling properties. Different predicted properties are tensile strength and modulus, elongation, compression, water permeability, air permeability and filtration, and diameter of fibres. Application of ANN modelling in classification of fabric defects and identifying the blend ratio of fibres in nonwovens is also discussed. Some of the shortcomings and future directions are also addressed.

10.2 Artificial neural network modelling in needle-punched nonwovens

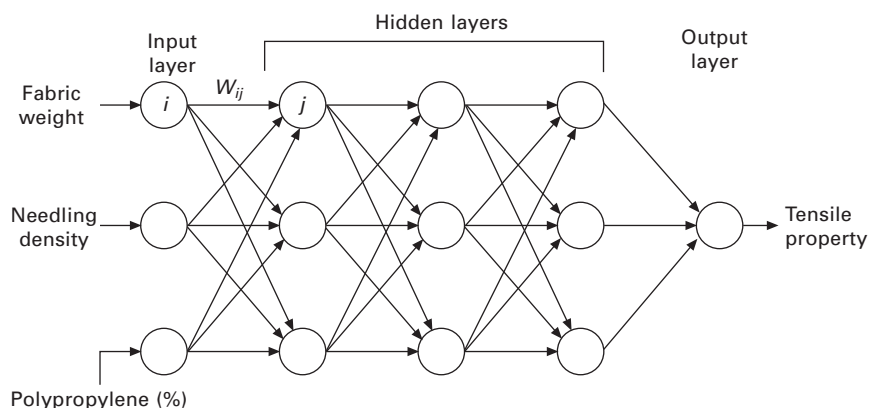
Needle-punching is a mechanical bonding method of producing nonwoven fabric. In this method, fibrous web is converted into a coherent structure by the action of barbed needles. These nonwovens are used in a wide range of application areas such as filtration, wipes, battery separators, insulating materials, automotive and aerospace components and interiors, etc. The desired properties of the final nonwoven product depend upon the raw material and processing parameters. Some of the important raw material and processing parameters are fibre types, fibre length and fineness, fibre crimp, fibre friction, cross-sectional shape of the fibres, blend ratio of fibres, feeding speed of the web, web area density, depth of needle penetration, punch density, etc. Important properties of the nonwovens can be classified into the following subgroups: mechanical (tensile strength, modulus, elongation and compression), physical (thickness and area weight), structural (pore size and its distribution, fibre diameter), performance (filtration, abrasion resistance, puncture resistance and hydraulic transmissivity) and fluid handling properties (water permeability, air permeability and water vapour permeability). In the following section we discuss the prediction of the above-mentioned properties by ANN. Prediction of blend ratio and classification of defects in nonwovens by ANN are also discussed. For further information on nonwoven manufacturing technology, readers are referred to the published literature (Butler, 1999; Russell, 2007).

10.2.1 Prediction of tensile properties

The tensile properties (tenacity and initial modulus) of needle-punched nonwovens produced from a blend of polypropylene and jute fibres have been predicted with the help of ANN and empirical models (Debnath *et al.*, 2000a).

Both the predicted values have been compared with the experimental results. Nonwoven fabric weight, needling density and blend ratio of polypropylene and jute fibres were taken as input parameters. The predicted outputs were tenacity and initial modulus, respectively. Jute fibres were blended with polypropylene fibres (0.44 tex, 80 mm) as per the Box–Behnken factorial design for three factors varied at three levels (Box and Behnken, 1960). An empirical equation has been developed using Box–Behnken factorial design. The levels of variables were varied at -1 , 0 and $+1$ levels. Fabric area weights were varied at 250, 350 and 450 g/m². Needling density was varied at 150, 250 and 350 punches/cm². Blend ratios of polypropylene to jute fibres were varied at 40:60, 60:40 and 80:20. The tenacity and initial tensile modulus were measured in both machine and transverse or cross-machine directions.

Multilayer feed-forward neural network architecture with a back-propagation algorithm was used for the prediction of tensile properties (Debnath *et al.*, 2000a). One input parameter, three hidden layers and one output parameter were used as shown in Fig. 10.1. The neuron (i) in one layer is connected with the neuron (j) in the next layer with weights (W_{ij}). The ANN was trained by presenting it with 15 data sets of input–output pairs. The data were scaled down between 0 and 1 by normalizing them with their respective values. The ANN was trained up to 64,000 cycles to obtain optimum weights. The error and correlation were calculated between the experimental and predicted values by ANN and empirical models. The ANN model shows a very good relationship between the experimental and predicted values of tenacity (in both machine and transverse directions) and initial modulus when compared to the empirical model. The ANN model also shows lower absolute percentage error compared to the empirical model. Also attempts were made at experimental



10.1 Neural architecture of the tensile properties (source: Debnath *et al.*, 2000a).

verification of the predicted values for the extrapolated input parameters (Debnath *et al.*, 2000a). The absolute error percentage in tenacity values for a particular sample in the machine direction and transverse direction for the ANN model are 13.02% and 10.40%, respectively. The corresponding values of tenacity obtained from the empirical model are 35.57% and 22.38%, respectively. This shows that the ANN model gives better results than the empirical model for tensile properties.

The ANN modelling has been used to predict the tensile properties (in machine and cross-machine directions) and bulk density of needle-punched nonwovens by relating them to the process parameters (Rawal *et al.*, 2009). The input parameters of the ANN model were web area density, punch density and depth of needle penetration. Twenty-seven samples were produced using a statistical design of three factors varied at three levels using polypropylene fibres (10 dtex, 100 mm) and properties were experimentally measured. The predicted properties obtained from the ANN model were compared with the experimental values.

One hidden layer was used for the prediction of tensile properties and bulk density. Two different ANN models have been developed (Rawal *et al.*, 2009). The number of nodes in the outer layer is two for tensile strength predictions and one for predicting the fabric bulk density. The log-sigmoid transfer function was used between hidden and output layers. The network training was done using a standard back-propagation algorithm. The number of nodes in the hidden layer, learning rate and momentum were optimized at 8, 0.6 and 0.8, respectively. Out of 27 data sets, 21 sets were randomly chosen for training the ANN and the remaining six sets were used for testing the model. Very good correlation has been reported between the experimental and predicted values, except in the case of bulk density data sets as shown in Table 10.1. It has been inferred that the ANN models have achieved a good level of generalization. Also the acceptable level of mean absolute error obtained between experimental and predicted results supports these findings.

10.2.2 Prediction of compression properties

Compression is one of the important mechanical properties of nonwovens, particularly in the field of geotextiles and high-efficiency filtration systems. Geotextiles are always used in conjunction with rocks and soils in pavements, roads and river embankments. Most of the time, these nonwovens are subjected to cyclic loading perpendicular to the plane due to vehicular movement, the weight of the rocks and soils or the weight of the water reservoir (Kothari and Das, 1992, 1993). Also during prolonged use of nonwovens in air filtration, they are subjected to cyclic compression at various stages due to cyclic variation in pressure (Patanaik *et al.*, 2007; Patanaik and Anandjiwala,

Table 10.1 Prediction and performance of ANN models

Statistical parameter	Bulk density		TMD*		TXMD†	
	Training	Testing	Training	Testing	Training	Testing
Coefficient of correlation (<i>R</i>)	0.986	0.907	0.997	0.986	0.997	0.982
Mean absolute error (%)	5.40	6.70	3.17	9.21	3.69	6.71

*TMD: Tensile strength in machine direction.

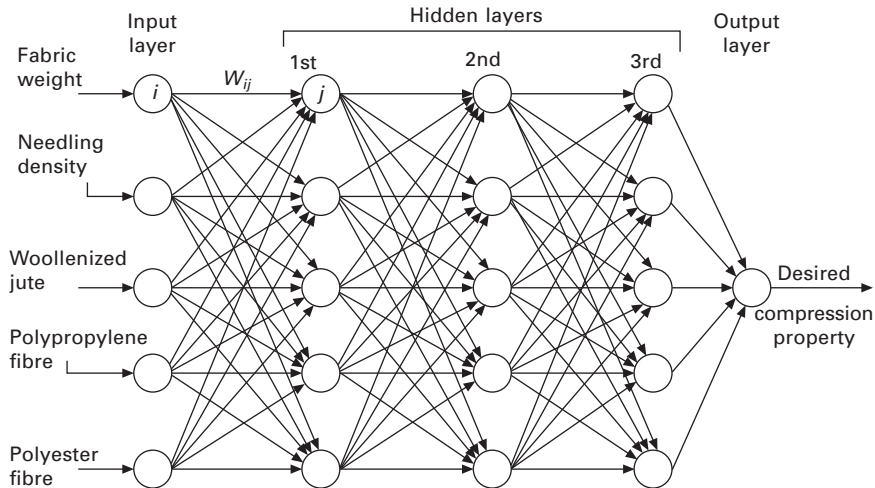
†TXMD: Tensile strength in cross-machine direction.

Source: Rawal *et al.* (2009).

2010). The probable reason for this cyclic compression is the deposition of layers of dust particles on the filters resulting in the obstruction of the airflow. This causes the build-up of pressure and cyclic variation in pressure, and influences the long-term performance characteristics of the filters. Some of the conditions imposed by the operating environment also play a role in the cyclic variation in pressure or compression. The compression of nonwovens plays an important role in the desired performance characteristics.

The compression properties of needle-punched nonwovens produced from blends of polypropylene (0.44 tex, 80 mm) and jute fibres and 100% polyester fibres (0.33 tex, 51 mm) have been reported (Debnath and Madhusoothanan, 2008). The compression properties selected for the study were initial thickness, percentage compression, percentage thickness loss and compression resiliency. The percentage compression is the ratio of the difference between initial thickness and thickness at maximum pressure to the initial thickness, expressed as a percentage. The percentage thickness loss is the ratio of the difference between initial thickness and recovered thickness to the initial thickness, expressed as a percentage. Compression resiliency percentage is the ratio of the work done during recovery and compression processes expressed as a percentage (Debnath and Madhusoothanan, 2008). These properties were predicted with the help of the ANN model and compared with the experimental values. The five selected input parameters were fabric area weight, needling density, percent woollenized jute, percent polypropylene fibres and percent jute fibres (Debnath and Madhusoothanan, 2008). The compression properties of the fabrics were taken as the output parameter. For the experimental measurement of compression properties, a thickness gauge was used.

Multilayer feed-forward neural network architecture with a back-propagation algorithm was used for the prediction of compression properties (Debnath and Madhusoothanan, 2008). Five input layers with five neurons, three hidden layers, each layer having five neurons, and one output layer with one neuron were used in the network architecture as shown in Fig. 10.2. The neuron (*i*) in one layer is connected with the neuron (*j*) in the next layer with weights (W_{ij}). The ANN was trained by presenting it with 25



10.2 Neural architecture of the fabric compression property (source: Debnath and Madhusoothanan, 2008).

data sets of input–output pairs. The data were scaled down between 0 and 1 by normalizing them with their respective values. The ANN was trained between 320, 000 and 512, 000 cycles to obtain optimum weights for initial thickness, percentage compression, percentage thickness loss and compression resiliency percentage.

The error and correlation were calculated between the experimental and predicted values by ANN models (Debnath and Madhusoothanan, 2008). The ANN model shows very good correlation between the experimental and predicted values of initial thickness, percentage compression and percentage thickness loss with three hidden layers as shown in Table 10.2. The ANN model with three hidden layers also shows lower absolute percentage error in comparison with the ANN model with two hidden layers for the above properties. The ANN model with two hidden layers performs better in the case of percentage compression resiliency. The ANN model with three hidden layers takes more time for computation during the training phase in comparison to the ANN model with two hidden layers. The advantage of using three hidden layers was that the predicted results were more accurate with less variation in the absolute error in the verification phase.

10.2.3 Prediction of air permeability

Air permeability is one of the important properties in the performance of nonwovens as filters, breathable liners, protective clothing and other applications such as hygiene clothing. It provides a measure of fabric porosity and relates directly to fabric thickness and density. Air permeability is defined

Table 10.2 Comparison of ANN structures for compression properties

Statistical parameter	Initial thickness (mm)*			Percentage compression (%)*			Thickness loss (%)*			Compression resiliency (%)*		
	1 HL	2 HL	3 HL	1 HL	2 HL	3 HL	1 HL	2 HL	3 HL	1 HL	2 HL	3 HL
Coefficient of determination (R^2)	0.986	0.987	0.987	0.983	0.994	0.997	0.992	0.995	0.999	0.991	0.999	0.997
Mean absolute error (%)	1.51	1.41	1.41	1.45	0.76	0.28	1.22	0.91	0.10	1.24	0.42	0.63

*1 HL: One hidden layer; 2 HL: Two hidden layers; 3 HL: Three hidden layers.

Source: Debnath and Madhusoothanan (2008).

as the rate of airflow passing perpendicularly through a known area under a prescribed air pressure differential between the two surfaces of a material. The air permeability behaviour of needle-punched nonwovens produced from a blend of polypropylene and jute fibres has been reported (Debnath *et al.*, 2000b). The air permeability of the nonwovens was predicted with the help of ANN and empirical models. An empirical model of the second-order polynomial was fitted to predict the air permeability from the experimental results. The predicted values from the models were compared with the experimental values. The experimental air permeability was measured on a Shirley air permeability tester with a test area of 5.07 cm² and a pressure head of 10 mm of water. The selected input parameters were nonwoven fabric area weight, needling density and blend ratio of polypropylene and jute fibres. The air permeability of the fabrics was taken as output parameter. An attempt was made to study the effect of the number of hidden layers on the prediction of air permeability. A maximum of three hidden layers was chosen for the prediction. Jute fibres were treated with 18% NaOH and blended with polypropylene (0.44 tex, 80 mm) as per the Box–Behnken factorial design for three factors varied at three levels (Box and Behnken, 1960). The levels of variables were varied at -1, 0 and +1 levels. Fabric area weights were varied at 250, 350 and 450 g/m². Needling density was varied at 150, 250 and 350 punches/cm². Blend ratios of polypropylene to jute fibres were varied at 40:60, 60:40 and 80:20.

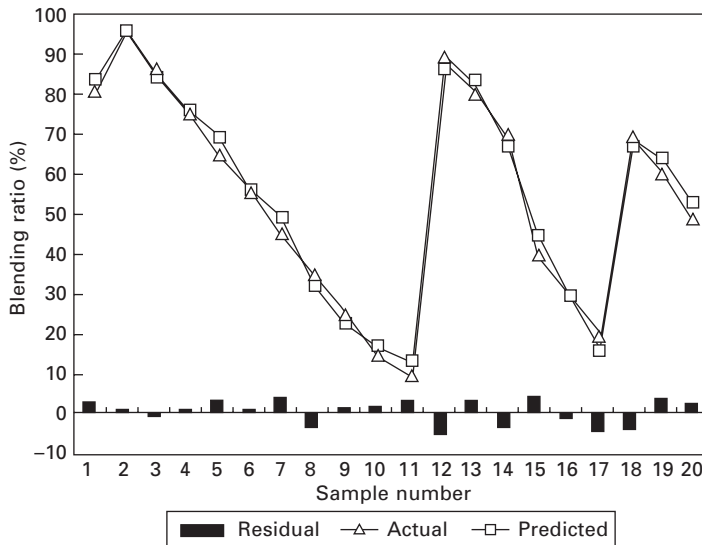
The ANN was trained by presenting it successively with 15 data sets of input–output pairs for the prediction of air permeability (Debnath *et al.*, 2000b). The ANN was trained up to 40,000 cycles to obtain optimum weights. The ANN models were trained with a learning rate of 0.01. The weights of the interconnection were adjusted using the back-propagation algorithm (Fan and Hunter, 1998). After training each time, the prediction error was calculated and the weights of interconnections between the neurons for all the layers were noted down. A similar procedure was followed for ANN models with one, two and three hidden layers. The one-hidden-layer ANN model has two neurons in the hidden layers. The two-hidden-layer ANN model has three and two neurons in the first and second hidden layers, respectively. The three-hidden-layer ANN model has three neurons in the first, second and third hidden layers, respectively. The prediction accuracy of the ANN with three hidden layers was the best among all the predicting models, because the large number of neurons and hidden layers generally provide good accuracy. The ANN with three hidden layers gives the highest correlation with the lowest error between the actual and predicted air permeability values, followed by the ANNs with two and one hidden layer. Although the correlation between the experimental values and those predicted by the empirical model was almost the same as that from the ANN model with two hidden layers, the mean percentage absolute error was higher in the case of the empirical model than for the ANN with

two to three hidden layers. The reason may be that the empirical model may require a large sample size when the relationship between input and output parameters is nonlinear (Rajamanickam *et al.*, 1997).

10.2.4 Prediction of blend ratio, detecting and classifying defects in nonwoven fabric

The blend ratio of nonwovens was predicted by neural network (Lai, 2002). The basic principle of this blend ratio prediction as suggested by the author is that different types of fibres will appear in different colours after dyeing. So fibres of different blending ratios will also appear in different colours (Wright, 1984). The colour values of the nonwovens measured by a spectrophotometer were taken as input parameters. Ten different combinations of needle-punched nonwovens were taken as the output parameters. Different fibres used for producing the needle-punched nonwoven were cotton, wool, acrylic, nylon and polyester. A multilayer ANN model with five input layers with five neurons, one hidden layer with four neurons and one output layer with one neuron was used in this study. The sigmoid transfer function was used between the hidden and output layers. For computation of the variation in weight values between the hidden and output layers, generalized delta learning rules were employed. The delta learning rule is a function of input value, learning rate and generalized residual. Twenty samples of each nonwoven fabric having blending ratios (%) between 0/100 and 100/0 were taken in the training process. Therefore, the total number of training samples was 200. It was found that the root-mean-square error (RMSE) decreases rapidly when the number of training cycles increases. When the number of training cycles reaches 920, the RMSE of the prediction model has already dropped to 0.01 or below. The number of cycles required for the RMSE of each nonwoven fabric prediction model to show convergence was between 900 and 1000. This indicates that the results of the network models trained in the study were satisfactory.

In order to test the model, the colour values of a cotton and polyester nonwoven fabric were measured by a spectrophotometer before being input to the classification model of the artificial neural network for assessment (Lai, 2002). The test results show that cotton and polyester nonwoven fabric was correctly classified. In order to know the fibre blending ratios of the 20 cotton and polyester nonwoven samples, colour values were input to the prediction model of the neural network. From the prediction results, it can be found that the residual between the actual blending ratio and the predicted network value was merely 2.82 as shown in Fig. 10.3. The high correlation coefficient between the actual blending ratio and its predicted value from the ANN model indicates the ability of the model to predict the blend ratio of nonwovens.



10.3 Residual plot for the cotton/polyester nonwoven fabric (source: Lai, 2002).

ANN in conjunction with wavelet transforms was used for detecting nonwoven fabric defects from the images of the fabrics (Huang and Lin, 2008). The wavelet transforms were used as a defect detector and ANN was used as a defect classifier. The wavelet transform decomposes an original nonwoven fabric image into four sub-images in different frequency bands. Four texture measures – the energy, contrast and correlation with grey level co-occurrence matrices as well as the energy with wavelet coefficients – were selected as defect features and computed based on the low frequency sub-images. These four texture measures were taken as the input parameters of the ANN model. Defects were classified into nine types of faults. An assortment of 90 different needle-punched, hydroentangled and chemically bonded nonwoven fabrics was used.

Three-layer feed-forward neural network architecture with a back-propagation algorithm was used for the defect classifications (Huang and Lin, 2008). The three-layer neural network consisted of the input layer with four nodes, one hidden layer with four nodes and the output layer with nine nodes as the nine kinds of defects to be classified. The unipolar sigmoid transfer function was used between hidden and output layers. Forty-five samples, five samples for each kind of defect, were randomly selected for training. The remaining 45 samples were selected for testing. Based on the training set of inputs and desired outputs, the output vector of the neural network was compared to the desired output vector. The error between them was propagated back by the gradient descent algorithm to adjust the weights

and thresholds with selection of the learning rate as 0.9 and the momentum factor of 0.6. The procedures continued until the mean square error (MSE) converged to an acceptably small value. The final weights and thresholds at the MSE of 0.0003 were used for testing. In the testing stage, the input layer received the normalized feature values and computations were performed forward from layer to layer until the output layer produced the results. The largest entry value among the nine entries in the resulting output vector determined the corresponding defect. Consequently, all 45 samples were correctly classified with the use of ANN.

10.3 Artificial neural network modelling in melt blown nonwovens

Melt blowing is a single-step process of producing microfibre nonwovens from polymer chips with the help of high-velocity hot air. The forces created by the high-velocity hot air attenuate the melt filaments coming out of the orifices, drawing them typically from an initial diameter of 400 μm to as low as 1 μm final diameter. Melt blown nonwovens are used in the following application areas: filtration, battery separators, thermal insulators, oil absorbents, etc. The desired properties of the final melt blown product depend upon the raw material and processing parameters used during the manufacturing stage. The fibre-forming mechanism in the melt blowing process is very complicated and is related to many interdisciplinary research areas, such as fluid mechanics, polymer and fibre science and textile and mechanical engineering. Melt blowing is a complex and nonlinear process which involves a lot of noisy data. The ANN is particularly suitable for this process for prediction modelling. All the published papers have focused on predicting the fibre (or filament) diameter by the application of ANN (Sun *et al.*, 1996; Chen *et al.*, 2005, 2006).

10.3.1 Prediction of fibre diameter during the melt blowing process

The fibre diameter of melt blown nonwovens was predicted from the processing parameters by ANN (Sun *et al.*, 1996). The network inputs were extruder temperature, die temperature, melt flow rate, air temperature at die, air pressure at die and die-to-collector distance. The output parameter of the network was the fibre diameter. The polymer used was polypropylene pellets with a melt flow index of 60 (g/10 min). The experiments were designed by the orthogonal experimental design L_{27} (9×3^9). The processing parameters were varied in the following ranges: extruder temperature 270–370°C, air temperature at die 260–340°C, melt throughput rate 16–32 g/min, air pressure at die 0.02–0.16 MPa, die-to-collector distance, 0.07–0.20 m. The

average diameter of 100 random fibres from 10 web samples was taken as the measured value.

Three-layered feed-forward neural network architecture with a back-propagation algorithm was used for the prediction of fibre diameter (Sun *et al.*, 1996). A network structure of 6-4-1 (six nodes in the input layer, four nodes in the hidden layer and two nodes in the output layer) was used. The sigmoid transfer function was used between hidden and output layers. The data were scaled down between 0 and 1 by normalizing them with their respective values. One hundred and sixty sample sets were used for network training. The testing of the network was accomplished with 70 sets of test samples which were different from the training data. The maximum absolute error between the predicted fibre diameter and the actual value was less than 1.5 μm , indicating ability of the ANN to predict the fibre diameter.

ANN along with physical and statistical models was used to predict the fibre diameter of melt blown nonwovens from the processing parameters (Chen *et al.*, 2005). The processing parameters, polymer flow rate, initial air velocity and die-to-collector distance were taken as the input parameters for both models. The output parameter of the models was the fibre diameter. The experiments were designed by the orthogonal experimental design $L_9(3^4)$ and a total of 13 sets of experiments were performed. The polymer used was polypropylene pellets with a melt flow index of 52 (g/10 min). The processing parameters were varied in the following manner: polymer flow rate 0.0017, 0.0025 and 0.0033 g/s; initial air velocity 87, 174 and 261 m/s; and die-to-collector distance 8, 11 and 14 cm. The image analysis method was used to measure the fibre diameter.

For the statistical model, the experimental data were divided into a fitting set with 12 data points and a testing set with one data point. The 12 data points were used to establish the multivariate nonlinear regression equation, the remaining one data point for testing the equation (Chen *et al.*, 2005). This procedure was repeated for all combinations of 12 and one data points. There were 13 cases being fitted and tested. The physical model of air drawing of polymers consists of the continuity equation, the momentum equation, the energy equation and the constitutive equation.

Three-layered feed-forward neural network architecture with a back-propagation algorithm was used for predicting the fibre diameter (Chen *et al.*, 2005). A three-layered ANN with an input layer, an output layer and a hidden layer was considered. The input layer had three neurons corresponding to the polymer flow rate, the initial air velocity and the die-to-collector distance. The output layer contained one neuron corresponding to the fibre diameter. To determine the number of neurons in the hidden layer, all the experimental data were divided into a fitting set with 11 data points and a testing set with two data points. The number of hidden neurons was changed from two to three. All combinations of 11 and two data points were used to train and

test the ANN. Altogether, there were 156 cases being trained and tested (78 for two hidden neurons and 78 for three hidden neurons). When comparing the average prediction error, the average error of two hidden neurons was 0.03%, which was lower than that of three hidden neurons (0.05%). So the number of neurons in the hidden layer was selected as two. The transfer functions of the hidden layer and output layer neurons were the hyperbolic tangent function and the pure linear function, respectively. Before training the ANN, the training data were normalized suitably. In order to test the ANN model, all the experimental data were split into a fitting set with 12 data points and a testing set with one data point. All combinations of 12 and one data points were used to train and test the ANN. Altogether, there were 13 cases being trained and tested (Chen *et al.*, 2005).

The authors took a different approach in reporting the average error: instead of reporting absolute error, they reported the real error (Chen *et al.*, 2005). For any regression model (statistical or neural network) the average error should be close to zero (exactly zero for perfect regression fit). When calculating an average error for the statistical or neural network model, and then a standard deviation, the inclusion of negative values is also important. This may be due to the wide data range covered by these negative values as compared to the absolute values. For example, from Table 10.3 for the statistical model, the percentage error range, which includes negative values, is -0.08 to 3.38 , whereas the percentage error range without negative values

Table 10.3 Measured and predicted fibre diameters

No.	Measured diameter (μm)	Physical model		Statistical model		ANN model	
		Predicted diameter	Error (%)	Predicted diameter	Error (%)	Predicted diameter	Error (%)
1	5.45	5.068	-7.00	5.634	3.38	5.446	-0.07
2	4.31	3.891	-9.72	4.167	-3.32	4.310	-0.00
3	3.66	3.322	-9.23	3.767	2.92	3.659	-0.01
4	3.69	3.358	-8.99	3.707	0.45	3.694	0.10
5	5.23	4.733	-9.50	5.225	-0.08	5.234	0.07
6	4.13	3.727	-9.75	4.101	-0.69	4.126	-0.09
7	4.04	3.592	-11.08	4.161	3.00	4.043	0.07
8	5.44	4.868	-10.51	5.345	-1.74	5.436	-0.07
9	5.38	4.922	-8.51	5.283	-1.80	5.389	0.16
10	5.82	5.348	-8.11	5.792	-0.48	5.819	-0.02
11	3.60	3.175	-11.80	3.718	3.28	3.600	0.01
12	4.04	3.604	-10.79	3.857	-4.53	4.039	-0.01
13	5.11	4.516	-11.62	5.140	0.59	5.112	0.03
Average			-9.74		0.07		0.01
Standard deviation			1.40		2.56		0.07

Source: Chen *et al.* (2005).

is 0.08 to 4.53 (Chen *et al.*, 2005). This implies that if negative values are included, the mean or average will be lower but the deviation is higher because of the dispersions. In another way, if absolute error is considered, all the values are averaged out and the data range will be smaller and the desired value far better and more stable, which is not the correct representation.

Table 10.3 shows the measured fibre diameters, predicted fibre diameters and prediction errors of the three models. The predicted fibre diameters of the statistical and ANN models are the average of 13 results. It can be seen from Table 10.3 that the performance of the ANN and statistical models are similar to each other, giving average errors of 0.01% and 0.07%, respectively. The physical model with average error of -9.74% performs worse than the previous models. The standard deviation of error was the lowest in the ANN model (0.07). The standard deviation of error in the physical model was 1.41, while in the statistical model it was 2.56. This indicates that the prediction errors of the statistical model are more discrete than those of the ANN and physical models. In all samples, the absolute error in the ANN model was lower than that in the statistical and physical models. ANN performs better than the other two models because the assumptions made in the latter have not taken all the important factors into consideration.

An ANN model was used to predict the fibre diameter of melt blown nonwovens from the processing parameters (Chen *et al.*, 2006). To minimize the prediction error, an attempt was made to study the effect of the number of hidden layers and their neurons. The processing parameters such as the polymer flow rate, initial polymer temperature, initial air velocity and initial air temperature were the input parameters of the models. The output parameter of the models was the fibre diameter. The polymer used was polypropylene with a melt flow index of 54 (g/10 min). The processing parameters were varied in the following manner: polymer flow rate 0.018, 0.035 and 0.070 g/s; initial polymer temperature 230, 260 and 290°C; initial air velocity 78, 168 and 235 m/s; and initial air temperature 280, 310 and 340°C. The image analysis method was used to measure the fibre diameter. Ninety nonwoven samples were used for the model, 60 for the training set and the remaining 30 for the testing set.

Multilayered feed-forward neural network architecture with a back-propagation algorithm was used for predicting the fibre diameter (Chen *et al.*, 2006). The one-hidden-layer ANN model had two to nine neurons in the hidden layer. The ANN model with two hidden layers containing two to five neurons in each hidden layer was developed. The ANN model with three hidden layers can only have two to five neurons in each hidden layer. For example, 4-5-3-3-1 means that there are 4, 5, 3, 3 and 1 neurons in the input, first, second and third hidden layers and the output layer, respectively. The transfer functions of the hidden layer and the output layer neurons were the hyperbolic tangent function and the pure linear function, respectively.

The average error and the coefficient of variation in the average error for the 4-5-3-3-1 ANN structure were 2.77% and 0.88%, respectively. Similarly, the values for the 4-5-3-2-1 and 4-5-2-3-1 ANN structures were 2.77% and 0.78%, and 2.79% and 0.72%, respectively. The ANN structure 4-5-2-3-1 with three hidden layers provided the minimum prediction error amongst the other structures and was selected as the preferred network. The square of the correlation coefficient between measured and predicted fibre diameters was 0.942, indicating the good performance of the model.

10.4 Artificial neural network modelling in spun bonded nonwovens

In the spun bonding process, the polymer is extruded through a spinneret, cooled down by an air stream and then spread over a conveyor belt. To keep the filaments over the conveyor belt, a vacuum is pulled through the porous conveyor belt. This belt transports the filaments to a calender roller, which presses the filaments and forms the spun bonded nonwovens. Spun bonded nonwovens are used in the following application areas: interlinings, geotextiles, carpet backing, filtration, bedding and roofing materials, packaging, cover materials for agriculture, etc. Some of the ANN models in predicting the filament (fibre) diameters, filtration and strength characteristics are discussed in subsequent sections.

10.4.1 Prediction of fibre diameter during the spun bonding process

ANN along with statistical models was used to predict the fibre (filament) diameter of spun bonded nonwovens from the processing parameters (Chen *et al.*, 2008). The processing parameters such as polymer melt index, polymer flow rate, initial polymer temperature, initial air temperature and initial air velocity were taken as the input parameters of both models. The output parameter of the models was the fibre diameter. Twenty-six different trials were carried out in this work. The polymer used was polypropylene resins with different melt flow indices. The image analysis method was used to measure the fibre diameter.

For the statistical model, the experimental data were divided into a fitting set with 25 data points and a testing set with one data point. The 25 data points were used to establish the multivariate nonlinear regression equation, the remaining one data point for testing the equation (Chen *et al.*, 2008). This procedure was repeated for all combinations of 25 and one data points. There were 26 such cases being fitted and tested.

Three-layered feed-forward neural network architecture with a back-propagation algorithm was used for predicting the fibre diameter (Chen *et al.*,

2008). A three-layered ANN with an input layer, an output layer and a hidden layer was developed. The input layer had five neurons corresponding to the five input parameters. The output layer contained one neuron corresponding to the fibre diameter. To determine the number of neurons in the hidden layer, all the experimental data were divided into a fitting set with 23 data points and a testing set with three data points. The number of hidden neurons was then changed from two to three. All combinations of 23 and three data points were used to train and test the ANN model. When comparing the average prediction error, the average error of three hidden neurons was 0.16%, which was lower than that of two hidden neurons (0.32%). So the number of neurons in the hidden layer was selected as three. The transfer functions of the hidden layer and output layer neurons were the hyperbolic tangent function and the pure linear function, respectively. A Bayesian network was employed in the training method to avoid over-fitting of the data sets. Before training the ANN, the training data were normalized suitably. In order to test the ANN model, all the experimental data were divided into a fitting set with 25 data points and a testing set with one data point. All combinations of 25 and one data points were used to train and test the ANN. Altogether, there were 26 cases being trained and tested, and the results were compared with the statistical model. The absolute value of the average prediction error of the ANN model was 0.13%, which was smaller than that of the statistical model (2.68%). Also the maximum of the absolute value of the prediction errors of the ANN model (9.70%) was smaller than that of the statistical model (38.05%). The standard deviation of the prediction errors of the ANN model (5.99) was also smaller than that of the statistical model (17.17), which implied that the prediction errors of the statistical model were more discrete than those of the ANN model. The ANN model yielded more accurate and stable prediction than the statistical model which showed poor stability. A reasonably good ANN model could be established with relatively few data points for predicting fibre diameter.

10.4.2 Prediction of filtration and strength characteristics of spun bonded nonwovens

ANN was used to model the relationship between the structural parameters and the filtration property of spun bonded nonwovens (Koehl *et al.*, 2005). The input structural parameters were fibre orientation ratio (MD/CD) in machine direction (MD) and cross-machine direction (CD), thickness, basis weight, fibre density, binder rate, total pore volume and basis weight uniformity. The output parameter was the filtration property. Some of the structural parameters such as the MD/CD ratio, total pore volume and basis weight uniformity were indirectly obtained from the image analysis. Other structural parameters were directly measured from the respective testers. A ranking

criterion was taken into account considering human knowledge of the product and data sensitivity criteria for selection of inputs. Then a generalized ranking criterion was selected from these two, for selection of structural parameters. The structural parameters were divided into two groups for the ANN model. One group used the general structural parameters similar to all different types of nonwovens (like spun bonded, needle-punched, spun laced, melt blown and others). These were termed public inputs. The other group included the more specific structural parameters for each types of nonwovens related to the manufacturing processes. Two kinds of ANN models were established: a general model, which used all the public structural parameters as inputs to the model, provided an estimation of filtration property; and the specific model, which integrated the use of the public and the more specific structural parameters, gave an estimation of filtration property. The prediction error of the specific model was lower than that of the general model.

ANN was used to model the relationship between the primary parameters and the measured secondary parameters for controlling the quality of spun bonded nonwovens. The primary variable was the minimum force necessary to pull apart a given size of the web, expressed as N/5 cm. Secondary parameters were thickness (mm), strength (N) and area weight (g/m^2) of the web. Seventy-one primary parameters were taken into consideration for training a neural network based on different parameters as per validation of the results. The back-propagation algorithm was used for the training; 80% of the data was used for training and 20% was used for validation of testing. With the results obtained in this work, product quality can be inspected at the frequency of the secondary measurements with an overall mean absolute percentage error close to 5%. To get a better result and to account for the change in process characteristics, the network needs to be retrained from the process data (Ressom *et al.*, 2000).

10.5 Artificial neural network modelling in thermally and chemically bonded nonwovens

Thermal bonding is achieved with the help of a heat process which uses low melt fibres, bi-component fibres and filaments, polymer melt, films, etc. The heat process can be calendering, embossing, ultrasonic bonding, hot air or radiant air bonding. Chemically bonded nonwovens are produced by bonding the fibres or filaments with chemicals. This can be achieved by the use of polymer emulsions, solvent or latex. Some of the polymers can be in powder, paste or film forms. The bonding can be done in one of the following ways: spray, foam, print or knife over roller coating. Chemically and thermally bonded nonwovens are used in the following application areas: wipes, interlinings, geotextiles, carpet backing, filtration, bedding and roofing materials, cover materials for agriculture, etc. Some of the ANN models in

predicting the air permeability, tensile properties, defect classifications and water permeability are discussed in the following sections.

10.5.1 Prediction of air permeability, strength characteristics and defect classifications in thermally bonded nonwovens and water permeability in chemically bonded nonwovens

ANN was used to model the relationship between the structural parameters and properties of the thermally bonded nonwovens (Chen *et al.*, 2007). Polyester fibre was used for the preparation of thermally bonded nonwovens. The structural parameters selected were fibre length, fibre linear density, total pore volume, basis weight uniformity, thickness, basis weight and fibre volume density. The output parameters were air permeability, strength and elongation at break in the machine direction (MD). These fabric properties were measured on an air permeability tester and an Instron tensile tester, respectively. Some of the structural parameters like basis weight uniformity were indirectly obtained from the image analysis. A ranking criterion was taken into account considering human knowledge of the product and data sensitivity criteria for selection of input structural parameters of the model. Then a generalized ranking criterion was selected from these two, for selection of structural parameters.

Multi-layered feed-forward neural network architecture with a back-propagation algorithm was used for the prediction of fabric properties (Chen *et al.*, 2007). The multi-layered neural network consisted of an input layer with five neurons, one hidden layer with two neurons and an output layer with one neuron. The transfer functions of the hidden layer and output layer neurons were the hyperbolic tangent and pure linear functions, respectively. To avoid over-fitting, a Bayesian network was employed in the training procedure. In order to test the ANN model, all the experimental data were divided into a training set with 17 data points and a testing set with one data point. All the combinations of 17 and one data points were used to train and test the ANN. There were 18 cases being trained, and the tested and average of the 18 results from ANN models were compared with the experimental data.

Based on the ranking criterion, five structural parameters, namely fibre volume density, thickness, basis weight uniformity, basis weight and total pore volume of nonwovens, were taken as the input parameters for the prediction of air permeability. Table 10.4 shows the error percentage between the experimental and predicted values of air permeability. The predicted values were the average of all 18 results. The average error of -0.78% shows the effectiveness of the ANN model. The input structural parameters for the prediction of strength at break were fibre volume density, fibre linear

Table 10.4 Results of ANN model: air permeability

Sample no.	Experimental value (l/m ² /s)	Predicted value (l/m ² /s)	Error (%)
1	1193.89	1079.78	-9.56
2	765.28	822.62	7.49
3	668.06	608.15	-8.97
4	488.61	442.18	-9.50
5	389.71	368.42	-5.46
6	364.72	336.18	-7.83
7	1698.00	1578.36	-7.05
8	1361.00	1493.41	9.73
9	930.00	969.49	4.25
10	715.00	679.42	-4.98
11	267.00	286.56	7.33
12	258.00	242.89	-5.86
13	756.00	825.37	9.18
14	722.00	767.87	6.35
15	360.00	324.87	-9.76
16	214.00	205.51	-3.97
17	187.50	204.74	9.19
18	131.00	137.96	5.31
Average error			-0.78

Source: Chen *et al.* (2007).

density, basis weight uniformity, total pore volume and fibre length. The average error was -0.88% between the experimental and predicted values of strength at break. Similarly, the input structural parameters for the prediction of elongation at break were fibre linear density, basis weight uniformity, fibre volume density, total pore volume and thickness of the web. The average error was -0.84% between the experimental and predicted values of elongation at break. In some cases the error between the experimental and predicted values was larger for all the predicted properties. This might be due to the small number of data sets considered in the ANN model and the removal of the some of the parameters by the ranking criterion, which might have affected the results. Nevertheless, the prediction ability of the ANN model was good (Chen *et al.*, 2007).

ANN in conjunction with the imaging technique was used for detecting defects in thermally bonded nonwovens (Payvandy *et al.*, 2008). Polypropylene fibre was used for the sample preparation. The box counting dimension was used as a feature extractor for defect detection and the back-propagation algorithm as defect classifier. The input information of the nonwoven images was reduced to the mean of pixel intensity, white pixel density and box counting dimension after the feature extraction. These properties of each image were fed to it as input parameters of the model. Non-defective, thick area, thin area and neps were taken as the output parameters of the model.

Multi-layered feed-forward neural network architecture with a back-propagation algorithm was used for defect classification (Payvandy *et al.*, 2008). The multi-layered neural network consisted of the input layer with three neurons, one hidden layer with six neurons and the output layer with four neurons. The sigmoid transfer function was used between hidden and output layers. A set of 30 input parameters were fed to the network. The network output was compared with the target. The error was calculated as the difference between the target and the network output. The overall success of the model in defect classification was 88%.

ANN was used to model the relationship between the structural parameters and the water permeability of chemically bonded nonwovens (Vroman *et al.*, 2008). A ranking criterion was taken into account considering the human knowledge of the product and data sensitivity criteria for selection of input structural parameters of the model. In this criterion, fuzzy logic was used to establish a good compromise or a fusion between these two uncertain and incomplete information sources for selection of structural parameters. Multi-layered feed-forward neural network architecture with a back-propagation algorithm was used for the prediction of water permeability (Vroman *et al.*, 2008). The input parameters of the model were basis weight, thickness, fibre density, total pore volume and basis weight uniformity. Another special structural parameter, namely the binder rate, was also added to the set of these five input parameters. Eighteen data sets were used to train and test the network. The average prediction error in water permeability given by this model was lower than that for the other ANN model.

10.6 Future trends

In spite of some published articles, the use of ANN in the field of nonwovens is still in its early stage. The main reason is probably the degree of variability in the materials and processing stages, which makes the prediction of desired properties a difficult task. Also, no benchmarking is yet available for any kind of nonwoven modelling. Application of other networks like support vector machine, tree network and pulse-propagation network needs to be explored. Other soft computing techniques like fuzzy logic and genetic algorithms also need to be explored in the future to control the processes more precisely and ultimately to predict the desired properties. User-friendly software needs to be developed which can be used easily by practitioners in the industry. Nevertheless, with the increasing use of soft computing tools in the field of nonwovens, a few years down the line it will be possible to come up with solutions in addressing the above challenges.

10.7 Sources of further information and advice

Further information on ANN is available from the following books listed in the reference section of this chapter: Beale and Jackson (1990), Bose and Liang (1998), Gurney (1997), Haykin (2004) and Hertz *et al.* (1991). The software packages Matlab and SPSS may also be used to obtain further information on ANN. For detailed information about nonwoven manufacturing processes and applications, readers are referred to Butler (1999) and Russell (2007), which are listed in the reference section.

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Abstract: This chapter discusses the modelling of the fitting alteration of garment pattern design according to the linguistic response of the wearer by fuzzy logic techniques. The garment pattern design process is a mapping between the three-dimensional garment surface and the garment flat pattern. The fitting alteration or the fine-tuning of the flat pattern is based on the fuzzy logic implementation to extract the fuzzy production rules according to the responses of the wearers. Future trends will see diversification to fuzzy-neural applications as well as the aesthetic aspects of the garment design.

Key words: garment pattern design, fuzzy logic, ease allowance, sensory response.

11.1 Introduction

Garment modelling is a very broad topic. It can refer to four aspects of the garment: (1) the three-dimensional formation of the garment from the flat garment pattern, (2) the engineering of the paper pattern for the functional aspect of the garment, (3) the sensory properties of the garment with respect to the wearer, and (4) the three-dimensional appearance of the virtual garment. In this chapter, the background to all four aspects of garment modelling will be introduced with a focus on the engineering of the paper pattern for the functional aspect of the garment. This focus in fact covers all four aspects, because when a garment pattern engineer designs a functional garment, one must consider the three-dimensional formation of the flat garment pattern and whether the garment is comfortable to wear, as well as its appearance.

From the historical perspective, the study of the three-dimensional formation of a garment can be traced back to the time of Tchebychev in 1878, who proposed to model a covering of any three-dimensional surface using a piece of woven fabric, and to trace out the boundary of the woven fabric. Hence, a collection of woven fabrics with various shapes can be found. This set of woven fabrics with specific shapes is called the flat garment pattern. Then Mark and Taylor (1956) proposed to develop a formula for a flat garment pattern wrapping a sphere. The formulation of the theory was accomplished by Samelson (1989). Samelson derived the condition on the curvature which determines if such a flat garment pattern can exist. Another method of isometric tree was proposed by Manning

(1980). In this method, a spine is defined along the surface. Then, a series of perpendicular branches extend from the spine along the surface, hence tracing the outline of the surface. The third method was introduced by Hinds *et al.* (1991), who defined a proportional radial coordinate system on the three-dimensional surface, with the origin to be set at the bust point, and the boundary defined at unit radius, so that any point on the surface can be expressed as (r, Θ) where r is restricted to 0 to 1, and Θ is restricted to 0 to 2π . This method is not designed for the formation of a three-dimensional garment, but rather for the design modification of the garment, matching the surface proportional coordinate to the flat Euclidean coordinate of the flat garment pattern. The original pattern flattening method using a polar coordinate system was invented by Efrat (1982). The fifth method, by Ng (1998), is to set up a bipolar geodesic coordinate system on the three-dimensional garment surface. Two isometric origins are mapped between the three-dimensional surface and the flat garment pattern. Then, all other points are mapped bijectively (one-to-one and onto) by preserving their geodesic distance between the points and both origins. Therefore, this method is partially isometric, because distortion cannot be avoided if the three-dimensional surface is not developable (i.e. zero curvature). This class of methods are geometry based, and their solutions are analytical.

There is another class of methods that is based on the finite element method, the finite shell method and the finite particle method (Breen *et al.*, 1992; Chen and Govindaraj, 1995; De Jong and Postle, 1977; Feynman, 1986; Freedman, 2007; Ghosh *et al.*, 1990; Gong *et al.*, 2000; Haumann and Parent, 1988; Hearle and Shanahan, 1978; House and Breen, 2000; House *et al.*, 1992; Hu and Teng, 1996; Huang, 1979; Kang and Kim, 2003; Kilby, 1963; Knoll, 1979; Koh *et al.*, 1995; Konopasek, 1980; Leaf and Anandjiwala, 1985; Lloyd, 1980; Love, 1954; Ly, 1985; Norton, 1987; Olofsson, 1964; Provot, 1995; Shanahan *et al.*, 1978; Simo and Fox, 1989; Tarfaoui and Akesbi, 2001; Teng *et al.*, 1999; Terzopoulos and Fleischer, 1989; Thingvold and Cohen, 1990; Yang and Zhang, 2007). The flat garment pattern is considered as a piece of woven fabric, and is subdivided into finite meshes or finite particles. Once the matching points of the meshes and particles are matched along the seam line and the hanging points are defined on the three-dimensional body, the simulation program can drape the virtually stitched flat garment pattern by minimizing the total energy of the garment. This class of method is now commercially available in many commercial garment pattern design computer-aided design software. In fact, the first system in the market was offered by Asahi Chemical of Japan, in the 1980s. At that time, such a system ran on a mini-computer with a mechanical three-dimensional contact-type body scanner and a parametric flat garment pattern design software. In the 1990s, Gerber Garment Technology acquired the licence from the Asahi Chemical Industry Co. Ltd of Tokyo

and sold it as APDS-3D*. In 2005, Gerber Garment Technology (CIMdata, 2005) licensed the Vstitcher† software from Browzwear. Finally, Lectra also developed their own three-dimensional drape simulation system. An important property of this class of drape simulation software is the fact that the software is intended to project a set of virtually sewn flat garment patterns to the three-dimensional virtual garment space, and returns critical points back to the flat garment pattern after alteration of the virtual garment. This class of method is designed for flat pattern designers who work in the sample room and hence follows a different design philosophy from the previous class of methods, which aimed at formulating the draping method (also known as the three-dimensional pattern design method) that is commonly used by fashion designers.

Furthermore, there are two minor classes of methods. The first is based on somatograph. Shen and Huck (1993) developed a flat pattern drafting method based on the somatographic data of the subjects. This class of method faces the challenge of robust and systematic procedure to improve the accuracy of the garment pattern. The second class of methods is based on statistics. Imaoka *et al.* (1989) and Imaoka and Masuda (2003) estimated the correlation of the shape of the garment and the measurements of the flat garment pattern. Wang *et al.* (2007) followed the same methodology in predicting the number of folds in the ladies' jacket.

Next, when the one-to-one corresponding relationship between the flat garment pattern and the three-dimensional garment has been established, there are two types of questions to be addressed. Firstly, does this set of patterns provide sufficient basic ease of movement to the wearer? Secondly, does this set of patterns provide the required appearance specified by the designer?

Again, the earliest study on the distribution of ease allowance can be traced back to the 1980s. Larmour (1988) studied best-fit garments for senior citizens based on body measurements. Prevatt (1991) asked subjects to perform a series of postures and evaluate their comfort level, while Burke (1994) also designed best-fit garments for senior citizens. Cho (2001) worked on the mobility of hospital gowns. These analyses are basically for finding the correlation between measurements and comfort level. Further examples are from the work of Ashdown and DeLong (1995), Chen (1987), Huck (1988), Ng *et al.* (2006) and Smith (1987) who analysed the relationship between range-of-motion and comfort levels with subjective responses using statistics. Tomita and Nakaho (1989) examined the structure of movement ease of pants, while Makabe and Momota (1991) focused on the upper limb motion and Hirokawa and Miyoshi (1997) worked on jackets.

* APDS-3D is a trademark of Asahi Chemical Industry Technology.

† Vstitcher is a trademark of Browzwear.

Finally, it is very easy to subjectively evaluate whether a set of patterns provide the required appearance specified by the designer. Objectively, although it is possible to measure whether a set of patterns can match the geometric appearance specified by the designer, it is extremely difficult to judge whether a set of patterns can match the silhouette specified by the fashion designer. This is a new area, because subjective evaluation of appearance involves aesthetic judgement, which is qualitative in nature and extremely complex to describe precisely.

In the rest of this chapter, the basic principles of garment modelling are introduced, followed by the modelling of garment alteration and comfort level using fuzzy logic. Then, the advantages and limitations are reviewed by comparing the fuzzy approach with other approaches. Finally, the foreseeable trend is anticipated based on the recent research results.

11.2 Basic principles of garment modelling

A garment is made up of fabrics, trimmings and accessories. The fabric must be cut into appropriate shapes and then be sewn up to form the garment. The function of trimming is to strengthen the shape and/or life span of the garment. Typically, in mathematical modelling of a garment, the researchers focus on the relationship between the flat garment pattern, which defines the shape of the fabric to be cut, and the three-dimensional garment, which has been sewn up. Such a model involves not only the shape, but also the mechanical properties of the fabric to be cut, such as fabric density, shrinkage, tensile strength and shearing, because once the garment is hanging on its own weight, it elongates, and the shape will change.

The first theoretical model describing the algebraic structure of the garment and flat pattern was proposed by Ng *et al.* (1995). In this theoretical framework, the relationship between garment and flat pattern forms a lattice structure, which can be used to prove two theoretical properties of garment sewing, namely (1) that the algebraic relationship between garment and flat pattern is a lattice structure; and (2) that the lattice structure of any garment is finite.

Next, the mathematical model of the bijective (one-to-one and onto) relationship between the three-dimensional garment and the flat garment pattern is a straightforward problem in differential geometry. However, the fine-tuning of the shape of the garment is non-trivial, and this is the entry point for the fuzzy logic formulation. After the discussion of the mapping, the shape definition and the fine-tuning of the shape are presented.

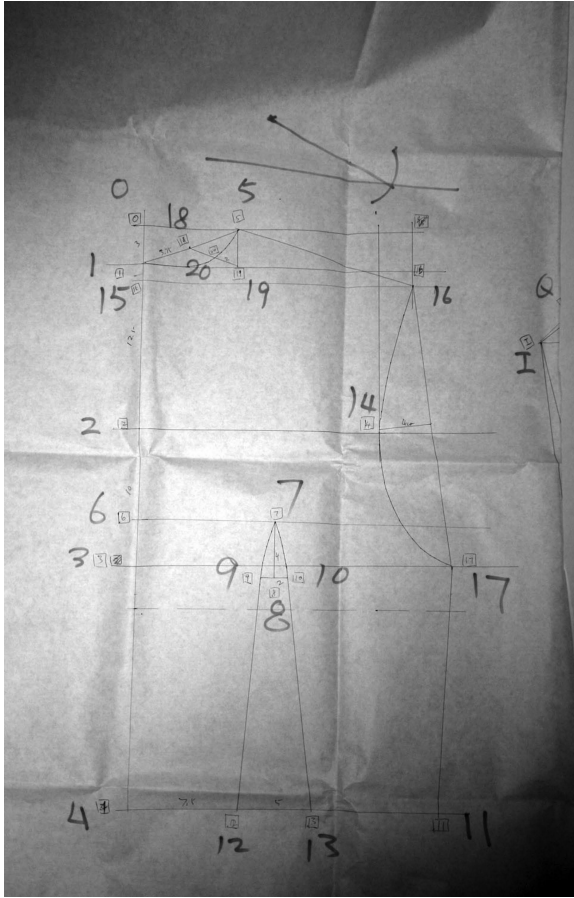
11.2.1 Mapping of garment pattern

The manual methods of creating the garment pattern are generally classified as the three-dimensional method (Jaffe and Relis, 2004; Joseph-Armstrong,

2008; Mee and Purdy, 1987; Newton *et al.*, 2004), commonly known as ‘draping’ or ‘modelling’, or the two-dimensional method (Aldrich, 2006, 2007, 2008, 2009; Bray and Haggard, 2003a, 2003b, 2003c; MacDonald, 2009; Ng, 2000; Rolfo *et al.*, 1991; Rosen, 2004), commonly known as ‘flat pattern’, which includes the techniques of ‘dart manipulation’, ‘cut and manipulate’, etc. Fashion designers typically put a piece of calico or muslin on the mannequin, fold out the garment, and trace back the outlines of the fabric pattern (Fig. 11.1). This is the three-dimensional method. Industrial pattern makers typically draw the flat pattern of a garment directly using the size measurements only (Fig. 11.2). The accuracy of this paper pattern



11.1 Draping of garment.



11.2 Flat garment pattern.

depends largely on the experience of the pattern maker and the formulae that are being used.

Mathematically, there are two classes of modelling methods, namely the variational method and the parametric method. In the variational method, one expresses the equations, or conditions, that define the garment, such as expressing the waist measurement as a constraint on the cross-sectional arc length of the waist. Hence, the solutions of these equations lead to a three-dimensional as well as a two-dimensional garment pattern. This method is similar to the draping method. In the parametric method, one expresses the flat pattern drawing procedure as a series of sequential and explicitly functional descriptions of the flat pattern. Hence, a set of two-dimensional garment patterns can be generated by a set of body measurements. This method is similar to the flat pattern method. In practice, the parametric

method is available in commercial software, such as Lectra, Gerber Garment Technology, etc. A quick analysis can review the differences between the two methods as in Table 11.1.

11.2.2 Defining the garment shape

A garment G (atlas) is composed of a set of garment pattern pieces (local charts). Each flat garment piece F_m is a closed shape that is defined by a set of regular points. The regular points on the boundary of the closed shape are connected pairwise by a curve or a straight line (a degenerated curve). Each curve segment is defined by two end points, which are regular points, and one or more shape control points (control vertices). Furthermore, there are many special matching points, which are regular points, with the matching point on another pattern piece, so as to provide a method of controlling the virtual sewing length as well as the quality of the physical garment. Hence, a garment piece is a set of points with two-dimensional coordinates s_{mi} and type attributes t_i in the form of $p_{mi} = \{s_{mi}, t_{mi}\}$:

$$G = \{F_m\} \quad 11.1$$

$$F_m = \{p_{mi}\} \quad 11.2$$

$$p_{mi} = \{s_{mi}, t_{mi}\} \quad 11.3$$

$$s_{mi} = \{x_{mi}, y_{mi}\} \quad 11.4$$

$$t_{mi} = \{\text{'regular'}, \text{'control vertex'}, \text{'matching point'}\}, \\ i = 1, \dots, N_m; m = 1, \dots, M \quad 11.5$$

where there are M flat garment pattern pieces, and each F_m has N_m regular points.

The sewing seams are defined as a mapping of regular points among different flat pattern pieces. A seam of more than two patterns being sewn together can be considered as a composite mapping of two pattern pieces

Table 11.1 Comparison of variational method and parametric method

	Variational method	Parametric method
Corresponding manual method	Draping	Flat pattern
Complexity in finding solution	Very complex	Simple
Uniqueness of solution	May not be unique	Unique
Efficiency	Low	High
Accuracy	High	Good
Style based	Yes	Yes
Commercial availability	No	Yes
Ease of converting into soft computing application	Difficult	Easy

at a time. So, a virtually sewn garment G_v is a collection of garment pieces and a virtual sewing map W :

$$G_v = \{\{F_m\}, W\} \quad 11.6$$

$$W = \{\{p_{mi}, p_{mk}\}\}, i, k = 1, \dots, N_r \quad 11.7$$

with t_{mi} and t_{mk} not equal to 'control vertex', where there are M flat garment pattern pieces and each F_m has N_r regular points. It should be noted that the sequence of matching of points along a seam has directional implication, for example $W_1 = \{p_{11}, p_{21}\}, \{p_{12}, p_{22}\}, \{p_{13}, p_{23}\}$ is different from $W_2 = \{p_{11}, p_{23}\}, \{p_{12}, p_{22}\}, \{p_{13}, p_{21}\}$, which is a twist of W_1 .

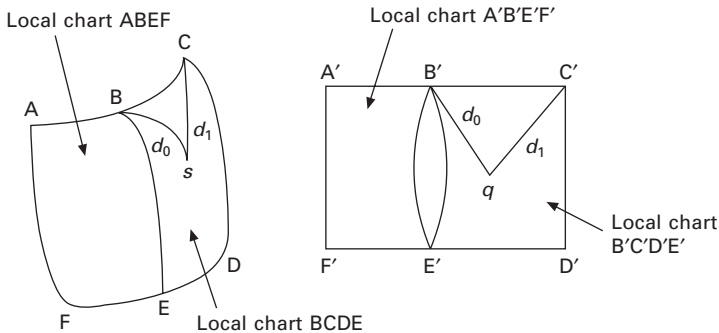
Once the three-dimensional virtual garment is sewn up, it becomes a surface. Each point on the garment surface can be mapped to a corresponding image point on the flat pattern piece bijectively. A proposed isometric mapping of hybrid-sum (Ng and Yu, 2006) can be defined as follows.

Consider p_0 (point B), p_1 (point C) and r_0 (point B'), r_1 (point C') (Fig. 11.3) to be reference points on the pattern panel, P^2 , and surface patch, P^3 , respectively; and s to be the point on P^3 to be mapped to the point q on P^2 . $\text{GEO}(r_0, s)$ is the shortest path P^3 .

$$\begin{aligned} & \text{HYBRID-SUM} (p_0, p_1, \text{GEO}(r_0, s), \text{GEO}(r_1, s), \\ & \text{ORIENTATION3}(r_0, r_1, s)) \\ & = \{q \in P^2 \mid \|p_0 - q\|_2 = \text{GEO}(r_0, s) = d_0; \|p_1 - q\|_2 \\ & = \text{GEO}(r_1, s) = d_1; \\ & \text{ORIENTATION3} (p_0, p_1, q) = \text{ORIENTATION3}(r_0, r_1, s)\} \quad 11.8 \end{aligned}$$

where

$$\begin{aligned} \text{ORIENTATION3}(r_0, r_1, s) &= \{1: \text{if } s \text{ lies above the geodesic;} \\ & 0: \text{if } s \text{ lies on the geodesic;} -1: \text{if } s \text{ lies below the geodesic}\} \quad 11.9 \end{aligned}$$



11.3 Mapping of points between 2D and 3D.

and $\|\cdot\|_2$ is the Euclidean distance and GEO is the geodesic on the garment surface.

There are many ways to compute this GEO function, for example if the surface $S(u, v)$ is parameterized by u and v , and the geodesic is parameterized in the form of $\alpha(t) = (u(t), v(t))$. The coefficients Γ_{jk}^i are the Christoffel symbols with explicit form (available in the book by Do Carmo, 1976). The first derivatives of u and v with respect to t are indicated by u' and v' , and the second derivatives are indicated by u'' and v'' . One can find the geodesics by solving equations, either analytically or numerically:

$$u'' + \Gamma_{11}^1 (u')^2 + 2\Gamma_{12}^1 u' v' + \Gamma_{22}^1 (v')^2 = 0 \quad 11.10$$

$$v'' + \Gamma_{11}^2 (u')^2 + 2\Gamma_{12}^2 u' v' + \Gamma_{22}^2 (v')^2 = 0 \quad 11.11$$

Ng (1998) used Ritz's method to calculate the shortest arc length on the surface, which is another way of defining the geodesics. Such a method is numerical.

There are many other methods which are collectively known as cartographic methods (Lock, 1997). However, all these methods unavoidably induce distance distortion or area distortion, unless the garment surface is developable (Farin, 2001).

11.2.3 Fine-tuning of garment shape

The fine-tuning of the garment shape depends on the concept of 'ease allowance'. There are three types of ease allowance, namely basic ease (also known as static ease or standing ease), movement ease (also known as dynamic ease) and styling ease. Basic ease is the extra spacing between the garment and the wearer for basic movement, such as standing, sitting, walking and breathing. Movement ease is the spacing between the garment and the wearer for the wearer to perform extreme postures, such as raising arms, ducking, stretching and climbing (Fig. 11.4). Styling ease is the extra spacing between the garment and the wearer for forming the required silhouette specified by the fashion designer.

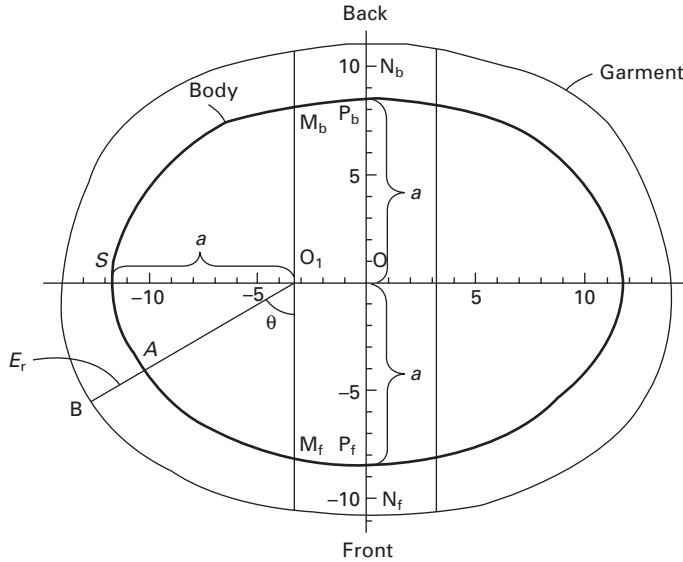
The concept of ease allowance can be confusing, because traditionally there are two commonly used systems. In the first system, which is used in the apparel industry and tailoring shops, ease allowance is defined as the difference in linear measurement of the body and garment. This so-called 'linear' measurement is linear in the sense that if the body waist measurement is 32 inches and the garment waist measurement is 32½ inches, the ease allowance is defined as the difference, which is half an inch. This definition greatly simplifies the information that the ease allowance should have provided. In practice, the pattern designer and the tailor distribute the ease allowance into the flat garment pattern. For example, if the garment is a T-shirt with only front and back panels, the pattern designer will divide



11.4 Example of posture.

the half an inch into one-eighth of an inch to each of the four seams (i.e. two seams for each side of the front panel, and two for the back panel) that make up the waist.

In the second system, which is used in research work, radial ease allowance (REA) is defined as the radial difference between the body and garment. This so-called 'radial' measurement is radial in the sense that it is measured from the shifted origin at a specific angle along the cross-sectional plane (Fig. 11.5) (Miyoshi and Kim, 1999). Firstly, the global centre O in the cross-section is located, which is the intersection of the half-width and half-thickness of the body. Then the cross-section of the waist is divided into three regions: two side parts similar to a semicircle and one mid-part similar to a rectangle. O_1 is located at a distance of the half-thickness (i.e. a) from the lateral side of the body, and this is the centre of the left semicircle. It gives a shifted radial coordinate system. O_1A is perpendicular to the tangent vector of the cross-section at point A . O_1B is perpendicular to the tangent vector of the cross-section at point B . So, the radial ease E_r is the difference between O_1A and O_1B . For the region from O to O_1 , the curvature of both curves M_fP_f and M_bP_b is relatively small. The radial ease allowances are determined as the distances P_bN_b and P_fN_f on the vertical axis respectively. This definition is indispensable for motion analysis, such as the determination of movement ease, because different amounts of movement ease in different directions imply different levels of restriction of movement. This definition is related to the linear definition by integrating, or summing up, the arc length elements along the boundary of the cross-section of the garment.



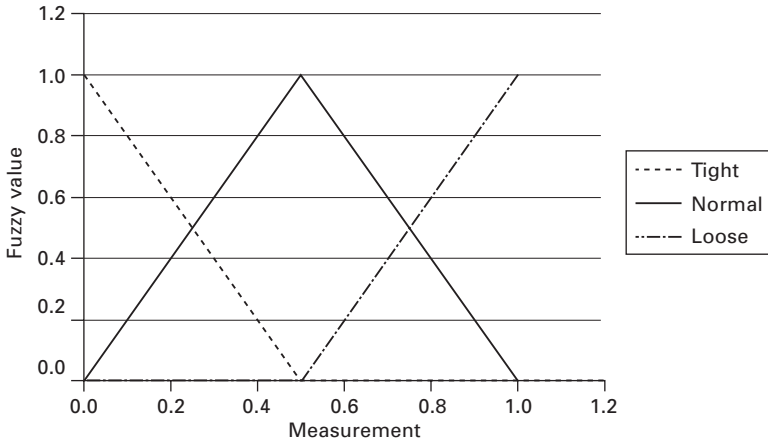
11.5 Radial definition of ease allowance.

11.3 Modelling of garment pattern alteration with fuzzy logic

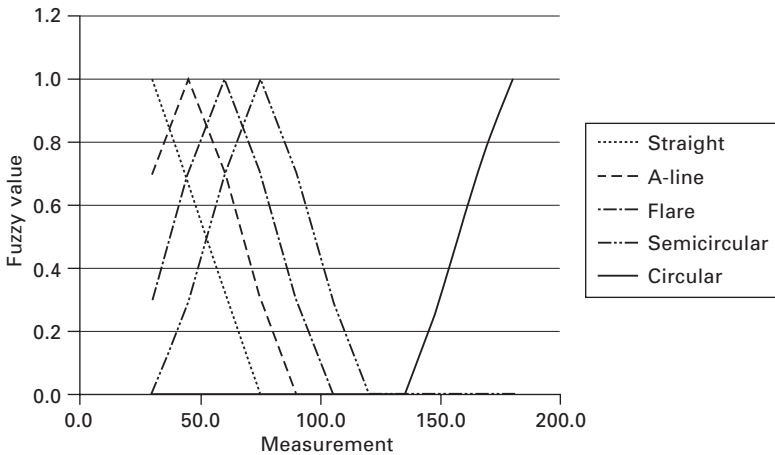
The main ideas in modelling garment alteration with fuzzy logic can be classified into three data domains: (1) amount of body measurement or ease allowance, (2) fabric properties, and (3) sensory response of the wearer or the comfort level. Once these domains are defined, the next step is to create production rules.

11.3.1 Defining universal and membership sets

The construction of the linguistic variable sets of body measurements can be achieved simply by using the smallest body measurements in the size table as 'min measurement' and the largest body measurements as 'max measurement'. Similarly, one can define the basic ease allowance as 'min basic ease' to 'max basic ease', monotonically increasing. The fuzzy comfort level of a garment with respect to different fitting requirements at the bust is expressed in Fig. 11.6. Similarly, one must define the comfort level with respect to the monotonically decreasing movement ease allowance. Then, one can define the styling ease as 'style A' to 'style B', where the minimum value of the styling ease corresponds to style A and the maximum value corresponds to style B. An example is shown in Fig. 11.7. Here, there is a hidden assumption which must be satisfied before this fuzzification process



11.6 Comfort level of different fitting requirement at bust (min. basic ease = 1 cm; max. basic ease = 5 cm).



11.7 Comfort level with respect to styling ease (Style A: straight line dress; Style B: circular dress).

is valid, namely the style transition must be ordinal. Next, the construction of the linguistic variable sets of fabric properties can be accomplished by using the database of the KES properties of textiles. For example, the minimal and maximal tensile strain values of any particular class of fabric can be decoded as ‘very stretchy’ and ‘very rigid’ respectively. Finally, the linguistic variable sets of the comfort level can be defined from ‘too uncomfortable to be worn’ to ‘too comfortable to feel the presence of the garment’, or simply as ‘very uncomfortable’ to ‘very comfortable’. Initially, all membership functions can be triangular.

11.3.2 Translating expert knowledge to production rules

Much of the expert knowledge, in the form of ‘condition–action rules’, relating to pattern alteration are based on the deviation of the body shape from the standard shape of a live model or mannequin. For example, when a gentleman has a stooped back, the length of the centre back measurement is longer than the average value. So, the back bodice must be cut-and-open along the back chest level, so as to increase the centre back length without affecting any other measurements (Aldrich, 2006). Such knowledge can easily be translated into a production rule:

Rule i : IF *condition_i* THEN *action_i* 11.12

However, the application of one production rule does not mean that the mission is accomplished. In many cases, follow-up actions are needed because the pattern pieces are supposed to be sewn together, and each pair of sewing seams must also be altered so that they can fulfil the sewing condition. For example, when the armhole of the bodice is lowered, the circumference of the armhole increases, and the arc length of the sleeve head must also be lengthened to match the increase, because they will be sewn together. Such a relationship must also be modelled by activating additional production rules, and can be incorporated as part of the actions. Most importantly, if there is no existing expert knowledge to be transformed, one must extract the knowledge from the experimental data.

11.3.3 Extracting knowledge to production rules

There are many fuzzy rule extraction methods. A straightforward method is based on learning the results of experiments under expert advice (Chen *et al.*, 2003). The steps of rule extraction are defined briefly as follows:

1. Choose the fuzzy inputs X and outputs Y .
2. Define their universal set and fuzzy set.
3. Define the linguistic variables and their membership functions.
4. For an input i_x one can use the membership function of input X to find out which linguistic variable IL_i it belongs to. The corresponding output O_y is associated with the linguistic variable OL_j by the membership function of output Y .
5. Take the linguistic variable of the fuzzy input and the corresponding linguistic variable of the fuzzy output. One can extract a fuzzy rule:

IF I_x is IL_i THEN O_y is OL_j 11.13

As an example, a fuzzy garment design system for parts which adjusts the ease allowance according to the textile properties can be designed. The fuzzy inputs are (1) tensile strain, (2) front body rise, (3) hip-to-knee and (4) front

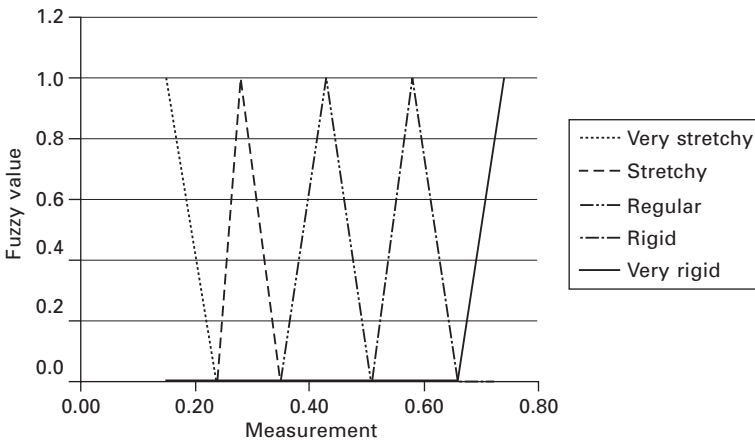
hip arc, while the fuzzy output is the aggregate ease allowance, which is the sum of the basic ease allowance and the dynamic ease allowance. The tensile strain is the input mechanical properties of a class of fabric. The front body rise, hip-to-knee and front hip arc are the key body measurements defining the pants.

Next, the linguistic variables of the tensile strain are defined as {'very rigid', 'rigid', 'average', 'stretchy', 'very stretchy'}, matching the normalized KES data of {0, 0.25, 0.5, 0.75, 1.0}. The membership value is also confined to the closed range of [0,1]. Similarly, the linguistic variables of the body measurement are defined as {'very small', 'small', 'average', 'big', 'very big'}, matching the normalized body measurements to {0, 0.25, 0.5, 0.75, 1.0}. The membership value is also confined to the closed range [0, 1]. Hence, it is important to scale the actual data to these normalized data before any further processing. The corresponding fuzzy membership sets of tensile strain and hip-to-knee are shown in Figs 11.8 and 11.9 respectively. The normalization is an indispensable step to ensure the stability of the system.

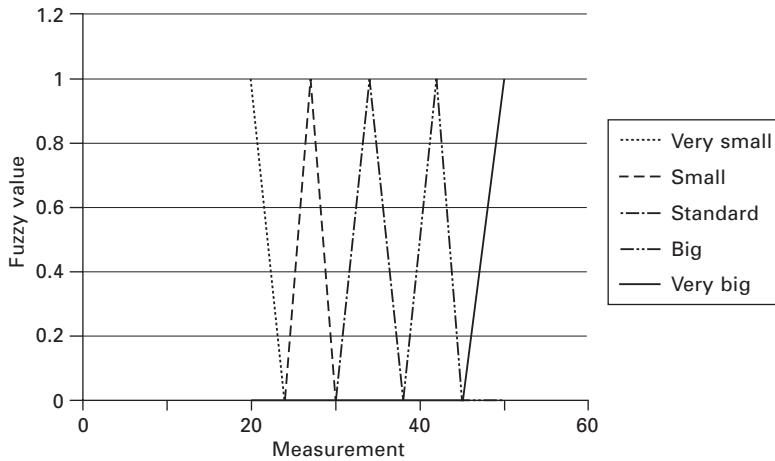
Then, a set of experimental data is collected. The measurements of all the inputs and outputs are recorded in the respective physical units. These data are then normalized accordingly, and mapped to the fuzzy linguistic variables. Finally, the production rules can be extracted from Table 11.2 by considering it as a parse tree. Then the first rule is 11.14 and so forth:

IF FBR == 'high' && FHA == 'very big' && HTK
 == 'long' && TEN == 'average' THEN AE := 'very big' 11.14

Once the modification rules are ready, one can then extract them based on



11.8 Membership function of tensile strength.



11.9 Membership function of hip-to-knee.

Table 11.2 Extraction of production rules using the parse table

Code	IF				THEN
	FBR	FHA	HTK	TEN	AE
Rule	Front body rise	Front hip arc	Hip-to-ankle	Tensile	Aggregate ease
1	high	very big	long	average	very big
2	high	very big	long	stretch	big
3	average	average	average	rigid	average
4	average	average	average	stretch	small
5	average	small	short	rigid	small
6	average	small	short	stretch	very small

the subjective response of the wearers, according to their comfort level (Chen *et al.*, 2008).

In this case, there is an additional piece of information, the comfort degree (CD) that must be collected from the wearers using questionnaires. Each wearer performs a standard set of movements (or postures) and responds with the comfort levels for wearing garments with different amounts of ease allowance. Taking one posture at a time, one can combine the CD, $\{z_i\}$, with the body measurements $\{x_{ij}\}$ to form an input/output data set (IODS) in the form of $\{(\{x_{ij}\}; z_i)\}$, where i runs from 1 to Q subjects and j runs from 1 to R reference body measurements. The required fuzzy rules can then be extracted by using the method of Mamdani and Assilian (1975). The corresponding membership functions can be constructed using the c -means clustering method (Bezdek, 1981).

Then, one needs to aggregate the ease allowance of different movements.

One appropriate method was proposed by Yager (1988), in which an ordered weight averaging (OWA) operator of dimension H maps the body parts (Bp_i) and movements (M_j), assigning a set of normalized weighting factors $\mathbf{W}$ to the individual ease allowance $y(Bp_i, M_j)$ vectors describing the ease allowance of all movements:

$$\text{OWA}(\{y(Bp_i, M_j)\}) = \mathbf{W}^T \mathbf{B}, i = 1, \dots, R; j = 1, \dots, H \quad 11.15$$

where matrix $\mathbf{W}$ is the weighting factor and $\mathbf{B}$ is the monotonically decreasing ordered values of the largest values of the ease allowance with respect to each movement, i.e. $\mathbf{B}(1)$ is the largest ease allowance and $\mathbf{B}(H)$ is the smallest ease allowance, and $\mathbf{B}(u) \geq \mathbf{B}(v)$ for all $u, v = 1$ to H . Hence, the choice of $\mathbf{W}$ has a direct impact on the final silhouette of the garment, from loose fit ($\mathbf{W}(1) = 1; \mathbf{W}(u) = 0; u = 2$ to H) to tight fit ($\mathbf{W}(H) = 1; \mathbf{W}(u) = 0; u = 1$ to $H - 1$). A full numerical example can be found in Chen *et al.* (2009).

11.4 Advantages and limitations

The fuzzy logic method has many inherent advantages, such as (1) translation of vague human description to fuzzy linguistic variables, (2) translation of human expert knowledge to production rules, (3) automatic extraction of knowledge and (4) efficient run-time performance. Moreover, when this method is compared to other artificial intelligent methods, such as artificial neural networks, one can better understand the superiority of using fuzzy logic.

Yet, the advantages are not unlimited. In this section, an argument is presented to show that a holistic approach is indispensable in clarifying some abstract and complex qualitative descriptions of the world. In particular, fashion design focuses on the aesthetic aspect of a garment, rather than the functional aspect.

11.4.1 Advantages

The fuzzy logic approach to the garment pattern design problem is superior to the traditional methods of using an engineering approach, such as the finite element method or differential geometry, because in practice, such as in a fitting session, fashion designers have difficulties in specifying their requirements in the same way as an engineer because of their different training route. A fuzzy set is an appropriate solution to translate their comments according to the linguistic variables.

Next, the fuzzy Logic approach is superior to the back-propagation artificial neural network (ANN) approach in many ways. Firstly, the construction of the ANN requires a large amount of data. Secondly, if only one ANN is used to derive the ease allowance, each output position of the regular

point must depend on a large number of body measurement inputs as well as fabric properties. The training of such a complex ANN will be difficult; in particular, a very large amount of learning data must be provided. Even if more than one ANN is used, such as one ANN for calculating the ease allowance and another for calculating the output position, the complexity is not significantly reduced. Thirdly, each ANN solution can correspond to only one garment of a specific style, so it is very difficult to generalize the results if one uses the ANN approach.

11.4.2 Limitations

There are two classes of limitation. The first class is related to the domain and scope of the linguistic variables, while the second class is related to the production rules.

The first step in modelling is to define the scope and the corresponding fuzzy set. Typically, the adjectives that are used to describe the fitting of a garment can be very vague. For example, 'tight fit' and 'loose fit' are ordinal, but 'sloppy' may mean that the fitting is very loose and uneven. Similarly, some adjectives that are used to describe the silhouette of a garment can be complex. For example, 'hour-glass' and 'pear-shaped' silhouettes can be expressed in terms of the ratio between bust, waist and hip measurements, but 'Dior's New Look' describes not only the silhouette of the dress, but also the silhouette of the hat, as a whole (*Fashion-era*, 2009a). Special care must be taken in dealing with such terms.

Another difficulty in defining the scope of the fuzzy set is the ambiguity of the adjectives or style names holding multiple meanings. For example the 'peasant dress' by Christian Dior takes up the 'A-line' silhouette (Chickdowntown, 2009), while other people define it as having an 'hour-glass' silhouette (Probertencyclopedia, 2009). The reasons for such ambiguity can be very complex, such as tradition, evolution of design, etc. A standard way to solve this problem is to use additional qualifiers to differentiate the ambiguous terms.

Thirdly, even if these adjectives concerning fitting and silhouette can be managed by using additional qualifiers, there is still another aspect of the pattern – the aesthetics of the final garment to be produced. Unlike the adjectives describing the fitting and silhouette, the quality of aesthetics is not a simple attribute in any respect. It is a holistic evaluation of the appearance of the garment. For example, a garment of Victorian beauty certainly means: (1) the silhouette of the garment belongs to one of the common styles in the Victorian period; (2) the fitting of the garment conforms to historical knowledge of fitting in the Victorian period; and (3) the design of the garment must resemble the essence of the type of beauty that people of the Victorian period were looking for. One can argue that lace bertha

neckline, silk flowers, froths of tulle and pleated gauze trims, detachable false under-sleeves, S-bend silhouette, bell-shaped skirt, etc., are the essence of Victorian beauty (*Fashion-era*, 2009b). Yet, these are only the physical design elements – the materialistic clue to the essence. The essence is the aesthetic movement, which is the differentiation of expensive upper-class dresses from the industrially made imitations of lower-class dresses.

The Aesthetic movement which they led was a revulsion to what they saw as ugly machine made products of the Industrial Revolution and to certain artifacts seen at the Great Exhibition of 1851. This ranged from a distaste felt for the ugliness of false veneers to the crudeness of aniline dyes and the over working of Victorian imagery. It ignored the fact that those on low incomes wanted to be able to have cheap goods that imitated upper class elegance and which could only be made by cheap mass methods.

Aesthetic dress may also have been a revulsion to the over use of the sewing machine which allowed excessive embellishment of dresses simply because it could achieve over trimming more easily. (*Fashion-era*, 2009c)

Now, it should be apparent that Victorian beauty is more than just the materialistic design elements. It is the spirit of differentiation of classes that makes the Victorian dress beautiful and long-lasting. Even today, the Victorian spirit is reviving through *haute couture*. The ultimate challenge is whether the concept of aesthetics can be modelled by fuzzy logic or other artificial intelligence methods.

Then, the production rules must be defined. Traditionally, pattern designers accumulated their experience, much of which was recorded in publications (Aldrich, 2006). It is a straightforward procedure to encode such expert knowledge into a fuzzy pattern design system which can produce a pattern. Recently, new research work has been completed to extend the possibility of alteration by self-extraction of knowledge instead of by known expert knowledge.

Another class of limitation is the availability of the expert knowledge. Almost all existing expert knowledge that came directly from human experts has very limited scope of application. There are many other situations and considerations that have not been covered by this set of existing knowledge, for example how to change the silhouette of an A-line skirt to a round-table skirt, or even more dramatically, how to dismantle a shirt and to recombine the pieces into a skirt. Another example is the lack of production rules relating the dynamic posture or movement of the wearer to the garment pattern in the form of known expert knowledge. Furthermore, there are unlimited possibilities in terms of styles and sizes. To date, there is no single fuzzy logic system that can handle this problem, so knowledge extraction becomes the hope of the future.

11.5 Future trends

There are two diverging paths that could be taken by garment modelling using fuzzy logic. The first path is the continuation of the modelling of the functional and engineering aspects of garments, such as ease determination, movement restriction, comfort level, silhouette creation, drapability, etc. The application of the fuzzy-neural system is certainly the next sensible move in this direction.

Another path is the modelling of the beauty of the garment. The aesthetic quality of a garment is an important aspect of fashion. Such aesthetic quality is typically linguistic in nature and abstract in the sense that it is associated with concepts which may not be ordinal.

At the same time, there is a major challenge to researchers to unite the computing and aesthetic aspects. To date, much effort has been devoted to applying the aesthetic concepts to the programming practice (Fishwick, 2006). For example, the design concept of 'deconstruction and reconstruction' can readily be adopted by programming practice to deconstruct large procedures into atomic procedures and then recombine them to form a different program architecture. The room for improvement in this area is unlimited and will bring eye-opening changes to the future of soft computing.

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Abstract: Thread need by the needle within the take-up disc zone of the sewing machine is analysed. The dynamics of the needle thread determined by the multibarrier frictional structure are solved by means of both genetic algorithms and classical programming. We simplify the stitch tightening to the 2D plane problem. The first phase is the elongation of the needle thread without feeding of the thread portion which is stopped by the spring. The mass is discretized in one point. The mathematical model contains a second-order differential equation and is solved by means of approximation methods. The second phase is the introduction of a new portion of needle thread.

Key words: sewing machine, take-up disc, needle thread dynamics, stitch tightening, genetic algorithms.

12.1 Introduction

The main goal of this chapter is to analyse the thread need of the needle by means of the thread geometry on the frictional barriers within the take-up disc zone. The take-up disc is a multibarrier frictional structure consisting of a variable number of barriers and different conditions. It is necessary to determine the dynamics of the needle thread portion. The conditions of thread control on the frictional barriers are analysed to formulate the thread control curve within the working zone of the take-up disc. The problem can be solved by means of different methods, for example genetic algorithms. We introduce the set of genotypes describing the location of randomly generated frictional barriers. The fitness function should be minimized, and the correlation between the theoretical configuration of barriers and the real take-up disc is evaluated. The alternative method is classical programming. The thread length can be determined as the geometrical distance between the active frictional barriers of the take-up disc. The number and sequence of the frictional barriers of the take-up disc should be also analysed. The predefined coordinates of stationary points and variable mobile barriers are introduced, and the thread length is the solution of the plane problem.

We next have to analyse the dynamics of stitch tightening. The needle

thread is elongated without feeding the next portion because the thread is stopped by the spring. The mass of the thread is discretized in one point situated within the stitch formation zone. The basic correlation is a second-order differential equation with respect to the acceleration of the discretized mass. Supplementary correlations of the problem are formulated by means of basic physical phenomena, i.e. friction, angle of contact, thread elongation and structural geometry. The set of equations is solved by means of approximation methods. The second phase of stitch tightening is the introduction of the new part of the needle thread.

12.2 Dynamic analysis of different stitches

The mechanism controlling the motion of the thread should be introduced into the formation process of the machine stitches, because the thread length that is necessary for stitch link formation changes several times in relation to the basic length within the analysed stitch. The thread is subjected to the fatigue load of the different barriers introduced, as well as the barriers of the take-up system.

Different solutions for the take-up mechanisms within the sewing machine are determined by the different tools inserting the threads into the stitch link (needles, bobbin hooks, interlacers), as well as by the structure of the stitch link. We can also introduce the stitches of both open and closed interlacements. The most important consideration is that the take-up mechanism of the needle thread within the stitch of the closed interlacement cooperates with the bobbin hook.

The structure of the take-up mechanism is independent of the stitch created by the sewing machine. The take-up mechanism of the needle thread within lockstitch machines has been modified over the years, the main reason being the efficiency requirements of sewing machines.

The test results of the stitch formation zone published in the literature do not contain any information concerning the take-up mechanism specifically for lockstitch machines. The take-up mechanism plays a complex role in connection with the bobbin hook and the dynamics of the stitch tightening (drawing an interlacement into the material). This has a significant influence on the stitch formation process and disturbances of that process, which can lead to the excessive breakage of thread and to undesirable properties in the stitch.

The stitch formation process is determined by the lockstitch formation, i.e. mainly during the making-up of textiles. The interlacement within stitches such as the double chainstitch is located on the surface of the connected materials. The interlacement is not introduced within the textile materials. There is no significant mathematical and technological correlation between the basic stitches.

12.3 Sources of information

The main function of the take-up mechanism of the lockstitch sewing machine is to create a stitch, together with the needle and the bobbin hook. Thus, the problem can be solved by means of different computer software applications. The main difficulty is designing a machine with an optimal number and configuration of frictional barriers. The problem has been discussed by a few authors: Więźlak and Elmrych-Bocheńska,^{17,18} Krasowska *et al.*^{10,11} and Korycki and Krasowska.¹² The complex interactions that take place at the fabric/machine interface have become the focus of a new scientific discipline, 'intelligent textile and garment manufacture'. The optimization of sewing machine settings is one of the important requirements of textiles and sewing machines, *cf.* Stylios and Sotomi.¹⁵ The problem can be solved by using the neuro-fuzzy control system, *cf.* Stylios and Sotomi.¹⁶

Many authors analyse and optimize the material characteristics of the thread introduced into a material package. Jaouadi *et al.*⁸ provided a rapid and accurate method of predicting the amount of sewing thread required to make up a garment. Hui *et al.*⁷ investigated the use of artificial neural networks to predict the sewing performance of fabrics. The purpose is to study and verify these techniques, which could emulate human decisions in the prediction of sewing performance. The extended normalized radial basis function neural networks were used by Hui and Ng⁶ to predict the sewing performance of fabrics in apparel manufacturing. This method was compared with the traditional back-propagation neural networks. The construction of an integrated tool consisting of a neural network and subjoined local approximation technique for application in sewing processes was discussed by Jeong *et al.*⁹ The specific application of this tool is selecting optimal interlinings for woollen fabrics.

The thread on the frictional barrier is subjected to the reaction forces of the mass discretized in the selected points. A simulation of forces acting in model yarns transported through the drawing zone was analysed by Włodarczyk and Kowalski.¹⁹ This model is characterized by two random variables: the length of yarn segment and the yarn's drawing rigidity. Włodarczyk and Kowalski²⁰ analysed the forces acting in a thread of random variable visco-elastic rheological properties, which is displaced through a model of the drawing zone. The variability of tensions in the displaced threads is caused by technological conditions and the non-uniformity of mechanical properties. Lomov¹³ proposed an algorithm for the computation of the maximum needle penetration force, which introduces the direct dependence of the penetration force on fabric structural parameters, and warp and weft geometrical mechanical properties. Alagha, *et al.*¹ compared the effect of sewing variables and fabric parameters on the shrinkage of chainstitch by means of the conventional method and positive feed. Ferreira *et al.*³ studied

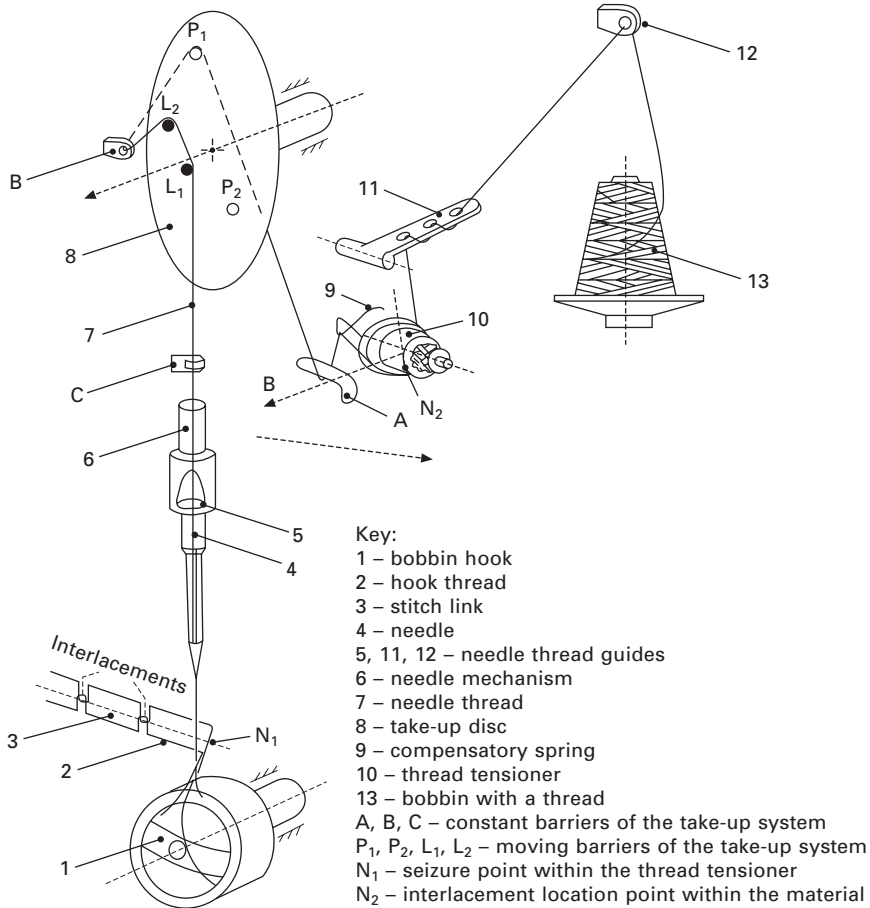
the thread tensions on a lockstitch sewing machine within the needle and the bobbin thread simultaneously. A knowledge-based and integrated process of planning and control was presented by Carvalho *et al.*² in relation to the most important mechanical effects of the sewing machine.

12.4 Thread need by needle and bobbin hook

12.4.1 Physical model of thread distribution

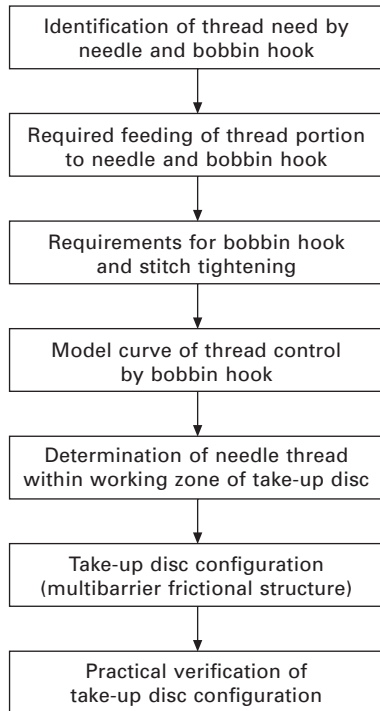
Let us first discuss the physical model of the take-up disc. The problem is defined by the characteristics of the take-up mechanism of the lockstitch sewing machine with closed stitch interlacement. The stitch is created by the needle and the bobbin hook in the two-phase working cycle of the mechanism: (1) the thread is fed to the needle and the bobbin hook; (2) the thread of the bobbin hook is supplied, which ends in the stitch tightening and creates the interlacement. In physical terms, the take-up disc (Fig. 12.1) is the multibarrier frictional structure. The crucial difficulty is creating the thread control curve according to the technological requirements of the needle and the bobbin hook. The stitch tightening process is connected with the interlacement formation within the material package, as well as the interactions between the disc and the needle thread. Thus, there are some factors influencing the dynamics of the thread need by the needle and the bobbin hook, for example the configuration of the stationary and mobile frictional barriers of the take-up disc, and the thread capacity control in the formation of the variable length of thread during the stitch link formation, *cf.* Krasowska *et al.*¹⁰ Consequently, we design the configuration of the take-up mechanism by controlling the needle thread capacity. The feeding of thread to the needle during the stitch link formation is a continuous process for both the prescribed stitch length and the material package thickness. The basic idea is to create a thread control curve for the take-up mechanism in order to solve the thread need by the needle and the bobbin hook, *cf.* Krasowska *et al.*¹¹ We create different configurations of frictional barriers for the take-up disc, and describe the control stages of the take-up mechanism, corresponding to the specific wearing properties of the textiles.

In order to determine the take-up configuration for the assumed thread control curve, we have developed the special software ‘Take-up disc 2.0’, described in the C++ environment, and supported additionally by the components of the standard library VCL Borland. The design algorithm of the take-up prototype is based on genetic algorithms (Fig. 12.2) and contains (1) identification of the thread need by the needle and the bobbin hook, (2) modelling of the thread control curve, (3) determination of the take-up configuration, and (4) evaluating tests of the take-up mechanism in assumed dynamic conditions.



12.1 View of the take-up disc in the lockstitch machine.

The take-up mechanism configuration that is obtained is characterized by the number and location of the stationary barriers (A, B, C) and the mobile barriers (P_1, P_2, L_1, L_2): cf. Fig. 12.3. We have just applied two different descriptions of location. Stationary barriers are described in terms of coordinates (x, y) in the 2D Cartesian coordinate system, whereas mobile barriers are described by polar coordinates: the radius r and the angle α between the needle line and the radius of the mobile barriers. A prototype of the mechanism is shown in Fig. 12.4. The structure needs to be evaluated by means of tests which can influence some input parameters, and consequently improve some parts of the thread control curve. For more details, we refer the reader to Korycki and Krasowska.¹²

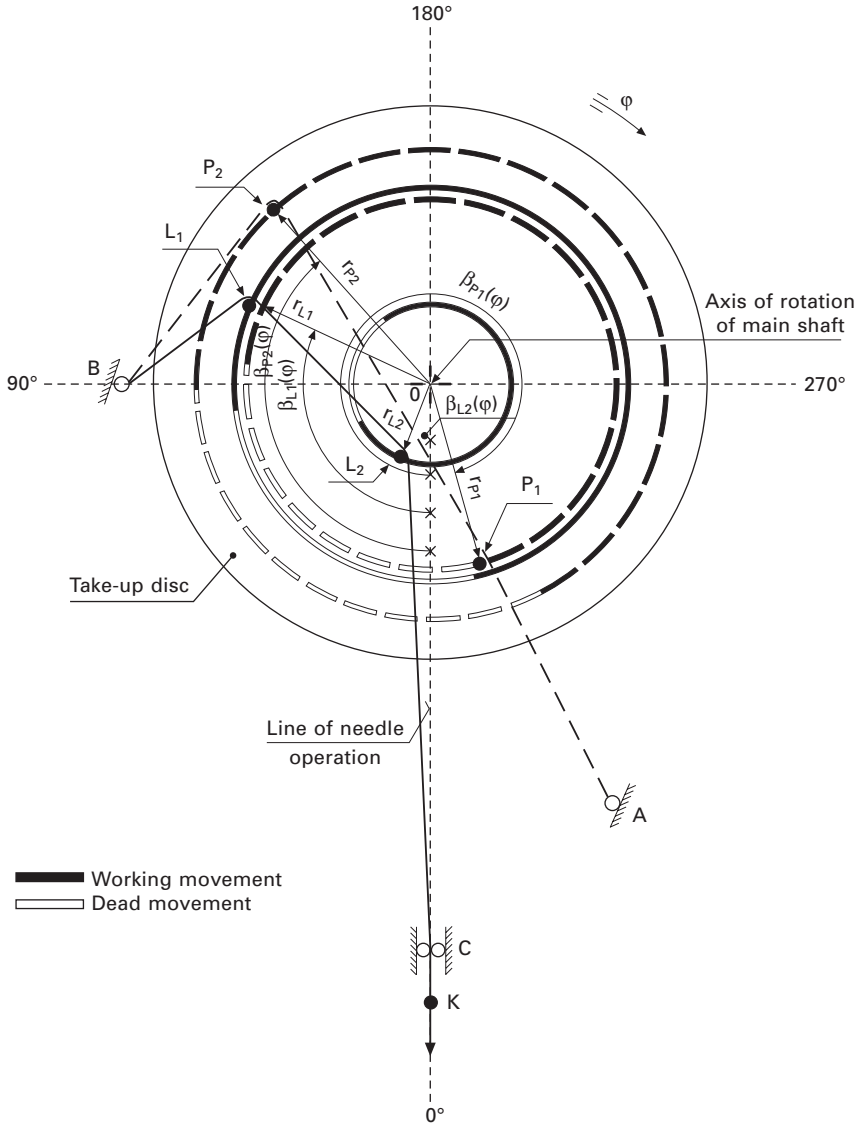


12.2 Algorithm for designing the multibarrier take-up disc.

12.4.2 Mathematical model of needle thread length defined as geometrical distance

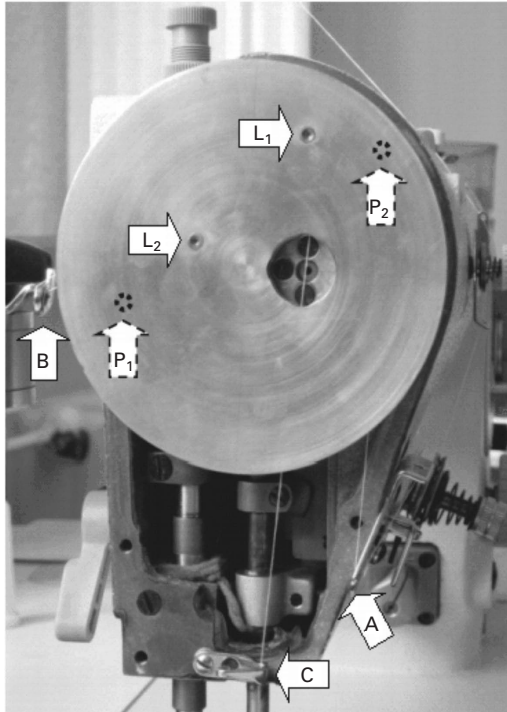
A mathematical model determines the length distribution of the needle thread during the stitch tightening process. The length can be determined as the geometrical distance between the mobile and stationary barriers of the take-up disc, as well as a function of the diameters of the mobile barriers. The thread need by the needle should be determined by the inelastic structure of the thread, separately for each side of the take-up disc. The total length is the sum of the partial thread lengths determined for the left- and right-hand sides of the disc.

First, we should define the following barriers: the thread braking apparatus (A), the mobile barriers on the right-hand side of the take-up disc (P_1 or P_2 or $P_1 + P_2$ simultaneously), the thread divider (B), the mobile barriers on the left-hand side of the take-up disc (L_1 or L_2 or $L_1 + L_2$ simultaneously) and the thread guide of the needle thread within the take-up disc zone (C). The needle thread contacts a different and changeable configuration of mobile frictional barriers on each side of the take-up mechanism during the full rotation range. The number and sequence of active barriers contacting the



12.3 Sewing thread in the working zone of the take-up disc with the circular cyclogram of constant and mobile barriers (angle of rotation of the main shaft $\varphi = 0^\circ$).

thread can be determined by means of a cyclogram (Fig. 12.5). The cyclogram is based on a graphical simulation of the take-up disc rotation in each of the different programs (for example AutoCad) as well as an experimental determination of the activity range of the rotation angles of the mobile barriers on both sides of the mechanism.

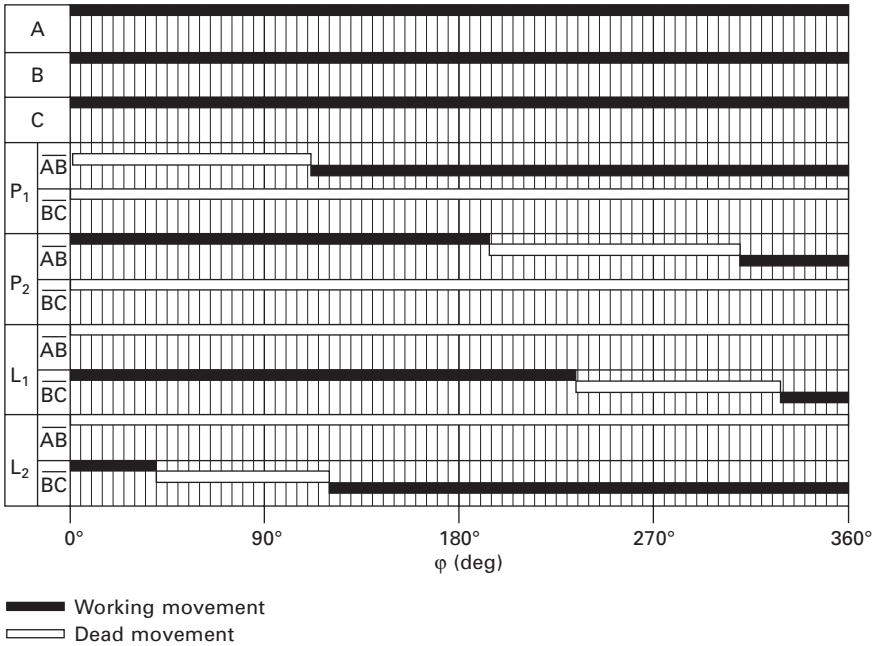


12.4 Prototype of take-up disc installed on sewing machine: A, B, C – stationary barriers; L_1 , L_2 – mobile barriers on left-hand side; P_1 , P_2 – mobile barriers on right-hand side.

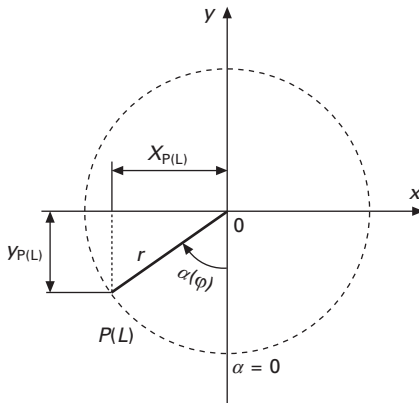
We describe the configuration of the take-up disc by using a different description of the stationary and mobile barriers. The stationary barriers have prescribed coordinates of constant value within the Cartesian coordinate system for the rotation centre (O), the thread braking apparatus (A), the thread divider (B) and the thread guide (C). The coordinates of the mobile barriers P_1 , P_2 , L_1 , L_2 are changeable and should be determined as a function of the rotation angle. The location of the mobile barriers within the 2D stationary Cartesian coordinate system can be finally described in polar coordinates by means of the constant radius and the variable rotation angle (Fig. 12.6):

$$x_{P(L)} = x_O - r \sin \alpha; y_{P(L)} = y_O - r \cos \alpha \quad 12.1$$

where α is the variable rotation angle $\alpha \in < 0, 2\pi >$ (rad); O is the rotation centre of the coordinates x_O , y_O ; r (m) is the constant radius of the mobile barrier; and $P(L)$ denotes alternatively the mobile frictional barrier P_1 , P_2 , L_1 or L_2 . The radius r is constant for each mobile barrier and equal to $r_{P1} = 40.6 \times 10^{-3}$ m, $r_{P2} = 49.3 \times 10^{-3}$ m, $r_{L1} = 40.6 \times 10^{-3}$ m, $r_{L2} = 16.8 \times 10^{-3}$ m. Thus, the length of the needle thread can be expressed by means of the simple correlation



12.5 Activity cyclogram of take-up disc: P_1 , P_2 , L_1 , L_2 – mobile barriers; A, B, C – stationary barriers.



12.6 Changeable polar and Cartesian coordinates of mobile barriers: O – rotation centre; $\alpha(\varphi)$ – variable rotation angle.

$$L = \sum_{k=1}^{KB} L_k; L_k = \sqrt{L_{kx}^2 + L_{ky}^2} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad 12.2$$

where k is the index of a particular segment; i and j are respectively the

end-point indexes of the thread portion $i, j = (A, P_1, P_2, B, L_1, L_2)$; and $KB \in \langle 4, 6 \rangle$ is the number of components of the geometrical distance, which changes with the function of the rotation angle of the take-up disc.

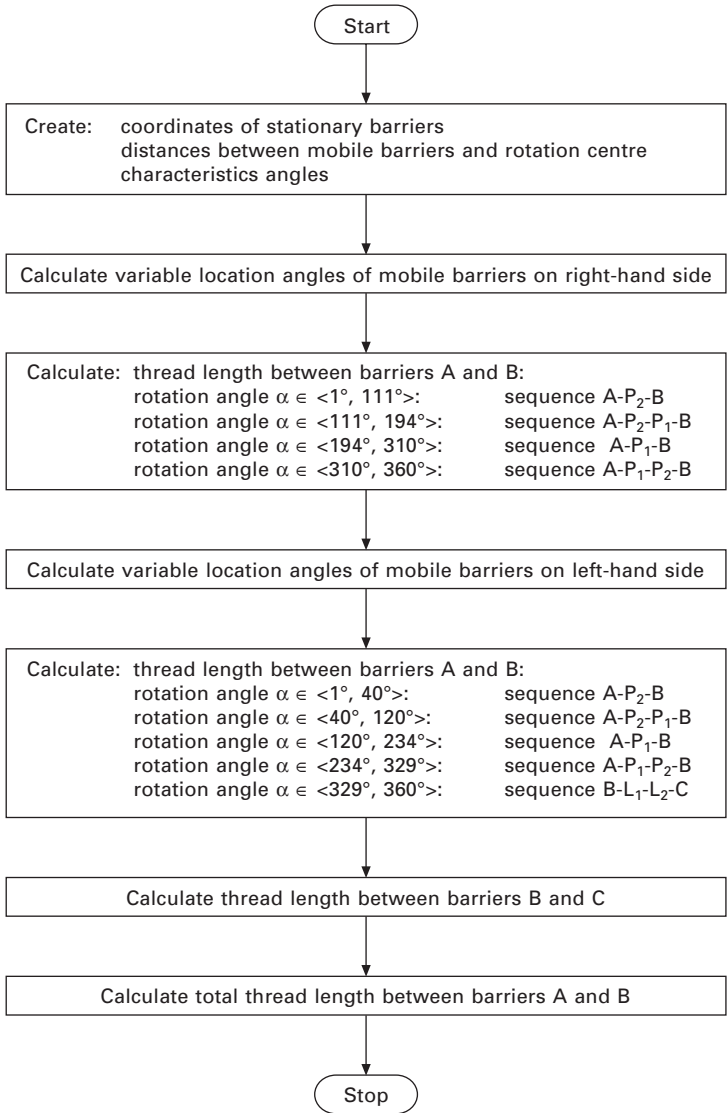
Let us next discuss the influence of the diameter of the mobile barriers on the dynamic reaction. The typical diameter of a mobile frictional barrier has a value of $d = 3 \times 10^{-3}$ m. The length difference determined for the structure with the barrier diameters introduced, and with the barriers reduced to points, is negligible (about 1–1.5% difference between diameters $d = 3 \times 10^{-3}$ m and $d = 0$), but the calculations are complicated and time-consuming. It follows also that, for simplicity, the diameters of the mobile frictional barriers are not included in the existing model of the take-up disc.

The algorithm of calculations of needle thread length is shown in Fig. 12.7. At first, the necessary input data should be introduced. Next, the rotation angles of the mobile barriers on the right-hand side of the take-up disc are determined. The variable coordinates are calculated according to Eq. 12.1 with respect to the adequate sequence of mobile barriers according to the cyclogram (Fig. 12.5). The length on the right-hand side is the sum of the prescribed number of segments between the points A and B of the calculated coordinates, *cf.* Eq. 12.2. The lengths are next determined for the left-hand side of the take-up disc by means of the same strategy. The thread length between the stationary barriers B and C can be calculated according to Eq. 12.2 as a geometrical distance, by introducing the activity sequence of the frictional barriers. Finally, the needle thread length is the sum of both the values for the left-hand side and the right-hand side of the take-up disc. The numerical program was described according to this algorithm in the languages Fortran and C++. The result is a distribution of thread length (Fig. 12.8) of the same characteristic as that determined by the reference diagrams given by other authors – see, for instance, Garbaruk.⁴

12.4.3 Mathematical model of needle thread length defined by genetic algorithms

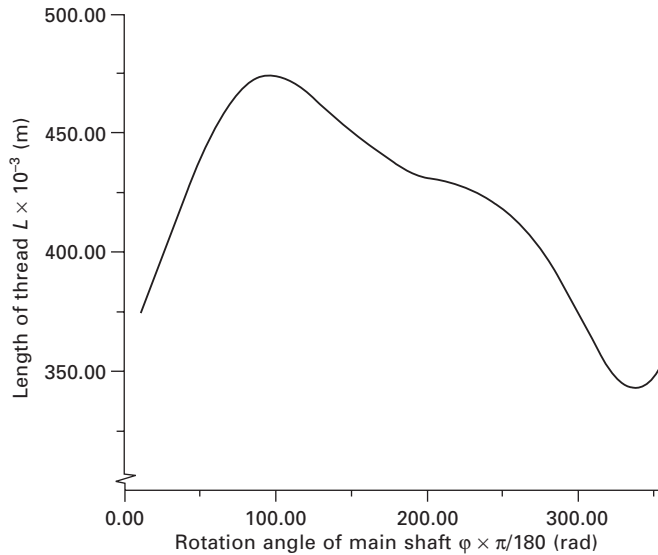
An alternative means of determining thread length is by genetic algorithms (GA). The necessary information is coded, analysed and converted within the genes of a chromosome, coded as floating point numbers, *cf.* for example Goldberg⁵ and Michalewicz.¹⁴

Let us introduce the basic definitions of the problem addressed by this strategy, and the block diagram of GA (Fig. 12.9). The state variables are the model thread lengths in the 2D Cartesian coordinate system. The real structure is the selected configuration of the take-up mechanism, which secures the assumed shape of the thread need by the needle for the prescribed material package. Thus, we should assume the thread control curve at the beginning of calculations, and it is the state variable for the real structure. The physical



12.7 Algorithm for thread length calculations determined as geometrical distance.

models are the consecutive accepted genotypes, i.e. the configurations of the take-up disc, which create the particular length of the needle thread. They are randomly generated at the beginning of the calculations, and the shape obtained from these calculations is evaluated from a physical point of view by the minimization of the fitness function. The genotypes that are not accepted are eliminated.

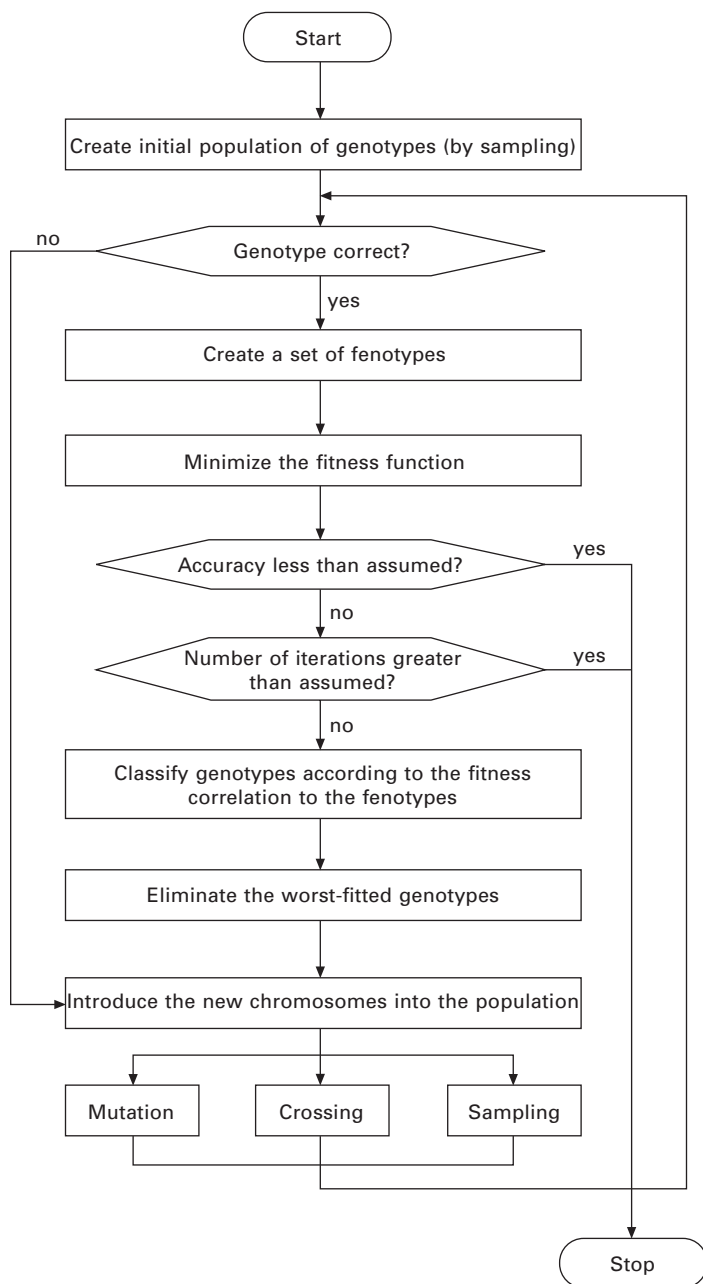


12.8 Needle thread length in the take-up disc zone.

The genotype is the determined shape configuration of the take-up disc of the sewing machine. Let us first create the initial population of genotypes by means of simple sampling, with chromosomes described as floating-point numbers. Mathematically speaking, the genotypes should be verified in each calculation step. The eliminated genotypes should be reconstructed; a new genotype is determined and introduced into the procedure. We can apply alternatively (1) mutation by means of the random noise of a gene within the chromosome, (2) the crossing of two chromosomes in the selected point, and (3) the simple sampling of a new gene within the chromosome. The improved genotype is a mathematical description of the configuration of the take-up disc, and should next be verified from a physical point of view. The accepted genotypes create a set of phenotypes, i.e. the accepted configurations of the take-up disc. Let us next evaluate the problem by minimization of the fitness function. The most used fitness function is described using the least-squares method. Thus, we minimize the ‘distance’ between the state variable for the real structure and the state variable for the calculation model. In other words, we have to compare the difference between the theoretical model and the existing structure. The discrete formulation of the fitness function has the form

$$G = \sum_{i=1}^N \frac{1}{2} (\Phi_i - \Phi_{im})^2 \rightarrow \min \quad 12.3$$

where Φ_i is the state variable for the real structure, Φ_{im} is the state



12.9 Algorithm for thread length determined by means of GA.

variable for the calculation model, and N denotes the number of evaluation points.

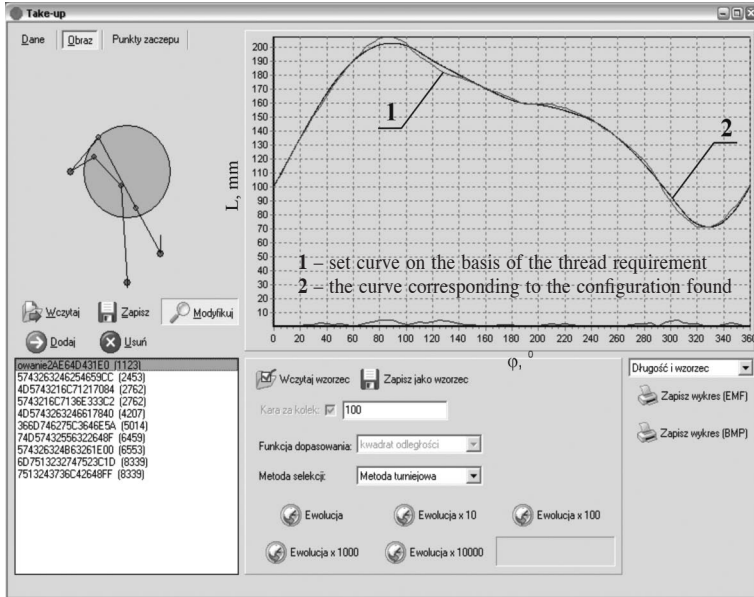
We should next introduce the exit criterion of the evaluation. The least-squares method in the discrete form is minimized in some particular points with assumed accuracy. The procedure is stopped at the point where the accuracy is less than that assumed, and the obtained shape of the take-up disc is the optimal configuration. Alternatively the procedure is stopped if the number of iterations is equal to the predefined number. In this case, the obtained shape is the best fitted to the prescribed thread control curve, but not the optimal one.

If the number of existing genotypes after the evaluation is less than the number assumed, and the number necessary for the calculations, we change the number of existing genotypes by means of selection. The classification criterion is the fitness correlation of the particular genotype, and we eliminate the worst-fitted genotypes. The set of genotypes is completed by introducing the new chromosomes into the set of GA. Physically speaking, it is equivalent to the existence of a new mobile frictional barrier within the take-up disc. In order to create a set of genotypes we can apply (1) the mutation of the chromosome, i.e. perturbation of the gene by means of the prescribed perturbation function; (2) the crossing of two chromosomes existing in the pattern population with the newly introduced cross-section, the children population always having a new chain of chromosomes; and (3) simple sampling of a new chromosome. The complete population should be physically evaluated, and the calculation sequence is repeated until the number of iterations is equal to that which was assumed.

The defined block diagram can be implemented into the special GA program of the interactive menu shown in Fig. 12.10. The shapes within the window are the assumed and the obtained curves of the needle thread lengths, respectively.

12.4.4 Conclusions concerning Section 12.3

- The results obtained from both methods (classical programming and GA) indicate the same length characteristics of the needle thread within the take-up disc zone. The shapes can be evaluated by the following experimental verification: (1) simulations of the sequence and geometry of the frictional barriers within the program AutoCad, and (2) experimental research using the take-up disc prototype. The needle length characteristics are the same as the diagrams published by other authors. Consequently, we can conclude that the algorithms and methods introduced are relatively simple and correct, and that the practical implementation is a question of personal choice.
- Both algorithms are universal and can be applied to describe complicated



12.10 Modelling of the thread control conditions by disc take-up in the Juki 2284 machine by the take-up disc 2.0 system.

geometry as well as the sequences of the frictional barriers of the take-up disc. Thus, the problem is much more complicated and depends on the limitations of the program and software implemented.

- The characteristics obtained for thread length within the take-up disc zone are an important parameter describing the dynamics and maintenance of the sewing machine. Thus, the distribution that is obtained for the thread need by the needle influences the thread deformation during the stitch tightening process, as well as the strength within the thread.

12.5 Modelling and analysis of stitch tightening process

12.5.1 Assumptions concerning physical and mathematical model

Let us formulate the basic assumptions concerning the physical and the mathematical model of the stitch tightening process in dynamic conditions. Some assumptions are determined according to Więźlak and Elmrych-Bocheńska.^{17,18} Summarizing, we have two basic subject fields – the geometric assumptions, and the assumptions concerning thread dynamics. The geometric assumptions are the following.

- The working zone of the sewing machine can be reduced from a 3D space to a 2D plane problem because the path of the needle thread and the bobbin thread within the lockstitch machine can be simplified. The thread guide elements, which are dynamically insignificant, are also neglected. Consequently, the calculations are considerably simplified.
- We introduce two thread systems: the needle thread, which introduces the bobbin thread into the needle channel. Both threads have the same diameter, physical structure and mechanical properties.

Assumptions concerning thread dynamics are the following.

- There is no dynamic interaction between the stitch links formed.
- We have assumed linear strains of the needle caused by stitch tightening, i.e. the field of application of Hooke's Law. The bobbin thread is very short and its elongation is negligible.
- Taking the thread off the bobbin hook is a continuous process, and is achieved during the stitch tightening process. The thread is stopped by means of the flat spring located on the side surface of the bobbin hook. The resisting force of the spring can be assumed to be constant during the stitch tightening process. Of course, the feeding of the thread portion is achieved because the dynamic reaction is greater than the resisting force of the spring.
- The resisting forces caused by the introduction of thread into the interlacement are the two friction forces which are applied in the opposite direction to the motion of the thread. The first friction force is caused by the flat spring acting on the straight section of the thread. The second friction force is within the interlacement, caused by the taking-off of the bobbin thread. Physically speaking, the friction of the thread is the friction on the curvilinear surface, as described by Euler's formula. The coefficient of friction on the curvilinear surface is introduced according to Więźlak and Elmrych-Bocheńska.¹⁷
- The physical model of the thread introduced into the interlacement should contain the discretized mass. The total mass of thread is the sum of the sectional masses concentrated in one point within the interlacement. Thus, we can formulate the dynamic equation for the concentrated mass during the stitch formation process, which considerably simplifies the description.
- The proposed model contains the friction forces of needle thread on the mobile barriers of the take-up disc. The problem is described by means of Euler's formula on the curvilinear surface of the needle channel. The real values of the angle of contact of the frictional barriers are assumed, according to the cyclogram, to be time independent. The problem was analysed in Section 12.4.2.

According to the assumptions defined above, we can formulate the 2D plane model of the interlacement location within the needle channel. The problem is illustrated by Fig. 12.11.

The location of interlacement within the needle channel is divided into two phases. First, the needle thread is introduced, whereas the thread end is blocked within the thread tension device. The mobile barriers of the take-up disc constitute active geometrical impulses, which cause the elongation of the thread. The needle thread is subjected to an elastic strain proportional to the geometrical imperfection $u_w(t)$. The second phase is the introduction of the new part of the needle thread into the stitch formation zone. The reaction within the thread is greater than the resisting force of the flat spring. The thread portion is fed by the thread tension device, and we assume that the geometrical impulse causes only a negligible elongation of the thread.

12.5.2 Dynamic model of lockstitch formation

Introduction of needle thread with blocking by thread tension device

Basic dynamic equations for the thread during the stitch tightening process are formulated for the mass discretized in one point within the interlacement. Introducing the variable coordinate $x = x(t)$ of the mass (Fig. 12.11), the equation can be formulated as follows:

$$Mx'' = -s_1 - s_2 + s_3 + s_4 - T \quad 12.4$$

where M (kg) is the mass of the thread discretized in one point within the interlacement, $x = x(t)$ (m) is the mass coordinate; s_1, s_2, s_3, s_4 (N) are the dynamic reactive forces in particular sections of thread; and T (N) is the friction force discretized within the needle channel.

To solve the dynamic equation, we have to determine the dynamic reactive forces s_1 to s_4 . The friction force was determined empirically according to Więźlak and Elmrzych-Bocheńska.¹⁷

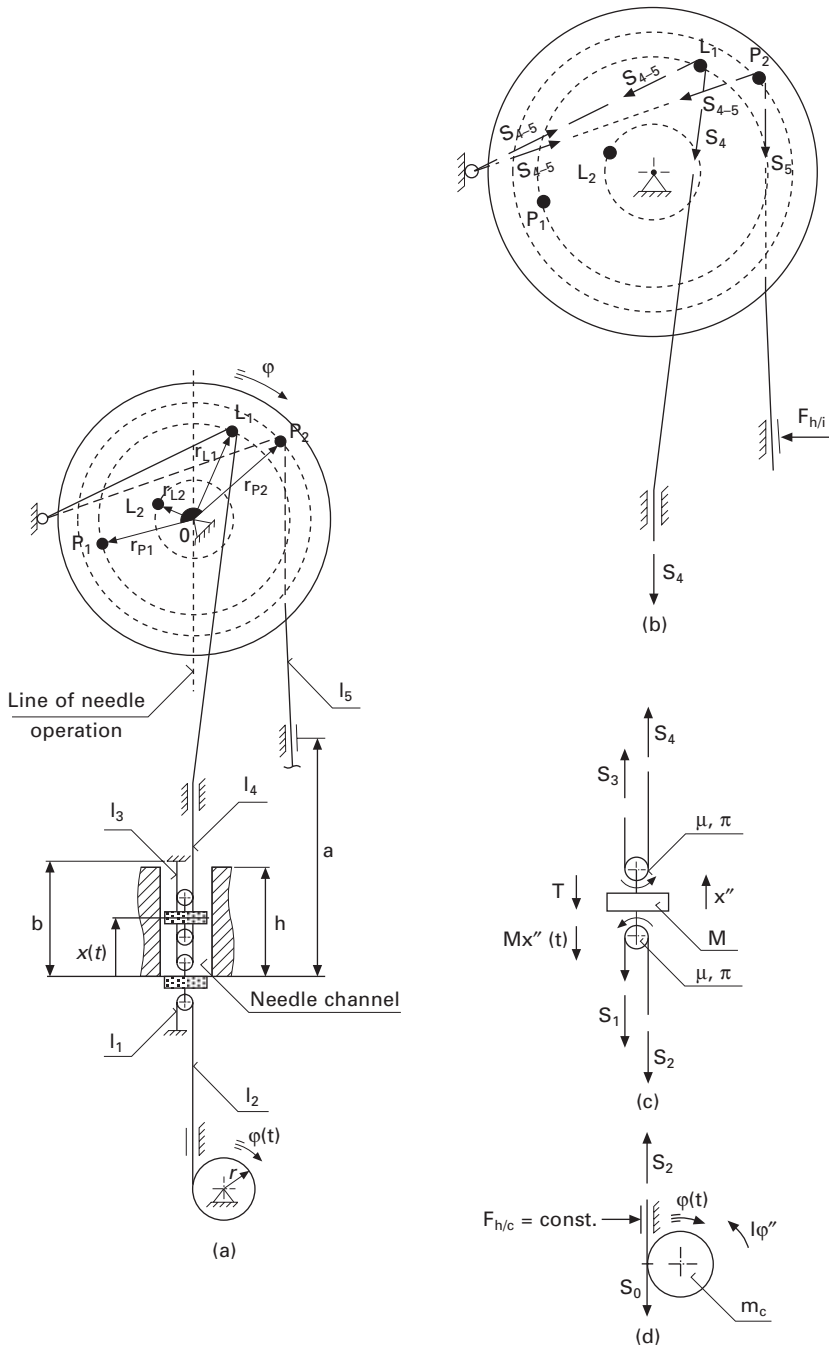
The bobbin thread is subjected to the forces s_1 and s_2 . The equilibrium equation on the curvilinear surface introduces Euler's formula in the form

$$s_1 = s_2 e^{\mu\pi} \quad 12.5$$

where s_1 (N) is the dynamic reaction within the last interlacement, s_2 (N) is the dynamic reaction of the bobbin thread, e is the Napierian base, μ denotes the dynamic coefficient of friction during the introduction of the thread into the interlacement, and π (rad) is the angle of contact.

The next dynamic equation can be formulated as follows for the rotated bobbin hook during the feeding of the thread to the needle:

$$(s_2 - s_0)R = J_z \varphi_c'' \quad 12.6$$



12.11 Two-dimensional plane physical model of the interlacement location within the needle channel.

where s_0 (N) is the breaking force of the flat spring acting on the bobbin thread, R (m) is the radius of the bobbin hook with the bobbin thread, J_z is the moment of inertia of the cylinder along the principal, central axis, and $\varphi_c(t)$ (rad) denotes the angle of rotation of the bobbin hook. This angle can be determined by the length balance of the bobbin thread during stitch formation.

The bobbin thread is located within the interlacement, and the process is described by the coordinate $x = x(t)$. The elongation of the bobbin thread is negligible because the thread is short. Thus, we obtain the simple correlation and its second-order derivative with respect to time:

$$\varphi_c R = 2x; \varphi_c''(t) R = 2x''(t) \quad 12.7$$

The bobbin hook is cylindrical in shape. The moment of inertia of the cylinder during rotation along the principal, central axis of inertia can be described by the equation

$$J_z = \frac{1}{2} m_c R^2 \quad 12.8$$

where m_c (kg) is the mass of the bobbin hook with the bobbin thread. Introducing Eqs 12.7 and 12.8 into Eq. 12.6, after simple transformations, we obtain

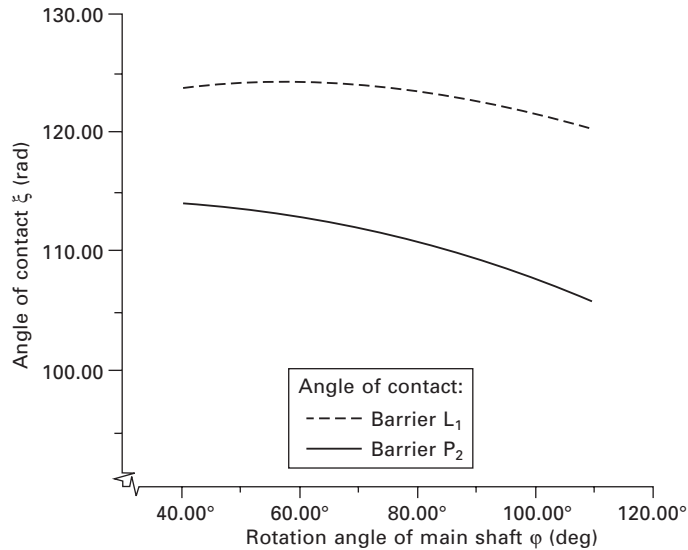
$$s_2 - s_0 = m_c x'' \quad 12.9$$

Let us discuss the first phase of stitch formation, i.e. the elastic tension of the needle thread of the end blocked by the thread tension device. Dynamic reactive forces in the particular sections of thread are equal, according to Fig. 12.11:

$$s_4 = s_3 e^{\mu\pi}; s_5 = s_4 e^{\mu\zeta} \quad 12.10$$

where ζ (rad) is the total angle of contact on the mobile barriers of the take-up disc. The total angle of contact was determined by means of two different methods from Korycki and Krasowska¹² and, in Section 12.4.2, as time-dependent, and is the sum of the angles of contact on both sides of the take-up disc. The first phase of stitch tightening is the introduction of the needle thread, with blocking by the thread tension device. The process is described by the rotation angle of the motion element $(40-115) \frac{\pi}{180}$ (rad) where two mobile barriers, L_1 and P_2 , are active. Both angles of contact for the mobile barriers are shown in Fig. 12.12.

We can introduce two different descriptions of the needle thread angle of contact on the mobile barrier during the first phase of stitch tightening. From Fig. 12.12 we conclude that the changes of both angles are negligible,



12.12 Angles of rotation for frictional barriers L_1 and P_2 active during the stitch tightening.

and equal to $5 \frac{\pi}{180}$ (rad) for barrier P_2 and $3 \frac{\pi}{180}$ (rad) for barrier L_1 . Both are almost constant during the first phase of stitch tightening, and can be expressed as unchangeable for this rotation angle. The calculation errors are negligible and the mathematical model is now much simpler. We do not introduce the time-dependent variables into the differential equation, but only a constant parameter. The angle of contact of the mobile frictional barriers of the take-up disc can be finally expressed as follows:

$$\zeta = \zeta_{L_1} + \zeta_{P_2} = \frac{225}{180} \pi (\text{rad}) \quad 12.11$$

According to the alternative description, we determine the time-dependent values of the angles of contact in the following general form:

$$\zeta(t) = \zeta_{L_1}(t) + \zeta_{P_2}(t) \quad 12.12$$

The elastic strains of the needle thread during the first phase of stitch tightening are described by Hooke's Law. The lengths and strains for the i th thread segment are determined by the correlations

$$l'_i = l_i(1 + e_i); \varepsilon_i = E_n A_p e_i \quad \text{for } i = 3, 4, 5 \quad 12.13$$

where l'_i (m) is the length of the deformed thread, l_i (m) is the initial length of the thread, e_i (m) is the unit elongation of the thread segment, ε_i denotes the strain within the i th segment of the thread, E_n (N/m²) denotes the dynamic

modulus of elasticity of the needle thread, and A_p (m^2) is the cross-sectional area of the thread.

Let us formulate the length balance of the needle thread during the stitch formation. We should determine the total initial length and the geometrical correlations for the deformed thread subjected to tension

$$\begin{cases} L = l_3 + l_4 + l_5 \\ l'_4 = a + l'_5 - x \\ l'_3 + l'_4 = l'_5 = l_3 + l_4 + l_5 + 2u - 2x \\ l'_4 - l'_5 - l'_3 = a - b \end{cases} \quad 12.14$$

where a and b denote the characteristic dimensions of the mechanism (*cf.* Fig. 12.11), whereas u is the dynamic increase in the thread length, which can be determined according to the thread control conditions, *cf.* Fig. 12.10. The set of equations above can be supplemented by Eqs 12.10 and 12.13 and transformed from a relationship of strains to a relationship of elongations as follows:

$$\begin{cases} L = l_3 + l_4 + l_5 \\ l_4 (1 + e_4) = a + l_5 (1 + e_5) - x \\ l_3 (1 + e_3) + l_4 (1 + e_4) + l_5 (1 + e_5) = l_3 + l_4 + l_5 + 2u - 2x \\ l_4 (1 + e_4) - l_5 (1 + e_5) - l_3 (1 + e_3) = a - b \\ e_4 = e_3 e^{\mu\pi} \\ e_5 = e_4 e^{\mu\zeta} \end{cases} \quad 12.15$$

Introducing the last two equations into the other equations of Eqs (12.15) we formulate the following length balance:

$$\begin{cases} L = l_3 + l_4 + l_5 \\ l_4 (1 + Ae_5) = a + l_5 (1 + e_5) - x \\ l_3 (1 + Be_5) + l_4 (1 + Ae_5) + l_5 (1 + e_5) = l_3 + l_4 + l_5 + 2u - 2x \\ l_4 (1 + Ae_5) - l_5 (1 + e_5) - l_3 (1 + Be_5) = a - b \\ A = e^{-\mu\zeta}; B = e^{-\mu\pi} e^{-\mu\zeta} \end{cases} \quad 12.16$$

where A and B are the parameters described within the set of Eqs 12.16. The angle of contact ζ can be determined as constant, according to Eq. 12.11, or time-dependent, by means of Eq. 12.12. The variables within the set of Eqs 12.16 are l_3 , l_4 , l_5 and e_5 , respectively. Solving the above set by

the elimination of l_3 , l_4 and l_5 , after some simple calculations we obtain the elongation e_5 as the following function:

$$\begin{aligned}
 & [2LAB]e_5^3 + [L(2A + B + AB) - 2u(1 + A)B + 2x(A + B) \\
 & - a(1 - A)B - b(2A - B - AB)]e_5^2 + [L(1 + A) \\
 & - 2u(1 + A + 2B) + 2x(2 + A + B) - a(1 - A) \\
 & - b(1 + A - 2B)]e_5 + 4(x - u) = 0
 \end{aligned} \tag{12.17}$$

Mathematically speaking, Eq. 12.17 contains the third power of e_5 and is difficult to solve by conventional analytical methods. Thus, we should apply processing programs to formulate the three roots of the equation, for example Mathematica v. 5.0.0 and CalculationCenter v. 1.0.0. Each obtained root contains more than 300 components and it is impossible to introduce the obtained solutions into the basic Eq. 12.4. We see at once that the obtained roots should be simplified. Let us discuss the parameters described in Eq. 12.16. The coefficient of friction during the introduction of the needle thread was determined experimentally by Więźlak and Elmrych-Bocheńska¹⁸ and assumed to be equal to $\mu = 0.4$. Both angles of contact are respectively equal to π and $\frac{225}{180} \pi$ (rad) and, consequently, the exponential functions caused by the following values are from the range $A, B \in (0, 1)$. The product of both parameters is negligible (i.e. $AB \rightarrow 0$) in relation to the parameters A and B determined separately. Under the assumptions outlined above, the elongation e_5 is finally described in the form

$$\begin{aligned}
 & [L(2A + B) - 2uB + 2x(A + B) - aB - b(2A - B)]e_5^2 \\
 & + [L(1 + A) - 2u(1 + A + 2B) + 2x(2 + A + B) - a(1 - A) \\
 & - b(1 + A - 2B)]e_5 + 4(x - u) = 0
 \end{aligned} \tag{12.18}$$

Introducing again the program Mathematica v. 5.0.0 to solve the above correlation, we obtain the following elongation e_5 as the positive root of Eq. 12.18.

$$\begin{aligned}
 e_5 &= \frac{C_1 + \sqrt{16(x - u)C_2 + C_1^2}}{2C_2} \\
 C_1 &= a(1 - A) + b(1 + A - 2B) - (1 + A)L + 2(1 + A + 2B)u \\
 &\quad - 2(2 + A + B)x \\
 C_2 &= -b(2A - B) - aB + (2A + B)L - 2Bu + 2(A + B)x
 \end{aligned} \tag{12.19}$$

where C_1 and C_2 are the parameters described in Eq. 12.19. Elongations of the other sections of thread can be determined by means of the fifth and sixth correlations of Eqs. 12.15 as follows:

$$\begin{aligned}
 e_4 &= Ae_5 = A \frac{C_1 + \sqrt{16(x-u)C_2 + C_1^2}}{2C_2} \\
 e_3 &= Be_5 = B \frac{C_1 + \sqrt{16(x-u)C_2 + C_1^2}}{2C_2}
 \end{aligned} \tag{12.20}$$

Dynamic reactions within the different sections of thread can be determined according to Eqs 12.5, 12.9, 12.10, 12.13, 12.19 and 12.20 by the following formulas:

$$\begin{aligned}
 s_1 &= s_2 e^{\mu\pi} = (s_0 + m_c x'') e^{\mu\pi} \\
 s_2 &= s_0 + m_c x'' \\
 s_3 &= E_n A_p e_3 = E_n A_p B e_5 = E_n A_p B \frac{C_1 + \sqrt{16(x-u)C_2 + C_1^2}}{2C_2} \\
 s_4 &= E_n A_p e_4 = E_n A_p A e_5 = E_n A_p A \frac{C_1 + \sqrt{16(x-u)C_2 + C_1^2}}{2C_2} \\
 s_5 &= E_n A_p e_5 = E_n A_p \frac{C_1 + \sqrt{16(x-u)C_2 + C_1^2}}{2C_2}
 \end{aligned} \tag{12.21}$$

Summarizing, the basic dynamic equation can be expressed in the form

$$\begin{aligned}
 [M + m_c(1 + e^{\mu\pi})] \\
 \times x'' &= E_n A_p e^{-\mu\zeta} (1 + e^{-\mu\pi}) \frac{C_1 + \sqrt{16(x-u)C_2 + C_1^2}}{2C_2} - s_0(1 + e^{\mu\pi}) - T
 \end{aligned} \tag{12.22}$$

The obtained dynamic equation is the second-order differential equation with respect to the coordinate x . The unknown parameter is the geometrical displacement caused by the take-up disc u_w . Our next goal is to determine the geometrical displacement u_w as the function of coordinate x , which allows us to solve Eq. 12.22. Mechanically speaking, u_w is the time-dependent distance of the mass, discretized in one point during the first phase of the stitch tightening. The standard description of the geometrical displacement is the second-order function of time. We can also describe the displacement as follows:

$$u_w(t) = z_1 t^2 + z_2 t + z_0 \tag{12.23}$$

where u_w (m) is the geometrical displacement, z_0 (m) is the initial distance, z_1 (m/s²) is the mean acceleration of the mobile frictional barriers of the

take-up disc during the stitch tightening, and z_2 (m/s) is the mean velocity of the mobile frictional barriers of the take-up disc v_{sr} . The initial distance is determined for the initial time $t = 0$ as equal to $z_0 = 0$.

The first phase of the stitch tightening process is characterized by the acceleration changing from the initial maximal value to the final value, equal to zero. Thus, we introduce the negative acceleration of the thread during the stitch tightening, i.e. the deceleration of the discretized mass. Let us approximate the typical decrease of the acceleration as the linear function of time, and the mean value of acceleration is now equal to half of the maximal value of acceleration p_{max} . The mean velocity is approximately time-independent. Both values z_1 and z_2 can be assumed according to Więźlak and Elmrych-Bocheńska.^{17,18} According to the remarks made above, Eq. 12.23 can be rewritten as follows:

$$u(t) = z_1 t^2 + z_2 t; \quad z_1 = \frac{1}{2} p_{0max} \text{ (m/s}^2\text{)}; \quad z_2 = v_{sr} \text{ (m/s)} \quad 12.24$$

Next, introducing Eq. 12.24 into Eq. 12.22, we obtain the following basic dynamic correlation:

$$\begin{aligned} & [M + m_c(1 + e^{\mu\pi})]x''(t) \\ & - E_n A_p e^{-\mu\zeta}(1 + e^{-\mu\pi}) \frac{C_1 + \sqrt{16(x(t) - z_1 t^2 - z_2 t)C_2 + C_1^2}}{2C_2} \\ & - s_0(1 + e^{\mu\pi}) - T = 0 \quad 12.25 \\ & C_1 = a(1 - A) + b(1 + A - 2B) - (1 + A)L + 2(1 + A + 2B) \\ & (z_1 t^2 + z_2 t) - 2(2 + A + B)x(t) \\ & C_2 = -b(2A - B) - aB + (2A + B)L - 2B(z_1 t^2 + z_2 t) + 2(A + B)x(t) \end{aligned}$$

Equation 12.25 is too complicated to solve accurately by means of analytical methods. We need to introduce approximate solutions, for example by means of Mathematica v. 5.0.0. This program contains the module NDSolve, which can solve the differential equation supplemented by the prescribed initial conditions, for the defined time interval t . The initial conditions can be determined by analysis of the thread motion during the stitch tightening process. The initial location of the discretized mass x , and its initial velocity x' (i.e. the first-order derivative with respect to time) can be assumed in the form

$$x(t = 0) = 0; \quad x'(t = 0) = 0 \quad 12.26$$

The needle thread is introduced into the needle channel in time, characterized by the initial value $t_0 = 0$ and the final time $t_k = 0.0026$ s.

Let us first assume the results obtained by Więźlak and Elmrych-

Bocheńska^{17,18} to be the model results for this case. We can compare these results with those obtained using the presented calculations. We visualize the obtained calculations by means of the Mathematica environment (command: Plot/Evaluate; time range: $t_0 = 0$; $t_k = 0.0026$ s). The geometric parameters are listed in Table 12.1, and the parameters of the thread dynamic in Table 12.2. The final result is the curve $x = x(t)$, depicted in Fig. 12.13, for the constant values of the angles of contact ζ (cf. Eq. 12.11). The alternative method of time-dependent angles of contact gives negligible differences of about 2%, and is not introduced in the performed calculations.

Table 12.1 Geometric parameters of the stitch tightening model

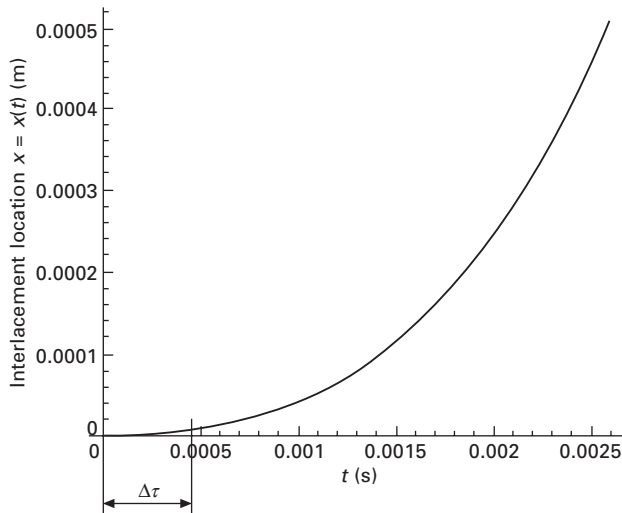
Geometric parameter	Symbol	Unit	Value
Total length of the needle thread within the stitch tightening zone	L	m	0.3
Distance between the lower surface of the material package and the blocking point by the thread tension device	a	m	0.2
Distance between the lower surface of the material package and the blocking point of the needle thread within the previous interlacement	b	m	0.006
Radius of the bobbin hook with the bobbin thread	R	m	0.009
Diameter of the needle and the bobbin thread	d	m	0.0002
Stitch stroke	s	m	0.0025
Material package thickness	h	m	0.002

Source: Więźlak and Elmrych-Bocheńska.^{17,18}

Table 12.2 Parameters of the thread dynamics of the stitch tightening model

Parameter of the thread dynamic	Symbol	Unit	Value
Dynamic modulus of initial elasticity of the thread	E_n	N/m ²	5×10^9
Thread mass after discretization (located within the interlacement)	M	kg	0.001
Dynamic coefficient of friction of the thread into the interlacement	μ	–	0.4
Maximal friction force of the interlacement within the needle channel	T	N	0.3
Breaking force of the bobbin thread	s_0	N	0.2
Breaking force of the needle thread	P	N	3.5
Mean acceleration of the eye of the take-up disc during the stitch tightening	z_1	m/s ²	–14.8
Mean velocity of the eye of the take-up disc	z_2	m/s	3.5

Source: Więźlak and Elmrych-Bocheńska.^{17,18}



12.13 Variable coordinates of the interlacement location $x = x(t)$ obtained by means of approximate solutions according to the Mathematica program.

Table 12.3 Specification of the coordinates $x = x(t)$ (m) for the selected values from the time range $t_0 = 0$ to $t_k = 0.0026$ s and needle thread length $L = 0.3$ m

$t(\text{s})$	0	0.00065	0.00130	0.00185	0.00260
$x = x(t)$ (m)	0	0.0000140314	0.0000772358	0.0001947020	0.0004952510

The obtained diagram is close to the model course determined by Więżlak and Elmrych-Bocheńska.¹⁷ Both diagrams contain a part of the curve, described in Fig. 12.13 by the time range $\Delta\tau$, which corresponds to the coordinates of the interlacement location close to zero, $x = x(t) \rightarrow 0$. Physically speaking, the existing geometrical displacement $u_w = u_w(t)$ does not cause the motion of the interlacement still located under the material surface. The time boundary value is $\Delta\tau \approx 0.0005$ s, which corresponds to the positive value of the interlacement location $x = x(t)$. The positive value describes the introduction of the needle thread into the needle channel within the material package. As the time t grows, the interlacement location $x = x(t)$ becomes strongly nonlinear. Some values of time t are specified by means of the command Evaluate of the Mathematica program, and are given in Table 12.3.

Comparing the obtained results and the model results according to Więżlak and Elmrych-Bocheńska,^{17,18} we conclude some basic differences caused by the different dynamic assumptions. The time boundary value $\Delta\tau \approx 0.0005$ s is comparable for both sources, i.e. the interlacement is located under the

material surface during the same time. The second part of the curve grows more rapidly in the model results,^{17,18} as presented in Fig. 12.13. Let us compare for simplicity the coordinates for the time $t = 0.0026$ s according to the model curve^{17,18} ($x = 0.347 \times 10^{-3}$ m) and in Fig. 12.13 ($x = 0.495 \times 10^{-3}$ m). The decrease in value obtained is equal to about 30%. The difference is caused by the greater value of reaction force s_4 , because the angle of contact ζ grows from the value π rad, according to Więżlak and Elmrzych-Bocheńska,^{17,18} to the value $225 \frac{\pi}{180}$ rad, assumed in this chapter. This is the consequence of the operation analysis of the mobile frictional barriers within the take-up disc. Consequently, the thread is located higher within the material package thickness in relation to the lower edge of the material, as assumed previously.^{17,18}

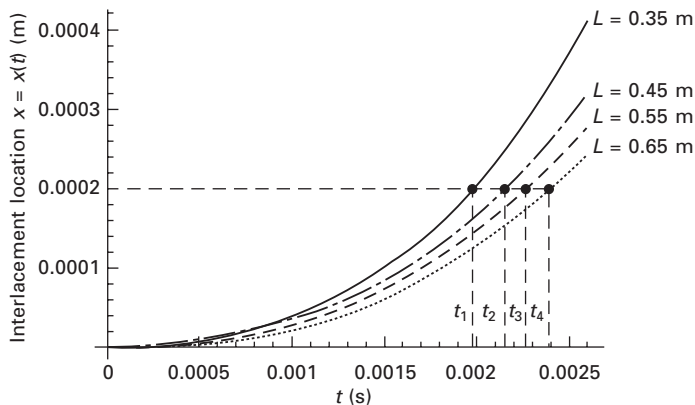
The comparable character of the courses of the time-dependent coordinates during interlacement shows that we have just verified the calculations of the first phase of the stitch tightening (i.e. the first phase connected with the elastic elongation of the needle thread). The coordinate $x = 0.495 \times 10^{-3}$ m obtained for the end time of the first phase in fact describes the location of the discretized mass introduced into the interlacement. The obtained results are comparable to, but not the same as, those obtained by Więżlak and Elmrzych-Bocheńska.^{17,18}

The verified calculations can next be applied to the consecutive analysis of the dynamic model of the interlacement location during the first phase of stitch tightening. Our next purpose is to analyse some characteristics of the dynamic model.

- Let us determine the value of coordinate $x = x(t)$ for the prescribed length of the needle thread, which is the consequence of the take-up disc configuration. The length of the needle thread of the applied take-up disc (i.e. characterized by the multibarrier frictional structure) is considerably greater than that of the reference model.^{17,18} According to the direct measurements, we can introduce a needle thread of a length equal to $L = 0.65$ m. Other structural parameters are given in Tables 12.1 and 12.2.
- Let us analyse the sensitivity of the coordinate $x = x(t)$ with respect to the length of the needle thread during the first phase of the stitch tightening process. Practically speaking, we determine the coordinate x for the different lengths of the needle thread L , and analyse the diagrams obtained. The calculation range of L is from the initial value $L_0 = 0.3$ m to the final $L_k = 0.65$ m. The different coordinates $x = x(t)$ obtained for the different lengths L during the first phase of the stitch tightening are shown in Table 12.4. Additionally, the selected diagrams $x = x(t)$ for the different lengths of the needle thread are shown in Fig. 12.14.

Table 12.4 Specification of the coordinates $x = x(t)$ (m) for the selected values from the time range $t_0 = 0$ to $t_k = 0.0026$ s and the different needle thread lengths (constant value of absolute increase)

L (m)	t (s)				
	0	0.00065	0.00130	0.00185	0.00260
0.3	0	0.0000140314	0.0000772358	0.0001947020	0.0004952510
0.35	0	0.0000128519	0.0000674209	0.0001654830	0.0004101160
0.4	0	0.0000121144	0.0000612196	0.0001467580	0.0003543190
0.45	0	0.0000116165	0.0000570822	0.0001344010	0.0003181400
0.5	0	0.0000112577	0.0000541224	0.0001256200	0.0002927010
0.55	0	0.0000109872	0.0000518983	0.0001190540	0.0002738100
0.6	0	0.0000107759	0.0000501665	0.0001139560	0.0002592190
0.65	0	0.0000106074	0.0000487792	0.0001098830	0.0002476020



12.14 Variable coordinates of the interlacement location $x = x(t)$ within the stitch link according to the Mathematica program for different lengths of the needle thread: $L = 0.35$ m, $L = 0.45$ m, $L = 0.55$ m, $L = 0.65$ m.

The obtained results indicate that, as well as being strongly nonlinear, every course has the same shape. The coordinate of the interlacement location $x = x(t)$ is considerably less for the multibarrier frictional structure of the take-up disc (needle thread equal to $L = 0.65$ m) than for the reference model^{17,18} (needle thread $L = 0.30$ m). The situation in which this is most evident is the final time of the first phase during stitch tightening, $t = 0.0026$ s. Considering the time $t = 0.65 \times 10^{-3}$ s, the change of length from $L = 0.3$ m to the assumed value $L = 0.6$ m decreases the coordinate x by about 25%. In the case of the time $t = 2.6 \times 10^{-3}$ s, the same change of the length L decreases the coordinate x by about 50%. The cause is the strong nonlinearity of the coordinate $x = x(t)$. The decrease of the coordinate x is caused by an increase in the active length of the needle thread. The bigger

the active length L , the bigger the thread elongation described by the linear correlation, according to Hooke's Law, *cf.* Eq. 12.13.

The differential equation 12.25 describing the coordinate $x = x(t)$ is very complicated, and can only be solved numerically. It is also impossible to determine the analytic form of the objective functional and analyse the sensitivity by means of classical analytical methods. The sensitivity can be analysed by consecutive approximate calculations, as well as the incorporation of the results previously obtained. As can be seen from Table 12.4 and Fig. 12.14, the coordinate x is very sensitive to the change of the needle thread length. The maximal changes of x are obtained for the length increase of the short needle thread (for example, increase from $L = 0.30$ m to $L = 0.35$ m); the changes of x are considerably less for the longer thread. Of course, the change of 0.05 m is equal to about 17% for the length $L = 0.30$ m, whereas it is equal to only about 8% for the length $L = 0.65$ m. It follows that the changes of the coordinate $x = x(t)$ are not proportional to the length increase of the needle thread. Consequently, the needle thread is more sensitive to the location of the frictional barriers for the minimal than for the maximal permissible length.

Our next goal will be sensitivity analysis for the constant relative increase of needle thread equal to 30%. The results are shown in Table 12.5. The change in the coordinate x is not proportional because the geometry of the needle thread is complicated, and the shape is not a straight line. The main geometric disturbances are the frictional barriers within the take-up disc zone. This is the main cause of the length increase within the presented

Table 12.5 Specification of the coordinates $x = x(t)$ for the selected values from the time range $t_0 = 0$ to $t_k = 0.0026$ s and the different needle thread lengths (constant value of relative increase)

L (m)	t (s)				
	0	0.00065	0.00130	0.00185	0.00260
0.3	0	0.0000140314	0.0000772358	0.0001947020	0.0004952510
0.39	0	0.0000122380 (decrease of coordinate $\approx$ 13%)	0.0000622533 (decrease of coordinate $\approx$ 19%)	0.0001498620 (decrease of coordinate $\approx$ 23%)	0.0003634800 (decrease of coordinate $\approx$ 27%)
0.507	0	0.0000112154 (decrease of coordinate $\approx$ 8%)	0.0000537738 (decrease of coordinate $\approx$ 14%)	0.0001245890 (decrease of coordinate $\approx$ 17%)	0.0002897270 (decrease of coordinate $\approx$ 20%)
0.6591	0	0.0000105806 (decrease of coordinate $\approx$ 5%)	0.0000485558 (decrease of coordinate $\approx$ 10%)	0.0001092280 (decrease of coordinate $\approx$ 13%)	0.0002457380 (decrease of coordinate $\approx$ 15%)

model of the take-up disc, in relation to the model of Więźlak and Elmrych-Bocheńska.^{17,18} The greater the active length of the needle thread, L , the longer the time taken for stitch tightening during the interlacement within the needle channel.

Introduction of the new part of the needle thread

The model of stitch tightening discussed above is characterized by the coexistence of two separated phases. The first phase is the introduction of the needle thread, blocked by the tension device, as described on pages 310 *et seq.* The second phase starts with a dynamic reaction within the needle s_4 greater than the resisting force of the flat spring $F_{h/i}$. Let us assume that the forces are equal to $s_4 = F_{h/i}$. The physical interpretation is that the thread tension device is unlocked and the new part of the needle thread is introduced into the interlacement. Applying the Eqs 12.4 and 12.21, we can determine the following description of the acceleration of the mass discretized in one point within the interlacement, during the second phase of the stitch tightening:

$$x'' = \frac{-s_0(1 + e^{\mu\pi}) + s_4(1 + e^{-\mu\pi}) - T}{M + m_c(1 + e^{\mu\pi})} \quad 12.27$$

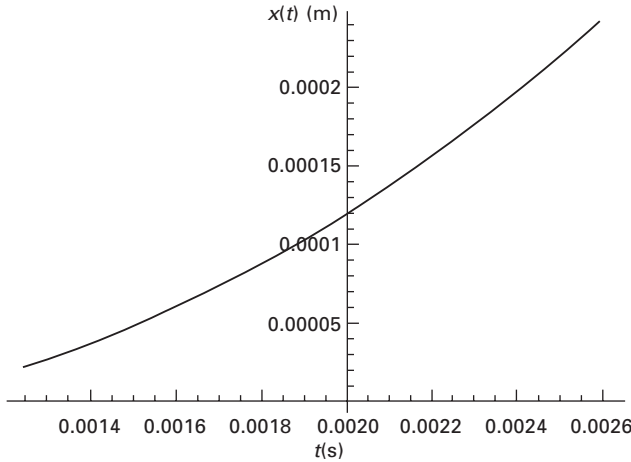
We can solve this by means of Mathematica program v.5.0.0. The module NDSolve should be implemented, which is necessary to solve the differential equation supplemented by the prescribed initial conditions within the defined time interval t . The initial conditions are the location and the velocity of the second phase of the stitch tightening process, given in the form¹

$$x(t = 0.00124) = 0.0000226 \text{ m}; x'(t = 0.00124) = 0.0829 \text{ m/s} \quad 12.28$$

The second phase of the stitch tightening process is introduced, for the time range from the initial $t_0 = 1.24 \times 10^{-3}$ s to the final time $t_k = 0.0026$ s. The obtained results are visualized by means of the Mathematica program, command Plot/Evaluate, as are the geometric parameters (*cf.* Table 12.1) and the parameters of the thread dynamic (*cf.* Table 12.2). The obtained variation curve of the coordinate x is shown in Fig. 12.15.

As the time t grows, the interlacement location described by the coordinate $x = x(t)$ becomes strongly nonlinear. The values of the coordinate x can be determined for the selected time arguments by means of the command Evaluate from the Mathematica environment. The results are listed in Table 12.6.

The next step is to determine the time function of the curve in Fig. 12.15. We can apply the Mathematica program to solve Eq. 12.27 by using the command DSolve, as well as the initial conditions described by Eq. 12.28. The final result is a quadratic function of time, described as follows:



12.15 Variable coordinates of the interlacement location $x = x(t)$ within the stitch link according to the Mathematica program for the second phase of the stitch tightening.

Table 12.6 Specification of the coordinates $x = x(t)$ for the selected values from the time range $t_0 = 0.00124$ s to $t_k = 0.0026$ s and needle thread length $L = 0.3$ m

$t(\text{s})$	0.00124	0.0017	0.0022	0.0026
$x = x(t)(\text{m})$	0.0000226000	0.0000731436	0.0001562300	0.0002438110

$$\begin{aligned}
 x(t) = & 1.26342 \times 10^{-14} (7.89078 \times 10^8 - 4.94909 \times 10^{12} t \\
 & + 4.64138 \times 10^{15} t^2)
 \end{aligned}
 \tag{12.29}$$

The second phase is generally described by an increase of the active length of the needle thread, caused by feeding the thread portion. The increase in length can be determined by the balance of the introduced needle thread, *cf.* Fig. 12.11, in the form

$$l'_3 + l'_4 + l'_5 + \Delta l = l'_3 + l'_4 + l'_5 + 2u - 2x
 \tag{12.30}$$

The transformation of the above correlation allows us to describe the thread elongation as follows

$$\Delta l = 2u - 2x
 \tag{12.31}$$

The displacement of the mobile frictional barriers of the take-up disc during the second phase of the stitch tightening process was determined within Section 12.4. Introducing, additionally, Eqs 12.25, 12.26 and Table 12.1, we formulate the following correlation, describing the elongation of the needle thread

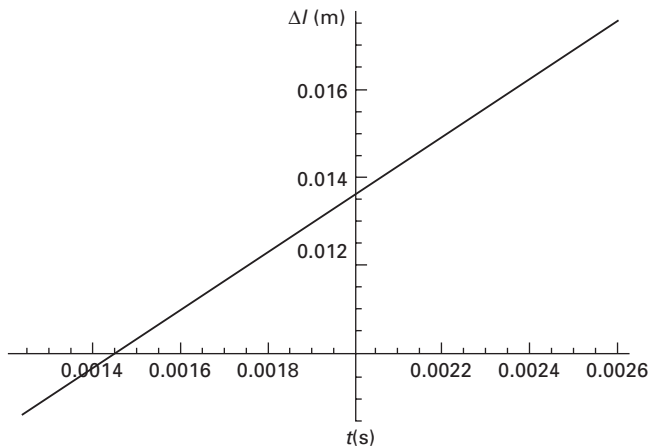
$$\Delta l = 2(3.50t - 14.8t^2) - 2.52684 \times 10^{-14} (7.89078 \times 10^8 - 4.94909 \times 10^{12}t + 4.64138 \times 10^{15}t^2) \quad 12.32$$

This solution can be visualized by means of the command Plot in the Mathematica program. We should also introduce Eq. 12.32 and the time range for the second phase of the stitch tightening process $t_0 = 1.24 \times 10^{-3}$ s to $t_k = 0.0026$ s. The result is the curve shown in Fig. 12.16. Let us apply the Mathematica environment, command Evaluate to obtain the values given in Table 12.7.

It is evident that the parabola obtained is remarkably flat for the whole range of time, and very close to a straight line. The elongation of the needle thread during the second phase of stitch tightening can be assumed to be linear.

12.5.3 Conclusions concerning Section 12.4

- The analysis of the number and configuration of the mobile barriers within the take-up disc during the stitch tightening process is difficult to describe



12.16 Elongation of the needle thread $\Delta l = \Delta l(t)$ obtained by means of approximate methods according to the Mathematica program for the second phase of the stitch tightening.

Table 12.7 Specification of the elongation of the needle thread $\Delta l = \Delta l(t)$ for the selected values from the time range $t_0 = 0.00124$ s to $t_k = 0.0026$ s and needle thread length $L = 0.3$ m

$t(s)$	0.00124	0.0017	0.0022	0.0026
$\Delta l = \Delta l(t)$ (m)	0.00858929	0.0116682	0.0149443	0.0175123

by means of analytical methods. The take-up disc configuration can be simplified geometrically, which reduces the problem from 3D space to the 2D plane. The calculation errors are negligible and the solution is not so time-consuming. We introduce, additionally, the coexistence of two thread systems, the needle thread and the bobbin thread of the same physical parameters. The dynamics of the stitch formation are shared by both thread sections.

- The assumed linear dependence between the stress and strain of the thread allows us to introduce Hooke's Law, and simplify the description of the dynamic equation. The number of components within the dynamic equation decreases because some of them can be neglected. The number and description of roots are now relatively easy.
- The taking-off of the thread from the bobbin hook is divided into two parts: the elongation of the needle thread, and the introduction of the new part of the thread. Of course, both phases are realized simultaneously and the process is continuous. The superposition principle allows us to analyse both phases separately.
- Frictional forces caused by the flat spring and mobile frictional barriers are changeable and their description is difficult. The diameters of the mobile barriers do not significantly influence the final result of the dynamic reactions.
- The mass should be discretized in the selected points within the interlacement. Thus, we have assumed that the whole mass of the thread is located in one point. The alternative solution is to divide the mass into a few parts located at different points along the thread. The problem is complicated because the basic dynamic equation should be formulated separately for each part of the thread. Practically speaking, the greater the number of points, the more complicated and time-consuming the calculations because the correlation is the second-order differential equation with respect to the coordinate x .

12.6 Conclusions and future trends

The take-up disc can be applied to optimize the length of the needle thread and the sequence of mobile frictional barriers. The next step can also be the shape optimization of the take-up disc (i.e. the location and the number of frictional barriers) as well as the optimization of its material characteristics.

The problem can also be solved by dividing the mass into a few points along the needle thread. The problem requires detailed description and analysis because the differential equations are coupled, and the mass coordinates $x_i = x_i(t)$ are connected.

Defining the future trends as scale-dependent, some problems are determined on the macro-scale, for example device control, parameter monitoring,

intelligent textiles, thinking sewing machines, etc. These problems are analysed more generally, and give the coupled solutions of the configuration, structure and materials. Other important problems are defined on the micro-scale. We have to determine the thread tensions and dynamic forces, improve the material and the thread consumption. Both classes of problems should be determined as coupled, to be solved by means of different methods of soft computing. The results obtained can be used to create the optimal shape and material properties of the take-up mechanism within the lockstitch machine.

12.7 References

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Artificial neural network applications in textile composites

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Abstract: This article elaborates the use of artificial neural networks (ANNs) in the prediction of static and dynamic mechanical properties, time-dependent properties like creep and stress relaxation, fatigue prediction, wear simulation, crack and damage detection of composites. Various recent developments and applications of ANNs, in the field of fibre reinforced composites have been discussed.

Key words: composites, artificial neural network (ANN), fibre, mechanical properties, viscoelastic properties, fatigue.

13.1 Introduction

Composite materials are becoming increasingly important in the field of materials science and engineering. Selection of correct composition and choosing the appropriate manufacturing process are very important in composite fabrication. A careful choice of different fillers and/or reinforcements results in varied possibilities to create polymer composites. Various properties of matrix and fillers/reinforcements, as well as the fibre orientations (in both discontinuous and continuous reinforcements), play an important role in influencing the final property of fibre reinforced composites. Manufacturing parameters like temperature, pressure and time of consolidation (speed) govern the final quality of the composites. Specialized engineering applications require a thorough investigation of properties for the composite materials.

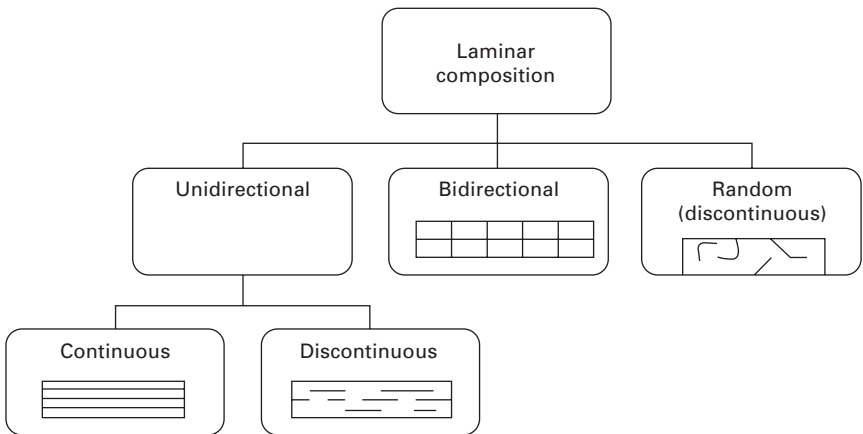
The manufacture of composites is often a tedious and time-consuming process. Thus accurate modelling of the ultimate properties of composite materials plays a pivotal role. Modelling of the complex relationships for composite manufacturing generally involves development of a mathematical tool derived from experimental data. The experimental work can be significantly reduced if the model was properly established.

The manufacture of fibre reinforced composites is more challenging than that of other materials, mainly due to the anisotropic nature of the structure. The challenge also endows the composite with the flexibility of selectively reinforcing the material in the desired direction. Thus fabrication of a curved structure without the necessity of a secondary forming operation,

or the formation of structures with minimal thermal expansion, is possible with composites. Composites reinforced with a chosen set of fibres and polymers can exhibit excellent dimensional stability over a wide temperature range. Composites have another advantage – that of absorption of energy at a microscopic scale. This property of slow mechanical deterioration leading to ultimate failure is essential in many cases and desirable in certain circumstances where catastrophic failures need to be avoided. The high internal damping of many fibrous composites makes them the most suitable material for automotive reinforcements where vibration damping is critical. However, composite materials have poorer impact resistance than metals and age with time. The interfacial properties of composites are also a matter of concern and significant research is being directed towards improving the interface behaviour of composites. For a thorough treatment of composite structures, readers are advised to consult mallick¹ and Gay *et al.*²

For fibre reinforced composites, the major constituents are the reinforcing phase, which is generally the fibres in different forms, incorporated into the matrix (a polymer) as a lamina as illustrated in Fig. 13.1; and generally coupling agent, coating or filler that is used to enhance the interphase behaviour. Unidirectional fibre reinforcements can be either continuous or discontinuous. There are also other possibilities like bidirectional and random reinforcements (Fig. 13.1), depending on the end user. Random reinforcements result in a more or less isotropic structure with similar mechanical and physical properties in all directions. Thus the mechanical properties of the composite can be achieved with a desired precision, depending on the nature of reinforcement.

Artificial neural networks (ANNs) are computational networks which attempt to simulate, in a gross manner, the networks of nerve cells (neurons) of the biological central nervous system. This simulation is a gross cell-by-cell



13.1 Laminar composition and classification.

(neuron-by-neuron, element-by-element) simulation.³ Each unit has an input/output (I/O) characteristic and implements a local computation or function. The output of each unit is determined by its I/O characteristic, its interconnection to other units and (possibly) external inputs, and its internal function. ANNs can be used to solve complex scientific and engineering problems. They allow the use of very simple computational operations (addition, multiplication and fundamental logic elements) to solve complex, mathematically ill-defined problems, nonlinear problems or stochastic problems. Complex mathematics and logic can yield a broad general frame for solutions and can be reduced to specific but complicated algorithms; neural network design aims at the utmost simplicity and utmost self-organization. A very simple base algorithmic structure lies behind a neural network, but it is one which is highly adaptable to a broad range of problems. The advantage of an ANN lies in the fact that (a) it is computationally and algorithmically very simple, and (b) it has a self-organizing feature which allows it to handle a wide range of problems. Artificial neural networks which have been successful in other fields have recently been introduced into the field of polymer composites to predict the complex relationship in polymeric composites.

Although there are not many publications about the use of ANNs in the polymer composite field, the available literature covers various research outputs related to prediction of ANNs in the field of static and dynamic mechanical properties, time-dependent properties like creep and stress relaxation, fatigue prediction, wear simulation, crack and damage detection of composites. The object of this chapter is to summarize the various developments and applications of ANNs in the field of fibre reinforced composites and discuss their suitability for further applications.

13.2 Quasi-static mechanical properties

Quasi-static mechanical properties are one of the most important parameters to be tested for fibre reinforced composites. Pidaparti and Palakal⁴ were among the first to address the modelling of composites using ANN. They developed a back-propagation neural network for predicting the non-linear stress-strain behaviour of graphite-epoxy laminates. In the network one input layer was used with three nodes, two middle layers, and one output layer with one node. The input parameters were fibre angles, initial and incremental stresses for which the trained network predicted corresponding total strain. A sigmoid transfer function with a learning coefficient of 0.7 and a momentum term of 0.85 was used in the learning algorithm. The feed data set consisted of 959 data points. The network was trained with 0°, 25°, 35°, 45°, 55°, 60° and 90° fibre angle for 25,000 iterations. The network was then tested with 15°, 20°, 30°, 40°, 50° and 75° fibre angles after the training phase had been completed. Different neural network configurations having

17, 21, 25 and 29 neurons in each hidden layer were studied. The results indicated that, overall, the $\langle 3-17-17-1 \rangle$ and $\langle 3-25-25-1 \rangle$ networks predicted better for all fibre-angles considered.

Labossière and Turkkan⁵ used ANN to predict failure of composites under plane stress conditions and the results were compared with the tensor polynomial theory. A $\langle 3-15-15-1 \rangle$ feed-forward neural network with back-propagation of the gradient methods was used. Using the convergence criterion of 6% the results successfully predicted the failure of the composite. However, the failure envelope obtained by the neural net did not need to adhere to the second-order degree surface as assumed by the tensor polynomial theory.

13.2.1 Shear

Shear is the stress to produce fracture in the plane of cross-section when the conditions of loading are such that directions of force and resistance are parallel and opposite, although their paths are offset a specified minimum amount. The maximum load in such cases divided by the original cross-sectional area of a section separated by shear is known as the shear strength.

In a work by Bezerra *et al.*,⁶ ANNs were considered specifically to predict the shear stress–strain behaviour from carbon fibre/epoxy and glass fibre/epoxy composites. The composites were prepared by film stacking technique. The carbon fibre/epoxy composite and the glass fibre/epoxy composite had 10 fabric layers each, and they have 58% and 55% fibre volume fraction. Three input parameters were considered by Bezerra *et al.* (specimen of fibre, orientation angle by layers, and shear strain) and one output quantity, i.e. shear stress, was evaluated. The maximum performance was reached using a multilayer perceptron composed of 30 neurons in two hidden layers using the Levenberg–Marquardt algorithm which was found to be one of the fastest methods for training medium-sized feed-forward neural networks. The use of artificial neural networks led to excellent prediction of shear mechanical behaviour of epoxy matrix composites reinforced with carbon and glass fibres for two different angles of layer orientation: $0^\circ/90^\circ \pm 45^\circ$, with 80% of standard error of prediction more than 0.9.

13.2.2 Compressive strength

Compressive strength is the capacity of a material to withstand axially directed pushing forces. In a work by Seyhan *et al.*,⁷ a three-layer feed-forward artificial neural network (ANN) model having three input neurons, one output neuron and two hidden neurons was developed to predict the ply lay-up compressive strength of VARTM processed E-glass/polyester composites. The composites were manufactured using fabric preforms consolidated with 0, 3 and 6 wt% of thermoplastic binder. The agreement between the measured and the

predicted values obtained was reasonably good. The model was tested within low average error levels of 3.28%. The predictions of the ANN model were subsequently compared with those obtained from a multi-linear regression (MLR) model. The ANN model was found to give better predictions than the MLR model for the experimental data. When the ANN model was subjected to a sensitivity analysis, it was found to have an ability to yield a desired level of ply lay-up compressive strength values for the composites processed with the addition of the thermoplastic binder.

The input variables used were the amount of thermoplastic binder, the initial fibre preform thickness prior to the VARTM process, and the composite fibre volume fraction. The output of the neural networks was the ply lay-up compressive strength of the composites. The input and output parameters are given in Table 13.1 with their minimum and maximum values.

There were a total of 45 data sets that were divided into two groups for training and testing, each containing 30 and 15 sets, respectively. The program was instructed to run for 100,000 iterations and the optimal weights were calculated with an average percentage training error of 3.28%. A multi-linear regression model with the same input data was also employed to evaluate the results with the ANN model. Figure 13.2 shows the training of the ANN model and the MLR predictions, respectively. The ANN model predicted the experimental strength measurements with a coefficient of determination (R^2) of 0.94, showing better agreement than those of MLR with a coefficient of determination (R^2) of 0.83.

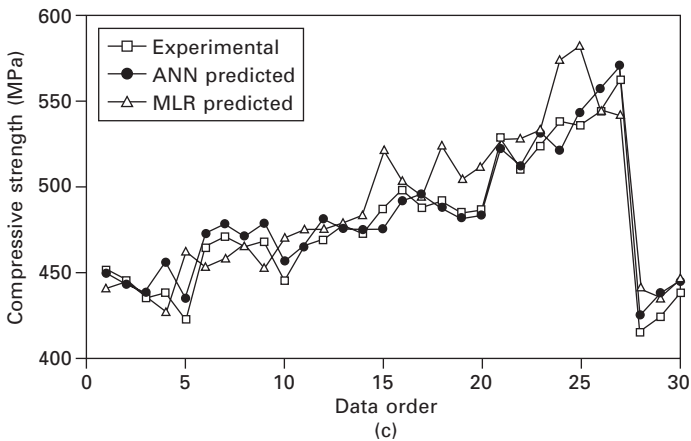
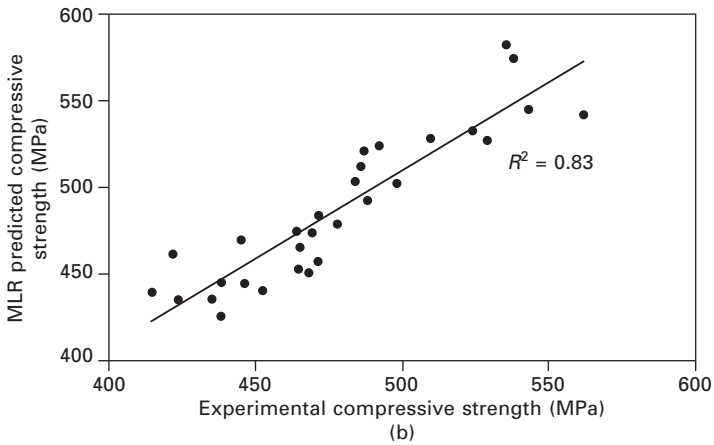
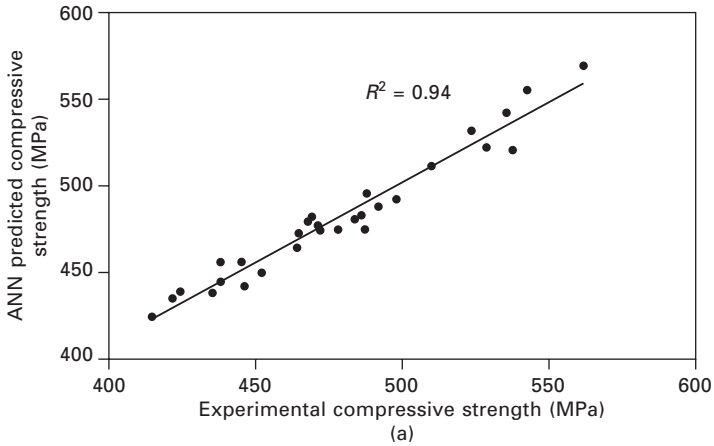
The compressive strength of ply lay-up composites was predicted using artificial neural networks with the variables being thermoplastic binder amount, fibre preform thickness prior to the VARTM process, and composite fibre volume fraction. Comparison of the ANN predictions with the experimental measurements was found to be satisfactory. The results showed that ANN had better predictions of the experimental compressive strength values than those with MLR.

13.2.3 Dynamic mechanical properties

Dynamic mechanical properties (storage modulus and damping) of short fibre reinforced composites were investigated by Zhang *et al.*⁸ in a range from

Table 13.1 Input (X) and output (Y) parameters of ANN

Code	Parameter	Minimum	Maximum
x_1	Thermoplastic binder amount (wt%)	0	6
x_2	Fibre preform thickness (mm)	13.15	21.80
x_3	Composite fibre volume fraction (–)	0.34	0.57
Y	Ply lay-up compressive strength (MPa)	415	574



13.2 Results of training: (a) ANN model prediction, (b) MLR prediction; (c) the model trend with data order (source: after Seyhan *et al.*⁷).

–150 to 150°C. Polytetrafluoroethylene (PTFE) composites blended with polyetheretherketone (PEEK) and reinforced with short carbon fibres (CF) were investigated. Dynamic mechanical analysis (DMTA) was employed using a three-point-bending test. Based on measured results an artificial neural network (ANN) approach was used for prediction purposes. The analysis showed that the number of training datasets plays an important role in ANN predictive quality. In addition, the increasing complexity and nonlinear relationship between input and output meant a larger requirement on the number of training datasets. Storage modulus prediction was possible even using only one-eighth of the training datasets. Based on measured results, an artificial neural network (ANN) approach was introduced for further prediction purposes. In the study the PTFE, the PEEK and the CF content were selected as input parameters, while the storage modulus or the damping factor was chosen as output data. A log-sigmoidal transfer function, $f(x) = \frac{1}{1 + e^{-x}}$, was used between the input and the hidden layer. A linear transfer function was employed between the hidden and the output layers. The learning procedure was based on a gradient search, with a least-sum squared optimality criterion of errors between the predicted and the desired values. In the minimization process, the weights of all the connecting nodes were adjusted until the desired error level was achieved or the maximum cycle was reached. Measurement results were divided into a training dataset and a test dataset. The training dataset was utilized to adjust the weights of all connecting nodes until the desired error level was reached. Thereafter, the network performance was evaluated by the use of the test dataset. Its quality was usually characterized by the coefficient of determination B :

$$B = 1 - \frac{\sum_{i=1}^M (O(p^{(i)}) - O^{(i)})^2}{\sum_{i=1}^M (O^{(i)} - \bar{O})^2}$$

where $O(p^{(i)})$ was the i th predicted property characteristic, $O^{(i)}$ was the i th measured value, $\bar{O}$ was the mean value of $O^{(i)}$, and M was the number of test data. Coefficient B is used to describe the fit of the ANN's output variable approximation curve with the actual test data output variable curve. It is important to appreciate that higher B coefficients indicate an ANN with better output approximation capabilities. The process was independently repeated 50 times, using a random selection of test datasets. Afterwards the percentage of $B \geq 0.9$ was calculated, since this value was identified as a high predictive quality — less than 15% of the root mean square error between the predicted and measured values. It was clear that the higher the percentage of $B \geq 0.9$, the better was the predictive quality.

To meet 100% of B values ≥ 0.9 , the modulus needs only 40 randomly selected training data; however, damping needs more than 120 for similar

predictive quality. It could be considered that the modulus has a stronger relationship than damping to temperature, as well as to those material compositions. In other words, the nonlinear behaviour of damping was higher than that of the storage modulus. It is an important finding that ANN needs more experience in learning a complex nonlinear relationship for damping than that for modulus. The study showed that the number of training datasets plays a key role in ANN predictive quality. In addition, for a more complex nonlinear relation between input and output a larger training dataset was required. The simulation result showed that ANN is a potential mathematical tool in the structure–property analysis of polymer composites.

13.3 Viscoelastic behaviour

The viscoelastic behaviour of fibre reinforced composites has become increasingly important due to the inherent nature of the polymeric materials which serve as the reinforcing phase. Viscoelastic or viscoplastic behaviour manifests itself in various ways, including creep under constant load, stress relaxation under constant deformation, time-dependent recovery after removal of a given load, etc.

13.3.1 Creep properties

Time-dependent strain under constant stress is known as creep. Creep is one of the principal properties which are of prime importance in developing and using composite materials. It had been repeatedly observed that the majority of materials respond differently depending on the time required to complete the mechanical test. The time-dependent stress–strain behaviour of composites in such situations becomes particularly important. There have been several studies on creep of fibre reinforced composites, through not many have used neural networks.

Al-Haik *et al.*⁹ investigated the viscoplastic behaviour of composites through two different modelling efforts. The first model was phenomenological in nature and utilized tensile and stress relaxation experiments to predict the creep strain. The model was constructed based on the overstress viscoplastic model. In the second model, the composite viscoplastic behaviour was captured via neural network formulation. The neural network model was built directly from the experimental results obtained after creep tests performed at various stress–temperature conditions. The universal approximation theory and the dimensionality of the creep problem (stress, temperature and time) were used to achieve the optimal structure of the neural network. The neural network model was trained to predict the creep strain based on the stress–temperature–time values. The performance of the neural model was represented by the mean squared error between the neural network prediction

and the experimental creep strain results. Several optimization techniques were examined to minimize this error. The authors observed that truncated Newton achieved the preferred quadratic convergence rate while limiting the waste of oversolving the model at points far from the solution. The truncated Newton method was simply modified to fit the neurocomputational creep model, eliminating the randomness encountered for choosing an optimal learning rate and momentum for the steepest descent method.

From the research it was evident that the neural network model, when compared to the explicit viscoplastic model, predicted more accurate results under different stress–temperature conditions. Another advantage of using neural networks was the necessity of using only one set of creep data at different thermomechanical histories, while the viscoplastic model required both tensile test data together with load relaxation data, and of course creep data were still required to verify the performance of the model.

Al-Haik *et al.*¹⁰ proposed an alternative model based on an artificial neural network (ANN) to predict the stress relaxation of a polymer matrix composite. The work utilized creep test data within a nonlinear viscoelastic formulation to predict the stress relaxation at different combinations of strain and temperature. Datasets were obtained from stress relaxation tests performed at various constant strain (initial stress) and constant temperature conditions. A servo-hydraulic machine was used for stress relaxation tests. To avoid sample slippage or readjustment in the specimen grips, they were controlled by a servo-hydraulic machine. Standard tensile specimens were loaded in the same load frame. The samples were loaded at a constant displacement rate of 2 mm/min until a desired strain was achieved. For the neural network training, three input quantities (temperature T , normalized stress, and time t) and one output quantity (relaxation stress $r(t)$) were used. It has been observed that three neurons are sufficient for the input layer and one neuron for the output layer. The Optimal Brain Surgeon (OBS) algorithm, a relatively new algorithm, was used to construct the neural networks and utilizes the scaled conjugate gradient algorithm to train the neural network to predict the stress relaxation behaviour of the composite based on learning different load relaxation tests performed at different temperature/strain levels. Two hidden layers were used in the neural network application.

It was apparent that prediction of the nonlinear viscoelastic model agrees very well with the experimental stress relaxation behaviour under conditions of low initial strain (initial stress 30% of strength) and low temperature (35°C). However, at higher stress levels and/or elevated temperatures a noticeable discrepancy was observed. In most cases, the theoretical model overestimates the stress relaxation. However, the neural network model was found to be more consistent in its prediction ability even at higher temperatures. The researchers commented that ‘ANNs or neural constitutive models have the potential to be a viable alternative to theoretical constitutive models for

nonlinear viscoelasticity. A properly trained ANN model can easily be stored in a hand-held computer and be used by an engineer to predict reliably and efficiently the time-dependent mechanical behavior of a viscoelastic or a viscoplastic material'.

Tyulyukovskiy and Huber¹¹ used ANNs to characterize time-dependent material behaviours for viscoplastic materials from nano-indentation creep responses. The input variables of their ANNs were unloading depth, stiffness to hardness ratio, and applied loads, while the output variables were elastic modulus, hardening material parameters, and coefficients of the power-law equation between strain and stress rates. ANN models were thus trained with dimensionless input and output variables combined with material parameters and FE simulation results (i.e., hardness and stiffness) generated for a specific predefined creep loading history. Predictions from ANN were compared with FE simulation results. Their three models showed overall good agreement with FE results. However, large relative errors ranging from 13% to 80% in the output of the third ANN and significant mismatches (maximum of 30%) in time–deflection curves generated from the second ANN were also found. Their ANN indentation creep models were limited to viscoplastic behaviour of metallic materials. The scope for using neural networks to investigate the viscoelastic behaviour of fibre reinforced composites is pending. The author has not found any significant reports of ANN studies dealing with the indentation creep behaviour of polymeric materials and stress relaxation. Therefore, similar and more general ANN models need to be generated to characterize the creep behaviour of polymeric materials.

13.4 Fatigue behaviour

Fatigue of a material is the phenomenon leading to fracture under repeated or fluctuating stresses having a maximum value less than the tensile strength of the material. It is important to note that fatigue fractures are progressive and grow under the action of the fluctuating stress. The use of composites in structural applications requires better understanding of the fatigue performance of these materials. The complexity of fatigue of composites under different loading conditions of the composite and the difficulties of prediction of their fatigue life have significantly limited the uptake and use of composite materials. This has resulted in various investigations into the fatigue life of composite materials.

Constant-stress fatigue data for five carbon-fibre-reinforced plastics and one glass-reinforced plastic laminate have been used by Lee *et al.*¹² to evaluate possible artificial neural network architectures for the prediction of fatigue lives and to develop network training methods. It has been found that artificial neural networks can be trained to model constant-stress fatigue behaviour at least as well as other life-prediction methods and can provide accurate (and

conservative) representations of the stress/ R -ratio/median-life surfaces for carbon-fibre composites from quite small experimental databases. Although their predictive ability for minimum life was less satisfactory than that for median life, and was non-conservative, the procedures developed in this work could nevertheless be used in design with little further modification. Some success had been achieved in modelling fatigue under block-loading conditions, but this problem was more difficult and requires much more effort before ANNs could be used with confidence for variable-stress conditions.

Subsequently the ANN was trained with data for four CFRP laminates. The database available contained the results of over 400 fatigue tests on carbon-epoxy materials over a range of five R ratios from +0.1 to +10. It was found that out of the various possible inputs, the peak and minimum stresses and the failure probability level were most important. The output, or training target, was the fatigue life, N_f cycles to failure. The number of optimized hidden layers was found to be three. The predictions for constant-stress fatigue conditions for one of the composite laminates, IM7/977, were compared and it was seen that, although based on quite different procedures, both models gave good predictions of the actual fatigue response of this material. It is important to note that the constant-life model did not capture the non-linear nature of the $\sigma/\log N_f$ curve at $R = -0.3$ as well as the ANN. Both methods modelled the behaviour at the inner R ratios, -1.0 and -1.5 , very closely but gave less satisfactory predictions for the R ratios of 0.1 and -0.3 . The predictions from the neural network algorithm compared favourably with those of the constant-life model.

An artificial neural network (ANN) was used to predict the specific wear rate and frictional coefficient¹³ based on a measured database for short fibre reinforced polyamide 4.6 (PA4.6) composites. The results showed that the predicted data were well acceptable when comparing them to the real test values. In the research work, a back-propagation neural network was developed, i.e. a multiple-layer feed-forward network with non-linear differentiable transfer functions. A database containing various testing details, like mechanical properties, material compositions and wear characteristics of PA4.6 composites was used to train and test the neural network. Afterwards, a well-trained neural network was employed to predict the wear properties according to new input data. The input and output variables, as summarized by the authors, are given in Table 13.2.

Several measuring details, i.e. material compositions, mechanical properties and testing conditions, were selected as input parameters, and wear characteristics such as coefficient of friction and specific wear rate were chosen as output results. A tan-sigmoid transfer function was used in the hidden layers. A linear transfer function was used between the hidden and the output layers.

It was observed by the authors that both the BR (Bayesian regularization)

Table 13.2 Input and output variables

<i>Input</i>	
Material compositions	Matrix volume (70–100%) Fibre volume (0–30%) PTFE volume (0–10%)
Mechanical properties	Compression modulus and strength Hardness and fracture toughness
Measuring parameters	Temperature (20–150°C) Normal force (5–30 N) Wear speed (0.02–0.2 m/s)
<i>Output</i>	
Wear characteristics	Specific wear rate/wear volume Frictional coefficient

and CGB (Powell–Beale conjugate gradient) algorithms possessed a high predictive quality, i.e. nearly 40% of B were found in the range of 0.9–1.0 at the related ANN configuration. Moreover, the BR was a more ideal algorithm but with a slow computing speed. CGB, on the other hand, was a fast algorithm for the problem with a high quality of training.

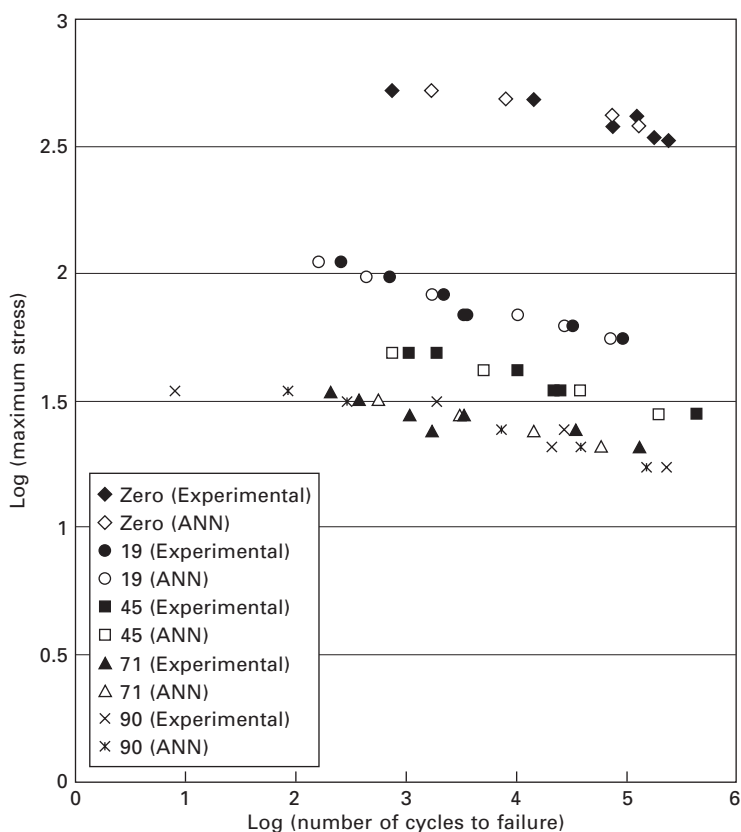
Based on the CGB algorithm, various ANN configurations were analysed and the 9–[15–10–5]₃–1 structure showed an excellent result of 66% of B coefficient in the range of 0.9–1.0. However, from the complexity of the configuration, it was also evident that the wear performance of short fibre composites had a very complex relationship with the input parameters chosen. Prediction quality improved when compared to the author's previous published data.¹⁴ Information about material compositions was not yet used as a part of the input data. The increase of the number of datasets, 103 instead of 72, also contributed to this improvement.

Al-Assaf and El Kadi¹⁵ investigated the fatigue behaviour of unidirectional glass fibre/epoxy composite laminate under tension–tension and tension–compression loading predicted using artificial neural networks (ANNs). Stress-life experimental data were obtained for fibre orientation angles of 0°, 19°, 45°, 71° and 90°. These tests were performed under stress ratios of 0.5, 0 and –1. The network provided accurate modelling between input parameters (maximum stress, R -ratio, fibre orientation angle) and the number of cycles to failure. Although a small number of experimental data points were used for training the neural network, the results obtained are comparable to other fatigue life prediction methods.

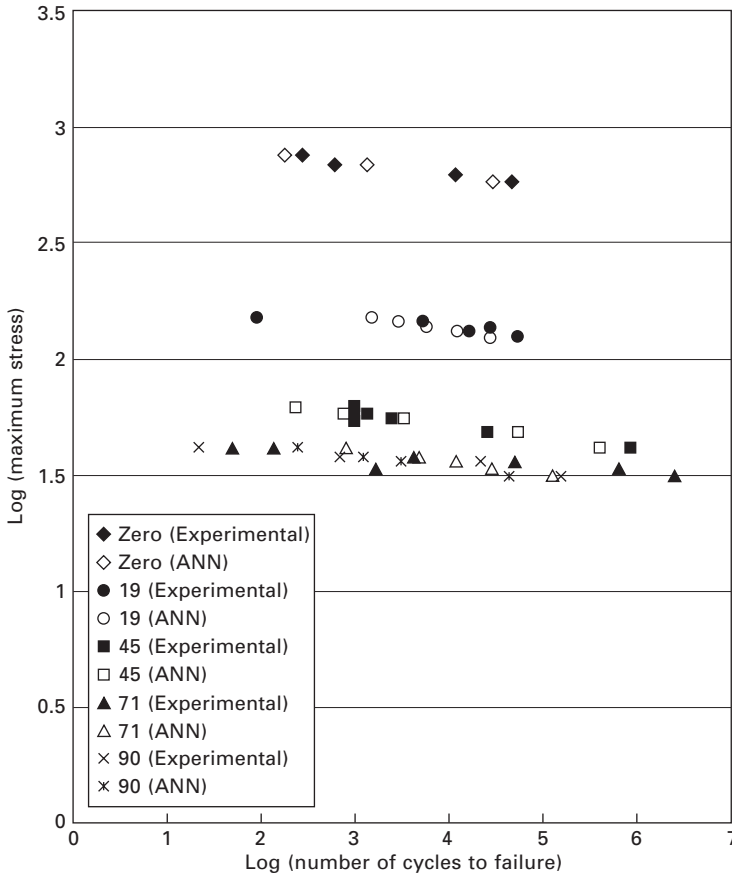
For life prediction analysis of glass fibre/epoxy composite laminae it was assumed that fatigue was a function of the fibre orientation angle (θ), minimum ($\sigma_{\min}$) and maximum ($\sigma_{\max}$) stresses applied to the specimen. Other parameters that could affect the material's life such as the microstructure and process parameters were not considered in this work. To make the output amenable for successful learning, the logarithmic values for the number of

cycles to failure were considered; this reduced the scale to lie between 0.5 and 6. The maximum stress applied varied between 13 and 760 MPa. The fibre orientation angle had five values, namely: 0°, 19°, 45°, 71° and 90°. The values for $\sigma_{\max}$ and θ were normalized between 0 and 1 for network training and testing. R had three values, namely 0, 1 and -1. There were 92 experimental points which made up the application data. Although a small number of experimental data points were used for training the neural network, the results obtained (Figs 13.3, 13.4 and 13.5) are comparable to other fatigue life prediction methods.

In a follow-up paper, El Kadi and Al-Assaf¹⁶ compared the predictions they had obtained using the feed-forward ANN with those obtained using four neural network classes; modular networks (MNN), radial basis function (RBF) networks and principal component analysis (PCA) networks were used in this work. The effect of the number of sub-networks in the MNN, the



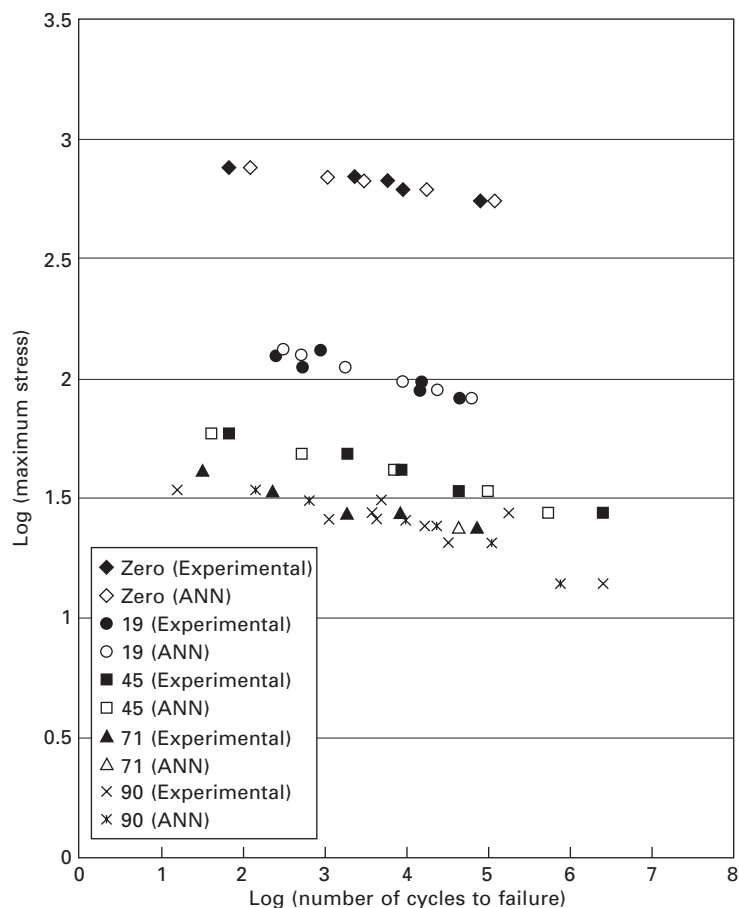
13.3 Comparison between experimental and ANN predicted number of cycles to failure for $R = 0$ (source: after Al-Assaf and El Kadi¹⁵).



13.4 Comparison between experimental and ANN predicted number of cycles to failure for $R = 0.5$. (source: after Al-Assaf and El Kadi¹⁵).

number of clusters in the RBF and the effect of map size in the SOFM were considered. The authors concluded that modular networks with their ability to decompose the modelling task showed the most significant improvement compared to the feed-forward network.

In another interesting work, El Kadi and Al-Assaf¹⁷ experimented with ANN complexity by reducing the number of inputs. The authors used one combined parameter, strain energy, defined as $\Delta W = \frac{1}{2} (\sigma_{\max} \epsilon_{\max} - \sigma_{\min} \epsilon_{\min})$, rather than using the maximum stress, the stress ratio and the fibre orientation as inputs to the network. The correlation obtained was lower (79.3%) and the normalized mean square error was higher (37%) than those obtained when the three parameters were used as inputs. However, the authors felt that the correlation obtained was more realistic compared to an over-correlation attempted by the ANN when the three parameters were used as inputs.



13.5 Comparison between experimental and ANN predicted number of cycles to failure for $R = -1$ (source: after Al-Assaf and El Kadi¹⁵).

Fatigue lifetime of a sandwich composite material was investigated by Bezazi *et al.*¹⁸ The structure was subjected to cyclic three-point bending loads. Twenty-seven samples were investigated to provide training, validation and testing data for a series of multi-layer perceptron ANNs. The network structure chosen for the ANN modelling was a multi-layer perceptron (MLP). Both maximum likelihood and Bayesian training methods were used to construct a series of ANN structures to model a set of fatigue data collected from a set of GFRP laminated PVC foam core sandwich samples undergoing three-point bending fatigue tests. A series of fatigue test measurements were performed on the samples at different values of loading value, defining the ratio of dynamic loading level with respect to the static rupture load. By fitting a series of neural networks, it was possible to identify ANNs that could predict

the fatigue lifetime of samples at different loading values. It was observed by the authors that the Bayesian training method produced an improved fit to the data compared with the maximum likelihood methodology.

13.4.1 Wear properties of composite materials

An artificial neural network (ANN) technique was applied by Jiang *et al.*¹⁹ to predict the wear properties of polymer-matrix composites. Using an experimental database for short fibre reinforced polyamide 4.6 composites, the specific wear rate, frictional coefficient and mechanical properties such as compressive strength and modulus were investigated and modelled using a well-trained ANN. The authors established the 3D plots for the predicted wear and mechanical characteristics as a function of material compositions and testing conditions. The results were in good agreement with measured data. They showed that the prediction accuracy was reasonable, and the network had potential to be improved if the experimental database for network training could be expanded.

The ANN technique was applied by Jiang *et al.*²⁰ to predict the mechanical behaviours of PA 6.6 composites and the wear properties of PA 4.6 composites. The properties of short fibre reinforced polyamide composites as a function of the compositions or testing conditions was well predicted by optimized and trained neural networks. The input variables were material compositions (volume or weight fraction of the matrix, the short fibres and the fillres), testing conditions for PA 4.6 (temperature, normal force, and sliding speed), and the manufacturing process of PA 6.6 composites (impact modification). The output variables included the wear characteristics of PA 4.6 composites (specific wear rate and frictional coefficient) and the mechanical properties of PA 6.6 composites (the Izod impact energy, the tensile and flexural strength, the tensile and flexural modulus). During the evaluation, the networks were trained by 80 data, and tested by 10 data, randomly selected from the databases. It was found that, especially for the single hidden-layer network, the mean relative error decreased with the increase of neurons in a certain range, and then increased again when more neurons were added. The curves showed that a network consisting of a single hidden-layer with three neurons gives the best quality for the prediction of frictional coefficient. With the aid of the predicted 3D profiles, the relationship between the input and output variables was well visualized by the ANN technique, which resulted in more efficient utilization of the relatively limited experimental databases.

A database containing 101 independent wear experiments of polyamide 4.6 composites, which were performed at various conditions and with different compositions, was used to train and test the ANN. The parameters which were measured included the material compositions (volume fraction of the matrix, the short fibres and the fillers), the testing conditions (temperature,

normal force, and sliding speed), the mechanical properties (compressive modulus, strength under compression, tension and bending, respectively), and the wear characteristics (specific wear rate and frictional coefficient),

An ANN configuration of 9–[15–10–5]₃–1 (a network possessing three hidden layers, with six material compositions and three testing conditions as the input, and the specific wear rate as the output) was chosen. The reason for choosing this structure was to compare the performance of these training algorithms. Seventy datasets were randomly selected to train the network, and 30 datasets were used for testing. This process was repeated 100 times. It was observed that the CGB and GDX algorithms gave a high prediction quality, i.e. a smaller mean relative error than that of the others. Various numbers of hidden layers were investigated and it was found that three layers gave the best performance. The accuracy of the data was achieved to the desired level when the training data reached a value of 160. This work showed the excellent capability of an ANN approach for the simulation of the property profile of short fibre reinforced polymer composites. A sufficiently trained neural network was used to predict wear and mechanical properties based on material compositions and testing conditions as input parameters. As is evident from the research, the prediction accuracy was found to be satisfactory, but its dependence on the number of training data indicates that the accuracy could be further improved by expanding the experimental database for network training.

13.4.2 Crack/damage detection

Detection of cracks or flaws in composite materials has become increasingly important due to the stringent requirements on the part of the engineering industry. Conventional ultrasonic techniques, such as ultrasonic B- and C-scan techniques, have been widely used for crack detection. However, measured signals from such scanning techniques are not adequate enough to provide clear images of the flaws, due to

- the inhomogeneous nature of the material and/or
- simultaneous wave reflections generated by the different laminate interfaces in the composite plate.

Okafor and Dutta²¹ devised a method for predicting the damage size and depth from C-scan results using neural networks. Two graphite fibre (Bismaleimide) composite plates and four aluminium plates were used for the study. Holes of varying depth were drilled to detect damage. Ultrasonic transmission tests were carried out on a DigitalWave immersion type C-scan system. PRF values from 100 to 5000 Hz were investigated for the scan. The defect locations were clearly observed as peaks in the C-scan mesh. From the C-scan plots, the equivalent hole diameter, the depth and the location of the

holes with respect to a predetermined edge were calculated and correlated with the actual values to determine the optimal pulse repetition frequency values. The authors developed a radial basis function (RBF) neural network using the results from the C-scan to predict the damage parameters (diameter and depth of drilled holes). For this particular network, the inputs were the diameter and depth of the holes as measured from the C-scan results, while the output parameters were the actual diameter and depth of the holes drilled in the composite plate. ANN was successful in predicting the damage parameters.

Haj-Ali *et al.*²² proposed the use of ANN to generate nonlinear micromechanical ANN models. The interfacial crack between the fibre and the matrix was considered as the damage variable. The crack angle was used as a damage parameter in the unit cell (UC) models for a unidirectional metal–matrix composite. ANN models were trained to generate plane stress–strain constitutive models along with their damage variable using 3D FE simulation results. The study was one of the first to show that ANN can be used to generate micromechanical material models with damage. However, their ANN was limited to monotonic behaviour and for a specific system of boron–aluminium metal matrix composite material.

In another work by Chakraborty,²³ embedded delaminations (in terms of their size, shape and location) in fibre reinforced plastic composite laminates were investigated using natural frequencies as indicative parameters and an artificial neural network as a learning tool. Numerical simulations were used to generate the data set. Various configurations of embedded delaminations in the FRP composite plate were modelled and three-dimensional finite element analyses were performed to extract the first 10 natural frequencies. In the research, a total of 201 FE models (with different combinations of delamination size, shape and location) were run and 201 data sets generated. The figures were normalized between 0.1 and 0.9. A total of 165 data sets were chosen at random for the purpose of training the network and the rest were reserved for testing.

The network consisted of 10 input nodes (corresponding to the first 10 natural frequencies) and three output nodes (one each for size, shape and location of the delamination). Based on the trial runs, the network architecture determined in the research was 10-9-3. Various combinations of learning rate and momentum parameter were tried to optimize the learning, based on their relative performances. It was observed from the results that the network can predict the delamination size and shape almost accurately with very little error. However, in predicting the location of delamination, for five samples the network could not predict accurately, which the author felt was due to the lack of training data. Neural networks were thus found capable of learning the information regarding embedded delamination in an FRP laminate.

In another study by Karnik *et al.*,²⁴ analysis of delamination behaviour

as a function of drilling process parameters was performed at the entrance of the CFRP plates. The delamination analysis in high-speed drilling was performed by an artificial neural network (ANN) model with spindle speed, feed rate and point angle as the affecting parameters. A multilayer feed-forward artificial neural network, trained using an error-back-propagation training algorithm (EBPTA), was employed for this purpose.

The laminates were produced using the hand lay-up technique and were made of 50 wt% epoxy matrix reinforced with 50 wt% plain woven carbon fibres with an orientation of 0/90°. The drilling parameters, spindle speed, feed rate and point angle were used as feed parameters and the delamination factor was taken as the output parameter. The ANN training was performed using first 30 input–output patterns, from the experimental database employed for ANN testing. The training of ANN for these 30 normalized input–output patterns was carried out using the NN toolbox of MATLAB software. The ANN was initially tested using 30 input patterns which were employed for the training purpose. For each input pattern, the predicted value of the delamination factor (F_d) was compared with the respective experimental value. It was found that the predicted F_d values were very close to the experimental values. The trained ANN was subsequently tested with the remaining six trials of FFD which were not used for the training purpose. It was observed that the predicted values were very close and followed almost the same trend as the experimental values. The maximum absolute error for testing patterns was found to be 12.5%.

13.5 Conclusion

Artificial neural networks have been pretty successful in predicting various mechanical properties of fibre reinforced composites. Most studies have stressed that the number of training datasets plays a key role in ANN predictive quality. For more complex nonlinear relations between input and output, larger training datasets were found to be more successful. The simulation results in several investigations as reported by researchers, using ANN, were found to be a powerful tool in the structure–property analysis of polymer composites. However, more directed research in the field of static mechanical properties and shear properties using artificial neural networks is required. Also the use of other types of neural networks such as recurrent, associative memory and self-organizing networks to improve prediction accuracy should be considered for further research.

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Fuzzy decision making and its applications in cotton fibre grading

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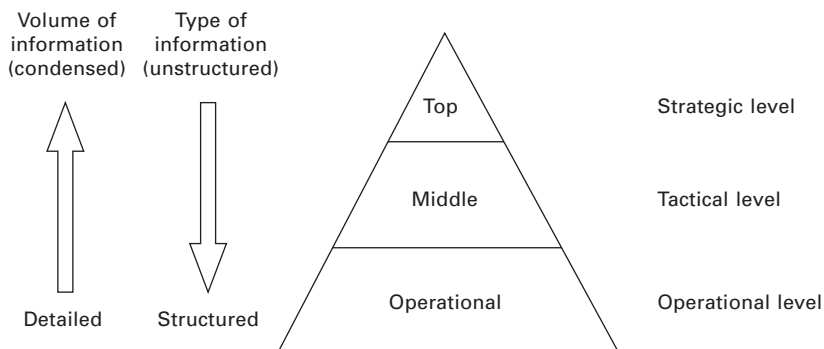
Abstract: Multi-criteria decision making (MCDM) is a branch of operations research (OR). Decision making often involves imprecision and vagueness which can be effectively handled by fuzzy sets and fuzzy decision making techniques. In recent years, a great deal of research has been carried out on the theoretical and application aspects of MCDM and fuzzy MCDM. This chapter provides an outline of decision making in general and fuzzy MCDM in particular. The algorithms of the popular MCDM processes (AHP and TOPSIS) are explained and their applications in cotton fibre grading and selection are discussed. Subsequently, fuzzy MCDM techniques (fuzzy AHP and fuzzy TOPSIS) are introduced and their applications are explained with some simplified examples of cotton fibre selection.

Key words: multi-criteria decision making, fuzzy multi-criteria decision making, analytic hierarchy process, TOPSIS, cotton fibre.

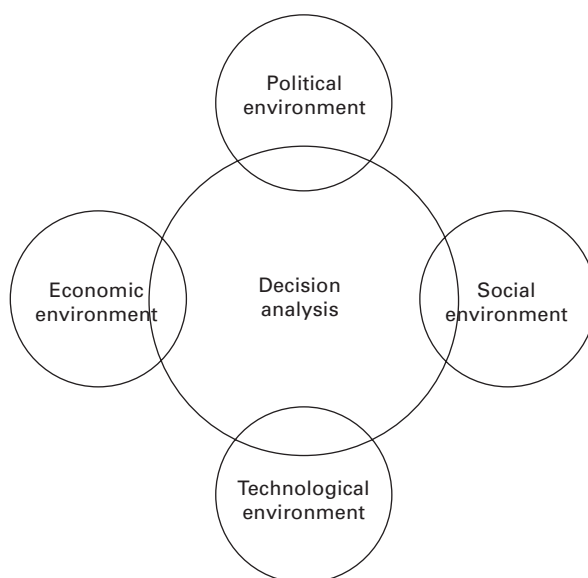
14.1 Introduction

Decision making is as old as human civilization, but fuzzy multi-criteria decision making processes are as new as DNA (deoxyribonucleic acid). Decision making analysts have been thinking about effective survival from the Stone Age to the present day. The nature of decision making changes with the passage of time. In the early period of human history, people depended on the forest for survival. Later, they began to control nature through science and technology. At each level, holistic ideas have been explored to overcome obstacles with a view to a better quality of life. Decision making is primarily based on the availability of information, then on assumption, emotion, communication and, finally, computation. In the twenty-first century, information plays a pivotal role in gaining competitive advantage and decisions are made at different levels of an organization: strategic, tactical and organizational. Figure 14.1 shows the different decision levels of an organization.

Decision analysts make plans through the decision making process. They carry out the exercise by envisaging political, economic, social and technological (PEST) analysis. Different factors, as mentioned above, play a pivotal role in shaping a decision as shown in Fig. 14.2. This is a multi-dimensional approach to making a decision of discrimination. The taxonomy of



14.1 Different levels of decisions.

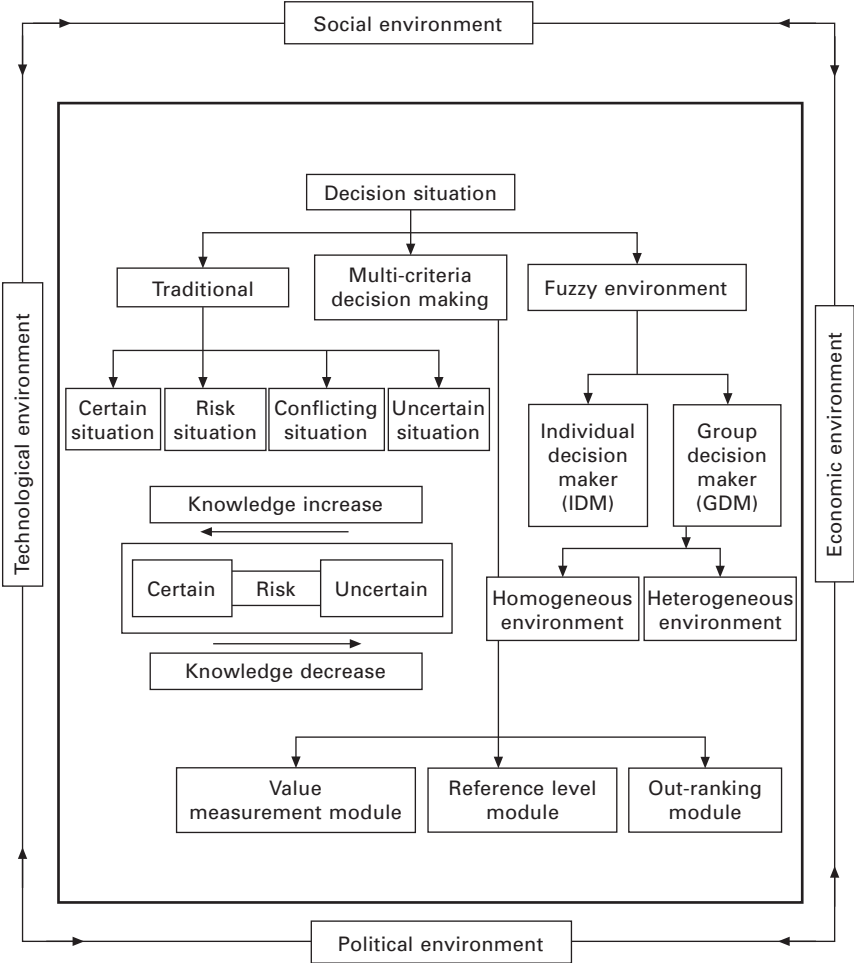


14.2 PEST diagram.

decision making situations is depicted in Fig. 14.3. In the traditional decision making situation, these are the factors primarily forming the environment:

- Decision making in a certain environment
- Decision making in a risk environment
- Decision making in a conflict environment
- Decision making in an uncertain environment.

The change from an uncertain to a certain environment is caused by the increase of knowledge and the reverse also obtains. That is why PEST analysis is an essential and basic requirement for comprehensive decision making.



14.3 Taxonomy of decision making.

Lao Tsu, a Chinese philosopher (600 BC), made a critical comment on knowledge: ‘knowing ignorance is strength, ignoring knowledge is sickness.’ The linear programming problem (LPP), break-even analysis, etc., are common examples of decision making under certain situations. Here, objective function coefficients, technological coefficients and availability of resources are known with certainty. Decision making under risk situations is handled by the decision matrix and the decision tree. In the case of the decision matrix, only one decision is taken, whereas in the decision tree, sequential decisions are taken. Game theory is primarily used in decision making in a conflict environment. The components in the decision matrix for solving problems in an uncertain environment are:

1. Set alternatives (A_i) shown by rows.
2. State of nature or event (E_j) shown by columns.
3. Conditional pay-off or outcomes represented by θ_{ij} shown by an element of the matrix.
4. Probability of occurrence of event, shown by P_j , is unknown.

The decision matrix is shown in Fig. 14.4. Mathematically speaking,

$$\theta_{ij} = f(A_i, E_j)$$

where

θ_{ij} = conditional pay-off at i th level of alternatives and j th level of event

i = number of alternatives = 1, 2, 3, ..., m

j = number of event/state of nature = 1, 2, 3, ..., n .

There are primarily four methods used for solving decision making problems in an uncertain environment:

- Laplace criterion
- Maximax criterion
- Maximin criterion
- Hurwicz criterion.

The Laplace criterion deals with the equal probability of the occurrence of events. The maximax criterion is the optimistic approach, whereas the maximin criterion is the pessimistic approach. The hurwicz criterion is a hybrid of the maximax and maximin criteria.

		State of nature					
		E_1	E_2	...	E_j	...	E_n
		P_1	P_2	...	P_j	...	P_n
Alternatives	A_1	θ_{11}	θ_{12}	...	θ_{1j}	...	θ_{1n}
	A_2	θ_{21}	θ_{22}	...	θ_{2j}	...	θ_{2n}
	...	..					
	...	..					
	...	..					
	A_i	..					
	...	θ_{i1}	θ_{i2}	...	θ_{ij}	...	θ_{in}
	A_m	θ_{m1}	θ_{m2}	...	θ_{mj}	...	θ_{mn}

14.4 Decision matrix.

14.2 Multiple criteria decision making (MCDM) process

Multiple criteria decision making (MCDM) is used when a finite number of alternatives have to be evaluated in terms of a finite number of decision criteria. A textile engineer is very much concerned with the quality of cotton fibre. He wishes to produce products at minimum cost with high quality, reliability and a quick response to changes of design and demand, in order to meet the taste and specification of valued customers. An organization cannot produce textile products while considering only one factor at a time. All the factors must be taken into account in order to gain competitive advantage in a highly competitive environment. But it is impossible to satisfy all factors simultaneously. Some level of compromise is unavoidable.

The MCDM method is broadly classified into two areas: (1) the multi-objective decision making (MODM) process, and (2) the multi-attribute decision making (MADM) process. The principal difference between these two methods is that the former is concerned with continuous decision space, while the latter is involved with discrete decision space.

Hwang and Yoon (1981) indicated different methods of multiple decision making (MADM) depending on

- type of information received from decision maker
- particular features of the information.

Existing MADM methods can be classified broadly into three areas (Loken, 2007) as follows:

1. Value measurement models, e.g. the analytic hierarchy process (AHP) and multi attribute utility theory (MAUT) are the best known methods in that class
2. Reference level models, e.g. technique for order preference by similarity to ideal solution (TOPSIS)
3. Outranking model, e.g. ELECTRE.

A taxonomy of widely used different MADM methods and their applications is shown in Table 14.1. Figure 14.5 shows flowchart of MADM methods.

14.2.1 Analytical hierarchy process (AHP)

The analytic hierarchy process (AHP) is a multi-criteria decision-support procedure developed by Saaty (1980). It uses a multi-level hierarchical structure of objective or goal, criteria, sub-criteria and alternatives as shown in Figs 14.6(a) and 14.6(b). The pertinent data are derived by using a set of pairwise comparisons. These comparisons are used to obtain the weight of importance of the decision criteria and the relative performance measures

Table 14.1 A taxonomy of widely used different MADM methods and their applications

Sl no.	Source	MADM methods	IDM/ GDM*	Application domain
1	Triantaphyllou <i>et al.</i> (1997)	AHP	IDM	Maintenance action
2	Triantaphyllou & Sanchez (1997)	AHP	IDM	Sensitivity analysis
3	Majumdar <i>et al.</i> (2004)	AHP	IDM	Selection of cotton fibre
4	Bhattacharya <i>et al.</i> (2004)	AHP	IDM	Plant location
5	Majumdar <i>et al.</i> (2005a, 2005b)	AHP & TOPSIS	IDM	Grading of cotton fibre
6	Bhattacharya <i>et al.</i> (2005)	AHP & TOPSIS	IDM	Robot selection
7	Jahanshahloo <i>et al.</i> (2006)	TOPSIS	IDM	Performance of different branches of bank
8	Agarwal <i>et al.</i> (2006)	ANP	IDM	Supply chain
9	Shih (2007)	TOPSIS	GDM	Robot selection
10	Bhattacharya <i>et al.</i> (2007)	TOPSIS	IDM	Inventory control
11	Istklar & Buyukozkan (2007)	TOPSIS	IDM	Selection of mobile phone
12	Ye & Li (2009)	TOPSIS (interval data)	GDM	Partner selection

*IDM: individual decision maker; GDM: group decision maker.

(score) of the alternatives in terms of each decision criterion. Belton and Gear (1983) first raised concerns over the theoretical basis of AHP. However, it has proven to be an extremely useful method for decision making.

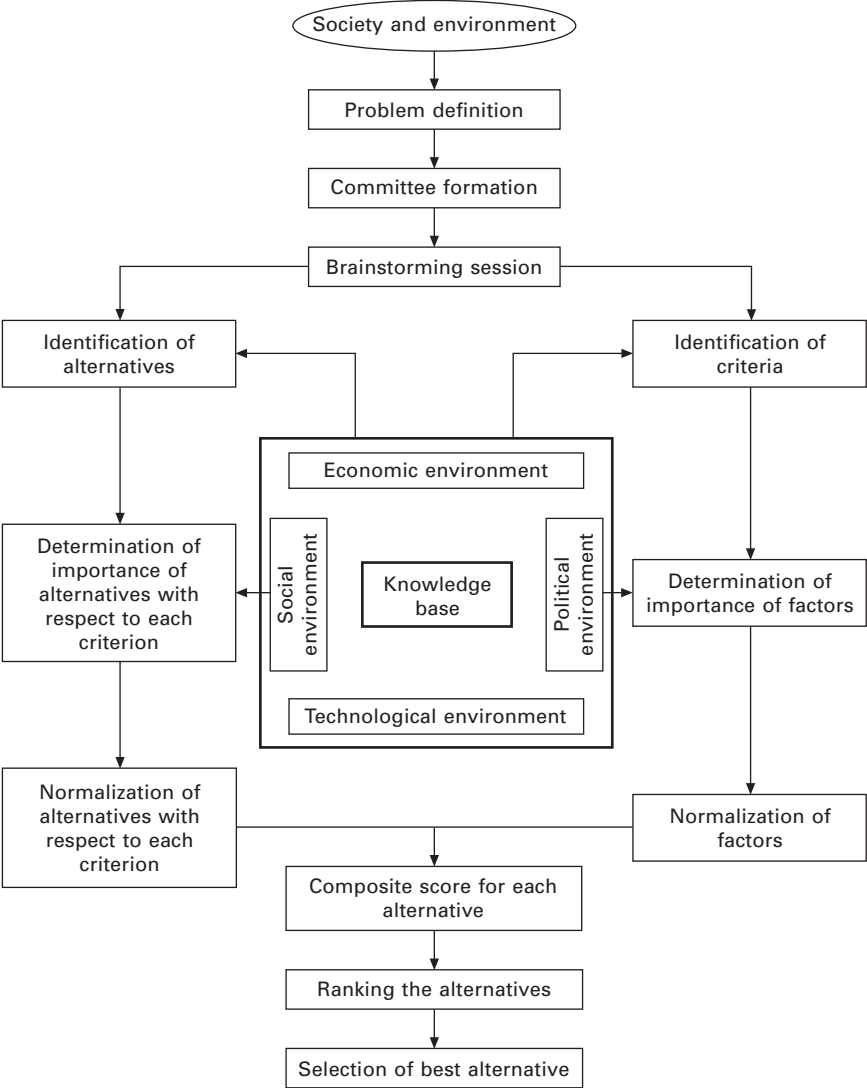
The four steps of AHP methodology are as follows:

1. Build a decision 'hierarchy' by breaking down the problem into various components, i.e. objective, goal, criteria, sub-criteria and alternatives.
2. Gather relational data for the decision criteria and encode them using the AHP relational scale.
3. Estimate the relative priorities (weights) of the decision criteria and alternatives.
4. Perform the composition (synthesis) of priorities of criteria and alternatives, which ranks the alternatives with respect to the problem objective.

Details of the AHP methodology are presented below.

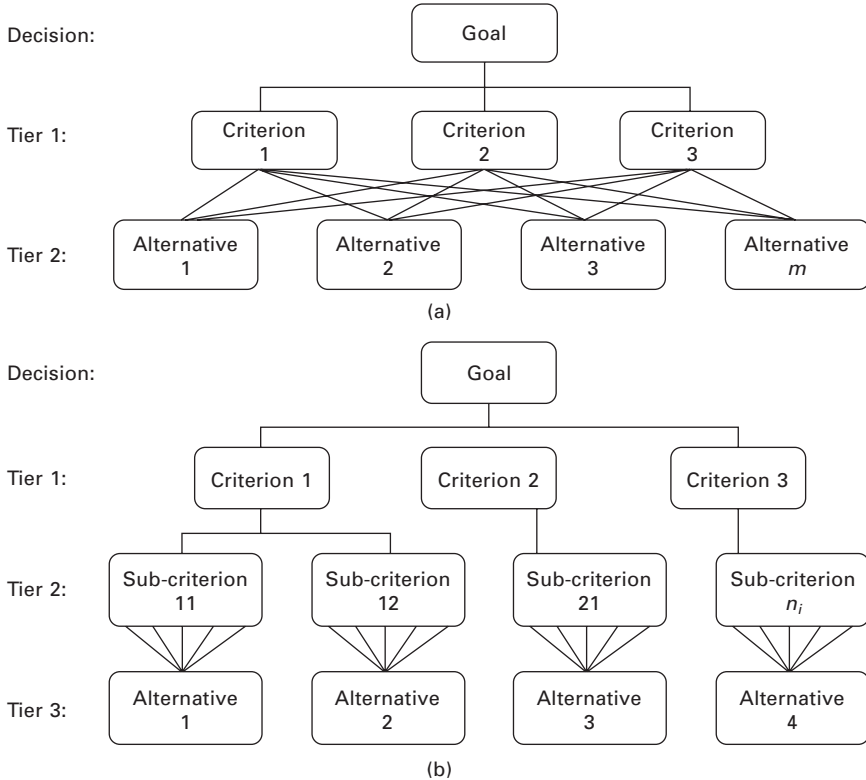
Step 1: The hierarchical structure of the decision problem is formulated. The overall objective or goal of the problem is positioned at the top of the hierarchy and the decision alternatives are placed at the bottom. The relevant attributes of the decision problem such as criteria and sub-criteria come between the top and bottom levels. The number of levels in the hierarchy depends on the complexity of the problem.

Step 2: The relational data are generated for comparing the alternatives. This requires the decision maker to formulate pairwise comparison matrices of



14.5 Flowchart for MADM method.

elements at each level in the hierarchy, relative to the activity at the next level up. In AHP, if a problem involves m alternatives and n criteria, then the decision maker needs to construct n judgement matrices of alternatives of order $m \times m$ and one judgement matrix of criteria of order $n \times n$. Finally, the decision matrix of order $m \times n$ is formed by using the relative scores of the alternatives with respect to each criterion. The AHP relational scale of real numbers from 1 to 9 and their reciprocals are used to assign preferences



14.6 (a) Hierarchical structure for two-tier AHP process; (b) hierarchical structure for three-tier AHP process.

in a systematic manner. When comparing two criteria (or alternatives) in respect of an attribute at the next level up, the relational scale proposed by Saaty (1980) is used, which is shown in Table 14.2.

Step 3: The relative importance of different criteria with respect to the goal of the problem and the alternative scores with respect to each of the criteria is determined. For n criteria the size of the comparison matrix (CM_1) will be $n \times n$ and the entry c_{ij} will denote the relative importance of criterion i with respect to criterion j . In the matrix, $c_{ij} = 1$ if $i = j$ and $c_{ji} = 1/c_{ij}$.

$$CM_1 = \begin{bmatrix} 1 & c_{12} & \dots & c_{1n} \\ c_{21} & 1 & \dots & c_{2n} \\ \dots & \dots & 1 & \dots \\ c_{n1} & c_{n2} & \dots & c_{nn} \end{bmatrix}$$

The relative weight or importance of the i th criterion (W_i) is determined by calculating the geometric mean (GM) of the i th row and then normalizing

Table 14.2 The fundamental relational scale for pairwise comparisons

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
3	Moderate importance of one over another	Experience and judgement slightly favour one activity over another.
5	Essential or strong importance	Experience and judgement strongly favour one activity over another.
7	Very strong importance	An activity is strongly favoured and its dominance is demonstrated in practice.
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation.
2, 4, 6, 8	Intermediate values between two adjacent judgements	When compromise is needed.
Reciprocals	If activity p has one of the above numbers assigned to it when compared with activity q , then q has the reciprocal value when compared with p .	

the geometric means of the rows of the above matrix. This can be represented as follows:

$$GM_i = \left\{ \prod_{j=1}^n c_{ij} \right\}^{\frac{1}{n}}, W_i = \frac{GM_i}{\sum_{i=1}^n GM_i}$$

Similarly, n pairwise comparison matrices, one for each criterion, of $m \times m$ order are formed where each alternative is pitted against all of its competitors and pairwise comparison is made. The eigenvector of each of these n matrices represents the alternative performance scores in the corresponding criterion and the eigenvectors form a column of the final decision matrix. The structure of the final decision matrix is shown below:

		Criteria				
		W_1	W_2	W_3	...	W_n
Alternatives	A_1	a_{11}	a_{12}	a_{13}	...	a_{1n}
	A_2	a_{21}	a_{22}	a_{23}	...	a_{2n}
	A_3	a_{31}	a_{32}	a_{33}	...	a_{3n}
	...	...	...	...	...	...
	A_m	a_{m1}	a_{m2}	a_{m3}	...	a_{mn}

where $\sum_{i=1}^m a_{ij} = 1$, $\sum_{j=1}^m W_j = 1$, a_{ij} represents the score of the i th alternative,

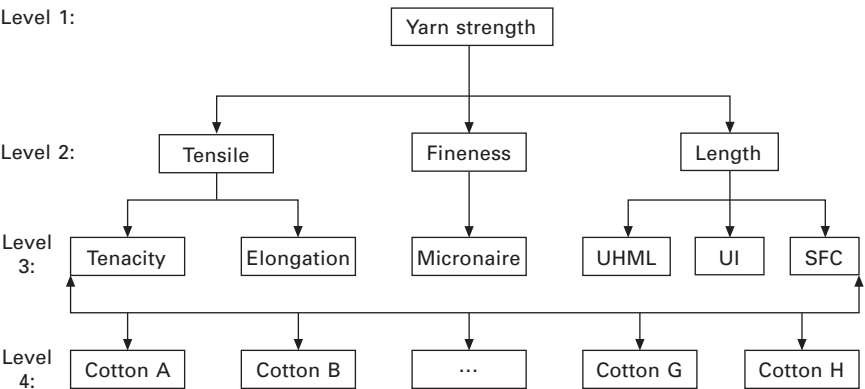
in terms of the j th criterion, and W_j is the weighting of the j th criterion with respect to the goal of the problem.

Step 4: The final priority of all the alternatives is determined considering the alternative scores (a_{ij}) in each criterion and the weight of the corresponding criterion (W_j) using the following equation:

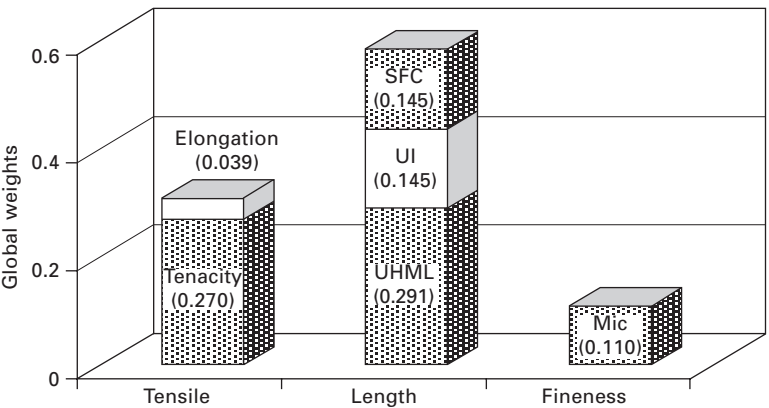
$$A_i = \max \sum_{j=1}^n a_{ij} W_j \text{ for } i = 1, 2, 3, \dots, m$$

Selection of cotton fibre using AHP

Majumdar *et al.* (2005a) used the AHP for the relative grading of cotton fibre from the point of view of yarn strength. The objective of the particular hierarchy is directed towards the selection of a cotton fibre from the available alternatives to maximize the ring yarn strength. This objective acquires a position at the top (Level 1) of the hierarchy. It has been an established perception in the spinning industries that the strength of ring spun yarns, for a given set of process conditions, is decisively influenced by the tensile, length and fineness properties of cotton fibre. Therefore, these three general attributes or criteria of cotton fibre form Level 2 of the hierarchy. Among the tensile properties of cotton fibres, bundle tenacity and elongation are the most commonly evaluated and consequently they become the sub-criteria (Level 3) of tensile properties. Likewise, the upper half mean length (UHML), length uniformity index (UI) and short fibre content (SFC) are the sub-criteria of length properties. Fineness properties do not have any sub-criteria and are almost solely represented by the micronaire value of the cotton fibre. Eight cotton fibre alternatives are placed at the lowest level (Level 4) of the hierarchy. The schematic diagram of the hierarchical structure is depicted in Fig. 14.7. Eight types of cotton fibres were graded according to their quality with respect to yarn strength. From the pairwise comparison matrix of criteria, the tensile weights, length and fineness properties were 0.309, 0.581 and 0.11, respectively. In the next step, a pairwise comparison of sub-criteria was performed with respect to the corresponding criterion. Finally, the global weights of all the six sub-criteria were obtained. For tenacity, elongation, UHML, UI, SFI and micronaire, the values of global weights are 0.270, 0.039, 0.291, 0.145, 0.145 and 0.110, respectively. The global weights of the sub-criteria are depicted in Fig. 14.8.



14.7 Hierarchical structure of cotton fibre selection problem (source: Majumdar *et al.*, 2004).



14.8 Global weights of cotton fibre properties with respect to yarn strength (source: Majumdar *et al.*, 2004).

14.2.2 Technique for order preference by similarity to ideal solution (TOPSIS) model

The TOPSIS model is an MADM process which was proposed by Hwang and Yoon (1981). It is based on the idea that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). In other words, the ideal solution is composed of all the best scores, whereas the negative ideal solution is made up of the worst scores.

The TOPSIS model considers the following decision matrix D which contains m alternatives associated with n criteria:

		Criteria					
		C_1	C_2	...	C_j	...	C_n
Alternatives	A_1	a_{11}	a_{12}	...	a_{1j}	...	a_{1n}
	A_2	a_{21}	a_{22}	...	a_{2j}	...	a_{2n}
	...	..					
	...	..					
	...	..					
	A_i	a_{i1}	a_{i2}	...	a_{ij}	...	a_{in}
	...	..					
	A_m	a_{m1}	a_{m2}	...	a_{mj}	...	a_{mn}

where

A_i = the i th alternative to be evaluated, $i = 1, 2, 3, \dots, m$

C_j = the j th criterion considered, $j = 1, 2, 3, \dots, n$

a_{ij} = score of the i th alternative with respect to the j th criterion.

The steps involved in TOPSIS are as follows.

Step 1: Formation of decision hierarchy. The relevant objective or goal, decision criteria and alternatives are identified in this step.

Step 2: Construction of a normalized decision matrix. The decision matrix formulated by the actual values or scores of alternatives is normalized in the following way:

$$r_{ij} = \frac{a_{ij}}{\left[\sum_{i=1}^m (a_{ij})^2 \right]^{0.5}}$$

Step 3: Construction of weighted normalized decision matrix. The weighted normalized decision matrix is obtained by multiplying each column with the associated criterion weight (W_j) corresponding to that column. Hence an element v_{ij} of the weighted normalized matrix V is represented as

$$v_{ij} = W_j r_{ij}, \sum_{j=1}^n W_j = 1$$

Step 4: Determination of positive and negative ideal solutions. This step produces the positive ideal solution (A^*) and the negative ideal solution (A^-) in the following manner:

$$\begin{aligned} A^* &= \{(\max v_{ij} | j \in J), (\min v_{ij} | j \in J') \text{ for } i = 1, 2, 3, \dots, m\} \\ &= \{v_1^*, v_2^*, \dots, v_n^*\} \end{aligned}$$

$$A^- = \{(\min v_{ij} | j \in J), (\max v_{ij} | j \in J') \text{ for } i = 1, 2, 3, \dots, m\}$$

$$= \{v_1^-, v_2^-, \dots, v_n^-\}$$

where $J = \{j = 1, 2, \dots, n | j \text{ associated with benefit or positive criteria}\}$
and

$J' = \{j = 1, 2, \dots, n | j \text{ associated with cost or negative criteria}\}$.

Step 5: Calculation of separation distance. The n -dimensional Euclidean distance method is applied as shown below, to measure the separation distance of each alternative from the positive and negative ideal solutions:

$$S_i^* = \left\{ \sum_{j=1}^n (V_{ij} - V_j^*)^2 \right\}^{0.5}, i = 1, 2, \dots, m$$

$$S_i^- = \left\{ \sum_{j=1}^n (V_{ij} - V_j^-)^2 \right\}^{0.5}, i = 1, 2, \dots, m$$

Step 6: Calculation of relative closeness. In this step, the relative closeness (C_i^*) value of each alternative is determined using the following equation:

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}$$

Step 7: Ranking of alternatives. All the alternatives are now arranged according to the descending order of C_i^* . The alternative at the top of the list is the most preferred and that at the bottom is the least preferred.

Selection of cotton fibre using TOPSIS

Majumdar *et al.* (2005a, 2005b) used the combined AHP-TOPSIS approach for the grading of cotton fibres. The AHP method was used to elicit the relative weights of cotton fibre properties like bundle tenacity, elongation, upper half mean length, uniformity index, short fibre content and micronaire. Then the TOPSIS approach was used to determine the closeness index of the different cotton fibres (alternatives). To validate the proposed method, the 33 cotton fibres were ranked according to their quality value determined by AHP-TOPSIS methodology. Yarns (22 Ne and 30 Ne) spun from those cotton fibres were also ranked according to their tenacity value. Then the rank correlation coefficient was determined between the fibre quality and yarn tenacity as follows:

$$R_s = 1 - \frac{6 \sum d^2}{m(m^2 - 1)}$$

where R_s is the rank correlation, d is the absolute difference between the two rankings and m is the total number of alternatives.

The values of rank correlation coefficient obtained by three different methods, namely spinning consistency index (SCI), revised AHP and AHP-TOPSIS, are shown in Table 14.3. It is seen that the AHP-TOPSIS approach outperforms the other two methods.

14.3 Fuzzy multiple criteria decision making (FMCDM)

Multiple criteria decision making is the procedure associated with the ranking and selection of an alternative from a pool of alternatives. It is based on the evaluation of multiple conflicting criteria. Decision makers, however, may find it difficult to identify the best alternative due to lack of certain information regarding organization, society, technological innovations and the political situation surrounding the system under examination. Lack of precision in assigning importance, weights of criteria and the rating of alternatives with respect to criteria, leads to development of fuzzy multiple criteria decision making (FMCDM) (Chen and Klein, 1997).

Zadeh (1965) introduced fuzzy set theory in order to resolve the vagueness and subjectivity of human judgement by using linguistic terms in the decision making process. Bellman and Zadeh (1970) were the first researchers to survey the decision making problem using fuzzy sets and initiated the fuzzy multiple criteria decision making (FMCDM) methodology. In most fuzzy MCDM problems, the ratings and scores are given in terms of triangular fuzzy numbers (TFN). Triangular fuzzy numbers can replace the crisp numbers of a pairwise comparison matrix. Use of TFNs is the simplest way to represent imprecision. A TFN is a collection of three points forming a triangle as shown below:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-L}{m-L} & \text{for } L \leq x \leq m \\ \frac{R-x}{R-m} & \text{for } m \leq x \leq R \\ 0 & \text{otherwise} \end{cases}$$

Table 14.3 Rank correlation between cotton quality and yarn tenacity

Method	Yarn count	
	22 Ne	30 Ne
SCI	0.401	0.459
Revised AHP	0.658	0.671
AHP-TOPSIS	0.772	0.729

where m is the most promising value, and L and R are the left and right spread (the smallest and largest values that m can take).

The basic operations of TFN are shown below:

$$\begin{aligned}\overline{n_1} \oplus \overline{n_2} &= (n_{1l} + n_{2l}, n_{1m} + n_{2m}, n_{1u} + n_{2u}) \quad \text{for addition} \\ \overline{n_1} \otimes \overline{n_2} &= (n_{1l} \times n_{2l}, n_{1m} \times n_{2m}, n_{1u} \times n_{2u}) \quad \text{for multiplication} \\ \frac{\overline{n_1}}{\overline{n_2}} &= \left(\frac{1}{n_{2u}}, \frac{n_{1m}}{n_{2m}}, \frac{n_{1l}}{n_{2l}} \right) \quad \text{for division} \\ \frac{1}{\overline{n_1}} &= \left(\frac{1}{n_{1u}}, \frac{1}{n_{1m}}, \frac{1}{n_{1l}} \right) \quad \text{for inverse}\end{aligned}$$

where $\overline{n_1} = (n_{1l}, n_{1m}, n_{1u})$ and $\overline{n_2} = (n_{2l}, n_{2m}, n_{2u})$ represent two triangular fuzzy numbers with lower, modal and upper values.

Chen and Hwang (1992) classified 18 fuzzy MADM methods into eight categories, depending on four factors:

1. Capability of solving large-scale problems
2. Types of data used
3. The classical MADM method to which each fuzzy MADM method relates
4. The technique each method uses.

Bozdag *et al.* (2003) outlined fuzzy MADM methods into seven classes as follows, for selection of computer integrated manufacturing systems:

1. Fuzzy simple additive weighing methods
2. Fuzzy analytic hierarchy process methods
3. Fuzzy conjunctive and disjunctive methods
4. Fuzzy outranking method
5. Maximin methods
6. Fuzzy TOPSIS method
7. Linguistic methods.

Perego and Rangone (1998) grouped fuzzy MADM methods into four major categories as follows:

1. Fuzzy goal methodology
2. Fuzzy linguistic models
3. Fuzzy hierarchical models based on pairwise comparison
4. Heuristic model based on fuzzy logic.

Table 14.4 shows the taxonomy of widely used FMADM methods and their area of application. Based on that, we concentrate on the following:

- Fuzzy AHP
- Fuzzy TOPSIS.

Table 14.4 A taxonomy of widely used fuzzy MADM methods and their application domains*

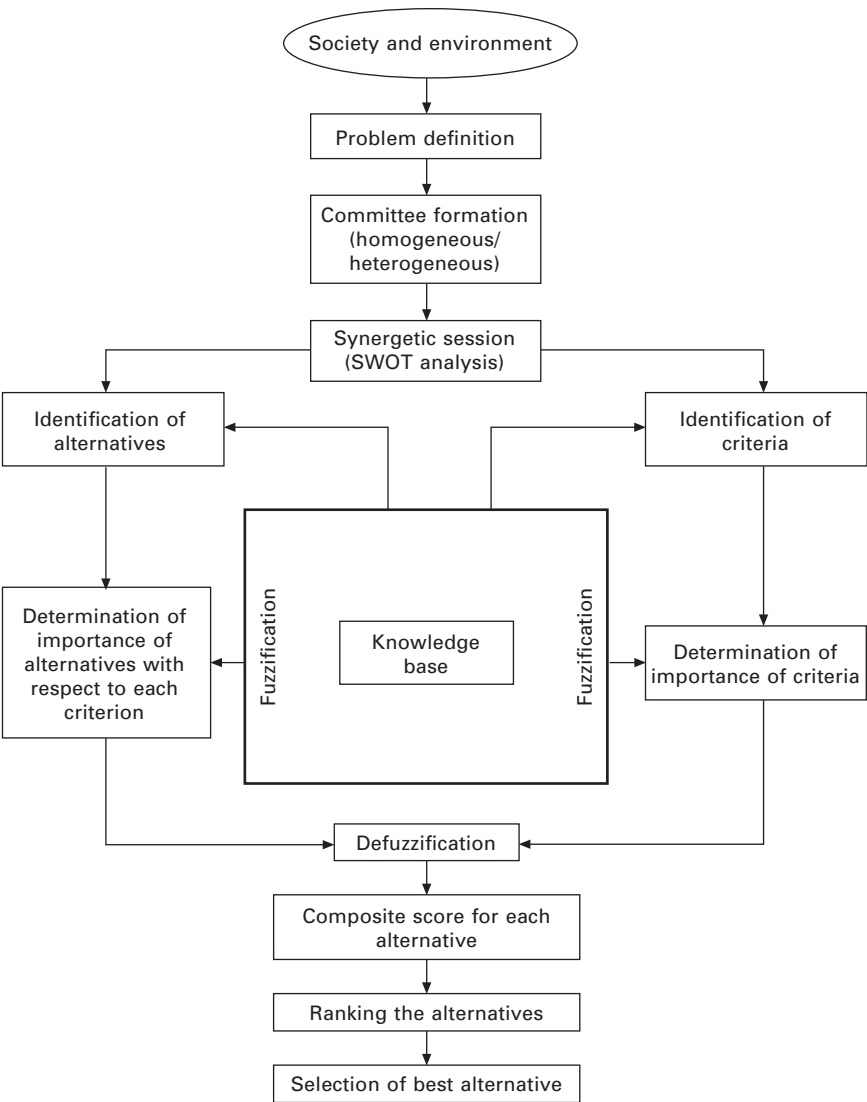
Sl no.	Source	FMADM method	Ranking method	Application area	Types of fuzzy membership function	Individual/group decision makers
1	Bayrak <i>et al.</i> (2007)	Integrated fuzzy approach	Chen (1985)	Supplier selection	Trapezoidal	GDM
2	Wang & Chang (2007)	Fuzzy TOPSIS	BNP values	Aircraft selection	Triangular	GDM
3	Chen (2000)	Fuzzy TOPSIS	Closeness coefficient	Personnel selection	Triangular	IDM
4	Chang <i>et al.</i> (2009)	FAHP	Composite weight	DVR selection	Triangular	IDM
5	Mahmoodzadeh <i>et al.</i> (2007)	FAHP & TOPSIS	Closeness coefficient	Project selection	Triangular	IDM
6	Bhattacharya <i>et al.</i> (2007)	Revised version TOPSIS (Karsak, 2002)	Closeness coefficient	Bearing material	TFN	IDM
7	Al-Ahmani (2008)	FAHP	Composite weight	Advanced manufacturing technology	TFN	IDM
8	Wadhwa <i>et al.</i> (2009)	Fuzzy distance function	Composite weight	Reprocessing alternative	Trapezoidal	GDM
9	Athanasopoulos & Romeva (2009)	Fuzzy distance function (negative ideal solution not considered)	Shortest distance (no ratio)	Coating selection	TFN	IDM
10	Chou <i>et al.</i> (2008)	FSAWS	Fuzzy total score	Facility location selection	Trapezoidal	GDM
11	Shen & Yu (2009)	Fuzzy aggregate rating	Signed distance	Facility location selection	TFN	GDM
12	Cheng (1999)	Fuzzy aggregate rating	Fuzzy mean and spread	Weapon system selection	TFN	GDM
13	Yeh & Chang (2009)	Fuzzy distance functions	α -cut in fuzzy set theory	Aircraft selection	TFN	GDM
14	Liang & Wang (1991)	Fuzzy linguistic models	Chen's method	Site selection	Trapezoidal	GDM
15	Perego and Rangone (1998)	Fuzzy AHP/fuzzy linguistic model	Maximizing set and minimizing set	Advanced manufacturing technology	TFN	IDM
16	Bozdag <i>et al.</i> (2003)	Fuzzy AHP/Yager's weighted goals method (Yagen, 1978)	Chang's extent analysis	Selection of computer integrated manufacturing system	TFN	GDM

*IDM: individual decision maker; GDM: group decision maker; BNP: best non-fuzzy performance; TFN: triangular fuzzy number; FSAWS: fuzzy simple additive weighting system.

A general flowchart for FMADM methods is shown in Fig. 14.9.

14.3.1 Fuzzy analytic hierarchy process (FAHP)

AHP was developed and expounded by Saaty (1980, 1988, 1990). Here we consider two models: model 1, developed by Triantaphyllou (2000), and model 2, developed by Chang *et al.* (2009).



14.9 Flowchart for fuzzy MADM method.

Fuzzy AHP model 1

Here, the fuzzy AHP approach developed by Triantaphyllou (2000) is demonstrated. It can be stated as follows:

1. The decision maker needs to ascertain fuzzy estimates of the relative importance of each decision criterion, and to decide about each cotton fibre based on each criterion.
2. Estimate the fuzzy eigenvector for each matrix thus developed in the previous step.
3. Normalize each vector by dividing each element by the sum of entries in the vector.
4. Calculate composite scores for each cotton fibre.
5. Rank each alternative and select the best cotton fibre.

Here, a cotton fibre selection problem is demonstrated where only two criteria (C_1 and C_2) and two alternatives (A and B) are considered. The scores given in this example are just representative and should not be used for generalization. Table 14.6 shows the fuzzy pairwise comparison of two criteria based on fuzzy linguistic terms and the corresponding fuzzy numbers given in Table 14.5. The scores given in the pairwise comparison matrix are in terms of fuzzy numbers to represent the vagueness present in the mind of the decision maker. Table 14.8 shows the priority vector of each cotton fibre corresponding to each decision criterion based on Table 14.7. Cotton fibre B is superior to cotton fibre A in terms of both the decision criteria C_1 and C_2 . The priority score of each cotton fibre and its ranking are represented in Table 14.9. The Lee and Li (1988) approach has been used here. Cotton fibre B is preferred to cotton fibre A. The final composite score of cotton B (0.879) is higher than that of cotton A (0.344). Therefore, cotton B is the preferred alternative.

Table 14.5 Fuzzy linguistic terms and corresponding fuzzy numbers for decision criteria

Importance	Fuzzy number
Very low	(0, 0.1, 0.3)
Low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
High	(0.5, 0.7, 0.9)
Very high	(0.7, 0.9, 1.0)

Table 14.6 Fuzzy pairwise comparison of decision criteria and priority vector

Criteria	C_1	C_2	Priority vector
C_1	(1, 1, 1)	(0.7, 0.9, 1.0)	(0.37, 0.47, 0.55)
C_2	(1.0, 1.11, 1.43)	(1, 1, 1)	(0.45, 0.53, 0.65)

Table 14.7 Fuzzy linguistic terms and corresponding fuzzy numbers for alternatives

Importance	Fuzzy number
Poor	(0, 0.1, 0.3)
Fair	(0.1, 0.3, 0.5)
Medium fair	(0.3, 0.5, 0.7)
Good	(0.5, 0.7, 0.9)
Very good	(0.7, 0.9, 1.0)

Table 14.8 Fuzzy pairwise comparison of cotton fibres and priority vector

Criteria		Cotton fibre A	Cotton fibre B	Priority vector
C ₁	Cotton fibre A	(1, 1, 1)	(0.5, 0.7, 0.9)	(0.30, 0.42, 0.54)
	Cotton fibre B	(1.11, 1.43, 2.0)	(1, 1, 1)	(0.45, 0.58, 0.8)
C ₂	Cotton fibre A	(1, 1, 1)	(0.1, 0.3, 0.5)	(0.08, 0.23, 0.41)
	Cotton fibre B	(2, 3.3, 10)	(1, 1, 1)	(0.36, 0.77, 1.827)

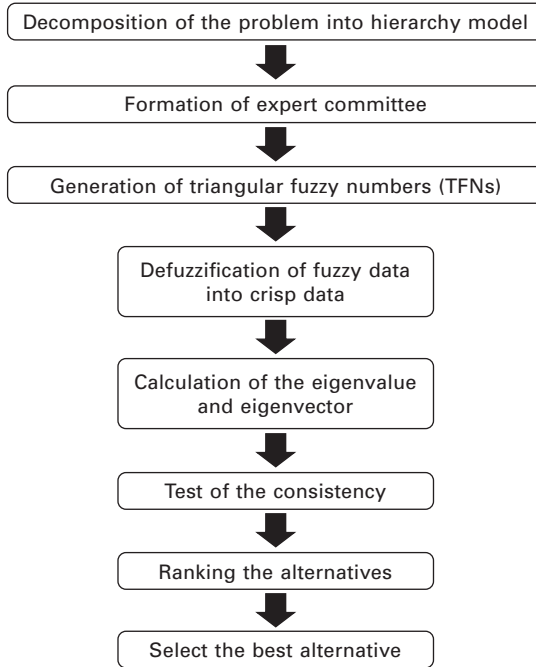
Table 14.9 Composite score of cotton fibres and their ranking

Criteria	Weights	Cotton fibre A	Cotton fibre B
C ₁	(0.37, 0.47, 0.55)	(0.30, 0.42, 0.54)	(0.45, 0.58, 0.8)
C ₂	(0.45, 0.53, 0.65)	(0.08, 0.23, 0.41)	(0.36, 0.77, 1.827)
Total		(0.147, 0.320, 0.563)	(0.33, 0.68, 1.627)
Average (Lee & Li, 1988)		0.344	0.879
Rank		2	1

Fuzzy AHP model 2

Chang *et al.* (2009) applied fuzzy hierarchy multiple attributes in the construction of expert decision making processes for the evaluation of digital video recording (DVR) systems. The procedural steps are depicted in Fig. 14.10. The authors considered six criteria for four DVR systems. An AHP questionnaire was distributed to 11 experts, each of whom made a pairwise comparison of the decision elements and assigned them relative scores. They used TFN(*a, b, c*) where *a* indicates the minimum numerical value, *c* indicates the maximum numerical value and *b* is the geometric mean representing the consensus of the majority. They used the ‘defuzzification’ method which was derived from Hus and Nian (1997) as well as Liu and Wang (1992). This method simultaneously considers the range of uncertainty of the decision making environment as well as the state of mind of the decision maker, as shown below:

$$(d_{ij}^{\alpha})^{\lambda} = [\lambda \times a_{ij}^{\alpha} + (1 - \lambda) \times c_{ij}^{\alpha}]; 0 \leq \lambda \leq 1, 0 \leq \alpha \leq 1$$



14.10 Steps of fuzzy AHP model.

where

α = range of uncertainty

d_{ij} = defuzzification value for two criteria i and j

λ = attitude of mind of the decision maker

$a_{ij}^{\alpha} = (b_{ij} - a_{ij}) \times \alpha + a_{ij}$ represents the left-end value of α - cut for d_{ij}

$c_{ij}^{\alpha} = (c_{ij} - b_{ij}) \times \alpha$ represents the right-end value of α - cut for d_{ij} .

If $\alpha = 0$, the range of uncertainty is greatest, and if $\lambda = 0$, the decision maker is more optimistic.

14.3.2 Fuzzy TOPSIS

The order preference technique based on similarity to the ideal solution (TOPSIS) was originally propounded and expounded by Hwang and Yoon (1981). Here, the chosen alternative should not only have the shortest distance from the positive ideal point (PIS), but also have the longest distance from the negative ideal point (NIP), in order to solve MADM problems. The positive ideal solution is that which maximizes the benefit criteria and minimizes the cost criteria. The negative ideal solution maximizes cost criteria and

minimizes benefit criteria. Fuzzy sets were introduced by Zadeh (1965) to manipulate the data and information containing uncertainties.

Fuzzy phenomena exist for the language of approximate situations. They contain inexact information about the importance of criteria as well as about the importance of the cotton fibre with respect to each uncertain criterion. The fuzzy set theory enables mathematical processes to capture the uncertainties associated with decision making. Here, the triangular fuzzy number (TFN) has been used for fuzzy TOPSIS, as it is intuitive for decision makers to use and to calculate. The algorithms of this method as expounded by Chen (2000) are described below.

Step 1: Establish the fuzzy decision matrix. The structure of the matrix D can be expressed as follows:

		Criteria				
		C_1	C_2	C_j	C_n	
Alternatives	A_1	$\tilde{\theta}_{11}$	$\tilde{\theta}_{12}$	$\dots$	$\tilde{\theta}_{1i}$	$\dots \tilde{\theta}_{1n}$
	A_2	$\tilde{\theta}_{21}$	$\tilde{\theta}_{22}$	$\dots$	$\tilde{\theta}_{2j}$	$\dots \tilde{\theta}_{2n}$
	$\dots$					
	$\dots$					
	$\dots$					
	A_i	$\tilde{\theta}_{i1}$	$\tilde{\theta}_{i2}$	$\dots$	$\tilde{\theta}_{ij}$	$\dots \tilde{\theta}_{in}$
	$\dots$					
	A_m	$\tilde{\theta}_{m1}$	$\tilde{\theta}_{m2}$	$\dots$	$\tilde{\theta}_{mj}$	$\dots \tilde{\theta}_{mn}$

where
 A_i denotes the i th alternative, $i = 1, 2, \dots, m$
 C_j denotes the j th criterion/attribute, $j = 1, 2, \dots, n$
 $\tilde{\theta}_{ij}$ represents the performance rating (score) of alternative A_i with respect to criterion C_j and also represents the linguistic variables which can be described by triangular fuzzy numbers (a_{ij}, b_{ij}, c_{ij})
 $\tilde{W} = [\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_j, \dots, \tilde{w}_n]$
 $\tilde{w}_j = [\tilde{w}_{j1}, \tilde{w}_{j2}, \tilde{w}_{j3}]$ denotes the weight of criterion C_j .

Step 2: Calculate the normalized fuzzy decision matrix. The initial data are normalized to eliminate anomalies with various measurement scales and units in several MADM problems. Primarily, the linear scale transformation is used to transform the various criteria scales and units into a comparable one. If R denotes the normalized fuzzy decision matrix, then

$$R = [r_{ij}]_{m \times n}, i = 1, 2, \dots, m, j = 1, 2, \dots, n$$

where

$$r_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right), j \in B; r_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), j \in C$$

$$c_j^+ = \max_i c_{ij} \text{ if } j \in B, a_j^- = \min_i a_{ij} \text{ if } j \in C$$

B = benefit criteria, C = cost criteria.

The normalization cited above is to preserve the properties of the ranges of normalized triangular fuzzy numbers $[0, 1]$.

Step 3: Establish the weighted normalized fuzzy decision matrix

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, i = 1, 2, \dots, m, j = 1, 2, \dots, n$$

where $\tilde{v}_{ij} = \tilde{r}_{ij} \cdot \tilde{w}_j$.

Step 4: Determine the fuzzy positive-ideal solution (FPIS, A^+) and the fuzzy negative-ideal solution (FNIS, A^-):

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-)$$

where $\tilde{v}_j^+ = (1, 1, 1)$ and $\tilde{v}_j^- = (0, 0, 0)$.

Step 5: Calculate the separation distance of each alternative from A^+ and A^- as follows:

$$d_i^+ = \sum_{j=1}^n d(v_{ij}, v_j^+), i = 1, 2, \dots, m, j = 1, 2, \dots, n$$

$$d_i^- = \sum_{j=1}^n d(v_{ij}, v_j^-), i = 1, 2, \dots, m, j = 1, 2, \dots, n$$

where

$d(\dots, \dots)$ = the distance measurement between two fuzzy numbers

d_i^+ = the distance of alternative A_i from FPIS

d_i^- = the distance of alternative A_i from FNIS.

Step 6: Calculate the closeness coefficient (cc_i) of each alternative (A_i) as follows:

$$cc_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \dots, m$$

Step 7: Rank the order of alternatives.

Step 8: Select the best one from among the set of feasible alternatives.

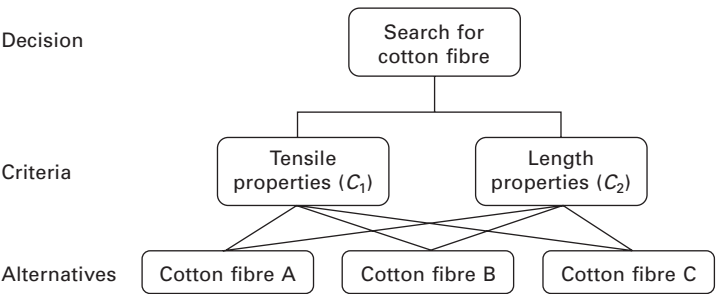
It may be noted that the fuzzy negative ideal solution (FNIS, A^-) was not considered by Athanasopoulos and Romeva (2009) in solving a coating selection problem. They considered an ideal solution or ideal performance as that which the designer wished the coating to have. This statement is made with a view to clarifying the fact that the ideal solution does not always give the maximum performance. Sometimes, the designer might need a coating to be soft or medium hard, so the ranking must be done in accordance with that value. The ranking is therefore based upon the distance from the ideal solution only, since the negative ideal solution is absent.

Here, some recently developed models of fuzzy TOPSIS are discussed. The cotton fibre selection example, with its limited number of alternatives and decision criteria, has been considered for ease of understanding. The values of different scores in the tables are representative in nature.

Fuzzy TOPSIS model I

In our original problem, we considered two alternatives. Here, we now consider three cotton fibres as shown in Fig. 14.11.

Suppose that an organization is desirous of procuring a cotton fibre. After preliminary screening, their cotton A, B and C remain for further evaluation. A committee of three decision makers, DM_1 , DM_2 and DM_3 , has been formed to conduct the study. Only two benefit criteria (tensile properties and length properties) have been considered, to simplify the situation. The procedural steps, as proposed by Chen (2000), are executed below. The decision makers use the linguistic weighting variables as shown in Table 14.10 in order to assess the importance of two criteria and present them in Table 14.11. The decision makers evaluate the alternatives with respect to each criterion (using the linguistic rating variables as shown in Table 14.12) and present them in Table 14.13. The fuzzy decision matrix as well as the fuzzy weighting of each criterion has been established in Table 14.14 by converting the linguistic evaluation (as represented in Tables 14.11 and 14.13) into triangular fuzzy



14.11 Screening of optimum cotton fibre.

Table 14.10 Linguistic scale for the importance or weight of criteria

Linguistic scale	Corresponding TFN
Very low (VL)	(0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very high (VH)	(0.7, 0.9, 1.0)

Table 14.11 The relative importance of two criteria

Criteria	DM ₁	DM ₂	DM ₃
C ₁	VH	VH	M
C ₂	H	M	H

Table 14.12 Linguistic scales for the rating of cotton fibres

Linguistic variable	Corresponding triangular fuzzy number
Very poor (VP)	(0, 1, 3)
Poor (P)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Good (G)	(5, 7, 9)
Very good (VG)	(7, 9, 10)

Table 14.13 The rating of three cotton fibres by three decision makers under two criteria

Criteria	Alternatives	DM ₁	DM ₂	DM ₃
C ₁	Cotton fibre A	VG	F	G
	Cotton fibre B	G	G	F
	Cotton fibre C	F	VG	VG
C ₂	Cotton fibre A	G	G	VG
	Cotton fibre B	F	G	VG
	Cotton fibre C	VG	F	VG

Table 14.14 The fuzzy decision matrix and fuzzy weight of two criteria

Alternatives	C ₁ (0.57, 0.77, 0.90)	C ₂ (0.43, 0.64, 0.84)
Cotton fibre A	(5.0, 7.0, 8.67)	(5.7, 7.7, 9.34)
Cotton fibre B	(4.34, 6.34, 8.34)	(5.0, 7.0, 8.67)
Cotton fibre C	(5.67, 7.67, 9.0)	(5.67, 7.67, 9.0)

numbers. In the next step, the fuzzy normalized decision matrix and the fuzzy weighted normalized matrix are developed as shown in Tables 14.15 and 14.16 respectively. The closeness coefficient (*cc*) for each cotton fibre and its ranking is shown in Table 14.17. Distances were calculated as follows:

Table 14.15 The fuzzy normalized decision matrix

Alternatives	C_1	C_2
Cotton fibre A	(0.56, 0.78, 0.96)	(0.61, 0.82, 1.0)
Cotton fibre B	(0.48, 0.7, 0.93)	(0.54, 0.75, 0.93)
Cotton fibre C	(0.63, 0.85, 1.0)	(0.6, 0.82, 0.96)

Table 14.16 The fuzzy weighted normalized decision matrix

Alternatives	C_1	C_2
Cotton fibre A	(0.32, 0.60, 0.84)	(0.26, 0.52, 0.84)
Cotton fibre B	(0.27, 0.54, 0.84)	(0.23, 0.48, 0.78)
Cotton fibre C	(0.36, 0.65, 0.9)	(0.25, 0.52, 0.8)
FPIS; A^+	(1, 1, 1)	(1, 1, 1)
FNIS; A^-	(0, 0, 0)	(0, 0, 0)

Table 14.17 Score of cotton fibres and their ranking

Alternatives	d_i^+	d_i^-	cc_i	Ranking
Cotton fibre A	0.982	1.214	0.553	2
Cotton fibre B	1.057	1.142	0.519	3
Cotton fibre C	0.9519	1.243	0.566	1

$$d_A^+ = \sqrt{\frac{1}{3}[(1 - 0.32)^2 + (1 - 0.6)^2 + (1 - 0.84)^2]} \\ + \sqrt{\frac{1}{3}[(1 - 0.26)^2 + (1 - 0.52)^2 + (1 - 0.84)^2]} = 0.982$$

Fuzzy TOPSIS model 2

Another approach of fuzzy TOPSIS, developed by Wu *et al.* (2009), is presented here using the same example as was illustrated in fuzzy TOPSIS model 1. Table 14.18 shows the membership function of the linguistic scale used for making a fuzzy pairwise comparison matrix of true criteria. Table 14.19 shows the fuzzy weighting of criteria by FAHP. The procedure of defuzzification (Hsieh *et al.*, 2004) locates the best non-performance (BNP) value. Utilizing the centre of area (COA) method to find the BNP is a simple and practical approach without the need to bring in the preference of any expert. It is used in the present study. The BNP value of a fuzzy number can be found as follows:

$$\text{BNP (best non-fuzzy performance)} = \frac{(c - a) + (b - a)}{3} + a$$

(STD_ BNP is the normalized BNP)

Table 14.18 Membership function used for comparison of criteria

Fuzzy number	Linguistic scale	TFN	Reciprocal of TFN
$\tilde{1}$	Equally important	(1, 1, 3)	$\left(\frac{1}{3}, 1, 1\right)$
$\tilde{3}$	Weakly important	(1, 3, 5)	$\left(\frac{1}{5}, \frac{1}{3}, 1\right)$
$\tilde{5}$	Essentially important	(3, 5, 7)	$\left(\frac{1}{7}, \frac{1}{5}, \frac{1}{3}\right)$
$\tilde{7}$	Very strongly important	(5, 7, 9)	$\left(\frac{1}{9}, \frac{1}{7}, \frac{1}{5}\right)$
$\tilde{9}$	Absolutely important	(7, 9, 9)	$\left(\frac{1}{9}, \frac{1}{9}, \frac{1}{7}\right)$
$\tilde{2}, \tilde{4}, \tilde{6}, \tilde{8}$	Intermediate value between two adjacent judgements		

Source: Mon *et al.* (1994) and Hsieh *et al.* (2004).

Table 14.19 Fuzzy weight of two criteria by FAHP

Criteria	C_1	C_2	Priority vector	BNP*	STD_BNP*
C_1	(1, 1, 1)	(3, 5, 7)	(0.54, 0.83, 1.25)	0.87	0.82
C_2	$\left(\frac{1}{7}, \frac{1}{5}, \frac{1}{3}\right)$	(1, 1, 1)	(0.12, 0.17, 0.27)	0.19	0.18

*See text for explanation.

Table 14.20 Average fuzzy judgement values of cotton fibres by different decision makers

Alternatives	C_1	C_2
Cotton fibre A	(5.0, 7.0, 8.67)	(5.70, 7.70, 9.34)
Cotton fibre B	(4.34, 6.34, 8.34)	(5.0, 7.0, 8.67)
Cotton fibre C	(5.67, 7.67, 9.0)	(5.67, 7.67, 9.00)

where (a, b, c) represents TFN.

Table 14.14 is reproduced as Table 14.20 in order to show the average judgement values of each criterion by different decision makers.

The performance matrix of three cotton fibres is shown in Table 14.21.

	C_1	C_2
Aspiration level	7.45	7.58
Worst level	6.34	6.89

Table 14.21 Performance matrix of cotton fibres

Alternatives	C_1	C_2
Cotton fibre A	6.89	7.58
Cotton fibre B	6.34	6.89
Cotton fibre C	7.45	7.45

Table 14.22 Normalized performance matrix

Alternatives	C_1 (0.82)	C_2 (0.18)
Cotton fibre A	0.49	1.00
Cotton fibre B	0.00	0.00
Cotton fibre C	1.00	0.81

Table 14.23 Weighted normalized matrix and ideal (aspired) and negative (worst) solutions

Alternatives	C_1	C_2
Cotton fibre A	0.40	0.18
Cotton fibre B	0.00	0.00
Cotton fibre C	0.82	0.16
Ideal (aspired) solution	0.82	0.18
Negative (worst) solution	0.00	0.00

Table 14.24 Results of fuzzy TOPSIS

Alternatives	d_i^+	d_i^-	cc_i	Rank
Cotton fibre A	0.42	0.438	0.51	2
Cotton fibre B	0.84	0.00	0.00	3
Cotton fibre C	0.02	0.84	0.97	1

The normalization performance matrix, as shown in Table 14.22, is obtained as follows:

$$\frac{|\text{Given value} - \text{worst level}|}{|\text{Aspiration level} - \text{worst level}|}$$

The weighted normalized matrix is shown in Table 14.23.

Table 14.24 shows the result of fuzzy TOPSIS and ranking of cotton fibres. Cotton fibre C is the best alternative among the three alternatives, followed by fibre A. Cotton fibre B is the worst alternative.

$$cc_i = \text{closeness coefficient} = \frac{d_i^-}{d_i^- + d_i^+}$$

where

d_i^+ = separation of each alternative from the ideal (aspired) solution

d_i^- = separation of each alternative from the negative ideal solution.

Calculation of the separation measures of each alternative (cotton fibre A) is illustrated below:

$$d_i^+ = \sqrt{(0.40 - 0.82)^2 + (0.18 - 0.18)^2} = 0.42$$

$$d_i^- = \sqrt{(0.40 - 0)^2 + (0.18 - 0)^2} = 0.438$$

14.4 Conclusions

Multi-criteria decision making and fuzzy multi-criteria decision making methods have been discussed in this chapter. These methods are very commonly used in engineering and management decision making situations. Some of the decision making scenarios of textile manufacturing industries are highly complex and often fuzzy in nature. The implementation of scientific decision making methods could pave the way for a new horizon in textile manufacturing industries. The application of AHP and TOPSIS methods in cotton fibre grading has been discussed. In addition, some examples of fuzzy AHP and fuzzy TOPSIS have also been demonstrated together with some random data. The decision making scenario in practice is more complex as the number of decision criteria and alternatives are much higher. However, the examples discussed in the chapter are expected to provide a very good starting point in the quest for scientific decision making.

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Silk cocoon grading by fuzzy expert systems

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Abstract: This chapter discusses using an intelligent fuzzy expert system as a grading method for silk cocoon selection problems. It begins by reviewing the need for an expert quality system for cocoon assessment and proposes fuzzy logic as the best approach for this. The chapter then offers a brief outline of fuzzy logic and the development of a fuzzy expert system for cocoon grading. The significance of shell ratio (%), defective cocoon (%) and cocoon size in governing the quality of cocoons has meant that these are the three main quality parameters used for cocoon grading. This provides a good flexibility in reflecting the expectations and visual grading into the results.

Key words: cocoon grading, cocoon size, defective cocoon, fuzzy expert system, shell ratio.

15.1 Introduction

Silk has long been regarded as the finest natural textile due to its lustre, strength and softness. Traditionally China, India, Japan and Korea have been at the forefront of silk production worldwide. Silk reeling is by far the most important of the technological processes that convert cocoons into an end product. The reeling operation is greatly influenced by three factors including cocoon quality, cocoon price and cocoon supply (Vasumathi, 2000). Nearly 90% of the cost of production in reeling is attributable to the cocoon price which, in turn, is solely governed by its quality. Therefore, the quality of cocoons plays a very important role in reeling and subsequently has great bearing on the end product. Silk producers around the world, however, have yet to realize the need for a high-quality system for cocoon assessment despite the need for an appropriate, quality-based method for fixing prices. The sale transactions of cocoons in many countries are still carried out on the basis of visual inspection and personal experience only, a method of cocoon grading which vitally lacks a true scientific basis. Moreover, no statutory provisions exist for compulsory testing and grading of cocoons. In this context, the cocoons are either simply auctioned off or, in certain instances, even sold at a price fixed by the local agencies. There is no direct correlation between price and quality of cocoons.

Cocoon quality is generally governed by various parameters, namely,

shell ratio percentage, defective cocoon percentage, colour, shape, length, perimeter, volume, weight, hardness, dryness, texture, average filament length, average unbroken filament length, raw silk percentage, reelability percentage, single cocoon filament denier, etc. (Sonwalkar, 1993). Each of these quality factors has its own relative significance for reeling efficiency and raw silk quality. Any serious endeavour to evolve a systematic grading procedure should consider all the aforementioned parameters holistically at their appropriate levels of importance. The procedures for assessment of some of these parameters, however, are quite troublesome and time consuming, while for others they are relatively easy. Of these several parameters for measuring cocoon quality, shell ratio percentage (SR%) and defective cocoon percentage (DC%) have been identified as the most significant ones (Sonwalkar, 1982, 1993; Vasumathi, 2000). They have a greater bearing on reeling efficiency as well as yarn quality and at the same time are relatively easy to determine, requiring minimum facilities, infrastructure and time. Vasumathi (2000) uses these two quality parameters for fixing a cocoon quality index (CQI) based on a very large database of cocoons. She proposed the following regression equation of CQI:

$$\text{CQI} = 8.85 - 0.682\text{SR}\% + 0.414\text{DC}\% \quad 15.1$$

The lower the value of CQI, the higher the cocoon quality. The subjective grading has a significant bearing on reeling performance, however, and grading indices developed without taking account of this aspect would eventually fail to produce good results in any comprehensive classification for transaction. The cocoon rearing environment is highly variable and can be affected by weather, technique, etc., but cocoons exhibit high variation due to their inherent morphological diversity. Fuzzy logic, therefore, would appear to represent a good approach for cocoon grading in this context. In this work an effort has been made to grade cocoons using a fuzzy expert system acting upon three input parameters, namely, SR%, DC% and cocoon size.

15.2 Concept of fuzzy logic

The foundation of fuzzy logic was laid by Zadeh (1965). The theoretical aspects of fuzzy logic and fuzzy sets have been explained in many standard textbooks, authored by Zimmermann (1996), Kartalopoulos (1996), Klir and Yuan (2000), Ross (2005), etc. A brief description of fuzzy logic theory is discussed as follows.

Classical crisp sets contain objects that satisfy precise properties of membership, whereas fuzzy sets contain objects that satisfy imprecise properties of membership, i.e. membership of an object in a fuzzy set is not a matter of affirmation or denial, but rather a matter of a degree of membership. For example, suppose we have an exhaustive collection of individual elements

x , which make up a universe of discourse X . Various combinations of the individual elements make up a crisp set, say A . For set A , an element x in the universe X is either a member of A or not. Mathematically, the membership of element x in set A can be expressed by the characteristic function,

$$\mu_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases} \quad 15.2$$

where $\mu_A(x)$ indicates the unambiguous membership of element x in set A . Suppose set A is the crisp set of cocoon length with $20 \leq x \leq 30$ mm. If two cocoons, say x_1 and x_2 , have lengths of 26.2 and 19.8 mm, respectively, then x_1 has the full membership and x_2 has no membership in set A , or symbolically, $\mu_A(x_1) = 1$ and $\mu_A(x_2) = 0$.

Now, consider a fuzzy set $\tilde{A}$ consisting of long cocoons which approximately range from 20 mm to 30 mm in length. A cocoon 20.3 mm long does not have the same membership to the set $\tilde{A}$ as a cocoon which is 29.8 mm long. The fuzzy set $\tilde{A}$ covers a range of cocoons of different lengths, but the degree to which a cocoon is a member of $\tilde{A}$ is represented by its degree of membership with a value between the real continuous interval $[0, 1]$. Therefore a key difference between crisp and fuzzy sets is their membership function; a crisp set has a unique membership function, whereas a fuzzy set can have an infinite number of membership functions to represent it. Mathematically a membership function can be defined as a function which maps its elements onto the interval $[0, 1]$. Symbolically the functional mapping is given by

$$\mu_{\tilde{A}}(x) \in [0, 1]$$

where $\mu_{\tilde{A}}(x)$ is the degree of membership of element x in fuzzy set $\tilde{A}$. Commonly fuzzy set $\tilde{A}$ is expressed in terms of ordered pairs as

$$\tilde{A} = \{x, \mu_{\tilde{A}}(x) \mid x \in X\} \quad 15.3$$

For the set $\tilde{D} = \tilde{A} \cup \tilde{B}$, called the union of fuzzy sets $\tilde{A}$ and $\tilde{B}$, the membership function is defined as

$$\mu_{\tilde{D}}(x) = \mu_{\tilde{A}}(x) \vee \mu_{\tilde{B}}(x) = \max \{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}, x \in X \quad 15.4$$

where the symbol $\vee$ stands for the maximum operator. For the set $\tilde{E} = \tilde{A} \cap \tilde{B}$, called the intersection of fuzzy sets $\tilde{A}$ and $\tilde{B}$, the membership function is defined as

$$\mu_{\tilde{E}}(x) = \mu_{\tilde{A}}(x) \wedge \mu_{\tilde{B}}(x) = \min \{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}, x \in X \quad 15.5$$

where the symbol $\wedge$ represents the minimum operator. The membership function of the complement of a fuzzy set $\tilde{A}$ is defined by

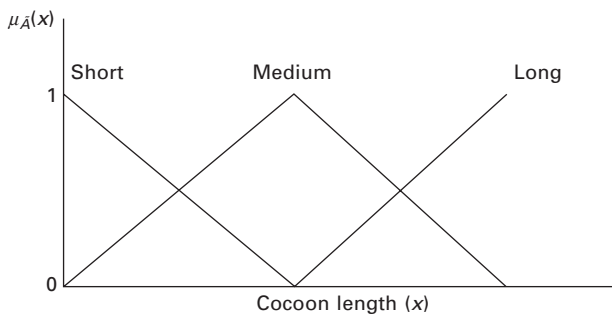
$$\mu_{\tilde{A}}^c = \{1 - \mu_{\tilde{A}}(x)\}, x \in X \quad 15.6$$

In more general terms, fuzzy intersection is defined by the fuzzy AND operator, fuzzy union is defined by the fuzzy OR operator, and complement by the fuzzy NOT operator. All properties of crisp sets are also applicable for fuzzy sets except for the excluded-middle laws. In fuzzy set theory, the union of a fuzzy set with its complement does not yield the universe, and the intersection of a fuzzy set and its complement is not null. This difference is shown below.

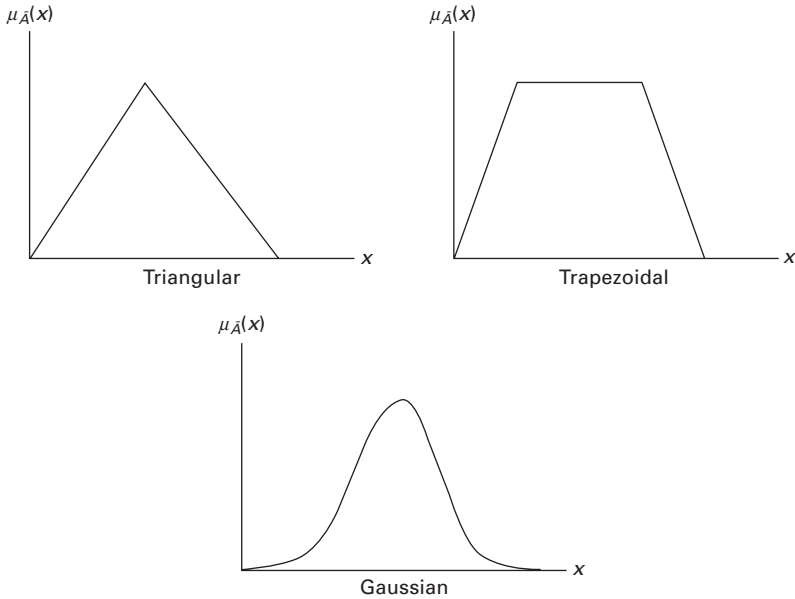
$$\begin{aligned} \text{For crisp sets, } A \cup A^c &= X \\ A \cap A^c &= \emptyset \end{aligned} \quad 15.7$$

$$\begin{aligned} \text{For fuzzy sets, } \tilde{A} \cup \tilde{A}^c &\neq X \\ \tilde{A} \cap \tilde{A}^c &\neq \emptyset \end{aligned} \quad 15.8$$

For each input and output variable of a fuzzy system, the fuzzy sets are created by dividing the universe of discourse into a number of sub-regions named in linguistic terms high, medium, low, etc. This accounts for the uncertainty inherent in such a linguistic description by using multi-valued sets. Once the fuzzy sets are chosen, a membership function for each set should be created. The process of assigning membership functions to the sets of data is referred to as fuzzification. In this process the crisp values are converted into fuzzy values to express uncertainties present in the crisp values. Figure 15.1 depicts the degree of membership of various cocoon lengths to the fuzzy subsets short, medium and long. The membership function can have various forms, such as triangular, trapezoidal, Gaussian, etc., which are illustrated in Fig. 15.2. The triangular membership function is the simplest and is a collection of three points forming a triangle. Dubois and Prade (1979) defined the triangular membership function as follows:



15.1 Membership function of cocoon length.



15.2 Various types of membership functions.

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-L}{m-L} & \text{for } L \leq x \leq m \\ \frac{R-x}{R-m} & \text{for } m \leq x \leq R \\ 0 & \text{otherwise} \end{cases} \quad 15.9$$

where m is the most promising value, and L and R are the left and right spreads (the smallest and largest values that m can take). The trapezoidal membership curve has a flat top and is just a truncated triangle curve producing $\mu_{\tilde{A}}(x) = 1$ in large regions of the universe of discourse. The trapezoidal curve is a function of a vector x and depends on four scalar parameters a , b , c and d , as shown below.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & \text{for } x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a} & \text{for } a \leq x \leq b \\ 1 & \text{for } b \leq x \leq c \\ \frac{d-x}{d-c} & \text{for } c \leq x \leq d \end{cases} \quad 15.10$$

The Gaussian membership function depends on two parameters, namely standard deviation (σ) and mean (μ), and is represented as shown below.

$$\mu_{\tilde{A}}(x) = \exp\left[-\frac{(x - \mu)^2}{2\sigma^2}\right] \quad 15.11$$

A fuzzy system maps an input space to an output space using linguistic rules which are based on human reasoning. The linguistic representation presents an intuitive, natural description of a system allowing for relatively easy algorithm development compared to numerical systems. A fuzzy linguistic rule consists of an IF–THEN statement. A fuzzy rule is evaluated by means of fuzzy operators such as ‘fuzzy AND’, ‘fuzzy OR’, etc. Theoretically there may be r^n of rules, where n is the number of input variables having r linguistic levels. The output of each rule is also a fuzzy set. All rules are evaluated in parallel and output fuzzy sets are then aggregated into a single fuzzy set. This step is known as ‘aggregation’. Eventually the resulting fuzzy set is resolved to a crisp output value by ‘defuzzification’. There are several methods of defuzzification such as centre of gravity, centre of sums, mean of maxima and left-right maxima, etc. The commonly used calculation of output in centroid is shown below:

$$x^* = \frac{\int \mu_{\tilde{A}}(x) x dx}{\int \mu_{\tilde{A}}(x) dx} \quad 15.12$$

where x^* is the defuzzified output and $\mu_{\tilde{A}}(x)$ is the output fuzzy set after aggregation of individual implication results.

15.3 Experimental

A sample of 20 lots of multibhi cocoons were collected from the cocoons market. The quality parameters of cocoons such as SR(%) and DC(%) were measured using the standard technique from each of the lots. The SR(%) was estimated as the ratio of the shell weight to the cocoon weight expressed as a percentage. Fifty cocoons were selected from each lot and the average SR(%) was calculated. The DC(%) was measured as a percentage of defective cocoons by number from a lot of one kilogram of cocoons.

Cocoon size was determined subjectively. Three experts were asked to evaluate the cocoon size in a five-point scale having the linguistic terms low, below average, average, above average and high, based on characteristics such as perimeter, volume, weight, shape, texture, dryness, hardness, etc. Figure 15.3 illustrates typical examples of cocoons having low, average and high sizes.



(a)



(b)



(c)

15.3 Different sizes of cocoons: (a) low, (b) average, (c) high.

15.4 Development of a fuzzy expert system for cocoon grading

Three parameters of the silk cocoon, namely, SR (%), size and DC (%), have been used as the inputs and cocoon score has been used as the output to the fuzzy expert system for cocoon grading. Among the input parameters, SR (%) and DC (%) are expressed objectively, whereas the size attribute is

expressed subjectively, i.e. it is not quantifiable; instead it is represented by linguistic terms such as low, average, high, etc. Since all inputs have to be presented to the fuzzy expert system in the form of crisp data, the subjective data of the size attribute is converted into appropriate objective data using the method proposed by Chen and Hwang (1992). A five-point scale having the linguistic terms low, below average, average, above average and high, as shown in Fig. 15.4, is considered. The detailed procedure of converting linguistic terms into a crisp score is discussed below.

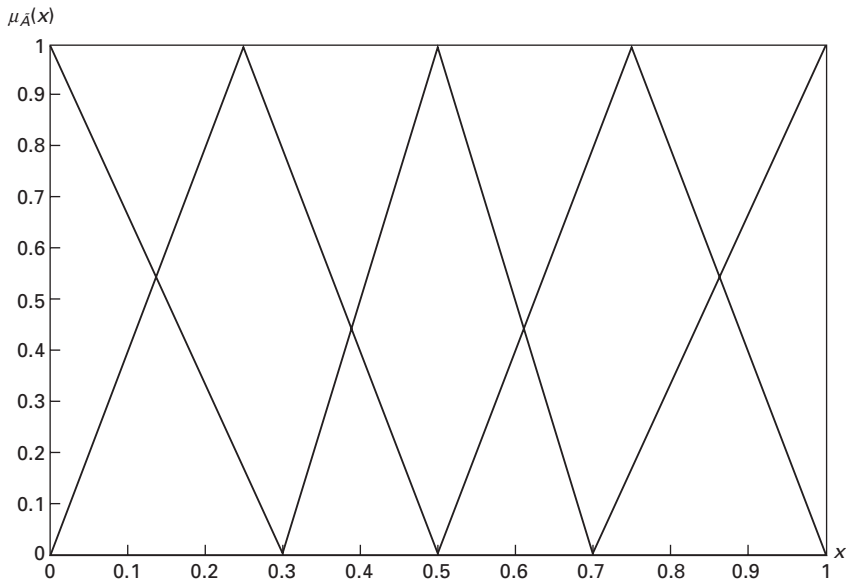
The crisp score of fuzzy number M is obtained as follows:

$$\mu_{\max}(x) = \begin{cases} x & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad 15.13$$

$$\mu_{\min}(x) = \begin{cases} 1 - x & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad 15.14$$

where $\mu_{\max}(x)$ and $\mu_{\min}(x)$ are the fuzzy maximum and fuzzy minimum of fuzzy numbers, defined in such a manner that absolute locations of fuzzy numbers can be automatically incorporated in the comparison cases. The left score of each fuzzy number M_i is defined as

$$\mu_L(M_i) = \sup_x [\mu_{\min}(x) \wedge \mu_{M_i}(x)] \quad 15.15$$



15.4 Linguistic terms to fuzzy numbers conversion (five-point scale).

where ‘sup’ is the abbreviated form of supremum, meaning the least upper bound. The $\mu_L(M_i)$ score is a unique, crisp, real number in $[0, 1]$. It is the maximum membership value of the intersection of fuzzy number M_i and the fuzzy minimum. The right score may be obtained in a similar manner:

$$\mu_R(M_i) = \sup_x [\mu_{\max}(x) \wedge \mu_{M_i}(x)] \quad 15.16$$

$\mu_R(M_i)$ is also a crisp number in $[0, 1]$. Given the left and right scores, the total score of a fuzzy number M_i is defined as:

$$\mu_T(M_i) = [\mu_R(M_i) + 1 - \mu_L(M_i)]/2 \quad 15.17$$

A five-point scale as shown in Table 15.1 is considered for conversion of fuzzy numbers into crisp scores. The maximizing and minimizing sets are defined as in Equations 15.13 and 15.14. From Fig. 15.4, membership functions of M_1, M_2, M_3, M_4 and M_5 are written as:

$$\mu_{M_1}(x) = \begin{cases} 1 & x = 0 \\ \frac{0.3-x}{0.3} & 0 \leq x \leq 0.3 \end{cases}$$

$$\mu_{M_2}(x) = \begin{cases} \frac{x-0}{0.25} & 0 \leq x \leq 0.25 \\ \frac{0.5-x}{0.25} & 0.25 \leq x \leq 0.5 \end{cases}$$

$$\mu_{M_3}(x) = \begin{cases} \frac{x-0.3}{0.2} & 0.3 \leq x \leq 0.5 \\ \frac{0.7-x}{0.2} & 0.5 \leq x \leq 0.7 \end{cases}$$

$$\mu_{M_4}(x) = \begin{cases} \frac{x-0.5}{0.25} & 0.5 \leq x \leq 0.75 \\ \frac{1-x}{0.25} & 0.75 \leq x \leq 1 \end{cases}$$

Table 15.1 Linguistic terms with fuzzy numbers

Linguistic term	Fuzzy number
Low	M_1
Below average	M_2
Average	M_3
Above average	M_4
High	M_5

$$\mu_{M_5}(x) = \begin{cases} \frac{x-0.7}{0.3} & 0.7 \leq x \leq 1.0 \\ 1 & x \leq 0.7 \end{cases}$$

The right, left and total scores are computed as follows for M_1 :

$$\mu_R(M_1) = \sup_x [\mu_{\max}(x) \wedge \mu_{M_1}(x)] = 0.23$$

$$\mu_L(M_1) = \sup_x [\mu_{\min}(x) \wedge \mu_{M_1}(x)] = 1$$

$$\mu_T(M_1) = [\mu_R(M_1) + 1 - \mu_L(M_1)]/2 = 0.115$$

Similarly, the right, left and total scores are computed for M_2 , M_3 , M_4 and M_5 and are shown in Table 15.2. The linguistic terms with their corresponding crisp scores are given in Table 15.3. Rather than assigning arbitrary values to the cocoon size attribute, this fuzzy method gives a better approximation of the linguistic descriptions by reflecting them in terms of crisp scores.

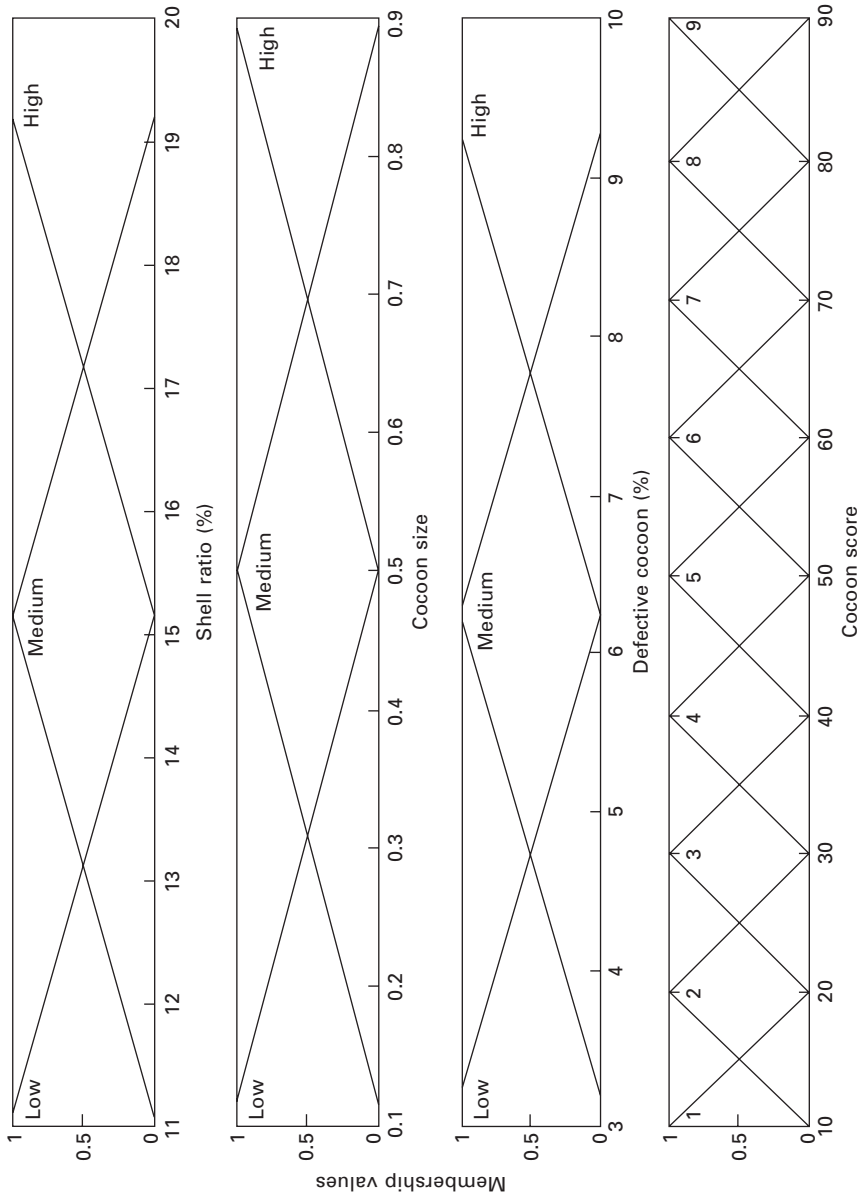
After converting the subjective size attribute into the objective score using the above-mentioned method, the process of fuzzification is performed by assigning the triangular form of membership functions to the crisp quantities of both input and output parameters. The triangular form is chosen because it is the simplest one. Three linguistic fuzzy sets, low, medium and high, are selected for each of the input parameters in such a way that they are equally spaced and cover the whole input spaces. Figure 15.5 depicts the triangular membership plots for input and output of the fuzzy expert system. Nine

Table 15.2 Right, left and total scores for different fuzzy numbers

i	$\mu_R(M_i)$	$\mu_L(M_i)$	$\mu_T(M_i)$
1	0.23	1.0	0.115
2	0.39	0.8	0.295
3	0.58	0.59	0.495
4	0.79	0.4	0.695
5	1.0	0.23	0.895

Table 15.3 Conversion of linguistic terms into fuzzy scores (five-point scale)

Linguistic term	Fuzzy number	Crisp score
Low	M_1	0.115
Below average	M_2	0.295
Average	M_3	0.495
Above average	M_4	0.695
High	M_5	0.895



15.5 Triangular membership function plots of inputs and output.

output fuzzy sets (level 1 to 9) are considered for cocoon scores ranging from 10 to 90, so that the fuzzy expert system can map the small changes in cocoon score with the changes in input variables. Levels 1 and 9 represent the worst and best cocoon qualities, respectively.

The next step is the development of fuzzy rules, which are integral to the fuzzy expert system. The fuzzy rules map an input space to an output space by means of a list of IF–THEN statements. There are three input variables each with three linguistic levels, therefore the total number of possible fuzzy rules could be $3^3 = 27$. Table 15.4 illustrates the 27 fuzzy rules in matrix form. For example, the first rule as given in Table 15.4 can be read as:

IF (SR% is high) AND (Size is high) AND (DC% is low)

THEN (Cocoon score is at Level 9)

Interpreting an IF–THEN statement of a fuzzy rule involves two distinct parts: first evaluating the antecedent, which involves the inputs, and second applying that result to the consequent (output). The ‘min’ and ‘max’ functions are used to represent ‘fuzzy AND’ and ‘fuzzy OR’ operators, respectively, between two fuzzy sets $\tilde{A}$ and $\tilde{B}$.

A schematic representation of a fuzzy expert system for cocoon grading is displayed in Fig. 15.6. All 27 rules are evaluated in parallel. The order of the rules is unimportant during their evaluation. The fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set by the process of aggregation. The input of the aggregation process is the list of truncated output functions evaluated by each rule. The ‘max’ function is used to aggregate the output of each rule into a single fuzzy set of the output variable.

The aggregate fuzzified output is then converted into a single crisp value by the process of defuzzification. The defuzzification is completed using the centroid method which returns the centre of the area under the curve as given in Equation 15.12.

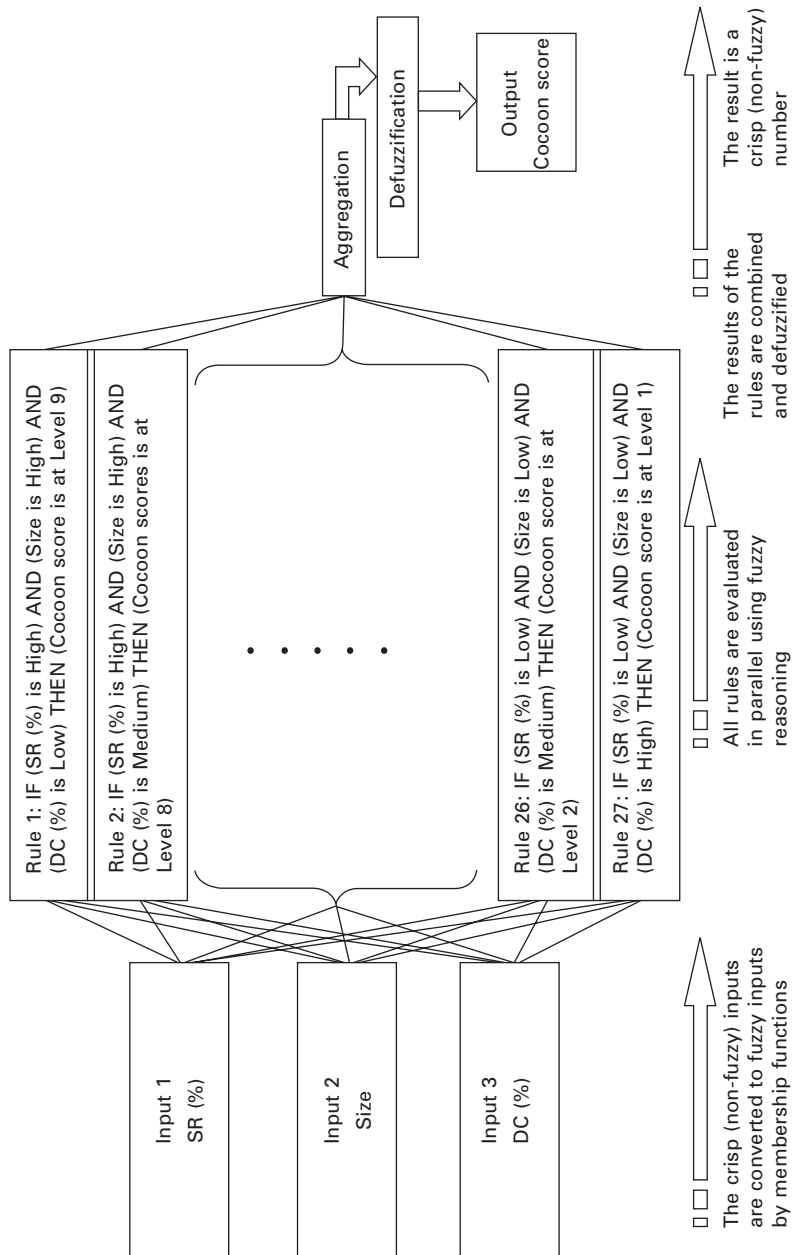
Figure 15.7 schematically demonstrates the operation of the developed fuzzy expert system with an example. For ease of illustration, out of 27 only two fuzzy rules have been depicted in Fig. 15.7. According to the first rule, if SR (%) and size are at medium levels and DC (%) is at a low level, then the output cocoon score will have level 6. According to the second rule, if all the input cocoon parameters are at a medium level then the output cocoon score will be at the lower level of 5. For example, if SR (%) is 16.6, the size is above average which corresponds to a crisp value 0.695 and DC (%) is 5.8, then by using the aforementioned two rules, the cocoon score works out to be 52.3. In practice all 27 fuzzy rules are used simultaneously to determine the cocoon score. Some of the rules may remain defunct because the ‘fuzzy AND’ function was used in the antecedent part of the rules, meaning that they will not produce any output fuzzy set. Outputs of active fuzzy rules are

Table 15.4 Matrix of fuzzy rules

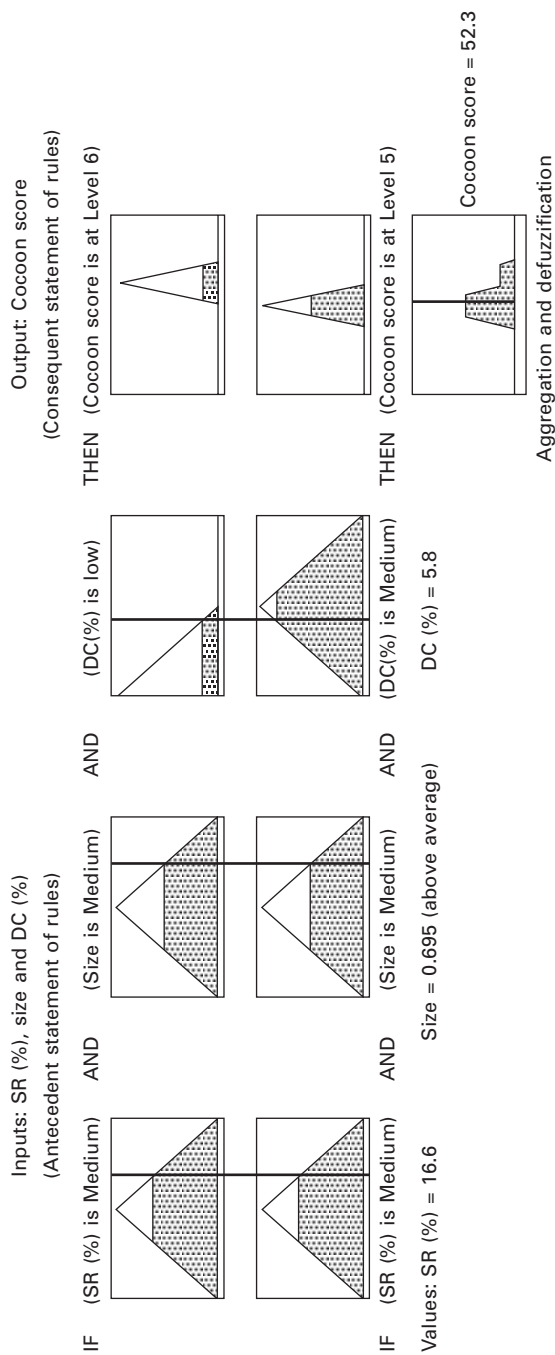
Rule number	Membership level			
	SR (%)	Size	DC (%)	Cocoon score
1	High	High	Low	9
2	High	High	Medium	8
3	High	High	High	8
4	High	Medium	Low	8
5	High	Medium	Medium	7
6	High	Medium	High	6
7	High	Low	Low	7
8	High	Low	Medium	6
9	High	Low	High	6
10	Medium	High	Low	7
11	Medium	High	Medium	6
12	Medium	High	High	6
13	Medium	Medium	Low	6
14	Medium	Medium	Medium	5
15	Medium	Medium	High	5
16	Medium	Low	Low	5
17	Medium	Low	Medium	4
18	Medium	Low	High	4
19	Low	High	Low	5
20	Low	High	Medium	5
21	Low	High	High	4
22	Low	Medium	Low	4
23	Low	Medium	Medium	3
24	Low	Medium	High	3
25	Low	Low	Low	2
26	Low	Low	Medium	2
27	Low	Low	High	1

then aggregated to get a final output fuzzy set, which is eventually defuzzified to produce the crisp output of the cocoon score. A MATLAB (version 7.0) based coding has been used to execute the proposed fuzzy expert system for cocoon grading.

The parameters of 20 lots of cocoons encompassing SR (%), size and DC (%) are given in Table 15.5. The cocoons are ranked according to their score as obtained using the fuzzy expert system. The cocoons are also ranked in accordance with the CQI value as estimated from Equation 15.1. The cocoon scores generated from the fuzzy expert system and their consequent CQI values are shown in Table 15.5. In fact, a higher value of cocoon score and a lower value of CQI correspond to better cocoon quality. Figure 15.8 depicts the ranking of different cocoon lots resulting from the fuzzy expert system as well as the CQI system. The rank correlation coefficient (R_s) is determined between these two systems of cocoon grading using the following equation:



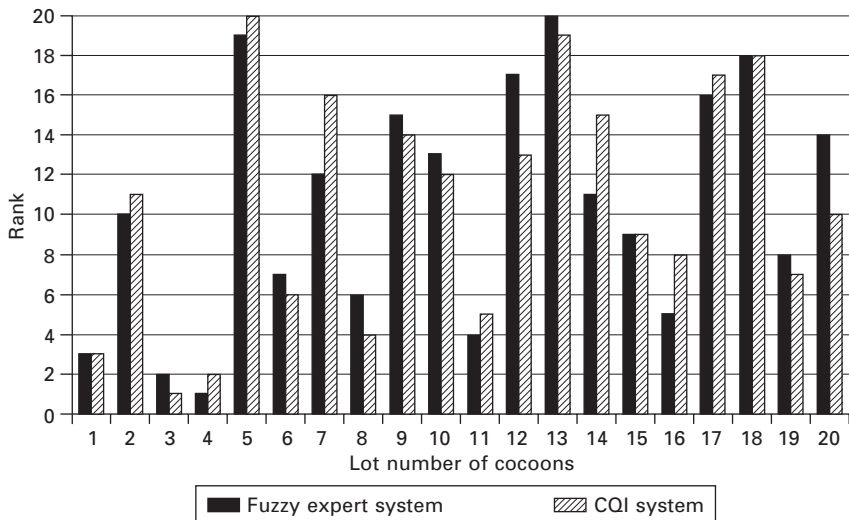
15.6 Schematic representation of fuzzy expert system for cocoon grading.



15.7 An example showing the operation of the fuzzy expert system.

Table 15.5 Cocoon parameters and their quality values

Lot no.	SR (%)	Size	DC (%)	Cocoon score	CQI value
1	16.8	Above average	3.2	70.4	-1.28
2	15.7	Average	7.6	54.4	1.29
3	18.7	High	4.2	77.4	-2.16
4	19.2	High	6.7	80.0	-1.47
5	11.6	Low	7.8	22.9	4.17
6	15.4	Average	3.2	61.7	-0.33
7	14.6	Average	9.1	45.2	2.66
8	16.4	Average	4.5	62.8	-0.47
9	13.1	Below average	5.4	38.0	2.15
10	14.4	Average	6.9	44.2	1.89
11	17.9	Above average	7.2	67.0	-0.38
12	12.6	Low	4.3	33.2	2.04
13	11.1	Low	5.2	20.0	3.43
14	15.3	Average	9.3	50.1	2.27
15	16.2	Average	6.7	56.2	0.58
16	18.1	Above average	8.6	66.3	0.07
17	12.2	Below average	5.7	34.9	2.89
18	11.9	Below average	6.5	30.5	3.42
19	15.7	Average	3.9	60.9	-0.24
20	13.6	Below average	4.0	41.8	1.23



15.8 Rank of 20 cocoon lots as derived from fuzzy expert system and CQI system.

$$R_s = 1 - \frac{6 \sum D_a^2}{n(n^2 - 1)} \quad 15.18$$

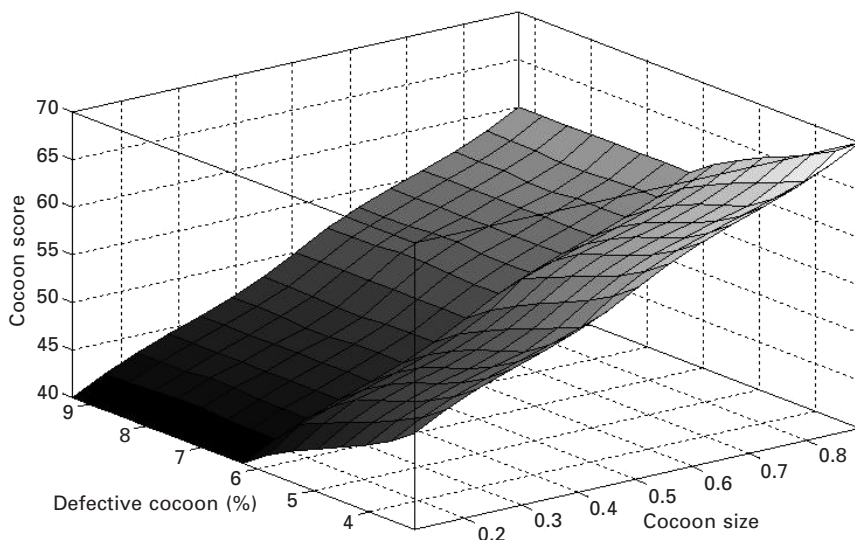
where D_a is the absolute difference between two rankings and n is the

total number of alternatives. The rank correlation coefficient is obtained as 0.934, which shows a high degree of agreement between the two methods of cocoon grading.

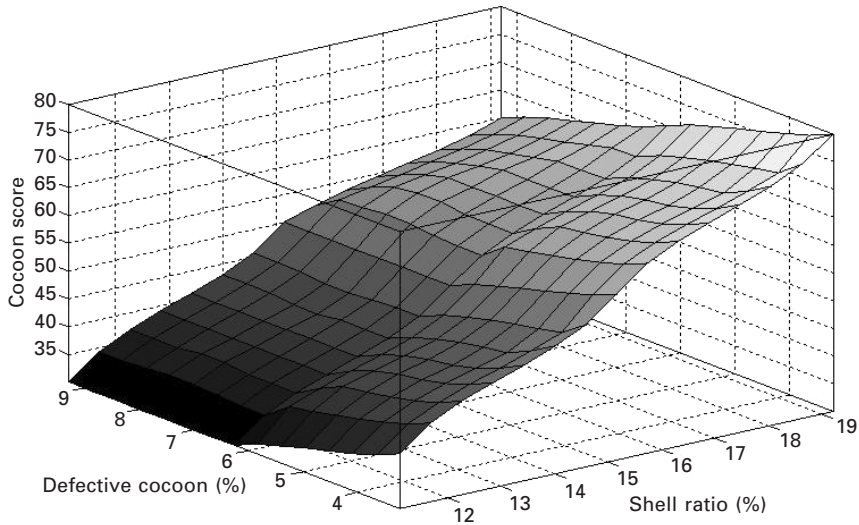
The surface plots shown in Figs 15.9–15.11 depict the impacts of cocoon parameters on the cocoon score. Figure 15.9 shows a higher value of cocoon size, and a lower proportion of defective cocoons improves the cocoon quality as expected. Figure 15.10 shows that the SR (%) has a similar influence on cocoon quality as the cocoon size. The cocoon quality reaches the apex when the SR (%) and cocoon size both reach their respective maximum level (Fig. 15.11).

15.5 Conclusions

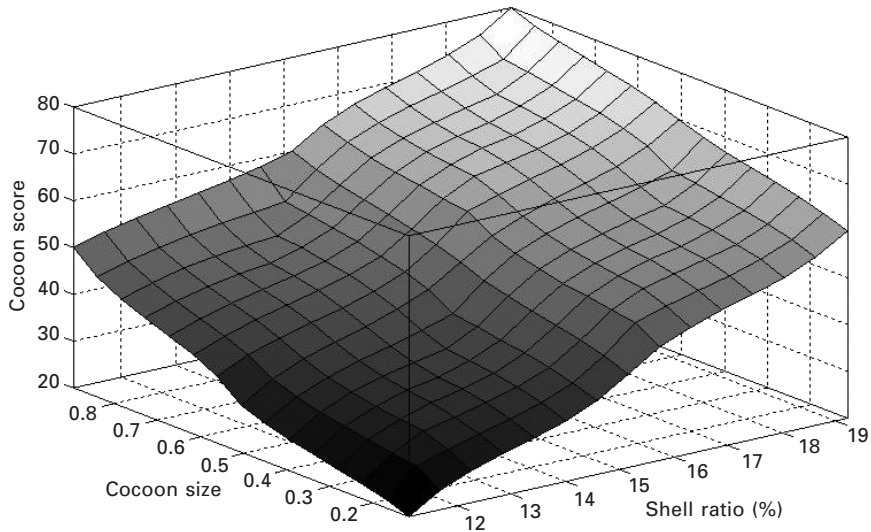
We investigated and verified our proposed fuzzy grading method that was intended to rectify the cocoon selection problem. The proposed system has been developed by translating our perception and experience into a fuzzy expert system. Three cocoon criteria including SR (%), DC (%) and size are used as the inputs to the fuzzy expert system for determining the cocoon quality. The system is easy to develop and is able to handle imprecisions present in the cocoon data. The subjective aspect of cocoon grading in the cocoon market has also been incorporated in the system. Therefore the system operates on both objective as well as subjective criteria. The ranking of cocoons attained by this method shows significant agreement with the



15.9 Surface plot showing the effect of defective cocoon (%) and cocoon size on cocoon score.



15.10 Surface plot showing the effect of defective cocoon (%) and shell ratio on cocoon score.



15.11 Surface plot showing the effect of cocoon size and shell ratio (%) on cocoon score.

ranking based on CQI. It thus provides a good flexibility in reflecting the expectations and visual grading into the results. This method could be used as a reference material for someone who solves cocoon marketing and subjective judgement problems. The present study is concentrated on a single

variety of cocoon. The same methodology can be applied by considering more cocoon varieties.

15.6 References

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Artificial neural network modelling for prediction of thermal transmission properties of woven fabrics

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Abstract: Artificial neural network (ANN) is a stochastic and heuristic tool that learns the relationship between the parameters and their responses when trained with a finite number of input data and predicts the values of response from the new set of independent variables based on its training experience. This chapter defines various ANNs, their architecture, development and usefulness in prediction of the steady state and transient thermal properties of textiles. The feed-forward back-propagation ANN can predict the thermal insulation of the fabrics based on fabric construction parameters like weave, yarn count, thread density, weight and thickness as input. The network is used to predict the thermal insulation of woven textile fabrics based on these parameters before they are manufactured.

Key words: artificial neural network, artificial neuron, network architecture, thermal transmission, thermal insulation, woven fabrics.

16.1 Introduction

Clothing has been one of the main applications of textile materials, although in recent times, the applications of textile materials have increased in many other engineering fields. One of the basic functions of textiles as clothing is thermo-regulation. This is accomplished by the creation of a micro-climate between the human body and clothing which regulates the temperature of the body at a safe range and prevents the wearer from suffering from any thermal shock in unsuitable environmental conditions. With the advent of applications of technical textiles in many high-performance applications, the thermo-regulation property of textile structures is not only confined to clothing but also utilized for insulations in buildings, spacecrafts, automobile, shelters, etc. In the context of clothing technology as well as technical applications, it becomes important to understand the thermal transmission behaviour of the textile material.

Prediction of thermal properties of textile materials has always been one of the major concerns for characterization of comfort and designing of

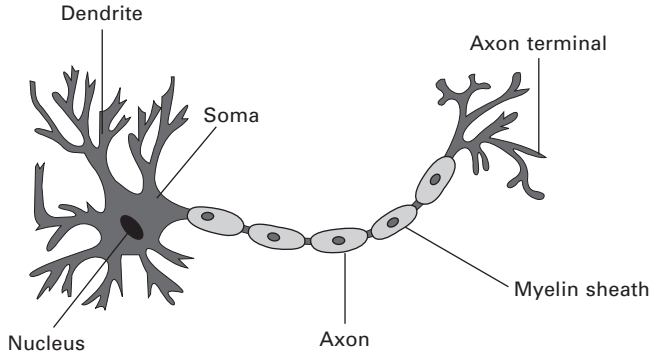
textile based insulation materials. The thermal properties of textile materials can be predicted by (a) statistical models, (b) mechanistic models, and (c) stochastic models. Statistical methods are based on the effect of different fabric and environmental variables on the thermal resistance. Good prediction by statistical models is possible when a large amount of data is used to make the model and also when there is a simple relationship between different parameters and the response variable. Furthermore, the presence of rogue data can decrease the predictability of the models. Mechanistic models are based on the physics of heat transfer and various mathematical treatments. One disadvantage with mathematical models is the assumptions that are considered to simplify the model. In real conditions, this can lead to high errors. Properties of textile materials, being inherently variable in nature, are more prone to these errors. In spite of these disadvantages, mechanistic models are useful in understanding the fundamentals of the phenomenon of heat transfer. Stochastic models take into account the randomness of any event and are based on probabilistic methods. Models like Monte Carlo, expert system, artificial neural network and genetic algorithms come in this group. However, the prediction performance of these models is greatly dependent on the database on which it is trained and the expertise of the network designer.

An artificial neural network (ANN) is a stochastic and heuristic (action based on prior experience) tool which can learn the relationship between the parameters and their responses when it is trained with a finite number of input data. After training, the network is able to predict the values of the response from the new set of independent variables and give a response based on its training experience. ANNs have been used in various applications including textiles, and their utility is well documented. However, prediction of thermal insulation has not been explored in detail. This chapter attempts to define various ANNs and their usefulness in prediction of the steady state and transient thermal properties of textiles.

16.2 Artificial neural network systems

16.2.1 Analogy with biological nervous system

Artificial neural networks are inspired by the biological nervous system. A unit of the biological nervous system is given in Fig. 16.1. The fundamental unit of the brain is the neuron. The sensory inputs to the neuron come from dendrites and the output from the neuron is transmitted along the axon to the next neuron in the system. The transmission of signals from one cell to another occurs at a synapse. It is an electrochemical process whose effect is to raise or lower the electrical potential of the body of the receiving cell; this adjustment is the learning process. The human brain is estimated to contain a densely interconnected network of approximately 10^{11} neurons,



16.1 Biological neuron (licence from Creative Commons Attribution – Share Alike 3.0).

each connected, on average, to 10^4 others. The fastest neuron switching times are known to be of the order of 10^{-3} seconds whereas computer switching speeds are of the order of 10^{-10} seconds. Yet humans are able to make complex decisions quickly. This is because the human brain has about 100 billion neurons and of the order of 60 trillion synapses or connections. This parallelism makes up for the slowness of individual neurons.

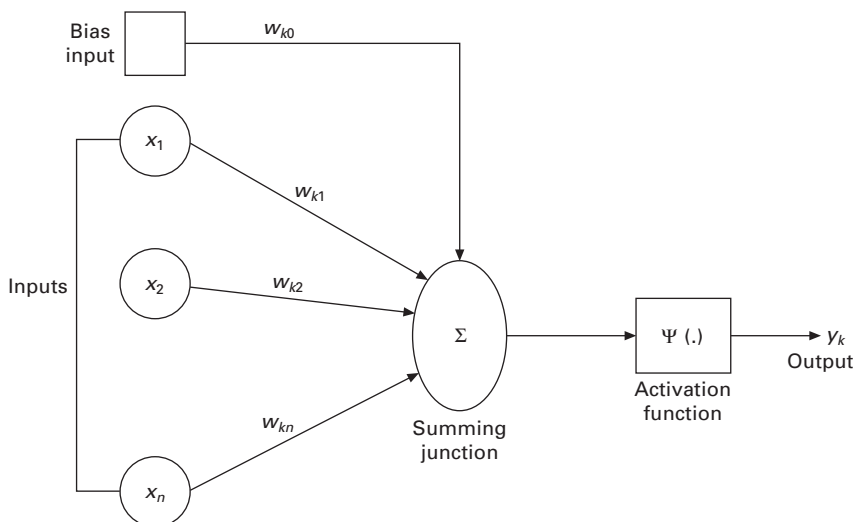
In order to design a computer that can emulate the properties of a human brain, it is necessary to define a simple unit or function, join a number of such units through connections or weights and allow these weights to decide the manner in which data are transferred from one unit to another. The whole system should be allowed to learn from examples by changing the weights iteratively. Once trained, the system will be capable of delivering an output for a given set of input parameters which were hitherto unknown to it.

16.2.2 Artificial neuron

A typical artificial neuron is shown in Fig. 16.2. ANNs can be defined as an interconnection of neurons such that the neuron outputs are connected through weights to all other neurons including themselves [1]. Information is passed from one neuron to the other through connecting links using a transfer function. Each connecting link is characterized by a weight. Generally, an external bias to each neuron is applied that increases the net input of the function.

There are n inputs to the neuron (x_1 to x_n). They are multiplied by weights w_{k1} to w_{kn} respectively. The weighted sum of the inputs, which is denoted by u_k , is given by

$$u_k = \sum_{j=0}^n w_{kj} x_j \quad 16.1$$



16.2 Architecture of a typical artificial neuron (perceptron).

u_k now becomes the input to the transfer or activation function and gets modified according to the nature of the transfer function. The output y_k is given by

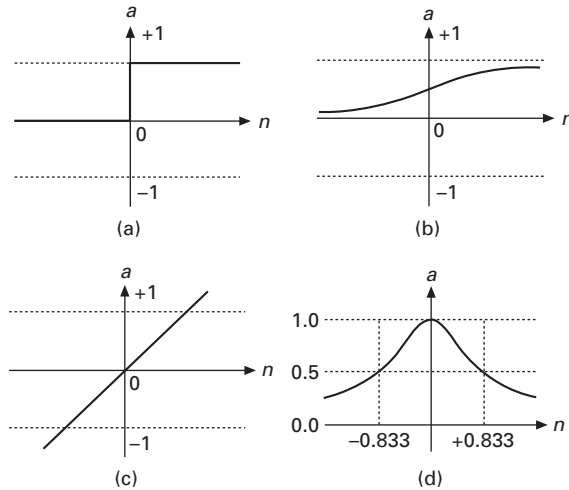
$$y_k = \Psi(u_k) \quad 16.2$$

where Ψ is a linear or nonlinear function of u_k and is termed the transfer function. Transfer functions can be threshold, sigmoid or linear, radial basis, etc. (Fig. 16.3). Thus, one layer ANN typically consists of neurons connected with a bias, connecting links or weights, and summation and transfer functions.

16.2.3 Network types

To prepare an ANN, the first step is to build the network architecture. A network architecture defines the number of neurons and the number of layers required in the model. The simplest ANNs consist of two layers, namely, the input and the output layer. Any layer in between these two layers is known as a hidden layer. The number of hidden layers decides the complexity of the network. The networks can be feed-forward or feed-back depending upon the direction of flow of information (Fig. 16.4). The simplest network is the perceptron. It is a feed-forward network and a binary classifier. The input–output relationship of a perceptron is given as

$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{else} \end{cases} \quad 16.3$$



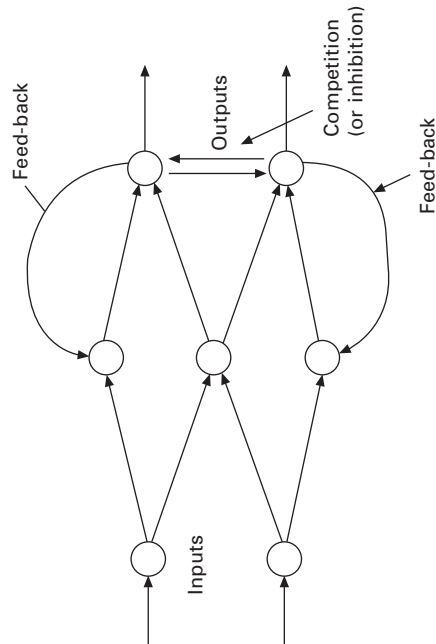
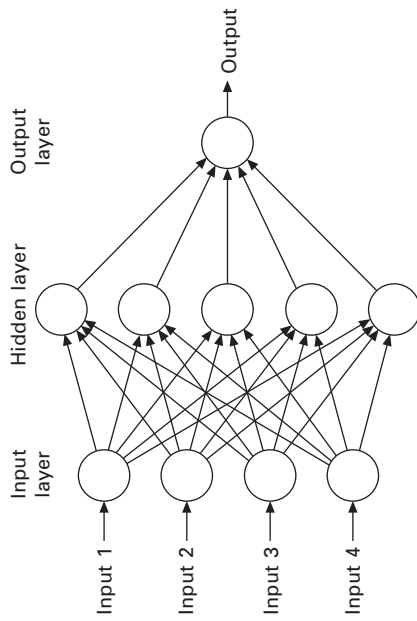
16.3 Transfer functions: (a) threshold, (b) sigmoid, (c) linear, (d) radial basis.

where b is the bias. The architecture of a perceptron is given in Fig. 16.5 [2]. In a feed-forward network, one or two hidden layers are able to map the response to a good degree of accuracy. However, it has been reported that increasing the number of hidden layers does not give a significant increase in the prediction performance of the network. The starting point for the number of neurons in the hidden layer can be chosen by a rule of thumb, i.e. $n_{\text{hidden}} > 2 \times [\max(\text{input neurons, output neurons})]$ [3].

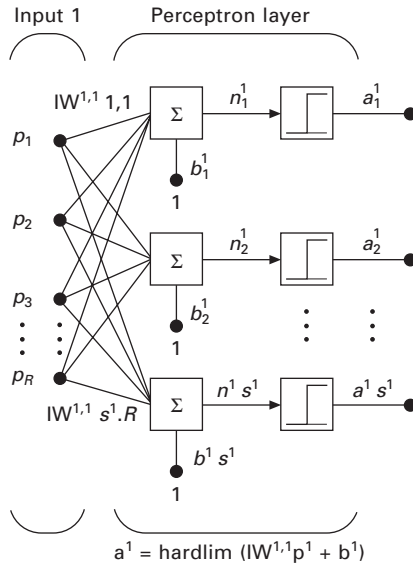
16.2.4 Applications in textiles

The field of ANNs has found important applications only in the past 15 years, and the field is still developing rapidly. Some applications where ANNs can be used are (1) *Aerospace and automotive*: high-performance aircraft autopilot, flight path simulation, aircraft control systems, autopilot enhancements, aircraft component simulation, aircraft component fault detection, automobile automatic guidance system; (2) *Defence*: weapon steering, target tracking, object discrimination, facial recognition, new kinds of sensors, sonar, radar and image signal processing including data compression, feature extraction and noise suppression, signal/image identification; and (3) *Electronics*: code sequence prediction, integrated circuit chip layout, process control, chip failure analysis, machine vision, nonlinear modelling, etc.

The main advantages of ANNs are that (a) they can be trained for any kind of complicated process which cannot be solved by mechanistic models and (b) the error between the actual and the predicted values can be reduced



16.4 Feed-back and feed-forward artificial neural network.



16.5 Input-output architecture of perceptron [2].

dynamically during the training of the network. However, artificial neural nets also have some disadvantages: (a) they cannot be reliably used to predict responses of input parameters that are outside the range of the training data set, and for this reason a large amount of data is required to train the network; (b) the training is a trial-and-error based method; and (c) the robustness and performance of the network depend upon the ability of the researcher.

In spite of these disadvantages, ANN has proved useful for many prediction-related problems in textiles such as for prediction of characteristics of textiles, identification, classification and analysis of defects, process optimization, marketing and planning. Chandramohan and Chellamani [4] give a comprehensive list of the researches carried out in yarn manufacturing by using ANN, while Mukhopadhyay and Siddiquee [5] have given a review of application of ANN in textile processing, polymer technology, composite technology and dye chemistry. Chen *et al.* [6] have given an artificial neural network technique to predict the end-use garment type of a fabric based on parameters obtained from Kawabata KES-FB. Desai *et al.* [7] have used ANN to predict the tensile strength of yarn with different fibre properties. Kuo and Lee [8] have developed an image processing based ANN to classify fabric defects in woven fabrics. Kuo *et al.* [9] also developed a neural network to predict the properties of melt spun fibres like tensile strength and yarn count with machine parameters like extruder screw speed, gear pump speed and winding speed.

16.3 Thermal insulation in textiles

The concept of clothing comfort and the factors influencing it have been investigated by various researchers ever since the 1930s. One of the most important aspects of clothing comfort is the thermal transmission property known as thermal comfort. Thermal comfort, as defined by ISO 7730, is 'That condition of mind which expresses satisfaction with the thermal environment'. This definition, although it gives a good idea about the phrase 'thermal comfort', cannot be easily converted into physical parameters. The thermal environment depends upon many parameters such as ambient temperature, relative humidity, wind speed, rain, snow, etc. The main condition to maintain thermal comfort is energy balance. This is carried out by the thermo-regulatory properties of the textile materials. The thermo-regulation behaviour of a textile material depends upon its material characteristics, design and construction. The material can be a single-layer woven, knitted or nonwoven fabric or an assembly of any or all of the three.

16.3.1 Heat transfer through textile structures

Heat transfer through a body can be steady state or transient. In steady state mode, the parameter measured is the thermal conductivity. Thermal resistance is the ratio of thickness to thermal conductivity. The most common instrument used for measurement of thermal conductivity is the guarded hot plate. The principle behind the guarded hot plate is derived from Fourier's equation of conduction:

$$\dot{q} = \frac{dQ}{d\tau} = -kA\nabla T \quad 16.4$$

where $\dot{q}$ is the rate of heat transfer, dQ is the quantity of heat conducted in time $d\tau$, ∇T is temperature gradient, A is the area of the specimen, and k is the coefficient of thermal conduction. A medium is said to be homogeneous if its thermal conductivity does not vary from point to point within the medium, and heterogeneous if there is such a variation. Furthermore, a medium is said to be isotropic if its thermal conductivity at any point in the medium is the same in all directions, and anisotropic if it exhibits directional variations. In an anisotropic medium the heat flux due to heat conduction in a given direction may also be proportional to the temperature gradients in other directions. The heat transfer through two isothermal plates is therefore given by

$$\frac{dQ}{d\tau} = -kA \frac{\partial T}{\partial z} \quad 16.5$$

where z is the thickness of the material. The steady-state parameters give an estimate of the insulation property of the fabric. But before reaching a

steady state, the temperature of the body is a function of space coordinates x , y and z as well as time, τ , i.e.

$$T = f(x, y, z, \tau) \quad 16.6$$

The parameters measured in transient mode are thermal diffusivity and thermal absorptivity. The temperature distribution is influenced by both the thermal conductivity and the heat storage capacity. The governing equation for transient heat flow is given by

$$Q = 2kA(T_s - T_0) \left(\frac{\tau}{\pi\alpha} \right)^{\frac{1}{2}} \quad 16.7$$

where T_0 is the initial temperature of the body, T_s is the raised temperature and α is the thermal diffusivity. In the case of steady-state heat conduction, the material property is the conductivity k which can be calculated once the heat loss from the body is known and the boundary temperature is measured. In the case of transient heat flow, the main factor is the diffusivity α which is equal to the ratio of the conductivity and the heat content of the body. Transient state heat conduction is related to instantaneous conduction of heat from the surface of the body to the clothing. Instantaneous heat transfer can be related to the warmth or coolness to touch and the warm-cool feeling of any clothing can be quantified.

16.3.2 Prediction of thermal properties

Studies on thermal transmission properties of textiles have been going on since the 1930s. Most of the investigations have been carried out with the purpose of observing the effect of different fabric and environment parameters on the thermal properties of the fabrics. Most of the work done can be categorized into three categories: (a) statistical prediction by studying the effect of material properties, (b) statistical prediction by studying the effect of environmental properties, and (c) prediction using mathematical models. Morris [10] categorized the work done by various workers and the methods employed along with the results and concluded that thickness was one of the main parameters that influence the thermal insulation of the fabric. Hes *et al.* [11] investigated the effect of fabric structure and composition of polypropylene knitted socks on the thermal comfort properties consisting of both dry heat and moisture vapour transfer. The effect of fibre type on the thermal properties and subsequent thermo-physiological state of the human body was considered by Zimmiewska *et al.* [12].

The effect of environmental parameters on the thermal properties was investigated by Niven [13] who studied the influence of the position of the specimen in the wind tunnel and the changes in thermal insulation obtained

thereof. Babu'sHaq *et al.* [14] found the effect of fibre type and fabric layers on thermal insulation under different wind velocities and concluded that natural fibres tend to provide more thermal insulation than man-made fibres. Kind and Broughton [15] found that the heat loss through multilayer clothing systems can be greatly reduced by introducing a layer that has low resistance to airflow between the exterior fabric sheath and the underlying batting layer. Another mathematical model considering the basic equations of airflow through clothing assembly and the hollow cylinder was proposed by Fan [16] for analysing the wind induced heat transfer through outer clothing and fibrous batting to give the effective clothing thermal insulation at different angle positions with reference to the wind flow direction. The effects of movement and wind on the heat and moisture vapour transfer properties in clothing were also studied by Parsons *et al.* [17].

To understand the heat flow characteristics of textile fabrics, many mathematical models have also been used. Hager and Steere [18] converted the radiation heat loss into a conduction model based on Fourier's equation. Farnworth [19] claimed that no convective heat transfer takes place even in very low density battings. Ismail *et al.* [20] used a fabric geometry considering the unit cell geometry of textile fabrics and presented an effective thermal conductivity value comprising all the modes of heat transfer. Holcombe [21] proposed a radiation–conduction model by arguing that infrared radiation plays an important part in determining the thermal resistance of the fabric when the density of the material is low enough. Daryabeigi [22] used the two-flux model combined with a genetic algorithm to give the radiation/conduction heat transfer through high-temperature fibrous insulations. Mohammadi *et al.* [23] gave a theoretical equation for combined conduction and radiation by neglecting convection altogether. More recently, the present authors [24] have given a model based on Peirce's fabric geometry and linear anisotropic scattering of thermal radiation that can be used to predict the thermal insulation of fabrics when their constructional parameters like weave, thread spacing, warp and weft linear density and areal density are known.

One of the main limitations of mechanistic models is the assumptions that are made to simplify the problem. Considering the variability in textile materials, it is very unlikely that the assumptions made, especially in terms of shape and cross-section, are valid in all conditions. This sometimes leads to high errors in prediction based on the model. Similarly, statistical models are only useful when the response has a very simple relationship with the variables considered. In the case of textile materials, when it comes to the constructional parameters, most of the properties are related to each other, e.g. warp and weft count influence the thickness of the fabric, the thread density effects the fabric weight, etc. In these cases, it is difficult to statistically assess the individual influence of one parameter on the response variable. Furthermore, a single rogue datum can completely spoil the model. The

ability to ignore such rogue data, known as the robustness of the model, is an area where ANNs score over statistical models. However, mechanistic models which provide the backbone of understanding the basic phenomena cannot be compared with ANNs.

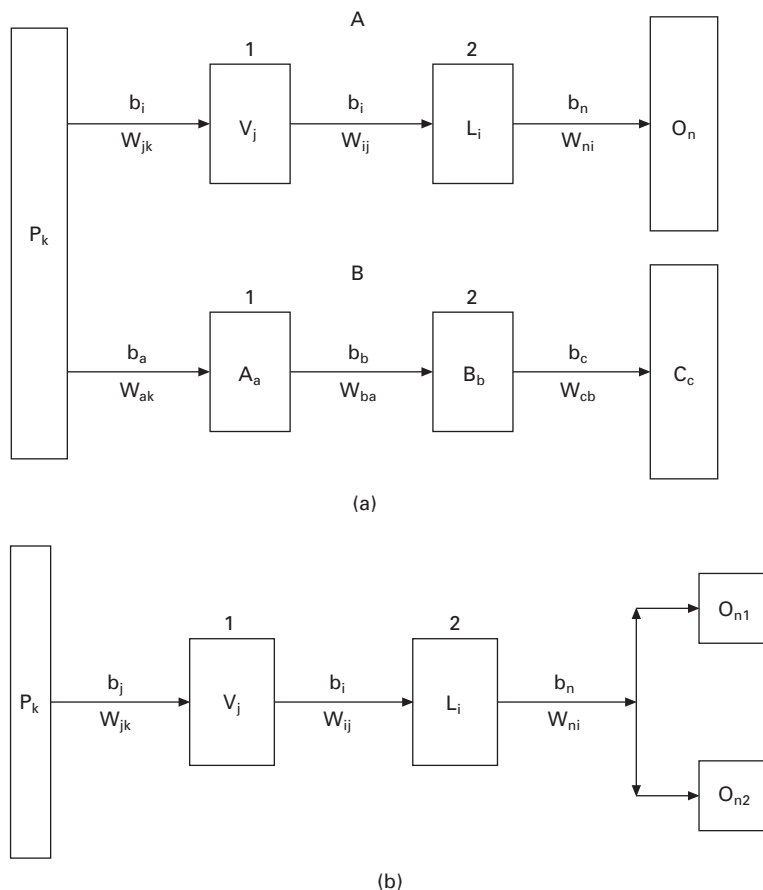
16.3.3 Application of ANN in clothing comfort

One of the most common problems faced during analysis of thermal insulation with deterministic models is the non-linear relationship of different fabric parameters with thermal comfort properties. Most of the fabric parameters which directly influence the thermal properties like thickness, fabric weight, porosity, etc., are related to each other and are derived from basic fabric specifications like yarn linear density, thread spacing, etc. Hence, it is difficult to study the effect of one parameter without changing the other. In this case the statistical modelling is not able to give a satisfactory analysis of the relationships. Therefore a system is required which can predict the thermal parameters of the fabric by considering all the fabric parameters at a time. ANN is one such tool where the collective influence of all the parameters can be taken together to predict the final output.

ANNs have also been used to predict comfort properties of fabrics. Wong *et al.* [25] have tried to predict the sensory comfort properties of clothing using a back-propagation feed-forward network to obtain the best prediction. El-Mogahzy *et al.* [26] have worked on empirical modelling of the fabric comfort phenomenon using a combination of physical, artificial neural network and fuzzy logic analysis. Park *et al.* [27] used fuzzy logic and ANNs to predict the total hand of knitted fabrics. Hui *et al.* [28] worked on application of ANN to predict human psychological perceptions of human hand. Luo *et al.* [29] developed a fuzzy back-propagation feed-forward neural network model to predict human thermal sensations according to various physiological parameters. These responses could be used for designing functional textile systems.

16.4 Future trends

It is possible to consider the collective effect of all the influencing parameters and observe their effect on thermal properties by using ANN. The utility of different ANN architectures and algorithms to predict thermal properties was studied in detail by the authors. Two different ANNs were designed to predict the steady-state and transient thermal transmission properties of fabrics. It was observed that two networks working in tandem were able to predict the thermal properties better than one network with two outputs (Fig. 16.6) [30]. However, it was also observed that when more than one parameter is considered in outputs like steady-state and transient thermal properties, the



16.6 Different network architectures for steady-state and transient thermal properties; P_k = input layer vector, W = weight vector, b = bias vector; (a) parallel networks, V_i , L_j , A_a , B_b = neurons in hidden layers 1 and 2, O_n , C_c = output layer vectors in networks A and B respectively; (b) network with two outputs, V_i , L_j = neurons in hidden layers 1 and 2, O_{n1} , O_{n2} = output layer vectors.

constructional properties alone are not enough to map the relationship between the variables and the output, and properties like the surface characteristics are also required, which are not considered as constructional properties. To improve the prediction performance as well as to optimize the manufacturing inputs for a fabric structures for specific thermal insulation value, it is more convenient to design the network architecture based on the basic fabric constructional parameters as input and thermal insulation as output.

The present study gives a detailed analysis on the design and optimization of one ANN for prediction of steady-state thermal resistance using only the

constructional parameters of the fabrics like weave, thread linear density, thread spacing, areal density, etc. The thickness value was also taken as it directly influences the thermal resistance (Equation 16.5).

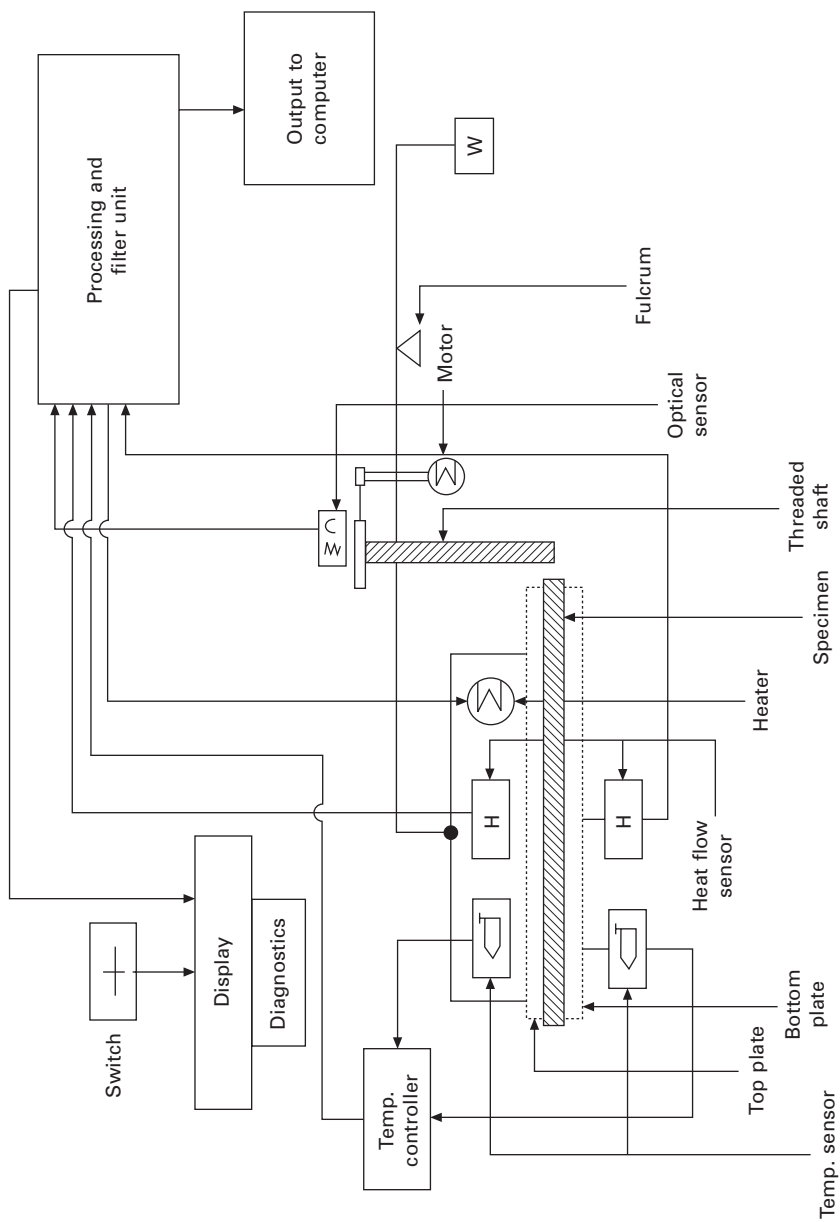
16.4.1 Materials and methods

Eight-five different woven fabrics were considered for the study, out of which 70 fabrics were taken to train the network and the remaining 15 to test for its prediction performance. These fabrics varied in weave, warp and weft counts, thread spacing, thickness and mass per unit area. The properties of the fabrics in the test set are given in Table 16.1.

The thermal resistance was measured in Alambeta [31]. A line diagram of Alambeta is given in Fig. 16.7. In this instrument the fabric is kept between the hot and cold plates; the hot plate comes in contact with the fabric sample at a pressure of 200 Pa. When the hot plate touches the surface of the fabric, the amount of heat flow from the hot surface to the cold surface through the fabric is detected by heat flux sensors. There is also a sensor which measures the thickness of the fabric. These values are then used to calculate the thermal resistance of the fabric. This instrument also gives the transient or instantaneous thermal properties of the textile material in terms of maximum heat flow ($Q_{\max}$) within 0.2 seconds of contact with the hot plate and thermal absorptivity (b).

Table 16.1 Specifications of the test set

Sample no.	Weave	Warp count (Ne)	Weft count (Ne)	Ends/ m	Picks/ m	Thickness (mm)	Fabric weight (g/m ²)	Thermal resistance (K.m ² /W)
1	3/1 twill (1)	2/40	2/40	4720	2160	0.49	210	0.0085
2	3/1 twill (1)	2/40	2/38	4960	2320	0.49	217	0.0090
3	3/1 twill (1)	20	20	4400	2320	0.41	210	0.0061
4	3/1 twill (1)	16	10	4160	2160	0.55	285	0.0082
5	2/2 twill (2)	2/39	2/38	4960	2480	0.50	226	0.0088
6	2/2 twill (2)	2/38	2/36	4640	2480	0.46	226	0.0079
7	4 end satin (3)	2/40	20	4880	2240	0.50	227	0.0091
8	4 end satin (3)	2/38	19	4640	2000	0.50	208	0.0091
9	Plain (4)	39	39	5680	2240	0.37	173	0.0075
10	Plain (4)	36	2/70	5760	3680	0.22	145	0.0047
11	2/1 twill (5)	12	20	3280	1840	0.41	227	0.0071
12	2/1 twill (5)	9	13	2880	1840	0.50	292	0.0092
13	Complex (6)	46	50	5760	3120	0.20	116	0.0037
14	Complex (6)	2/64	2/70	6560	2480	0.09	139	0.0016
15	Complex (6)	2/35	2/36	7680	2560	0.29	134	0.0034



16.7 Line diagram of Alambeta.

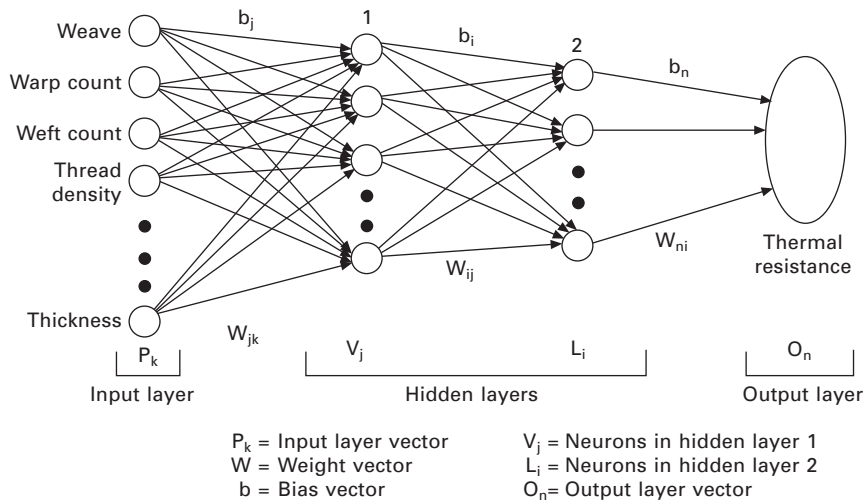
16.4.2 Network architecture and optimization of the parameters

The architecture of the network is given in Fig. 16.8. The number of nodes in the input layer was seven, which was equal to the number of input parameters, namely, weave, warp and weft linear density, warp and weft spacing, thickness and areal density, while the output layer neuron was one corresponding to the thermal resistance. The number of neurons in the hidden layers was five and 14 in the first and second layers, respectively. This number was achieved by training the ANN system with different numbers of hidden layers and obtaining the best combination possible with maximum coefficient of correlation and minimum error for the test set. The MATLAB neural network tool box was used for all the programming [32].

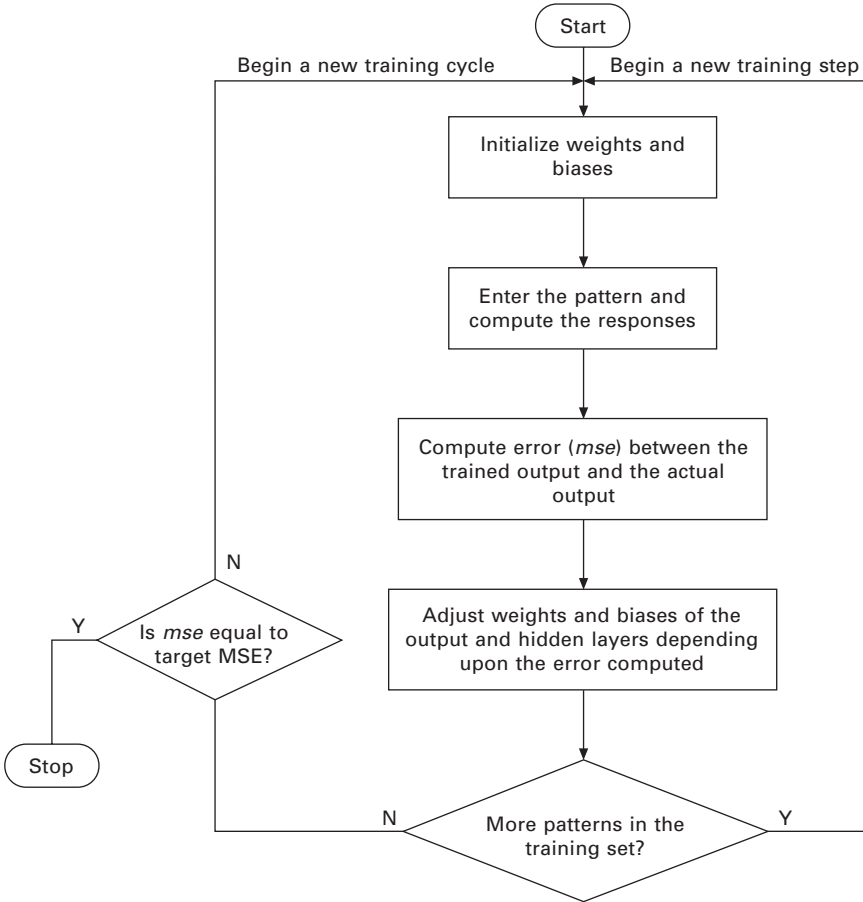
The error was reduced by checking the output values with the original 'training' output. One way to reduce the error is through back-propagation (error back-propagation). One iteration of the back-propagation is given as follows:

$$x_{k+1} = x_k - \alpha_k g_k \quad 16.8$$

where x_k is a vector of current weights and biases, g_k is the current gradient, and α_k is the learning rate. Here the weights and biases are adjusted according to the error between the output layer and the training outputs. A typical back-propagation algorithm is given in Fig. 16.9. A combination of feed-forward



16.8 Architecture of a three-layered ANN used to predict the thermal insulation of woven fabrics: P_k is the input layer; W_{jk} is the weight matrix; b_j is the bias; V_j and L_i are the number of nodes in the hidden layers; and O_n is the output layer.



16.9 Back-propagation algorithm flowchart [1].

and back-propagation makes the network more robust, less complicated and faster to train. The initial values of weights are randomly chosen from -0.1 to $+0.1$. The network first uses the input vector to produce its own output vector and then compares it with the desired or target output vector. Based on the difference the weights are adjusted in such a manner that the error (in this case the ‘mean square error’ or ‘mse’) becomes equal to the target error. The mean square error is given as follows

$$mse = \frac{1}{Q} \sum_{k=1}^Q [t(k) - a(k)]^2 \quad 16.9$$

where t is the target output, a is the predicted output from the network and Q is the number of input vectors. At the completion of the training, the network is capable to recall all the input–output patterns in the training set.

It is also able to interpolate these data. A sigmoid transfer function ‘*tansig*’ was used for input and hidden layers and a linear function was used for the output layer. The network was scaled by normalizing the mean and standard deviation. This was done by the function ‘*prestd*’ so that the inputs and targets have zero mean and a standard deviation of 1.

One of the problems that occur during ANN training is over-fitting. The error on the training set is driven to a very small value, but when new data are presented to the network, the error becomes very large. Here, although the network is able to map the training set, it cannot generalize to new situations. Hence, some of the test data points give very high errors. One method for improving network generalization is to use a network that is just large enough to provide an adequate fit, but it is difficult to know beforehand how large a network should be for a specific application. There are two other methods for improving generalization, namely regularization and early stopping. In the present study regularization was carried out to avoid over-fitting. This is done by modifying the performance function *mse* with a new function called *msereg* given by

$$msereg = \gamma mse + (1 - \gamma)msw \quad 16.10a$$

and

$$mse = \frac{1}{n} \sum_{j=1}^n w_j^2 \quad 16.10b$$

where *msw* is mean square weights, and γ is the performance ratio (default value 0.5). The value of *msereg* becomes lower than *mse* hence the total error will be reduced.

16.4.3 Prediction performance of the network

The performance parameters of the network are given in Table 16.2. The total computing time taken by the network is 7.92 seconds in an Intel dual-core processor with a speed of 2×1.66 GHz. The total number of epochs or iterations taken is 104. The average error obtained in the case of the training set is 2.41%. The average error obtained for the test set is 5.83%. The maximum error is 14.22% which is comparatively high for an ANN prediction. This is because the network was unable to predict one data point properly. The individual errors between the actual and predicted values are given in Table 16.3. When the predicted values are plotted against experimental values, it can be seen that the coefficient of determination is 0.96 (Fig. 16.10).

16.5 Conclusions

The fabric construction parameters like type of weave, thread linear density, thread density, fabric weight and thickness of the fabric are sufficient input

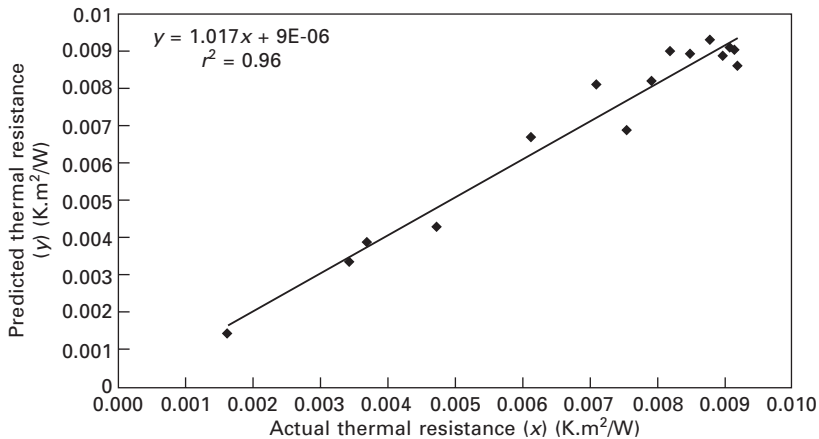
Table 16.2 Performance parameters of the ANN

Network architecture	7-5-14-1
Goal (<i>mse</i> _{reg})	0.029
Epochs	104
Performance ratio	0.8
Average elapsed time (s)	7.92
<i>Training set</i>	
Average error (%)	2.41
Maximum error (%)	13.51
Minimum error (%)	0.07
Coefficient of determination (r^2)	0.99
<i>Test set</i>	
Average error (%)	5.83
Maximum error (%)	14.22
Minimum error (%)	0.47
Coefficient of determination (r^2)	0.96

Table 16.3 Individual errors between actual and predicted values of resistance for the test set

Sample no.	Actual values of thermal resistance (A) (K.m ² /W)	Predicted values of thermal resistance (P) (K.m ² /W)	Error $\frac{ A - P }{A}$
1	0.0085	0.0089	0.049
2	0.0090	0.0089	0.006
3	0.0061	0.0067	0.094
4	0.0082	0.009	0.099
5	0.0088	0.0093	0.058
6	0.0079	0.0082	0.036
7	0.0091	0.009	0.015
8	0.0091	0.0091	0.004
9	0.0075	0.0069	0.085
10	0.0047	0.0043	0.087
11	0.0071	0.0081	0.142
12	0.0092	0.0086	0.063
13	0.0037	0.0039	0.056
14	0.0016	0.0015	0.067
15	0.0034	0.0034	0.005
Average error			0.0582
Maximum error			0.1422
Minimum error			0.0047

parameters for an ANN to be able to predict the steady-state thermal resistance with good correlation and less error. The feed-forward back-propagation neural network designed here could correctly predict the thermal insulation of the fabric with coefficient of determination of 0.96. The time taken by



16.10 Correlation between actual values and predicted values for thermal resistance for the test set for a feed-forward back-propagation neural network using a three-layered network architecture.

the network to analyse the input–output relationships was extremely short. This network can be used to estimate the thermal insulation of woven textile fabrics based on their constructional parameters before they are actually manufactured and tested. ANNs can therefore be useful in saving the time and cost of designing textile assemblies for specific thermal applications where the thermal insulation value can be known before manufacturing and subsequent testing.

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Modelling the fabric tearing process

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Abstract: The study of textile material strength measurement, especially tear strength, has its roots in the work of a textiles designer for the US army. Since then, research has continued in the area of technical textiles, and finally has been adopted in industries manufacturing textiles for daily use. Now, static tear strength is one of the most important criteria for assessing the strength parameters of textiles designed for use in protective and work clothing, everyday clothing and sport and recreational clothing, as well as in textiles for technical purposes and interiors, upholstery and so on. This chapter presents the existing models of fabric tearing, as well as a new model for the tearing of a fabric sample from a wing-shaped specimen. Traditional models of fabric tearing are based on the distribution of mechanical forces. Additionally, the model of predicting the tearing of a wing-shaped sample by use of an artificial neural network (ANN) is presented. The latter can predict the tear force with greatest precision.

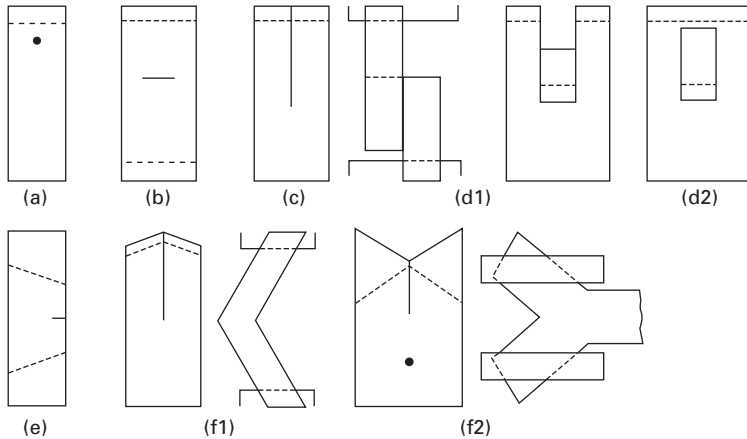
Key words: cotton fabric, tear force, tearing process, wing-shaped sample, theoretical tearing model, ANN tearing model.

17.1 Introduction

The current interest in and research on textile material strength, especially tearing strength, is rooted in the examination of textiles destined for the US Army. The creation of the modern army during the First and Second World Wars led to mass production of uniforms, which needed to function as more than just daily clothing. One of the first aspects addressed by textile engineers at the time was that of strength parameters. Subsequently, research on the strength parameters of a material has been extended to include first technical materials and finally textiles for everyday purposes.

17.1.1 Methods used for determination of static tear strength

Since the study of fabric static tear resistance began in 1915 (Harrison, 1960), about 10 different specimen shapes have been proposed (Fig. 17.1). Depending on the assumed specimen shape, different investigators have proposed their own specimen sizes and measurement methodology, and have



17.1 Shape of specimens: (a) specimen tearing on a nail; (b) specimen cut in the middle; (c) rectangular – tongue tear test (single tearing); (d) rectangular – tongue tear test (double tearing): (d1) three tongues, (d2) three uncut tongues; (e) trapezoidal; (f) rectangular: (f1) Ewing's wing shape specimen, (f2) wing specimen according to the old Polish standard PN-P-04640 used up to 2002 (source: authors' own data on the basis of different standards concerning static tearing).

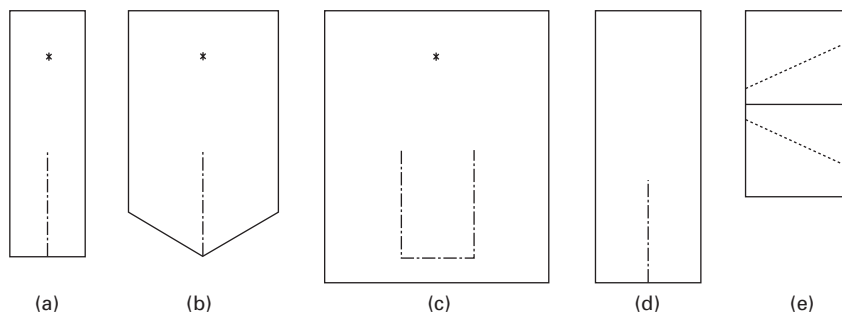
also developed individual methods of assessing fabric tearing strength and expressing the results. The tear strength (resistance) of a particular fabric determines the fabric strength under the static tearing action (static tearing), kinetic energy (dynamic tearing) and tearing on a 'nail' of the appropriate prepared specimen.

Different methods of tearing were reflected in the measurement methodology. The methods were diversified by the shape and size of the specimen, the length of the tear and the method of determining the tear force. The most popular methods were standardized, and the tear force is now the parameter used to characterize the tear strength of a fabric in all methods. In the static as well as the dynamic tearing methods, the tearing process is a continuation of a tear started by an appropriate cut in the specimen before the measurement.

The specimen shapes currently used in laboratory measurements of static tear strength are presented in Fig. 17.2, while Table 17.1 presents important data concerning applied specimen shapes and the measurement methodology used for each.

As well as the shapes and sizes of specimens, the method of tear force calculation has changed over the last 95 years. The process of change culminated in a standardized method of calculating the static tearing strength. The result of static tearing can be read:

- directly from the measurement device, or



17.2 Actual used shapes of specimens: (a) trousers according to PN-EN ISO 13937-2 and PN-EN ISO 4674-1 method B (for rubber or plastic-coated fabrics); (b) wing according to PN-EN ISO 13937-3; (c) tongue with double tearing according to PN-EN ISO 13937-4 and PN-EN ISO 4674-1 method A (for rubber or plastic-coated fabrics); (d) tongue with single tearing according to ISO 4674:1977 method A1; (e) trapezoidal according to PN-EN ISO 9073-4 (for nonwoven) and PN-EN 1875-3 (for rubber or plastic-coated fabrics) (source: authors' own data on the basis of present-day standards concerning static tearing).

- from the tearing chart, depending on the assumed measurement methodology.

It is now possible to read the tear forces from the tearing chart for all current measurement methods of static tearing, i.e., for specimens of tongue shape with single (trousers) and double tearing, and for the wing and trapezoidal shapes. The tearing chart forms a curve, charting the result of sample tearing using a particular tearing method. The initial point of the tearing curve is a peak registered at the moment of breakage of the first thread (or thread group) of the tear, and the end of the tearing curve is at the moment of breakage of the last thread (or thread group) of the tear. Typical graphs of the tearing process are presented in Fig. 17.3.

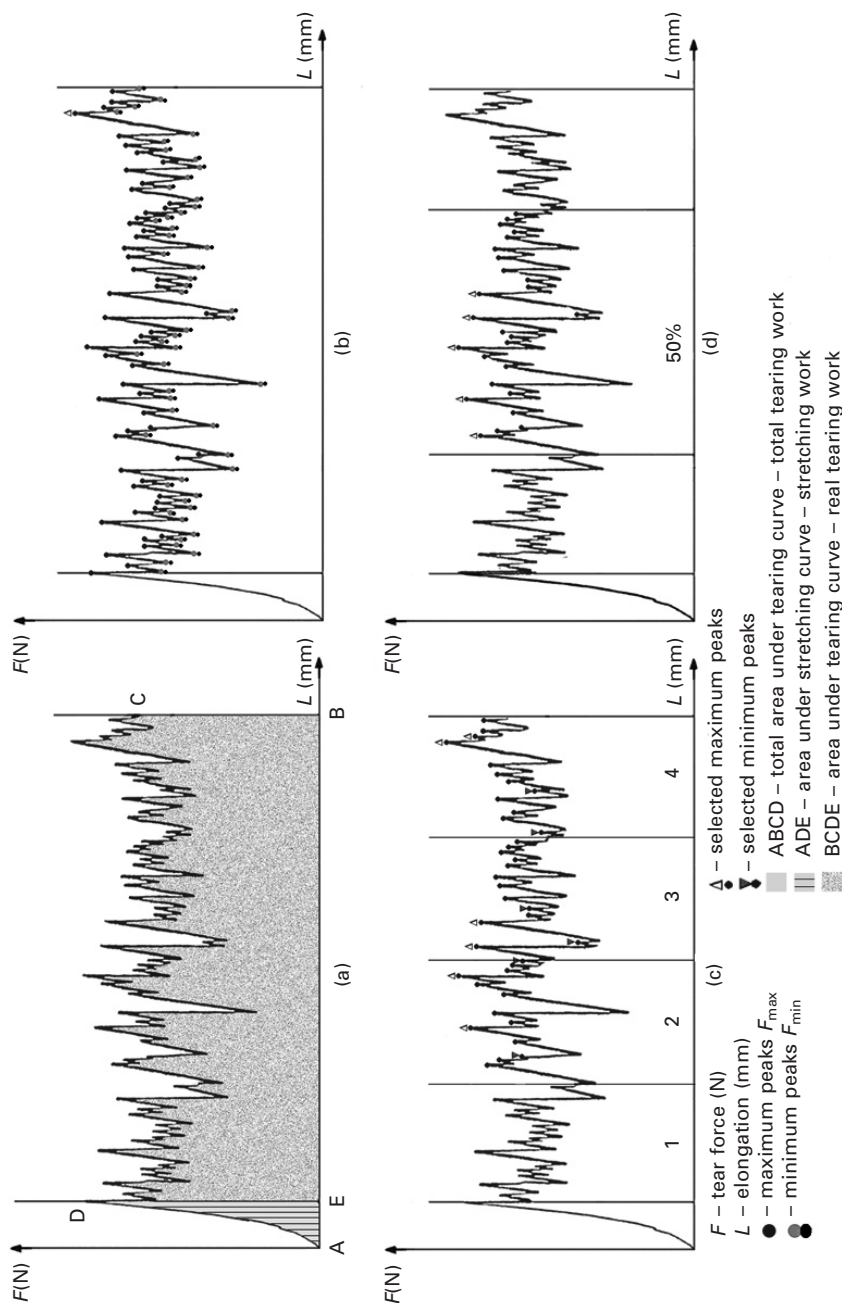
According to the standardized measurement procedure the following methods are now used:

1. The methods described in the standard series PN-EN ISO 13937 part 2: trousers, part 3: wind and part 4: tongue – double tearing (Witkowska and Frydrych, 2004). The tearing graph is divided into four equal parts, starting from the first and finishing on the last peak of the tearing distance. The first part of the graph is ignored in the calculations. From the remaining three parts of the graph, the six highest and lowest peaks are chosen manually, or alternatively all the peaks on three-quarters of the tearing distance are calculated electronically. From the results, the arithmetic mean of the tear forces is calculated (Fig. 17.3(c)).

Table 17.1 Description of static tearing methods

Standard	Single or double tearing	Tearing direction: ⊥ or to the acting force	Tearing distance (mm)	Measurement rate (mm/min)	Distance between jaws (mm)	Specimen dimensions (mm)		Length of cut (mm)
						Length	Depth	
PN-EN ISO 13937-2 PN-EN ISO 4674-1 (method B) Fig. 17.2(a)	Single		75	100	100	200	50	100
PN-EN ISO 13937-3 Fig. 17.2(b)	Single	⊥	75	100	100	200	100	100; angle 55°
PN-EN ISO 13937-4 PN-EN ISO 4674-1 (method A) Fig. 17.2(c)	Double		75	100	100	220	150	100
ISO 4674:1977 (method A1) Fig. 17.2(d)	Single		145	100	70	225	75	80
PN-EN ISO 9073-4 PN-EN 1875-3 Fig. 17.2(e)	Single	⊥	120	100	25	150	75	15

Source: authors' own data on the basis of present-day standards concerning static tearing.



17.3 A way of calculating static tear force from the tearing chart: (a) tearing chart with the marked area, which represents the tearing work (Krook and Fox, 1945); (b) tearing chart with marked so-called minimum and maximum peaks; (c) according to PN-EN ISO 13937: Parts 2, 3, 4 (hand and electronic methods); (d) according to ISO 4674:1977 method A1 (source for (a): authors' own data on the basis of standards concerning static tearing).

2. The method A1 described in ISO 4674:1977, in agreement with the American Federal Specifications (Harrison, 1960) proposed in 1951. This method relies on a median determination, from five tear forces represented by maximum peaks, for the medium graph distance creating 50% of the tearing distance (Witkowska and Frydrych, 2004).
3. The method described in PN-EN ISO 9073-4 for nonwovens and according to PN-EN 1875-3 for rubber and plastic-coated fabrics relies on the calculation of the arithmetic mean from registered maximum peaks on the assumed tearing distance (Fig. 17.3(b)).

17.1.2 Significance of research on static tear strength

The variety of different fabric tearing methods, as well as the variety of measurement methods, often raises the problem of choosing the appropriate method for a given fabric assortment. The choice of static tearing measurement method for the given fabric should be preceded by critical analysis of the criteria for fabric assessment. Usually, the following criteria are used:

- Standards harmonized with the EU directives concerning protective clothing (Directive of the European Union 89/686/EWG) (Table 17.2)
- Other standards – domestic, European or international (Table 17.3)
- Contracts between textile producers and their customers.

Table 17.3 classifies static tearing methods depending on the chosen fabric assortment.

It is also necessary to consider which tearing methods are applicable to a given fabric structure. It is often the case that only one tearing method is applicable, for example for fabrics of increased tear strength, i.e., above 100 N; for fabrics destined for work and protective clothing (cotton or similar) of diversified tear strength depending on the warp and weft directions; and for fabrics with long floating threads. This is illustrated in PN-EN ISO 13937 Part 3 (Fig. 17.2(b)). When using the correct method, the specimen size and the method of its mounting in the jaws of the tensile tester will enable a higher area of sample clamping than in other methods. Thanks to this, the specimen will not break in the jaws of the tensile tester, and the measurement will be correct (Witkowska and Frydrych, 2008a).

In summary, the significance of fabric static tear strength measurement has increased. Laboratory practice indicates that this parameter has become as important in fabric metrological assessment as tensile strength. The main reason for such a situation is the increase in the importance attributed to safety in textiles, especially in the case of protective clothing. It is worth pointing out that fabric manufacturers, who must pay attention to the significance of strength parameters, use better quality and more modern raw materials, such as PES, PA, PI and AR, both alone and blended with natural fibres, as

Table 17.2 Harmonized standards – strength properties – assessment requirements for the chosen groups of protective clothing

Kind of protective clothing	Harmonized standard	Kind of hazard	Requirements concerning mechanical properties
High-visibility warning for professional use	PN-EN 471	Mechanical	Tear resistance (background), tensile strength (background), abrasion resistance (reflex mat.), bursting (background), damage by flexing (reflex mat.)
Protection against rain	PN-EN 343	Atmospheric	Tear resistance, tensile strength, abrasion resistance, seam strength, damage by flexing
Protection against liquid chemicals	PN-EN 14605	Chemical	Tear resistance, abrasion resistance, seam strength, damage by flexing, puncture resistance
Protection against cold	PN-EN 342	Atmospheric	Tear resistance
For firefighters	PN-EN 469	Mechanical, thermal, atmospheric, chemical	Tear resistance, tensile strength before and after exposure to radiate heat, seam strength

Source: authors' own data on the basis of present-day standards concerning static tearing.

this guarantees the required level of strength parameters (Witkowska and Frydrych, 2008a). Tear strength is a complex phenomenon, the character of which is difficult to explain in detail. The large number of tearing methods and the small number of theoretical models makes tear strength prediction difficult; therefore, experiments are necessary.

17.1.3 Factors influencing woven fabric tear strength

Research on the influence of yarn and woven fabric structure parameters on static tear strength was carried out in parallel with the theoretical analysis of phenomena taking place in the tearing zone, the aim of which was elaboration of the model of static tear strength. Krook and Fox (1945), who in 1945 created the first ready-made specimen in the tongue shape, stated that the strength properties of the second thread system have an influence on the value of tear force for the given thread arrangement in the fabric. The authors proposed three practical methods of increasing the fabric tear force, i.e.:

1. Diminishing the thread count per unit (length) of the untorn thread system. This causes a decrease in the number of friction points between

Table 17.3 Classification of static tearing methods depending on fabric application

Textiles – static tear strength method		Uncoated fabric			
Rubber- or plastic-coated fabric					
PN-EN 1875	ISO 4674:1977	PN-EN ISO 4674-1	PN-EN ISO 9073-4	PN-EN ISO 13937-2	PN-EN ISO 13937-3 PN-EN ISO 13937-4
• Technical textiles • Method A1 Protective clothing (high-visibility warning for professional use; protection against the rain) • Method A2 Textiles for tarpaulins		• Method A Protective clothing (protection against cold) • Method B Protective clothing (for firefighters)	• Protective clothing (protection against liquid chemicals) • Textiles for mattresses – nonwoven • Textiles for awnings and camping tents	• Protective clothing (for firefighters) • Work clothing (overalls, shirts, trousers) • Mattresses – woven • Daily textiles • Textiles for flags, banners	• Upholstery (furniture) textiles • Bedding, textiles for beach chairs • Technical textiles (roller blinds) • Work clothing (like PN-EN ISO 13937-2)

Source: authors' own data on the basis of present-day standards concerning static tearing.

the threads of the two systems and wider areas of so-called ‘pseudo-jaws’. The investigations showed also that for thread systems with a smaller number of threads, the tear strength does not drop or decrease significantly.

2. The application of higher tensile strength to the threads of the untorn system in the fabric than to those of the torn one. This method can be used together with the first method described above. In this way (in the authors’ opinion) an insignificant decrease of tear strength in the second thread system can be avoided.
3. Diminishing the friction between threads by using threads with a lower friction coefficient or longer thread interlacements in the fabric.

On the basis of experimental results for the trapezoidal shape specimen, Hager *et al.* (1947) stated that the properties of a torn thread system do not influence the fabric tear strength. Among the most significant parameters influencing this property, they included the fabric tear strength (for a stretched thread system) calculated on one thread, the scale of the stretched thread system, the number of threads of the stretched thread system per unit (length) and the elongation of the stretched thread system at break.

Steel and Grundfest (Harrison, 1960), who continued the research by Hager *et al.* concerning the trapezoidal specimen shape, added to the above-mentioned parameters the fabric thickness and the relationship between the stretched thread system stress and the thread strain at break.

Teixeira *et al.* (1955) carried out an experiment with the tongue shape specimen using single tearing. They used fabrics differentiated by thread structure (continuous and staple), weave (plain, twill 3/1 and 2/2), the warp and weft number per unit length (three variants) and also by the twist number per metre (three variants). On the basis of this experiment, the authors stated that the tear strength depends mainly on the following factors:

- *Fabric weave*: for fabric weave in which the threads have a higher possibility of mutual displacement, the tear strength is on the higher level than for fabric weaves in which more contact points exist between the threads. This conclusion applies to fabrics made of continuous as well as staple fibres.
- *Thread structure*: in the experiment carried out, the tear strength for fabrics made of continuous fibres was higher than for fabrics made of staple fibres. The main reason for this was the higher tensile strength and strain at break for threads made of continuous fibres than those made of staple ones.
- *Number of threads per unit length in the fabric*: for weaves of longer interlacements, i.e., for twill 3/1 and 2/2, it was noticed that the tear strength tended to increase as the number of torn thread systems diminished. This conclusion also applies to fabrics made of continuous as well as staple

fibres. For plain fabrics, the authors did not obtain results showing such a clear-cut relationship between the number of threads per unit length and fabric tear strength.

On the basis of research applying single tearing to a tongue-shaped specimen, Taylor (1959) and Harrison (1960) stated that the fabric tear strength of cotton fabrics depends upon the tensile strength of the threads of the torn thread system, the number of threads in the torn system per length, the amount of friction between threads of both systems, and the mean distance about which the space between the threads can be diminished.

Research carried out on the tear strength of cotton plain fabric using a tongue-shaped specimen with a single tearing was presented by Scelzo *et al.* 1994a, b). An experiment was carried out on several fabrics which were differentiated by the cotton yarn structure as determined by the spinning process (classic and open end yarn – OE), the yarn linear density – single yarns of 65.7 tex and 16.4 tex (the same yarn in the warp and weft), and the number of threads per unit length for the warp system (three variants).

Independent of the spinning system, for any given linear density of yarn, the same number of weft threads per unit length was assumed. The experiment was carried out at two tearing speeds (5.1 cm/min and 50.8 cm/min). The main conclusions drawn from the experiment were as follows:

- *Tearing speed influence:* for the higher tearing speed, i.e. 50 cm/min, the tear strength is higher than for the lower speed (5.1 cm/min). This conclusion applies to cotton yarns made using both spinning systems.
- *Spinning system influence:* for the fabrics made of ring spun yarns, independent of the (warp/weft) linear density, the tear strength is higher than for fabrics made of OE yarns.
- *Influence of number of threads per unit length:* for fabrics with lower thread density, the authors observed a higher tear strength. This conclusion applies to cotton fabrics made of ring spun as well as OE yarns.

Scelzo *et al.*, who were interested in an analysis of fabric static tearing phenomenon, carried out theoretical as well as experimental investigations which aimed at relating the tearing strength of a fabric to the yarn and the fabric structure parameters. The most important parameters influencing the fabric tear strength are fabric tensile strength, tensile force calculated per single thread, and thread tensile strength (for yarns on the bobbin as well as those removed from the fabric). Those in the range of fabric structure include the fabric weave, the number of threads per unit length, and the thread linear density. Depending on the author, the above-mentioned parameters concerned either the stretched or the torn thread system or both thread systems in the fabric under discussion.

An experiment carried out by the authors of this chapter confirmed the conclusions of previous researchers. The experiment on cotton fabrics presented in detail later in this chapter (Section 17.5) yielded the following conclusions:

- The tear strength of cotton fabrics depends mainly on such parameters of yarn and fabric as the tensile strength of the yarn in the torn and stretched thread systems, the number of threads of both systems per unit length, and the fabric mass per unit area.
- The yarn strain at break and the crimp of the threads have the least significant influence on the tearing of cotton fabric.

The above conclusions were drawn on the basis of analysis of correlation and regression, in which the tear forces of stretched and torn thread systems were chosen as dependent variables, whereas the parameters of fabric and yarn of both system structures were assumed as independent variables. Moreover, it was stated that the change of yarn and fabric structure parameters enables the modelling of tear strength. The most effective method of improvement of tear strength is to change the fabric weave, especially if we apply a weave of big float lengths (with the possibility of displacement). Similarly, diminishing the number of torn threads allows an increase in tear strength. The diminishing of the number of points of mutual jamming between threads is dealt with, at the same time increasing the possibility of thread displacement in the fabric. Changing the torn thread linear density is also an effective method of increasing the mean value of the tear force. This results from the fact that, using yarn of higher linear density in the torn thread system than that of the yarn in the stretched thread system, we diminish the number of threads per unit length of this system. Therefore, the result described above is obtained; but with the increase of the yarn linear density, the higher the tensile strength, the greater the influence on the tear force.

The significance of such parameters as the yarn tensile strength, the number of threads per unit length for both systems and the weave is represented by the so-called 'weave index' for cotton fabric tear strength, as confirmed during the building of the ANN tear model (Section 17.7).

17.2 Existing models of the fabric tearing process

Krook and Fox (1945) were among the pioneers of research on predicting the cotton fabric tear strength. In 1945, these authors made an analysis of photographs of torn fabric specimens of tongue shape with single tearing; next, they separated the fabric tearing zone. They stated that this zone is limited by two threads of the stretched system originating from cut strips of the torn specimen and by the thread of the torn thread system being positioned 'just

before the breakage'. Krook and Fox were the first to describe the mechanism of tearing the fabric sample, as well as to propose methods for the practical modelling of fabric strength using the yarn and fabric structure parameters. Their research became an inspiration for successive scientists. Subsequent researchers often based their considerations on hypotheses elaborated by Krook and Fox.

Further research on tearing of the trapezoidal fabric sample was undertaken by Hager *et al.* in 1947. The authors, analysing the strain values in the successive threads of the stretched thread system on the tearing distance, proposed the mathematical description of tear strength. They achieved good correlation between the experimental results and those calculated on the basis of the relationships they had proposed, but only for experiments using tensile machine clamps equal to 1 inch (25.4 mm). The correlation was diminished with the increase of the distance between clamps. The measurements concerning the trapezoidal specimen were continued by Steel and Grundfest (Harrison, 1960), who in 1957 proposed the relationship enabling the prognosis of tear force, which takes into consideration the specimen shape, earlier omitted in research but important for the described relationship between the thread stress (tension) and their strain and parameters.

Research on the fabric tearing process for the tongue-shaped specimen with a single cut was undertaken by Teixeira *et al.* in 1955. The authors proposed a rheological fabric tearing model built of three springs. These springs represented three threads, limiting the tearing zone defined by Krook and Fox in 1945. Teixeira *et al.* described the fabric tearing phenomenon, providing more detail than previous research had yielded, and also carried out an analysis of phenomena occurring in the fabric tearing zone. Their experiments assessed the influence of yarn and fabric structure parameters on the tearing force.

Further research was carried out by Taylor (1959), who proposed the mathematical model of cotton fabric tearing for the tongue-shaped specimen with single and double tearing. Taylor continued the work undertaken by Krook and Fox as well as that of Teixeira *et al.*, but was the first to take into account the influence of phenomena taking place in the interlacement points (i.e. the influence of friction force between the threads) and phenomena occurring around the mutual displacement of fabric threads. Taylor (1959) also introduced the parameter connected with the fabric weave (weave pattern) into the relationship.

In 1974 Taylor (De and Dutta, 1974) published further research, modifying his own tearing model. Taylor also took the thread shearing phenomenon into consideration, which (in his opinion) takes place during the fabric tearing, and stated that a shear mechanism is analogous to the mechanism occurring during thread breakage in the loop. Taylor's model replaced the

'simple' thread strength with the thread strength in the loop, giving a better correlation between the experimental and theoretical results.

Further research on tearing strength was published by Hamkins and Backer (1980). These authors conducted an experiment comparing the tearing mechanism in two fabrics of different structures and raw materials. The first fabric had a loose weave made of glass yarn, increasing the possibility of yarn displacement in the fabric, and the second had a tight weave of elastomer yarns, with a small possibility of yarn displacement in the fabric. The authors concluded that the application of earlier proposed tearing models was not fully satisfying for different variants of fabric structures and raw materials.

In 1989 Seo (Scelzo *et al.* 1994a) presented his analysis of fabric static tearing and a model which was very similar to Taylor's model. Seo adapted the initial geometry according to Peirce and concentrated his attention on thread stretching in the tearing zone. This model had a different acting mechanism: Taylor's model was based on stress, whereas Seo's model was based on strain. Moreover, Seo assumed an extra variable: an angle in the tearing zone.

Subsequent to Seo's research, Scelzo *et al.* (1994a,b) published their considerations on the possibility of modelling the cotton fabric tear strength for the tongue-shaped specimen with single tearing. These authors distinguished three tearing components: the pull-in force, which determined how the force applied to the stretched thread system was transferred to the threads of the torn system; the resistance to jamming, i.e., the force on the threads during the mutual jamming of both thread systems; and the thread tenacity of the torn system, i.e., the ratio of thread breaking force and its linear density.

Scelzo *et al.* proposed a rheological model presenting the fabric as a system of parallel springs. This model was analogous to the model proposed in 1955 by Teixeira *et al.* In their experiment the authors presented the results concerning the influence of such parameters as the spinning system (ring or rotor), the yarn linear density, the number of warp threads used with a constant number of weft threads, and the speed of measurements on the tearing strength of cotton fabrics.

Summing up, it is worth noting that, in the range of specimen shapes, parameters of tearing strength and methods of calculation, many solutions were offered by different authors, whereas in the range of phenomenon modelling, fewer proposals were offered. This confirms that the phenomena occurring during fabric tearing are very complex, and there are many difficulties to be faced when elaborating a tearing model which would predict this property accurately.

Models elaborated so far have concerned only two specimen shapes: trapezoidal and tongue-shaped with single tearing. The researchers concerned

with these models presented two research approaches to modelling. The first approach concerned analysis of the influence of thread and fabric structure parameters on tearing strength, and took into consideration the geometry of the fabric tearing zone. Examples of this approach are the models proposed by Taylor (1959) for the tongue-shaped specimen with single tearing and by Hager *et al.* (1947) as well as by Steel and Grundfest (Harrison, 1960) for the trapezoidal specimen shape.

The other approach, as presented in Teixeira *et al.*'s model (1955) and developed by Scelzo *et al.* (1994a,b), was an analysis of phenomena taking place in the fabric tearing zone. Scelzo *et al.* reduced the fabric tearing model to three components: two resulting from the force acting on the threads in the cut specimen strip named by the authors, namely the pull-in force and resistance to jamming; and a torn thread system tenacity. This is the only approach which takes into consideration the phenomena taking place in both thread systems of the torn fabric specimen, i.e., in both the stretched and torn systems. It is worth pointing out that the analysis of the phenomenon of fabric tearing carried out by Scelzo *et al.* is very penetrating, and aids recognition of the phenomena in each stage of fabric tearing for the tongue-shaped specimen with single tearing.

It is worth looking at the models proposed so far in terms of their utility or ability to help in the process of fabric design. Many parameters (for example coefficients, as proposed by the authors) are not available in the fabric designing process, and determining these parameters through experiments is practically impossible. A similar situation exists in the case of the model proposed by Scelzo *et al.* (1994a,b), which uses computer simulation of the tearing process and predicts the tear force value on the basis of introduced data. Without the appropriate data for this software, the practical application of this model is impossible. Moreover, for many manufactured fabrics, especially fabrics of increased tear strength as well as fabrics of different tear strength for each thread system, the application of the tongue-shaped specimen with single tear is practically impossible due to the tendency of the cut strip to break in the tensile tester clamps and of the threads of the torn system to slip out of the threads of the stretched system. Therefore, there is a need for a model of the fabric tearing process which on the one hand will guarantee correct measurement, and on the other will be based on the available parameters, or those which can be determined quickly and easily through experimentation.

Taking all these arguments into consideration, the model for the wing-shaped specimen is proposed. It combines the fabric tear strength with the yarn and fabric structure parameters and the geometry of the fabric tearing zone, as well as with the force distribution in the fabric tearing zone.

17.3 Modelling the tear force for the wing-shaped specimen using the traditional method of force distribution and algorithm

17.3.1 Stages of the static tearing process of cotton fabrics for the wing-shaped specimen

The tearing process of the wing-shaped cotton fabric sample (according to PN-EN ISO 13937-3, Fig. 17.2(c)), started by loading the specimen with the tensile force, was divided into three stages, which are presented schematically in Fig. 17.4. In Fig. 17.4 the following designations are used:

Point 0 – start of the sample tearing process, i.e., start of the movement of the tensile tester clamp; point 0 also indicates the beginning of the thread displacement stage (for both thread systems)

Point z_1 – the end of the thread displacement stage, and the beginning of the stretching of the torn thread system

Point z_2 – the end of the stretching stage and the beginning of thread breakage – point r

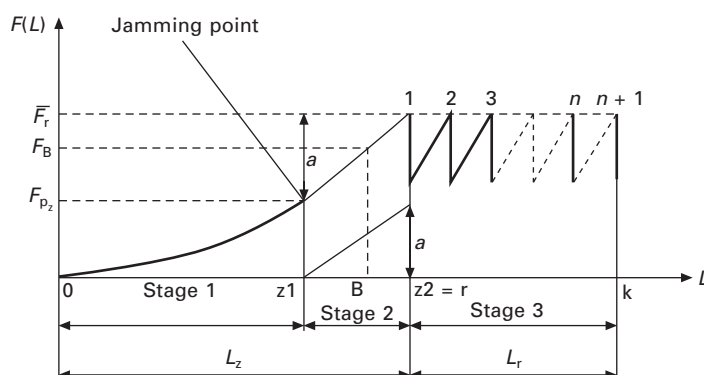
Point k – the end of the specimen tearing process, i.e., the end of measurement

Point B – any point in the range z_1 – z_2

Distance a – the value of the breaking force, i.e., the value which is ‘added’ to the value of displacement at the moment at which the jamming point is achieved

L – the extent of movement of the tensile tester clamp

L_z – the extent of movement of the tensile tester clamp up to the first thread breakage on the distance L_r



17.4 Graph of tear force of specimen as a function of tensile tester clamp displacement, i.e., the tearing process graph. Stages of tearing process of cotton fabric for the wing-shaped specimen (source: authors' own data).

L_r – the tearing distance, i.e., the distance of the displacement of the tensile tester clamp, measured from the moment of the first thread breakage up to the breakage of the last thread on the marked tearing distance

$F(L)$ – the stretching force acting on the torn sample, determined by the distance of displacement of the tensile tester clamp

$\bar{F}_r$ – the mean value of the tearing force, calculated as the arithmetic mean of local tear forces represented by peaks 1, 2, 3, ..., n , $n + 1$ on the tearing distance L_r , (for ideal conditions, where $F_{r1} = F_{r2} = F_{r3} = F_{rn} = F_{rn+1}$)

F_B – the value of the tensile force at any point B

Line z1 – the end of distance a : the relationship between the breaking force and the strain for a single thread, i.e., $W_z = f(\varepsilon_z)$

Curve 0 – the jamming point: the relationship between the distance travelled by the tensile tester clamp and the force causing the displacement of both thread systems of the torn specimen, up to the thread jamming point

Curve 0 – 1 – the relationship between the distance travelled by the tensile tester clamp and the stretching force, up to the first thread breakage. Curve 0–1 on the distance z1–z2 is the value of line z1 – the end of a distance – moved about the displacement force value at the jamming point.

This analysis of the different stages of tearing is presented with the assumption that the process of forming the fabric tearing zone on the assumed tearing distance starts at the moment that the tensile tester clamp begins to move (Witkowska and Frydrych, 2008a). Depending on the stage of tearing, the following areas in the tearing zone can be distinguished: displacement, stretching and breaking.

- *Stage 1.* The mutual displacement of both sample system threads and the appearance of the displacement area in the tearing zone. The phenomena occurring at this stage are initiated at the moment that the tensile tester clamp begins to move. The clamp movement along the distance 0–z1 (Fig. 17.4) causes the displacement of both thread systems of the torn fabric sample, i.e., the threads of the stretching system, mounted in the clamps, and the threads of the torn system, perpendicular to the thread system mounted in the clamps. It was assumed that at this stage the threads of the torn system are not deformed.
- *Stage 2.* The stretching of the threads of the torn system. This occurs due to the further increase of the load on the threads of the stretched system, but without the mutual displacement of both thread systems of the torn fabric sample. At this stage there are two areas of the tearing zone: displacement and stretching. Due to the lack of possibility of further mutual displacement of both thread systems in the fabric at this stage, the movement of the tensile tester clamp on the distance z1–z2 (Fig. 17.4) causes the first thread of the torn system (in the displacement area) to move into the stretching area and begin to elongate up to the

point at which the critical value of elongation is reached, i.e. the value of elongation at the given thread breaking force. Therefore, it was assumed that in the successive tearing process moments in the stretching area there was only one thread of the torn system, with a linear relationship between load and strain.

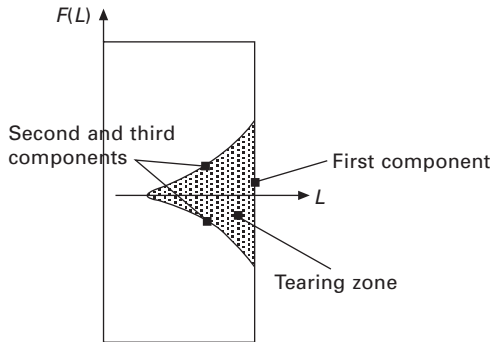
- *Stage 3.* The breakage of the torn system thread along the assumed tearing distance. In this stage of tearing process the tearing zone is built from three areas: displacement, stretching and breaking. The continued movement of the tensile tester clamp on the distance $r-k$ (Fig. 17.4) causes the breakage of successive threads of the torn system along the tearing distance, up to the point at which the tearing process ends (point k , Fig. 17.4).

Between stages 1 and 2 there is the so-called jamming point (Fig. 17.4), i.e., the point at which the fabric parameters and values of the friction force between both system threads make the further mutual displacement of both system threads in the fabric sample impossible. Therefore, stage 1 ends with the achievement of the jamming point, and stage 2 ends with the breakage of the first thread of the tearing distance.

Since the moment of the first thread breakage of the tearing distance, the phenomena described in stages 1, 2 and 3 occur simultaneously up to the moment of breakage of the last thread of the torn system on the tearing distance.

The characteristics of the tearing process stages have some similar features to the description of this phenomenon for the wing-shaped specimen presented by previous researchers of the tearing process, i.e.:

1. Distinguishing two thread systems in the torn fabric sample: the stretched thread system, mounted in the tensile tester clamps; and the torn thread system, which is perpendicular to the stretched one (Krook and Fox, 1945; Teixeira *et al.*, 1955; Taylor, 1959; Scelzo *et al.*, 1994a,b). The systems can also be designated 'untorn' and 'torn'.
2. Distinguishing the fabric tearing zone (Krook and Fox, 1945; Teixeira *et al.*, 1955; Taylor, 1959; Scelzo *et al.*, 1994a, b) in the torn wing-shaped specimen.
3. Stating that, in the torn fabric sample, displacement and stretching of both system threads occurs (Taylor, 1959 – displacement of stretched system of threads, Teixeira *et al.*, 1955 – displacement of both thread systems).
4. Limiting the fabric tearing process to three components (Fig. 17.5) represented by threads in the tearing zone (Teixeira *et al.*, 1955; Scelzo *et al.*, 1994a,b): the first component is the torn system thread positioned 'just before the breakage'; and the second and third components are threads of the stretched system (threads on the inner edge of cut sample elements) 'at the border of the tearing zone'.



17.5 Components of the tearing zone (source: authors' own data).

The most important differences between the descriptions of the fabric tearing process presented in this chapter and those by previous authors include:

1. Division of the fabric tearing zone into the areas of displacement, stretching and breaking.
2. Distinguishing the jamming point of both thread systems of the torn sample.
3. Stating that the displacement of both thread systems (stage 1) and the stretching (stage 2) of the torn system threads are not taking place at the same time. This statement is true, assuming that it is possible to find a point at which the first thread of the torn system is in the displacement area and cannot be further displaced. This thread travels into the stretching area and starts to elongate up to the critical value of elongation and the point at which it breaks.
4. Stating that the tear force is the sum of the vector forces; i.e. the force which causes displacement without deformation of both system threads, up to the so-called jamming point, and the force which causes the elongation of the torn system thread up to the critical value of elongation and the breakage of the thread.

17.4 Assumptions for modelling

During the construction of this model of the cotton fabric tearing process for the wing-shaped specimen, the following assumptions were made:

1. The fabric tearing process in the plane x - y was considered. Bending, twisting and abrasion phenomena, which take place in both system threads, were not taken into consideration.
2. Two thread systems take part in the fabric tearing process: the stretched thread system, mounted in the tensile tester clamps, and the torn thread

system perpendicular to the stretched one. The properties of both thread systems influence the tearing resistance.

3. Considerations on the elaboration of the model are carried out for the stretched and torn thread systems in the tearing zone. Three areas of the tearing zone can be mentioned: displacement, stretching and breaking.
4. In the stretching area of the tearing zone there is only one torn system thread.
5. Deformations of the single torn system thread in the stretching area of the tearing zone are elastic and can be described by the Hookean law. Deformations of the single stretched system thread, i.e., the thread on the inner edge of cut specimen elements, are also elastic and can be described by the Hookean law.
6. Thread parameters and fabric structure for both the stretched and torn thread systems are identical (in the same thread system). The cotton thread cross-section in the fabric was assumed to have an elliptical shape.
7. The basic source of the resistance taking place during the displacement of both system threads is the friction forces between them (at the interlacement points). Working on the assumption that threads in the same system are parallel, friction forces between threads of the same system were not considered. The forces acting on the stretched system threads are described by the Euler's equation.
8. The wrap angle by the threads of the perpendicular system on the assumed tearing distance is constant and does not change during the fabric tearing process.
9. The threads of the torn system in the tearing zone are parallel, irrespective of the area.
10. The basic cause of thread disruption in the breaking area of the tearing zone is the breakage of the thread (the phenomenon of slippage of the torn thread system away from the stretched thread system was not taken into consideration).

17.4.1 Theoretical model of tearing cotton fabric for the wing-shaped specimen

In Fig. 17.4, the relationships between the force loading the torn sample and the tearing distance of the tensile tester clamp are presented schematically. Generally, the relationships $F = f(L)$ can be written as follows:

$$F = f(L) = F_p(L) + F_{w_z}(L) \quad 17.1$$

where

$F_p(L)$ = a force F in the function of distance moved by the tensile

tester clamp during the displacement of both thread systems in the torn specimens

$Fw_z(L)$ = a force F in the function of distance moved by the tensile tester clamp during the stretching of one torn system thread in the stretched area of tearing zone.

On the basis of assumption 5 to the tearing model, the relationship $Fw_z(L)$ is described by the Hookean law.

In the relation to the proposed tearing process stages, equation 17.1 can be written as follows:

$$\text{Stage 1: } F = f(L) = F_p(L) \quad 17.2$$

$$\text{Stages 2 and 3: } F = f(L) = F_p(L) + Fw_z(L) \quad 17.3$$

and for thread breakage in the breaking area of the tearing zone:

$$F = f(L) = F_r \quad 17.4$$

where F_r = a local value of the tear force.

The value of the fabric tear force at the first moment of thread breakage on the tearing distance on the border of the stretching and breaking area of the tearing zone is described by the following relationship:

$$F_r = F_p(z_1) + Fw_z(r) = F_{pz1} + Fw_z \quad 17.5$$

where

r = the end of the stretching stage of the torn thread system and the beginning of the thread breaking stage (Fig. 17.4)

F_{pz1} = the value of the displacement force at the point of jamming both thread systems of the torn sample

Fw_z = the value of the breaking force of the torn system thread.

The distribution of forces $F(L)$, $F_p(L)$ and $Fw_z(L)$ at point B (Fig. 17.4), at any point on the distance $z1-z2$ is presented in Fig. 17.6. Taking point B into account, the following equation can be written:

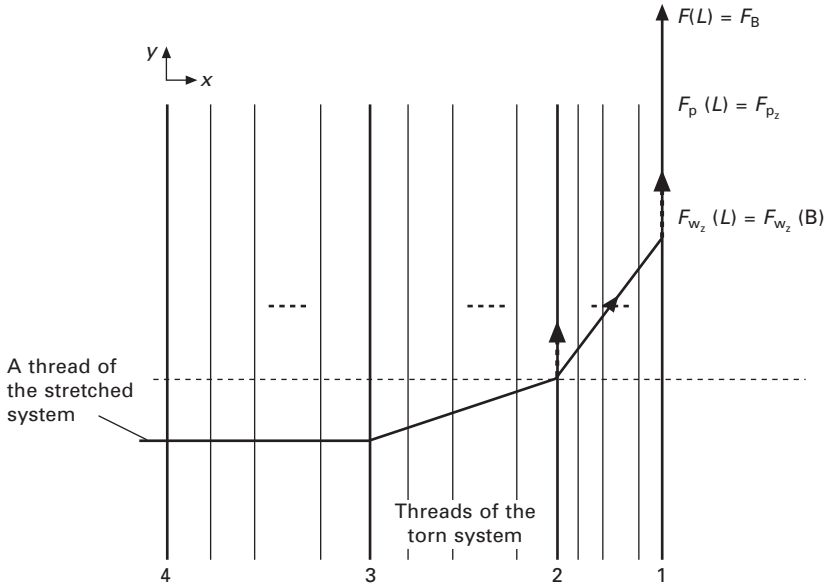
$$Fw_z(L) = Fw_z(B) = Fw_z \quad \text{for } B = z2 \quad 17.6$$

Further considerations tend to the $F_p(L)$ relationship determination.

Forces acting in the displacement area of the tearing zone are presented schematically in Fig. 17.7. In each interlacement of the thread systems there, the force $\vec{F}_n(n)$ is distinguished. This is a vector sum of forces $\vec{F}_{p1}(n)$ and $\vec{F}_m(n)$:

$$\vec{F}_p(n) = \vec{F}_{p1}(n) + \vec{F}_m(n) \quad 17.7$$

Taking into account Fig. 17.7 and the relationships set out in equation 17.7, the following designations were assumed:



17.6 Distribution of forces $F(L)$, $F_p(L)$ and $F_{wz}(L)$ for point B at any place on the distance z_1 – z_2 in Fig. 17.1; 1, 2, 3, n are threads of the torn system in the tearing zone. Thread 1 is a thread in the stretching area of the tearing zone, i.e., 'just before the break'; F_B is the value of the stretching force acting on the torn specimen for the distance B between the tensile tester clamps; and $F_{wz}(B)$ is the value of the stretching force of the torn system thread for the distance B between the tensile tester clamps (source: authors' own data).

$\vec{F}_p(n)$ = the pull-in force of the stretched system thread for the n th torn system thread

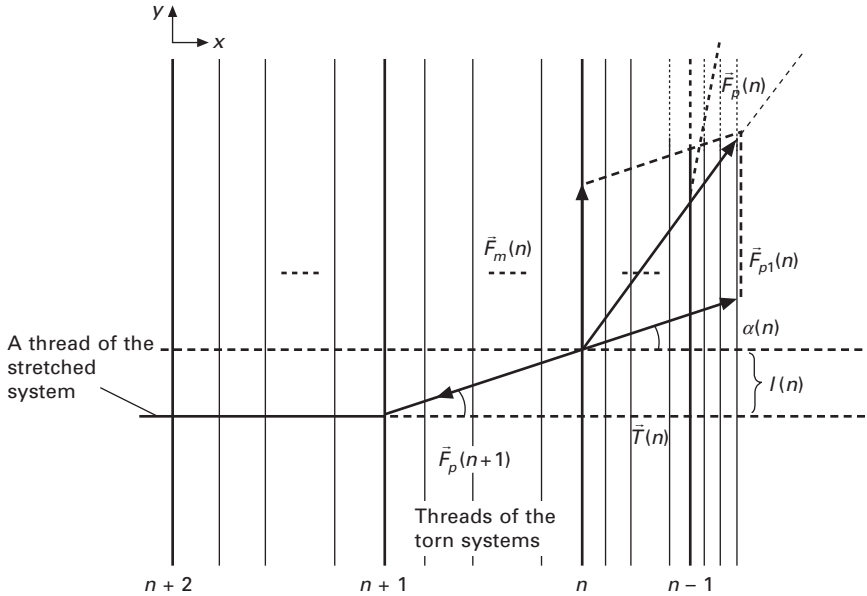
$\vec{F}_{p1}(n)$ = the tension force of the stretched system thread for the n th torn system thread

$\vec{F}_m(n)$ = the force causing the stretched system thread displacement in relation to the n th torn system thread

$\vec{F}_p(n+1)$ = the pull-in force of the stretched system thread for the $(n+1)$ th torn system thread

$\vec{T}(n)$ = the friction force between the stretched system thread and the n th torn system thread. The friction force depends on the load (normal force) and the friction coefficient (μ) between both system threads. It was stated that:

- The value of the force $\vec{F}_p(n+1)$ depends on the value of displacement of the previous interlacement points of both thread systems (angle $\alpha(n)$ between both system threads) and the value of the tension force $\vec{F}_{p1}(n)$



17.7 Force distribution in the stretching area of tearing zone (stage 2) for the wing-shaped specimen; threads marked $n + 2$, $n + 1$, n and $n - 1$ are torn system threads, which have interlacements with the stretched thread system in the weave pattern; between threads $n + 2$, $n + 1$, n and $n - 1$ there are threads which in the weave pattern for the given thread do not have any interlacement; there is one thread of the stretched system, which creates one edge of the tearing zone (represented by the broken line); and $l(n)$ is the y component of the distance between interlacements of both thread systems in the torn fabric specimen (source: authors' own data).

- The value of the force $\vec{F}_m(n)$ depends on:
 - force $\vec{F}_p(n)$ depending on forces acting on the previous threads (i.e. the $(n - 1)$ th). It can be written as follows: $\vec{F}_p(n) = -\vec{F}_{p1}(n - 1)$
 - force $\vec{F}_{p1}(n)$ depending on forces acting on the previous threads (i.e. the $(n - 1)$ th). Threads move only when the force $\vec{F}_m(n)$ is higher than the friction force $\vec{T}(n)$. The force $\vec{F}_{p1}(n)$ tends to achieve the value, sense and direction of force $\vec{F}_p(n)$ at the so-called local jamming point of both the stretched and torn system threads.
- Equalization of the values of forces $\vec{F}_m(n)$ and $\vec{T}(n)$ causes local displacement of threads to stop, and the so-called local jamming of threads on the distance $0-z1$ (Fig. 17.4).
- When the force $\vec{F}_p(n)$ achieves the value of force F_{pz} , then the force $\vec{F}_m(n) \leq \vec{T}(n)$, which is the condition necessary for thread jamming.

The values of force $F_p(n + 1)$ at the interlacement of the threads of both systems determine the shape of the fabric tearing zone 'arms':

$$F_p(n+1) = F_p(n) \frac{1}{\sqrt{\left[\exp^2(\varphi\mu) + 2 \exp(\varphi\mu) \mu \cos \frac{\beta}{2} (1 + \exp(\varphi\mu)) \frac{l(n)}{O_r} \right] + \mu \cos \frac{\beta}{2} (1 + \exp(\varphi\mu))^2}} \quad 17.8$$

where

$F_p(n+1)$ = the pull-in force of the stretched system thread for the $(n+1)$ th torn system thread

$F_p(n)$ = the pull-in force of the stretched system thread for the n th torn system thread

φ = the wrap angle of the torn system thread by the stretched system thread

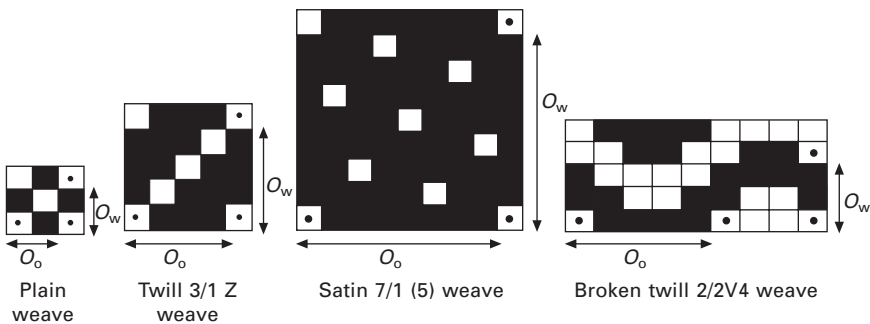
μ = the static friction coefficient between threads of both systems in the torn fabric

β = the angle between the forces: tensile and pulling out of stretched system threads

O_r = the initial distance between the successive thread interlacements, on the assumption that between them there are torn system threads

$l(n)$ = the distance between the interlacement points (in the torn fabric specimen) in the direction of the torn thread system.

The initial distance between the successive thread interlacements, on the assumption that between them there are torn system threads, is described as follows (Fig. 17.8):



17.8 A way of determining the distance between the successive thread interlacements in the fabric for the given weaves. O_o is the initial distance between the successive weft thread interlacements on the warp threads in the fabric; O_w is the initial distance between the successive warp thread interlacements on the weft thread in the fabric (source: authors' own data).

$$O_r = A_r m_r = A_r (1 + L_{n-r(z)}) = \frac{100}{L_{n-r}} (1 + L_{n-r(z)}) \quad 17.9$$

where

A_r = thread spacing between the torn system threads (mm)

L_{n-r} = the number of torn system threads per 1 dm

$L_{n-r(z)}$ = the number of torn system threads between the successive thread interlacements

m_r = the overlap factor of the torn system threads (Table 17.4).

The value of the overlap factor for the considered weaves and thread systems is presented in Table 17.4.

Finally, the distance between the interlacement points (in the torn fabric specimen) in the direction of the torn thread system is calculated from the relationship

$$l(n) = \sqrt{2 \sqrt{F_p(n)^2 - \left(\mu F_p(n) \cos \frac{\beta}{2} \left(\frac{1}{\exp(\phi \mu)} + 1 \right) \right)^2} O_r \sigma_{rc} - \left(F_p(n)^2 - \left(\mu F_p(n) \cos \frac{\beta}{2} \left(\frac{1}{\exp(\phi \mu)} + 1 \right) \right)^2 \right) \cdot \sigma_{rc}^2} \quad 17.10$$

$$\delta_{rc} = \frac{1}{l_z a} a_e L_{n-rc/5cm} \quad 17.11$$

where:

δ_{rc} = a coefficient of elongation of the stretched system threads for the wing-shaped specimen (mm/N)

a = a direction coefficient of the straight line $W_z = f(l_{bw})$ found experimentally (point 4, Table 17.10), (N/mm)

l_z = the distance between the tensile tester clamps during the determination of the relationship $W_{zn} = f(l_{bw})$, i.e., $l_z = 250$ mm

a_e = the length of half axis of the ellipse, according to assumption 6 of the model that the shape of cotton yarn cross-section is elliptical. The value is determined experimentally, in mm

$L_{n-rc/5cm}$ = the number of stretched system threads on the distance of 5 cm, i.e., half the width of the wing specimen.

Table 17.4 Dependence of the set of overlap factors m_o and m_w on fabric weave and thread system

Weave/overlap factor m	Plain	Twill 3/1 Z	Satin 7/1 (5)	Broken twill 2/2 V4
m_o (for example, m_r)	2	4	8	5
m_w (for example, m_{rc})	2	4	8	3

Summing up, the elaborated general model of fabric tearing for the wing-shaped specimen is presented by equation 17.1. The value of the fabric tearing force can be calculated from equation 17.5, where $F_p(z_1) = F_p(L)$ for $L = z_1$ is the value calculated on the basis of recurrence equations, and Fw_z is the value of the breaking force of the torn thread system.

On the basis of recurrence equations taking into account equation 17.9, the following values were calculated:

- The values of force $\bar{F}_p(n + 1)$ at the interlacement points (equation 17.8); these points determine the shape of the fabric tearing zone ‘arms’
- The values of distances $l(n)$ between the interlacement points in the direction of the torn thread system (equation 17.10).

The practical application of the proposed model of the fabric tearing process is presented using an algorithm describing the method. It is also presented graphically in Fig. 17.9.

1. Choose the initial value of force $F_p(1)$.
2. Choose $n = 1$.
3. Calculate the $l(n)$ value on the basis of $F_p(n)$, using equation 17.10.
4. Calculate the $F_p(n + 1)$ force value, using equation 17.8.
5. Increase $n = n + 1$.
6. Go to point 3 of the algorithm.

This algorithm is repeated using ascending values of $F_p(1)$. When $l(1)$ achieves the value of $l(1) = \sqrt{O_r^2 - (2a_c)^2}$, $F_p(1)$ takes the value of the thread jamming point F_{pz1} (equation 17.5). The value of Fw_z is added to the value of force F_{pz1} , and in this way the fabric tear force F_r is obtained.

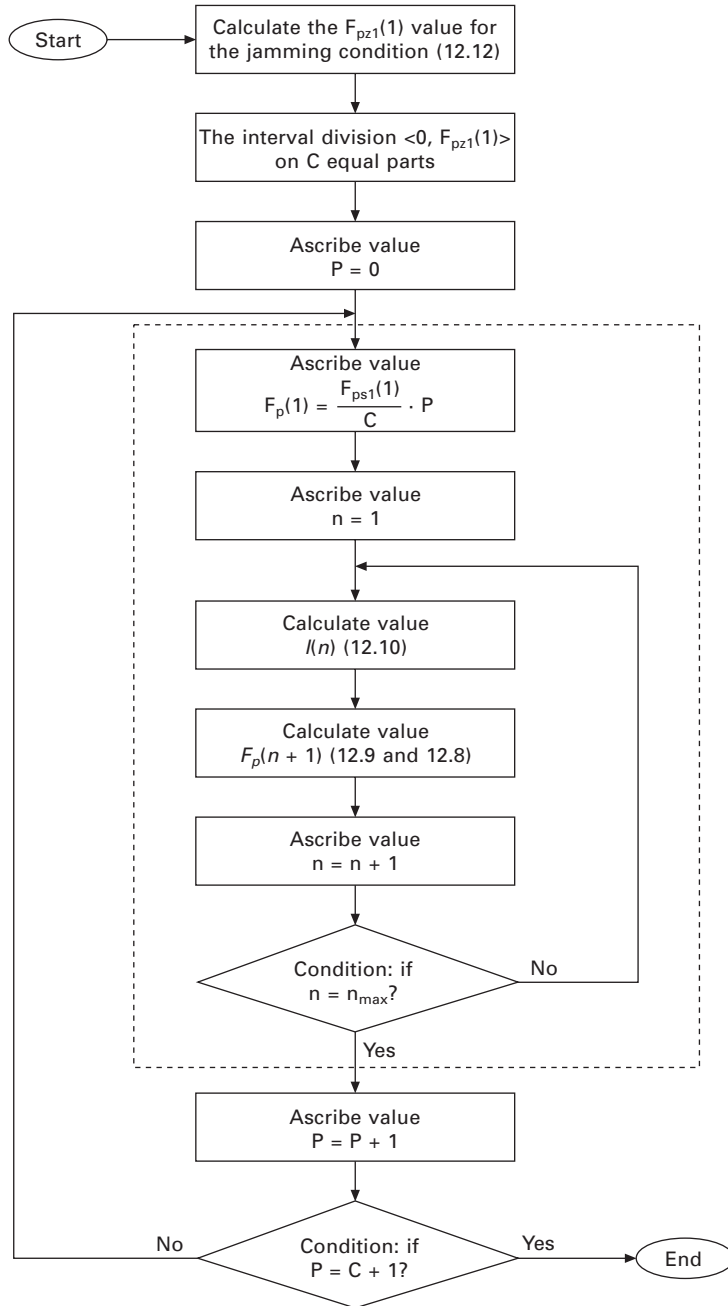
17.5 Measurement methodology

The full characteristics of the cotton fabric static tearing process should be based on its model description and experiments, the results of which on the one hand will confirm the ‘acting effectiveness’ of the proposed theoretical model in predicting the value of the tearing force, and on the other will allow the influence of yarn and fabric structural parameters on its tearing strength to be determined.

All experiments presented in the chapter were done in the normal climate on conditioned samples according to PN-EN ISO 139.

17.5.1 Model cotton fabrics – assumptions for their production

Plied cotton yarns were manufactured using the cotton carded system on ring spinning frames in five variants of yarn linear density, i.e., $10 \text{ tex} \times 2, 15$



17.9 An algorithm of the theoretical model (source: authors' own data).

tex $\times$ 2, 20 tex $\times$ 2, 25 tex $\times$ 2 and 30 tex $\times$ 2, and were statistically assessed in order to determine such parameters as tenacity and strain at break, the real yarn linear density and the number of twists per metre. Parameters of yarns applied to the manufacture of the model cotton fabrics are presented in Table 17.5.

In the assumptions for model yarn manufacturing, a circular shape for the cotton yarn cross-section was assumed, and the diameter was calculated using Ashenhurst's equation (Szosland, 1979). On the basis of microscopic images of fabric thread cross-sections it was stated that the real shape of thread cross-sections is close to elliptical. Their sizes were determined experimentally on the basis of microscopic images.

The model cotton fabrics were produced on the STB looms in four weave variants: plain, twill 3/1 Z, satin 7/1 (5) and broken twill 2/2 V4. Weaves are differentiated by the floating length, defined as the number of threads of the second thread system between two interlacements. For the plain, twill 3/1 Z and satin 7/1 (5) weaves, the floating length is the same for the warp as well as for the weft and equal successively to 1, 3 and 7, whereas for the broken twill 2/2 V4 the floating length is diversified depending on the thread system and is equal successively to 4 and 2. Due to this fact, two indices were proposed, the so-called warp weave index ($I_{w \text{ warp}}$) and the weft weave index ($I_{w \text{ weft}}$). It was assumed that the weave index is a ratio of the sum of coverings and interlacements in the weave pattern.

The weft and warp density on 1 dm was calculated on the basis of assumptions concerning the value of the fabric filling factor by the warp and weft threads:

1. Constant value of warp filling factor, i.e., $FF_o = 100\%$
2. Variable value of weft filling factor, i.e., $FF_w = 70\%$ and $FF_w = 90\%$
3. For the plain fabric, additional structures of weft filling factor $FF_w = 60\%$ and $FF_w = 80\%$ were designed.

Filling factors FF_o and FF_w were calculated according to equations:

$$FF_o = L_{n-o} D \rightarrow L_{n-o} = \frac{FF_o}{D} \quad 17.12$$

$$FF_w = L_{n-w} D \rightarrow L_{n-w} = \frac{FF_w}{D} \quad 17.13$$

where

FF_o = warp filling factor,

FF_w = weft filling factor,

L_{n-o} = warp thread number per 1 dm,

L_{n-w} = weft thread number per 1 dm,

D = the sum of diameters $D = d_o + d_w$ where d_o = theoretical diameter of

Table 17.5 Set of results for cotton yarn measurements

Parameter	Method	Unit	Nominal linear density of yarn (tex)					
			10 × 2	15 × 2	20 × 2	25 × 2	30 × 2	
Mean linear density	PN-EN ISO 2060	tex	9.8 × 2	15.1 × 2	19.5 × 2	24.9 × 2	29.2 × 2	
Variation coefficient		%	1.3	1.1	0.8	1.5	1.0	
Indicators CV – <i>Uster</i>	PN-P-04804	%	11.2	10.1	9.8	8.0	7.9	
Thin places per 1000 m		–	1	1	–	–	–	
Thick places per 1000 m		–	26	4	2	2	1	
Neps per 1000 m		–	90	20	18	8	6	
Theoretical diameter of yarn (nominal linear density)	According to Ashenhurst's equation	mm	0.177	0.217	0.250	0.280	0.306	
Real shape of yarn cross-section (elliptical):	Microscopic method*	mm	0.266	0.408	0.478	0.521	0.559	
Length of ellipse axis, $2a_e$			6.1	4.9	4.1	3.0	5.9	
Variation coefficient			50	50	50	50	50	
Number of tests			0.253	0.300	0.335	0.409	0.380	
Length of ellipse axis, $2b_e$			6.3	6.1	7.1	6.3	6.3	
Variation coefficient			50	50	50	50	50	
Number of tests								
Twist direction	PN-ISO 2	–	S	S	S	S	S	
Mean number of twists	PN-ISO 2061	m ⁻¹	854	697	609	533	485	
Variation coefficient		%	4.1	4.6	6.3	4.7	3.6	
Twist coefficient α		–	120	121	120	119	117	

Table 17.5 Continued

Parameter	Method	Unit	Nominal linear density of yarn (tex)				
			10 × 2	15 × 2	20 × 2	25 × 2	30 × 2
Breaking force	PN-EN-ISO 2062	cN	416	581	672	1075	1126
Variation coefficient		%	7.3	7.1	7.4	6.0	4.2
Elongation at breaking force		%	6.4	8.7	7.8	8.6	8.5
Variation coefficient		%	9.1	8.2	7.1	6.0	6.8
Tenacity	PN-P-04656	cN/tex	21.2	19.2	17.2	21.6	19.3
Loop breaking force		cN	738	1026	1248	1941	1929
Variation coefficient		%	6.8	5.9	5.2	5.7	6.6
Loop tenacity		cN/tex	18.8	17.0	16.0	19.5	16.5

*Microscopic images of cotton yarn cross-section were made using an Olympus SZ60 stereoscopic microscope.

the warp thread system, and d_w = theoretical diameter of the weft thread system.

Using the above-described principles of calculating the weft and warp numbers per 1 dm, the following fabric variants were obtained:

- In the range of the given linear density, the warp was characterized by the same number of threads per 1 dm.
- In each weave version and applied criterion of weft filling factor there is an appropriate 'equivalent' variant.
- They were characterized by the same value of the warp thread number per 1 dm (for the given weave variant), and have a changeable weft thread number per 1 dm.
- They were characterized by the same value of warp and weft filling factor, and have a different linear density.

The linear density of warp and weft thread of the cotton model fabric was assumed according to the following assumptions:

1. In each weave variant for the warp of linear density ' n ' the weft of linear density ' n ' was also applied (for example, if the warp linear density = $10 \text{ tex} \times 2$, the weft linear density = $10 \text{ tex} \times 2$). The number of threads was calculated on the basis of assumed values of the warp and weft filling factors.
2. In each weave variant for the warp of linear density ' n ' the weft of linear density ' $n + 1$ ' was applied (for example, if the warp linear density = $10 \text{ tex} \times 2$, the weft linear density = $15 \text{ tex} \times 2$). The number of threads was calculated on the basis of assumed values of the warp and weft filling factors.

On the basis of the above assumptions, 72 variants of model cotton fabrics were designed and manufactured. The fabrics were finished by the basic processes used for cotton, i.e., washing, chemical bleaching, optical bleaching and drying. The assumptions for manufacturing model cotton fabrics are presented in Tables 17.6 and 17.7, while in Table 17.8 the fabric symbols are described.

In order to obtain the values of the applied yarn parameters for cotton fabrics and threads removed from fabrics, and to determine the values in the model theoretical tearing process, the following measurements were carried out: the static friction yarn/yarn coefficient, and the breaking force of threads removed from fabrics. The values of static friction yarn/yarn coefficients are presented in Table 17.9.

Additionally, the relationships between the load and strain acting on applied cotton yarns were determined. On the basis of analysis of the determination coefficient, it was assumed that relationships between the load and strain

Table 17.6 Assumptions for model cotton fabric manufacture

No.	Weave	Nominal linear density (tex)		Diameter (mm)		Sum of diameter	Number of threads/dm depending on value of filling factor		
		Warp	Weft	Warp	Weft		Warp* $FF_w = 100\%$	Weft $FF_w = 70\%$	$FF_w = 90\%$
1	Plain	20	20	0.177	0.177	0.354	282.8	198.0	254.6
2	Plain	20	30	0.177	0.217	0.393	254.3	178.0	228.8
3	Twill 3/1 Z	20	20	0.177	0.177	0.354	282.8	198.0	254.6
4	Twill 3/1 Z	20	30	0.177	0.217	0.393	254.3	178.0	228.8
5	Satin 7/1 (5)	20	20	0.177	0.177	0.354	282.8	198.0	254.6
6	Satin 7/1 (5)	20	30	0.177	0.217	0.393	254.3	178.0	228.8
7	Broken twill 2/2 V4	20	20	0.177	0.177	0.354	282.8	198.0	254.6
8	Broken twill 2/2 V4	20	30	0.177	0.217	0.393	254.3	178.0	228.8
9	Plain	30	30	0.217	0.217	0.433	230.9	161.7	207.8
10	Plain	30	40	0.217	0.250	0.467	214.4	150.1	192.9
11	Twill 3/1 Z	30	30	0.217	0.217	0.433	230.9	161.7	207.8
12	Twill 3/1 Z	30	40	0.217	0.250	0.467	214.4	150.1	192.9
13	Satin 7/1 (5)	30	30	0.217	0.217	0.433	230.9	161.7	207.8
14	Satin 7/1 (5)	30	40	0.217	0.250	0.467	214.4	150.1	192.9
15	Broken twill 2/2 V4	30	30	0.217	0.217	0.433	230.9	161.7	207.8
16	Broken twill 2/2 V4	30	40	0.217	0.250	0.467	214.4	150.1	192.9
17	Plain	40	40	0.250	0.250	0.500	200.0	140.0	180.0
18	Plain	40	50	0.250	0.280	0.530	188.9	132.2	170.0
19	Twill 3/1 Z	40	40	0.250	0.250	0.500	200.0	140.0	180.0
20	Twill 3/1 Z	40	50	0.250	0.280	0.530	188.9	132.2	170.0
21	Satin 7/1 (5)	40	40	0.250	0.250	0.500	200.0	140.0	180.0
22	Satin 7/1 (5)	40	50	0.250	0.280	0.530	188.9	132.2	170.0
23	Broken twill 2/2 V4	40	40	0.250	0.250	0.500	200.0	140.0	180.0
24	Broken twill 2/2 V4	40	50	0.250	0.280	0.530	188.9	132.2	170.0

25	Plain	50	50	0.280	0.280	0.280	0.559	178.9	125.2	161.0
26	Plain	50	60	0.280	0.280	0.306	0.586	170.7	119.5	153.7
27	Twill 3/1 Z	50	50	0.280	0.280	0.280	0.559	178.9	125.2	161.0
28	Twill 3/1 Z	50	60	0.280	0.280	0.306	0.586	170.7	119.5	153.7
29	Satin 7/1 (5)	50	50	0.280	0.280	0.280	0.559	178.9	125.2	161.0
30	Satin 7/1 (5)	50	60	0.280	0.280	0.306	0.586	170.7	119.5	153.7
31	Broken twill 2/2 V4	50	50	0.280	0.280	0.280	0.559	178.9	125.2	161.0
32	Broken twill 2/2 V4	50	60	0.280	0.280	0.306	0.586	170.7	119.5	153.7

***Bold type** indicates the finally assumed number of warp threads per 1 dm, i.e.:

- I variant of warp linear density, i.e., 10 tex $\times$ 2 – warp number per 1 dm = 283
- II variant of warp linear density, i.e., 15 tex $\times$ 2 – warp number per 1 dm = 231
- III variant of warp linear density, i.e., 20 tex $\times$ 2 – warp number per 1 dm = 200
- IV variant of warp linear density, i.e., 25 tex $\times$ 2 – warp number per 1 dm = 180.

Table 17.7 Additional assumptions for model cotton fabric manufacture

No.	Weave	Nominal linear density (tex)		Diameter (mm)		Sum of diameter	Number of threads/dm depending on value of filling factor		
		Warp	Weft	Warp	Weft		Warp*	Weft	
							$FF_o = 100\%$	$FF_w = 60\%$	$FF_w = 80\%$
1	Plain	20	20	0.177	0.177	0.354	282.8	170.3	226.4
2	Plain	30	30	0.217	0.217	0.433	230.0	138.6	185.0
3	Plain	40	40	0.250	0.250	0.500	200.0	120.0	160.0
4	Plain	50	50	0.280	0.280	0.559	178.9	107.3	143.1

* See note to Table 17.6.

Table 17.8 Assumed symbols for model cotton fabrics

Nominal linear density of yarn (tex)		Value of FF_w	Symbol for fabric of weave*			
Warp	Weft		Plain	Twill 3/1 Z	Satin 7/1 (5)	Broken twill 2/2V4
$FF_0 = 100\%$						
10×2	10×2	60%	1p (I)	—	—	—
		70%	2p (I)	7s (I)	11a (I)	15l (I)
		80%	3p (I)	—	—	—
		90%	4p (I)	8s (I)	12a (I)	16l (I)
	15×2	70%	5p (I)	9s (I)	13a (I)	17l (I)
		90%	6p (I)	10s (I)	14a (I)	18l (I)
	15×2	60%	1p (II)	—	—	—
		70%	2p (II)	7s (II)	11a (II)	15l (II)
		80%	3p (II)	—	—	—
		90%	4p (II)	8s (II)	12a (II)	16l (II)
		70%	5p (II)	9s (II)	13a (II)	17l (II)
		90%	6p (II)	10s (II)	14a (II)	18l (II)
20×2	20×2	60%	1p (III)	—	—	—
		70%	2p (III)	7s (III)	11a (III)	15l (III)
		80%	3p (III)	—	—	—
		0%	4p (III)	8s (III)	12a (III)	16l (III)
	25×2	70%	5p (III)	9s (III)	13a (III)	17l (III)
		90%	6p (III)	10s (III)	14a (III)	18l (III)
	25×2	60%	1p (IV)	—	—	—
		70%	2p (IV)	7s (IV)	11a (IV)	15l (IV)
		80%	3p (IV)	—	—	—
		90%	4p (IV)	8s (IV)	12a (IV)	16l (IV)
		70%	5p (IV)	9s (IV)	13a (IV)	17l (IV)
		90%	6p (IV)	10s (IV)	14a (IV)	18l (IV)

* I, II, III, IV: variants of warp and weft linear density: $10 \text{ tex} \times 2$, $15 \text{ tex} \times 2$, $20 \text{ tex} \times 2$, $25 \text{ tex} \times 2$; p = plain weave, s = twill 3/1 Z weave, a = satin 7/1 (5) weave, l = broken twill 2/2 V4 weave.

Table 17.9 Dependence of values of static friction yarn/yarn coefficients on cotton yarn linear density

Nominal linear density of cotton yarn	$10 \text{ tex} \times 2$	$15 \text{ tex} \times 2$	$20 \text{ tex} \times 2$	$25 \text{ tex} \times 2$	$30 \text{ tex} \times 2$
Static friction coefficient μ	0.295	0.320	0.336	0.294	0.311

of cotton fibres are linear, i.e., they are described by the Hookean law. The linear functions are presented in Table 17.10.

In order to establish the values of the model cotton fabric structure parameters and to determine the values of parameters in the theoretical tearing model, the following measurements were made: fabric mass per unit area,

Table 17.10 Forms of approximate functions for the applied cotton yarn

Linear function $W_z = f(l_{bw})$	Nominal linear density of yarn (tex)
$W_z = 0.267l_{bw} + 0.442$	10×2
$W_z = 0.289l_{bw} + 0.686$	15×2
$W_z = 0.334l_{bw} + 0.700$	20×2
$W_z = 0.461l_{bw} + 0.172$	25×2
$W_z = 0.499l_{bw} + 0.312$	30×2

the number of warp and weft threads per 1 dm, and warp and weft crimp in the fabric. These tests were carried out according to standard methods. The thread wrap angle by the perpendicular system of threads in the fabric was also determined.

17.5.2 Measurements of the parameters of cotton fabric tear strength

The experimental verification of the elaborated model of the tearing process for the wing-shaped specimen was carried out using the tear forces obtained according to PN-EN ISO 13937-3. From the tearing charts on the whole tearing distance (from the first to the last maximum peak) the following values were read: the tear force (F_r), the number of maximum peaks on the tearing distance ($n_{\max}$), the length of the tearing distance (L_r), and the coefficient of peak number (W_w). For each model cotton fabric (for the warp as well as for the weft system), 10 specimens were measured; next, the arithmetic means and variation coefficients of the above-mentioned parameters were calculated.

The coefficient of the peak number was calculated from equation 17.14:

$$W_w = \frac{\bar{L}_{n/7.5\text{cm}}}{\bar{n}_{\max}} \quad 17.4$$

where

$\bar{L}_{n/7.5\text{cm}}$ = the mean number of threads in the measured fabric system on the distance of 7.5 cm (the length of the tearing distance marked on the wing-shaped sample)

$\bar{n}_{\max}$ = the mean number of maximum peaks registered on the tearing distance.

The coefficient of the peak number indicates the mean number of threads of the torn sample which were actually broken at the moment at which the local value of the breaking force was achieved. The coefficient W_w takes a value of 1 when threads on the tearing distance are broken singly, rather than in groups.

17.6 Experimental verification of the theoretical tear strength model

Practical application of the theoretical model of the tearing process requires a lot of calculations in order to obtain the predicted tear force values, and indirectly the force at the jamming point and the distance between interlacements in the fabric tearing zone. The form of recurrent equations in the model suggests automation of the calculation process by the computer using a high-level programming language. Visual Basic, an application of Microsoft Office (EXCEL), has often been used for mathematical calculations and was used in this case. The input data for the model, which are related to the fabric structure and the structure of stretched and torn system threads, are as follows:

- The parameters resulting from the relationships between threads of the stretched and torn systems, the yarn/yarn (thread/thread) friction coefficient and the wrap angle of the torn system thread and the stretched system thread
- The parameters of stretched system threads: the coefficient of thread strain related to the specimen shape
- The fabric structure parameters: the overlap factor of the torn system threads and the number of torn system threads
- The parameters of the torn system threads: the breaking force of the torn system threads.

17.6.1 Forecasting the value of the cotton fabric tear force

Using equations 17.8–17.10, the predicted values of tear forces of fabrics were calculated, characterized by the above-mentioned weave and in each weave by the torn thread system (warp/weft). According to the assumptions, the proposed theoretical model does not take into account all the phenomena taking place during the fabric tearing process. Therefore, for the given values of model parameters the appropriate coefficients were defined:

- Coefficient C , taking into consideration the strength of thread removed from the fabric related to the strength of yarn taken from the bobbin. The values of coefficient C were calculated based on the following equation:

$$C = \frac{100 - \%W_{z(p/n)}}{100} \quad 17.15$$

where

C = coefficient of changes in tensile strength of thread removed from the fabric related to the bobbin yarn strength

- $\%W_{z(p/n)}$ = percentage change of tensile strength assumed (Table 17.11) for the applied linear densities and system of threads (weft/warp).
- Coefficient of peak number W_w . The range (calculated for each weave for the torn thread direction (warp/weft)) of coefficients W_w was calculated for cotton fabrics of the above-mentioned weaves, and in each weave for the torn system of threads (warp/weft) on the basis of the obtained values of coefficient variations. The range of assumed values of coefficient W_w , depending on the fabric weave and torn thread system, is presented in Table 17.12.
 - Coefficient δ_{rc} of stretched system thread elongation related to the sample shape is one of the parameters of the proposed tearing process model. The values for this parameter were calculated from equation 17.11 for the stretched thread system of torn fabric depending on the thread linear density, the number of threads in half the width of the specimen, and dimension $2a_c$ of the shape of the thread cross-section.

17.6.2 Comparison of experimental and theoretical results

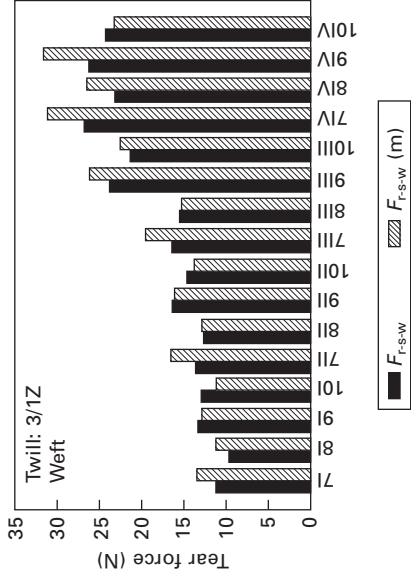
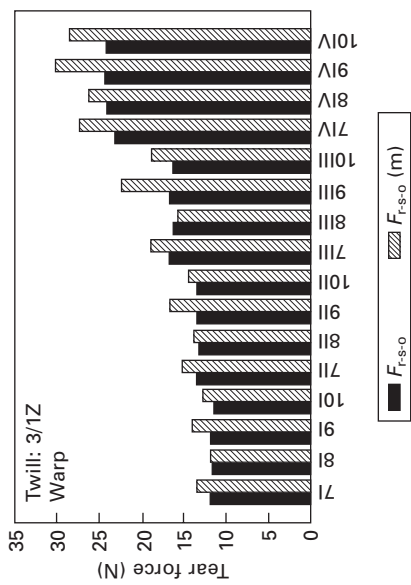
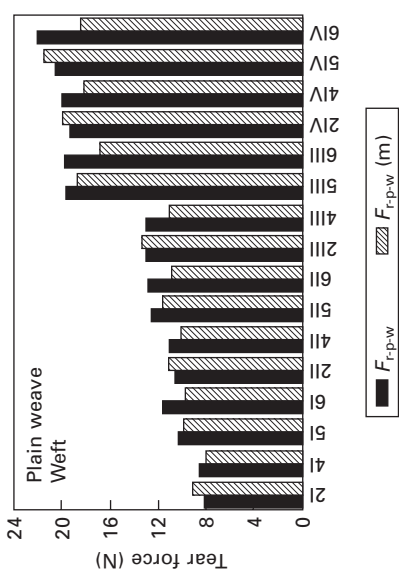
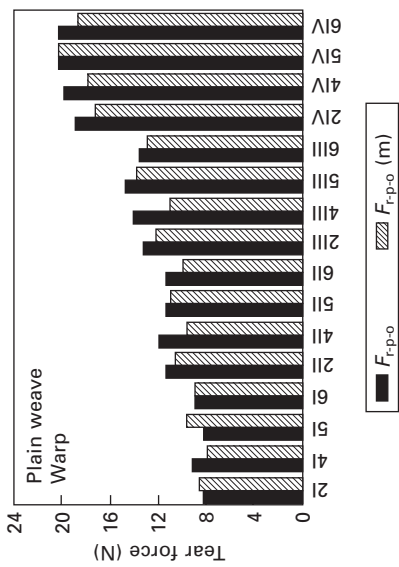
The sets of values as predicted on the basis of the model, and the mean values of the tear forces obtained as a result of experiments, are presented in Fig. 17.10, while Fig. 17.11 presents the regression equations of the predicted values of tear forces versus the experimental values of tear forces, with a 95% confidence interval. Table 17.13 presents values of correlation coefficients and determination coefficients between the predicted and experimental values

Table 17.11 Results of percentage changes of tensile strength of threads removed from the fabrics of linear densities of warp and weft 10 tex $\times$ 2 and 25 tex $\times$ 2

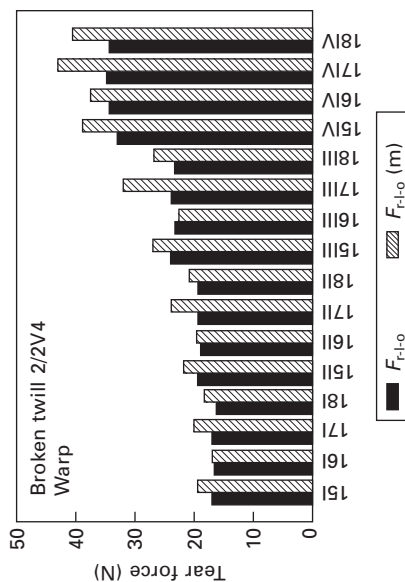
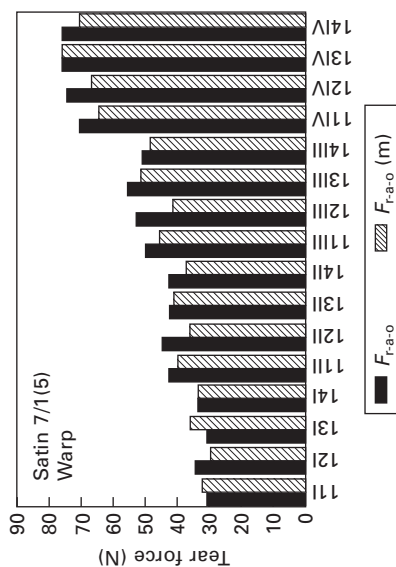
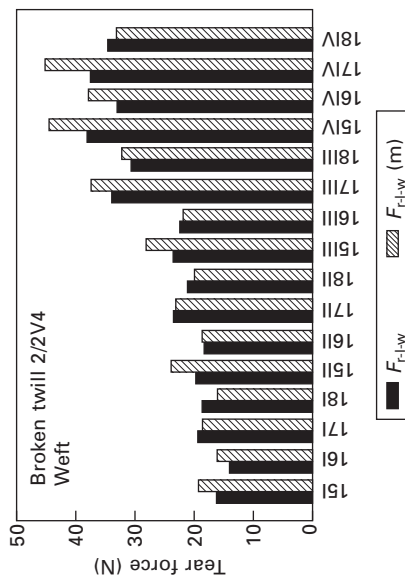
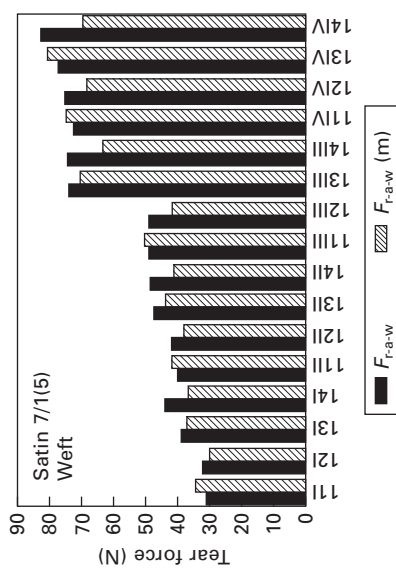
Nominal linear density of yarn 10 tex $\times$ 2		Nominal linear density of yarn 25 tex $\times$ 2	
Mean change of tensile strength for warps	Mean change of tensile strength for wefts	Mean change of tensile strength for warps	Mean change of tensile strength for wefts
8.6	6.3	8.6	7.3

Table 17.12 Range of assumed values of coefficient W_w depending on fabric weave and torn thread system (warp/weft)

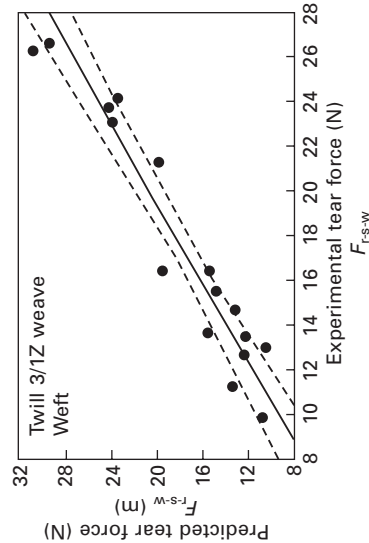
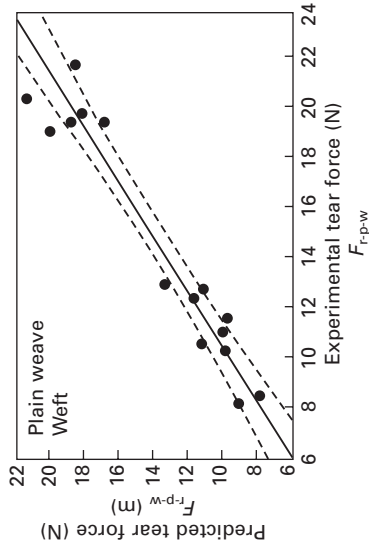
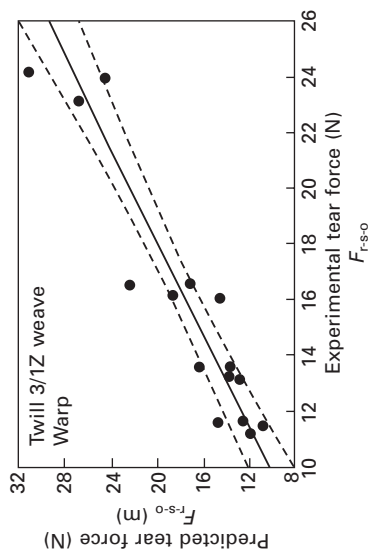
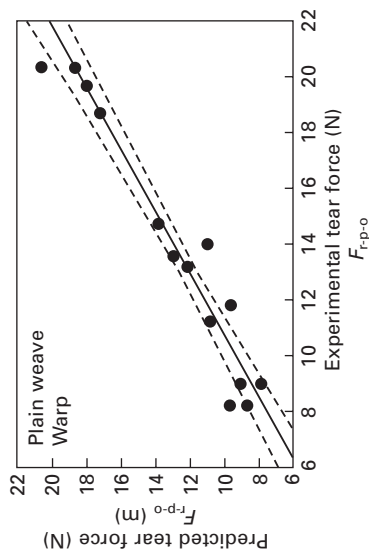
Plain weave		Twill 3/1 Z		Satin 7/1 (5)		Broken twill 2/2 V4	
Warp, W_{w-o}	Weft, W_{w-w}	Warp, W_{w-o}	Weft, W_{w-w}	Warp, W_{w-o}	Weft, W_{w-w}	Warp, W_{w-o}	Weft, W_{w-w}
1.04–1.12	1.03–1.10	1.11–1.22	1.06–1.16	1.65–1.87	1.43–1.69	1.71–1.82	1.19–1.42



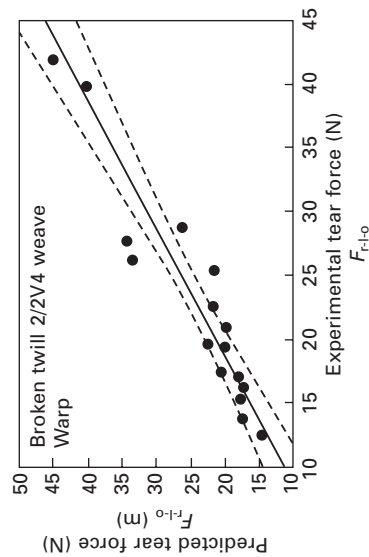
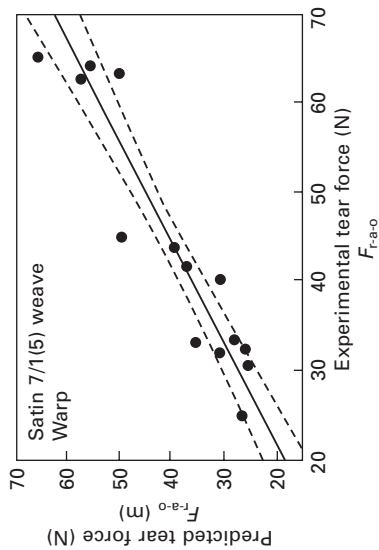
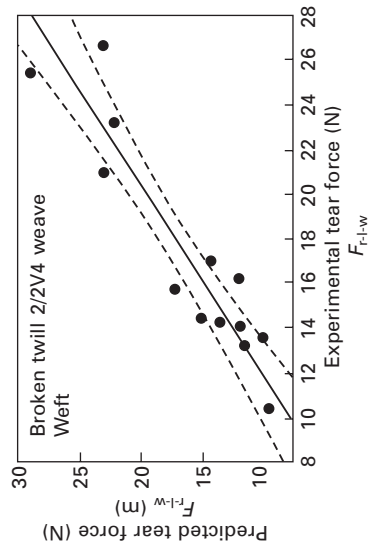
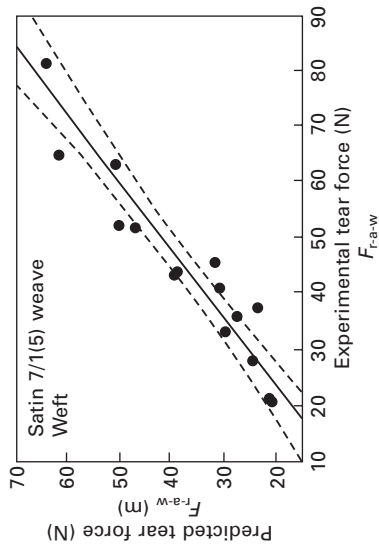
17.10 Comparison of static tear forces, experimental and theoretical, depending on fabric weave and torn thread system (warp/weft): F_{r-p-o} , F_{r-p-w} , F_{r-s-o} , F_{r-s-w} , F_{r-a-o} , F_{r-a-w} , F_{r-l-o} and F_{r-l-w} are the mean values of warp and weft system tear forces of fabrics of the following weaves: plain, twill 3/1Z, satin 7/1 (5) and broken twill 2/2 V4; $F_{r-p-o}(m)$, $F_{r-p-w}(m)$, $F_{r-s-o}(m)$, $F_{r-s-w}(m)$, $F_{r-a-o}(m)$, $F_{r-a-w}(m)$, $F_{r-l-o}(m)$ and $F_{r-l-w}(m)$ are the values predicted on the basis of the proposed model of tear forces of fabrics of the following weaves: plain, twill 3/1Z, satin 7/1 (5) and broken twill 2/2 V4.



17.10 Continued



17.11 Charts of regression equation of predicted values of the tear force related to the experimental values depending on the cotton fabric weave and the torn thread system: a dashed line indicates the confidence interval; F_{r-p-o} , F_{r-p-w} , F_{r-s-o} , F_{r-s-w} , F_{r-a-o} , F_{r-a-w} , F_{r-l-o} and F_{r-l-w} are the mean values of warp and weft system tear forces of fabrics of the following weaves: plain, twill 3/1Z, satin 7/1 (5) and broken twill 2/2 V4; $F_{r-p-o}(m)$, $F_{r-p-w}(m)$, $F_{r-s-o}(m)$, $F_{r-s-w}(m)$, $F_{r-a-o}(m)$, $F_{r-a-w}(m)$, $F_{r-l-o}(m)$ and $F_{r-l-w}(m)$ are the values predicted on the basis of the proposed model of tear forces of fabrics of the following weaves: plain, twill 3/1Z, satin 7/1 (5) and broken twill 2/2 V4.



17.11 Continued

Table 17.13 The set of absolute values of correlation coefficient r and coefficient of determination R^2 between the experimental and theoretical results depending on fabric weave and torn thread system (warp/weft) of cotton fabric

Plain weave				Twill 3/1 Z weave			
$F_{r-o}(m)$		$F_{r-w}(m)$		$F_{r-o}(m)$		$F_{r-w}(m)$	
r	R^2	r	R^2	r	R^2	r	R^2
0.964	0.939	0.959	0.929	0.949	0.882	0.949	0.920
Satin 7/1 (5) weave				Broken twill 2/2 V4 weave			
$F_{r-o}(m)$		$F_{r-w}(m)$		$F_{r-o}(m)$		$F_{r-w}(m)$	
r	R^2	r	R^2	r	R^2	r	R^2
0.947	0.898	0.952	0.907	0.943	0.890	0.928	0.861

of the tear force. The border value of the correlation coefficient for $\alpha = 0.05$ and $k = n - 2 = 14$ is equal to 0.497.

In order to determine the regression equation between the predicted and experimental tear force values the following linear form was assumed:

$$y = a + bx \quad 17.16$$

where

y is a dependent variable, i.e., the predicted tear force of warp system $F_{r-o}(m)$ or weft system $F_{r-w}(m)$ calculated on the basis of the tearing process model, (m) meaning that the tear force was calculated on the basis of the theoretical model

x = an independent variable, i.e., the mean value of tear force $\bar{F}_t$ determined experimentally

b = the directional coefficient of a regression equation, also called a regression coefficient

a = a random component.

The analysis of correlation and determination coefficient values implies the following conclusions:

- The absolute values of correlation coefficients between the experimental and predicted values of the tear force which were obtained are similar for all weaves, and for each weave in the given thread system (warp/weft). The highest absolute values of correlation coefficients between the experimental and predicted values of tear forces were obtained for plain fabrics: 0.964 for the warp thread system and 0.959 for the weft thread system. For fabrics of broken twill 2/2 V4 the lowest values of correlation coefficients were obtained: 0.943 for the warp thread system and 0.928 for the weft thread system. The obtained values of correlation

coefficients confirm that there is a strong correlation between the variables characterizing the mean and predicted tear force, and that the proposed tearing model is also sensitive to the changes of cotton fabric structure parameters.

- Values of the determination coefficients varied depending on the fabric weave. A good fit of the regression model to the experimental data on the level of determination coefficient $R^2 = 0.93$ was observed for plain fabrics for both torn thread systems. Therefore, in addition to the good correlation between the theoretical and experimental results, the theoretical model accurately predicts the value of the tear force. Higher differences between the theoretical and experimental values were observed for fabrics of the following weaves: twill 3/1, satin 7/1 (5) and broken twill 2/2 V4. In the case of broken twill fabrics for the weft thread system, the lowest value of determination coefficient R^2 (equal to 0.861) was obtained. The differences between the theoretical and experimental values of tear force for the above-mentioned weave are presented in chart form in Fig. 17.11.
- The graphs presented show the differences between the experimental and theoretical tear forces; they do not show the points outside the confidence limits, which could disturb the calculated values of the correlation coefficient (Fig. 17.11).

An important element of the analysis carried out was the assessment of the sensitivity of the model to changes in those model parameters concerning the relationship between the threads of the torn and stretched systems.

The predicted values of the tear forces were calculated for the changeable values of the friction coefficient between threads of the torn and stretched systems in one interlacement, and for the changeable values of the wrap angle of the torn system thread and the stretched system thread. The model of the tearing process was elaborated on the assumption that the tear force is a vector sum of the following forces: a displacement force at the moment the so-called jamming point of both system threads is achieved; and a force which causes elongation of the torn system thread up to the point at which the critical value of elongation and thread breakage are achieved. Therefore, diminishing the value of the friction coefficient between both system threads, or the thread wrap angle, gives a high possibility of thread displacement. In such a case, in order to cause the jamming of both system threads, a higher tension force acting on the stretched system thread $F_{p1}(n)$ is needed. The higher value of force $F_{p1}(n)$ causes an increase of pull in the force acting on the stretched system thread $F_p(n)$, which implies an increase of the displacement force F_{pz1} in the jamming point of both system threads, and consequently an increase of the value of the tear force, F_r .

The predicted values of the tear force for fabrics of three weaves were calculated based on the following assumptions:

- Constant parameters of fabric of a given weave and of the torn thread system
- A constant value of the wrap angle of the torn thread system and the stretched system, $\varphi = 85^\circ$ (Table 17.14), and variable values of static friction coefficient μ ,
- A constant value of the static friction coefficient $\mu = 0.294$ (Table 17.15) and a variable value of the wrap angle of the torn system thread and the stretched system thread, φ .

The following examples of fabrics were analysed: 4p (IV), 8s (IV), 12a (IV) and 16l (IV) with 25 tex $\times$ 2 warp and weft linear densities. The results obtained confirmed the influence of the static friction coefficient between both system threads in one interlacement and of the thread wrap angle on the tear force of cotton fabric. The diminishing of the wrap angle and static friction coefficient caused a small increase in the tear force value for fabrics of all weaves examined, and in one weave depending on the torn thread

Table 17.14 Values of the predicted tear force depending on the value of static friction coefficient between both system threads in one interlacement for $\varphi = \text{const}$

Value of static friction coefficient, thread-to-thread, μ	Predicted values of tear force based on the tearing model (N)							
	Plain 4p(IV)		Twill 3/1 Z 8s(IV)		Satin 7/1 (5) 12a(IV)		Broken twill 2/2 V4 16l(IV)	
	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
0.294	17.8	17.9	26.4	26.6	49.9	50.2	32.3	31.0
0.295	17.8	17.9	26.3	26.6	49.9	50.1	32.3	30.9
0.311	17.6	17.7	25.8	26.0	48.6	48.8	31.7	30.2
0.320	17.5	17.6	25.5	25.8	47.9	48.1	31.5	29.8
0.336	17.4	17.2	25.1	25.3	46.8	47.0	31.0	29.2

Table 17.15 Values of the predicted tear force depending on the value of wrapping angle of torn thread system by the thread of stretched system for $\mu = \text{const}$

Thread wrapping angle, φ ($^\circ$)	Predicted values of tear force based on the tearing model (N)							
	Plain 4p(IV)		Twill 3/1 Z 8s(IV)		Satin 7/1 (5) 12a(IV)		Broken twill 2/2 V4 16l(IV)	
	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
60	18.9	19.1	30.0	30.3	58.8	58.8	35.9	35.8
65	18.6	18.7	29.0	29.3	56.2	56.5	34.9	34.5
70	18.4	18.5	28.2	28.5	54.3	54.5	34.1	33.4
75	18.1	18.2	27.5	27.8	52.6	52.8	33.4	32.5
80	17.9	18.1	26.9	27.1	51.2	51.4	32.8	31.7
85	17.8	17.9	26.4	26.6	49.9	50.2	32.3	31.0
90	17.6	17.7	25.9	26.2	48.9	49.1	31.9	30.4

system. The analysis also confirmed the validity of the proposed model of fabric tearing in terms of its sensitivity to the changes of the values of the static friction coefficient of thread by thread and the thread wrap angle.

In practice, it is difficult to design a fabric according to the thread-by-thread wrap angle value, because this value depends on the fabric structural parameters. Nevertheless, the value of the static friction coefficient between cotton threads can be reduced by applying lubricants to the fibre or yarn surface, for example by mercerization. It should, however, be remembered that the chemical treatment of fibre or yarn can cause a decrease in strength, which can lower the fabric tear force.

17.6.3 The chosen relationships described in the cotton fabric tearing model for the wing-shaped specimen

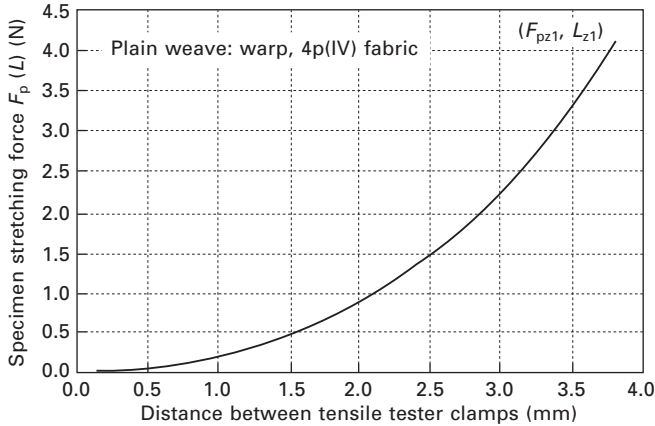
The novelty of the proposed tearing process model is the possibility of determining any relationship described by the parameters of the cotton fabric tearing zone. It concerns the forces considered in the tearing zone as well as tearing zone geometry. Below, characteristics describing the chosen phenomena in the tearing zone are presented.

Graphs are presented for the chosen plain fabric examples produced from yarn of linear density in the warp and weft directions $25 \text{ tex} \times 2$, and for the thread density per 1 dm calculated on the basis of an assumed value of fabric filling factor (for warp $E_o = 100\%$ and for weft $E_w = 90\%$).

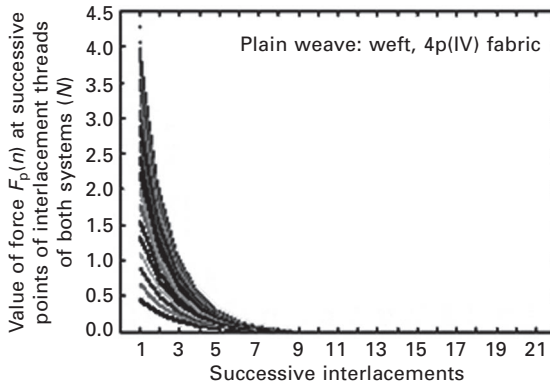
On the basis of the fabric tearing process model, it is possible to predict the specimen stretching force up to the so-called jamming point of both thread systems as a function of tensile tester clamp displacement. In Fig. 17.12, the relationship $F_p = f(L)$ is presented for the model cotton fabric of plain weave. Figure 17.12 shows the predicted value of force $F_p(L)$ for the first thread of the torn system in the displacement area of the fabric tearing zone. The point (F_{pz1}, L_{z1}) in Fig. 17.12 indicates the end of the thread displacement process and the value of the displacement force in the thread jamming point.

Below, an analysis of force values is presented for local jamming as a function of successive stretched thread interlacements with torn system threads in the tearing zone.

Figure 17.13 presents the relationship $F_p = f(n)$ for plain cotton fabric. The lines in the graph present the increase of tension force $F_p(1)$ values, where the value of force $F_p(1)$ changes from 0 to F_{pz1} . The changes of $F_p(1)$ force values can be related to the tensile tester clamp displacement in time. Point (F_{pz1}, L_{z1}) indicates the value of the thread displacement force on the stretched system thread. In order to improve the readability of the graph, the force $F_p(n)$ changes are marked by continuous lines, although they represent discrete variables.

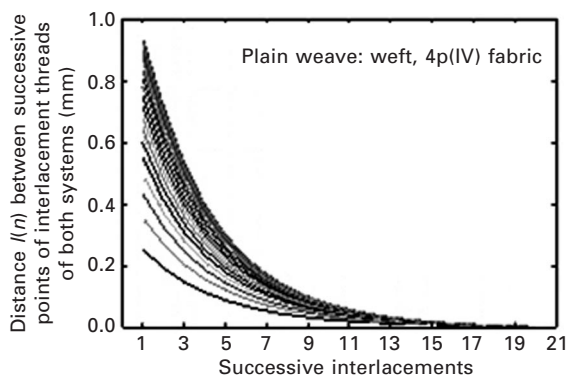


17.12 Predicted values of specimen tear force up to achievement of the jamming point of both thread systems as a function of tensile tester clamp displacement.



17.13 The relationship between values of forces of local jamming as a function of successive interlacements of stretched system thread with the torn system thread in the fabric tearing zone.

On the basis of the tearing process model it is possible to determine the distances between interlacements in the direction of torn system threads as a function of successive interlacements of both system threads in the tearing zone. Figure 17.14 presents the relationship $l = f(n)$ for plain fabric. Lines on the graphs represent the increase in distance between successive interlacements $l(1)$, where the distance $l(1)$ changes from 0 to $\sqrt{O_r^2 - (2a_e)^2}$ (jamming condition – relationship 17.12). The changes of distances $l(1)$ can be related to the change in the tensile tester clamp placement in time. On the basis of the calculated values of distances $l(n)$ the distance between the tensile tester clamps at any point in Stage 1 of the tearing process can be



17.14 Values of distances $l(n)$ between the interlacement points in the torn system thread direction as a function of successive interlacements of stretched system thread with the torn system threads in the fabric tearing zone.

directly calculated, i.e., to the thread jamming point. In order to improve the readability of the graph, the changes in distances $l(n)$ are marked by continuous lines, although they represent discrete variables.

17.6.4 Summing up

Considering all this, the following conclusions can be formulated:

1. The obtained absolute values of correlation coefficients between the theoretical (predicted based on the model) and experimental values of tear forces are similar for all the examined weaves; and for the torn system thread (warp/weft) in each weave. The absolute values of correlation coefficients r range from 0.928 (for predicted tear force values of weft threads of fabrics of broken twill 2/2 V4) to 0.964 (for predicted tear force values of warp threads of plain fabrics). These values of r confirm that there is a strong linear correlation between variables characterizing the experimental and predicted values on the basis of the model. Moreover, the proposed model is characterized by good sensitivity to the cotton fabric structure parameter changes.
2. The obtained values of determination coefficients R^2 show much differentiation depending on the fabric weave. The best fit of the model to the experimental data, with determination coefficient $R^2 = 0.93$, was observed for plain fabrics for both thread systems, whereas the worst fit of regression to the experimental data, with determination coefficient $R^2 = 0.86$, was obtained for the predicted tear force of weft threads for fabrics of broken twill 2/2 V4.
3. The analysis of the influence of the coefficient of static friction between

the threads of the torn and stretched systems and values of the wrap angle of the torn system thread and the stretched system thread showed that the decrease of the mentioned parameter values influences the improvement in tearing resistance of cotton fabrics. The analysis confirmed the accuracy of the proposed model of the fabric tearing process in terms of its sensitivity to the thread-by-thread static friction coefficient and the thread wrap angle.

4. The proposed model can be successfully applied to a description of phenomena taking place in the fabric tearing zone. On the basis of the model, it is possible to determine any relationship in the cotton fabric tearing zone between the parameters described in the model, whether for the forces considered in the tearing zone or for the geometric parameters of this zone.
5. The practical application of the tearing process model requires introducing the specific values of both system thread parameters and fabric structure parameters and appropriate coefficients into the elaborated relationships every time. It should be pointed out that experimental measurements are not necessary in order to obtain the majority of these parameters. The torn system thread number per 1 dm, the thread-by-thread static friction coefficient, the thread wrap angle, the overlap factor of the torn system thread, the coefficient of changes of tensile strength of thread removed from the fabric related to the bobbin yarn strength, and the coefficient of the peak number are all parameters which can be obtained from the design assumptions and this research. However, experimental measurements are necessary to obtain the breaking force of both system threads and the shape of both system thread cross-sections. This in turn enables the calculation of the stretched system thread strain related to the specimen shape. These measurements are both expensive and time-consuming. Therefore, it can be stated that the proposed model of the fabric tearing process for the wing-shaped specimen can find practical application in the cotton fabric design process, when considering tear resistance.

17.7 Modelling the tear force for the wing-shaped specimen using artificial neural networks

Artificial neural networks (ANNs) are more commonly used as a tool for solving complicated problems. One of the main reasons for the interest in ANNs is their simplicity and resistance to local damage and the possibility of parallel data processing accelerating the calculations. The basic disadvantage of neural network modelling is the difficulty of connecting the neural parameters with the functions they carry out, which creates difficulties with interpreting their acting principles as well as the necessity of building a

big learning set of data (Tadeusiewicz, 1993). This section discusses the possibility of multi-layered perceptron (MLP) application for predicting the cotton fabric static tear force. The aim of the research was a comparison of the ANN method of data analysis with a classic method of linear regression known as the REG method.

The application of ANN for predicting cotton fabric tearing strength can be explained in two ways. First, the increase in electronic design and control system shares in textile technologies is observed; second, and more important, is the fact (proved in previous sections) that the tearing process is very complex and depends on many factors such as warp and weft parameter, fabric structure and force distribution during the tearing process in the tearing zone as well as its geometric parameters. Obtaining these data has often been difficult for fabric designers; therefore, there are difficulties with the theoretical model of static tearing application. Taking this into account, we decided to use ANN to predict fabric tear strength, and the learning data set was built based on the simple data available in the fabric design process.

17.7.1 Neural network model structure

Choice of entry and exit data for the ANN

The building of the input data was preceded by two assumptions concerning its content. Assumption 1 is that the input data should be represented by the fabric and thread parameters. Assumption 2 is that the thread and fabric structure of the warp and weft system influence the fabric tear strength in the warp direction, and similarly the thread and fabric structure of the warp and weft system influence the fabric tear strength in the weft direction.

The input data set for ANN based on experiments was described in Section 17.5. Due to the fact that for the ANN model a large amount of tearing data is required, all the single values of warp and weft tear force were used. For the purposes of the experiment, 72 fabrics were designed and manufactured; and for each of these, 10 measurements in the weft and warp directions were carried out. In total, 720 cases of learning data for warp/weft thread systems were obtained.

As the input data for building the ANN model, the following parameters were taken into consideration: the weave index of warp ($I_{w \text{ warp}}$) and weft ($I_{w \text{ weft}}$), the mean value of the warp and weft real linear density in tex, the mean value of the warp and weft breaking force and elongation at breaking force, the mean value of warp and weft loop breaking force, the mean value of warp and weft twist, the mean value of mass per unit area, and the mean value of warp and weft thread number per 1 dm. The output data of ANN models were the warp tear force and weft tear force.

In order to determine a data set from the above-mentioned set of input data, which would guarantee obtaining the best acting network data, the rang

correlation Pearson's coefficients r between data were calculated. The choice of input set of data led to building a six-element set, which was applied for the elaboration of two neural MLP models predicting the warp and weft tear force of cotton fabric. Input and output data with their symbols are presented in Table 17.16.

The models of cotton fabric static tear strength prediction for the warp and weft directions were designated respectively ANN-warp and ANN-weft.

Preparing the learning ANN set of data

The learning ANN set of data was prepared using the scale method (Duch *et al.*, 2000). The principle of this method is the modification of data in order to obtain the values in the determined interval. In order to select the activation function for the ANN model, the network learning was carried out for the linear and logistic activation function. In order to use the logistic activation function the scaling was used to transform the data into the interval $[0, 1]$. The scaling principle (Duch *et al.*, 2000) used for input (symbol x) and output (symbol y) data is presented below:

$$z' = \frac{z - z_{\min}}{z_{\max} - z_{\min}} = z \frac{1}{z_{\max} - z_{\min}} - \frac{z_{\min}}{z_{\max} - z_{\min}} \quad 17.17$$

where

z' = the value of data after scaling (x' or y')

z = the value of data before scaling (the real value of x or y)

$z_{\max}$ = a maximum value in the whole set of data, for example max x or max y

$z_{\min}$ = a minimum value in the whole set of data, for example min x or min y

$\frac{1}{z_{\max} - z_{\min}}$ is the value of scale

$\left[-\frac{z_{\min}}{z_{\max} - z_{\min}} \right]$ is the value of displacement.

Table 17.16 Symbols for input and output data

Input data	Output data
l_w warp – index weave of warp	Warp TS – warp tear strength (N)
l_w weft – index weave of weft	Weft TS – weft tear strength (N)
Warp BF – warp breaking force (cN)	
Weft BF – weft breaking force (cN)	
Warp TN – warp thread number (tex)	
Weft TN – weft thread number (tex)	

Table 17.17 presents the values of scale and displacement for the input and output data of the ANN-warp and ANN-weft models.

The data division in the learning, validation and test sets was done according to the following principle: 50% of all data was ascribed to the learning set, i.e. 360 data; 25% of all data made up the validation set, i.e. 180 data; and 25% of all data was the test set, i.e., 180 data. The qualification of the case for the determined set was done randomly using one of the Statistica version 7: Artificial Network modules.

Determination of ANN architecture

The number of neurons in the hidden layer was assumed using the so-called 'increase method' (Tadeusiewicz, 1993). The building process was started from the smallest network architecture and gradually increased the number of hidden neurons.

In order to determine the ANN architecture of the activation function (linear or nonlinear) as well as the number of neurons in the hidden layer, the learning trials were performed under the following assumptions::

- *Assumption 1:* The type of activation function:
 - *Linear*, in which the function does not change the value. At the neuron output its value is equal to its activation level. The linear activation function is described by the relationship

$$y = \sum_{i=1}^n w_i x_i \quad 17.18$$

- *Nonlinear*, i.e., a logistic function of the relationship:

$$y = \frac{1}{1 - \exp\left(-\sum_{i=1}^n w_i x_i\right)} \quad 17.19$$

Table 17.17 Calculated values of scale and displacement for input and output data to built models ANN-warp and ANN-weft

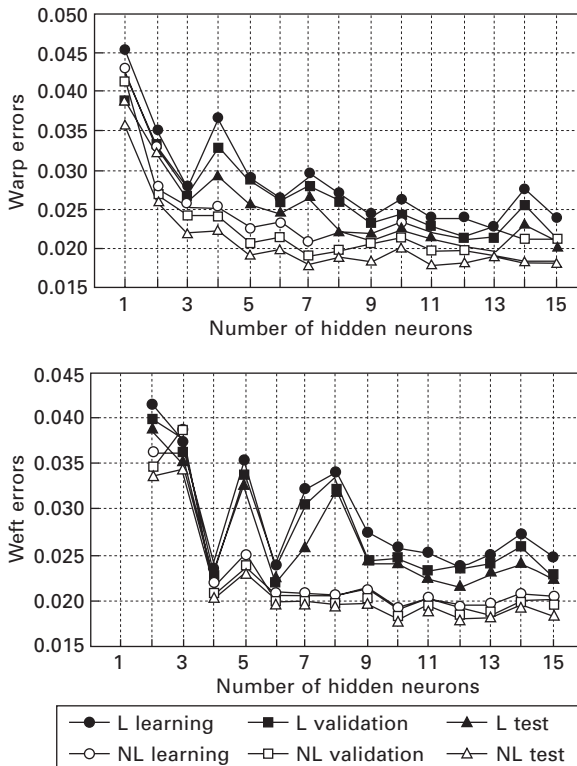
Input data/output data	ANN-warp model		ANN-weft model	
	Displacement	Scale	Displacement	Scale
l_w warp	−0.333	0.167	−0.333	0.167
l_w weft	−0.333	0.167	−0.333	0.167
Warp BF	−0.629	0.002	−0.629	0.002
Weft BF	−0.614	0.002	−0.614	0.002
Warp TN	−1.752	0.010	−1.752	0.010
Weft TN	−0.718	0.006	−0.718	0.006
Warp TS	−0.064	0.015	–	–
Weft TS	–	–	−0.060	0.015

where for equations 17.18 and 17.19 x_i is the input signal, y the output signal and w_i the weight coefficients.

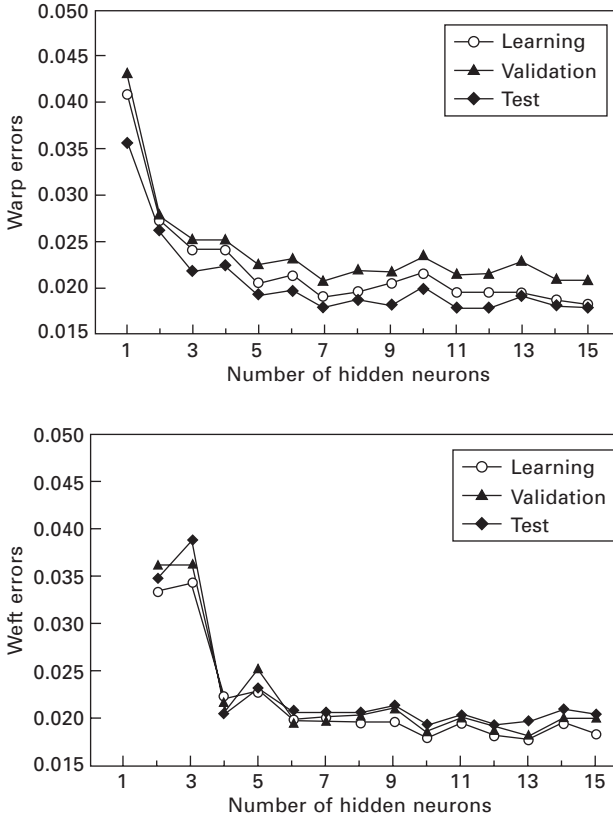
- *Assumption 2:* The number of hidden layers = 1.
- *Assumption 3:* The number of neurons in the hidden layer is from 1 to 15.

Fulfilling the above assumptions, the MLP ANN learning process was carried out. The values of error results so obtained, which, depend on the activation function and the number of neurons in the hidden layer, are presented in Figs 17.15 and 17.16. When analysing these error values, it was stated that the margin of error for the logistic activation function is lower than the margin of error for the linear activation function. Therefore, for building the regression neural cotton fabric tearing process model for the wing-shaped specimen, the logistic activation function was chosen.

For the logistic activation function (Fig. 17.16) the error values for the sets of data for learning, validation and test at the seven neurons in the hidden



17.15 ANN errors depending on activation functions for warp and weft directions: L = linear activation function; NL = nonlinear activation function.



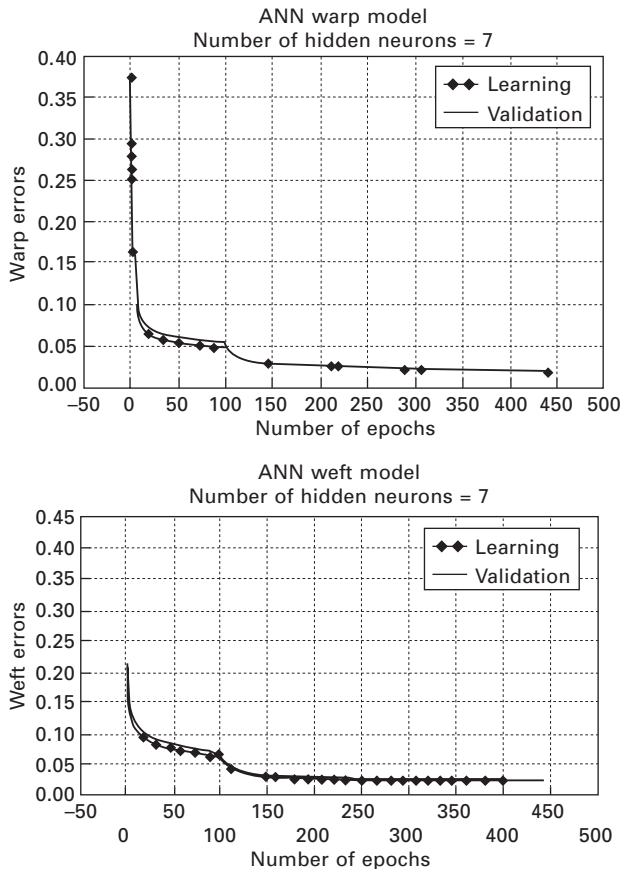
17.16 ANN errors depending on the number of neurons in the hidden layer for warp and weft directions.

layer for the warp direction and the six neurons for the weft direction started to oscillate around the given value, meaning that it was not rapidly changed. Then we can say that the error function is ‘saturated’. Adding the successive neurons to the hidden layer does not cause a significant improvement in the quality of the model, and may necessitate fitting the neural models to outstanding learning data and large network architecture. Moreover, it was noticed that from six or seven neurons in the hidden layer, the error for the validation data after achievement of the minimum starts to increase again, which is a disadvantage. This is seen especially in the warp direction. The test error for six or seven neurons in the hidden layer is low, which guarantees the ability of the network to generalize. Taking the above into account, the network architecture with seven neurons in the hidden layer was chosen.

Learning process of fabric tearing in the warp and weft directions

Neural network learning aims to determine the optimal values of the weight coefficient, i.e., those for which the error function value will be lowest. After the initial trials, the network learning was carried out in two phases. In the first one, programmed on 100 epochs of learning, the back-propagation algorithm was applied; in the second phase, programmed on 150 epochs of learning, the conjugate gradient method was applied. The learning processes for ANN models predicting the tear force in the warp and weft directions are presented in Fig. 17.17, while the obtained weight coefficients are presented in Table 17.18.

These graphs of ANN learning errors enable checking of the level of network error calculated based on the learning and validation data sets. The values of learning and validation errors decrease to the given constant value. Further learning does not improve the model quality.



17.17 Learning process for ANN-warp and ANN-weft tearing models.

Table 17.18 Weight coefficient values for ANN-warp and ANN-weft models

Input layer	Weight of network – warp system									
	Hidden layer									
	2.1	2.2	2.3	2.4	2.5	2.6	2.7	Output layer		
Threshold	-0.40814	0.52492	-2.53741	1.66084	1.86032	-3.09468	0.63198	-1.16558		
1.1	-1.92884	-0.64564	-1.12312	0.04544	-1.10020	-0.68717	2.26476			
1.2	-1.23269	-1.20870	-1.03602	-1.78514	-1.02704	-5.25045	-1.20593			
1.3	2.00949	-2.23507	-0.09056	-0.48143	1.41070	-0.09844	-1.67058			
1.4	0.28330	0.18615	0.19205	0.75037	0.59641	0.21647	-1.76453			
1.5	1.02618	-0.09025	3.00952	-1.22164	0.74492	-0.76096	-0.99326			
1.6	0.81795	0.02583	0.67726	0.34550	0.32855	2.75366	-0.00455			
								1.02147		
								-1.07465		
								-3.05884		
								1.20403		
								-0.26321		
								-1.44376		
								-1.20184		

Input layer	Weight of network – weft system									
	Hidden layer									
	2.1	2.2	2.3	2.4	2.5	2.6	2.7	Output layer		
Threshold	1.84483	-0.17391	1.806082	1.081593	-0.94840	-0.60755	-3.41827	-1.77392		
1.1	-1.08386	-0.03475	0.980825	0.974876	0.07251	-0.93191	-2.42384			
1.2	-0.59319	1.29955	1.701587	-0.834870	-1.84210	-0.44932	1.04942			
1.3	-0.38394	0.91901	3.565370	0.511086	0.77073	-1.68838	0.68099			
1.4	-0.86453	-3.56093	1.919368	0.722166	1.75811	2.43767	-2.20518			
1.5	0.94323	0.70351	0.682433	2.170601	-0.99271	0.24244	-0.65167			
1.6	-0.99460	-0.37241	-0.442268	1.265792	0.16226	1.42462	2.02350			
								-1.27350		
								-1.07005		
								0.38190		
								0.75086		
								-0.65764		
								-2.21675		
								-3.42484		

17.7.2 Neural network model of cotton fabric tearing process for the wing-shaped specimen and its verification

On the basis of the logic presented in section 17.7.1, the following ANN model predicting the cotton fabric tear force was built:

$$y = f \left[\sum_{k=0}^7 w1_k \left(f \left(\sum_{i=0}^6 w2_{ik} x_i \right) \right) \right] \quad 17.20$$

where

$w1$ and $w2$ = weights of the output and the hidden layer

y = output ANN

x_i = input ANN

i = number of the input from 1 to 6 plus so-called threshold 0

k = number of the neuron in the hidden layer from 1 to 7 plus so-called threshold 0

$f()$ = logistic activation function (equation 17.2.1):

On the basis of above considerations architecture of ANN model was presented in Fig. 17.18.

$$f(s) = \frac{1}{1 - e^{-s}} \quad 17.21$$

17.7.3 Assessment of the neural network model of static tearing of the wing-shaped fabric specimen

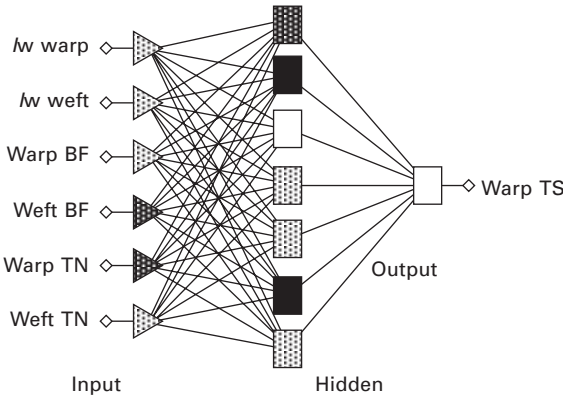
Assessment of the presented ANN models predicting the cotton fabric tear force in the warp and weft directions was carried out in two steps:

1. The quality parameters of the ANN-warp and ANN-weft models were calculated.
2. The ANN model was compared with the REG classic statistical model built using linear multiple regression.

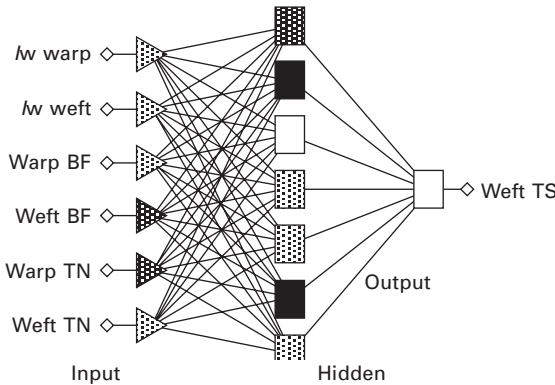
Quality coefficient of ANN models

The standard deviation ratio, i.e., the ratio of standard deviation of errors to standard deviation of independent variables (error deviation divided by a standard deviation), and the r (Pearson correlation coefficient) between the experimental and obtained data of tear forces (the latter obtained from the ANN-warp and ANN-weft models) were calculated. The obtained values of the model quality coefficients are presented in Table 17.19.

Warp: ANN architecture: Type MLP 6:7:1; Errors;
Learning = 0.018716; Validation = 0.020597; Test = 0.017762



Weft: ANN architecture: Type MLP 6:7:1; Errors;
Learning = 0.01999; Validation = 0.020398; Test = 0.020573



17.18 ANN architecture for models predicting the static tear resistance in cotton fabrics.

Table 17.19 Values of quality coefficients of ANN models

	ANN-warp			ANN-weft		
	Learning	Validation	Test	Learning	Validation	Test
Standard deviation ratio	0.096	0.100	0.105	0.099	0.110	0.101
r (Pearson)	0.995	0.995	0.995	0.995	0.994	0.995

It is worth noting that for the ANN-warp and ANN-weft models the values of the standard deviation ratio are confined to the interval (0, 0.100) or are close to it. The obtained values of standard deviation ratio confirm the following:

- The high ability of the network to approximate the unknown function. This is confirmed by the values of the standard deviation ratio for the learning data; for warp 0.096 and for weft 0.099
- The high ability of the network to describe relationships in the validation data. This is confirmed by the values of the standard deviation ratio for the validation data: for warp 0.100 and for weft 0.110
- The high capability of the network for generalization, i.e., for the proper network reaction in the cases of test data. This is confirmed by the values of the standard deviation ratio for the test data: for warp 0.105 and for weft 0.101.

The results for the correlation coefficients can be similarly analysed. For all the data sets (independent of the thread system) – learning, validation and test – the obtained values of the correlation coefficients are around 0.995 (the differences being in the third decimal place). This confirms the very good correlation between the experimental results and those obtained on the basis of the ANN-warp and ANN-weft models.

Methods of multiple linear regression

Further assessment of the obtained ANN model was carried out using multiple linear regression. Regression equations were built based on the same input data as used in the ANN models. The following model of multiple linear regression was assumed:

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 \quad 17.22$$

where

y = dependent variable, i.e., tear force of appropriate thread system: warp (Warp TS) or weft (Weft TS)

x_1 to x_6 = independent variables, i.e., for REG in the warp and weft directions: index weave of warp ($I_{w \text{ warp}}$), index weave of weft ($I_{w \text{ weft}}$), warp breaking force (Warp BF), weft breaking force (Weft BF), warp thread number (Warp TN), weft thread number (Weft TN)

b_1 to b_6 = the coefficients of multiple linear regression

a = a random component, also called the random distortion.

In regression equations 17.23 and 17.24, all the regression coefficients were taken into consideration, independently of their statistical significance (statistically insignificant coefficients are underlined). Such an approach enables the comparison of the ANN and REG models. REG models were built for 720 data as follows:

$$\begin{aligned} \text{Warp TS} = & 3.3378I_{w \text{ warp}} + 1.4722I_{w \text{ weft}} + 0.0249\text{Warp BF} \\ & + \underline{0.0026\text{Weft BF}} + \underline{0.0137\text{Warp TN}} - 0.0314\text{Weft TN} \\ & - 14.5156 \end{aligned} \quad 17.23$$

$$\begin{aligned}
 \text{Weft TS} = & 7.5829I_{w \text{ warp}} - 3.0234I_{w \text{ weft}} + 0.00468\text{Warp BF} \\
 & + 0.01705\text{Weft BF} + \underline{0.01588\text{Warp TN}} \\
 & - 0.05336\text{Weft TN} - \underline{6.4021}
 \end{aligned}
 \quad 17.24$$

The predicted values of tear forces Warp TS and Weft TS were compared with the experimental ones. The values of linear correlation and determination coefficients were calculated. The obtained values of coefficients r_{720} and R_{720}^2 for the REG-warp and REG-weft models are presented in Table 17.20.

Analysing the values of coefficients of linear correlation r_{720} and determination R_{720}^2 , it is worth noting that the values are similar for the REG-warp as well as the REG-weft models. However, the obtained values of the correlation coefficient are lower than for the ANN-warp and ANN-weft models. The REG-warp and REG-weft models confirm good correlation between the experimental and predicted values of the tear forces. Nevertheless, an analysis of the charts presented in Fig. 17.19 shows clear differences in the absolute values of experimental and predicted tear force. This is confirmed by the obtained values of the determination coefficients R_{720}^2 .

17.7.4 Summing up

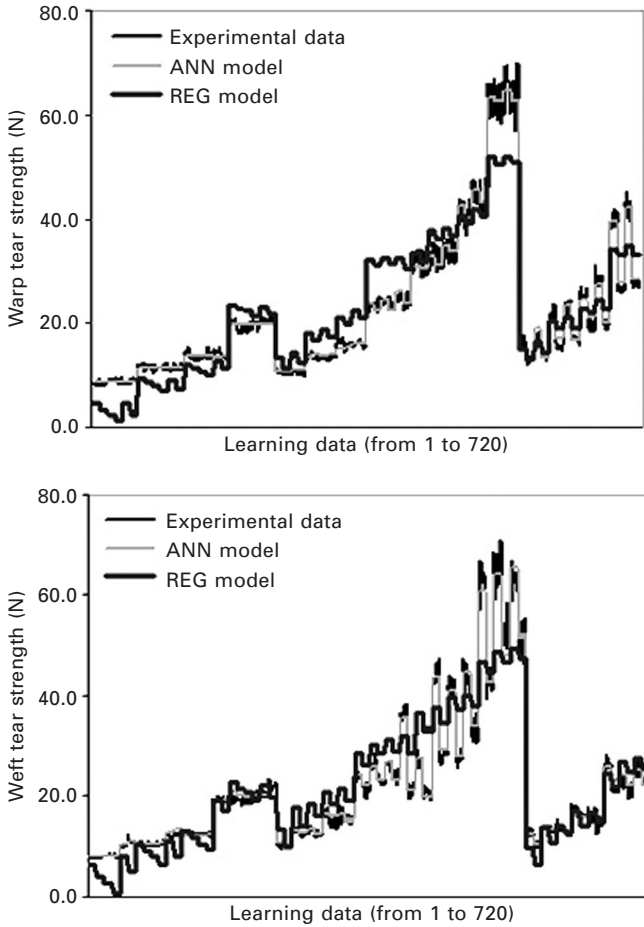
Section 17.7 has described the application of ANN models for predicting the cotton fabric tear strength for the wing-shaped specimen. The following conclusions can be drawn:

1. As a result of some considerations, the structure of a one-directional multilayer perceptron neural network was built. In this network the signal is transferred only in one direction: from the input through the successive neurons of the hidden layer to the output. Two neural models were elaborated for the wing-shaped specimen:
 - ANN-warp predicting the tear force in the warp direction
 - ANN-weft predicting the tear force in the weft direction.

As an output of the ANN-warp and ANN-weft tearing models, such simple data as the cotton yarn and fabric parameters were used. The best results forecasting the tear force in the warp and weft directions were obtained for ANN models built from six neurons in the input layer, seven

Table 17.20 Set of absolute values of correlation and determination coefficients calculated for REG-warp and REG-weft models predicting the cotton fabric tear strength

REG-warp		REG-weft	
r_{720}	R_{720}^2	r_{720}	R_{720}^2
0.924	0.854	0.920	0.847



17.19 Prediction of the static tear strength for the warp and weft depending on the applied model.

neurons in the hidden layer (logistic activation function) and one neuron in the output layer (logistic activation function). Network learning was carried out in two phases: in the first, one back-propagation algorithm was used; whereas in the second, the conjugate gradient method was used.

2. The ANN-warp and ANN-weft models were assessed in two stages:
 - 2.1 Coefficients of tearing ANN model parameters were calculated, i.e., a standard deviation ratio and a correlation coefficient. The obtained values of the standard deviation ratio for the learning, validation and test sets of data were confined to the interval $[0, 0.100]$ or close to it, which confirms:

- the high ability of the network to approximate an unknown function
- the high capability of the network for generalization.

The obtained values of the correlation coefficient between the experimental values and those predicted on the basis of the ANN-warp and ANN-weft model tear forces are around 0.99, which confirms their correlation.

- 2.2 Tear forces from the ANN-warp and ANN-weft models were compared with the classic regression REG-warp and REG-weft models built using the same data. The obtained values of correlation coefficients at 0.92 and determination coefficients at 0.85 confirm good correlation between the experimental and theoretical (on the basis of the REG-warp and REG-weft models) data. Nevertheless, the clear differences between the absolute values of predicted and experimental tear force results showed that REG models are less efficient for forecasting fabric tear strength.

17.8 Conclusions

This chapter presents the problem of forecasting the cotton fabric tearing strength for a wing-shaped specimen. Fulfilling the aims of the chapter required the manufacture of model cotton fabrics of assumed structural parameters and experiments carried out according to a plan.

The theoretical model of the cotton fabric tearing process for the wing-shaped specimen was elaborated based on force distribution in the tearing zone, the geometric parameters of this zone and the structural yarn and fabric parameters.

The need for such a model elaboration is proved by review of the literature as well as the significance of tear strength measurements in the complex assessment of the properties of fabrics destined for different applications. The proposed model enables the description of phenomena taking place in the fabric tearing zone, and the determination of any relationships between the defined and the described model parameters. Moreover, the theoretical model can be used in practice during fabric design, when considering the tearing strength. The initial input data for the model are the parameters and coefficients of the yarn and fabric structure, which are available at the time of the design process, whereas experimental determination of the remaining model parameters is possible using methods commonly used in metrological laboratories.

On the basis of experiment, it was stated that the proposed theoretical model of the fabric tearing process enables prediction of the tear force of cotton fabrics, which is confirmed by the absolute values of linear correlation and determination coefficients between the predicted and experimental values

of tear forces. The absolute values of the correlation coefficients are similar for all the fabric structures mentioned and range from 0.930 for the predicted tear forces of weft threads for fabrics of broken twill 2/2 V4 to 0.960 for the predicted tear forces of warp threads for plain fabrics. The values of the correlation coefficients confirm that there is a strong linear correlation between the variables characterizing the mean experimental and predicted tear forces; and the proposed model of the tearing process is sensitive to structural cotton fabric parameter changes. The values of the determination coefficient show that the variability depends on the fabric weave. The best fit of regression to the experimental data on the level of $R^2 = 0.930$ was observed for plain fabrics for both torn thread systems; whereas the worst fit of regression to the experimental data on the level of $R^2 = 0.860$ was obtained in the case of predicted values of the tear force for weft threads for broken twill fabrics 2/2 V4.

The analysis also confirmed the accuracy of the proposed model in its sensitivity to the changes resulting from the relationships between the threads of both systems of the torn sample, i.e., the static friction coefficient between the torn thread and a thread of the stretched system, and the values of the wrapping angle of the torn system thread and the stretched system thread.

The neural network model of the cotton fabric tearing process of MLP type was also elaborated, taking into account the relationships between yarn and fabric structural parameters and fabric tear strength. This model coincides with the actual trends to use electronic systems of design and control in fabric manufacturing technologies. On the basis of experiments it was stated that the elaborated ANN model of the cotton fabric tearing process for the wing-shaped specimen is a good tool for predicting fabric tearing strength. The calculated values of the standard deviation ratio for the learning, validation and test data introduced into ANN fall in the interval (0, 0.100) or close to it, which confirms very good abilities of ANN-warp and ANN-weft models to approximate an unknown function or for generalization of knowledge. The obtained values of the correlation coefficient between the predicted and experimental data at the 0.990 level confirm a very good correlation between the above-mentioned force values. The ANN-warp and ANN-weft models were compared with the classic regression models REG-warp and REG-weft, built based on the same input data. The values of the correlation coefficient r and the coefficient of determination R^2 between the predicted and experimental values of tear forces of $r = 0.920$ and $R^2 = 0.805$ confirm a good correlation between them. Nevertheless, the statistically significant differences between the absolute values of experimental and predicted tear forces indicate that REG models are less efficient for predicting cotton fabric tear strength than ANN models.

17.9 Acknowledgements

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Textile quality evaluation by image processing and soft computing techniques

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Abstract: Textile faults have traditionally been detected by human visual inspection. Textile quality evaluation by soft computing techniques has infused fresh vitality into the conventional textile industry using advanced technologies of computer vision, image processing and artificial intelligence. Computer-vision-based automatic fibre grading, yarn quality evaluation and fabric and garment defect detection have become one of the hotspots of applying modern intelligence technology to the monitoring and control of product quality in textile industries. This chapter describes the methods of textile defect detection, quality control, grading and classification of textile materials on the basis of image processing and modern intelligence technology operations.

Key words: fibre grading, yarn quality, fabric and garment defects detection, image processing, real-time inspection.

18.1 Introduction

At the present time, industries such as the textile industry are in constant need of modernization. Thus, their presence in the high technology area of high performance computing (HPC) based inspection is of strategic interest. Quality control is an indispensable component of modern manufacturing, and the textile industry is no different from any other industry in this respect. Textile manufacturers have to monitor the quality of their products in order to maintain the high-quality standards established for the clothing industry (Anagnostopoulos *et al.*, 2001). Thus, textile quality control is a key factor for the increase of competitiveness of their companies. Textile faults have traditionally been detected by human visual inspection. However, human inspection is time consuming and does not achieve a high level of accuracy. Therefore, industrial vision units are of strategic interest for the textile industry as they could form the basis of a system achieving a high degree of accuracy on textile inspection. The development of automated visual inspection systems has been a response to the shortcomings exhibited by human inspectors. Advanced technologies of computer vision and artificial intelligence have infused fresh vitality into the conventional textile industry. Computer-vision-based automatic fabric defect detection has become one of

the hotspots and also represents a difficulty in the research area of applying modern intelligence technology to the monitoring and control of product quality during the last two decades. However, the great majority of textile mills still employ the traditional manual way of fabric inspection, which suffers from a low inspection speed, being incapable of real-time inspection, high labour cost, high labour intensity, high missing rate of defect detection, etc.

This chapter describes the systems that are useful for regular textile defect detection and quality control of fibre, yarn, fabric and garment on the basis of simple image-processing operations. The prerequisites of the overall systems are briefly discussed, as well as the limitations and the restrictions imposed due to the nature of the problem. The software algorithm and the evaluation of the first results are also presented in detail.

This chapter is organized as follows. Section 18.2 describes the principles of the image processing technique. Section 18.3 illustrates the configuration of the system employed in fibre quality evaluation and foreign contaminant detection. Section 18.4 gives a detailed description of yarn fault detection. Section 18.5 discusses automatic fabric defect detection. Section 18.6 discusses the computer simulation aids for the intelligent manufacture of quality clothing and method of classifying garment defects. The chapter concludes with Section 18.7 which describes directions for future trends.

18.2 Principles of image processing technique

The digital image is a two-dimensional array of numbers whose values represent the intensity of light in a particular small area. Each small area to which a number is assigned is called a pixel, which is the smallest logical unit of visual information that can be used to build an image. The size of the physical area represented by a pixel is called the spatial resolution of the pixel. Resolution is the smallest resolvable feature of an object. It is a measurement of the imaging system's ability to reproduce object detail. This is often expressed in terms of line pairs per millimetre (lp/mm). The resolution varies greatly, from a few nanometres in a microscope image to hundreds of kilometres in satellite images. Each pixel has its value, plus an x coordinate and a y coordinate, which give its location in the image array. Normally, it is assumed that images are rectangular arrays, that is, there are R rows and C columns in the image. The minimum value of a pixel can be typically 0, and the maximum depends on how the number is stored in the computer. One way is to store each pixel as a single bit, i.e. it can take only the values 0 and 1, i.e. black or white.

Image-processing supports four basic types of image, as described in the following. An indexed image consists of a data matrix, X , and a colourmap matrix, map . Each row of map specifies the red, green, and blue components of a single colour. An indexed image uses direct mapping of pixel values to

colourmap values. An intensity image is a data matrix whose values represent intensities within some range. The elements in the intensity matrix represent various intensities, or grey levels, where intensity 0 usually represents black and intensity 255 full intensity, or white.

In a binary image, each pixel assumes one of only two discrete values. Essentially, these two values correspond to on and off. A binary image is stored as a two-dimensional matrix. It can be considered a special kind of intensity image, containing only black and white. Other interpretations are also possible, and one can think of a binary image as an indexed image with only two colours.

An RGB image, sometimes referred to as a true colour image, is stored as an m -by- n -by- i data array that defines red, green, and blue colour components for each individual pixel.

Digital image processing involves the computer processing of the picture or images that have been converted to numerical form. The principal aim of digital image processing is to enhance the quality of images, i.e. to improve the pictorial information in the image for clear human interpretation and to process acquired data for autonomous machine perception. The elements of a general-purpose system are capable of performing the image-processing operations.

Two elements are required to acquire digital images. The first is a physical device that is sensitive to a band in the electromagnetic energy spectrum, such as visible light, ultraviolet radiation, infrared radiation or X-ray bands, and this produces an electrical signal output proportional to the level of energy sensed. The second element, called a digitizer, is a device for converting the electrical output of the physical sensing device into digital form. Image acquisition transforms the visual image of a physical object and its intrinsic characteristics into a set of digitized data, which can be used by the processing unit of a computer system. The image-acquisition functions are in three phases: illumination, image formation, and image detecting or image sensing.

Illumination is a key parameter affecting the input to a computer vision system, since it directly affects the quality of the input data and may require as much as 30% of the application effort. Many types of visible lamp are used in the industrial environment, including incandescent, fluorescent, mercury-vapour, sodium-vapour, etc. Fluorescent lamps provide a highly diffuse, cool, white source of light. Halogen lamps furnish a high-intensity light source that has a broad spectrum. Halogen light sources may provide a fibre-optic cable that directs light to specific points for front and back lighting. Fibre-optic lamps can shape light into slits, rings and other forms. Light-emitting diodes, or LEDs, supply monochromatic light that one can pulse or strobe. Xemm lamps, or flash lamps, provide high-intensity sources that find use primarily when one has momentarily to stop a moving part or

assembly. However, the use of illumination outside the visible spectrum, such as X-rays, ultraviolet radiation and infrared radiation, is increasing owing to the need to achieve special inspections not possible with visible light.

The surfaces on any product have optical properties that fall into one of three general reflectance categories: specular, diffuse or directional. The individual components in the product often incorporate several surface types, so one should understand how light interacts with them. Lighting techniques play an important role in illuminating the products, particularly when inspection is to be carried out. For most applications, inspection systems rely on front, back, dark-field, and light-field illumination techniques. Some inspection systems may use a combination of two or more techniques.

Image-sensing involves the most basic knowledge of images. It is the science of automatically understanding, predicting and creating images from the perspective of image sources. Image-source characteristics include illuminant spectral properties, object geometric properties, object reflectance and surface characteristics, as well as numerous other factors, such as ambient lighting conditions. The essential technologies of the science include image component modelling, image creation and data visualization.

Image processing can be used for the following functional operations to achieve the basic objectives of the operation. The uses include removing a blur from an image, smoothing out the graininess, speckle or noise in an image, improving the contrast or other visual properties of an image prior to displaying it, segmenting an image into regions such as object and background, magnifying, reducing or rotating an image, removing distortions (optical error in the lens) from an image, and coding the image, in some efficient way for storage or transmission. The main objective of image enhancement is to process a given image so that the resulting image is of better quality than the original image for a specific application. Images may be enhanced through two methods: the frequency-domain method and the spatial-domain method.

Modifying the Fourier transform of an image is used to enhance an image by the frequency-domain method, and the spatial-domain method involves the direct manipulation of the pixels in an image. Image improvisation or image enhancement operations are conducted to correct some of the defects in acquired images that may be present because of imperfect detectors, inadequate or non-uniform illumination, or an undesirable viewpoint. It is important to emphasize that these are the corrections that are applied after the image has been digitized and stored and will therefore be unable to deliver the highest-quality result that could have been achieved by optimizing the acquisition process in the first place. Image-measurement extraction involves the extraction of data from images. It usually means identifying individual objects on the images. It is done by either edge detection or corner detection. Edge-enhancement filters are used in edge detection. Edge-enhancement filters

are a form of high-pass filters and work on the principle that is opposite to that of low-pass filters. They are used to enhance or boost edges. Edge detection is also used for detecting meaningful discontinuities in grey level.

There are several examples of operators, such as gradient operators, Laplacian operators, Marr operators, etc. During the image-processing operation, the data obtained in the digital form and required to be processed are very considerable and therefore need to be reduced. This is done by using a different kind of transformation such as fast Fourier transform (FFT), discrete Fourier transform (DFT), discrete cosine transform (DCT), Karhunen–Loeve transform (KLT), Walsh–Hadamard transform (WHT), wavelet transform (WT), etc. It may be noted that, apart from the use of transformation techniques to reduce data, there are also techniques to extract specific features discussed earlier, such as contrast and angular second moment, from the image. This is done by using co-occurrence based methods. Transform-coding systems based on the Karhunen–Loeve (KLT), discrete Fourier (DFT), discrete cosine (DCT), Walsh–Hadamard (WHT) and various other transforms can be used to map the image into a set of transform coefficients. The choice of a particular transform in a given application depends on the amount of reconstruction error that can be tolerated and the computational resources available. Compression is achieved during the quantization of the transformed coefficients (and not during the transformation step).

The images are normally obtained by dividing the original image into sub-images of size 8×8 , each sub-image being represented by its DFT, WHT or DCT, and by truncating 50–90% of the resulting coefficients and taking the inverse transform of the truncated coefficient arrays. In each case, the rational coefficients are selected on the basis of the maximum magnitude. In all cases, the discarded coefficients have little visual impact on the quality of the reconstructed image. Their elimination, however, used to be accompanied by some mean-square error. It has been proved that the information-packing ability of the DCT is superior to that of the DFT and WHT. Although this condition usually holds for most natural images, the KLT, not the DCT, is the optimal transform in an information-packing sense, that is, the KLT minimizes the mean-square error for any number of retained coefficients. However, because the KLT is data-dependent, obtaining the KLT-basis images for each sub-image is, in general, a non-trivial computational task. For this reason, the KLT is seldom used in practice. Instead, a transform such as the DCT whose basic images are fixed (input independent) is normally selected; of the possible input-independent transforms, the non-sinusoidal transforms (such as the WHT or Haar transform) are the simplest to implement. The sinusoidal transforms (such as the DFT or DCT) more closely approximate to the information-packing ability of the optimal KLT.

18.3 Fibre classification and grading

In the textile industry, different types of foreign contaminant may be mixed in fibres such as cotton and wool that need to be sorted out to ensure the quality of the final textile products. A framework and working principle of detecting and eliminating isomerism fibre in a cotton system online is introduced. Various techniques have been employed to implement automatic inspection and removal of foreign contaminant in lint; these include ultrasonic-based inspection, sensor-based inspection, machine-vision-based inspection, etc. In recent years, machine-vision systems have been applied in the textile industries (Tantaswadi *et al.*, 1999; Millman *et al.*, 2001; Abouelela *et al.*, 2005) for inspection and/or removal of foreign matter in cotton (Lieberman *et al.*, 1998), wool (Su *et al.*, 2006) or composites (Chiu *et al.*, 1999; Chiu and Liaw, 2005).

18.3.1 Cotton fibres

The automated visual inspection (AVI) system is a popular tool at present for real-time foreign contaminant detection in bulk fibre. Image processing is one of the key techniques in the AVI system. In technological methods of cleaning and rippling the cotton, cotton is loosened sufficiently and impurities are removed. The images from a linear CCD camera are sent to the industry control computer through a high-speed frame grabber equipped with a digital card and operated by the computer. The HSI (hue, saturation, intensity) colour model, the threshold method and a binarization algorithm are used to distinguish cotton from isomerism fibre. After pre-processing, the images are segmented to make the foreign fibres stand out from the lint background according to the differences of image features. The positions of foreign matter in the processed image are identified and transmitted to the sorting equipment to control the solenoid valves, which switch the high-pressure compressed air on to blow the foreign matter off the lint layer to the trash box.

Through a series of experiments and local debug analyses, a sample machine system has been developed. Through testing it can satisfy the needs of control and exactly distinguish the cotton and isomerism fibre in real time and eliminate the foreign matter. In this system, the ginned lint is transferred to an opening machine to generate a uniform thin layer which will be inspected by an AVI system. A report about the content of foreign contaminant in the sample is issued after the visual inspection, the cotton corresponding to this sample is classified to a certain level, and finally a price is determined according to the given level.

The execution speed of an image segmentation algorithm is one of the key factors limiting the inspection speed of an on-line automated visual inspection

system. Histogram analysis indicates that the optimal threshold must be in the range of 150–230, because the maximal grey value of the objects is less than 230 in general and the minimal grey value of the background must be larger than 150 (Yang *et al.*, 2009). Therefore, the range for searching the optimal threshold can be reduced from 0–255 to 150–230, and then the speed of calculation in this stage is more than doubled. Of course, this searching range is really an empirical one which should be adjusted when the experimental environment changes.

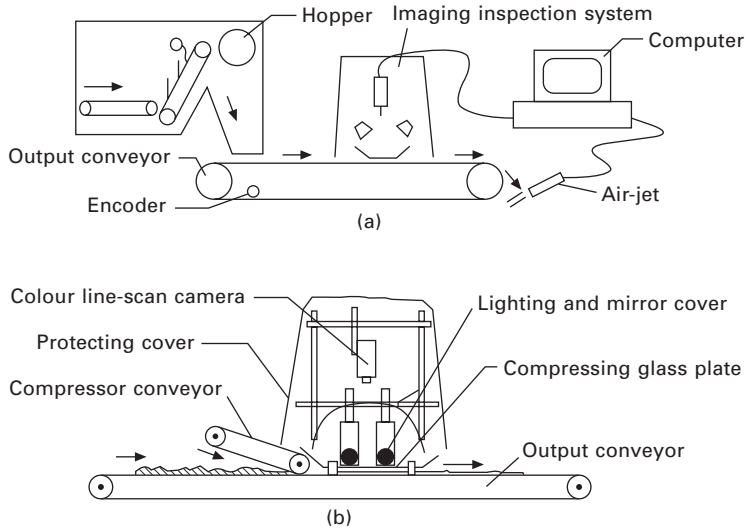
18.3.2 Wool fibres

The physical properties of wool are quite different from those of cotton. When implementing a machine vision system to detect and remove contaminants in wool, three problems must be solved:

- Wool fibres are not monochromatic. The colours of pure wool vary from white, light grey through light yellow to light fawn. The contaminants in wool include colours of white, grey, yellow, fawn, red, blue and so on. It is very difficult to distinguish them when the background wool and the contaminants are of a close colour or the same colour, such as white contaminants mixed with white wool.
- Wool fibres are longer than cotton fibres and are usually entangled together forming lumps and tufts in the scouring line. Under illumination, these lumps or tufts form shadows, which are very difficult to eliminate by a mechanical system or image-processing techniques.
- Most of the existing vision systems in the textile industry only inspect and grade the products without a sorting function. The main reason is the difficulty in using the live image data for real-time control, especially when the speed of the moving samples is unstable in practice.

The machine vision system for automated removal of contaminants consists of six parts, as shown in Fig. 18.1, where the modified hopper machine opens the scoured wool and delivers the small wool tufts as a thin and uniform layer on the output conveyor. By using the opening process, the contaminants buried inside the wool are brought to the wool surface to be 'seen', and the shadows of the wool become small and easy to eliminate by a compressor force (Zhang *et al.*, 2005; Su *et al.*, 2006).

In on-line detection of contaminants in scoured wool, the colour image should be split into red, green and blue grey-scale images. Because the distribution of pixel values of the background wool with shadows in the histogram obeys the normal distribution rule, the deep colour contaminants can be separated by an auto-threshold method. To detect the contaminants, instead of the edge-detection method that is too slow and too difficult to use for the machine vision system above, a local adaptive threshold method is



18.1 (a) Outline of the machine vision system; (b) the image acquisition system (Su *et al.*, 2006).

proposed and used for the detection of contaminants. The algorithm includes four steps:

1. Split the image into blocks of 16×8 pixels.
2. Calculate the standard deviation and mean values of the pixels in each block.
3. Calculate the difference of the standard deviations and the means.
4. If the difference is larger than the given threshold, there is a contaminant in the block.

The threshold is derived from tests and depends on the accuracy and speed of the inspection, which can be adjustable in practice. Finally, after filtering out the image noise, the red, green and blue images combine together, and then the system software makes a decision on where the sorting system should be actuated to remove the contaminants. The main steps of the algorithm for making the decision to remove a contaminant are as follows:

1. Scan the binary image to find and record the size of all the non-zero objects. If the object size is smaller than the given threshold value, take it as the image noise and remove it.
2. For a large object, its blowing section is the place where its central coordinate is located.
3. Divide the whole image into eight sections (because eight air-jets are used for removal of the contaminants).

If the sum of the pixel values of all the objects in a section is larger than the given threshold value, the solenoid valve in the section should be actuated, because the edges of the contaminants concentrate in that section. Here, the two threshold values control the inspection quality, which must be flexible and adjustable because the types of wool, opening degree and required quality and productivity of the inspection may change case-by-case in practice.

Two factors are considered to affect the detection accuracy of the system:

- The camera can only detect contaminants on the wool surface and its ability to distinguish light-coloured and white contaminants from white wool is limited.
- The developed mechanical system cannot fully open the entangled wool and distribute it as a thin and uniform layer on the conveyor surface. Thus, when the contaminants are mixed with wool, the buried contaminants cannot be 'seen'. Reducing the thickness of the wool layer may bring some of the buried contaminants to the wool surface and improve the accuracy of detection, but it will also decrease the productivity of the machine vision system and the wool scouring line.

18.3.3 Fibre classification by cross-section

The cross-section of the fibres is one of the most important parameters in identifying different types of fibres in a product when its quality is being controlled. Berlin *et al.* (1981), Hebert *et al.* (1979), Thibodeaux and Evans (1986), Xu *et al.* (1993), Schneider and Retting (1999), Semnani *et al.* (2009) and many other researchers have worked on identifying and measuring different characteristics of fibre cross-sections. There are different approaches to analysing the cross-section of fibres. Cross-sectional shapes are characterized with the aid of geometric and Fourier descriptors. Geometric descriptors measure attributes such as area, roundness and ellipticity. Fourier descriptors are derived from the Fourier series for the cumulative angular function of the cross-sectional boundary and are used to characterize shape complexity and other geometric attributes. Moreover, image-processing-based methods have been used for identifying different types of fibres in cross-section. To recognize fibres, some of their shape features are measured and variations in these features for different types of fibres result in their identification.

The most recent method uses images of the cross-section of a textured yarn acquired by a CCD camera embedded in a compound microscope. The images are in RGB format, which must be converted to grey-scale. After conversion of the images, a sobel filter is used to recognize the edges of objects in the image. In the second stage of the process, the images are converted to binary format and then reversed for easier detection of the cross-section of

each fibre. The reversed image is used to evaluate the cross-section of the fibres and measure their physical properties. Every fibre is separated from the others and its properties are measured. The method of separation uses a labelling procedure for the binary objects in the image. After separation, the different parameters of the fibres are measured by the MatLab image processing toolbox. These parameters are surface area, perimeter, equivalent diameter, large diameter, small diameter, convexity, stiffness, eccentricity and hydraulic diameter.

18.3.4 Fibre classification by length

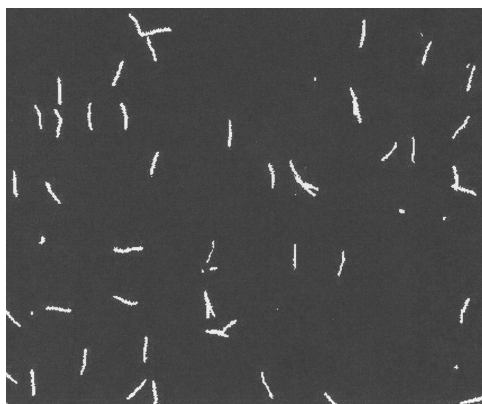
Another parameter that is important in fibre quality control is the length of fibres. The advanced fibre information system (AFIS) is a commonly used system in the industry for length measurements. AFIS individualizes fibres mechanically and transports single fibres aerodynamically through an optical sensor that produces signals when the fibre blocks the light path. The duration of the signal pulse reflects the length of the fibre. However, the curvature of the fibre in the airstream can cause an underestimation of fibre length, and substantial fibre breakage in the high-speed opening roll of AFIS can skew the data. Recently, various imaging systems have been adapted for fibre length measurements. Although they have all demonstrated effectiveness in making accurate length measurements, these methods require manual preparation to individualize fibres so that folding and entangling of fibres can be avoided. The manual selection of test fibres not only incurs bias in the data, but also makes the imaging systems unsuitable for high-volume measurements. A new method for measuring the fibre length measures the length of the fibre spread on a black background from its image which was scanned using a regular scanner.

In a binary image, boundary pixels of a fibre are those having three or fewer neighbouring pixels. The image is scanned pixel by pixel to search for white pixels (fibres) and to determine if they were boundary pixels, and then the locations of all boundary pixels are registered. Whether or not a boundary pixel is removed from the image depends upon its connection situation with its neighbours; for example, if the pixel is the only one connecting its neighbours, it is not removed because this pixel is one of the skeleton pixels being sought. The connection checking thus prevents skeletons from being broken. This process is repeated until no more removable boundary pixels are found. In addition, because the skeleton is extremely sensitive to noise contained in the image, small isolated dots are deleted, and small holes in fibres are filled before skeletonization. A sample of the result is presented in Fig. 18.2.

A snippet pixel (white) is randomly selected as a reference pixel, and white pixels in its 3×3 neighbourhood are searched in a clockwise direction.



(a)



(b)



(c)

18.2 (a) Scanned snippet image; (b) thresholding snippet image; (c) thinning snippet image.

These pixels are either on two diagonals (numbered 1–3–5–7), or on four sides (numbered 0–2–4–6). The reference pixel is shifted to its neighbouring white pixels in the numbering order, and the neighbours are searched at each new reference pixel. Note that before the reference pixel is moved to a new location, it is marked as black to avoid it being sought again. The side pixels correspond to a one-pixel shift, while the diagonal pixels correspond to a 1.41-pixel shift. The same procedure continues until no connected white pixels are detected. The traced white pixels represent one isolated snippet if the total traced length is around the snippet cutting length, l_0 (1.5 to 2.5 mm). If multiple fibre snippets intercept each other, the number of the traced snippets could be determined by dividing the total traced length by l_0 .

At the i th cut, the distance to the baseline L_i equals $i \times l_0$ ($1 \leq i \leq m$). Let n_{i-1} and n_i be the snippet counts in the $(i-1)$ th and i th cuts, respectively. As there may be fibres that end in the $(i-1)$ th cut, n_{i-1} is normally larger than n_i . The number (N_i) of fibres with length L_i is the difference between these two counts, that is, $N_i = n_{i-1} - n_i$ ($1 \leq i \leq m$). N_i is also the fibre frequency at length L_i in the fibre length distribution. From these number–length data, the maximum length, mean length, length uniformity (variation) and other fibre statistics could be computed.

18.4 Yarn quality evaluation

Attempts have been made to replace the direct observation method of ASTM with computer vision to resolve the limitation of human vision in yarn quality evaluation. In most of these methods, the image of a single yarn is considered to specify the fault features of the yarn (Semnani *et al.*, 2005a,b,c,d, 2006). In the method developed by Cybulska (1999), the edge of the yarn body is estimated from the image of a thread of yarn and the thickness and hairiness of the sample yarn are measured. Other studies are based on the classification of events along a thread of yarn and measuring the percentage of the different classes of events (Nevel *et al.*, 1996a, 1996b; Strack, 1998) or nep detection along the yarn (Fredrych and Matusiak, 2002). In all the above methods, although it is possible to define a classification for yarn appearance based on unevenness, classification of faults and grading of yarn samples based on standard images is found to be impossible.

18.4.1 Yarn hairiness

Single-yarn analysis methods have focused on yarn hairiness measurement. Length of hairs can only be measured by scanning the yarn under a microscope and obtaining a trace of hairs. Yarn images are captured under transmitted light shining from the back of the yarn and reflected or incident light. The yarn images taken in reflected light contain many regions where

light is reflected from the fibres. This is seen in the image as a white patch and cannot be identified as a fibre by image analysis. The images taken in transmitted light shows the fibres as dark lines surrounded by lighter regions where the light is shining through. These images are easier to analyse and are used for further analysis. In order to analyse a yarn image and obtain the true length of hairs, it is necessary to capture an image of the correct magnification and high enough resolution (Guha *et al.*, 2010). In capturing the image of a moving yarn, the yarn axis does not remain in the constant position or parallel orientation in every image.

The captured image is usually in colour mode and has to be converted to grey-scale mode. Luminance represents grey-scale mode, while hue and saturation represent chrominance. The contrast of the grey-scale image is enhanced by the contrast enhancer functions, and then smoothed with multi-dimensional filtering techniques. After pre-processing, determination of the region that can be considered the body of the yarn is important, since this region will not be considered while extracting information about hair length from the image.

The task is easier if it is known that the yarn axis is horizontal. The binary image can be scanned row-wise or column-wise. The rows or columns have a pixel value more than a certain percentage of the image width or length. The pixels of rows or columns form a rectangle which can be removed from the image. When the yarn core is supposedly full of pixels, the yarn core selected is too narrow. In this case, the edges of the yarn core are counted as hairs and a high value for hairiness is measured. The ovals in the image show the regions where the yarn core has been clearly left behind even after removal of the rectangular region. Supposing the yarn core to be partially full of pixels leads to some faulty regions of the yarn such as neps, slubs or tightened fibres being estimated as yarn core.

Often, finding the yarn core is a trial-and-error method. The preceding discussion assumes that the axis of the yarn is horizontal or vertical. The yarn transporting device will indeed be designed to ensure that the yarn axis is nearly straight in the images, while some vibration is unavoidable in actual situations. This may lead to rotation of the yarn position by unpredictable angles. Rotation of the image by an angle that makes the yarn axis horizontal is done in the following manner. The binary image is rotated in small angular steps. The width of the yarn core in all these rotated images is measured. The image with the maximum yarn core width indicates the rotation necessary to get a horizontal yarn axis. The corresponding enhanced grey-scale image and binary image are used for further analysis. Rotation causes additional black edges to appear in the images. Other improved methods are based on using transformation methods such as Hugh or Radon transformation. These transformations indicate the true angle of the rotated image by maximum peaks in the intensity histogram of the power spectrum of the transformed image.

Identification of the edge of every hair is a crucial step in measuring the length of hairs. The edge of a fibre can be identified by looking for places in the image where the intensity changes from a pixel value to the opposite pixel value. The most common methods detect whether the derivative of the intensity is larger in magnitude than a threshold and whether derivative of the intensity is zero. Canny (1986) defined an objective function which needs to be optimized in order to get the 'optimal' edge detector. This was designed to maximize the signal-to-noise ratio, achieve good localization and minimize the number of responses to a single edge. Canny's method was applied on both binary images and enhanced rotated grey-scale images. It computes the threshold and standard deviation of the Gaussian filter automatically. Better results than these can be obtained by borrowing the threshold value from Otsu's (1979) method and choosing the standard deviation of the Gaussian filter manually.

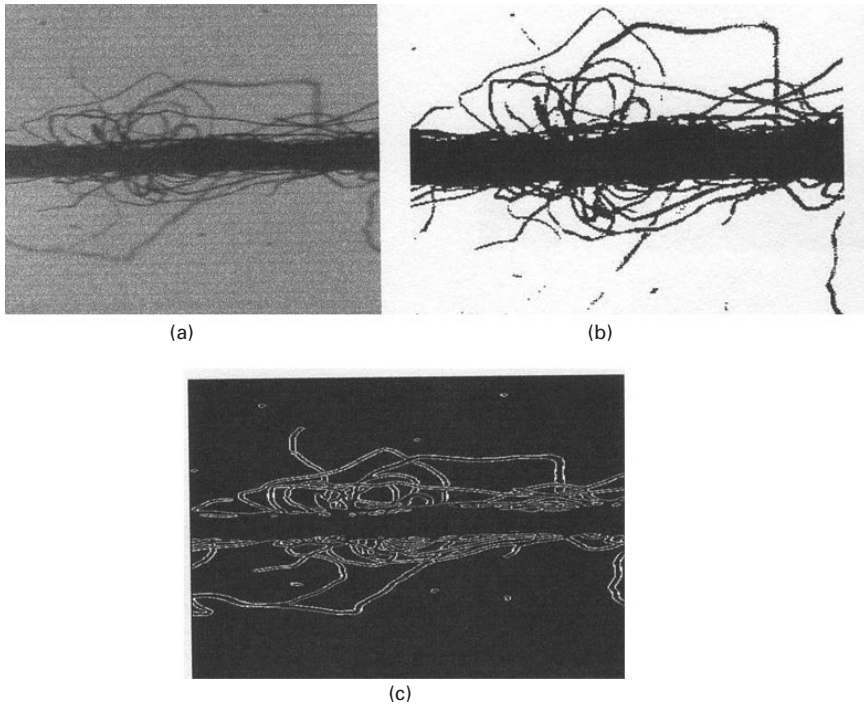
Rectangles in the figures indicate the regions where $\sigma = 1.0$ has worked better, while circles in the figures are the regions where $\sigma = 1.3$ has shown better results. To get the benefit of both, the pixel information from the two images is combined and truncated to unity. The apparently simpler technique of applying edge detection methods on binary images causes fewer hairs to be detected. The number of hairs at different distances from the edge of the yarn core gives an indication of the hairiness of the yarn in its current condition. The number of hairs is counted from 0 to 1.5 mm at intervals of 0.1 mm on both sides of the edge of the yarn core. Mere counting of pixels at a specific distance from the core is not the correct method. If a fibre is aligned along the measuring line, then the pixel count will be high and erroneous. This error is very common near the yarn core. This is avoided by edge toggling along the measuring line on the edge-detected image. The hair count is increased by 1 whenever the pixel value changes from 1 to 0 or from 0 to 1. The total count is divided by 4 and rounded to the nearest integer.

The hairiness indicated by the above method can change if the yarn is subjected to a process which causes the hairs to be flattened or raised. The true hairiness or intrinsic hairiness can be measured only by measuring the true length of all the hairs and dividing it by the length of yarn. An easy way of doing this is to count the number of pixels of the edge-detected image and divide it by 2. However, this ignores the fact that if a pixel has only diagonally placed neighbours, then the pixel count must be increased by $\sqrt{2} \times \text{pixel length}$. This is taken into account by an algorithm which increases the pixel count by 1 for pixels with only vertical or horizontal neighbours and by $\sqrt{2}$ for pixels with diagonal neighbours. Pixels with no neighbours are ignored since they are usually generated by noise. The run code is applied to the edge-detected image for obtaining the true length of hairs. This is divided by the length of the yarn core to obtain the hair length index – a

dimensionless quantity. This is the value usually quoted in literature as hairiness.

Clusters of hairs or the presence of a large number of hairs very close to each other is a common occurrence in many images that are inspected. These do not allow the edges of all hairs to be identified in the transmitted lighting mode. As a result, the 'total hair length' counted from these images is much lower than the expected value. This problem is expected to occur frequently at positions close to the yarn body, since fibres may be temporarily aligned nearly parallel to the yarn axis due to some process immediately prior to the test, e.g. transporting the yarn through the nip of a pair of soft rollers. One could perhaps argue that fibres so close to the core are usually not counted as hairs, and it is good that the hair length counter has ignored them. However, the assumption that the alignment of hairs close and parallel to the yarn core might be a temporary phenomenon urged us to look for a measure that would be a better indicator of these hairs. The area covered by hairs is found to be such a measure. The run code is applied on the inverted binary-enhanced image to obtain the total area covered by hairs. This is divided by the area of the yarn core to obtain a dimensionless quantity which is called the 'hair area index'. It has been seen that the hair area index calculated in this manner gives values which are an order of magnitude smaller than the 'hairiness' as defined in literature. The hair length index ignores the yarn count, while the hair area index includes it in the calculation. This means that if two yarns of two different counts have the same hair length index, the finer one will have a higher hair area index. This may make the value more meaningful, since the same hair length index might be acceptable for a coarser yarn, but unacceptable for a finer yarn because finer yarns are expected to have more stringent quality specifications. Figure 18.3 shows a kind of hair detection in a single thread.

A 'hairiness index' that is more sensitive for finer yarns than for coarser yarns can be considered an improvement over the currently used index. The proposed 'hair area index' has the area of yarn core in the denominator. This makes it more sensitive for finer yarns. A word of caution: the hair area index is affected by yarn evenness, while the hair length index is not. If the section of yarn captured in the image contains a thick place, then the hair area index for that image would be low. If it contains a thin place, the hair area index would be high. However, these effects are likely to cancel each other out over a large number of images. Moreover, for a typical yarn, the total length of such faults is a small fraction of the total yarn length. The chances of capturing such faults are thus small. A highly uneven yarn (with high yarn CV%) should show higher variation in hair area index than in hair length index. In such cases, the results of a large number of images taken from a long length of yarn should be averaged out.



18.3 (a) Original image of yarn thread; (b) binary image of yarn thread; (c) final edge detected image.

18.4.2 Yarn appearance

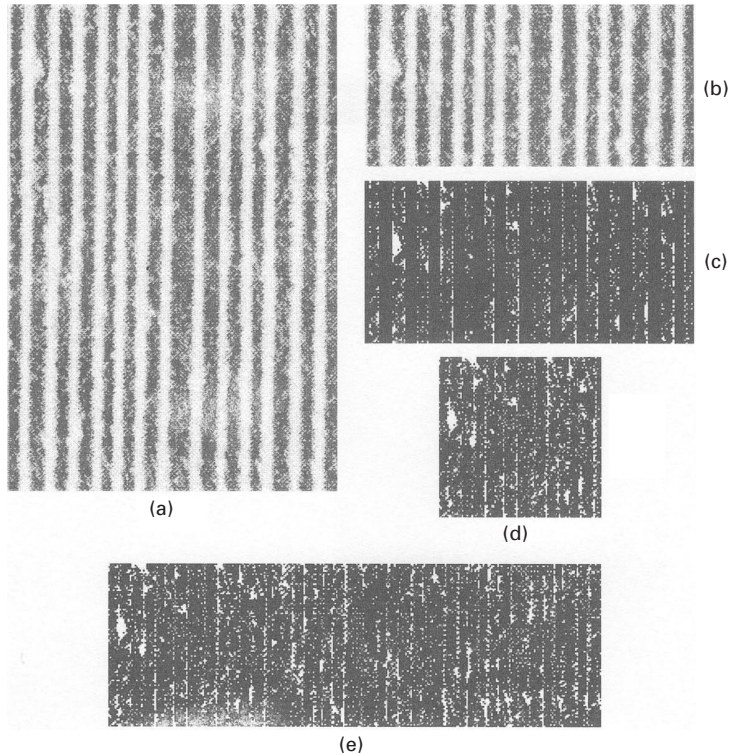
Although analysing a single yarn can help us to make an overall observation on yarn evenness or quality, the hairiness of yarn is not the most important defect of the yarn surface and many other parameters contribute to yarn quality. The appearance quality of yarn is directly related to the configuration of fibres on its surface and a greater unevenness in the yarn surface implies poorer apparent quality. There are four categories for faults of yarn surface in section D 2255 of ASTM. In this standard, the yarn grade is based on fuzziness, nepness, unevenness and visible foreign matter. In almost all definitions of yarn appearance features, the grading method is based on the surface configuration of the yarn which is explained by Booth (1974) and modified by Rong *et al.* (1995). Regarding the standard definition, yarn faults that have an effect on its appearance are classified in the following categories: nep with thickness less than three times the yarn diameter, nep with thickness more than three times the yarn diameter, foreign trash, entangled fibres with a thickness of less than three times the yarn diameter, such as a small bunch, slug or slub, and entangled fibres with thickness more than three times the

yarn diameter, such as large bunch, slug or slub, unevenness in the coating of the yarn surface or poor covering of the yarn with excessive fuzziness, and untangled fibre ends that protrude from the surface of a yarn. These fibres are named fuzz. The fuzz should not be confused with the cover of yarn with excessive fuzziness.

To measure the yarn faults, photographs of standard yarn boards of four grades are scanned using a scanner. The images are then converted to binary, forming a defined threshold. The binary image consists of the yarn body, the background and the faults. We only need the image of faults, so we need to detect and eliminate the yarn body and background. In the original images, the threads of yarn are not completely in the vertical direction. This was a major obstacle to the elimination of the yarn body in one stage. Therefore it is necessary to divide the original image into narrow tapes. The bodies of threads could then be eliminated from the binary images. In the scanned images of the yarn boards, which are divided into uniform tapes, there are some columns of pixels without the image of yarn body and faults; this is called the image of background. To obtain the images of faults, these columns are also eliminated using a small threshold from the image of the yarn board.

After eliminating the yarn body and background columns, the remaining images of the tapes are connected to each other end to end longitudinally. The resulting long, narrow tape is called the fault image. The fault image of each grade is divided into uniform blocks. For each image, the blocks are classified according to newly defined fault classes based on area and configuration of faults. Each block of fault image is classified on the basis of the number and adherence of fault pixels in it. The classified blocks are counted and four fault factors are calculated from the counted blocks. For each category of yarn count, the calculated fault factors and index of yarn degree are presented to an artificial neural network. After training of each neural network, a grading criterion is calculated. In the classification process, the matrix of faults should be divided into blocks of estimated size. The ideal classification would be obtained when each individual fault is located in one block. However, as the fault sizes are different and the image of the faults has to be divided into blocks of equal size, the ideal classification is impossible. A procedure of the presented method can be followed in Fig. 18.4.

The best possible classification with this method is obtained by considering the best block size for each images that could be estimated from the deviation of the means of blocks in the image. If the block size is too large, different faults are included in the same block. Furthermore, if the block size is too small, a large fault may be divided into more than one block. In both cases, the deviation of means of blocks is very small. Such block sizes cause poor classification of the faults. Therefore a suitable block size is defined as a



18.4 (a) Original image of yarn board; (b) image of divided tapes; (c) image of faults of one tape; (d) elimination of yarn body and background from image of faults of one tape; (e) consequent image from processed tapes.

block size that provides the maximum deviation of means of blocks. For each block, the mean and deviation of the intensity values of the pixels are calculated. Then the means and deviations are sorted in two separate vectors in ascending order.

The point of inflection for each curve of the sorted vector is selected as a classification threshold (T_p); thus there are two thresholds for a fault matrix (Semnani *et al.*, 2005b). One of them is the threshold of means of blocks (T_{fm}) and the other is the threshold of deviations (T_{fv}). T_{fm} classifies the blocks according to fault size and T_{fv} classifies them based on the distribution of faults.

After the classification of the fault blocks to the above classes, the numbers of blocks classified in each class are counted. Therefore, the yarn faults that have an effect on the appearance of the yarn can be detected and counted with this method using yarn boards.

18.4.3 Index of yarn appearance

Criteria for an index of yarn appearance are required. The numerical index of degree for yarn or fabric appearance is calculated from fault factors by a grading function. An index of yarn appearance is assigned to grade of appearance by fuzzy conditions. A linear criterion is used for estimation of grading criteria. The index of degree for yarn appearance, *ID*, could be calculated by Equation 18.1, for fault factors vector *P* and weight of faults *W*.

$$ID = W.P \quad 18.1$$

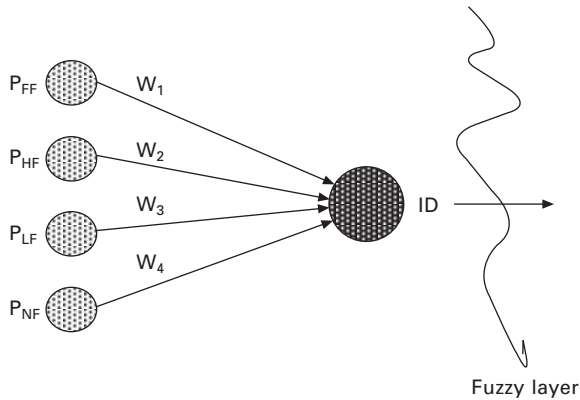
where *W* is a 1×4 vector of fault weight and *P* is a 4×1 vector of fault factors.

The index of degree is assigned to the grade of appearance by the defined fuzzy conditions of Table 18.1. The fuzzy conditions can be defined in desired equal series. We defined the range of fuzzy conditions from 0 to 100, as with a percentage.

Images of pictorial standard boards of yarn are used to estimate fault weights (vector *W*). To reach the best fault weights, fault factors are calculated from ASTM standard images after elimination of yarn bodies and background. Then initial weights are selected for different series of yarn counts by a trial-and-error method. The initial weights are introduced to a perceptron artificial neural network which has one layer. The input and output nodes of neural networks are fault factors (*P*) and index of degree (*ID*), respectively (Fig. 18.5). In the training process the inputs are fault factors of ASTM standard images of yarns and the outputs are middle values of *ID*, i.e. 25, 50, 70 and 90 for grades A, B, C and D respectively. For each series of yarn counts, an independent neural network is trained. The grading functions are obtained by calculation of fault weights (vector *W*) by training of neural networks.

Table 18.1 Fuzzy condition of index of degree for yarn appearance grades

ASTM grades	Developed grades	Range of index of degree 'ID'
A	A+	0–20
	A	20–30
	A–	30–40
B	B+	40–50
	B	50–60
C	C+	60–70
	C	70–80
D	D+	80–90
	D	90–100
	D–	Above 100



18.5 Perceptron artificial neural network with a fuzzy layer.

18.5 Fabric quality evaluation

In the textile industry, the desired characteristics of the finished product depend on the stage of production. Using a reliable method for detection and measurement of defects might lead to evaluation of the quality of products and correctness of the working machines. In the last two decades, the wool industries have shown a strong interest in research into textile-finishing processes and quality control of the product. In particular, great efforts have been made to perform real-time fabric defect detection during the finishing phase by using non-intrusive systems like machine-vision-based ones and the application of image processing.

Pilling and other fabric defects are the most important parameters of fabric appearance quality. The testing of pilling appearance and fabric defects is conventionally done visually. In the ASTM D3511 and D3512 pilling resistance test methods, an observer is guided to assess the pilling appearance of a tested specimen based on a combined impression of the density, pill size and degree of colour contrast around pillied areas. A frequent complaint about the visual evaluation method is its inconsistency and inaccuracy. Using a reliable method for detection and measurement of pilling defects might lead to better evaluation of the quality of products and correctness of the working machines (Abril *et al.*, 1998, 2000).

Conventionally, the inspection of fabric is also carried out by operators on an inspection table with a maximum accuracy of only 80%. Existing methods of inspection of fabric vary from mill to mill. The inspectors view each fabric as it is drawn across the inspection table. This task of visual examination is extremely exhausting, and after a while the sight can no longer be focused accurately, and the chance of missing defects in the fabric becomes greater. More reliable and objective methods for pilling evaluation and fabric defect detection are desirable for the textile industry.

18.5.1 Pilling evaluation

Computer vision technology provides one of the best solutions for the objective evaluation of pilling. Researchers in various institutions have been exploring image analysis techniques effective for pill identification and characterization. To present a comparative method for judging the pilling intensity and controlling the quality, researchers have introduced different approaches. Image-processing based methods were developed for pilling evaluation which combined operations in both the frequency and the spatial domains in order to segment the pills better from the textured web background (Hsi *et al.*, 1998a, 1998b; Konda *et al.*, 1988, 1990). Fazekas *et al.* (1999) located pill regions in the non-periodic image by using a template matching technique and extracting by using a threshold in the image. Density, size and contrast are the important properties of pills that describe the degree of pilling and are used as independent variables in the grading equations of pilling.

Xu (1997) used a template matching technique for extracting pills from fabric surface. The limitation in this approach is that one has to ensure that all imaging conditions are always constant and that the non-defective fabric samples are all identical. Moreover, dust particles, lint and lighting conditions on the template sample may introduce false defects.

In other research, Abouelela *et al.* (2005) employed statistical features such as mean, variance and median to detect defects. In that research, due to the method of the utilized algorithm, only large defects such as starting marks, reed marks, knots, etc. could be extracted and the system is unable to detect minute defects like pills. In several other research programs, digital image processing is used to determine pill size, number, total area and the mean area of pills on a fabric surface.

New methods have been applied to detect and classify pills in fabric surfaces. A new approach to pilling valuation based on the wavelet reconstruction scheme using an un-decimated discrete wavelet transform (UDWT), which is shift-invariant and redundant, has been investigated. A method of digital image analysis to attenuate the repetitive patterns of the fabric surface and enhance the pills has been presented. A preliminary evaluation of the proposed method was conducted to SM50 European standard pilling images. The results show that the reconstructed resolution level, wavelet bases and subimage used for reconstruction can affect the segmentation of pills and thus pilling grading. The area ratio of pills to total image is effective as a pilling rating factor.

In another method, a quite new technique has been used by Semnani and Ghayoor (2009), which is an improvement on the method of Kianiha *et al.* (2007). First the images are converted to the double format to enable mathematical calculations on them. Then a wiener filter is used to decrease the noises in the image. Wiener filtering is one of the earliest and best approaches

to linear image restoration. This method works by considering the images and noises as random processes and minimizing the mean square error between the image and its differential. Following that step, the detection is started by finding corners in the image. These can be defined as the intersection of two edges; a corner can also be defined as a point for which there are two dominant and different edge directions in a local neighbourhood of the point. An interest point for detecting is a point in an image which has a well-defined position and can be robustly detected. This means that an interest point can be a corner but it can also be, for example, an isolated point of local intensity maximum or minimum, line endings, or a point on a curve where the curvature is locally maximal. As a consequence, if only corners are to be detected, it is necessary to do a local analysis of detected interest points to determine which of them are real corners. A Harris corner detector is used for this approach. The Harris corner detector finds corners by considering directly the differential of the corner score with respect to direction, instead of using shifted patches.

These detected corners are actually the crossing points of weft yarns and warp yarns. The point is that pilling happens when the fibres entangle outside the yarn and fabric structures; as a consequence these entangled fibres cause the disturbance in the visual pattern of crossing points. Pills cause perturbation in the structure of woven yarns. As a result, the points which are distinctly the crossing points of a warp yarn and a weft yarn, and not disordered by the pills and other unevenness origins such as a corner, can be detected. After applying the corner detector to separate the defective areas from the background of fabric, first a histogram equalization technique is used. This technique expands the grey scales of the image into the 256 layers, which makes the image more distinguishable and visually more meaningful. Then a threshold applies to the histogram-equalized picture. The threshold value is set according to the histogram of the grey-scale-equalized image, and set for all images about 0.1. The remaining threshold is those areas which are not detected as a corner, but most of these areas are small areas which are neither a defect nor a corner. In fact these are the body of yarns or the small spaces between two parallel yarns. These areas should be eliminated from the detection matrix. Since these areas are slight we can use the size as a criterion for deciding whether a detected spot is a defect. In consequence, the detected areas whose squares are less than 400 pixels are eliminated from the final result. The result of applying the threshold and omitting slight areas is the defected areas matrix. Assessing these areas leads to quality control of fabric and finding a standard for the pill density and abrasion resistance.

The result of the detection algorithm is a matrix whose elements have a value of zero in the fine areas and 1 in the defective areas. The black areas are the zero-valued elements and the white areas have the value of 1. This matrix is multiplied by the original image, and the result is a matrix which

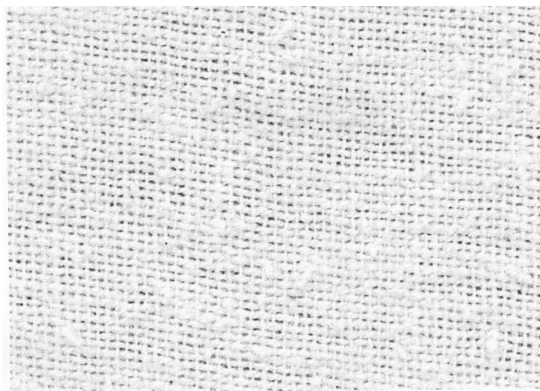
has a value of zero in the fine areas and the original value of the fabric image in the defective areas. The final matrix is a key to 3D modelling of the fabric surface. The 3D model is simulated by using the intensity values of elements. The brightest point has the maximum value of intensity in the image and should be considered as the point in the fabric which has the maximum height. Accordingly the zero elements in the matrix have the minimum value in the fabric. The lowest point in the fabric is on the background surface of the fabric and its height is equal to the thickness of the fabric. The thickness of the fabric was measured by a micrometer. The highest point in the fabric is the summit height of the highest pill. This height is measured by scanning from the side of the fabric and counting the vertical pixels of the highest pill. Then the height is calculated by multiplying the number of pixels of height in the DPI of image. This calculated height plus the thickness of the fabric is the highest point in the fabric. The zero elements considered as the points with the 0.83 mm height in the fabric and the maximum element has 2.015 mm height in the fabric. Lastly, a linear relationship is considered between the value of the elements and the height of fabric at that point. The higher the point is, the closer it is to the illumination. Consequently, it absorbs more light and appears more brightly in the image than the points with lower height. To present this function, the grey level of the darkest point in the processed image is considered as the point with height 0.83 mm, and the grey level of the brightest point is considered as the point with height 2.015 mm. As the images were acquired in the 256 levels of grey scale, Equation 18.2 describes this function:

$$H(i, j) = 0.83 + \frac{1.185}{255} I(i, j) \quad 18.2$$

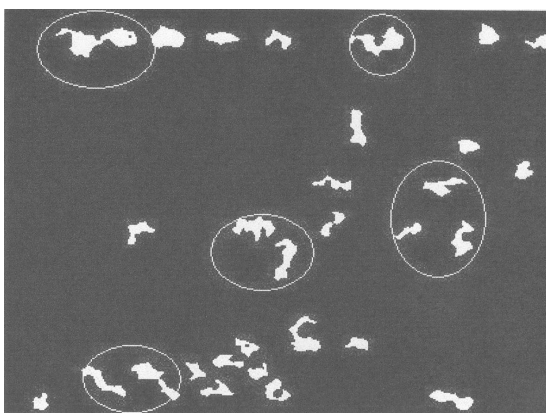
where $H(i, j)$ describes the height of points and $I(i, j)$ describes the illumination of points. Using this function we could simulate the fabric surface. Fig. 18.6 demonstrates the method presented.

18.5.2 Fabric defect detection

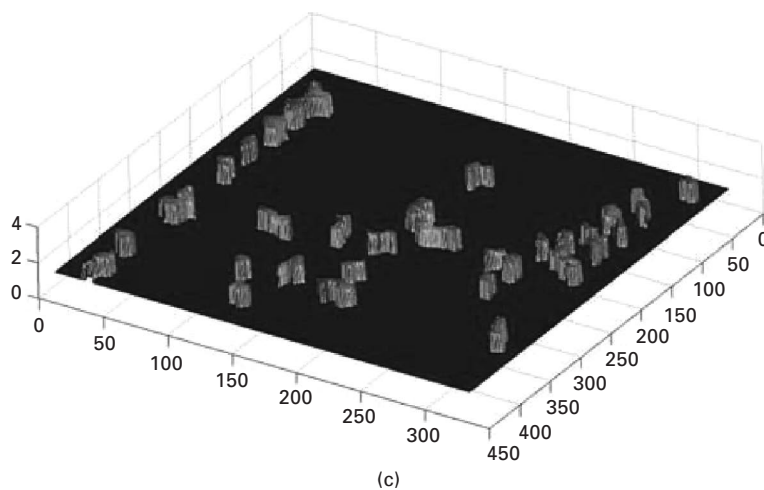
Detection of fabric faults can be considered as a texture segmentation and identification problem, since textile faults normally have textural features which are different from features of the original fabric. Textile fault detection has been studied using various approaches. One approach (Sari-Sarraf and Goddard, 1999) uses a segmentation algorithm, which is based on the concept of wavelet transform, image fusion and the correlation dimension. The essence of this segmentation algorithm is the localization of defects in the input images that disturb the homogeneity of texture. Another approach consists of a pre-processing step to normalize the image followed by a second step of associating a feature to each pixel describing the local regularity of the texture; candidate defected pixels are then localized.



(a)



(b)



(c)

18.6 (a) Original image of fabric; (b) image of pills; (c) simulated surface of pills.

There is substantial research work available for the objective evaluation of woven fabrics. Most of these works are based on detecting and classifying fabric faults, including weaving and yarn faults, by using analysis of fabric images. Some of these works have been presented by Kang *et al.* (2001) and Sawhney (2000). Sakaguchi *et al.* (2001) and Stojanovic *et al.* (2001) suggested the evaluation of fabric quality by the inspection of fabric irregularity by image analysis of its surface. Tsai *et al.* (1995) classified four types of fabric defects, namely broken end, broken pick, oil stain and neps, using image analysis and a back-propagation ANN. Choi *et al.* (2001) used image processing techniques and fuzzy rules to identify fabric defects, such as neps, slubs and composite defects. Huang and Chen (2001) also classified nine types of fabric defects using extracted features of the image as inputs to the neural-fuzzy system. There are methods of fabric inspection via wavelet or Fourier transformation which have not been successful in application (Millán and Escofet, 1996; Jasper *et al.*, 1996; Ralló *et al.*, 2003). Tsai and Hu (1996) identified fabric defects using Fourier-transformed image parameters as the inputs of an ANN.

The classification of weft-knitted faults is a subject with little research that we explain in detail here. Aboulhiana *et al.* (2003) presented an assessing work for detecting the structure changes in knits during the knitting process by image processing. In other research, reformation of knitted fabric reinforced by composites was considered by the image processing technique and 3D-CAD (Tanako *et al.*, 2004). For prediction of fabric appearance, a modelling technique using images of yarn of various sections has been presented, but in this method the knitted fabric is not subjected for apparent grading.

For detaching the knitted fabric fault image from the original image of the fabric, a different procedure has been designed by Semnani *et al.* (2005c). This procedure is similar to converting a grey-scale image to a three-scale image by two thresholds. In the procedure, the points with an intensity greater than the upper threshold and smaller than the lower threshold are replaced with zero. There are two picks in every histogram of fabric images. The first and second picks include points with a black background under the fabric and body of loops, respectively. The region between two picks includes the points of apparent faults.

The apparent faults of fabric such as tangled fibres, neps, slubs, free fibres, fettling fibres and unevenness of loop surfaces are similar to the apparent faults of yarn. These faults are seen with grey-scale level of the region between the two picks of the histogram. Therefore, the upper and lower thresholds are located before the second pick and after the first pick, respectively. In an experiment by the trial-and-error method the suitable upper threshold T_{fu} and lower threshold T_{fl} are determined by the equations $T_{fu} = \mu_f + \sigma_f$ and $T_{fl} = \mu_f - \sigma_f$, where μ_f and σ_f are the mean and standard deviation of the image matrix of the fabric, respectively. By using these thresholds the

background and loop pixels are replaced with zero values. The remained matrix is a matrix of the faults image. This image is converted to a binary image using a small threshold. For counting faults, a similar method to box counting in image processing is used to classify faults from the matrix. Both size and adherence of fault are the main parameters for its recognition and classification. The size of fault is defined by means of intensity values of points in each block of the matrix, and its adherence is estimated by deviation of intensity values of points in a block.

When the block size is too big, different faults are located in the same block, so the deviation of means is decreased. Also, when the block size is too small, a big fault is located among different blocks, so the deviation of means is too little. For estimating a suitable block size for the fabric faults image, the mean and deviation of the faults matrix are calculated, then for different block sizes the means and deviations of blocks are calculated. This procedure is repeated for various block sizes ranging between the largest and the smallest block size. The suitable block size is defined as a block size which provides the maximum deviation of means. The faults of each loop of knitted fabric are separated by neighbouring loops. Therefore a suitable block size for the fabric faults image is estimated from the loop size, which is approximately four times the yarn diameter.

After determination of a suitable block size, the faults matrix is divided into blocks of equal size. For each block, the mean and deviation of the pixel intensity values are calculated. Then, the means and deviations are sorted into two separate vectors in ascending order. The turning point of curvature for each vector is selected as a classification threshold T_b . So there are two thresholds for a fault matrix. One of them is the threshold of means of blocks T_{bm} and the other is the threshold of deviations T_{bv} . T_{bm} classifies blocks according to fault size and T_{bv} classifies them based on distribution of faults.

The blocks of the fault matrix are classified in four definition classes by a decision tree algorithm based on calculated thresholds for means and deviation of block pixels according to the following conditions:

- Class I: $\mu_{b_i} \geq 1.2 T_{bm}$
- Class II: $T_{bm} \leq \mu_{b_i} \leq 1.2 T_{bm}$ and $v_{b_i} \leq T_{bv}$
- Class III: $T_{bm} \leq \mu_{b_i} \leq 1.2 T_{bm}$ and $v_{b_i} \geq T_{bv}$
- Class IV: Any other blocks of fault images of yarn which are not classified in the above classes. This condition changes to $\mu_{b_i} \geq 0.8 T_{bm}$ in the case of blocks of fault images of fabric because the points with zero intensity are not removed.

In the above conditions, μ_{b_i} and v_{b_i} are the mean and deviation of the i th block, respectively.

18.5.3 Fault factors of fabrics

After classification of fault blocks in the above classes, the number of blocks classified in each class is counted and shown as N_1 , N_2 , N_3 and N_4 for class I, II, III and IV, respectively. Then the fault factor of each class is calculated using Equations 18.3. The fault factors PF1, PF2, PF3 and PF4 show the percentage of faults of class I, II, III and IV in a knitted fabric, respectively.

$$PF_i = \frac{N_i \times K \times K}{M \times N} \times 100 \quad i = 1, 2, 3, 4 \quad 18.3$$

In this equation, $K \times K$ is block size, and M and N are length and width of the original image before core elimination, respectively.

The numerical index of degree for fabric appearance is also calculated from fault factors by a grading function (Equation 18.1) as described in Section 18.4.3.

18.6 Garment defect classification and evaluation

The inspection of semi-finished and finished garments is very important for quality control in the clothing industry and plays an important role in the automated inspection of fabrics and garment products. Unfortunately, garment inspection still relies on manual operation while studies on garment automatic inspection are limited. Although clothing manufacturers have devoted a great deal of effort and investment to implement systematic training programs for sewing operatives before they are assigned to work on the production floor, the sizing, stitching and workmanship problems can still be found during the online and final inspections. Quality inspection of garments is an important aspect of clothing manufacturing and still relies heavily on trained and experienced personnel checking semi-finished and finished garments visually. However, the results are greatly influenced by human inspectors' mental and physical conditions. To tackle the manual inspection limitations, it is necessary to set up an advanced inspection system for garment checking that can decrease or even eliminate the demand for manual inspection and increase product quality. Therefore, automatic inspection systems (AISs) are becoming fundamental to advanced manufacturing. In automatic inspection systems, it is necessary to solve the problem of detecting small defects that locally break the homogeneity of a texture pattern and to classify all different kinds of defects. Various techniques have been developed for fabric defect inspection. Most of the defect detection algorithms tackling the problem use the Gaussian Markov random field, the Fourier transform, the Gabor filters or the wavelet transform. Most previous researches on fabric inspection systems during the last two decades have been about fabric or general web material,

and there are few on garment inspection. The development of automatic garment inspection to replace manual inspection in the clothing industry is still relatively limited. There are many aspects of garment inspection where defects need to be detected, i.e. stitching, garment sizing, cloth cutting, cloth pressing, dyeing and so on.

Automatic garment inspection using machine vision was proposed to classify the general faults of shirt collars for mono-coloured materials (Norton-Wayne, 1995). A quality inspection system was developed to detect shirt collar defects using variance filtering with the moving group and divided group average methods (Mustafa, 1998).

The most important factor in garment quality is the size and shape of the garment and stitching quality. Generally, the size and shape of the structuring element are determined by experience or trial-and-error, which is time-consuming and may not achieve a satisfactory performance, particularly when the size of the image is large or the image is analysed in a real-time situation. Therefore it is necessary to develop a method to acquire the best structuring element of the morphological filtering for image analysis.

The type of garment defects can be detected using a hybrid model combining a genetic algorithm (GA) and a neural network (Yuen *et al.*, 2009). In this model a segmented window technique is developed to segment images of the garment into three classes using monochrome single-loop ribwork of the knitted garment: (1) seams without sewing defects, (2) seams with pleated defects, and (3) seams with puckering defects caused by stitching faults. The stitching defects of single-loop ribwork of knitted garments can be detected and classified by processing a morphological image with a GA-based optimal filter and a BP neural network classifier.

Two typical texture properties of the knitted fabric are (1) the texture structure is periodic and can be composed of repeat units, and (2) the intensity difference of pixels in the texture repeat unit is very big. If a general edge-detection method such as Sobel or Laplacian is used to segment the regions of seams or defects from a sample image, the detection results will be disturbed by the normal fabric texture. Therefore, it is necessary to find an appropriate filter to smooth the texture of sample images. After the morphological filtering, a threshold value should be computed with two intensity statistic values of the filtered image, i.e. the average intensity value and the standard deviation, and then a binary image should be produced. Subsequent image processing is needed to enhance the properties of the segmented regions: (1) noise filtering, and (2) detecting, connecting and filling the neighbouring regions segmented from the same object.

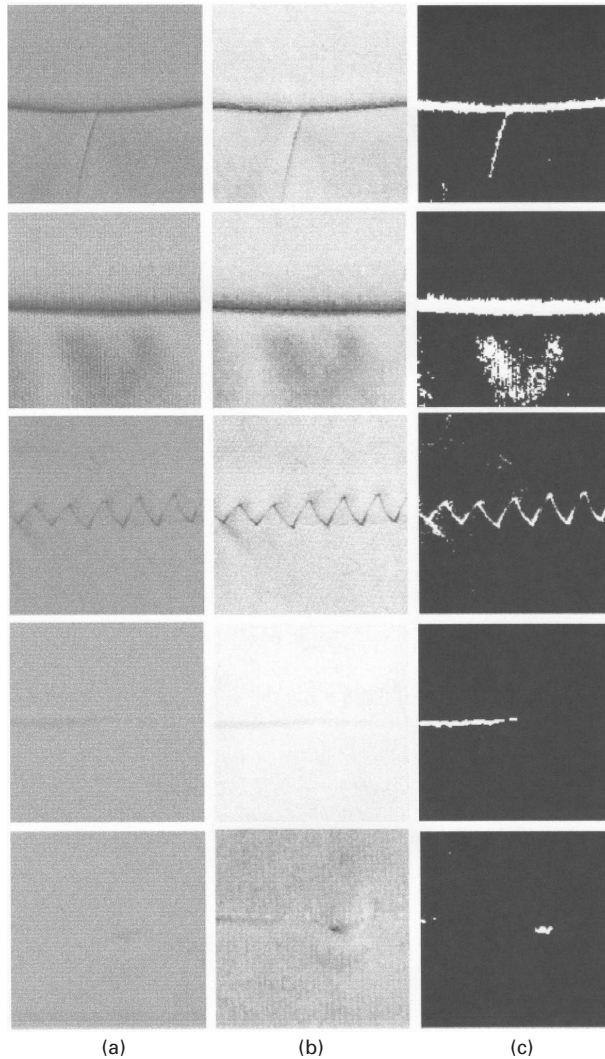
A segmented window technique segments images into pixel blocks under three classes. When the values of pixel blocks including seam or stitching defects are very different from those of normal blocks, a new image composed of pixel blocks is produced and a threshold value used to transform intensity

images into binary images is calculated. By thresholding processing, a binary image is obtained from which four characteristic variables, namely (1) size of the seams and defective regions, (2) average intensity value, (3) standard deviation, and (4) entropy value, are collected and input into a three-layer BP classifier to execute recognition work. The recognition rate by this system is 100% and the experimental results show that this method is feasible and applicable.

In order to detect and classify stitching defects, it is necessary to segment them from the texture background accurately. The textural analysis methods based on the extraction of texture features in the spatial and spectral domains result in high dimensionality (Tsai and Chiang, 2003). Although the methods not relying on textual features are successfully applied to thick fabric defect detection (Ngan *et al.*, 2005; Sari-Sarraf and Goddard, 1999; Tsai and Chiang, 2003), they are not effective in the thin surface anomalies.

An effective way to detect and classify defects in stitches of fabric has been based on a multi-resolution representation of the wavelet transform with the stages of image smoothing, thresholding and noise filtering. The direct thresholding which is based on the wavelet transform method improves the performance of the method. After the binary image is obtained, the BP neural network is used to classify the stitching defects. Therefore, as the dimensions of stitching defects are very thin, the thresholding method based on single-resolution level wavelet transform leads to better results. The quadrant mean filter can further attenuate the background and accentuate the stitching defects. The smoothed images are obtained by applying the wavelet transform and the quadrant mean filter. Thresholding is applied to localize the stitch region and remove the background. The stitch regions are well detected and located from the binary image as shown in Fig. 18.7(c). In the experimental study, the success rate of this method is about 100% (Wong *et al.*, 2009).

In classifying stitching defects, feature extraction is a key step. The nine features are obtained using the texture spectral method. There are great differences in the spectral measurement results among the five classes of stitching defects. The features decrypted by the spectral measure are effective. Nine characteristic variables based on the spectral measure of the binary images are collected and input into a two-layer feed-forward network trained with back-propagation (BP) in order to identify the class by responding to a three-element output vector representing five classes of site suitability. A tangent function between the input and hidden layers and a logarithmic function between the hidden and output layers are used. The hidden layer contains 10 neurons. With this method, five classes of stitching defects can be identified effectively.



18.7 Detection of the five types of stitching defective images: (a) the original images, (b) the quadrant mean filtered images, and (c) the binary images after thresholding and noise filtering (Wong *et al.*, 2009).

18.7 Future trends

Textile manufacturers have to monitor the quality of their products in order to maintain the high-quality standards established for the clothing industry. Textile quality evaluation by soft computing techniques made substantial progress and established itself well in the textile quality control, grading

and classification sector. It has potential for providing high quality for the textile industries. The cost of inspection is very low and its accuracy is higher than that of the conventional human visual method. Very high quality products could be achieved using soft computing techniques without the need for higher costs. This approach is an indispensable component of modern intelligence technology in manufacturing textile products and is a key factor for the increase of competitiveness of the companies. Therefore, the computer-vision-based automatic defect detection system has become one of the hotspots in the textile industries for monitoring and controlling product quality. Meanwhile, the technical problems and hardware needs are the main subjects to dominate this new technique in worldwide textile industries. More research and efforts are needed to commercialize the new methods of fault inspection in products and to grade them. Further developments are focusing on optimizing the fibre feed for finer yarn counts. Nevertheless, the current systems offer ample scope to researchers and textile technologists for engineering yarns with desired characteristics through optimization of a wide range of process parameters and the processing of a wide variety of selected raw materials. New developments in textile quality evaluation by soft computing techniques are, however, essential in order to further improve textile product quality and the competitiveness of the companies.

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