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Artificial Neural Network Prosperities in Textile Applications

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1. Introduction

Such as other fields, textile industry, deal with numerous large inputs and possible outputs parameters and always feed with a complex interdependence between parameters, it is highly unlikely that an exact mathematical model will ever be developed. Furthermore, since there are many dependent and independent variables during different textile progress, it becomes difficult to conduct and to cover the entire range of the parameters. Moreover, the known and unknown variables cannot be interpolated and extrapolated in a reasonable way based on experimental observations or mill measurements due to the shortage of knowledge on the evaluation of the interaction and significance at weight contributing from each variable. For example, it is quite difficult to develop some universal practical models that can accurately predict yarn quality for different mills (Chattopadhyay & Guha, 2004).

Statistical models have also shown up their limitations in use—not least their sensitivity to rogue data—and are rarely used in any branch of the textile industry as a decision-making tool. The mechanistic models proposed by various authors overtly simplify the case to make the equations manageable and pay the price with their limited accuracy. In any case, the vast volume of process parameter- related data is hardly ever included in these models, making them unsuitable for application in an industrial scenario.

By using neural networks, it seems to be possible to identify and classify different textile properties (Guruprasad & Behera, 2010). Some of the studies reported in recent years on the application of neural networks are discussed hereunder.

2. Fiber classification

The usual tests for fiber identification (usually chemical tests), in addition to being difficult to perform, are almost always destructive in nature.

Leonard et al., 1998 had used Near-infrared (NIR) spectroscopy as input data to a neural network to identify fibers in both original and normalised spectra. The performance of the network was judged by computing the root mean square error of prediction (RMSEP) and was compared with similar results given by multiple linear regressions (MLR).

Accurate classification of animal fibers used in the wool industry is very difficult. Some techniques distinguish these fibers from patterns of their cuticular scales and others from their physical and chemical properties. However, classification of animal fibers is actually a typical task of pattern recognition and classification (Leonard et al., 1998). She et al., 2002

developed an intelligent fiber classification system to objectively identify and classify two types of animal fibers, merino and mohair, by two different methods based on image processing and artificial neural network. There are considerable variations in the shape and contour of the scale cells and their arrangement within the cuticle. They used these two systems based on how the scale features of the animal fibers were extracted. The data was cast images of fibers captured by optical microscopy. Then they applied principal component analysis (PCA) to reduce the dimension of input images and extract an optimal linear feature before applying neural network. Furthermore neural network classifiers generalize better when they have a small number of independent inputs. Finally they used an unsupervised neural network in which the outputs used as inputs in the supervised network (a multilayer perception with a back propagation algorithm) for classification while the fiber classes were the outputs of the output layer. For the unsupervised network, learning rate at 0.005 (step size) was set which linearly decayed to 0.0005 within the first 100 epochs and three different numbers of units in the hidden layer (80, 50, and 20) was used. Multilayer perception used for fiber classification had a hyperbolic tangent activation function in the processing elements of the hidden layer and output layer. They also compared their two systems and concluded that neural network system was more robust since only raw images were used and by developing more powerful learning strategies, the classification accuracy of model would be improved (She et al., 2002).

There are some studies which have been introduced different design of neural network classifier to categorize different type of fibers based on their colors too.

Raw cotton contains various kinds of trash, such as leaf, bark, and seed coat. The content of each of these trash particles is vital for deciding upon the cleaning process (Xu et al., 1999). For instance, the trash and color of raw cotton are very important and decisive factors in the current cotton grading system that determine spinning quality and market value.

For many years, the USDA (United States Department of Agriculture) has used both a visual grading method by trained classers and an instrumental method with HVI (High Volume Instrument) systems to evaluate the color and trash of raw cotton. However it is expensive, slow, and a time consuming process (Kang & Kim, 2002). Xu et al., 1999 used three classification techniques (sum of squares, fuzzy, and neural network) into four groups (bark, leaf, hairy seed coats, and smooth seed coat). They applied two hidden layer with four and six neurons and their results showed that the neural network clustering method outperformed the other used two methods (Xu et al., 1999).

Kang & Kim, 2002 developed an image system to characterize trash from a raw cotton image captured by a color CCD camera and acquired color parameters. They trained and tested neural network based on back propagation algorithm using color parameters as input data from physical standard samples. A sigmoid function was used for an error back propagation model and the number of input and output nodes was eight and seven respectively in accordance with the color parameters and seven grades in the subcategories. The results predicted by neural network were compared with the grades that classers judged (Kang & Kim, 2002).

3. Yarn, fabric, nonwoven and cloth defect detection and categorization

In general, textile quality control is determined by measuring a large number of properties (including mechanical and physical properties, and etc), which in many cases can only be done by skilled workers or expensive equipments (Lien & Lee, 2002). Generally, In textile

industry, textiles are inspected manually for defects, but some problems arise in this visual inspection, such as excessive time consumed, human subjective factors, stress on mind and body, and fatigue. These problems further influence production volume and inspection accuracy. Therefore, techniques that can replace manual inspection have emerged (Kuo & Lee, 2003). In recent years, neural networks have been used to inspect yarn, fabric and cloth defects and to identify their types (Kuo, 2003). Neural networks are among the best classifier used for fault detection due to their non-parametric nature and ability to describe complex decision regions.

A key issue in many neural network applications is to determine which of the available input features should be used for modeling (Kumar, 2003). Mostly, researchers have used different ways for feature selection based on image processing methods in conjunction with neural network. An image acquisition setup that yields suitable images is crucial for a reliable and accurate judgment. This system is usually including the specimen, the camera or scanner and the illumination assembly (Bahlmann et al., 1999). Some studied have used near sensor image processing (NSIP) technology as well. Most researchers had converted the original color image to gray level image to improve the computer processing speed and reducing the dimensions of information. However, Tilocca et al., 2002 presented a method to fabric inspection based both on gray levels and 3D range profile data of the sample (Tilocca, 2002). Most studies usually have employed histogram equalization, noise reduction operation by filtering, etc to improve visual appearance of the image (Jeon, 2003). When they use image technology in conjunction with neural networks, some problems may occur; For example recognizable rate of defect may be related to light source conditions (Kuo & Lee, 2003). Since a fine feature selection can simplify problem identification by ranking the feature and those features that do not affect the identification capability can be removed to increase operation efficiency and decrease the cost of evaluation systems without losing accuracy (Lien & Lee, 2002). So some studies have applied principal component analysis (PCA) as pre processing methods to reduce the dimension of feature vectors (Kumar, 2003).

Usually, in ANN, the available data are divided into three groups. The first group is the training set. The second group is the validation set, which is useful when the network begins to over-fit the data so the error on the validation set typically begins to rise; during this time the training is stopped for a specified number of iterations (max fails) and the weights and biases at the minimum of the validation error are returned. The last group is the performance test set, which is useful to plot the test set error during the training process (Liu, 2001).

Data are further processed to extract specific features which are then transmitted to either supervised or unsupervised neural network for identification and classification. This feature extraction step is in accordance with textural structure, the difference in gray levels, the shape and size of the defects and etc (Kuo et al., 2003) and it is necessary to improve the performance of the neural network classifier (Tilocca, 2002). Consequently, a large amount of study is usually related to this step to extract useful information from images and feed them to neural network as input to recognize and categorize yarn, nonwoven, fabric, and garment defects.

In supervised systems, the neural network can establish its own data base after it has learned different defects with different properties. Most researchers have been used multi layer feed forward back propagation Neural network since it is a nonlinear regressional algorithm and can be used for learning and classifying distinct defects.

There are numerous publications on neural network applications addressing wide variety of textile defects including yarn, fabric and garment defects. Some of the studies reported on this application of neural networks are discussed hereunder.

3.1 Yarn defects

Sliver levelness is one of the critical factors when producing quality yarn products in spinning processes. However, it is difficult to model the drafting process exactly since these controls do not need to model the process and can handle very complicate processes, they are useful. Moreover, they possess the ability to improve the intelligence of systems working in an uncertain, imprecise, noisy environment. Therefore, Huang & Chang, 2001 developed an auto leveling system with a drawing frame using fuzzy self-organizing and neural network applied on a laboratory scale drawing frame with two drafting zones and two-sliver doubling samples. They used a three layer neural network model to compute the Jacobean matrix, which was needed in training the weights and thresholds on-line. A back propagation learning algorithm was used to tune the connection weights and thresholds and the unipolar sigmoid function as the activation function to compute the output of a node. Levelness performance was evaluated by the CV% of sliver products in which their results showed that neural network controller yielded more level slivers than the fuzzy self-organizing controller. The neural network controller kept learning from the feedback of the output linear density and generated the control action by the feed linear density and the desired output linear density. The weight and thresholds of the neural network controller were tuned on-line, leading to reduced variance in the output with respect to the desired value (Huang & Chang, 2001).

It is well known that spinning process is a complex manufacturing system with the uncertainty and the imprecision, in which raw materials, processing methodologies, and equipments and so on all influence the yarn quality (Yin & Yu, 2007). Yarn physical properties like strength, appearance, abrasion and bending are the most important parameters, affecting on the quality and performance of end products and also cost of the yarn to fabric process (Cheng & Lam, 2003).

Lien & Lee, 2002 reported feature selection for textile yarn grading to select the properties of minimum standard deviation and maximum recognizable distance between clusters to achieve effectiveness and reduce grading process costs. Yarn features were ranked according to importance with the distance between clusters (EDC) which could be applied to either supervised or unsupervised systems. However, they used a back propagation neural network learning process, a mathematical method and a normal algebraic method to verify feature selection and explained the observed results. A thirty sets data were selected containing twenty data as training sets and the other ten data as testing sets. Each of these data were the properties of single yarn strength, 100 meter weight, yarn evenness, blackboard neps, single yarn breaking strength, and 100-meter weight tolerance (Lien & Lee, 2002).

A performance prediction of the spliced cotton yarns was estimated by Cheng & Lam, 2003 using a regression model and also a neural network model. Different spliced yarn properties such as strength, bending, abrasion, and appearance were merged into a single score which was then used to analyze the overall performance of the yarns by those two models. The appearance of the spliced yarns was expressed as the retained yarn appearance (RYA) which 5 was identical, 3 was acceptable and 1 was fail values. They used the transfer functions of hyperbolic tangent sigmoid transfer function and linear transfer function.

According to their analytical results, the neural network model (R=0.98) gave a more accurate prediction that the regression model (R=0.74) (Cheng & Lam, 2003).

It is well known that worsted spinning process is a complex manufacturing system and there are many dependent and independent variables during spinning which becomes difficult to conduct and cover the entire range of the parameters using mathematical and empirical models. Yin & yu, 2007 firstly analyze all the variables collected from the mill through grey superior analysis (GS) in order to select the important variables and as a result better improve the yarn quality before ANNs model (multi-layer perceptron) was used by adopting the back-propagation neural network (BP) to estimate the validity of the input variables. In their research, they evaluated yarn qualities i.e. yarn unevenness, strength, extension at break, and ends-down per 1000 spindle hours; by means of inputs including the processing parameters such as fiber properties, spinning method, and process variables influencing on the yarn properties and spinning performance. From the 77 sets of data, 69 lots were selected at random to serve as learning set and the residual eight sets data were recorded as test sets. A one layer hidden layer was decided based on experiments by achieving the highest coefficient using back propagation learning. The prediction accuracy, A (%) and relative coefficient, R (%), between the predicted values and achieved values were calculated in order to validate the approaches of the variables selection. The comparison of the performance of ANNs model using grey superior analysis (GS), subjective and empirical approach (SE), and multilinear regress method (MLR) showed that the model using the input variables selected by GS was superior to that by SE and MLR. They also simulated the spinning of the worsted yarn with the high coincidence using the processing data in the mills based on the artificial neural networks and grey superior analysis (Yin & yu, 2007).

One of the important properties of yarns is unevenness. Mass or weight variation per unit length of yarn is defined as unevenness or irregularity. It can adversely influence many of the properties of textile materials such as tenacity, yarn faults, twist variation, abrasion, pilling, soil retention, drape, absorbency, reflectance or luster. Unevenness in blended yarns is depended mainly on the physical properties of fibers (fiber cross section deviation, length and length uniformity etc.), number of fibers and fiber location or positioning in the yarn cross section, blend ratio and working performance of the yarn spinning machine. Therefore, Demiryurek & Koc, 2009 developed an artificial neural network and a statistical model to predict the unevenness of polyester/viscose blended open-end rotor spun yarns. They used a back propagation multi layer perceptron network and a mixture process crossed regression model with two process variables (yarn count and rotor speed). They selected blend ratio, yarn count and the rotor speed as input parameters and unevenness of the yarns as output parameter. Sigmoid function was used as activation function, and number of hidden layer was determined as 25, the learning rate and momentum were optimized at 0.2 and 0.0 respectively in this study. They compared the result of both presented model and it was concluded that both models had satisfactory and acceptable results, however the correlation coefficient of neural network (0.98) was slightly greater than statistical model (0.93) and the mean square errors (0.077) were identical. The mean absolute percentage error was also calculated and was %1.58 and %0.73 for the ANN and statistical model respectively. Contrary to general opinion of the more reliable prediction of ANN than statistical models, they reported that statistical model developed was more reliable than ANN and by increasing the number of experiments, prediction performance of ANN would increase (Demiryurek & Koc, 2009).

2.2 Woven fabric defects

Image processing analyses in conjunction with neural networks have been widely used for woven and knitted fabric defect detection and grading.

Karras et al., 1998 investigated a vision based system to detect textile defects from the textural properties of their corresponding wavelet transformed images. They applied supervised (multilayer perceptrons trained with the back propagation algorithm) and unsupervised (Kohonen's self organizing feature maps) neural classification techniques by exploiting information coming from textural analysis and SVD in the wavelet transformed original images to provide second order information about pixel intensities and localize important information respectively. They considered defect detection as the approximation of the defect spatial probability distribution within the original image. The inputs to the MLP and SOFM networks were the 24 features contain 1009 patterns of the feature vector extracted from each sliding window. 280 out of the 1009 patterns belonged to the long and thin defective area of the upper side, while the rest belonged to the class of non defective areas. Reported classification accuracy was an overall 98.50% (Karras et al., 1998).

Tilocca et al., 2002 presented a direct method to fabric inspection based both on gray levels and 3D range profile data of the sample. They used a smart vision sensor for image acquisition system. The neural network was trained to classify three different categories which were normal fabric, defect with a marked 3D component and defect with no 3D component. A three layered feed forward neural network with sigmoid activation function and back propagation learning algorithm by a fixed learning rate at 0.2. They extracted 1500 training patterns including nondefective region, defects with marked 3D characteristics, and defects without 3D marks and another group of 500 patterns constituted the test sets. The number of hidden neurons was adjusted by trial and error at 24. They obtained the percentage of right, unknown, and wrong classifications for each class, both for the training and test sets. Percentage of test clean patterns correctly classified was almost 92%, showing that the ANN was able to identify and separate defective from nondefective regions. They suggested using this system for on-line monitoring of fabric defects since no further transformation of the data was needed before classification (Tilocca et al., 2002).

At present, fabric inspection still relies on the human eye, and the reliability and accuracy of the results are based on inspectors. Wrinkles in cloth usually develop with deformation during wearing, after washing and drying, and with folding during storage and it is not easy even for trained observers to judge the wrinkles. Mori & Komiyama, 2002 used gray scale image analysis of six kinds of plain fabrics to evaluate visual features of wrinkles in plain fabrics made from cotton, linen, rayon, wool, silk, and polyester using neural network. The angular second moment, contrast, correlation, and entropy were extracted from the gray level co-occurrence matrix and fractal dimension from fractal analysis of the image as input and the mean sensory value presenting the grade of wrinkled fabrics as output. The hidden units had logistic function as transfer function. Eight sets of data were selected arbitrarily as training data and the seven remaining data sets for testing the neural networks were used. They used a training algorithm with Kalman filter to tune the network in order to maximize the accuracy of the visual evaluation system. Sum of the square error (SSE) was used as total output error of the network. Overtraining was occurred in the region of more than 200 learning cycles, therefore they decided 150 learning cycles for checking or testing the network. They also compared the accuracy of the evaluating system for wrinkled images captured by the digital camera method with that for wrinkled images captured by the color scanner method and observed better accuracy for the color scanner than digital camera (Mori & Komiyama, 2002).

Kuo & Lee, 2003 used a back-propagation neural network for recognizing woven fabric defects. They used an image system (filtered and threshold images) to distinguished holes, oil stains, wrap-lacking and weft-lacking defects. Maximum length, maximum width and gray level of the defects were presented as the input units of the neural network. They used a back propagation neural network by eight defect samples for off line training. The initial learning rate was 0.1; keeping reducing to 0.01 and the momentum factor was 0.5. The error mean square value converged to 0.05 after 45000 iterations. According to their test, the recognizable rate of warp-lacking and weft-lacking was up to 95%, and up to 100% for holes and oil stains (Kuo & Lee, 2003). Kuo et al., 2003 used an image system for dynamic inspection of plain white fabrics using a linear scan digital camera with direct light to take images. The corresponding fabric conveying speed was 50 cm/s. the back propagation neural network of this research comprised an input layer with three input units (maximum length of the defect, maximum width of defect, and gray level value of the defect), a hidden layer, and an output layer by three output units. They reported average overall recognition rates up to 90% (Kuo et al., 2003).

Segmentation of defects provides accurate distinguishing of size and location of defects. Therefore, Kumar, 2003 investigated an approach to segment a variety of local textile (twill and plain weave fabrics) defects using feed-forward neural network. Since every fabric defect alters the gray-level arrangement of neighboring pixels, he extracted the feature vector for every pixel of backlighting captured images and applied a pre-processing using normalization of the feature vectors followed by principal component analysis (PCA) to reduce the dimension of feature vectors. He also used post-processed operation (a 9*9 median filtering) to generate the required output values. Hyperbolic tangent sigmoid activation function was chosen and the weights were updated using Levenberg-Marquardt algorithm for faster convergence rate. The network was trained for the maximum of 1000 steps with the learning rate of 0.01 and the training was stopped if the maximum performance gradient of 1e-10 was reached. Finally, a low-cost web inspection system based on linear neural network with a single layer to evaluate real fabric samples was proposed since the web inspection based on defect segmentation required additional DSP hardware, which would increase the cost of the inspection system (Kumar, 2003).

Pilling may be defined as a surface fabric fault comprising of circular accumulations of entangled fibers that cling to the fabric surface thereby affecting the appearance and handle of the fabric. The pilling of fabrics is a serious problem for the apparel industry and in particular wool knitwear fabrics. The formations of pills occur as a consequence of mechanical action during washing or wear (Beltran et al., 2005). The development of pills on a fabric surface, spoils the original appearance and hand, initiates garment attrition and reduces serviceability. Therefore evaluating pilling degree (from grade 5 which means no pilling to grade 1 which is very severe pilling) of fabric is important and usually it is inspected visually. Because of the inconsistency and inaccuracy of rating results obtained with the visual method, more reliable and objective methods for pilling evaluation are desirable for the textile industry. Chen & Huang, 2004 evaluated and graded fabric pilling based on light projection using image analysis and neural network to overcome the common difficulty of interference with fabric pill information from fabric color and pattern. Firstly, they eliminated interference with pilling information from fabric color and pattern. Their method was included a device to acquire the projected cross-sectional images, detecting the profile of projected images, segmenting pills appearing on converted gray images, extracting of a pill's feature index, and finally assessing pilling grade by Kohonen self

organizing feature map neural network. There were ten input neurons corresponding to ten feature indexes and five output nodes representing five cluster centers (five pilling grades) by training twenty kinds of samples including colored and patterned pilled worsted fabrics. The total number of iterations in the training process was 400, and the learning rate was initialized to be 0.02.They concluded that the objective pilling grade was in good agreement with the subjective pilling grade. The correlation coefficient for training and testing samples were reported up to 0.94 and 1 respectively (Chen & Huang, 2004).

Beltran et al., 2005 also used artificial neural networks to model the multi-linear relationship between fiber, yarn and fabric properties and their effect on the pilling propensity of pure wool knitted fabrics. They used key fiber (diameter, CV, diameter > 30 µm and curvature), top (Hauteur, CV, short fiber <30mm, bundle strength and strain), yarn (count, hairiness, thin and thick places, twist factor, folding twist ratio) and fabric properties (cover factor) as quantitative inputs (normalized data) along with their corresponding pilling intensities in an ANN to predict the pilling performance of knitted wool fabrics. The corresponding mean pill rating was served as the target output. 105 sets of randomized data were assigned to training, 20 sets were assigned for cross validation and 10 data sets were selected for testing the network. The network consisted of a single hidden layer multi layer perception trained with the error back propagation algorithm possessing hyperbolic tanh activation function in both the hidden and output layers (Beltran et al., 2005).

Zhang et al., 2010 investigated an approach for fabric defect classification using radial basis function (RBF) network improved by Gaussian mixture model (GMM). First, the gray level arrangement in the neighborhood of each pixel was extracted as the feature. This raw feature was subject to principal component analysis (PCA) which adopted the between class scatter matrix as the generation matrix to eliminate the variance within the same class. Second, the RBF network with Gaussian kernel was used as the classifier because of the nonlinear discrimination ability and support for multi-output. To train the classifier, GMM was introduced to cluster the feature set and precisely estimate the parameter in Gaussian RBF, in which each cluster strictly conforms to a multi-variance Gaussian distribution. Thus the parameter of each kernel function in RBF network could be acquired from a corresponding cluster. The proposed algorithm was experimented on fabric defect images with nine classes (mould, miss weft, damaged, double pick, cloud pick, coarse end, color smear, broken edge, and filling end) and achieved superior performance. Fabric images were collected under the back-lighting condition with the cloth moving speed of 100 m/min. in the training process, 30 images of each class were processed and repeated 5 times. They also compared the performance of three classifiers including ANN (9-16-10 feed forward structure using back propagation algorithm), SVM (Support Vector Machine which can automatically determine support vectors from the sample set which is normalized and preprocessed by PCA using Gaussian function as kernel), and RBF network on fabric defect classification. These schemes were evaluated on the same nine classes of fabric defect images. The training and test process was repeated five times to get an average performance. The result was measured by correct classification rate (CCR) which was defined as the number of correctly classified images divided by the number of total images. They found that ANN had the worst performance with an average CCR of 74% while the performance of RBF network was the best with CCR of 83.2% and the performance of SVM was sensitive to the parameters. Therefore, they reported that RBF network was an appropriate choice for the real time fabric defect classification. It has to be noted that this work was the first time that the RBF network was applied in fabric defect classification

which achieved excellent performance in combination with GMM in comparison with classical feed forward network (Zhang et al., 2010).

2.3 Knitted fabric defects

The apparent quality of knitted fabrics can be divided into two categories. First, the fabrics with a large number of area faults that were occurring in the knitting process and eventually make them useless. In the second category, there are inputted faults that originate from yarn faults and the apparent quality of yarn is directly related to the configuration of fibers on its surface (Liu et al., 2001). Different studies have been reported and identified both problems simultaneously or separately.

Detecting and classifying knitted fabric defects using image analysis and neural network were performed by Shady et al., 2006. They utilized two approaches including statistical procedures and fourier transforms to extract image features for six different knitted fabric defects using a defect free fabric as a control sample. All images were processed using histogram equalization and then converted to grayscale images. The feature vectors were used as input vectors to the network and six types of defects including broken needle, fly, hole, barre, thick yarn and thin yarn were identified and classified. Two neural networks were trained and tested for each feature extraction approach. The first one contained seven neurons in the input layer representing the seven features of the statistical approach, and seven neurons in the output layer representing the sic different defects and the free defect sample. This network was successful only in classifying broken needle, hole, thick and thin yarn defects. In the second neural network, six neurons were used in the input layer representing the features and seven neurons in the output layer representing the six defects and the free defect sample. The worst results were observed for the barre defects. In their work, the neural network was trained by the learning vector quantization (LVQ) algorithm to detect and classify the knitted fabric defects. Their results showed success in classifying most of the defects excluding barre defects (Shady et al., 2006).

Fabric spirality is a problem which affects the esthetics and quality of knitted fabrics. This problem is complex and there is a large amount of data required to establish quantitative relationship to model this phenomenon accurately. an artificial neural network model was proposed by Murrells et al., 2009 for the prediction of the degree of spirality of single jersey fabrics made from 100% cotton conventional and modified ring spun yarns from a number of factors considered to have the potential to influence fabric spirality after wash and dry relaxation such as twist liveliness, yarn type, yarn linear density, fabric tightness factor, the number of feeders, rotational direction, gauge of knitting machine and dyeing method. They compared ANN model (R=0.976) with a multiple regression model (R=0.970) and concluded that ANN model produced superior results to predict the degree of fabric spirality after three washing and drying cycles. The hyperbolic tangent sigmoid transfer function was assigned as the activation function in the hidden layer and the linear function was used in the output layer. During the process, 60%, 20%, and remaining 20% of the original data were set aside for training, validation, and testing respectively. They also investigated the relative importance of the investigated factors influencing the spirality of the fabric and tried various network structures with one hidden layer and finally demonstrated that multilayer feed forward network based on Levenberg-Marquardt learning algorithm had better results. Furthermore, both the ANN and the regression approach showed that twist liveliness, tightness factor, and yarn linear density were the most important factors in predicting fabric spirality (Murrells et al., 2009).

Semnani & Vadood, 2009 applied the artificial neural network (ANN) to predict the apparent quality of weft knitted fabrics. They considered, only the appearance of the safe knitted fabric without any knitting faults, tightened fibers with uniform configuration, big faults with less area, non-uniform and extended faults with spread configuration, and small spread faults such as non-uniform coating fibers and short tangled hairs had been considered (Semnani & Vadood, 2009).

There are some variables in the applied neural network where their variation affects on the obtained results are significant. These variables include the number of hidden layers, the number of neurons in hidden layers, the value of max fail and the percentage of validation and testing data.

Therefore, Semnani & Vadood, 2009 applied genetic algorithm in their research because of its intuitiveness, ease of implementation and the ability to effectively solve highly nonlinear, mixed integer optimization problems. Their results showed that the ANN could be optimized very well by the genetic algorithm method and the designed ANN was very accurate and applicable to predict the apparent parameters. Their optimized ANN was formed from two hidden layers, in which the first hidden layer had 8 and the second layer had 7 neurons, one neuron for output layer, five epochs for max fail, 20% available data for test and 10% of available data for validation (Semnani & Vadood, 2009).

2.4 Nonwoven defects

Liu et al., 2010 proposed an algorithm based on wavelet transform (feature extraction procedure) and learning vector quantization (LVQ) neural network for nonwoven uniformity identification and grading. Six hundred and twenty-five nonwoven images of five different grades, 125 images of each grade, were decomposed at four different levels with five wavelet bases of Daubechies family, and two kinds of energy values L^1 and L^2 extracted from the high frequency subbands were used as the input features of the LVQ neural network solely and jointly. The network outputs were class labels, which were defined with five integer numbers, from 1 to 5, denoting five different uniformity grades. The number of neurons in hidden layer, training epochs and goal, of the LVQ neural network were as 5, 200 and 0.01 respectively. They used the identification accuracy of each grade and average identification accuracy (AIA%) of five grades as performance parameters. Their results were expressed and compared five wavelet bases (db_2, db_4, db_6, db_8, and db_{10}) and even different features (L^1, L^2, and L^1UL^2) at the four levels (level 1 to 4). They noted three points as Firstly, with the same feature set and decomposition level, the length of the filter had little effect in performance in all methods. Secondly, with the same feature set and wavelet base, the decomposition level had a significant effect in the performance in all methods. Thirdly, the highest identification accuracy was gotten at the crossing point db_4 or db_6 and level 3 (Liu et al., 2010).

Liu et al., 2010 presented a method to recognize the visual quality of nonwoven by combining wavelet texture analysis, Bayesian neural network and outlier detection. Each nonwoven image was decomposed with orthogonal wavelet bases at four levels and two textural features, norm-1 and norm-2, which were used as the input of Bayesian neural network for training and test. To detect the outlier in the training set, the scaled outlier probability was introduced to increase its robustness. All nonwoven samples were classified into five grades according to visual qualities (such as surface uniformity, the condition of pilling, wrinkles and defects). Each image was individually normalized to zero mean and

unit variance before wavelet transform. They reported with the increase of decomposition level, the average classification error and cross entropy of training and test set decreased sharply and the recognition accuracy of the five grades was also affected (Liu et al., 2010).

2.5 Cloth defects

Quality inspection of garments is an important aspect of clothing manufacturing. For many textile products, a major quality control requirement is judging seam quality visually by human experts. Presently, this is still accomplished by human experts, which is very time consuming and suffers from variability due to human subjectivity. Consequently, investigations about automated seam quality classification and an implementation of an automated seam classificator are highly desirable. Bahlmann et al., 1999 presented a method for automated quality control of textile seams by a scale of five grades (from grade 5 which was best to grade 1 which was worst). Their system was consisting of an image acquisition setup (to record seams structures), an algorithm for locating the seam (transforming acquired seam images to normalize position), a feature extraction stage (based on fourier coefficients of one dimensional image columns) and a neural network of the self organizing map type (SOFM) for feature classification. The classification results were documented by three aspects including the classification confusion matrix, the inspection of the NMSE (normalized mean square error), and an investigation of the resulting Kohonen map. The classification rate amounted to 80% correct classifications, the rest differed from the correct grade by one and their results were not worse than the human exports error (Bahlmann et al., 1999).

Because of the special property of the knitted fabric which is very easy to be pleated, puckered or distorted in stitching, automatic inspection of stitching is necessary. Yuen et al., 2009 proposed a hybrid model (integration of genetic algorithm and neural network) to classify garment defects. Firstly, to process the garment sample images captured by digital camera, they used a morphological filter and a method based on genetic algorithms to find out an optimal structuring element. They also presented a segmented window technique to segment images into pixel blocks under three classes using monochrome single-loop ribwork of knitted garments caused by stitching (seams without swing defects, seams with pleated defects and seams with puckering defects). Four characteristic variables (size of the seams and defective regions, average intensity value, standard deviation and entropy value) were collected to describe the segmented regions and input into back propagation neural network to provide decision support in defect classification. The number of the nodes was set as 10 by many experiments. The training function of the neural network was a gradient-descending method based on momentum and an adaptive learning rate. The learning function of connection weights and threshold values was a momentum-learning method based on gradient descending. Twenty two images of each class were used as training samples and the other ten images were testing samples. They did not report any misclassified sample and the identification rate was 100% (Yuen et al., 2009).

3. Yarn and fabric properties prediction and modeling

The main objective of many scientific studies in textile is to reveal the complex functional relationships that exist between structural parameters of fiber, yarn and fabric properties. If the relationships between different parameters that determine the specific yarn or fabric property are known, they can be used to optimize that particular property for different end-use applications so as to minimize the cost. Predictive modeling methodologies, which are

complex and inherently nonlinear, can be used to identify the different levels of combinations of process parameters and material variables that yield the desired fabric property. Since the network can accurately capture the nonlinear relationships between input and output parameters, they have extremely good predictive power (Behera & Muttagi, 2005). The use of an artificial neural network model as an analytical tool may facilitate material specification/selection and improved processing parameters governed by the predicted outcomes of the model (Khan et al., 2002).

An ANN model adjusts itself to establish the relation between the input and the output. In spite to this, an ANN model does not require any explicit formula but instead it is an implicit model by itself where it can be trained to adopt and adjust itself to perform certain tasks (Nirmal, 2010).

3.1 Mechanical behavior prediction of textiles

Breaking elongation properties of yarns influence the performance of them during winding, warping, and weaving. Yarn elongation like other yarn properties is chiefly influenced by fiber properties, yarn twist, and yarn count. Because there is a strong correlation between yarn elongation and loom efficiency, it would be very helpful if a prediction model could forecast yarn elongation accurately (Majumdar & Majumdar, 2002). Furthermore, breaking strength of yarn is the one of the most important physical property of yarn as it is the main parameter for physical quality control. It takes a long time for the yarn producer to get the experimental results for the physical properties of yarn. Therefore, faster determination of yarn physical properties is needed (Dayik, 2009). Generally, modeling and prediction of yarn properties based on fiber properties and process parameters have been considered by many researchers such as mechanistic models, statistical regression models (Gharehaghaji et al., 2007). In recent years, artificial neural network models have been widely used to predict different kind of yarn and fabric mechanical properties based on process parameters and fiber and yarn parameters. Among the various kinds of learning algorithms for the neural network, back propagation is the most widely used.

Majumdar & Majumdar, 2004 predicted the breaking elongation of ring cotton yarns by three modeling methodologies including mathematical, statistical and artificial network by back propagation learning algorithm. 72 and 15 samples, respectively, were used for training and testing the three prediction models. They tried five different network structures with one hidden layer by different number of neurons (6, 8, 10, 12, and 14) in the hidden layer. Learning rate and momentum were optimized at 0.1 and 0.0, respectively. The neural network with ten nodes in the hidden layer had the best prediction results in the testing sets after 2500 iterations. Inputs to these models were constituent cotton fiber properties (fiber bundle tenacity, elongation, upper half mean length, uniformity index, micronaire, reflectance degree, and yellowness) measured by high-volume instruments (HVI) along with yarn count (Ne). They used statistical parameters such as the correlation coefficient (R) between the actual and predicted breaking elongation, mean squared error, mean absolute error (%), cases with more than 10% error, maximum error (%), and minimum error (%) to judge the predictive power of various models and concluded that neural network model had showed the best prediction results. The correlation coefficient between actual and predicted elongation was R=0.938 for the ANN model, R=0.731 for the mathematical model and R=0.870 for the statistical model. Percent of maximum error was also reported for ANN, mathematical and statistical models which were 13.23%, 34.04%, and 15.60% respectively. The only output of each prediction model was the breaking elongation

of yarns. They also measured the relative importance of various cotton fiber properties using neural network model (Majumdar & Majumdar, 2004).

Behera & Muttagi, 2005 compared the ability of three modeling methodologies based on mathematical, empirical and artificial neural network based on radial basis function (RBF) (using orthogonal least square learning procedure) to predict fabric properties. The inputs to the network were fabric constructional parameter, yarn bending rigidities and outputs were fabric initial tensile moduli. Before feeding to network, the input-output data set was scaled down to be within (0, 1), by dividing each value by the maximum value of the overall data. Data were randomly divided into 14 sets and 4 sets of input-output pairs for training and testing the network respectively. They also studied the effect of network design parameters on error of prediction. The effects of neurons number of the hidden layer, error goal, and bias constant on prediction performance of RBF network were assessed. They observed that ANN model produced the lease error as well as minimum range of error as compared to the other modeling methods and ANN required a much smaller data set than the one required for conventional regression analysis. For example, percentage prediction error for warp and weft way fabric tensile modulus were respectively 10.2% and 8.63% for ANN, 20.4% and 12.33% for empirical model and 20.53% and 13.65% for mathematical model. They also predicted bending rigidity of woven fabric by these three models and ANN had a better and accurate result than those two models (Behera & Muttagi, 2005).

Gharehaghaji et al., 2007 investigated tensile properties modeling of cotton-covered nylon core yarns by artificial neural networks based on back propagation algorithm and multiple linear regression methods which the first method had better performance than the second. They predicted breaking strength and breaking elongation simultaneously as output and by using count of core part, count of sheath part, twist factor of core-spun yarn and pretension as input. In order to eliminate the effect units of input and output parameters, data normalizing was carried out. The data set of 54 samples was divided randomly into 5 subsets, each containing 10 or 11 samples, to train and test the network five times by using four sets as training set and one subset as testing set. Overfitting was prevented by using weight decay technique. The adaptive learning rate with momentum training algorithm (optimized at 0.9) was used to enhance the training performance. They determined the number of hidden neurons and the number of hidden layers by trial and error by using 20 topologies with different number of hidden layers and numbers. Their results showed a two hidden layers by eight nodes into first hidden layer and six nodes into second hidden layer gave the best topology. They assessed their models using verifying mean square error (MSE) and correlation coefficient (R-value). The difference between the MSE value of two models for predicting breaking elongation and breaking strength of testing data were 0.119 and 0.365 respectively (Gharehaghaji et al., 2007).

Dayik, 2009 determined the breaking strength of 100% cotton yarn properties by using Gene expression programming, neural network and classical statistical approach (multiple regression algorithms) and compared the predictive power of them by correlation coefficient (R-square) and mean square error (MSE). The inputs were included foreign matter, micronaire, uniformity, elongation, strength of fiber, length of fiber, short fiber index and neps which were collected for a three month period data. He used seven different neural network architectures which were including multilayer perception, Generalized feed forward, Modular network, Jordan/Elman, Self organizing map, Principal component and Recurrent network to identify the best one. However the best results were obtained from the generalized feed forward neural network algorithms. He examined the predictive power by

multiple linear regression analysis. The statistical method showed very much worse performance than genetic and neural network since physical properties of yarn depends on many various factors and the relations between these factors are highly nonlinear and complex. Performance of genetic model (98.88%) was better than artificial neural network (94.00%) in his research (Dayik, 2009).

The effects of splicing parameters, fiber and yarn properties on the tenacity and elongation of spliced yarns were investigated by Unal et al., 2010 using artificial neural network (ANN) and response surface model (RSM). In the ANN analysis, a multilayer feed-forward network with one hidden layer trained by back propagation algorithm was used. In the first phase, the back propagation algorithm was applied for 100 epochs. The optimum learning rate of 0.01 and momentum coefficient of 0.3 used in back propagation was determined in terms of several trials. In the second phase of training, 500 epochs were performed for conjugate gradient descent algorithm. As activation functions, a hyperbolic function was used in the hidden layer and linear functions were used in the input and output layers. Of the 89 yarn samples, 76 samples were chosen as the training set at random, while 22 samples (25%) were chosen for the testing set.

They produced yarns from eight different cotton types, having three different counts and three different twist coefficients. Six parameters including fiber length, fiber diameter, yarn count, yarn twist, opening air pressure and splicing air pressure in the input layer were selected and a neural network with seven hidden neurons for yarn tenacity analysis and another neural network with six parameters including fiber length, short fiber content, yarn count, yarn twist, opening air pressure and splicing air pressure in the input layer and six hidden neurons for breaking elongation were determined as well. The results of the ANN analysis were similar to the results of RSM except for the effect of splicing air pressure and ANN showed more powerful results in comparison RSM model since it is more capable of explaining non-linear relations (Unal et al., 2010).

ANN appears to be a reliable and useful tool in characterizing the effect of some critical manufacturing parameters on the seam strength of webbing, if a sufficient number of replicated experimental data are available to train the ANN. Onal et al., 2009 studied the effect of fabric width, folding length of joint, seam design and seam type on seam strength of notched webbings for the parachute assemblies using both Taguchi's design of experiment (TDOE) and an artificial neural network (ANN) and then compared them with strength physically obtained from mechanical tests on notched webbing specimens. They used a four layer, feed forward, back propagation ANN model with a five hidden layer neurons and one output neuron to output seam strength. Input variables were fabric width, folding length of joint, seam design and seam type. 60 training patterns and 10 testing patterns were used to train and test the network. It was established from these comparisons, in which the root mean square error was used as an accuracy measure, that the predictions by ANN were better in accuracy than those predicted by TDOE (Onal et al., 2009).

Hadizadeh et al., 2009 presented an ANN model for predicting initial load-extension behavior of plain weave and plain weave derivative fabrics. They developed a single hidden layer feed forward ANN based on a back propagation algorithm with four input neurons (using a combination of parameters of Leaf's equation instead of individual parameters) and one output neuron to predict initial modulus in both warp and weft directions. In their research, the input and measured values were normalized so that they would have zero mean and unity standard deviation and they used Levenberg-Marquardt learning algorithm. Five different cases of ANN with different number of neurons in hidden layer

and different data were considered to train and test the network. The number of neurons in the hidden layer was experimentally verified on the basis of the performance factor. In case one, 18 Leaf and Kandil's data were inputted to the network. In case two, the ANN was consist of 31 samples of plain weave experimental values of produced fabrics. They used their data in conjunction Leaf's data in case three. In case four, their fabric samples of plain weave and plain weave derivatives were considered while in case five, Leaf's data in addition to their data were applied to network. The model's suitability was confirmed by the low performance factor (PF/3) and the high coefficient of correlation. Their proposed ANN model was suitable for the prediction load-extension behavior of plain weave and plain weave derivatives of fabrics (Hadizadeh et al., 2009).

Shear stiffness is one of the important properties of worsted fabrics which depends on yarn properties and fabric parameters. As a nonlinear problem, predicting the shear stiffness can be realized by an alternative modeling method, that is, by using the artificial neural network (ANN) model. Chen et al., 2009 modeled the relationship between yarn properties, fabric parameters, and shear stiffness of worsted fabrics using two stage neural network models. First, the yarn properties and fabric parameters were selected by utilizing an input variable selection method to find the most relevant yarn properties and fabric parameters as the input variables to fit the small-scale artificial neural network model. The first stage was consisting two parts. The first part took the human knowledge on the shear stiffness into account (VAk) and the second part was a data sensitivity criterion based on a distance method (Sk). Second, the artificial neural network model of the relationship between yarn properties, fabric parameters, and shear stiffness of fabrics was established.

They used a feed forward ANN by six yarn properties and fabric parameters (warp cover factor, warp twist factor, weft twist factor, warp linear density, weft linear density, and fiber specific surface area) as inputs, one hidden layer with four neurons, and shear stiffness of fabrics as output trained with the help of the error back propagation algorithm. In order to avoid overfitting, the Bayesian framework were used in the training procedure. 39 data points and 1 data point were used for training and testing set respectively. They used the primitive variables to rank data, not their transformations as those in the PCA. Hence, the variables had clear physical meanings. Their results showed accurate prediction (up to average error of 0.209%) by the small-scale artificial neural network model and a reasonably good artificial neural network model could be achieved with relatively few data points by integrating with the input variable selecting method developed in their research (Chen et al., 2009).

Needle punching is a well-known nonwoven process of converting fibrous webs into self-locking or coherent structures using barbed needles. The barbed needles pull the fibers from the surface of web and reorientate them in the thickness direction leading to a complex three-dimensional (3D) structure. The nonwoven structural depends on different parameters. Rawal et al., 2009 predict the bulk density and tensile properties of needle punched nonwoven structures from main process parameters including web area density, depth of needle penetration, and punch density by Artificial Neural Network (ANN) modeling technique (back propagation learning algorithm). Two different ANN models were developed, one for predicting fabric bulk density and another for predicting the tensile strength in the machine and cross machine directions. Only one hidden layer with 8 nodes was used and transfer function in the hidden and output layers was log-sigmoid. Learning rate and momentum was optimized at 0.6 and 0.8 respectively. Web area density, punch density, and depth of needle penetration were considered as inputs. Training was stopped when the error in the unseen or testing data sets approached at the minimum level. 21 data

sets were randomly chosen for the training of ANN and 6 sets were used for the testing purpose. The simultaneous effect of more than one parameter on bulk density and tensile properties of needle punched nonwoven structures have been investigated based upon the results of trained ANN models. A comparison was also made between the experimental and predicted values of fabric bulk density and tensile strength in the machine and cross machine directions in unseen or test data sets. It has been inferred that the ANN models had achieved good level of generalization that is further ascertained by the acceptable level of mean absolute error obtained between predicted and experimental results (Rawal et al., 2009).

3.2 Prediction of the other textile properties

The material properties of engineering fabrics that are used to manufacture airbag can not be modeled easily by the available nonlinear elastic-plastic shell elements. A nonlinear membrane element that incorporates an elaborate tissue material model has been widely used by the auto industry for the airbag simulation studies, this model is highly computation intensive and does not differentiate between the various physical properties of the fabrics like fiber denier, the polymer fiber, and weave pattern. Keshavaraj et al., 1996 introduced a feed forward neural network to determine permeability and biaxial stress-strain relationships for nylon and polyester fabrics used in airbags. The network used for permeability prediction was a three input nodes (281, 323, and 373 K temperature levels), four hidden nodes and one output node. The predictions provided by the neural network model were better for the polyester fabrics than they were for the nylon fabrics. The effects of the type of fabrics, i.e., denier and weave type, with nylons and calendering in case of polyester, biaxial strain, biaxial stress, and pressure drop while predicting biaxial stress of fabric under a biaxial deformation were considered in their model. The model prediction was within a ±3 MPa error limit which was agreed very well with the experimental data (Keshavaraj et al., 1996).

Classical pressure drop models set up for porous media do not accurately model pressure drops through fabric structures but they give information about the location of flow through fabric structures and about the specific characteristics of cloths which may influence pressure drop values. A neural network (NN) approach is then carried out in order to model experimental data by taking into account specific characteristics of cloths as input neurons, and to analyze the relative importance of each input variable on pressure drops. Brasquet & Cloirec., 2000 studied pressure drops through several textile fabrics using classical models (Ergun's equation, Carmen's dimensionless approach, and Comiti-Renaud's model), statistical tool, and neural network. The models were tested by three different definitions for the specific surface area, on the fabric, yarn, and opening scale, respectively. Different kinds of cloth were used, in terms of fiber type such as activated carbon fibers and their precursors, rayon fibers. In the first part, they measured air and water pressure drops induced by these different cloths as a function of fluid velocity experimentally and secondly, using classical models set up for particular media in order to locate the flow and then a statistical approach by neural network were considered. They chose input neurons in a multilayer perceptron network (fluid properties-μ, ρ, Re- and fabric characteristics – thickness, density, number of openings and raw material) in order to predict pressure drop values as the output neuron. The number of hidden neurons was statistically optimized as four with hyperbolic tangent function as transfer function. Network training set was carried out with 400 data and a validation set of 183 data was also performed. 200 data was used to

test the generalization ability of the trained neural network. They calculated absolute averaged relative errors (AARE) to assess the performance of their network (Brasquet & Cloirec., 2000).

The work 'bagging' is essentially a perception by people of the three dimensional shape of a bagged garment. Subjective judgments of the degree of garment bagging vary with different people and also depend on garment types. Garment bagging is a kind of three-dimensional residual deformation during wear, which can be characterized by a few parameters such as bagging height, volume, shape, and fabric surface pattern. Yeung et al., 2002 developed a method to evaluate garment bagging by image processing with three different modeling including multiple regression, liner modeling and neural network. These models were able to provide predictive powers of R² value of 0.92, 0.93, and 0.94 respectively. Firstly, they evaluated fabric bagging by capturing digitized images of bagged fabrics, image processing of the capture images, and recognizing bagging magnitude from these criteria. They used the eight criteria as input variables to predict subjective perceptions of bagging, employing a two-layer feed forward neural network with back propagation learning algorithm. The hidden layer included thirteen neurons with tan-sigmoid transfer functions to learn nonlinear and linear relationships between input and output. Ten samples and six samples were used to train and test the network respectively. The ability of network to predict bagging was reported R²=0.94 (Yeung et al., 2002).

Tokarska, 2004 presented modeling of woven fabric permeability (dynamic air permeability) features by means of neural network (multilayer perceptron). His analysis of the flow properties was based on observations of their behavior during impact air flow. He used apparent density, warp twist, and weft twist for the input layer, while the output layer was the integral of the function *p(t)*, that is the actual pressure impulse generated on a fabric under impact air flow conditions, using a back propagation method to teach the network. He obtained the quality of his neural model by means of an index ρ, which is given the standard deviation of errors for the output variables divided to the standard deviation of the target output variable (Tokarska, 2004).

Fabric hand is commonly used for assessing fabric quality and prospective performance in a particular end use. Subjective assessments treat fabric hand as a psychological reaction obtained from the sense of touch, based on the experience and sensitivity of humans. Prediction of these psychological perceptions of hand based on fabric properties is very difficult. Hui et al., 2004 predicted sensory hand based on fabric properties using a resilient back propagation multilayer feed forward neural network. Twelve fabric properties were fed into the input layer then they propagated forward through two hidden layers and then fourteen biopolar pairs of sensory fabric hand attributes arrived at the output layer. The output was normalized since the log sigmoid activation functions were used on each layer. Mean square error (MSE) was set to 1e-8 and to avoid network over fitting, they used Larsen's early stopping methodology to reduce the generalization error of the network. Correlation between output and target values were reported greater than 0.9 (Hui et al., 2004).

There are numerous factors which broadly classified into yarn quality, condition of warp preparation, and loom actions and conditions which can affect the performance of warp yarns in weaving. The weaving performance of a yarn is generally expressed in terms of warp breakage rate in weaving. Yao et al., 2005 investigated the predictability of the wrap breakage rate from a sizing yarn quality index using a feed forward back propagation network. They rated an eight quality index including size add-on, abrasion resistance, abrasion resistance irregularity, hairiness beyond 3 mm, breaking strength, breaking

strength irregularity, breaking elongation and breaking elongation irregularity as input layer and warp breakage rates as output layer in controlled conditions. Hidden layer with 1, 4, and 8 neurons were tested. The learning method was back propagation with momentum, and single step learning with a sequential presentation sequence was selected as learning strategy. They suggested a model with a single sigmoid hidden layer with four neurons to produce better predictions than the other models and prepared sixty records for training and ten records for testing the network. The stop condition had been mean absolute error (MAE= 0.148), mean square error (MSE= 0.0364), root mean square error (RMSE= 0.191), and mean absolute percentage error (MAPE= 5.58) and correlation was reported R= 99.5%. (Yao et al., 2005).

Comfort is one of the most important attributes of textiles used in clothing. Clothing comfort is influenced by different fabric, environment and human factors. Thermal properties of clothing are one of the most important aspects of clothing comfort in which analyzing the relationship between various fabric parameters and comfort properties are essential. Bhattacharjee & Kothari, 2007 reported a study on the predictability of the steady-state and transient thermal properties of fabrics (thermal resistance and maximum instantaneous heat transfer) using a feed forward, back propagation artificial neural network system. They made a comparison with two different network architectures, one with two sequential networks working in tandem fed with a common input and another with a single network that gave two outputs and the first one (mean error percentage of 8.61%) gave better results than the second one (mean error percentage of 10.42%). First model was able to predict the steady-state and transient thermal behavior with a good coefficient of determination (R^2= 0.94) as compared with the second model (R^2= 0.69). A three layered network with two hidden layers was used in both of the cases. The input parameters including type of weave warp and weft count, thread density, thickness and areal density were considered. A sigmoid transfer function 'tansig' was used for input and hidden layers and a linear function was used for the output layer. The training function used was a quasi-Newton algorithm based on the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update and regularization was carried out to avoid over fitting (Bhattacharjee & Kothari, 2007).

Capillary rise in porous media is a frequently occurring phenomenon which occurs in dyeing of textile fabrics, and a variety of other fields. An artificial neural network was employed by Ahadian et al., 2007 to predict the time of capillary rise for a known given height. Their network's inputs were density, surface tension, and viscosity for the liquids and particle size, bulk density, packing density, and surface free energy for the powders. The output layer of the network corresponded to the time of capillary rise in order to reach a given height (i.e. 0.036 m). A training set (136 times of capillary rise) and a testing set (18 times of capillary rise) was chosen for the network. Networks were trained using the Levenberg- Marquardt back propagation algorithm. A linear activation function was used in output layer of the networks. All the input and output data were normalized to the interval [-1 to 1] before training and testing. Two statistical parameters namely the product moment correlation coefficient (r^2) and the performance factor (PF/3) were used to correlate the actual experimentally obtained times of capillary rise. The results showed that their artificial neural network was able to predict the time of capillary rise (i.e. r^2 = 0.91, PF/3=55). In comparison, the Lucas-Washburn's calculations gave the worst correlations (r^2 = 0.11, PF/3 = 1016) (Ahadian et al., 2007).

Furthermore, thermodynamic and transport properties of liquids are fundamental in processes involving liquid flow and heat and mass transfer. Two most important of these

properties are surface tension and viscosity which are modeled using two artificial neural networks (ANNs) by Ahadian et al., 2008. The surface tension predictor network had six inputs, namely: particle size, bulk density, packing density and surface free energy of the powders as well as the density of the probe liquids together with the capillary rise time of the liquids in the corresponding powders. The viscosity predictor network had surface tension as an extra input. The results of the present work clearly showed that the artificial neural network approach is able to predict the surface tension (i.e. r2 = 0.95, PF/3 = 16) and viscosity (i.e. r2 = 0.998 , PF/3 = 13) of the probe liquids with unsurpassed accuracy (Ahadian et al., 2008).

There is a need for a reliable forecasting system which can quantitatively predict the hairiness of a resultant yarn from its processing parameters prior to yarn formation. The development of such a system is potentially challenging owing to the complex nature of the worsted spinning pipeline, where wool fibers undergo a series of different processes before being converted into a yarn. Khan et al., 2009 evaluated the performance of multilayer perceptron (MLP) and multivariate linear regression (MLR) models for predicting the hairiness of worsted-spun wool yarns from various top, yarns and processing parameters. Their results indicated that MLP model predicted yarn hairiness more accurately than the MLR model. They used some factors including yarn twist, ring size, average fiber length, fiber diameter and yarn count on the basis of sensitivity analysis as inputs. Five different random partitions of the database into training and validation sets were generated. For each partition, both models were independently trained using the training set and their responses to the validation set assessed. Both MLR and MLP models were capable of achieving a good fit to the measured hairiness values, as evidenced by the high mean R2 values of 0.910 and 0.949, respectively. This study also demonstrated that the hairiness of a yarn could be predicted to a high precision from limited top, yarn and processing parameters, and that the ANN-based yarn hairiness prediction model had the potential for wide mill specific applications (Khan et al., 2009).

One of the most important properties of clothes is their ability to help the body's thermal system to keep the body temperature in its natural range, even if the environmental conditions or physical activities are outside the body's ideal range. Perspiring is one of the most important effects of physical activities in warm weather for shedding the body's excessive heat. Therefore, the basic requirement of a fabric worn next to the skin is to transfer this moisture to the atmosphere to reach comfort through the avoidance of a feeling of wetness and clamminess and also through the generation of a situation for the best surface evaporation of moisture. Mokhtari Yazi et al., 2009 evaluated the transmission of heat and moisture by differential modeling as an artificial neural network a double-surface knitted fabric containing hydrophilic and hydrophobic fibers. Input data was made from temperature and moisture values for the bottom and top surfaces of the fabric; the number depended on the time of each experiment and was different for each sample. The connections of network nodes corresponded to the partial differential equation of propagation as forward time-centered spaces (three advanced Euler methods). The results were analyzed to find a suitable fabric with optimum comfort. The final results showed that a fabric made of micro polyester filaments and cotton yarns on the bottom and top surfaces, respectively, had the best heat and moisture transfer (Mokhtari Yazi et al., 2009).

Giri Dev et al., 2009 modeled and predicted water retention capacities of the membranes under different hydrolyzing conditions using empirical as well as artificial neural network (ANN model) by alkali concentration, temperature and time as inputs. Both statistical model

and ANN model had showed a very good relationship (R^2) between the experimental and predicted response values and both models had an error percentage less than 2% indicating the reliability of the model developed (Giri Dev et al., 2009).

Needle punching is a well-known nonwoven process of converting fibrous webs into self-locking or coherent structures using barbed needles. Rawal et al., 2009 predict the bulk density and tensile properties of needle punched nonwoven structures from main process parameters including web area density, depth of needle penetration, and punch density by Artificial Neural Network (ANN) modeling technique (back propagation learning algorithm). Two different ANN models were developed, one for predicting fabric bulk density and another for predicting the tensile strength in the machine and cross machine directions. The number of nodes in the hidden layer and learning parameters, i.e., learning rate and momentum was optimized at 8, 0.6, and 0.8, respectively. Training was ceased when the error in the unseen or testing data sets approached at the minimum level. Out of 27 available data sets, 21 sets were randomly chosen for the training of ANN and remaining six sets were used for the testing purpose. The simultaneous effect of more than one parameter on bulk density and tensile properties of needle punched nonwoven structures have been investigated based upon the results of trained ANN models. A comparison was also made between the experimental and predicted values of fabric bulk density (R= 0.907) and tensile strength in the machine (R= 0.986) and cross machine directions (R= 0.982) in unseen or test data sets. It has been inferred that the ANN models had achieved good level of generalization that is further ascertained by the acceptable level of mean absolute error obtained between predicted and experimental results (Rawal et al., 2009).

Bio-composite materials are gaining high popularity due to its various advantages such as renewable, biodegradable, low in cost, light weight, low density, widely available and possess high specific mechanical properties. Nirmal, 2010 predict frictional performance of treated betelnut fiber reinforced polyester (T-BFRP) composite using artificial neural network configuration. To predict the friction coefficient of the T-BFRP composite, the ANN model was subjected to three different input parameters; normal loads (5–30 N), sliding distances (0–6.72 km) and fiber orientations (anti-parallel, parallel and normal orientations). Prior to inputting the data to the ANN network, data coding was performed to the input parameters. Network had a two hidden layer with 10 neurons in the first hidden layer followed by 20 neurons in the second hidden layer. The learning process of a developed ANN model was based on a gradient search with least preferred sum squared errors between the predicted and the actual values. He considered the trial and error ANN model based on method where various neuron configuration, layer configuration and transfer function configuration. Results obtained from the developed ANN model were compared with experimental results. It was found that the experimental and numerical results showed good accuracy when the developed ANN model was trained with Levenberg– Marqurdt training function (Nirmal, 2010).

4. Process behaviour prediction

Yarn properties and spinning performance are influenced by fiber properties (mean fiber diameter, mean fiber length, diameter distribution, fiber strength, and etc), yarn specifications (linear density, twist level), and operational parameters (ring size, traveler weight, spinning speed). Because there are many independent variables, it becomes difficult to cover the entire range of parameters in order to interpolate and extrapolate experimental

observations or mill measurements and take into account the interactive contribution of each independent variable. Unlike conventional techniques, which are often limited by strict assumptions of normality, linearity, and variable independence, ANN's are universal approximators, which, by possessing the capacity to learn directly from the data being modeled, are able to find associations or discover regularities within a set of patterns, where the volume or variation within the data is large or the relationships between variables are dynamic and nonlinear. For a given fiber spun to pre-determined yarn specifications, the spinning performance of the yarn usually varies from mill to mill. For this reason, it is necessary to develop an empirical model that can encompass all known processing variables that exist in different spinning mills, and then generalize this information and be able to accurately predict yarn quality for an individual mill (Beltran et al., 2004).

The degree of spinnability of a fiber is very difficult to assess with the current range of instruments available. Pynckels et al., 1995 described an experiment of 29 fiber properties of twenty types of cotton to predict spinnability of fibers. A yarn was considered to be unspinnable if there were more than five breakages during the first three minutes of spinning. They trained a neural network with 700 spinnable and 700 unspinnable yarns data to predict the spinnability from fiber properties and process parameters. In the test data set, 90% of spinnable fibers and 95% of the unspinnable fibers was classified correctly (Pynckels et al., 1995).

Beltran et al., 2004 reported a method for predicating worsted spinning performance with an artificial neural network trained with back propagation learning rule. The applicability of ANN for predicting spinning performance was first evaluated against a well established prediction and benchmarking tool. The ANN was then subsequently trained with commercial mill data to assess the feasibility of the method as a mill specific performance prediction tool. Incorporating mill specific data resulted in an improved fit to the commercial mill data set. Top properties, yarn specifications, and processing information were designated as the input vectors for the input layer. They found that as the number of mill-specific data sets increased, further improvements in prediction accuracy would arise (Beltran et al., 2004).

Mean fiber diameter, diameter distribution, hauteur, fiber length distribution, fiber bundle tenacity, curvature, short fiber content, yarn count, twist, draft, spinning speed, ring size, and traveler weight served as inputs to the neural network and the number of fibers in a cross section, unevenness CV%, unevenness U%, thin places per kilometer, neps per kilometer, yarn tenacity, elongation at break, breaking force, end-down per 1000 spindle hours, index of irregularity, thick places per kilometer, and hairiness served as the target spinning performance outputs. A total of 250 sets of training data were randomly generated. The first 180 data sets were used for network training, 20 data sets were set aside for cross-validation, and the last 50 data sets were used to evaluate the trained network's performance. The input data were normalized so those were bounded within the prescribed range of 1 and 0. They tested different numbers of neurons in hidden layer and indicated that a reduction in the training error occurred as the number of hidden nodes increased. To overcome the likelihood of over-fitting from excessive training, they invoked the cross-validation stop criteria. They observed that the cross validation mean squared error exponentially fell to $6.0 * 10^{-3}$ over 800 training epochs. Therefore 800 epochs represented the point where sufficient training had occurred prior to over fitting of the specific solutions within the training set. By incorporating mill-specific data results in an improved fit to the

commercial mill data set, suggesting that their proposed method had the ability to predict the spinning performance of a specific mill accurately (Beltran et al., 2004).

Melt spinning is the most economically useful method for producing artificial fibers in the industry. In melt spinning, as-spun fibers are evaluated according to yarn count and tensile strength, and the draw ratio is the major factor affecting the quality of as-spun fibers. The neural network computation can be divided into two parts: pre-teaching computation and reversing the adjusted weight value. Kuo et al., 2004 considered the extruder screw speed, gear pump gear speed, and winder winding speed of a melt spinning system as the inputs and the tensile strength and yarn count of as-spun fibers as the outputs for neural network by the delta learning rule. The data from experiments were used as learning information for the neural network to establish a reliable prediction model. They had adopted a three layer neural network consisting of a three neuron input layer, a twelve neuron hidden layer, and a two neuron output layer; focusing on the tensile strength and yarn count of as-spun fibers. They applied the delta learning rule to the neural network, with a sigmoid transfer function. The neural network prediction model was verified by ten entries of new data. In tensile strength prediction, the error of the neural network was ±2%. When compared with one standard difference of the experiment, 96.86% of the predictive values lied within ±1 σ=3.1419%. In yarn count prediction, the error of the neural network was ±2%. When compared with one standard difference of the experiment, 97.96% of the predictive values lied within ±1 σ=2.0418%. Their neural network model could predict the tensile strength and yarn count of as-spun fibers to provide a very good and reliable reference for as-spun fiber processing (Kuo et al., 2004).

Meltblowing has become an important industrial technique because of its ability to produce fabrics of microfiber structure, which are ideally suited for filtration media, thermal insulators, battery separators, and oil sorbents. In this process, the fiber forming mechanism is very complicated and the quality of the produced web depends on many processing variables such as die temperature, air temperatures, air flow rate, extruder temperature, die to collector distance, polymer throughput rate, resin melt flow rate, die geometry parameters and etc. therefore meltblowing is a highly complex, multivariable, and nonlinear process, leading to the extreme difficulty in theoretically modeling the process. However, process modeling is essential for the control of optimization and an on-line prediction is very useful for process monitoring and quality control. Melt blown process is of highly dimensional and nonlinear complexity. Sun et al., 1996 investigated back-propagation neural networks (BPNNs) for modeling the melt blown process and on-line predicting the product specifications such as fiber diameter and web thickness. By comparison of several network topology structures (6-3-1, 6-4-1, 6-5-1, 6-6-1, 6-4-3-1, etc) and different transfer functions (sigmoid, quadratic), the network 6-4-1 (i.e. six nodes in the input layer, four nodes in the hidden layer and two nodes in the output layer) was chosen using a sigmoid function as its transfer function. The network inputs were included extruder temperature, die temperature, melt flow rate, air temperature at die, air pressure at die, and die-to collector distance (DCD) and they were normalized. The output of the fiber diameter was obtained by neural computing. The network training was based on 160 sets of the training samples and the trained network was tested with 70 sets of test samples which were different from the training data. The test results showed a good agreement to the actual measurements. The maximum absolute error between the predicted fiber diameter and the actual values was less than 1.5 μm. By using the tested neural network, they also predicted the effect of process variables on the fiber diameter. The most valuable result of their

research was development of a technique which had been proved to be suitable for modeling and on-line preidicting of the meltblowing process in order to optimal control of the process and of practical significance to advanced meltblown processes (Sun et al., 1996).

5. Color coordinates conversion, color separation and categorization, color matching recipe prediction

One of the most important textile characteristics is undoubtedly color (Thevenet et al., 2002). Color quality control is one very important step in any textiles, however excellent the fabric material itself is, if it lacks good color, then it may still result in dull sale (Kuo et al., 2007). Many transformations affect the color of textile materials. Nevertheless, they can be divided into two groups. The first group concerns dyeing and printing stages, and is mainly governed by chemical rules, because the color attributes, which are added to the textile structure, are chemically fixed to the product (Thevenet et al., 2002). Expected depth of shade, color, color fastnesses and surface characteristics etc. are very important qualities which are necessary to be achieved in the dyed goods. If, these properties are different from that of the expected standard, the product has to either been reprocessed or discarded (Balci et al., 2008). Color separation is most important item in pattern printing process so as to secure integrity of printed fabrics product (Kuo et al., 2007). Furthermore, in textile printing it is very difficult to control all the process parameters; therefore using artificial neural networks for recipe calculation (concentration of each dye in the printing paste) have been investigated which enable the relationship between reflectance values and concentrations to be mapped.

Once the selected neural network is sufficiently trained with a set of known input (colour values) and output data (concentrations of each dye), it will predict the concentrations for an unknown set of coloured samples. One of the advantages of neural networks is their capability to establish relations between input and output data without explicit programming of Kubelka-Munk equations or analytical knowledge into the model (Golob et al., 2008).

The second group concerns blending and the transformations of structure of roving (assembly of fibers), which is spun and then woven or knitted. In this case, the color transformation is not governed by chemical rules, because during blending or spinning, no chemical compounds are added. So this group is rather physically governed, because color alterations are just produced by a different fibers organization. The aim of the model is to predict the color obtained when fibers, with different colors, are blended. When the blend is homogenous, the color obtained can be predicted very well by theoretical and empirical models (Thevenet et al., 2002).

Thevenet et al., 2002 described a model based on neural networks to predict color alteration after spinning process (roving to yarn). Their network was a multilayer feed-forward network. The first system using to predict the entire reflectance spectra was wavelength dependent, but its performance is not very satisfactory. The scaled conjugate gradient algorithm was incorporated into the back propagation procedure to reduce the training phase. Once the wavelength independence of the transformation was established, a second system, whose performances agree with the experimental curves, was proposed (Thevenet et al., 2002).

Kuo et al., 2007 proposed a printed fabrics computerized color separation system based on backward-propagation neural network, whose primary function was to separate rich color

of printed fabrics pattern so as to reduce time-consuming manual color separation color matching of current players. What it adopted was RGB color space, expressed in red, green, and blue. Genetic algorithm was used to pre-process as the first phase of operation process. A gene algorithm was used to find smaller sub images alternative of original fabric in color distribution, for later color separation algorithm use to reduce the operation of color separation. In order to find sub-images with same color distribution as original image, they adopted Histogram Intersection to measure color similarity of sub-image and original image. In terms of color separation algorithm, their research relied on supervised backward-propagation neural network to conduct color separation of printed fabrics RGB sub-image, and utilized PANTONE® standard color ticket to do color matching, so as to realize accurate color separation (Kuo et al., 2007).

Balci et al., 2008 presented an artificial neural network (multilayer perceptron) modeling by Levenberg-Marquardt (LM) algorithm for predicting the colorimetric values of the stripped cotton woven fabrics dyed using commercial reactive dyes. They used 90 different network structures with 15 different number of nodes in the hidden layer, 3 level of inputs (10 inputs, 7inputs, and 6 inputs) and 2 level of MSE value of results as stopping criteria in order to get the best fitting model to predict the L^* and ΔE colorimetric values of stripped cotton samples. In order to establish these networks, they used type of the reactive dyes, type of the reducing agents, concentration of the reducing agents and caustic, working temperature and time, presence of the leveling agent and original colorimetric values (L^*, a^*, b^*) of dyed samples measured before stripping processes as inputs, and L^* and ΔE values of stripped samples measured after stripping process as outputs. After the prediction, the suitable working parameters can be chosen and the processes can be started. Therefore, this may make the stripping process for re-correction of the faulty materials more cost-effective [A5].

Golob et al., 2008 demonstrated the possibility of using counter-propagation neural networks (based on Kohonen ANN) to identify the combinations of dyes in textile printing paste formulations. An existing collection of 1430 printed samples produced with 10 dyes was used for neural network training. The reflectance values served as input data and the known concentrations of single dye or two dyes were used for printing each sample. Some variations of neural network parameters were tested to determine the best model, and a cross-validation method was used to estimate the generalization error. Also, some modifications of input and output data were made to improve the learning capabilities (Balci et al., 2008).

Metamerism is one of the most fundamental perceptual phenomena of the visual system and can be visualized when a part of colored samples in spite of having different spectral reflectance data give the same color coordinates (i. e. match in color) under one specified condition. Moradian & Amani Tehran, 2000 studied the application of artificial neural network (fully connected feed forward network) for the quantification of metamerism. Data from 98 real metameric pairs with visual assessment values were used for training (90 data set) and testing (8 data set) of the network. Many types of networks with different architecture, activation function and input were examined to achieve the best results. A network comprising of one hidden layer with 5 nodes with Tansig as the activation function provided the best prediction. The normalized L^*C^*H was regarded as the best-input candidate for the network. The final trained network showed a good degree of correlation with visual assessment deviating only by 20% (PF/4=20) and could therefore be a good candidate as a substitute for the previously proposed metameric indices. Metameric indices at their best, deviate by approximately 40% (PF/4=36) from visual assessments.

Fluorescent dyes present difficulties for match prediction due to their variable excitation and emission characteristics, which depend on a variety of factors. An empirical approach is therefore favored, such as that used in the artificial neural network method. Bezerra & Hawkyard, 2000 described the production of a database with four acid dyes (two fluorescent and two non-fluorescent) along with the large number of mixture dyeing that were carried out. The data were used to construct a network connecting reflectance values with concentrations in formulations. Their multilayer perceptron network was trained using back propagation algorithm. Network topology was constituted of one input layer (three nodes), one hidden layer (four nodes) and one output layer (five nodes). the networks' input layers were fed with SRF, XYZ or L*a*b* values of each sample in order to predict, in the output layer, the dye concentrations (C) applied. A linear activation function was used in the input and output layers, and the logistic sigmoid function in the hidden layers. All the data were normalized before training and testing, and all the networks were trained using the same learning rate ($0.5 ® 0.01$) and momentum term ($0.5 → 0.1$). The 311 samples produced were divided in two groups: a training set (283 samples) and a testing set (28 samples). Their results showed that, although time consuming, the presented approach was viable and accurate (Bezerra & Hawkyard, 2000).

Ameri et al., 2005 used the fundamental color stimulus as the input for a fixed optimized neural network match prediction system. Four sets of data having different origins (i.e. different substrate, different colorant sets and different dyeing procedures) were used to train and test the performance of the network. The input layer was consistent of the measured surface spectral reflectance of the target color centers at 16 wavelengths of 20 nm intervals throughout the visible range of the spectrum between 400-700 nm. The output layer was corresponded to the concentrations of the colorants. The network was trained using the scaled conjugate gradient back propagation algorithm. A positive linear activation function was used in the output layer whilst the logsig function was used in the hidden layer. Training was made to continue over 100000 epochs running three times. The results showed that the use of fundamental color stimulus greatly reduced the errors as depicted by the MSE and Δ Cave data and improved the performance of the neural network prediction system (Ameri et al., 2005).

Ameri et al., 2006 used different transformed reflectance functions as input for a fixed genetically optimized neural network match prediction system. Two different sets of data depicting dyed samples of known recipes but metameric to each other were used to train and test the network. The transformation based on matrix R of the decomposition theory showed promising results, since it gave very good colorant concentration predictions when trained by the first set data dyed with one set of colorants while being tested by a completely different second set of data dyed with a different set of colorants (PF/4 always being less than 10). The network was trained using the Levenberg-Marquardt back propagation algorithm. The error goal was fixed at MSE 0.001. All the input and output data were normalized before training and testing (Ameri et al., 2006).

6. Conclusion

Neural network technique is used to model non-linear problems and predict the output values for given input parameters. Most of the textile processes and the related quality assessments are non-linear in nature and hence, neural networks find application in textile technology.

ANN may be defined as structures comprised of densely interconnected adaptive simple processing elements that are capable of performing massively parallel computations for data processing and knowledge representation. There are many different types of neural networks varying fundamentally. The most commonly used type of ANN in textile industry is the multilayered perceptron (MLP) trained neural network. MLP is a feed-forward neural network. In most textile applications a feed-forward network with a single layer of hidden units is used with a sigmoid activation function for the units (Balci et al., 2008).

Some studies have decided the number of unites in the hidden layer upon by conducing the trail and error, or genetic algorithm or other optimizing methods and a network with the minimum test-set error is to be used for further analysis.

The number of input and output neurons depends on the type of textile problems.

Many of the techniques reported require many feature extraction procedures before the data can feed to a neural network and data is afforded by different measurements including feature extracted from images, experiments based on standards based on their own tests or other gathered measurements.

Some studies have discussed different type of pre processing and post processing methods.

Many papers have applied and compared the performance of different mathematical, statistical, or experimental models and predictions with neural network for different textile applications and in most of them, neural network models predict process, grading, or behavior of features more accurate than other methods.

The performance of the network is judged by computing the root mean square error (MSE), Sum of the square error (SSE), moment correlation coefficient (r), percentage error (%E), coefficient of variation (%CV), gamma factor (γ), performance factor (PF/4), and etc in order to analyze the results.

Since neural networks are known to be good at solving classification problems, it is not surprising that much research has been done in the area of textile classification, particularly fault identification and classification. The current 2D-based investigation needs to be extended to 3D space for actual manual inspection.

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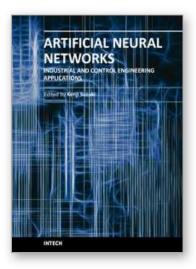
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Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications. The purpose of this book is to provide recent advances of artificial neural networks in industrial and control engineering applications. The book begins with a review of applications of artificial neural networks in textile industries. Particular applications in textile industries follow. Parts continue with applications in materials science and industry such as material identification, and estimation of material property and state, food industry such as meat, electric and power industry such as batteries and power systems, mechanical engineering such as engines and machines, and control and robotic engineering such as system control and identification, fault diagnosis systems, and robot manipulation. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in industrial and control engineering areas. The target audience includes professors and students in engineering schools, and researchers and engineers in industries.

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