Journal of Applied Sciences Research, 4(11): 1380-1386, 2008

A Method of Predicting the Breaking Load of Egyptian Extra Long Staple Cotton by Using Neural Networks

[1]M.H. Elshakankery, [2]M.A.M. El-Sayed and [2]Suzan H. Sanad

[1]Textile Dept. National Research Center, Dokki, Giza, Egypt.
[2]Cotton Research Institute, Agricultural Research Center, Giza 12619 Egypt.

Abstract: This paper presents the prediction of yarn breaking load properties by using artificial neural network. A single hidden layer neural network trained by using the back propagation algorithm performance a functional between HVI fiber properties, yarn count from several Egyptian cotton fiber qualities and yarn breaking load. The neural network was trained and used to predict the yarns breaking load properties, to compare with experimental yarns breaking load results. In each case, the prediction error was less than the standard deviation of experimental results. The back- propagation network model is not constrained by any assumptions about statistical properties of the data.

Key words: Egyptian cotton variety, Ring and Compact spinning, Extra Fine yarn count, Neural Networks, High Volume Instrument (HVI)

INTRODUCTION

Literature Survey: The Spinning process is one of the important production processes in the textile industry. The properties of resulting yarn are very important in determining their possible applications. Prediction of yarn properties from fiber specifications and process parameters has been investigated by various researchers. The breaking load of spun yarn is one of the most important properties in determining the yarn quality, since it is directly affect the winding, weaving and knitting efficiency. Predicting the spun yarns breaking load is very important from a fiber properties, technological and machine parameters. Fast and accurate measurement of fiber properties by means of High Volume Instrument (HVI) and more powerful computers are the two main reasons for this tendency. There are essentially five modeling tools for predicting yarn breaking load, namely the mathematical model, the statistical model, the empirical model, the computer simulation model and the neural network model.

Mathematical models proposed by Bogdan[1,2], Hearle *et al.*[3], Subramanian[4], Kim and El-Sheikh[5,6] Zurek *et al.*[7], Frydrych[8], Onder and Baser[9] Rajamanickam *et al.*[10] and Morris *et al.*[11] have made significant contributions in this filed. They derived from the fundamental laws of science can be used to explain the effects of various parameters on yarn breaking load. These models are based on certain idealized assumptions.

Statistical tools, e.g. regression analysis proposed by Neelkantan and Subramanian[12], Hafez[13], Smith and Water[14], El-Mogahzy[15], Hunter[16], and Mostafa *et al.*[17] to name a few, have made significant contributions in this filed. They established the relation between cotton fiber properties and yarn breaking load using the classic regression method.

Hearle *et al.*[3] reviewed various mathematical and empirical models concerning yarn breaking load which were published between 1926 and 1969. Hunter[16] reported on more than 200 published papers about the prediction of yarn quality parameters, particularly tensile properties.

From the mid – 1990s, artificial neural networks (ANN) have been received much attention from researchers to use in various textile related applications. Among the yarn- property – applications, the majority have dealt with predicting yarn properties from fiber properties and processing parameters. The work of Cheng and Adams[17], Ramesh *et al.*[18], Ethridge and Zhu[19], Pynckels *et al.*[20], Rajamanickam *et al.*[21], Anirban *et al.*[22] and Majumdar *et al.*[23] have successful employed ANN models for the prediction of various coarse and medium yarn count properties. In all these investigations, the performance of neural network models has been evaluated, either without comparing them with any other models or at most by comparing them with statistical models. In two instance alone: First one Rajamanickam *et al.*[21], have compared the performance of four different models- mathematical, empirical (regression equation), computer simulation and neural network – and have discussed their merits and demerits, with two different data sets have been used for this study. The mathematical and computer simulation models have been applied on one data set and empirical and neural net work models have been applied on the other.

Corresponding Author: M.H. Elshakankery, Textile Dept. National Research Center, Dokki, Giza, Egypt.
E-mail: mhmoude2003@yahoo.com

Second, Anirban *et al.*[22] have compared the performance of three different models – Frydrych's model, statistical model and neural network based model by using the data set available in Frydrych's paper, which pertains to cotton yarns. The results are expected to give a clear indication of the relative success of these models in predicting yarn breaking load.

Neural Network: An artificial neural network is a parallel processing architecture consisting of a large number of interconnected processors, called neurons organized in layers.

Figure 1 shows the structure of neural network. There are two kinds of elements in the network- the neuron node and the connection weight.

A neuron node is the basic processing unit that has an activation function. Neuron modes are arranged in a layered structure. The neuron modes in consecutive layers are fully connected by connection weights. The first layer is called the input layer and the second and third are called hidden and output layers, respectively. A connection weight has a weighting value for the node connection weights are important because their value determine the behavior of the network or represent the information being used by the net to solve a problem.

Each neuron has an internal stat, called its activity level, which is a function of the inputs it has received. Typically- a neuron sends its activation as a signal to several other neurons It is important to note that a neuron can send only one signal at a time, although that signal is broad cast to several other neurons.

For example, consider a neuron j, which receives input from neurons X_1 , X_2 , X_3 , ...X_n. Input to this neuron is created as weighted sum of signals from other neurons. This input is transformed to the scalar output Y_i. The output is defined as:

$$Y_i = h.\ (\Sigma_j (W_{ij} . X_j - M_j)) \qquad (1)$$

Where: Y_i = is output value of hidden mode number i
(X) = 1 for $X \geq 0$
(X) = 0 for $X \leq 0$

- W_{ij} = is the weight of mode I of the hidden layer for the input coming from input j.
- M_j = is the adjustable thresh old.

The appropriate selection of the learning data and of the network structure is of the utmost importance in the process of the modeling functional dependencies with the use of artificial networks. In the analysis under consideration, the measurements on whose basis the learning data vectors for the network have been constructed were designed in such a way that the particular measuring points were regularly sited throughout the measurement space. After a set of inputs has been fed through the network, the difference between true or desired output and computed output represent an error. Sum of squared errors is direct measure of performance of the network in mapping inputs to desired outputs. By minimizing of sum of squared errors is possible to obtain the optimal weights and parameters of activation function.[24]

Experimental set-up: In the present work, the back-propagation neural network is used to predict yarn breaking load for ring spun and compact yarns.

Neural networks are composed of multiple computational elements (nodes) connected by means of weight which are adapted during the training process such that desired output is achieved.

Four Egyptian cotton varieties and two promising crosses belonging Extra Long Staple category were used in this study and measured by HVI and Micromat fiber data were used as input vectors and the yarn breaking load the output vector as shown in Table 1.

A wide series of yarn counts was spun on a RST 1 Marzoli ring and compact spinning machine. The yarn count range was 80 Ne, 100 Ne, 120 Ne and 140 Ne at constant twist multiplier 3.6. For each count, yarn breaking load was measured on a Statimat ME instrument with 120 breaks per sample. All samples could be run simultaneously, each on sixteen spindles. The tested yarn quality parameters were average over the sixteen bobbins.

Matlab software was used for neural network modeling.

RESULTS AND DISCUSSION

The network model has an input layer consisting of input nodes, single hidden layers and an output layer consisting of output nodes which are all connected into a complete network. The advantage here is that the complex non-linear relationship between the input and output vectors can handled more easily each node has a transfer function f, one output value y, and several input value x_i. Each input value is multiplied by a corresponding weight factor w_i. The relationship between the input and the output of each node is given in the following equation:

$$y = f\left(\sum_{j=1}^{n} w_i . x_i\right)$$

In implementing the back-propagation network model, total of eleven input parameters consisting of ten fiber properties and yarn count were used. The HVI properties considered were: fiber mean length, length

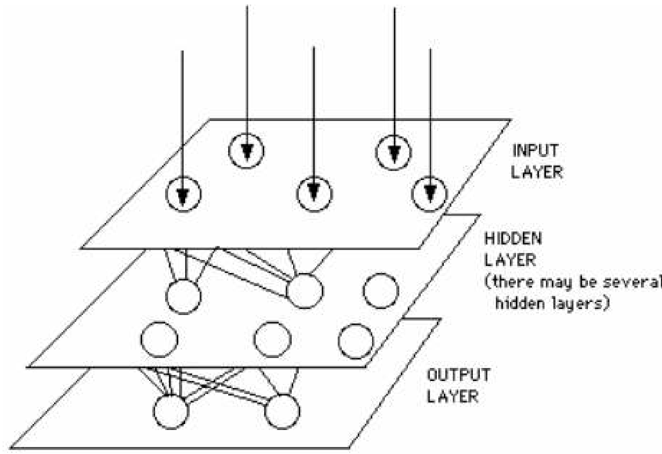

Fig. 1: Structure of three layered neural network model

Table 1: Fiber origins properties and yarn breaking load

	HVI properties							Micromat Properties		Breaking load (gf)							
	UHM (mm.)	Uniformity (%)	Strength cN/tex	Elongation %	Mic. reading	Yellowness b+	Brightness Rd %	Maturity	Fineness (mtex)	80 Ne		100 Ne		120 Ne		140 Ne	
										Ring	Compact	Ring	Compact	Ring	Compact	Ring	Compact
							Extra Long Extra fine										
Giza 45	35.8	89.4	43.2	6.1	3.1	74	8.9	0.92	120	203.7	210.9	144	160.5	111.2	121.1	87	95.6
Giza 87	35.3	85.8	45.0	6.4	3.0	72	9.4	0.91	121	178.6	182.5	129.4	144.4	101.8	104.1	72.1	80.1
Giza 77 ×bima	36.2	89.3	46.2	6.2	2.9	66.2	11.6	0.91	115	193.4	215.7	150.6	158.2	112	118	79.6	92.3
							Extra Long Staple										
Giza 70	35.4	87.5	44.6	6.3	4.1	73	9.5	0.92	145	165.2	186.8	128.9	146	97.46	106.1	71.2	84.4
Giza 88	35.4	88	46.5	6.2	3.9	66.4	11.4	0.91	139	194.5	202.3	141.8	154.9	109.7	116	72	85.1
Giza 74 × Giza 66	33.9	88.5	48.6	6.3	3.7	70.6	9.1	0.92	142	185.7	188.1	130.2	142.5	105.4	111.7	75.9	82.4

Table 2: Experimental and predicted values of *ring spun* breaking load

Yarn count (Ne)	Breaking load (gf)		Error (gf)	Error %	SD load Experimental (gf)
	Experimental	Predicted			
80s	186.85	188.42	1.55	0.829	13.25
100s	137.48	141.54	2.02	1.469	13.58
120s	106.26	111.2	3.94	3.71	18.36
140s	76.3	80.1	3.8	4.98	22.33

Table 3: Experimental and predicted values of *compact yarn* breaking load

Yarn count (Ne)	Breaking load (gf)		Error	% Error	SD load Experimental (gf)
	Experimental	Predicted			
80's	197.7	194.2	-1.3	-0.66428	12.01
100's	151.1	154.3	3.2	2.117803	14.56
120's	112.8	108.4	-3.4	-3.04114	12.44
140's	86.5	80.52	-1.98	-2.4	19.73

Table 4: Mean of the percentage error and standard deviation in predicting breaking load by the four trained nets

Training run	Ring spun yarn		Compact spun yarn	
	Error mean %	SD	Error mean %	SD %
1	0.191	1.225	0.2461	1.5755
2	0.391	2.544	0.1327	0.8499

Table 4: Continued

3	0.357	2.286	0.1282	0.8207
4	0.547	3.51	0.2130	1.3642
Over all mean	0.3715	2.39125	0.18	1.152575

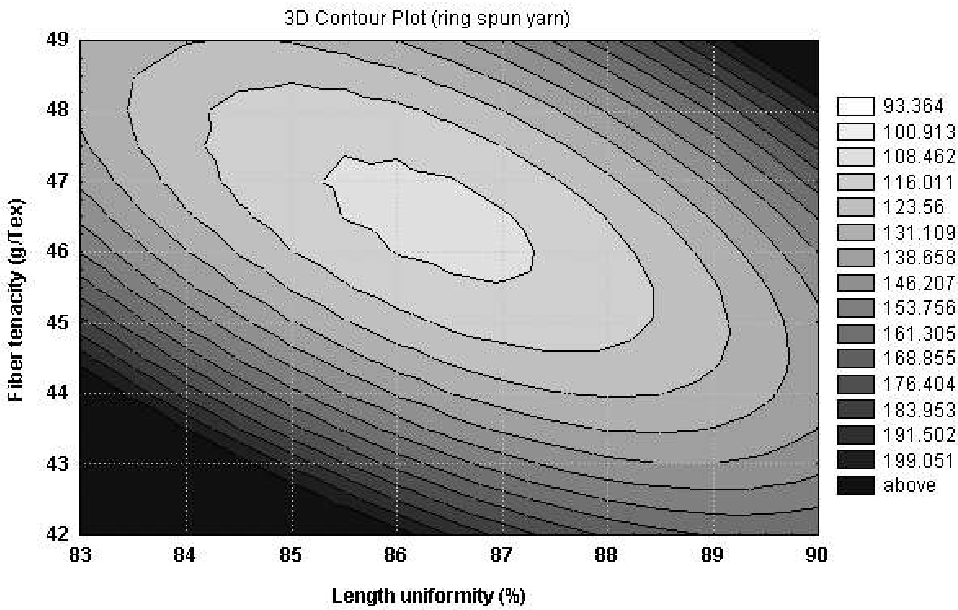

Fig. 2: Effect of length uniformity and fiber tenacity on ring yarn breaking load

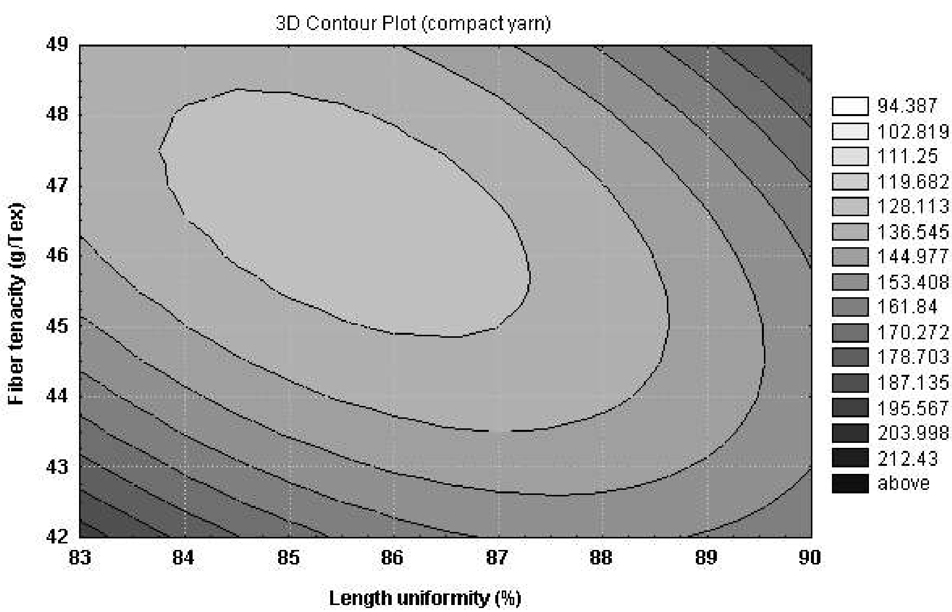

Fig. 3: Effect of, length uniformity and fiber tenacity on compact yarn breaking load

uniformity, fiber strength, elongation at break, micronaire, yellowness and brightness micromate properties considered were: Maturity and fineness. The output parameter for the model was the yarn breaking load. The study results were divided in two groups for testing (25% of the experimental data) and learning (75% of the experimental data). The learning data were used to train the network to get minimum absolute error between measured and calculated yarn breaking load was achieved for the test data, in the present study, predicting breaking load by the four trained neural networks for each yarn type were done

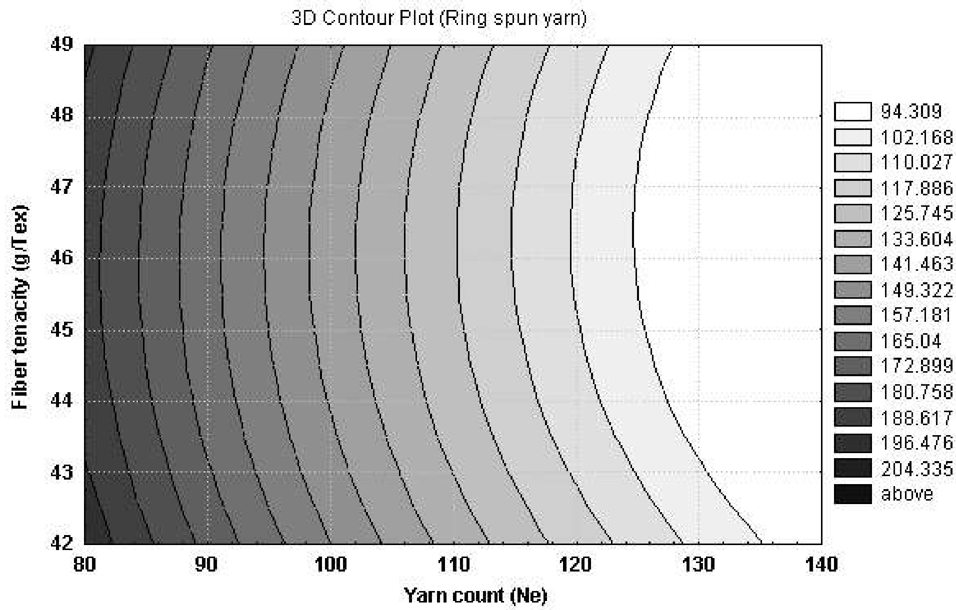

Fig. 4: Effect of yarn count and fiber tenacity on ring yarn breaking load

(totaling 40 predictions), the absolute error is based on following equation:

$$Absolute.Error = \sum_{j=1}^{n} \frac{|y_0 - y_1|}{y_0} \quad \text{.........(3)}$$

Where:

- y_0 = measured yarn breaking load.
- y_1 = network predicted yarn breaking load.

The learning data of the back- propagation algorithm involves of the connection weights values, presentation of an input for each input layer node, and specification of the desired output for output node layer then actual outputs calculation of all the nodes by using the presented values followed by adaptation of weights to give the desired output. Anon – linear transfer function was used for all the nodes of the network. The transfer function is based on following equation

$$f(x) = \frac{1}{1+\exp^{-x}} \quad \text{.............................(4)}$$

After training was completed, the network configuration adopted was as follows:

- Number of input nodes (11 fiber parameters and yarn count).
- Number nodes in hidden layer: it was found that 5 and 6 nodes are needed in the hidden layer 800 ring and compact yarn respectively.
- Number of output nodes: measured yarn breaking load.

Table 2 and 3 show experimentally determined output, predicted outputs and percentage errors of prediction for ring and compact yarn respectively. From the tables, it is clear that in each case the prediction error was much lower than the standard deviation of experimental, and the percentage absolute error are low. For example in the cases of the yarn count 80_s ring spun the actual and predicted values were 186.85 and 188.42 respectively, the error 1.55 gf was within the experimental standard deviation of 13.25 gf. Similar results were obtained for all yarn count trained.

The mean and standard deviation of the percentage error in predicting breaking load by the four trained nets are shown in table (4) for ring and compact yarn respectively. From the table, it can be seen the over all mean and standard deviation of the percentage error in predicting breaking load by the four trained nets were 0.3715 and 2.391 respectively for ring yarn, and the corresponding values for compact yarns were 0.18 and 1.1525 respectively.

Figures 2-5 show the relationship between the fiber tenacity, length uniformity, yarn count and yarn breaking load for both ring and compact yarn. From Figures 2 and 3, it is observed that as the fiber tenacity increases, there is concomitant increase in yarn breaking load but this depends on yarn count. For both the ring and compact yarns, the effect of length uniformity is pronounced when the fiber tenacity and yarn count are less. However, when the fiber tenacity

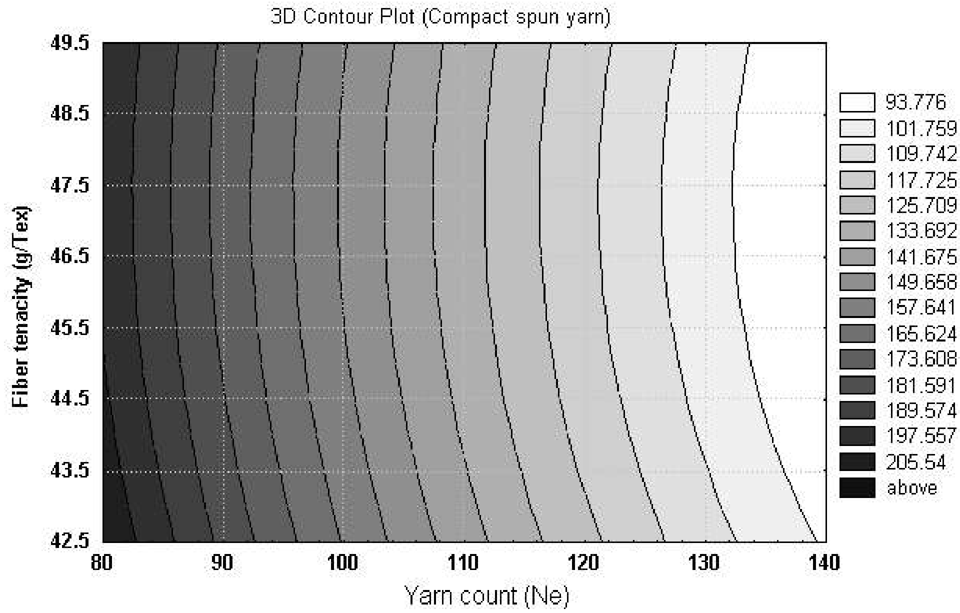

Fig. 5: Effect of yarn count and fiber tenacity on compact yarn breaking load

reaches its apex the influence of length uniformity decreases. From figures 4 and 5, it is observed that as the yarn becomes finer the yarn breaking load decreases. This is due to the higher unevenness of finer yarn as compared to less one.

Conclusion: Ring and compact yarn breaking load has been predicted by an artificial neural network. The neural network based on the back-propagation algorithm used HVI properties and yarn count of several cotton fibers qualities as input. Yarn breaking load was the output of the neural-net model. Anural net was trained and then used to predict the yarn breaking load properties. The errors of prediction in each case were less than the standard deviation of experimental data results. For both the ring and compact yarns, the effect of length uniformity is pronounced when the fiber tenacity and yarn count are less. Also, the yarn becomes finer the yarn breaking load decreases.

REFERENCES

1. Bogdan, J.E., 1956. “The Characterization of Spinning Quality”, Textile Res. J., 720-730.
2. Bogdan, J.E., 1967. “The Prediction of Cotton Yarn Strength”, Textile Res. J., 536-537.
3. Hearle, J.W.S., P. Grosberg and S. Backer, 1969. 'Structural Mechanics of Fibres, Yarns and Fabrics”, Wiley-Interscience, New York.
4. Subramanian, T.A., K. Ganesh and S. Bandyopadhyay, 1974. “A Generalized Equation for Predicting the Lea Strength of Ring-Spun Cotton Yarns”, J. Text. Inst., 65: 307-313.
5. Kim, Y.K. and A. El-Sheikh, 1984. Tensile Behavior of Twisted Hybrid Fibrous Structures. Part I: Theoretical Investigation, Text. Res. J., 526-534.
6. Kim, Y.K. and A. El-Sheikh, 1984. Tensile Behavior of Twisted Hybrid Fibrous Structures. Part II: Experimental Study, Text. Res. J., 534-543.
7. Zurek, W., I. Fredrych and S. Zakrzewski, 1987. “A Method of Predicting the Strength and Breaking Strain of Cotton Yarn”, Text. Res. J., 439-444.
8. Fredrych, I., 1992. 'A New Approach for Predicting Strength Properties of Yarn,' Text. Res. J., 62: 340-348.
9. Onder, E. and G. Baser, 1996. A Comprehensive Stress and Breakage Analysis of Staple Fiber Yarns. Part II: Breakage Analysis of Single Staple Fiber Yarns, Text. Res. J., 634-640.
10. Rajamanickam, R., S.M. Hansen and S. Jayaraman, 1998. “A Model for the Tensile Fracture Behavior of Air-jet Spun Yarns”, Text. Res. J., 68: 654-662.
11. Morris, P.J., J.H. Merkin and R.W. Rennell, 1999. “Modeling of Yarn Properties from Fiber Properties”, J. Text. Intst., 322-335.
12. Neelkantan, P. and T.A. Subramanian, 1976. ”An Attempt to Quantify the Translation of Fibre Bundle Tenacity into Yarn Tenacity”, Text. Res. J., 46: 822-827.
13. Hafez, O.M.A., 1978. “Yarn strength Prediction of

American Cotton", Textile Res. J. 68: 701-705.
14. Smith, B. and B. Waters, 1985. "Extending Applicable Ranges of Regression Equation for Yarn Strength Forecasting", Textile Res. J., 55: 713-717.
15. EL-Mogahzy, Y.E.E., 1988. "Selecting Cotton Fibre Properties for Fitting Reliable Equations to HVI data", Textile Res. J., 58: 392-397.
16. Hunter, L., 1988. "Prediction of Cotton Processing Performance and Yarn Properties from HVI Test Results", Melliand Textilberichte., 229-232.
17. Mustafa, E. and K. Huseyin, 1995. "Regressional Estimation of Ring Cotton Yarn Properties from HVI Fiber Properties", Textile Res. J. 76: 360-366.
18. Cheng, L. and L. Adams, 1995. "Yarn Strength Prediction Using Neural Networks", Textile Res. J. 65: 495-500.
19. Ramesh, M.C., R. Rajamanickam and S. Jayaraman, 1995. "The Prediction of Yarn Tensile Properties by Using Artificial Neural Networks", J. Text. Intst., 459-469.
20. Ethridge, D. and R. Zhu, 1996. "Prediction of Rotor Spun Cotton Yarn Quality: A Comparison of Neural Networks and Regression Algorithm", Proceeding of the Beltwide Cotton, 1314-1417.
21. Pynckels, F., P. Kiekens, S. Sette and K. Impe, 1997. "The Use of Neural Nets to Simulate the Spinning Process", J. Text. Intst., 440-4447.
22. Rajamanickam, R., S.M. Hansen and S. Jayaraman, 1997. "Analysis of Modeling Methodologies for Predicting the Strength of Air-jet Spun Yarns", Text. Res. J., 67: 39-44.
23. Anirban, G., R. Chattopadhyay and Jayadeva, 2001. "Predicting Yarn Tenacity: A Comparison of Mechanistic, Statistical, and Neural Network Models", J. Text. Intst., 139-145.
24. Majumdar, A., P.K. Majumdar and B. Sarkar, 2005. "Application of an Adaptive Neuro – Fuzzy System for The Prediction of Cotton Yarn Strength from HVI Fiber Properties", J. Text. Intst., 55-60.
25. www. Artificial Neural Networks Technology