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PREDICTING COTTON FIBRE MATURITY BY USING ARTIFICIAL NEURAL NETWORK

Assad Farooq[1], Muhammad Ilyas Sarwar[2]*, Muhammad Azeem Ashraf[1], Danish Iqbal[2], Azmat Hussain[3], Samander Malik[4]

[1]Department of Fibre and Textile Technology, University of Agriculture, Faisalabad, Pakistan
[2]Central Cotton Research Institute Multan, Pakistan. 061-9200340.
[3]University College of Textile Engineering, Bahauddin Zakariya University, Multan.
[4]Institute of Textile Machinery and High-Performance Material Technology, Technical University Dresden, Germany
*Corresponding Author Email: mianilyas222@yahoo.com, Tel: +92-3017637320, Fax: +92-619200342

Abstract:

Cotton fibre maturity is the measure of cotton's secondary cell wall thickness. Both immature and over-mature fibres are undesirable in textile industry due to the various problems caused during different manufacturing processes. The determination of cotton fibre maturity is of vital importance and various methods and techniques have been devised to measure or calculate it. Artificial neural networks have the power to model the complex relationships between the input and output variables. Therefore, a model was developed for the prediction of cotton fibre maturity using the fibre characteristics. The results of predictive modelling showed that mean absolute error of 0.0491 was observed between the actual and predicted values, which show a high degree of accuracy for neural network modelling. Moreover, the importance of input variables was also defined.

Keywords:

Cotton Fibre Maturity, Fibre Fineness, Artificial Neural Networks

1. Introduction

Cotton is the purest form of cellulose found in nature and cotton fibres have considerable economic significance. Therefore, a fundamental understanding of cotton fibre structure and properties is important. Studies on the development of cotton fibre have concentrated on the biochemical and cell structures from genetic and environmental perspectives [1]. Cotton fibres develop over four stages: (i) initiation; (ii) elongation; (iii) secondary-wall thickening; and (iv) maturation. Fibre initiation begins during flowering and fibres arise from the epidermal cells on the ovule surface [2], [3]; the days after flowering are referred to as days post-anthesis (dpa). Fibre elongation begins on the day of flowering by spherical expansion above the ovular surface and continues with primary cell wall deposition for 20–25 days [3] until reaching final fibre lengths of 22 to 35 mm. Secondary cell wall synthesis begins around15–22 dpa and continues for 30–40 days. Fibre maturation is evident by a twisted ribbonlike structure beginning at 45–60 dpa [2,4].

With the growth of cotton fibres, the hollow secondary cell wall also thickens. The thickening of secondary cell wall thickness of cotton fibres is called maturity and is measured [5]. Immature or over-mature fibers pose serious problems during spinning and deteriorate the yarn quality. The immature fibers are weak and thus break frequently especially during opening, cleaning and carding processes and form small tightly wound balls called neps, which appear as white specks in the dyed fabric [6]. Moreover, loss of yarn strength, high proportion of short fibers and variation in dye-ability of fabric are some other key problems caused by immature fibres as far as the textile industry is concerned [7]. Similarly, the stiff and bristle nature of over-mature fibers make them undesirable in the spinning process. The over-mature fibres result in the formation of virtually closed lumen by extra growth of cell wall and ultimately creates high resistance to bending during the spinning process [6]. All these changes make it mandatory to measure the cotton fiber maturity prior to spinning in order to avoid drop in yarn and fabric quality.

Normally, fineness of the cotton fibre is measured using the resistance to air flow method [8]. This method is considered to be reliable for the measurement of cotton fiber fineness until and unless immature or over-mature fibers put forth their impact upon the measured value of cotton fiber fineness. This scenario indicates that the measurement of cotton fibre maturity is highly influential for the accurate determination of fibre fineness.

There are various methods adopted to measure fibre maturity such as image analysis technique [9], caustic air method [10] differential dyeing test [11], Uster AFIS [12], infrared spectroscopy [13], X-ray diffraction [14], among others. Moreover, some previous researches are aimed at the calculation of fibre maturity and its association with fibre fineness using both mathematic and statistical techniques.

The most important parameter to estimate the degree of thickening is called θ in microscopic cross-sectional viewing as given by the ratio of the cross-sectional area of the total fibre wall by the area of a circle of the same perimeter. We may transform this expression using geometrical considerations and characteristics of a cross-sectional cotton fiber as

$$\theta = 4\pi A/P^2 \quad (1)$$

where *A* is the cross-sectional fibre area and *P* is the fibre cross-sectional perimeter. θ value varies between 0 and 1. Mature fibers have high θ values, while immature and dead fibres have low θ values. A reference degree of thickening is defined θ_{ref}=0.577 corresponding to an optimal amount of cellulose in cotton fibre. With this value, maturity ratio, *M*, is defined as:

$$M = \theta / \theta r \quad (2)$$

$$M = \theta / .577 \quad (3)$$

Cotton with maturity ratio *M* closer to unit value (1) is considered mature and is estimated. Cotton with maturity ratio *M* lower than 0.8 is composed of a high percentage of immature fibres, causing difficulties in spinning and dyeing processes [5,15].

A direct relationship between micronaire and the fineness and maturity [16] product MH was first examined by Lord [17,18].

$$MH = 3.86\ Mic^2 + 18.16Mic + 13 \quad (4)$$

where *M* is the maturity ratio while *H* is the fineness taken in gravimetric terms and Mic represents the micronaire value of cotton.

Artificial neural networks (ANN) is a latest technique that can model the complex linear as well as nonlinear interactions between the input and output parameters. Artificial neural networks have been the employed in the textile industry for more than two decades now. The neural networks have been the topic of various research studies in the textile industry like prediction of tensile properties of ternary blended open-end yarn [19], thermal resistance of knitted fabrics [20], segregation of cotton bales on its fibre attributes in yarn properties [21], classification of card-web defects [22], predicting the levelling action point at draw frame [23], control of sliver evenness [24] and predicting the spin ability of the yarn [25]. Similarly, artificial neural network can be used to model the spinning process by taking the machine settings and fibre quality parameters [26] and fibre to yarn predictions [27] as the input. In this regard, [28] the values of high-volume instrument (HVI) and advanced fiber information system (AFIS) as used as input parameters in the artificial neural network model. As cotton fibre maturity is the determining factor in fibre and textile processing as it has a direct relationship with fibre quality, it is measured by Advanced Fiber Information System (AFIS) [14]. By considering all these contributions of ANN in the textile industry, the aim of this study is to predict fibre maturity on the basis of other cotton fibre characteristics by using ANN.

2. Materials and Methods

2.1. Materials

The cotton samples of different varieties (*Gossypium hirsutum* L.) grown in Pakistan were collected from various saw ginning factories. In Pakistan, cotton is almost entirely hand-picked. The cotton samples from different pickings are assumed to have varying maturity levels. On this basis, a total of approx. 1300 cotton samples having different levels of maturity were collected and subjected to following testing procedures.

2.2. Methods

The cotton samples were conditioned for 24 hours in standard atmospheric conditions (relative humidity of 65 ± 2 % and a temperature of 20 ± 2 ˚C) before testing. The fibre characteristics were determined by using High Volume Instrument (HVI 900A), while the maturity testing was performed on fineness maturity tester (FMT). All the important fibre characteristics viz, fibre length, micronaire, strength, colour, trash and maturity were measured.

The neural networks were trained using the MATLAB algorithm (trainbr), which is the inclusion of Levenberg–Mamrquardt algorithm and Bayesian regularization in back propagation. In back propagation Levenberg–Marquardt algorithm and Bayesian regularization theorem train the neural network to reduce the computational overhead of approximation of the Hessian matrix and to produce good generalization capabilities. This algorithm provides a measure of the network parameters being effectively used by the network. The effective number of parameters should remain the same irrespective to the total number of parameters in the network. This eliminates the guesswork required in determining the optimum network size. Moreover, the problem associated with over-fitting can also be avoided.

The selected fibre characteristics were used as the input for ANN and the fibre maturity was selected as the output. The collected data was normalized between 0 and 1 and after training and testing it was post-processed to its original form. Training was done in different phases by changing the number of inputs (Fig. 1). Different network architectures, learning rates and momentum were tested to determine the optimum network structure. The network prediction values were compared with the actual tested values and mean absolute error (MAE) was calculated. The trained networks were validated using the 10% cross validation technique.

3. Results and Discussion

3.1. Neural Network Modelling

In first phase, on the basis of initial subject knowledge, four fibre properties (upper half mean length, uniformity index, micronaire, fibre strength) were selected as the input parameters to predict fibre maturity ratio. Multilayer feedforward ANN with one input layer, two hidden layers and one output layer was trained in Matlab toolbox function ‘trainbr’. It consists of five hidden neurons in the input layer, three and two neurons in first and second hidden layer, respectively, and one neuron in the output layer (4-[3-2]-1). The parameters of the used network are expressed in Table 1.

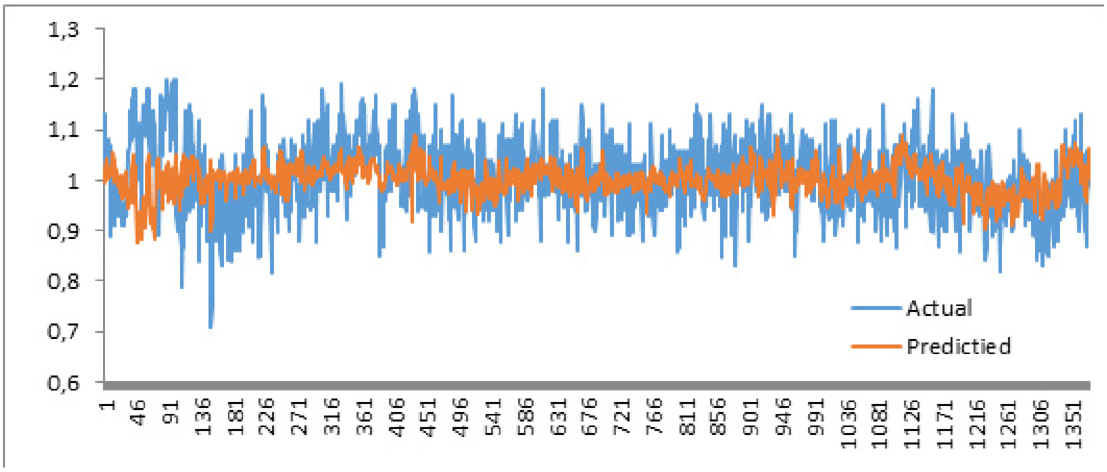

Figure 1. Training of artificial neural networks using 1300 data points.

Table 1. Network Parameters

Network structure	
Network	[3 2 1]
Transfer functions	{logsig, logsig, purelin}
Inputs	4
Output	1
Learning rate	0.05
Mu	0.2
Epochs	2000
Performance goal	0.001
Training algorithm	Trainbr

Sigmoid (logsig) and linear transfer functions were used in the hidden and output layers, respectively, while mean square error (MSE) was used as the performance function.

The network was trained using training (1172 samples) and test data sets (130 samples). The trained network had generalized well and has training MAE of 10.37% and testing MAE 10.31%, which accounts for MAE 0.0495 expressed in terms of fibre maturity as shown in Figure 2.

Then the trained network was validated with the help of 10% cross-validation; the results were obtained with a mean absolute error in terms of maturity ratio of test set. The detailed picture of the 10% cross validation is given in Table 2.

The results reveal that neural network has generalized well by learning the underlying relationship between input and output variables within acceptable mean absolute error (MAE) in both training and test sets.

3.2. Influence of Input Parameters on Fibre Maturity

Furthermore, to analyse the relative importance of input variables, rank analysis was carried out with the help of artificial neural networks. Using the same network architecture, the values of one input variable, whose importance is measured, are set zero and increase or decrease in error percentage was measured. In this phase,

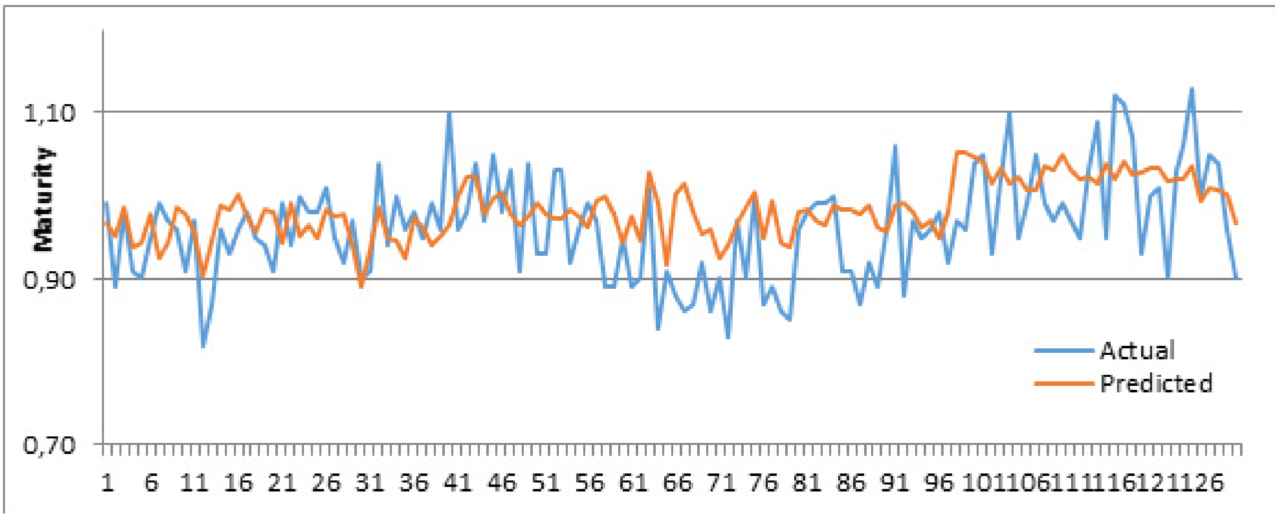

Figure 2. Test Performance of Trained Neural Network

hold-out training mode was used by selecting 1172 samples for training and 130 samples for testing. The results of rank analysis are expressed in Table 3.

As expected, the micronaire value is the most important variable to predict maturity of cotton fibres. The second important variable is fibre strength, whereas uniformity index has negative influence on the model and by removing it from input pairs, some reduction in error has been observed. The final neural network model is presented in Figure 3.

4. Conclusion

In the present research work, the model of predicting the cotton fibre maturity is presented. It is concluded that cotton fibre maturity can be predicted using the input variables such as fibre micronaire, upper half mean length and fibre strength. A mean absolute error of 0.0491 was observed between the actual and predicted values, which show a high degree of accuracy for neural networks modelling. It is anticipated that tedious fibre maturity testing and calculations can be avoided.

Table 2. Mean absolute errors of 10% cross validation

Mean absolute error [%] Training	Mean absolute error [%] Testing	Mean Absolute Error (test)
10.06	11.2	0.0536
10.46	9.59	0.046
10.28	11.22	0.0538
10.36	10.26	0.0493
10.47	9.29	0.0446
10.3	10.7	0.0513
10.41	9.76	0.0468
10.37	10.26	0.0492
10.36	10.31	0.0495
10.30	10.92	0.0524
Mean: 10.337	10.351	0.0507

Table 3. Relative importance of input parameters

Excluded Inputs	Mean Absolute Error	% Increase/Decrease in MAE	Rank
No exclusion	0.0495	-	-
UHML [mm]	0.0498	0.61	4
Uniformity Index [%]	0.0491	- 0.81	3
Strength [gram/tex]	0.0496	2.20	2
Mirconaire [μg/inch]	0.0560	13.13	1

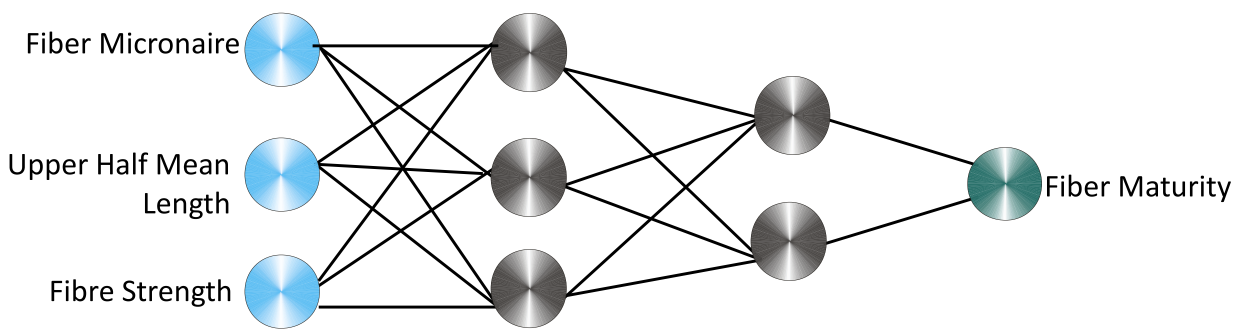

Figure 3. Neural Network Structure

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