Application of linear regression, artificial neural network and neuro-fuzzy algorithms to predict the breaking elongation of rotor-spun yarns

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The breaking elongation of rotor-spun yarns has been predicted by using linear regression, artificial neural network and neuro-fuzzy models. Cotton fibre properties measured by high volume instrument and yarn count have been used as inputs to the prediction models. Prediction accuracy is found to be better for artificial neural network and neuro-fuzzy models than that for regression model. The relative importance of yarn count and cotton fibre properties to rotor yarn elongation has also been studied. Yarn count and cotton fibre micronaire are found to be dominant input factors influencing the breaking elongation of rotor-spun yarns.

Keywords: Artificial neural network, Breaking elongation, Cotton fibre, High volume instrument, Neuro-fuzzy model, Rotor-spun yarns

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1 Introduction

Breaking elongation of spun yarns is a very important property as it influences the end-breakage rate in warping and weaving. Several efforts have been made to construct prediction models, which can forecast the breaking elongation of spun yarns from the input fibre and process parameters. Unfortunately, most of these models encompass ring yarn elongation only. Mathematical or “white” models developed by Aggarwal, Frydrych and Zurek et al. are based on the physical knowledge of spun yarn mechanics. Therefore, these models are not only very appealing but also give thorough insight into the mechanism of yarn elongation. However, to cope with the inherent complexity of yarn structural mechanics, certain assumptions are introduced into these models. This ultimately leads to relatively low prediction accuracy of mathematical models. On the contrary, the empirical models, which use statistical techniques, have relatively higher predictive power. But they do not provide as deep an understanding of the relationship between inputs and outputs as mathematical models. In recent years, the widespread use of artificial intelligence (AI) has created a revolution in the domain of prediction modelling. Artificial neural network (ANN), which is one of the major facets of AI, has been successfully used for the prediction of spinnability, strength, elongation, unevenness, hairiness and imperfections of spun yarns. ANN models are called as “black box” as they simply connect the inputs and outputs without unearthing any physical information about the process. However, the prediction accuracy of ANN model is higher as compared to that of mathematical and empirical models. Fuzzy logic is another important component of AI and it is particularly popular in situations which involve uncertainty and imprecision in decision making. This kind of system could be termed as “gray modelling” as it maps the relationship between input and output parameters and generates some linguistic physical information about the process which are interpreted by the rule set. Neuro-fuzzy systems are formed by amalgamating the fuzzy logic systems with the learning capabilities of

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ANN. This is also known as “hybrid” system and has already been applied in predicting garment drape and classifying fabric and dyeing defects

An important aspect of prediction modelling is to determine the relative saliency of input parameters. This helps us to discriminate between the important and trivial inputs while the fibre selection is done. Researchers have demonstrated that the fibre elongation is the most important contributor to ring yarn elongation followed by fibre strength in the second place. However, due to the difference of structure and yarn forming mechanism between ring- and rotor-spun yarns, this ranking may be void in case of the latter.

In the present work, three models have been developed for the prediction of rotor yarn elongation using linear regression, ANN and neuro-fuzzy algorithms. Cotton fibre properties measured by High Volume Instrument (HVI) and yarn count were used as inputs to these models. Prediction accuracy of these models was determined and compared against each other. Ranking of inputs was done in accordance with the statistical and ANN models.

1.1 Artificial Neural Network and Back Propagation Algorithm

Artificial neural network is a potent data-modelling tool that is able to capture and represent any kind of input-output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that can perform intelligent tasks similar to those performed by human brain. A typical multilayer neural network is shown in Fig. 1. Here, one or more hidden layers can be sandwiched between the input and output layers. The number of hidden layers and the number of neurons per layer vary depending on the complexity of the problem in hand. Each neuron receives a signal from the neurons of the previous layer and these signals are multiplied by separate synaptic weights. The weighted inputs are then summed up and passed through a transfer function (usually a sigmoid), which converts the output to a fixed range of values. The output of the limiting function is then transmitted to the neurons of next layer.

Back-propagation algorithm is the most popular among the existing neural network algorithms. According to this algorithm, training occurs in two phases, namely a forward pass and a backward pass. In the forward pass, a set of data is presented to the network as input and its effect is propagated, in stages, through different layers of the network. Finally, a set of outputs is produced. The calculation of error vector is done from the difference between actual and predicted outputs according to the following relationships:

\[ E = \sum_{j=1}^{P} E_j \]  

where \( E \) is the error vector; \( E_j \), the error associated with the \( j \) th pattern; and \( P \), the total number of training patterns.

The expression of \( E_j \) is given in the following equation:

\[ E_j = \frac{1}{2} \sum_{r=1}^{S} (T_r - O_r)^2 \]  

where \( T_r \) and \( O_r \) are the target output and predicted output respectively at output node \( r \); and \( S \), the total number of output nodes.

In the backward pass, this error signal is propagated backwards to the neural network and the synaptic weights are adjusted in such a manner that the error signal decreases with each iteration process. Thus, the neural network model approaches closer and closer of producing the desired output. The corrections necessary in the synaptic weights are carried out by a delta rule, which is expressed by the following equation:

\[ \Delta W_{pq(n)} = -\eta \left[ \frac{\partial E}{\partial W_{pq(n)}} \right] \]  

where \( W_{pq(n)} \) is the weight connecting the neurons \( p \) and \( q \) at the \( n \)th iteration; \( \Delta W_{pq(n)} \), the correction
applied to \( W_{pq(n)} \) at the \( n \)th iteration; and \( \eta \), a constant known as learning rate.

1.2 Fuzzy Logic, Membership Functions and Fuzzy Rules

In crisp logic, such as binary logic, variables are true or false, black or white and 1 or 0. In fuzzy logic, a fuzzy set contains elements with only partial membership ranging from 0 to 1 to define uncertainty for classes that do not have clearly defined boundaries. For each input and output variable of a fuzzy inference system (FIS), the fuzzy sets are created by dividing the universe of discourse into a number of sub-regions, named in linguistic terms. A classical set may be expressed as follows:

\[
A = \{ x | x > 6 \}
\]

A fuzzy set is an extension of a classical set. If \( X \) is the universe of discourse and its elements are denoted by \( x \), then a fuzzy set \( A \) in \( X \) is defined as a set of ordered pairs as:

\[
A = \{ x, \mu_A(x) | x \in X \}
\]

where \( \mu_A(x) \) is the membership function of \( x \) in \( A \).

Once the fuzzy sets are chosen, a membership function for each set should be created. A membership function is a typical curve that converts the input from 0 to 1, indicating the belongingness of the input to a fuzzy set. This step is known as "fuzzification". Membership function can have various forms, such as triangle, trapezoid, sigmoid and Gaussian. The linguistic terms are then used to establish fuzzy rules. Fuzzy rules provide quantitative reasoning that relates input fuzzy sets with output fuzzy sets. A fuzzy rule base consists of a number of fuzzy if-then rules. For example, in the case of two-input and single-output fuzzy system, it could be expressed as follows:

If \( x \) is \( A_i \) and \( y \) is \( B_i \) then \( z \) is \( C_i \)

where \( x \), \( y \) and \( z \) are linguistic variables representing two inputs and one output; and \( A_i \), \( B_i \) and \( C_i \), the linguistic values of \( x \), \( y \) and \( z \) respectively. The output of each rule is also a fuzzy set. Output fuzzy sets are then aggregated into a single fuzzy set. This step is known as aggregation. Finally, the resulting set is resolved to a single output number by "defuzzification".

1.3 Neuro-fuzzy Systems and ANFIS

Neuro-fuzzy system combines the fuzzification technique of fuzzy logic with the learning capability of ANN. Therefore, it possesses the merits of both approaches. Fuzzification maps an input value to fuzzy sets in a certain universe of discourse, thus increasing the separability of classes in the feature space. This can make the neuro-fuzzy model fit the training set of input-output data more accurately. Neural network technique aid the fuzzy modelling procedure to learn the information about the data set and compute the membership function parameters that best allow the associated FIS to track the given input-output data. ANFIS (adaptive neuro-fuzzy inference system) is a class of adaptive network that is functionally equivalent to FIS. Using a given input-output data set, ANFIS constructs a FIS whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm or a hybrid learning algorithm (a combination of back-propagation and least squares method).

2 Materials and Methods

2.1 Data Collection and Analysis

Cotton crop study results of 1997 and 1998 of International Textile Centre, Texas Tech University, USA, were used in this study. Seven cotton fibre properties measured by HVI, namely fibre bundle tenacity, elongation, upper half mean length (UHML), uniformity index, micronaire, reflectance degree and yellowness, were used as inputs to the regression and ANN models. Yarn count (Ne) was also introduced in the prediction models as an input. Fibre maturity was not included in our prediction model, as it is not measured by the HVI system. The summary statistics of fibre properties and yarn count is shown in Table 1. The only output from the prediction models was breaking elongation of rotor-spun yarns. From the crop study results, 108 sets of input-output data were obtained. These were then divided into training and testing sets. Eighty-eight sets of data were used for the training and remaining 20 sets of data were used for the testing of prediction performance of developed models.

2.2 Optimisation of Neural Network Parameters

In this study, the single hidden layer neural network was used. However, the number of neurons or nodes in the hidden layer was varied from 6 to 14 with an increment of 2 in each step. The learning rate and
momentum were optimised by trial and error method at 0.1 and 0.0 respectively. The training was stopped when the minimum error in the testing set was achieved. It was observed that the network with 12 nodes in the hidden layer is giving the best prediction performance after 700 cycles or iterations. Training was done with back-propagation algorithm using the Easy NN Plus software. The logistic transfer function used in the study was as follows:

\[ f(Z) = \frac{1}{1+e^{-Z}} \]  

... (4)

where \( Z \) is the weighted sum of inputs to a neuron; and \( f(Z) \), the transformed output from that neuron.

### 2.3 Optimisation of ANFIS Parameters

Even though theoretical studies show that very complex mappings are possible using ANFIS, they do not reveal anything regarding the best choice of configuration, i.e. kind of membership function and number of membership function for each input. The number of membership function for each input is especially important, since it determines the number of rules to be trained. If \( m \) is the number of membership function for each input and \( n \) is the number of inputs, then there are \( m^n \) rules to be trained. As there were only 88 data sets for training, the number of rules was kept at such a level that they could be adequately trained using the available data. Therefore, only the three important input parameters (yarn count, micronaire and elongation) were used for the neuro-fuzzy modelling. Triangular, trapezoidal, sigmoid and Gaussian type membership functions were tried and it was found that the trapezoidal form with two membership functions for each input gave the best prediction accuracy. For neuro-fuzzy modelling, the Fuzzy Logic Toolbox of MATLAB software (version 6.1) was used.

### 3 Results and Discussion

#### 3.1 Prediction Performance of Regression, ANN and Neuro-fuzzy Models

The linear multiple regression equation, developed from the training data, relating rotor yarn elongation and cotton fibre properties is given as follows:

\[
\text{Yarn elongation} = -1.714 - 0.050 \text{ fibre bundle tenacity} + 0.176 \text{ fibre elongation} + 1.779 \text{ UHML} + 0.102 \text{ uniformity index} - 0.541 \text{ micronaire} - 0.019 \text{ reflectance} - 0.006 \text{ yellowness} - 0.045 \text{ yarn count (Ne)}
\]

\[ R^2 = 0.725 \]

This equation can account for around 73% variability in rotor yarn elongation. Remaining 27% variability that remains unexplained from the equation depends on the factors which are not included in this study. This regression equation was subsequently used to predict the rotor yarn elongation from the unseen testing data.

Tables 2 and 3 show the comparison of prediction performance of regression, ANN and neuro-fuzzy models. It is observed from Table 2 that the prediction accuracy is reasonably good for all the three models. The mean absolute error of prediction is 3.059%, 3.062% and 2.921 for regression, ANN and neuro-fuzzy models respectively. However, the ANN and neuro-fuzzy models exhibit slight edge over the regression model when correlation coefficient between actual and predicted values and RMS error of prediction are considered. The reason may be attributed to the prevailing nonlinear relationship.
between the fibre properties and the rotor yarn elongation, which is probably more accurately mapped by the ANN and neuro-fuzzy models. Moreover, it is assumed in multiple regression model that the inputs are mutually independent. However, Guha\textsuperscript{16} demonstrated that the quality parameters of cotton fibres are highly correlated which nullifies the aforesaid assumption. ANN and neuro-fuzzy models probably handle the autocorrelation problem more aptly than the regression model. This is another factor undermining the prediction accuracy of regression model. From Table 3 it is observed that for regression model one prediction result is even exhibiting 11.809\% error whereas there is no such prediction result exhibiting more than 10\% error in case of ANN and neuro-fuzzy models. It is interesting to note that in spite of using only three input parameters in case of neuro-fuzzy model, the prediction accuracy was at par with the ANN model and better than the regression model. Availability of more input-output data will make it possible to incorporate more number of input parameters and fuzzy rules, thereby improving the prediction performance of neuro-fuzzy models.

Figs 2 and 3 depict the surface curves, which show the relationship between input parameters and rotor yarn elongation in accordance with the developed

<table>
<thead>
<tr>
<th>Actual elongation</th>
<th>Regression model</th>
<th>ANN model</th>
<th>Neuro-fuzzy model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predicted</td>
<td>Error %</td>
<td>Predicted</td>
</tr>
<tr>
<td>6.88</td>
<td>6.86</td>
<td>0.291</td>
<td>6.93</td>
</tr>
<tr>
<td>6.39</td>
<td>6.45</td>
<td>0.939</td>
<td>6.49</td>
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<td>6.44</td>
<td>6.41</td>
<td>0.466</td>
<td>6.15</td>
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<tr>
<td>6.16</td>
<td>5.99</td>
<td>2.760</td>
<td>5.91</td>
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<tr>
<td>7.03</td>
<td>6.97</td>
<td>0.853</td>
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<tr>
<td>6.42</td>
<td>6.49</td>
<td>1.090</td>
<td>6.43</td>
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<td>6.69</td>
<td>5.99</td>
<td>11.809</td>
<td>6.15</td>
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<td>6.51</td>
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<td>6.66</td>
<td>6.34</td>
<td>4.805</td>
<td>6.34</td>
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<td>5.80</td>
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<tr>
<td>5.42</td>
<td>5.61</td>
<td>3.506</td>
<td>5.66</td>
</tr>
<tr>
<td>5.51</td>
<td>5.63</td>
<td>2.178</td>
<td>5.49</td>
</tr>
</tbody>
</table>

Table 3—Details of prediction performance
neuro-fuzzy model. From Fig. 2 it could be inferred that the low micronaire and high fibre elongation increase the rotor yarn elongation. However, the curve reveals that the maximum yarn elongation is achieved when micronaire and fibre elongation are both at their lowest level. This goes against our established perception. This anomaly may be ascribed to the inadequate training of rules at this zone arising from lack of training data. Fig. 3 shows that the yarn elongation reduces with the increase in yarn fineness at any level of fibre elongation. Fig. 4 gives schematic representation of eight fuzzy rules developed by the ANFIS. It is observed that when fibre elongation, micronaire and yarn count are 5.2, 4.05 and 20.3 respectively, all the eight fuzzy rules produce an output or yarn elongation. All these output membership functions are then aggregated into a single membership function, which is shown in the lowest rectangle of the yarn elongation column (Fig. 4). Aggregated membership function is then “defuzzified” using the weighted average method to get the final yarn elongation value of 6.16. Therefore, it is possible to predict the output parameter and to extract some physical information (rule set) about the mechanism of the process using the neuro-fuzzy principle. Fuzzy rules give better insight about the process, making neuro-fuzzy logic more appealing than the ANN.

3.2 Analysing the Impacts of Cotton Properties and Yarn Count

The relative contribution of each of the inputs to the rotor yarn elongation has been studied using regression and ANN models. The ranking of input parameters was done according to the Beta coefficients in case of the regression model. However, for the ANN model, an input significance test was conducted by eliminating one designated input from the model at a time. The network was trained again and the prediction was made from the testing data. The percent increase in the mean squared error of prediction as compared to that of parent network was considered as the indicator of importance of the eliminated input. Ranking of fibre properties according to the regression and ANN models are shown in Tables 4 and 5 respectively. It is observed from Table 4 that according to the linear regression model, the yarn count, micronaire and fibre elongation are the major contributing parameters to the rotor yarn elongation in the order of descending importance. All these parameters are statistically significant at 1% level. Uniformity index of cotton is

<table>
<thead>
<tr>
<th>Input parameter</th>
<th>Beta coefficient</th>
<th>t-value</th>
<th>p-level</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fibre bundle tenacity</td>
<td>-0.122</td>
<td>-1.572</td>
<td>0.1200</td>
<td>6</td>
</tr>
<tr>
<td>Fibre elongation</td>
<td>0.179</td>
<td>2.733</td>
<td>0.0078</td>
<td>3</td>
</tr>
<tr>
<td>UHML</td>
<td>0.146</td>
<td>1.948</td>
<td>0.0550</td>
<td>5</td>
</tr>
<tr>
<td>Uniformity index</td>
<td>0.179</td>
<td>2.564</td>
<td>0.0122</td>
<td>4</td>
</tr>
<tr>
<td>Micronaire</td>
<td>-0.389</td>
<td>-5.779</td>
<td>0.0000</td>
<td>2</td>
</tr>
<tr>
<td>Reflectance degree</td>
<td>0.081</td>
<td>1.407</td>
<td>0.2982</td>
<td>7</td>
</tr>
<tr>
<td>Yellowness</td>
<td>-0.007</td>
<td>-0.103</td>
<td>0.9185</td>
<td>8</td>
</tr>
<tr>
<td>Yarn count</td>
<td>-0.633</td>
<td>-10.603</td>
<td>0.0000</td>
<td>1</td>
</tr>
</tbody>
</table>

![Fig. 4—Schematic representation of fuzzy rules and defuzzification](image)
significant at 5% level. Other fibre parameters, such as bundle strength, UHML, reflectance degree and yellowness, do not have any appreciable effect on the rotor yarn elongation according to the regression model. From the values of Beta coefficients, it can be inferred that the contribution of yarn count, micronaire, fibre elongation and uniformity index to rotor yarn elongation is 26.79%, 16.46%, 7.59% and 7.58% respectively.

Table 5 shows that similar to the statistical model, the yarn count and micronaire hold the first and second places respectively in the hierarchy of input parameters according to ANN model. As the yarn becomes finer, the frequency of thin and weak spots in the yarn increases, resulting in decrease in tenacity and elongation. Therefore, the yarn count emerges as the most important determinant of rotor yarn elongation. Lower micronaire probably causes tighter wrapping of the yarn body by the wrapper fibres due to the lower bending rigidity of fibres. Washer fibres or belts extend during the axial straining, thereby reinforcing the yarn matrix to restrict the fibre slippage. As a result, the yarn elongation increases. However, in stark contrast to the ranking of fibre properties in regression model, the colour properties of cotton fibres, namely reflectance degree and yellowness, acquire the third and fourth place respectively as the contributors. Fibre elongation is positioned in the fifth place. This difference of ranking may be attributed to the non-linear relationship between the colour properties of cotton and the rotor yarn elongation. The linear regression model probably fails to discover this non-linear relationship, resulting in lack of significance of reflectance degree and yellowness. In a similar study, Ethridge and Zhu found that the yarn count, yellowness, micronaire and reflectance are the first four parameters in the order of descending influence to rotor yarn elongation. This ranking extends reasonable support to our findings.

4 Conclusions

4.1 Rotor yarn elongation can be predicted with more than 95% average accuracy from the cotton fibre properties and yarn count by using linear regression, ANN and neuro-fuzzy models.

4.2 Prediction performance of ANN and neuro-fuzzy models is better than the regression model in spite of using lower number of inputs in case of neuro-fuzzy model. Linguistic rules, which relate the input parameters with the yarn elongation, could be extracted from the neuro-fuzzy model and a better understanding about the process is achieved.

4.3 Yarn count and cotton micronaire are the major determinants of rotor yarn elongation.

References