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

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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 performed 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.[3,11], Subramanian[12], Kim and El-Sheikh[13,14], Zurek et al.[15], Frydrych[16], Onder and Baser[17] Rajamanickam et al.[18,19] and Morris et al.[20] 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[21], Hafez[22], Smith and Water[23], El-Mogahzy[24], Hunter[25], and Mostafa et al.[26] 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[27] 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[28], Ramesh et al.[29], Ethridge and Zhu[30,31], Pyne[32-36] and Majumdar et al.[37] 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 network models have been applied on the other.
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 state, 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 broadcast to several other neurons.

For example, consider a neuron j, which receives input from neurons X_{i1}, X_{i2}, X_{i3}, …..X_{in}. 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:

\[ Y_i = h(\Sigma_j (W_{ij} \cdot X_j - M_j)) \]  

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

- \( W_{ij} \) = is the weight of mode I of the hidden layer for the input coming from input j.
- \( M_i \) = is the adjustable threshold.

The appropriate selection of the learning data and the network structure is of 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 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:

\[ y = f \left( \sum_{i=1}^{n} w_i \cdot x_i \right) \]

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

<table>
<thead>
<tr>
<th>Fiber origins properties</th>
<th>Micromat Properties</th>
<th>Breaking load (gf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HVI properties</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UHM (mm.)</td>
<td>Uniformity</td>
<td>Strength</td>
</tr>
<tr>
<td></td>
<td>(%)</td>
<td>cN/tex</td>
</tr>
<tr>
<td>80 Ne</td>
<td>100 Ne</td>
<td>120 Ne</td>
</tr>
<tr>
<td>Ring</td>
<td>Compact</td>
<td>Ring</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fiber</th>
<th>Uniformity</th>
<th>Strength</th>
<th>Elongation</th>
<th>Mic. reading</th>
<th>Yellowness b+</th>
<th>Brightness Rd %</th>
<th>Maturity</th>
<th>Fineness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Giza 45</td>
<td>35.8</td>
<td>89.4</td>
<td>43.2</td>
<td>6.1</td>
<td>3.1</td>
<td>74</td>
<td>8.9</td>
<td>0.92</td>
</tr>
<tr>
<td>Giza 87</td>
<td>35.3</td>
<td>85.8</td>
<td>45.0</td>
<td>6.4</td>
<td>3.0</td>
<td>72</td>
<td>9.4</td>
<td>0.91</td>
</tr>
<tr>
<td>Giza 77 shima</td>
<td>36.2</td>
<td>89.3</td>
<td>46.2</td>
<td>6.2</td>
<td>2.9</td>
<td>66.2</td>
<td>11.6</td>
<td>0.91</td>
</tr>
<tr>
<td>Giza 70</td>
<td>35.4</td>
<td>87.5</td>
<td>44.6</td>
<td>6.3</td>
<td>4.1</td>
<td>73</td>
<td>9.5</td>
<td>0.92</td>
</tr>
<tr>
<td>Giza 88</td>
<td>35.4</td>
<td>88</td>
<td>46.5</td>
<td>6.2</td>
<td>3.9</td>
<td>66.4</td>
<td>11.4</td>
<td>0.91</td>
</tr>
<tr>
<td>Giza 74 x Giza 66</td>
<td>33.9</td>
<td>88.5</td>
<td>48.6</td>
<td>6.3</td>
<td>3.7</td>
<td>70.6</td>
<td>9.1</td>
<td>0.92</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Yarn count (Ne)</th>
<th>Breaking load (gf)</th>
<th>Error (gf)</th>
<th>Error %</th>
<th>SD load Experimental (gf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experimental</td>
<td>Predicted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>80s</td>
<td>186.85</td>
<td>188.42</td>
<td>1.55</td>
<td>0.829</td>
</tr>
<tr>
<td>100s</td>
<td>137.48</td>
<td>141.54</td>
<td>2.02</td>
<td>1.469</td>
</tr>
<tr>
<td>120s</td>
<td>106.26</td>
<td>111.2</td>
<td>3.94</td>
<td>3.71</td>
</tr>
<tr>
<td>140s</td>
<td>76.3</td>
<td>80.1</td>
<td>3.8</td>
<td>4.98</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Yarn count (Ne)</th>
<th>Breaking load (gf)</th>
<th>Error</th>
<th>% Error</th>
<th>SD load Experimental (gf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experimental</td>
<td>Predicted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>80’s</td>
<td>197.7</td>
<td>194.2</td>
<td>-1.3</td>
<td>-0.66428</td>
</tr>
<tr>
<td>100’s</td>
<td>151.1</td>
<td>154.3</td>
<td>3.2</td>
<td>2.117803</td>
</tr>
<tr>
<td>120’s</td>
<td>112.8</td>
<td>108.4</td>
<td>-3.4</td>
<td>-3.04114</td>
</tr>
<tr>
<td>140’s</td>
<td>86.5</td>
<td>80.52</td>
<td>-1.98</td>
<td>-2.4</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Training run</th>
<th>Ring spun yarn</th>
<th>Compact spun yarn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Error mean %</td>
<td>SD</td>
</tr>
<tr>
<td>1</td>
<td>0.191</td>
<td>1.225</td>
</tr>
<tr>
<td>2</td>
<td>0.391</td>
<td>2.544</td>
</tr>
</tbody>
</table>
Table 4: Continued

<table>
<thead>
<tr>
<th></th>
<th>0.357</th>
<th>2.286</th>
<th>0.1282</th>
<th>0.8207</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.547</td>
<td>3.51</td>
<td>0.2130</td>
<td>1.3642</td>
</tr>
<tr>
<td>Over all mean</td>
<td>0.3715</td>
<td>2.39125</td>
<td>0.18</td>
<td>1.152575</td>
</tr>
</tbody>
</table>

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

\[
\text{Absolute Error} = \frac{1}{\sum_{j=1}^{n} \left| y_{0j} - y_{1j} \right|}
\]

Where:

- \( y_{0j} \) = measured yarn breaking load.
- \( y_{1j} \) = network predicted yarn breaking load.

The learning data of the back-propagation algorithm involves 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

\[
f(x) = \frac{1}{1 + \exp^{-x}}
\]

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

- Number of input nodes: 11 fiber parameters and yarn count.
- 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, 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.

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