Prediction of NEP of Rotor Spinning Yarn by Means of Intelligent Theory

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Abstract

In this work, we use a multi-layer perceptron (MLP) artificial neural network (ANN) model to predict the nep of rotor spun cotton yarn from the processing parameters. Statistical performance indicators such as MSE, MAE, and MAPE values of ANN are lower. Hence it can be said that the ANN gives more promising results. We believe that if the quantity of training data is increased, the results of the ANN model can also be improved. The predicted and experimental values agree well, indicating that the ANN models yield a better prediction, which is an excellent method for predictors.

Keywords: nep; rotor spinning; cotton yarn; processing parameters; artificial neural network, prediction.

1. Introduction

Rotor spinning yarn nep is the most significant parameter in the process of spinning process, there are many factors influencing yarn properties because rotor yarn production is a complex multi-step technological process, and the structure of yarns is complicated. However, it is rather difficult to establish a physics model to describe the process-property relation of the nep of rotor spinning yarn.

In recent years, artificial neural network model [1-5] has been used to predict various yarn properties. With the characteristics of self-learning, self-organization and self-adapting, neural network expressed its

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superiority on the model setting of complicated system. Artificial neural networks (ANN)[6-10] are potent data-modeling tools that are able to capture and represent any kind of input-output relationship. They can gather their knowledge by detecting the relationships and patterns in data; in other words, they are able to learn from experience.

Presently, it becomes more and more important in the research and production of textile industry. However, there is dearth of published work that encompasses the scope of predicting rotor yarn nep from spinning parameters with ANN models. In this work, we use multi-layer perceptron (MLP) neural network model to predict the nep of rotor spun cotton yarn with the processing parameters.

The modeling results are reliable. Therefore, the results also demonstrate that the ANN theory is an effective, precise and accurate modeling approach.

2. Experimental Procedure and Results

2.1. Experiment variety

The yarn with linear density of 36.4 tex was manufactured with the use of the BD 200-RCE rotor spinning machine.

2.2. Experiment machine type

BD 200-RCE rotor spinning machine is used in this work, rotational speed of the rotor is 40000-30000r/min, and rotational speed of the opening roller is 5000-7000r/min.

2.3. Experiment conditions

Test samples were conditioned in a standard atmosphere of 25°C temperature and 65% relative humidity for minimum of 24 hours.

2.4. Experiment contents

The parameter such as yarn nep (num./1000m) was tested by using Uster-III yarn evenness tester.

2.5. Experimental program

Table 1. Experimental program of rotor spinning process parameters

<table>
<thead>
<tr>
<th>No.</th>
<th>Opening roller speed (r/min)</th>
<th>Opening roller diameter (mm)</th>
<th>Rotor speed (r/min)</th>
<th>Rotor diameter (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6200</td>
<td>60</td>
<td>30000</td>
<td>60</td>
</tr>
<tr>
<td>2</td>
<td>6300</td>
<td>62</td>
<td>40000</td>
<td>67</td>
</tr>
<tr>
<td>3</td>
<td>5600</td>
<td>63</td>
<td>35000</td>
<td>62</td>
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<tr>
<td>4</td>
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<td>65</td>
<td>37000</td>
<td>65</td>
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<tr>
<td>5</td>
<td>5800</td>
<td>65</td>
<td>38000</td>
<td>61</td>
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<tr>
<td>6</td>
<td>6800</td>
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<td>8</td>
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<td>62</td>
<td>34000</td>
<td>65</td>
</tr>
<tr>
<td>11</td>
<td>6400</td>
<td>62</td>
<td>40000</td>
<td>60</td>
</tr>
</tbody>
</table>
3. Artificial neural network model

There are a lot of kinds of neural networks, in which multi-layer perceptron (MLP) network model [11] is one of the most researched and applied model. It is a feed forward connecting network model and trained by the error propagation algorithm, which contains the input layer, the hidden layer and the output layer, as shown in Figure 1. The multi-layer perceptron (MLP) neural network model has a hierarchical structure. The nodes are connected each other between different layers, but without interconnections in the same layer. Each node in every layer consists of a summer which adds up the input variable and connection weight between the node concerned and the input node. The signal flows from the input layer to the output layer via unidirectional connections. Neurons in the same layer do not link each other, but neurons in neighboring layer are connected by the weight.

In this work, we adopt multiple-lay perception (MLP) network which is a feed-forward network and trained by the back-propagation algorithm to predict the nep of rotor spinning yarn.

3.1. The Multi-Layer Perceptron Neural Network Model

The multi-layer perceptron (MLP) neural network model applied in this research is a kind of learning by updating errors called the back propagation algorithm. The structure of the MLP is divided into three layers, i.e., input layer, hidden layer and output layer. Every unit within a layer is connected with all of the units in the previous layer. These connections are not all equal; each connection has a different strength or weight. The weights of these connections encode the knowledge of the network. Data enters at the input layer and passes through the network, layer by layer, until it arrives at the output layer. During normal operation, there is no feedback between layers, and hence it is called a feed-forward neural network. By applying an artificial neural network, a prediction model for studying the compressive properties of woven fabrics is developed.

![Fig. 1. Structure and architecture of an ANN model](image)

3.2. Multi-Layer Perceptron Algorithm

The Multi-layer perceptron (MLP) algorithm generates input-to-output mappings based on computations of interconnected nodes arranged in layers. The number of nodes in the input and output layer is equal to the dimension of respective input and output factors. The number of hidden nodes in each particular case is...
determined taking into account the complexity of problem. Any node of a given layer is connected to all nodes of the proceeding layer via adjustable weights. Each nodes output is a nonlinear function of the weighted sum of inputs from the nodes in the preceding layer. Its input output equation follows

\[ y_j = \varphi \left( \sum_{i=1}^{N_{i-1}} w_{ji} x_i \right) \]  

(1)

Where \( N_{i-1} \) is the number of input of the \( k-1 \) layer, \( x_i \) is the input to the \( j \)th node and \( w_{ji} \) is the weight connecting the \( i \)th node of \( k-1 \) to the \( j \)th node of layer \( k \). For this study \( \varphi \) is in the form of a sigmoid activation function, defined by

\[ \varphi(x_j) = 1/(1 + \exp(-y_j)) \]  

(2)

After the network parameters are defined, the weights are adapted iteratively to minimize some predefined error function according to the back propagation learning algorithm. After the presentation of the \((k+1)\) input exemplar, each weight change is computed according to

\[ \Delta w_{ji}(k+1) = -\eta \frac{\partial E}{\partial w_{ji}} - \alpha \Delta w_{ji}(k) \]  

(3)

Where \( \frac{\partial E}{\partial w_{ji}} \) is the partial derivative of the error with respect to the weight \( w_{ji} \), \( \eta \) is the learning rate and \( \alpha \) is the momentum value.

3.3. Training of artificial neural network model

Training a feed forward back propagation neural network consists of giving the network a vectorized training data set each epoch. Each individual vector’s inputs are propagated through the network, and the output is incorporated with the vector’s experimental output in the error equation above. Training the network consist of minimizing this error in the space of the weight function, and adjusting the network’s weights using unconstrained local optimization methods. This study utilises Mathworks neural network software to establish a prediction model. For non–linear transformation, from input layer to hide layer, the function is

\[ f(x) = 2/(1 + e^{-2x}) - 1 \]  

(4)

And from hide layer to output layer, the function is

\[ f(x) = x \]  

(5)

The learning network was designed to reduce the margin between the target value and prediction output. The quality of learning was evaluated using the energy function, is as following:

\[ E = \frac{1}{2} \sum_k (Y_{dk} - Y_k)^2 \]  

(6)

Where \( Y_{dk} \) is the output layer target value, and \( Y_k \) the output value prediction value. The weights updated themselves by using error function as

\[ \Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \]  

(7)

Here \( \eta \) is the learning and determines the performance of the learning capability of network.

3.4. Algorithm Configuration
In the learning network, the degree of convergence can be repressed in a mean square error (MSE), a mean absolute error (MAE), a mean absolute percentage error (MAPE) and a correlation coefficient (R).

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - x_i)^2
\]  

(8)

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - x_i|
\]  

(9)

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - x_i}{x_i} \right|
\]  

(10)

\[
R = \frac{\sum_{n=1}^{N} (x_n - \bar{x})(y_n - \bar{y})}{\sqrt{\sum_{n=1}^{N} (x_n - \bar{x})^2 / \sum_{n=1}^{N} (y_n - \bar{y})^2}}
\]  

(11)

Where \( N \) is the number of objects, \( y_i \) the neural network predicted values, and \( x_i \) the actual output values. The values of MSE lie within the range of \([0, 1]\).

4. Results and Discussion

To evaluate the model, the neural network predicted values of the model are calculated and compared with actual output values. The various error measurements can be determined from this. We have used the following error measurements in our work: MAE (mean absolute error), MSE (mean squared error), MAPE (mean absolute percentage error), and Correlation R. Table 2 gives the analysis results. It can be seen from table that a better correlation between predicted and actual results indicate the nep of rotor spinning yarn is predictable with neural networks.

Table 2. Analysis results of artificial neural network model.

<table>
<thead>
<tr>
<th></th>
<th>MAE</th>
<th>MSE</th>
<th>MAPE</th>
<th>Correlation R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>0.124</td>
<td>0.0229</td>
<td>2.87%</td>
<td>99.734%</td>
</tr>
<tr>
<td>Test</td>
<td>0.158</td>
<td>0.0397</td>
<td>4.84%</td>
<td>98.017%</td>
</tr>
</tbody>
</table>

5. Conclusions

In this work, the nep of rotor spinning yarns are predicted by using an ANN model. The Artificial neural network prediction models can be built easily and rapidly. It can predict the nep of rotor spinning yarns well. Its predicting errors are lower, all results correspond with their theory basis well. Therefore, ANN models are more powerful in predicting warp breakage rates. Statistical performance indicators such as MSE, RMSE, MAE, and MAPE values of ANN are lower. The artificial neural network model with back-propagation can predict the nep of rotor spinning cotton yarn to provide a very good and reliable reference for rotor spinning processing parameters.

References


