# SELECTING COTTON BALES BY SPINNING CONSISTENCY INDEX AND MICRONAIRE USING ARTIFICIAL NEURAL NETWORKS

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## *Abstract*

*This paper presents a method of selecting cotton bales to meet the specified ring yarn properties using artificial neural networks. Five yarn properties and yarn count were used as inputs, whereas the Spinning Consistency Index (SCI) and micronaire were the outputs to the neural network models. Bales were selected according to the predicted combinations of SCI and micronaire. The properties of yarns spun from selected bales show good association with the target yarn properties.*

## *Key words:*

*high volume instrument, micronaire, neural network, ring yarns, spinning consistency index*

## Introduction

Cotton is a major natural fibre which displays great variation in its properties. For centuries, the grade and staple-length evaluation of cotton has served as the mainstay of cotton fibre selection for the spinning industry. Gradually, micronaire, bundle strength and length characteristics gained the industry's attention. In the 1970s, the High Volume Instrument (HVI) was introduced. The HVI's ability to produce such a great abundance of fibre quality data revolutionised the perception of fibre testing and selection. However, the use of HVI data seems very complex, as much more is actually learned than can be utilised in a real situation. Therefore, the selection of suitable cotton fibre to meet the customer's end-use requirement has remained a perennial challenge to the spinner. Researchers have developed several mathematical [1-6], statistical [7-12] and artificial neural network [13-17] models to predict the yarn properties from the properties of constituent fibres. However, there is a lack of efforts which cover the scope of cotton fibre selection from the given yarn properties. Therefore, the problem of cotton bale selection remains unresolved.

In this work, an effort has been made to formulate a bale selection procedure with the aid of an artificial neural network (ANN) model considering only two cotton fibre attributes, namely SCI and micronaire.

## Spinning Consistency Index (SCI)

The spinning consistency index (SCI) is a calculation for predicting the overall quality and spinnability of the cotton fibre. The regression equation uses most of the individual HVI measurements, and is based on the data taken from United States Department of Agriculture's (USDA) annual crop reports.

The SCI is calculated using the average fibre and yarn data of five consecutive years of USDA annual crop reports. The main use of SCI in selecting bales is to gain the advantage that all major cotton properties have been selected in a controlled way, and a consistency in fibre properties exist between fibres obtained from the selected bales throughout a season. Without the SCI, the spinner faces an insurmountable task. For instance, in evaluating HVI data there may be 4 categories of length, 3 of length uniformity, of reflectance (Rd) and of yellowness (+b), and 5 of strength and of micronaire, making the total of 2700 possible varieties of cotton from which consistent selection must be made. Pragmatically the task is impossible.

However, the SCI could be used to solve the complexity of cotton bale selection [18]. Within the SCI there are various fibre properties which allow us to take the advantage of inherent correlation prevailing among the fibre properties. Thus, the use of the SCI will drastically reduce the real number of cotton varieties available for selection. Practically, the SCI could be used as the first priority for the selection of bales, followed by micronaire as the second priority, in order to exert additional control in the fibre selection. As the SCI contains six interrelated properties, good distribution control of all the cotton properties could be achieved by controlling the SCI and micronaire. The regression equation [19] used to calculate the SCI is as follows:

$$SCI = -414.67 + 2.9\times strength - 9.32\times micronaire + 49.17\times UHML + 4.74\times UI + 0.65\times Rd + 0.36\times(+b)$$

Where:

UHML is upper half mean length in inches,
UI is the uniformity index,
Rd is the reflectance degree, and
(+b) is the yellowness of cotton fibre.

## The Neural Network and Back Propagation Algorithm

Computation by artificial neural networks (ANN) has emerged in the last decade as a powerful paradigm which has found applications in almost all branches of engineering. The development of ANN was inspired by the mechanisms by which real biological neurons work in the human brain. The decision-making process of the brain is emulated by an artificial network of processing elements (PE) or neurons. A properly trained network can predict the output response to a higher degree of accuracy than conventional mathematical or statistical models. A typical single output neural network is shown in Figure 1. In this kind of network, each neuron receives a signal from the neurons of the previous layer, and each of these signals is multiplied by a separate weight known as synaptic weight. The weighted inputs are then summed up and passed through a transfer function, which converts the output to a fixed range of values. The output of the transfer function is then transmitted to the neurons of the next layer.

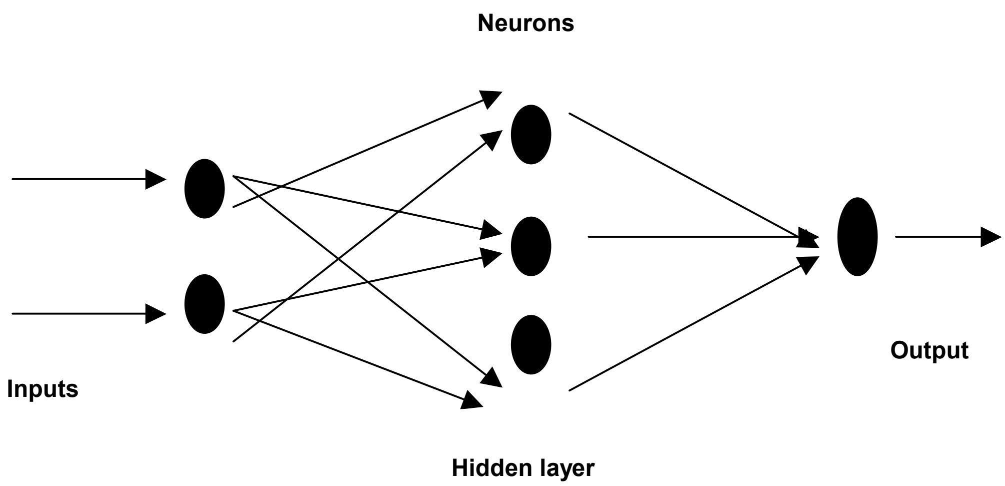


**Figure 1.** An example of a single-output neural network model

The back-propagation algorithm (also known as the generalised delta rule) is the most commonly used training method for the ANN models. The generalised delta rule basically performs a gradient-descent on the error surface. The 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 the error vector is made from the difference between actual and predicted output according to Equation 1:

$$E = \frac{1}{2}\sum\left(T_r - O_r\right)^2 \tag{1}$$

where $E$ is the error vector, $T_r$ and $O_r$ denote the target output and predicted output respectively, at output node $r$.

In the backward pass, this error signal is propagated backwards to the neural network, and synaptic weights are adjusted so that the error signal decreases with each iteration process, and the neural network model comes closer and closer to producing the desired output. The corrections necessary in the synaptic weights are carried out by the delta rule, which is expressed in Equation 2.

$$\Delta w_{pq(n)} = -\eta\left[\partial E / \partial w_{pq(n)}\right] \tag{2}$$

where:

$w_{pq(n)}$ - 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 nth iteration,
$\eta$ - is a constant known as the learning rate.

## Experimental

### Sample preparation

Ring-spun carded yarn samples were produced from the cotton fibres of known SCI and micronaire values. All the bales of cotton fibres were tested with HVI before the spinning operation. The yarns were spun into three different counts, making a total of 90 samples. We used the data from 75 samples for training the neural networks. The remaining 15 sets of data were used for testing the trained networks. Six major yarn properties, i.e. CSP (count strength product), tenacity, elongation, unevenness, hairiness and yarn count, were used as the selected inputs for the ANN model. The outputs from the neural networks were the SCI and micronaire.

### Neural network parameters

Construction of a proper network skeleton and optimisation of learning parameters are of paramount importance in order to achieve good prediction results from the ANN models. The important structural parameters to be determined are the number of hidden layers and the number of neurons in each hidden layer. We decided to employ the single hidden layer structure, as it is capable of handling non-linear relationships. However, the number of neurons in the hidden layer was varied from 2 to 12, by an increment of 2 in each step. The optimised values of learning rate and momentum were 0.1 and 0.0 respectively. Training was stopped after every 200 iterations, and the error in the testing set was monitored. Training was permanently halted when the error in the testing set reached the minimum level. In this study, we used the logistic transfer function as shown below:

$$f(Z) = \left(1 + e^{-Z}\right)^{-1}$$

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

## Results and Discussion

### Prediction of SCI and micronaire by the ANN models

After the completion of training, the unseen testing data was presented to the trained ANN models to verify their predictive power. The statistical parameters used to judge the prediction accuracy of various models are the correlation coefficient (R) and the mean error percentage (%). The results are shown in Table 1. It is observed that the ANN model with six nodes in the hidden layer exhibits the highest prediction accuracy. Correlation coefficients (R) between actual and predicted values are 0.800 and 0.853 for SCI and micronaire respectively. The overall mean error percentage is only 4.70. While analysing the impacts of number of nodes on the prediction performance, it is observed that as the number of hidden nodes increases the prediction accuracy improves. The prediction performance becomes optimum when six nodes are used in the hidden layer. However, no improvement in the prediction performance is noticed when the number of nodes in the hidden layer is increased beyond six. The reason for this may be attributed to the memorisation of training data by networks with too many nodes. The detailed prediction performance of the ANN model with six nodes in the hidden layer is shown in Table 2. It is observed that there are only one and two individual cases with more than 10% prediction error for the SCI and micronaire respectively.

**Table 1.** Prediction of SCI and micronaire by ANN models

| Number of nodes | Mean error, % | | | Correlation coefficient R | |
|---|---|---|---|---|---|
| | SCI | Micronaire | Overall | SCI | Micronaire |
| 2 | 4.56 | 6.79 | 5.68 | 0.786 | 0.422 |
| 4 | 4.99 | 4.87 | 4.93 | 0.760 | 0.845 |
| 6 | 4.08 | 5.35 | 4.72 | 0.800 | 0.853 |
| 8 | 4.31 | 5.12 | 4.72 | 0.791 | 0.844 |
| 10 | 4.40 | 5.16 | 4.78 | 0.782 | 0.784 |
| 12 | 4.32 | 5.16 | 4.74 | 0.783 | 0.869 |

**Table 2.** Detailed prediction performance of ANN model with six nodes

| SCI | | | Micronaire | | |
|---|---|---|---|---|---|
| Actual | Predicted | Error, % | Actual | Predicted | Error, % |
| 124 | 127.7 | 2.98 | 4.4 | 4.04 | 8.18 |
| 124 | 120.5 | 2.82 | 3.8 | 3.85 | 1.32 |
| 124 | 124.1 | 0.08 | 4.5 | 4.3 | 4.44 |
| 112.7 | 114.4 | 1.51 | 4.5 | 4.22 | 6.22 |
| 128 | 125.1 | 2.27 | 4.2 | 3.98 | 5.24 |
| 128 | 127.9 | 0.08 | 4.2 | 4.09 | 2.62 |
| 121.2 | 119.2 | 1.65 | 3.8 | 3.5 | 7.90 |
| 123 | 129.9 | 5.61 | 3.9 | 3.5 | 10.26 |
| 122.3 | 134.5 | 9.98 | 3.8 | 3.64 | 4.21 |
| 114.2 | 126.3 | 10.60 | 4.7 | 4.19 | 10.85 |
| 128.6 | 121.7 | 5.37 | 4.2 | 4.16 | 0.95 |
| 120.1 | 116.1 | 3.33 | 4.5 | 4.82 | 7.11 |
| 97.2 | 105.8 | 8.85 | 4.6 | 4.97 | 8.04 |
| 132.4 | 137.7 | 4.00 | 4.3 | 4.22 | 1.86 |
| 105 | 107.2 | 2.10 | 4.9 | 4.95 | 1.02 |
| R=0.800 and mean error =4.08% | | | R=0.853 and mean error =5.35% | | |

**Properties of yarns made from the selected bales**

To verify the extent of viability of the proposed bale selection method, 14 new yarn samples were spun from cotton bales chosen on the basis of predicted combinations of SCI and micronaire. Only one predicted combination of SCI and micronaire (107.2 and 4.95) could not be used, due to the unavailability of bales of that category. The properties of these newly spun yarns were evaluated and compared against the targeted yarn properties (Figures 2-6). The error analysis results for various yarn properties are shown in Table 3. It is observed that for individual yarn properties, the mean error ranges from 3.82% to 7.52%. The strength parameters (CSP and tenacity) of yarn, which receive the greatest attention from the spinner, show a nominal mean error of 5% or less. Moreover, there are one and zero cases with more than 10% error in the cases of CSP and tenacity respectively. In contrast, the mean error percentage was relatively higher (around 7.5%) in the cases of elongation and unevenness. Besides, there are four and five individual cases with more than 10% error for elongation and unevenness respectively. Yarn elongation is mostly influenced by fibre elongation [8], and the SCI equation does not include fibre elongation as a parameter. This may be the most plausible reason for the higher error percentage in the case of yarn elongation. Tenacity and hairiness also exhibit good correlation (0.83 and 0.85) between the targeted and achieved values.

**Table 3.** Error analysis of yarns spun from the selected bales

| Yarn sample no. spun from selected bales | Error, % | | | | |
|---|---|---|---|---|---|
| | **CSP** | **Tenacity** | **Elongation** | **Unevenness** | **Hairiness** |
| 1 | 6.16 | 0.81 | 1.19 | 1.97 | 3.24 |
| 2 | 5.89 | 2.35 | 0.00 | 13.33 | 4.29 |
| 3 | 5.39 | 4.79 | 0.75 | 3.42 | 5.46 |
| 4 | 2.58 | 6.80 | 20.99 | 2.74 | 10.12 |
| 5 | 0.12 | 6.57 | 2.81 | 9.59 | 1.27 |
| 6 | 1.77 | 3.99 | 7.73 | 2.82 | 4.59 |
| 7 | 9.20 | 4.38 | 11.77 | 13.67 | 7.32 |
| 8 | 0.08 | 2.71 | 3.31 | 5.67 | 2.56 |
| 9 | 7.90 | 7.15 | 7.08 | 11.20 | 5.63 |
| 10 | 8.16 | 1.37 | 6.97 | 5.74 | 3.24 |
| 11 | 1.80 | 4.16 | 8.38 | 2.61 | 4.39 |
| 12 | 4.43 | 0.51 | 2.83 | 6.61 | 8.81 |
| 13 | 14.89 | 4.87 | 18.44 | 10.30 | 5.43 |
| 14 | 1.66 | 3.05 | 13.04 | 12.82 | 9.98 |
| Average | 5.00 | 3.82 | 7.52 | 7.32 | 5.45 |

## Conclusion

We have demonstrated a method of cotton bale selection from the given yarn properties using artificial neural networks. The complexity of bale selection was reduced by using SCI and micronaire as the comprehensive indexes of cotton fibre quality. Yarns spun from the bales selected in accordance with the proposed method have good association in terms of properties with the target yarns. The mean error of individual yarn properties ranges from 3.82% to 7.52%. The accuracy is very good in the cases of CSP, tenacity and hairiness. Incorporating the fibre elongation in the SCI equation could probably enhance the accuracy of bale selection.

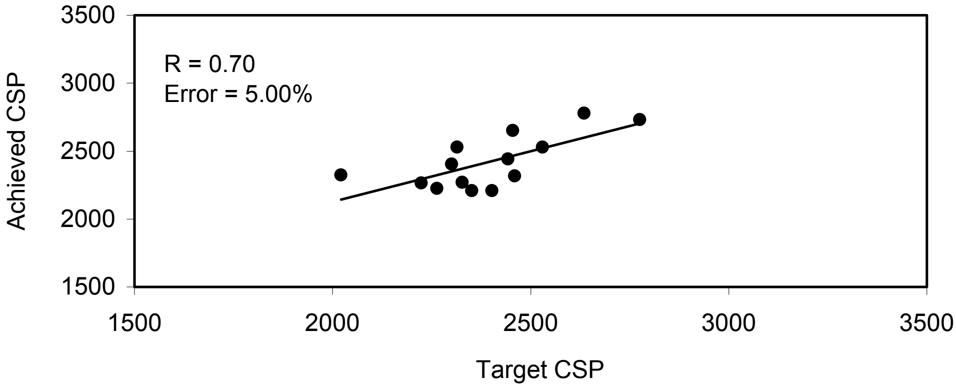


**Figure 2.** Scatter plot of achieved CSP vs target

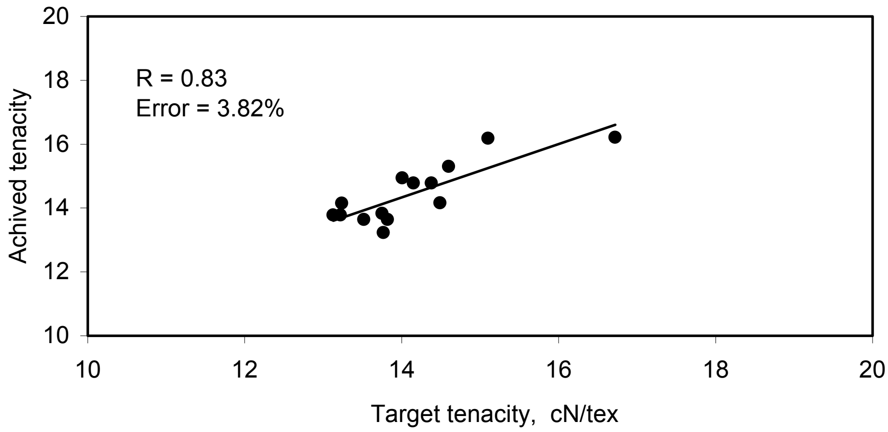


**Figure 3.** Scatter plot of achieved tenacity vs target

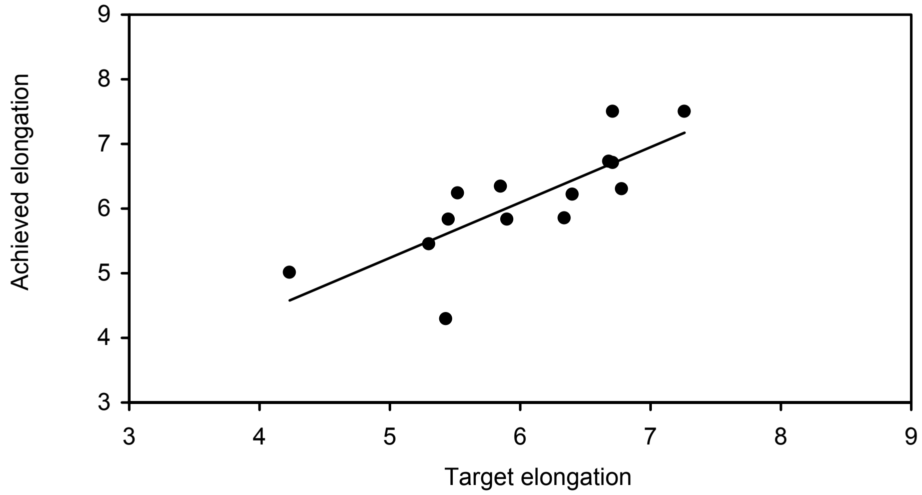


**Figure 4.** Scatter plot of target vs achieved elongation

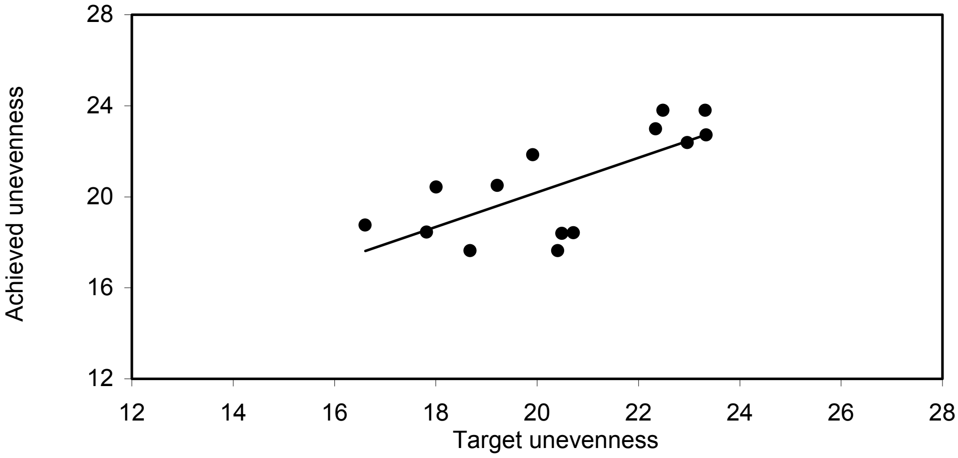


**Figure 5.** Scatter plot of target vs achieved unevenness

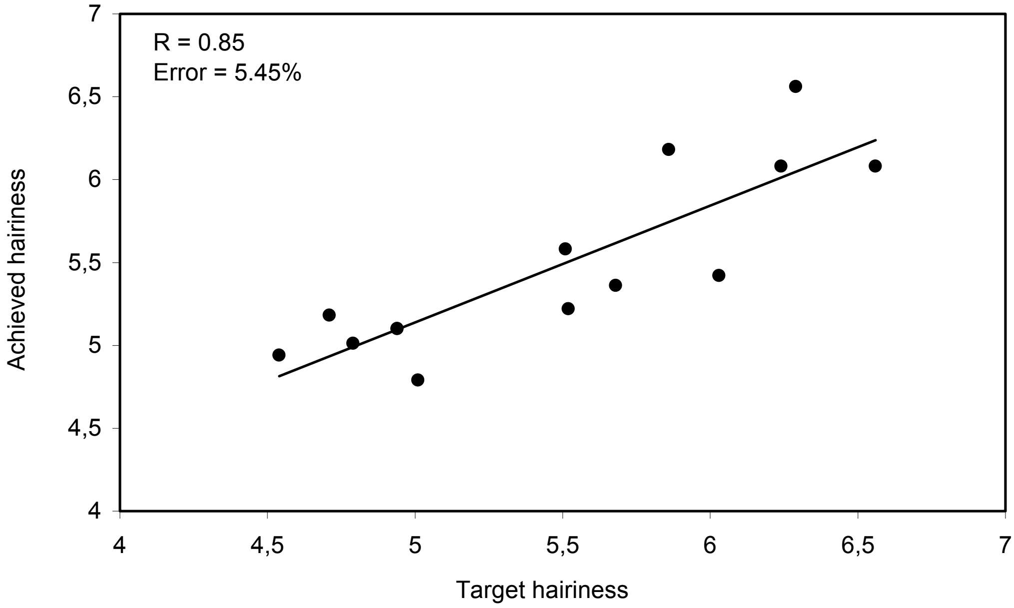


**Figure 6.** Scatter plot of target vs achieved hairiness

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