Highest standard count estimation from fibre parameters using neural network techniques

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Artificial neural network (ANN) model has been developed for predicting highest standard count (HSC) from fibre properties, namely 2.5% span length, uniformity ratio, micronaire and bundle strength. The developed ANN model was compared with the multiple regression and fibre quality index (FQI) based regression models. ANN ranking of fibre properties was carried out using difference in test performance values as indicator and in case of multiple regression, standardized regression coefficients were used. It has been observed that in both ANN and multiple regression models, the ranks of span length and bundle strength are the same. The span length is the largest contributor for HSC and the bundle strength is the least contributor. The mean absolute errors of ANN and multiple regression equation are found to be less by 15% and 11% respectively in comparison with FQI-based linear regression equation.

Keywords: Artificial neural network, Back propagation neural network, Cotton, Fibre quality index, Highest standard count, Lea CSP, Multiple regression model

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1 Introduction

The commercial value of a cotton variety is related to its spinning performance, which, in turn, is dependent on the yarn count that can be spun from the given cotton and the yarn quality obtained for that count. The quality of any yarn spun from cotton depends on its fibre quality, particularly length, strength, fineness, uniformity ratio, short fibre content and breaking elongation. The prediction of yarn quality and spinnability of a particular cotton is necessary for a better product design. Presently, the test for yarn quality is done by processing a small quantity of a cotton sample to a particular count and ascertaining the quality of yarn so produced. The process adopted for the evaluation of spinning quality differs from country to country. For example, in USA, all cottons are spun to two known counts depending on the staple category, viz. short staple is spun to 8s and 22s, medium staple and long staple to 22s and 50s and extra long staple to 50s and 80s (ref.1). The processing technique adopted is dependent on the group to which cotton belongs. The average CSP for two counts is also determined. In Egypt, all cottons are spun to single count and their yarn CSP is used to rank the cotton\(^2\). However, both the approaches are not suitable for Indian cottons due to wide range of varieties produced and the range of counts spun out of them. One of the problems with the single count approach is that some of the cottons may not be spinnable to that particular count. Moreover, it is certainly doubtful whether this method would distinguish between two cottons at the other end of the spinning value scale, i.e. if cotton A is slightly better in lea strength at 20s count, it is by no means certain that cotton A would also be better than cotton B in say 80s count\(^1\).

Central Institute for Research on Cotton Technology (CIRCOT), one of the several research institutes of Indian Council of Agricultural Research, has two test methods for evaluating the spinnability of cotton, namely microspinning and full spinning. Microspinning is mainly used for screening varieties in the preliminary stages where the quantity of cotton available is in the order of 50 - 100g. In this test,
samples belonging to particular trial (number of samples per trial may range from 5 to 15) are spun to one appropriate count and the spinnability is decided on the basis of its CSP value. However, one of the drawbacks in this method is that one trial cannot be compared with the other if both are spun to different counts. In addition to that the decision of appropriate count involves the problem of subjectivity. These issues are not of big concern as far as preliminary breeding trials are concerned. Limitation of time and the quantity of sample are the major reasons for choosing microspinning test. Whenever the quantity of sample available is 5kg, a full spinning test is carried out using normal processing methods adopted in spinning mills. In this test, two counts are spun, one under-spun and the other over-spun as decided by CIRCOT CSP norms. The two counts with their CSP are reported. Here again the comparison between two cottons is difficult, if they are spun to different sets of counts. Understanding this problem, an integrated index called highest standard count (HSC) was developed long back.

HSC is the finest count of yarn that can be spun economically with a standard medium twist and has a certain standard lea CSP. The counts that are spun higher than HSC will have less CSP and counts that are spun lower than HSC will have more CSP than the standard (Fig. 1). Thus, the HSC of cotton is a single integrated index, which provides an easy way for comparing the quality of cottons. Measurement of HSC involves the spinning of under-spun and over-spun counts using a full spinning test and calculating HSC from their CSP values. This is a time consuming, and labour and machine intensive process. To overcome these problems, regression equations were used to predict HSC from fibre properties. Recent studies reveal that the artificial neural network (ANN) models are outperforming the traditional regression and mathematical models, when the relationships between the variables are non-linear. Hence, in this paper, an attempt has been made to develop an ANN model for the prediction of HSC from fibre properties and to compare it with regression models.

2 Materials and Methods

Eighty samples covering many varieties of cotton were selected and tested for their fibre parameters. The 2.5% span length, micronaire, bundle strength and uniformity ratio were measured by using High Volume Instrument (HVI). All the samples were spun to two counts using CIRCOT full spinning test. The two counts were spun in such a way that one is under-spun and the other is over-spun as decided by CIRCOT CSP norms (Table 1). The yarn samples were tested for count and lea strength using a computerized lea strength tester. Thirty readings were taken per sample and the mean lea CSP calculated. Finally, the HSC was calculated using a newly developed method described below.

2.1 Calculation of HSC

Presently, CIRCOT uses graphical method for calculating HSC. In this method, first standard CSP values are plotted against count and are joined together to form a straight line. Then experimentally determined CSP values of a particular sample are plotted in the same graph and are joined. These two lines will intersect at a point and the count corresponding to this intersecting point is known as HSC (Fig 1). As this is a time consuming process, a new method is developed using the principles of algebra and analytical geometry to quickly calculate HSC. First, a straight-line equation is developed from the under-spun and over-spun counts and its CSPs. The other equation readily available is the standard
CSP equation, i.e. \( \text{CSP} = 9.2(C+200) \), where \( C \) is the English yarn count. By solving these two equations, HSC is obtained. A small computer programme has been developed and the entire calculation is automated. This programme is used to calculate the HSC for the eighty samples studied. The HSC calculation algorithm works as follows:

(i) Fit a straight-line equation for the experimental count and CSP values. In a two dimensional case, the form of a linear function can be obtained, if coordinates of two points on a straight line are known. Suppose \( x_1 \) and \( x_2 \) are the two given values (count) and the corresponding \( y \) values (CSP) are \( y_1 \) and \( y_2 \). Then, the slope of the line is:

\[
m = \frac{y_1 - y_2}{x_1 - x_2}
\]

The intercept is:

\[
a = y_1 - \left( \frac{y_1 - y_2}{x_1 - x_2} \right) x_1
\]

The straight line equation is:

\[
y = mx + a
\]

(ii) Solve the Eq (1) and the CIRCOT standard CSP equation, i.e. \( y = 9.2x + 1840 \) and find out the value of \( x \). This is the value of HSC, which can be obtained using the following formula:

\[
x = \frac{a - 1840}{9.2 - m}
\]

2.2 Neural Network Parameters

'Statistica' neural network software was used for the development of model. The data set was divided into three sets in the ratio of 2:1:1. That is, 40 data sets for training, 20 data sets for testing and 20 data sets for validation. The training data set is the set of data used by neural network for learning the problem. The test set is used during training to monitor the learning performance. The validation set is used after training as a final check to determine how well the model performs. Back propagation neural network was used for model development. Sigmoid function of the following type was used for the output transformation:

\[
F'(l) = \frac{1}{1 + \exp(-F(l))}
\]

where \( F(l) \) is the weighted sum of inputs to a node; and \( F'(l) \), the transformed output from a node.

Using the same data set, two regression models were also developed for comparison purposes. In one of the regression model, fibre quality index (FQI) was calculated using the CIRCOT FQI formula and it was used as independent variable in the model development. In the other model, all the fibre parameters, such as 2.5% span length, uniformity ratio, micronaire and bundle strength, were used as independent variable and HSC as dependent variable. CIRCOT's FQI formula is given below:

\[
\text{FQI} = \frac{2.5\% \text{ Span length} \times \text{Bundle tenacity}}{\text{Micronaire}}
\]

2.3 Back Propagation Neural Networks

The back propagation neural networks perform as follows:

(i) Perform the forward phase for an input pattern and calculate the output error.

- First, it computes the total input \( X_j \) using the following formula:

\[
X_j = \sum Y_i W_{ij}
\]

where \( Y_i \) is the activity level of \( i \)th unit in the previous layer; and \( W_{ij} \), the weight of connection between \( i \)th unit and \( j \)th unit.

- Next, the unit calculates the activity \( Y_j \) using the following sigmoid function:

\[
Y_j = \frac{1}{1 + e^{-x_j}}
\]

- Once the output of all the units is determined, the network computes the error \( E \), which is defined by the following expression:

\[
E = \frac{1}{2} \sum (y_j - d_j)^2
\]

where \( y_j \) is the activity level of the \( j \)th unit; and \( d_j \) the desired output of the \( j \)th unit.

(ii) Calculate the local error gradient for each weight and update the weights using the following formula:

\[
W(\text{new}) = W(\text{old}) + \Delta W(t)
\]

\[
\Delta W(t) = \eta \delta y_i + \alpha \Delta W(t-1)
\]

where \( \Delta W(t) \) is the weight increment; \( \eta \), the learning rate; \( \delta \), the error gradient; \( y_i \), the output of \( i \).
th unit; $a$, the momentum; and $\Delta W(t-1)$, the old weight increment.

(iii) Repeat the steps (i) and (ii) until the maximum number of epochs or target error is reached.

2.4 Neural Network Terminologies

2.4.1 Error Gradient

The error gradient ($\delta$) represents the slope of error surface. In a linear model, the error surface is parabola (quadratic), which means that it is a smooth bowl shape with a single minimum. It is therefore easy to locate the minimum analytically. But neural network error surface is much more complex, as shown in Fig 2, with local and global minimum. Hence, locating a minimum in neural network surface is a difficult task and this is achieved by training the network. Neural network training is essentially an exploration of error surface. From initially random configuration of weights (random points in the error surface), the training algorithm incrementally seeks for global minimum. Typically, this is done by calculating the gradient of error surface at the current point and then using this information to make a downhill move.

The local error gradient ($\delta$) calculation depends on whether the unit is in the output layer or in the hidden layer. Local gradient in the hidden layers is the weighted sum of units outgoing weights and local gradient of the units to which these weights connect. Local gradient in output layers is the product of derivative of the network's error function and the unit's activation function, as shown below:

$$\delta = \frac{\partial E}{\partial y} \times \frac{\partial y}{\partial x} = (y_j - d_j) y_j (1-y_j)$$

2.4.2 Learning rate

Learning rate ($\eta$) controls the size of weight changes made by the algorithm. The learning rate value must be chosen between 0 and 0.9. Choosing the value for learning rate is very delicate. If it is assigned a large value then local minima can be easily avoided by just jumping over them. But this might end the system up in oscillation (i.e. jumping forward and backward over a global minimum without getting there). However, if the learning rate is given a smaller value then may be global minimum cannot be missed, if there are any around, but the system is more likely to be trapped in a local minimum. The default value for learning rate in statistica neural network is 0.6.

2.4.3 Momentum

Momentum ($\alpha$) also controls the size of weight change similar to learning rate. Momentum value chosen should be in the range of 0-0.9. The momentum times the old weight increment is added whenever a new weight increment is calculated. This way the learning rate value can take a large value and the risk to end up in an oscillating state is minimized. When the network is homing in a minimum (whether local or global), the size of $\Delta W$ is getting smaller and smaller. A degree of sluggishness is introduced into the rate at which $\Delta W$ becomes smaller by adding in last time's value of $\Delta W$. This value of $\Delta W$ will exhibit characteristic analogous to momentum, which tends to resist the efforts to reduce it. The hope is that this will tend to bulldoze the weight over the local minima where the weight is being adjusted rapidly (i.e. where $\Delta W$ is large). At the same time, this will allow the weight to settle gently on the true minimum where the weight is being adjusted slowly (i.e. where $\Delta W$ is small). The default value for momentum in statistica neural network is 0.3.

2.4.4 Epoch

A single pass through the entire training set, followed by the testing of verification set is called one epoch. The statistica neural network default value for epoch is 100. This means that 100 epochs will be executed before terminating the training session. Epoch is used as a stopping condition.

2.4.5 Bias

This refers to pseudo input of a neural net with any value except zero. Its purpose is to generate different inputs to neurons even when the values of input pattern are zero. If the values of the input pattern are zero, the weights in the net would never be changed.

![Fig. 2—Neural network error surface](image)
for that pattern and net could not learn it. This is due to the fact that the pseudo input called bias is created that has a constant output value except zero24. In case of statistic neural networks, this value is 1. By sending a output of 1, it is guaranteed that the input values of those neurons are always differing from zero.

3 Results and Discussion

‘Statistica’ neural network software was used for the development of the neural network model. The 2.5% span length, uniformity ratio, micronaire and bundle strength were used as independent variable (input variable). HSC was used as dependent variable (output variable). Different values of neural network parameters, such as number of hidden neurons, learning rate and momentum, were tried to find out the optimum value for these parameters. The statistical parameters, such as mean absolute error (MAE), mean absolute percentage error (MAPE) and correlation coefficient, were used as indicative values for model optimization. The mean absolute error is simply the average deviation of the predicted values from the actual values across the data set without referring the direction (or sign) of the error. It is expressed in the units of output variable. The mean absolute percentage error is the average per cent the predicted outputs vary from the actual outputs. The correlation coefficient ($R$) is the Pearson correlation between the predicted and the actual outputs. The input values were scaled from 0 to 1 and the output values were scaled between 0.2 and 0.8. Finally, a neural network with 14 hidden neurons, 0.05 leaning rate and 0.05 momentum was found to give maximum correlation coefficient and minimum MAE and MAPE. Twenty data sets were validated using this ANN model.

Two regression models were developed using a statistical package. The multiple regression equation for predicting HSC from individual fibre properties is:

$$\text{HSC} = 0.790 \times \text{BS} - 4.845 \times \text{MIC} + 2.575 \times \text{SL} + 1.43 \times \text{UR} - 92.17$$

where BS is the bundle strength in g/tex; MIC, the micronaire; SL, the 2.5% span length in mm; and UR, the uniformity ratio.

The equation for predicting HSC from FQI is:

$$\text{HSC} = 0.132 \times \text{FQI} + 4.151$$

The 20 data sets, validated by ANN, were used for the verification of these two regression models (Table 2). MAE, MAPE and correlation coefficient were calculated and their values were used to compare all the three models. The results are presented in Fig. 3. The ANN model is able to

<table>
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<tr>
<th>Cotton</th>
<th>SL (mm)</th>
<th>UR (%)</th>
<th>MIC (µg/in)</th>
<th>BS (g/tex)</th>
<th>Actual</th>
<th>ANN</th>
<th>Multiple</th>
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*Obtained using the developed calculation algorithm.
SL — 2.5% Span length, UR — Uniformity ratio, MIC — Micronaire, BS — Bundle strength and HSC — Highest standard count
estimate HSC with a mean absolute error of 4.69 and a correlation coefficient of 0.88 between predicted and actual values. The multiple regression model also perform equally well with an MAE of 4.85 and correlation coefficient of 0.88. It can be seen from Fig. 3 that the MAE of ANN is 3% less than that of multiple regression, which is a marginal difference. The MAPE and correlation coefficient of these two equations are almost equal. However, both these models perform better than FQI-based equation. FQI-based model gives the highest MAE (5.37) and MAPE (15.51), and lowest correlation coefficient (0.86). The MAE of ANN and multiple regression equation are less by 15% and 11% respectively in comparison with FQI-based linear regression equation. Similarly, MAPE and correlation coefficient are also lower for these two equations than FQI-based equation.

Presently, FQI is used to compare two cotton qualities. As FQI gives poor prediction with HSC, one can use ANN or multiple regression equation to predict HSC values, which can be used to compare two cotton qualities. Another problem with FQI is that each research institute has different FQI models and this results in confusion among the industries to which one to use. In addition to that the FQI formula has changed over the years. Since the Industry is very much familiar with the concept of count, as such there would not be any problem in understanding and using HSC as an index. HSC being an integrated index reflecting the spinnability of cotton, is more suitable index to compare cottons than FQI. These developed models will also be useful in situations where there is a shortage of time to process cottons and to spin two

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<tr>
<th>Parameter</th>
<th>Root mean square error</th>
<th>Difference in test performance</th>
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<td>-</td>
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<td>Span length</td>
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<td>-0.0892</td>
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<tr>
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<td>Micronaire</td>
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<td>Bundle strength</td>
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<table>
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<td>0.132</td>
<td>0.760</td>
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3.1 Ranking of Fibre Properties

In case of ANN, to understand the effect of each input, an input significance test was conducted. This test works by eliminating the designated input or inputs from the trained model and then by applying the test set through the neural network model. The performance was then compared with the performance of all the inputs included to measure the change in fit, when the designated inputs are removed. The large reduction in performance is then indicative of the key input variable. The ranking of fibre properties can be done using the difference in test performance values (Table 3). It can be seen that when all inputs are included, the root mean square error is only 0.0850. However, the root mean square error increases to 0.1742, when the span length is removed. Hence, the difference in test performance works out to -0.0892 for span length and this is the largest value. Accordingly, the order of fibre properties for HSC is: span length, uniformity ratio, micronaire and bundle strength. Span length is the largest contributor for HSC and the bundle strength is the least contributor.

In case of multiple regression, standardized regression coefficients are used for ranking the fibre properties. The examination of standardized regression coefficients (Table 4) reveals that the span length has the greatest impact on HSC and the bundle
strength has the least. In both ANN and multiple regression models, the ranks of span length and bundle strength are the same. However, according to ANN, the second most influencing factor in HSC is uniformity ratio whereas it is micronaire with multiple regression. The impact of micronaire is negative, indicating that the higher micronaire gives less HSC, when other independent variables are constant.

4 Conclusions

The ANN model is able to estimate HSC with a mean absolute error of 4.69 and a correlation coefficient of 0.88 between predicted and actual. The multiple regression model also performs equally well with an MAE of 4.85 and correlation coefficient of 0.88. FQI-based linear regression does not predict HSC with expected accuracy. It has got the highest MAE and MAPE, and lowest correlation coefficient. Span length is the largest contributor for HSC and the bundle strength is the least contributor. As FQI is having poor prediction with HSC, one can use ANN or multiple regression equation to predict HSC and bundle strength are the same. However, according to ANN, the second most influencing factor in HSC is uniformity ratio whereas it is micronaire with multiple regression. The impact of micronaire is negative, indicating that the higher micronaire gives less HSC, when other independent variables are constant.

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