Use of Input Selection Techniques to Improve the Performance of an Artificial Neural Network During the Prediction of Yarn Quality Properties

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ABSTRACT: The performance of an artificial neural network (ANN) is affected by the number and types of inputs. The aim of this article is to study the performance of ANN algorithms, used for the prediction of cotton yarn strength, elongation, and evenness, as the input units are subtracted (skeletonized) and added to the input layer. Nineteen factors, consisting of fiber properties, processing parameters, and yarn quality properties, were used as the main source of inputs. The initial sets of inputs, which were selected on the basis of their relationship with the output factors, were 13, 13, and 12 for yarn strength, elongation, and evenness, respectively. The final sets of inputs were 14 factors for the three yarn quality properties being predicted, and the new ANN algorithms showed performance improvement of 40, 37, and 47% for strength, elongation, and evenness, respectively, when compared to the algorithms with 19 factors. Yarn twist, fiber length, and fiber length uniformity were common among the five most influential factors affecting yarn strength, elongation, and evenness, accounting for 40, 37, and 37% for the prediction of yarn strength, elongation, and evenness, respectively. © 2007 Wiley Periodicals, Inc. J Appl Polym Sci 108: 320–327, 2008

Key words: fibers; networks

INTRODUCTION

Yarn occupies an intermediate position in the manufacturing of fabric from fibers. The important factors that affect yarn quality properties include fiber quality properties, spinning technology, and machine settings.[1–5] Consequently, the prediction of yarn quality properties from fiber quality characteristics and machine settings has been reported by several researchers[6–10] who used mathematical, statistical, and artificial neural network (ANN) models. Desai et al.,[11] and Majumdar and Majumdar[12] reported that the use of ANN algorithms for the prediction of yarn quality properties for ring-spun yarns showed a higher prediction efficiency than mathematical and statistical models. The design of an ANN prediction algorithm involves the selection of several factors, which include the network architectures, number of layers in the network, number of neurons in the layers, and training, learning, and transfer functions.[13,14] Other factors such as improving generalization (the ability of the ANN to function well when presented with new data) and data before and after processing are also involved in the design process. In a prediction model, an ANN algorithm tries to establish the relationship (if any) between the inputs and the outputs. Therefore, the types of inputs used will also affect the performance and design of an ANN algorithm. This article endeavors to study the performance of ANN algorithms used for the prediction of yarn strength, elongation, and evenness properties of cotton ring-spun yarn as the number of units in the input layer are varied.

FACTORS AFFECTING YARN EVENNESS AND TENSILE PROPERTIES

A review of the literature covering the prediction of yarn tensile properties indicated that the factors that affect the prediction of cotton yarn strength include fiber properties (fiber length, length uniformity, strength, elongation, color, micronaire, and trash particles), yarn properties (count and twist), and ring-spinning machine settings (spinning draft, traveler mass, and spindle speed).[15–19] According to Ishtiaque et al.[16] and Mustafa and Kadoglu,[6] the machine and yarn factors that affect the yarn breaking elongation are the spindle speed, traveler mass, machine draft, yarn count, and twist. With respect to fiber properties, the most important factors that

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TABLE I
Classification of Inputs

	Strength	Elongation	Evenness
Length	A	A	A
Uniformity	A	A	A
Strength	A	A	A
Elongation	A	A	A
Reflectance	A	A	A
Yellowness	A	A	A
Micronaire	A	A	A
Trash weight	A	B	A
Trash area	B	B	B
Trash grade	B	B	B
Maturity	B	B	B
SCI	B	B	B
SFI	B	A	A
Yarn count (tex)	A	A	A
Twist	A	A	B
Spindle speed	A	A	B
Draft	A	A	A
Traveler mass	A	A	A
Ring diameter	B	B	B

affect yarn elongation are the fiber elongation and fineness. Other important fiber parameters are the fiber strength, length uniformity, color (reflectance and yellowness), and short fiber index (SFI).[12,19,20] Apart from yarn strength and elongation, yarn evenness is another important factor that affects yarn and fabric quality. Yarn evenness is the measure of the variation of yarn fineness.[21] Yarn evenness is highly correlated to yarn count and traveler mass.[6,17] Other factors that affect yarn evenness are fiber strength, reflectance, length, elongation, length uniformity, yellowness, fineness, trash content, short fiber content, and draft at the ringframe.

The aforementioned results give the correlation between yarn quality properties (strength, elongation, and evenness) and several fiber properties, machine settings, and yarn quality properties (count and twist). The introduction of faster cotton fiber measuring systems such as a high volume instrument (HVI) has brought other cotton properties [spinning consistence index (SCI), trash area, and SFI] to the fore. The effects of these new HVI characteristics on yarn quality properties need to be evaluated. Because of the aforementioned considerations, we considered 19 factors—13 HVI characteristics, 4 ringframe machine settings, and 2 yarn properties (count and twist)—as the main source of inputs for the prediction of yarn quality properties (Table I). These factors were further subdivided into two subgroups; class A consisted of factors that were reported to have a strong to medium effect on yarn quality properties, whereas class B was for those factors that were reported to have little effect on yarn quality properties.

ANN DESIGN

The design of an ANN algorithm involves the choice of many factors, which are governed by the nature of the task that the ANN is to perform. One of the commonly used ANN models is the multilayer feedforward perceptron (MLP). In its basic form, MLP[14,21–23] consists of a finite number of successive layers (Fig. 1). Each layer consists of a finite number of units (often called neurons or perceptrons). The layers between the input and the output layers are called the hidden layers.

The MLP network for special use, as is the case in this article, is usually designed according to the Cybenko theorem,[24] which can be described as follows: for X being an input in vector space ϑ, that is, $X \in \vartheta$, and assuming that the real mapping from X to y can be expressed with the function $y = \hat{f}(X)$, then the mapping worked out by the MLP can be expressed by the function $f(X,\xi)$, where ξ is the parameter of MLP, which may include the number of layers, number of neurons in the layers, weights, biases, and transfer functions. If the MLP contains only one hidden layer and the transfer functions for hidden and output layers are sigmoid and linear functions, respectively, then for $\hat{f}(X)$ being a single-valued continuous function and ϑ being finite, the performance function of the MLP (i.e., the square error) can be approached with arbitrary precision as follows:

$$\int_{\vartheta} \left[f(X,\xi) - \hat{f}(X)\right]^2 dx < \varepsilon \quad \text{for any arbitrary } \varepsilon > 0 \qquad (1)$$

For most engineering problems, the condition under which $\hat{f}(X)$ is a single-valued continuous function and ϑ is finite can be fully met. Therefore, the Cybenko theorem,[24] as discussed previously, was used to design the MLP (Fig. 1) for the prediction of yarn strength, elongation, and evenness. The parameters of the MLP were as follows:

- Architecture: MLP.
- Number of hidden layers: one.

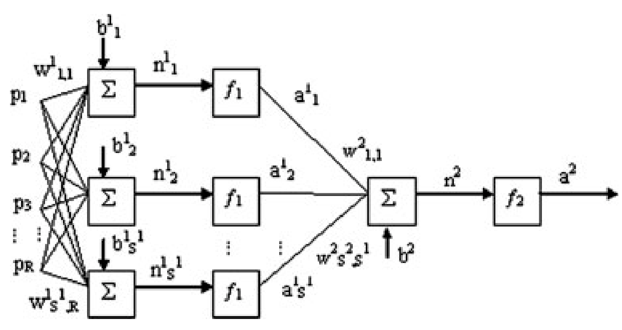

Figure 1 Architecture of the MLP network.

- Hidden layer function: sigmoidal.
- Transfer function in the output layer: linear.
- Number of neurons in the hidden layer: optimum number of neurons determined by trial and error.

The designed MLP was trained with Levenberg–Marquardt.[13,14]

INPUT SELECTION METHODS

The problem of input selection in an MLP network consists of selecting a subset of factors from a larger set containing the potential factors. Fewer inputs are an advantage to the performance of the network because the MLP will be simpler and hence require less computational resources. Several authors[25–28] have reported the use of the determination of the importance (saliency) of the weights or inputs as a means of selecting optimum weights or inputs for an MLP network. This technique, which can be used to remove less important weights or inputs in the MLP network, was applied by Jayadeva et al.[29] to study the saliency of units in the input layer [eq. (2)]. This method has been termed *skeletonization*:

$$S_i = E_{\text{without}\,i} - E_{\text{with}\,i} \tag{2}$$

where S_i is the saliency of unit i, $E_{\text{without}\ i}$ is the training error of the network without unit i, and $E_{\text{with}\ i}$ is the training error of the network with unit i.

By expressing the change in the performance error as a percentage, eq. (2) can be modified as shown in eq. (3), which can then be used to monitor any changes caused by the removal of a unit from the input layer:

$$\Delta E_{\text{remove}\,i} = \frac{(E_{\text{without}\,i} - E_{\text{with}\,i})}{E_{\text{with}\,i}} \times 100 \tag{3}$$

where $\Delta E_{\text{remove}\ i}$ is the change of the error in percentage when unit i is removed.

This method can be extended to study the effect of a unit that has been added to the input layer of an MLP network as follows:

$$\Delta E_{\text{add}\,i} = \frac{(E_{\text{with}\,i} - E_{\text{without}\,i})}{E_{\text{without}\,i}} \times 100 \tag{4}$$

where $\Delta E_{\text{add}\ i}$ is the change of the error in percentage when unit i is added.

The value of $\Delta E_{\text{remove}\ i}$ will be negative if the performance of the MLP has been negatively affected by the removal of the unit and positive if the removal of the unit has caused an improvement in the performance of the algorithm. The former case implies that the added unit causes deterioration in the performance of the MLP, so it will be better for the unit to be excluded from the final list of inputs. Similarly, when $\Delta E_{\text{remove}\ i}$ is positive, it implies that the removed unit has caused an improvement in the performance of the MLP, so it is better to add it to the final list of inputs. With the same reasoning, if $\Delta E_{\text{add}\ i}$ is negative, then the unit should be added to the final list of inputs, and if $\Delta E_{\text{add}\ i}$ is positive, then the unit should be excluded from the final list of inputs.

EXPERIMENTAL

Materials

Cotton lint and carded ring-spun yarn samples were collected from textile factories in Kenya. For every yarn sample collected, a sample of the corresponding cotton lint mixture used to spin the yarn was also collected. During the study period, the spinning factories, which were in operation in Kenya, were located either in Nairobi and its environs or in Nakuru. It was necessary to select factories with as many similarities as possible, in terms of machinery technology, work culture, quality, and maintenance policies, to minimize differences that may arise because of interfactory differences. For a given sample collected from a selected factory, care was taken to ensure that all the machinery used was of the same technology/age to minimize intrasample differences. The quality properties of the cotton lint and yarn samples (Table II) were all tested under standard laboratory conditions at Donghua University and its affiliated HVI fiber testing institution in Shanghai, China.

Training of the ANN algorithm

ANN algorithms for predicting yarn strength, elongation, and evenness were designed, and their performance was studied. The architecture of the ANN was MLP with one hidden layer (Fig. 1). The main features of the algorithm involved data acquisition, data before processing, network training, and data after processing. The acquired data (inputs and

TABLE II
Details of Cotton Lint and Yarn Samples

Cotton lint	Mill code	Yarn (Ne)	Number of cops	Spindle speed (rpm)
Voi AR	B	30	25	11,000
Voi AR	B	20	25	10,000
WT AR	A	30	25	12,000
Kitui AR	A	30	25	12,000
Kitui AR	A	24	25	11,000
Kitui AR	C	24	25	8,000

targets) were normalized so that they had zero mean and unity variance. The data were divided into training, validation, and test subsets in the ratio of 4 : 1 : 1, respectively, as equally spaced points. Initially, the MLP networks were trained with select inputs (designated class A inputs in Table I), and an optimum MLP was identified. By trial and error, the optimum number of neurons in the hidden layers of the prediction algorithms with class A inputs (see Table I) was fixed at 10. Once an optimum MLP for the prediction of yarn quality properties (strength, elongation, and evenness) was identified, the inputs were subjected to a skeletonization and addition process as described in the Input Selection Methods section. During skeletonization, the class A inputs were subtracted one by one, and their effects on the performance of the MLP were evaluated, whereas during the addition process, the class B inputs were added one by one, and their effects on the MLP were also evaluated. In this way, the effects of all the inputs on the performance of the MLP networks were evaluated, and an optimum list of inputs was selected for the strength, elongation, and evenness prediction algorithms. Once the final lists of the inputs were made, skeletonization was used to study the impact of the input factors on yarn quality properties.

RESULTS AND DISCUSSION

MLP for yarn strength prediction

The prediction of yarn strength using class A inputs (Table I) resulted in an MLP network with a mean squared error (mse) value of 0.004598. The process of skeletonization and addition of inputs for the prediction of yarn strength yielded a final list of 14 inputs, which are given in Figure 2. Because of the small change in the number of inputs (from 13 to 14), the number of neurons in the hidden layer for the optimized MLP was maintained at 10.

With respect to fiber properties, the order of decreasing importance for the fiber quality characteristics was as follows: fiber length, length uniformity, strength, SCI, micronaire, trash weight, SFI, and elongation. This agrees with the Uster ranking of fiber properties.[30] Among the 19 factors considered, the five most influential factors were yarn twist, fiber length, yarn count, length uniformity, and fiber strength. These five factors accounted for 63.4% of the yarn strength prediction (Fig. 2).

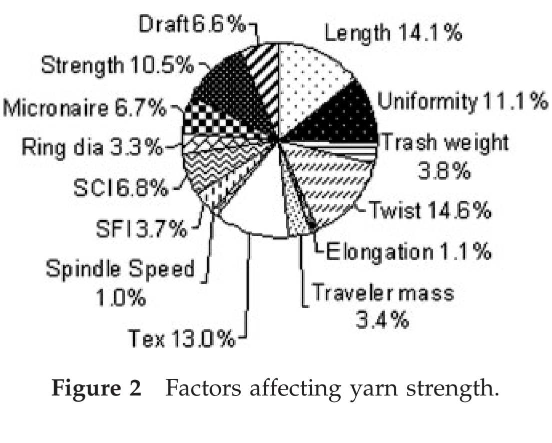

Figure 2 Factors affecting yarn strength.

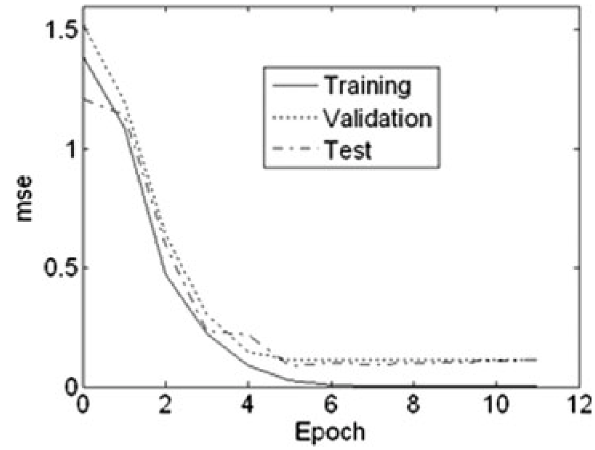

Figure 3 Performance of strength MLP.

Yarn twist showed the highest impact on yarn strength. Ring-spun yarns are twisted to induce lateral forces, which act by means of friction to prevent fibers from slipping over one another. Higher yarn twist will lead to higher yarn strength subject to limiting value because of increased interfiber cohesiveness. The influence of fiber length on yarn strength was high (14.1%), very close to the most influential factor yarn twist, which showed an influence of 14.6%. Higher fiber length increases fiber-to-fiber overlap distance, which in turn increases interfiber friction, leading to correspondingly higher yarn strength. Apart from fiber slip, yarn breakage can also be caused by fiber breakage. This could account for the presence of fiber strength among the five most influential factors affecting yarn strength. Stronger fibers will produce stronger yarn, and weaker fibers will produce weaker yarn.

To study the quality of generalization (the ability to function well when presented with new data) of the MLP, the errors for the training, test, and validation data sets were plotted against the network's epochs. The results given in Figure 3 are reasonable because the test and validation errors have similar characteristics, and it does not appear that any significant overfitting has occurred.

The correlation coefficient (R) between the MLP outputs and targeted values, as shown in Figure 4, was 0.975 (close to 1), which indicated a good fit. The final mse value for the optimized MLP for the prediction of yarn strength was 0.00072. This was far

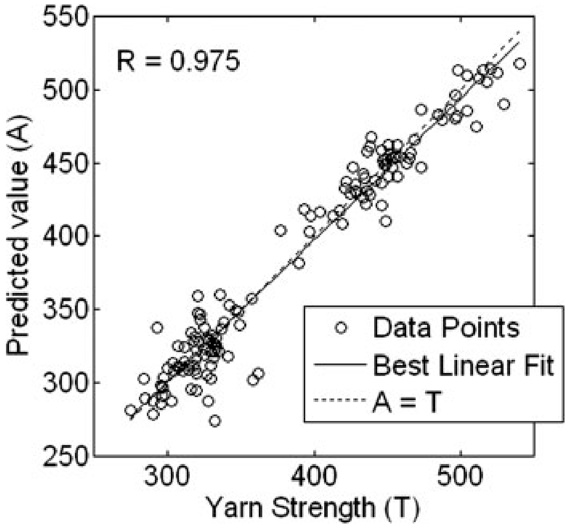

Figure 4 Prediction of yarn strength.

better than the performance of the MLP with all the inputs (19), which showed an mse value of 0.001194.

MLP for yarn elongation prediction

With the class A inputs (Table I), the predication of yarn elongation yielded a performance of 0.0116. The optimized MLP, which had an mse value of 0.0057, had 14 factors (Fig. 5). Because of the small change in the number of inputs (from 13 to 14), the number of neurons in the hidden layer was maintained at 10. The performance of the optimized elongation prediction MLP was better than that with 19 inputs, which had an mse value of 0.00908. The five most influential factors for yarn elongation (Fig. 5) were yarn twist, fiber elongation, length, length uniformity, and yarn count (tex), which accounted for 56%. This agrees with the results of Mustafa and Kadoglu,[6] who reported that fiber elongation, yarn twist, and count are the most important characteristics affecting yarn elongation. A comparison of strength and elongation algorithms showed that four factors (yarn twist, yarn count, fiber length, and length uniformity) were featured among the five most influential factors for both algorithms. From the point of view of fiber characteristics, the important characteristics influencing yarn elongation were elongation, length, length uniformity, SFI, micronaire, SCI, trash weight, strength, and maturity.

Yarn breakage occurs when either the fibers slip over one another or the fibers break. Yarn twist causes fibers to be deformed (rotated) so that they make an angle with the yarn axis, and the amount of twist is a function of this angle. As tensile force is applied to the yarn, the deformed fibers have to be straightened. This action increases the length of the fiber with respect to the yarn axis, which in turn increases the yarn length and hence gives a higher yarn elongation. When yarn breaks because of the breakage of fibers, the increase in fiber length occurring before breakage contributes to the overall increase in yarn elongation; this explains the high correlation between yarn elongation and fiber elongation. The trends of the training, testing, and validation errors for the prediction of yarn elongation are given in Figure 6. The test and validation graphs tracked each other carefully, indicating a good level of generalization.

With the new set of 14 inputs, the optimized MLP for the prediction of yarn elongation showed an R value of 0.907 for the regression correlation between the predicted and targeted values of yarn elongation (Fig. 7).

MLP for evenness prediction

The initial performance of the evenness MLP using the class A input data (Table I) showed an mse value of 0.04744. The optimized MLP had 14 inputs,

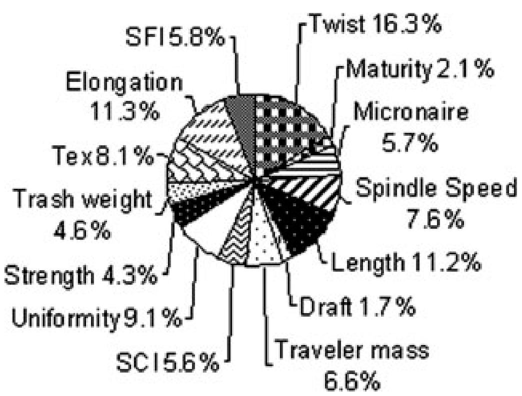

Figure 5 Factors affecting yarn elongation.

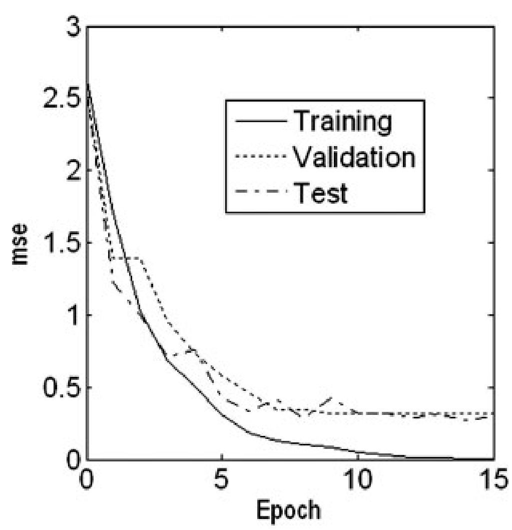

Figure 6 Performance of elongation MLP.

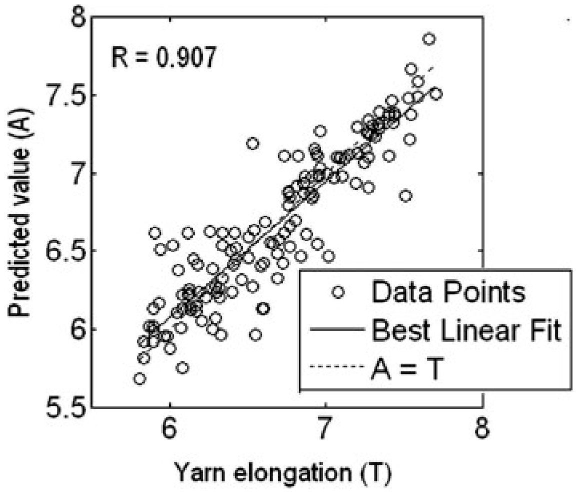

Figure 7 Prediction of yarn elongation.

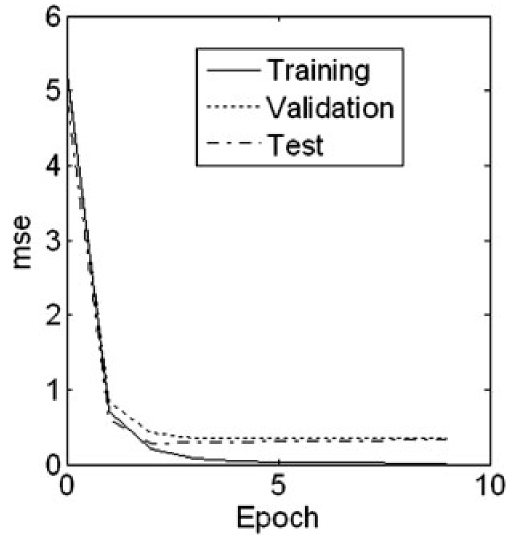

Figure 9 Performance of evenness MLP.

as shown in Figure 8, with the five most influential factors being yarn twist, fiber length, length uniformity, micronaire, and maturity, accounting for 53%. The mse of the optimized evenness prediction MLP was 0.01196, whereas that of the 19-input MLP was 0.022768. Just as in the case of strength and elongation algorithms, the number of neurons for the hidden layer was maintained at 10.

Yarn twist appears to have the highest influence on yarn evenness. This could be due to the fact that one of the consequences of yarn evenness is variation in yarn strength. Because yarn twist, fiber length, and length uniformity are among the five most influential factors affecting yarn strength, it is expected that these factors will also have a great influence on yarn evenness.

As indicated in Figure 8, the order of decreasing importance for the influence of fiber quality characteristics on yarn evenness is as follows: fiber length, length uniformity, micronaire, maturity, SCI, elongation, strength, and trash grade. Fiber length affects yarn evenness because fiber length contributes to the overall cohesiveness of the yarn structure. A longer fiber will give a more even yarn, whereas a shorter fiber will produce yarn of inferior evenness. Length uniformity accounts for the distribution of fiber length in the yarn structure and will therefore affect yarn evenness. Higher fiber length uniformity will produce a more even yarn. Micronaire and maturity could show such a high influence on yarn evenness because the finer the fiber is, the greater the number is of fibers needed for a given yarn cross section. The increase in the number of fibers leads to an improvement of the spinning limit, which in turn leads to better yarn evenness. The graphs of the training, testing, and validation data sets for the optimized evenness MLP are shown in Figure 9, where the validation error traces the testing error fairly well. This is a sign of good generalization of the MLP.

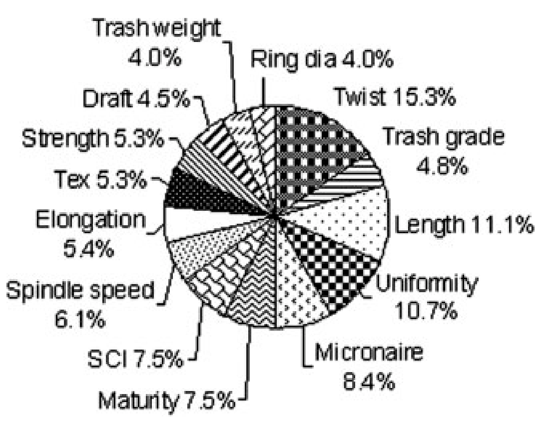

Figure 8 Factors affecting yarn evenness.

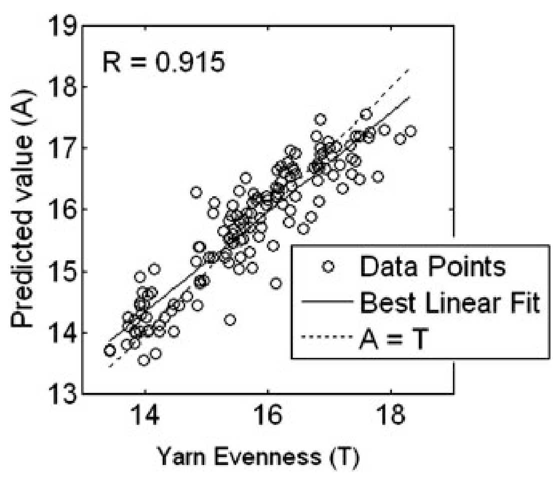

Figure 10 Prediction of yarn evenness.

TABLE III
Change of the mse Value Compared to MLP with 19 Inputs

	Initial inputs		Final inputs	
Output	Number of units	Change (%)	Number of units	Change (%)
Strength	13	285	14	−40
Elongation	13	28	14	−37
Evenness	12	108	14	−47

The optimized MLP for the prediction of yarn elongation, which had 14 inputs, showed an R value of 0.915 between the predicted and targeted values of yarn evenness (Fig. 10).

Comparison of the MLP networks

The performance of the optimum MLP networks used for the prediction of yarn strength, elongation, and evenness was compared to the performance of a similar MLP with 19 units in the input layer. The percentage change in the performance of the algorithms showed that although the initial set of inputs (class A inputs) did not improve the performance of the prediction algorithms, the final set of inputs showed an improvement of the mse value of 40, 37, and 47% for the strength, elongation, and evenness prediction MLPs, respectively (Table III). The new sets of inputs were fewer (14) compared to the 19 inputs. Although the final list of inputs for the prediction of strength, elongation, and evenness were different, yarn twist, fiber length, and length uniformity were common factors among the five most influential factors for the three yarn properties and showed an influence of 40, 37, and 37% for yarn strength, elongation, and evenness, respectively. With respect to fiber quality characteristics, the common factors among the five most influential factors affecting yarn strength, elongation, and evenness were fiber length, length uniformity, and micronaire.

CONCLUSIONS

The design of ANN algorithms used to predict the strength, elongation, and evenness properties of carded cotton ring-spun yarn was undertaken with 19 inputs: 4 spinning process parameters, 13 HVI cotton properties, and 2 yarn quality properties (yarn count and twist). The ANN algorithms were designed to give single outputs (yarn strength, elongation, or evenness). The architecture and training algorithms used for the ANN algorithms were MLP and Levenberg–Marquardt backpropagation algorithms, respectively. The input units were first selected by the use of the reported relationships between the 19 inputs and the outputs. The final groups of inputs were selected by both subtraction (skeletonization) and addition of inputs to the input layer of the MLP while the change in the performance of the initial MLP was monitored. This method had the advantage of working with a smaller MLP model in comparison with using the skeletonization method only, which would have worked with 19 inputs. The initial sets of inputs were 13, 13, and 12 for strength, elongation, and evenness prediction algorithms, respectively. The optimum algorithms had different sets of 14 inputs for the prediction of yarn strength, elongation, and evenness. Compared to the prediction algorithms using 19 inputs, the optimum algorithms showed an improvement of 40, 37, and 47% for the prediction of strength, elongation, and evenness, respectively. The study of the influence of the factors on the yarn characteristics showed that yarn twist, fiber length, and length uniformity were the common factors among the five most influential factors affecting yarn strength, elongation, and evenness, accounting for 40, 37, and 37% for the prediction of yarn strength, elongation, and evenness, respectively. With respect to fiber quality characteristics, the common factors among the five most influential factors affecting yarn strength, elongation, and evenness were fiber length, length uniformity, and micronaire.

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