TEKSTİL VE KONFEKSİYON

VOL: 33, NO. 1
DOI: 10.32710/tekstilvekonfeksiyon.904406

Predictive Modeling of Yarn Quality at Ring Spinning Machine using Resilient Back Propagation Neural Networks

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ABSTRACT

The final attenuation and twisting of fiber take place at ring spinning machine and hence its optimized performance is very crucial in terms of yarn quality. Drafting at ring spinning machine has a decisive effect on quality. There exist many influencing parameters in the spinning geometry that have to be optimized for manufacturing of quality yarn. The present research work was carried out to develop the Artificial neural networks (ANN) based prediction model for the polyester/cotton blended ring spun yarns by using these influencing parameters as inputs. ANN prediction model was developed using resilient backpropagation algorithm. Yarn quality parameters like yarn evenness, hairiness and tensile parameters were predicted. The low mean absolute error values for the yarn quality parameters proved that it is possible to predict the yarn quality on the basis of spinning geometry for cotton/polyester blended ring spun yarns using Resilient Back Propagation Neural Networks.

ARTICLE HISTORY

Received: 06.04.2021
Accepted: 07.07.2022

KEYWORDS

Ring Spinning, Artificial Neural Networks, Resilient Back Propogation Neural Networks, Draft zone settings, Yarn Quality

1. INTRODUCTION

Ring spinning hold the top position among other spinning processes due to its excellent quality, high count range and flexibility of processing variety of materials. Draft zone is the heart of heading spinning machine. The quality of drafting procedure is directly associated with the quality of the yarn produced. During the movement of the fibres in the drafting zone the fibres have to change their speed from a lower level to a higher level so that the draft can be accomplished. However, this acceleration can be smooth or can be abrupt. The smooth acceleration of the fibres indicates that drafting process is being performed with minimum variations. On the other hand, abrupt acceleration can cause the high number of imperfections in the yarn. In this backdrop the drafting force must be kept as uniform as possible by overcoming the cohesive friction among the fibers. The acceleration of fibers inside the drafting zone is influenced by the cohesion between the fibers, the draft zone settings, amount of draft and the processing speeds. The draft quality as well as the ultimate yarn quality is the combined effect of the interaction of these influencing variables with the fibrous material. The optimization of draft zone settings using different modeling and optimization techniques has been the topic of research in last few decades [1-8]. Similar researches had been carried out for the rotor spun yarns [9, 10]. The aim of the presented research is to optimize these technological parameters for optimal yarn quality.

To cite this article: Farooq A, Khan N, Irshad F, Nasir U. 2023. Predictive Modeling of Yarn Quality at Ring Spinning Machine using Resilient Back Propagation Neural Networks. *Tekstil ve Konfeksiyon* 33(1), 9-14.

By changing the total draft of ring frame, the yarn count range can be altered. However, the same yarn count can be manufactured by changing the amount of draft. This can be done by changing the hank roving along with changing the amount of draft to produce the same yarn count. However, it does not mean that characteristics of the yarn produced at various draft settings even having the same count would be same. This implies that influence of the amount of draft cannot be ignored at any stage of yarn formation, as it plays a key role in deciding the quality parameters of ring spun yarn.

Top arm pressure is one of the significant draft zone setting at ring spinning machine and greatly influence the quality and performance of drafting. As the top arm pressure increased the fibre friction field increases, which lead to better control over the fibre flow in the drafting zone, but if the top arm pressure is too high it can obstruct the drafting process. Similarly, a lower top arm pressure is associated with poor fibre control. Hence, the amount of pressure exerted depends upon types of raw material and its volume and other process parameters and therefore, must be optimized accordingly [11-13].

Another vital drafting parameter is the apron spacing. In the main drafting zone, the top aprons are forced by a spring pressure against the lower aprons. The distance between the top and bottom apron is known as apron spacing and is set by the "spacer". The intensity of fibre clamping, and thus fibre guidance, depend upon the size of the spacer. Spacers exert major influence during drafting process, which can be exhibited from yarn evenness. Similarly, spacers are also associated with end breakages at ring spinning machine thus influencing the yarn production.
Artificial neural network (ANN) is a powerful tool to model and simulate the non-linear processes where a large number of influencing variables are involved. The artificial neural networks are capable of understanding the complex relationship that exist between the input and output variable and can make accurate and precise prediction on the basis of the provided experimental data. The artificial neural networks have been applied to various areas of the textile and yarn spinning in past [14-17]. In this research work, keeping in view the power of ANN to predict the output parameters using the experimental data of input parameters, ANNs have been selected in order to establish a quantitative relationship of yarn properties and ring machine variables. The present research study will be useful for textile researchers as a tool for further investigation and optimization the quality of ring spun yarn by adjusting the different parameters of ring spinning machine.

2. MATERIAL AND METHOD

The presented research work was conducted on Polyester / Cotton blended yarns having blend ratio of (52:48). Both possibilities of producing PC blended yarns, i.e. blending of PES with carded cotton slivers and blending of PES with combed cotton slivers were taken into consideration. After processing from the blow room and card the slivers of 70 grains/yards were produced for both cotton and polyester. For carded yarns the card slivers were blended at draw frame. The second passage was autolevelling draw frame. The resulted sliver were fed to roving frame and different hank rovings as mentioned in the table 1 were manufactured.

For the preparation of combed yarns, the polyester slivers were drafted at a pre-drawing passage at Draw frame while cotton is fed to the Lap former (UNI-LAP) after pre-drawing. Then the combing was performed and 14% waste (noil) was extracted at this stage. Then the combed cotton slivers were blended with the pre-drawn polyester slivers for two draw frame passages to produce the slivers of 70 grains/yard. The drawing slivers were fed to roving machine to produce the desired rovings.
The produced hank rovings were subjected to yarn manufacturing at the miniature ring spinning as per following plan.

As four different counts were produced from three different kinds of hank rovings, therefore, the amount of draft in each case is different. The said situation for the 30S is depicted in the following figure1.

The yarn samples were tested under Standard atmospheric conditions (20±2°C and 65% RH). Yarn uneveness U%, yarn imperfections and hairiness were measured using the Uster Evenness tester UT-3. The tensile strength parameters were determined by using the different tensile strength testers for single yarn and yarn skiens.

Table 1 Experimental Plan

Material	Roving Hank	Yarn Count	Top arm pressure	Spacer	Spindle Speed
H_1= (carded)	0.8	C_1= 20^s	P_1= 14 lb	S_1= 2.00mm	14500 rpm
		C_2= 22^s	P_2= 16 lb	S_2= 2.5mm	16000 rpm
H_2= (combed)	1.0	C_3= 26^s	P_3= 18 lb	S_3= 3.5mm	17000 rpm
		C_4= 30^s		S_4= 4.00mm	18000 rpm
	1.2				

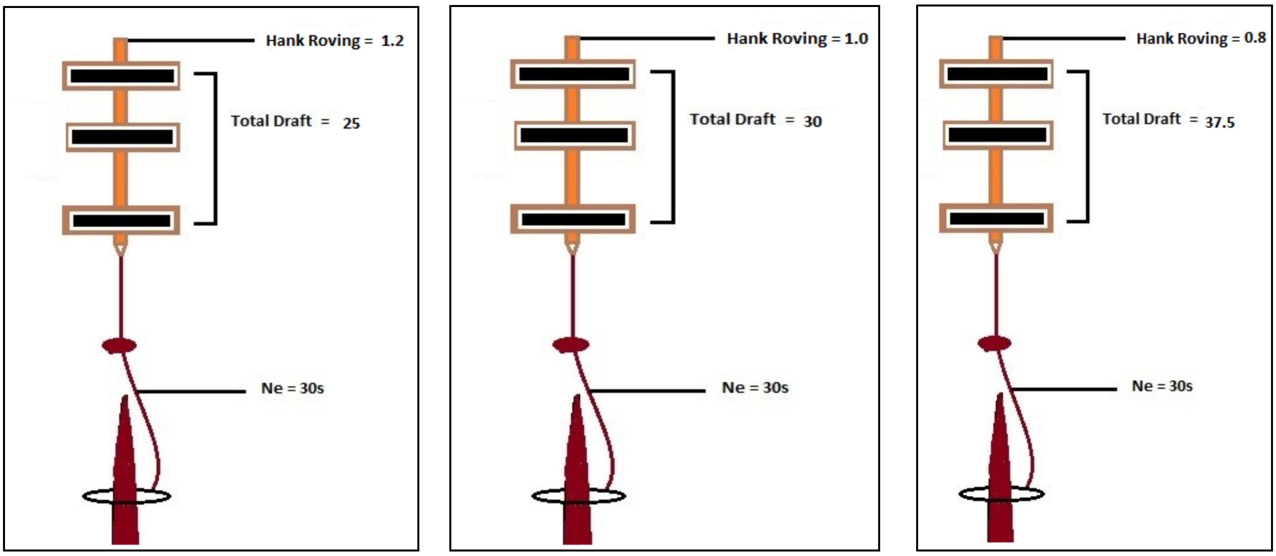

Figure 1. Draft settings for experimental phase

Artificial Neural Networks Modeling and Simulation

In order to train the artificial neural networks for the present research work, a Graphic User Interface (GUI) is programmed using Matlab software.

The precision in modeling of artificial neural networks is of prime importance which can only be achieved with correct input selection and correct choice of network parameters and training algorithm. The most commonly used training algorithm for predictive modeling is backpropagation. However, it has the problems like getting stuck in local minima and overfitting. By using the resilient backpropagation algorithm, the shortcomings of backpropagation can be compensated. In resilient backpropagation the sign of derivatives is used to find out the increase or decrease in weights whereas the magnitude of weights is updated by a separate value. Backpropagation being the conventional gradient descent method uses the partial derivatives. The magnitude of these partial derivatives is too small and hence the possibility of getting stuck in the local minima is higher. Moreover, it takes long time for training [18-22].

The weights are updated in backpropagation by using the following terms

$$\Delta wij(t) = \alpha * xi(t) * \partial j(t)$$

Where

$\triangle$w= Weight Change

α $^{\alpha}$ = Learning Rate

∂ = Error Gradient

$xi(t)$= Inputs propagation back at time step t.

However, individual delta $\triangle$ij are calculated for each connection to determine the direction & size of the weight update.

$$\Delta_{ij}(t) = n^{t} \times \Delta ij^{(t-1)}, \qquad if \frac{\partial E^{(t-1)}}{\partial W_{ij}} \times \frac{\partial E^{t}}{\partial W_{ij}} > 0$$

$$\Delta_{ij}(t) = n^{-} \times \Delta ij^{(t-1)}, \qquad if \frac{\partial E^{(t-1)}}{\partial W_{ij}} \times \frac{\partial E^{t}}{\partial W_{ij}} < 0$$

$$\Delta_{ij}^{(t-1)} \quad , \qquad \text{else}$$

Where

An evolution of Δ_{ij} (updated value) takes place during the learning process, which is determined by the sign of error gradient of the $\frac{\partial E^{(t-1)}}{\partial Wij}$ last cycle and error gradient of current cycle $\frac{\partial E^{(t-1)}}{\partial Wij}$.

The commonly used method for testing the performance of artificial neural networks on the unseen data is ‘Hold out Method’. This implies that 90% of data is used for training while randomly selected 10% data is used for the testing of the performance of trained networks. Another method is the cross-validation technique in which the data is divided into 10 subsets and the network is trained 10 times using the same network architecture every time using one of the subsets for testing while remaining 9 for the training. The mean absolute error in each case was calculated and mean absolute error was determined by taking the average of 10 values the law mean absolute error values resulted from cross validation ensure the good generalization ability of the train network [23]. After validation, the post-processed data was de-normalized to get the original values from the normalized data.

3. RESULTS AND DISCUSSION

Yarn Unevenness (U%):

The data regarding yarn unevenness is used for neural network training under the below mentioned parameters in the table 2. The accuracy in the prediction of the trained network is presented in the following figure 2. Mean absolute error on the test set as given in term of yarn unevenness values is 0.479. The little difference between the experimental and predicted values shows the aptness for the neural networks.

Table 2. Neural Network Training Parameters for Yarn Unevenness (U%)

Network Parameters Values	NN_ Unevenness
Number of Neurons in Input Layer	8
Number of Neurons in First Hidden Layer	7
Number of Neurons in Second Hidden Layer	8
Number of Neurons in Output Layer	1
Learning Rate	0.06
Momentum	0.7
Number of Epochs	2000
Stopping Error	0.001

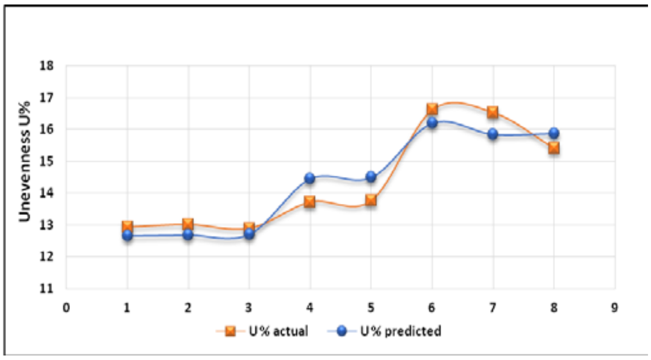

Figure 2. Test Set Performance of U%

The three levels in the figure 2 shows that the values of all blends were included in the unseen data used for the testing and simulation of the trained neural network for yarn unevenness (U%). The cross validation was also applied to the data which shows the results of 0.39 and 0.57 for 10% and 20% cross validations respectively.

Yarn Lea Strength:

The data relating to yarn lea strength is subjected to neural network training using the following training parameters mentioned in the table 3. It is worth to mention here that the network structure used for the training of the blended yarns is complex in comparison with that of used for cotton. This is because of more number of materials used and presence of more complex relationships among the influencing parameters.

The accuracy of the prediction of trained network is showed in the following figure 3. The four levels of yarn lea strength shows that for the unseen data set all four materials; PES/CO 70:30, 50:50, 30:70 and 100:0 were used to observe the performance of the trained neural network. Mean absolute error on the test set as given in term of lea strength values is 9.84. The slight difference in the actual and predicted values indicates the suitability for the neural networks. 8.43 lbs and 10.15lbs mean absolute error was observed in case of 10% and 20% cross validation respectively.

Table 3. Neural Network Training Parameters for Yarn Lea Strength

Network Parameters Values	NN_Lea Strength
Number of Neurons in Input Layer	8
Number of Neurons in First Hidden Layer	7
Number of Neurons in Second Hidden Layer	6
Number of Neurons in Output Layer	1
Learning Rate	0.01
Momentum	0.6
Number of Epochs	2000
Stopping Error	0.001

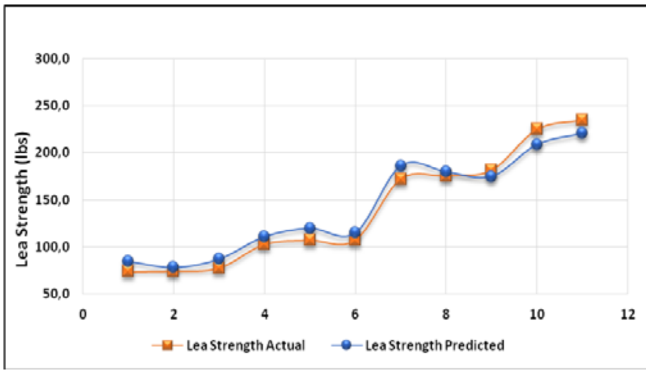

Figure 3 Test Set Performance for Yarn Lea Strength

Yarn Single End Strength

The data pertaining to SES is subjected to the neural network training using the training parameters written in the table 4. The prediction accuracy of the trained network using the hold out method is depicted in the following Figure 4. Mean absolute error on the test set as given in term of SES values is 9.12. The Cross-validation analysis, i.e. 10%, 20% cross validations, is conducted on the data and the mean absolute error in terms of SES values is 8.3 and 13.7 is reported respectively. The little difference between the experimental and predicted values indicates the goodness of fit for the neural networks.

Table 4. Neural Network Training Parameters for Yarn Single End Strength

Network Parameters Values	Values
Number of Neurons in Input Layer	8

Number of Neurons in First Hidden Layer	7
Number of Neurons in Second Hidden Layer	5
Number of Neurons in Output Layer	1
Learning Rate	0.08
Momentum	0.3
Number of Epochs	2000
Stopping Error	0.001

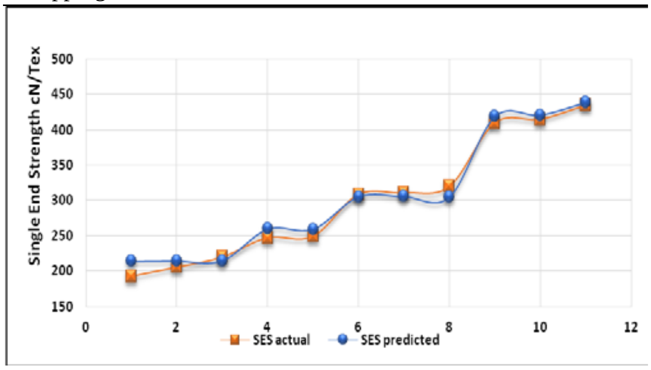

Figure 4. Test Performance for SES

Yarn Elongation:

The data relating to the yarn elongation is subjected to neural network training using the training parameters mentioned in the table 5. The accuracy in the prediction of the trained network is demonstrated in the figure 5. Mean absolute error in the test set as given in term of yarn elongation values is 0.24. The minute differences between the experimental and estimated values illustrate the fitness for the neural networks. The cross validation was also applied to the data which shows the results of 0.29 and 0.42 for 10% and 20% cross validations respectively.

Table 5. Neural Network Training Parameters for Yarn Elongation

Network Parameters Values	**Values**
Number of Neurons in Input Layer	8
Number of Neurons in First Hidden Layer	5
Number of Neurons in Second Hidden Layer	3
Number of Neurons in Output Layer	1
Learning Rate	0.02
Momentum	0.5
Number of Epochs	2000
Stopping Error	0.001

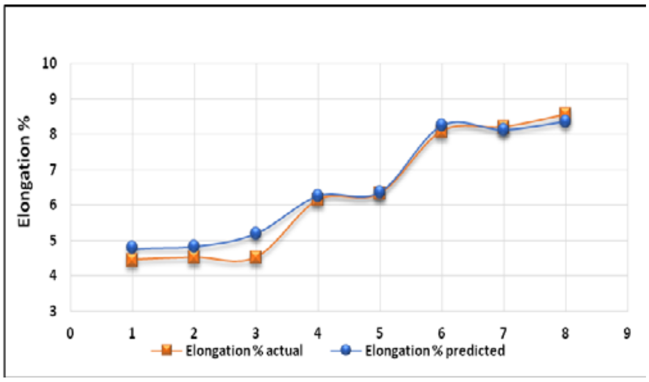

Figure 5 Test Performance for Elongation %

Yarn Hairiness:

The data regarding yarn hairiness is used for neural network training under the network parameters mentioned in the following table 6. In comparison with other yarn characteristics, the network structure for yarn hairiness is complex, because of the dependance of yarn hairiness on different material parameters.

Table 6 Neural Network Training Parameters for Yarn Hairiness

Network Parameters Values	Values
Number of Neurons in Input Layer	8
Number of Neurons in First Hidden Layer	8
Number of Neurons in Second Hidden Layer	7
Number of Neurons in Output Layer	1
Learning Rate	0.05
Momentum	0.3
Number of Epochs	2000
Stopping Error	0.001

The prediction accuracy of the trained network is portrayed in the figure 6. Mean absolute error in the test set as given in term of yarn hairiness values is 0.44. The difference between the experimental and predicted values depicts the aptness for the neural networks.

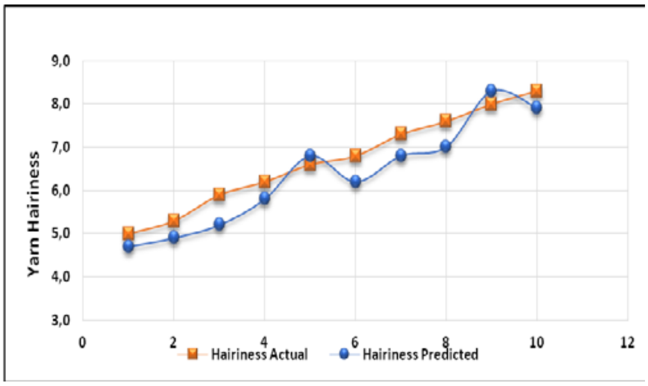

Figure 6 Test Performance for Hairiness

The 10% cross validation results in the MAE of 0.48 while 20% cross validation results in MAE of 0.69 expressed in terms of yarn hairiness H value. However, here that the prediction accuracy is not as good as with the other yarn quality characteristics. This is due to the fact that yarn hairiness is not entirely dependent on the ring spinning parameters. The fiber control during the spinning is one of the major factors influencing the yarn hairiness, however, fibre characteristics are also very important in case of yarn hairiness.

4. CONCLUSION

The influence of yarn count, spacer size and top arm pressure and draft settings on the quality of ring spun cotton carded as well as combed yarn was studied. In each case, the optimum conditions within the industrially acceptable limits of the process were established. The data of yarn quality thus obtained was used to train the artificial neural networks. The trained neural networks were tested using hold out method and cross validation methods.

The results showed that neural networks have accurately predicted the cotton yarn quality, both with carded and combed rovings. Higher degree of prediction accuracy was found while predicting the all the vital characteristics like, yarn lea strength, single end strength and yarn unevenness. However, the prediction accuracy in case of IPI is relatively low which is mainly attributed to the amount of neps present in the rovings. In this backdrop it can be concluded that artificial neural networks have proved success for predicting the yarn properties using ring spinning frame settings as input.

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