

Prediction of polyester/cotton blended rotor-spun yarns hairiness based on the machine parameters

Vahid Ghorbani¹, Morteza Vadood^{2,a} & Majid Safar Johari¹

¹Department of Textile Engineering, Amirkabir University of Technology, Tehran, Iran

²Department of Textile Engineering, Yazd University, Yazd, Iran

Received 10 May 2014; revised received and accepted 25 August 2014

Effect of rotor type, rotor diameter, doffing-tube nozzle, and torque-stop on polyester/cotton rotor-spun yarn hairiness have been studied. To model the hairiness of polyester/cotton blended yarn, artificial neural networks and regression models have been used. The results show that there are significant differences in performance of network with different architectures and training algorithms. The network with two hidden layers has the best performance and can predict hairiness with high accuracy. Relative importance of input variables is studied with partial derivatives method based on the optimum network. The results indicate that rotor type and rotor diameter have the greatest and least effect on the blended yarn hairiness.

Keywords: Artificial neural network, Partial derivatives method, Polyester/cotton blended yarn, Rotor spinning, Yarn hairiness

1 Introduction

Nowadays, hairiness is one of the most important parameters of yarn, similar to the strength, evenness and twist. Hairiness has a great influence on yarn quality as well as on porosity, permeability, transport of moisture, comfort, aesthetic properties and handle¹⁻⁴. Yarn hairiness is usually considered as a negative factor because substantially this hairiness often entangles and hampers the formation of perfect and distinct shed in the weaving looms⁵. Moreover, augmentation of hairiness causes fibre fly during spinning, and only when a good and soft handle for specific goal is required, hairiness is a desirable factor. Yarn can be divided into two parts, viz the surface hairs and stem⁶. Hairiness of yarns is characterized by the filaments or free fibres (fibre loops, fibre ends) protruding from the yarn stem and uniformly distributed along the yarn length⁷. Generally, the hairiness is related to the fibre physical characteristics, features of sliver, spinning methods, spinning machines and their setting, yarn twist, and linear density. Many researchers have attempted to find the relationship between fibre characteristics and resultant yarn⁸⁻¹². Few researchers devoted their studies on the effects of machine parameters on the yarn hairiness, especially on the rotor-spun yarn^{8,13}.

As mentioned above the yarn hairiness is important and hence it is essential to develop a system for prediction of hairiness before yarn production to prevent wasting of time, energy and materials. Commonly the yarn hairiness is controlled through the trial and error method especially when a spinning mill receives new demand from a consumer. There are two approaches for modeling yarn properties, viz theoretical and experimental. Due to complexity of theoretical modeling and simplifying assumptions, and also the poor performance of theoretical approaches¹⁴, experimental modeling is preferred. Statistical and intelligence methods are two important ways of experimental modeling. A growing trend has been observed, in recent two decades, towards artificial intelligence methods due to their better performance in prediction than statistical approaches. Artificial neural networks (ANNs) are computational modeling tools that have found extensive acceptance in many disciplines for modeling real-world complex problems¹⁵. There are many literature using ANNs and regression approaches to model yarn properties¹⁶⁻²². Some researchers designed a model for predicting yarn hairiness based on fibre properties measured by three different systems namely HVI, AFIS and FMT¹². Babay *et al.*¹ built a model using a back-propagation neural network from cotton fibre properties measured by HVI. They also used an approach called “virtual leave on out” to deal with

^aCorresponding author.

E-mail: mortezavadood@gmail.com

over fitting problem. The objective of Üreyen and Gürkan⁷ work was to develop ANN and linear regression models for the yarn hairiness prediction. Entering the roving properties as an input variable was their novelty. Khan *et al.*⁴ studied on the evaluation of the performance of multilayer perceptron and multivariate linear regression models for worsted spun yarn hairiness prediction from various top, yarn and processing parameters. Bo¹³ tried to predict yarn hairiness according to spinning conditions. Haghghat *et al.*³ used an ANN model and multiple linear regression (MLR) for predicting the hairiness of polyester/viscose blended ring-spun yarns based on various process parameters.

By reviewing the literature, it is found that there is hardly any comprehensive work on the analysis of the influence of machine parameters and their relative importance on the hairiness of polyester/cotton blended rotor-spun yarns. Therefore, in this study, two models have been developed using ANN and MLR to predict rotor-spun yarns hairiness according to machine parameters namely rotor type, rotor diameter, doffing-tube nozzle, and torque-stop. Another part of this work refers to altering the network characterization parameters in order to find the best and optimum network for yarn hairiness prediction. Finally, relative importance of input variables is determined using partial derivatives method which is explained in later section.

2 Materials and Methods

All the yarns used in this study were produced in a running spinning mill (Nafis Nakh Co.). As the aim of this research was to present an applicable model in industrial scale, the severe technical limitations in changing machine settings and machine apparatus were considered. Following most effective factors influencing the yarn hairiness were considered:

- Rotor type
- Rotor diameter
- Doffing-tube novels
- Torque-stop
- The rotor diameter, groove shape, groove roughness, and surface quality are the parameters affecting on the resultant yarn properties²³. In order to include the most of rotor parameters, two kinds of rotor (T and G) were selected which are universally applicable. Rotor with two different diameters, 33 mm (less than fibre length) and 40 mm (more than fibre length) were used. The configuration

of the doffing-tube nozzle itself has a quite substantial influence on yarn appearance. In order to investigate the effects of take-off nozzle, the fluted and spiral nozzles namely *KN4*, *KN8*, and *KS* were used. *K* specifies the material used for nozzle production which is ceramic in this study. The numbers 4 and 8 indicate the number of flutes in the nozzle and *S* refers to the spiral state. Torque-stop with red clip was used in this study. Experimental specimens for rotor-spun yarns were prepared from blended polyester/cotton (75/25) slivers. The characteristics of fibres, slivers and produced yarns are given in Table 1.

Slivers were spun into yarns on Schlafhorst machine with 70000 rotational speed of rotor and 7500 rotational speed of beater. Eighteen types of yarns were produced with different machine settings according to machine factors mentioned above. The processing program is shown in Table 2. In every level, one of the machine parameters was changed and the other parameters were kept constant. Fourteen bobbins were produced for each setting. To eliminate the spinning variations, all the yarns were produced in the same position on the same machine. Total of 252 bobbins of yarns were evaluated for hairiness on the Shirley tester in the standard atmosphere (25°C temperature and 65% relative humidity) and the average of measured hairiness for each yarn type was determined (Table 2).

3 Results and Discussion

In order to design the ANN models, data set was divided randomly in three groups so that 60% of the data was assigned for training, 20% for validation

Table 1 – Specification of fibres, slivers and yarns used

Parameters	Value
Fibre	
<i>Polyester</i>	
Length, mm	38
Fineness, dtex	1.67
<i>Cotton</i>	
Length, mm	29
Fineness, dtex	1.58
Sliver	
Count, tex	4000
CV, %	4.46
Yarn	
Count, tex	29.5
Twist multiplier (α_c)	3.8
Opening roller	S21

and 20% for testing of the developed models. Training set was used for computing the gradient and updating the network weights and biases. The error on the validation set was monitored throughout the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to over fit the data, the error on the validation set typically begins to rise. The network weights and biases are saved at the minimum of the validation set error²⁴. Since regression model does not require the validation set, both training and validation sets are used for determination of the model parameters. It is important to note that the same test data has been used for all developed models.

3.1 Statistical Model

One of the approaches used intensively as a supervised learning method is regression. When the response in regression equation is the linear function of more than one predictor variable, it is called MLR. In this study, the MLR model is used for developing the polyester/cotton blended rotor-spun yarn hairiness model. The predictor variables are rotor type (RT), rotor diameter (RD), doffing-tube nozzle (DTN), and torque-stop (TS). Using the training and validating data set, following regression equation is obtained:

$$\text{Hairiness} = -1.2619(\text{RT}) + 0.6769(\text{RD}) - 0.3202(\text{DTN}) + 0.0702(\text{TS}) + 4.8989 \quad \dots (1)$$

The result of analysis of variance (ANOVA) of regression model is given in Table 3.

The value of *Sig* indicates that the input variables are not the same and the model is significant in 95% significance level. In order to assess the performance of developed regression model, test data are entered to the model and correlation coefficient (R-value=0.33) is calculated. Correlation quantifies the strength of a linear relationship between two variables. When coefficients are close to +1 or -1, it indicates that there is a strong direct or inverse relationship between the variables respectively, while the coefficient closes to 0 suggests that there is no relationship between the variables. Here, R-value indicates the capability of model to predict, so it can be said that the higher the R-value, the higher is the accuracy. Unreliable R-value of linear regression shows that MLR is not appropriate for yarn hairiness prediction based on the machine factors. There are two ambivalent attitudes towards this fact, namely one refers to existence of nonlinear relationship between the parameters, and the other is existence of interaction between the parameters. Table 4 indicates the correlation between variables.

As can be seen in Table 4, there is only negative correlation between rotor type and rotor diameter and the negligible correlation exists between the other parameters. But two uncorrelated variables are not necessarily independent, because they might have a nonlinear relation. In order to investigate the interaction between parameters, a quadratic regression model is fitted to data. The nonlinear model includes

Table 2 – Sampling process in spinning mill

Sample	Rotor type	Rotor diameter mm	Novel	Torque-stop	Hairiness 'hairs/m
1	T	40	KN4	-	31.18
2	T	40	KN8	-	34.26
3	T	40	Spiral	-	24.62
4	T	40	KN4	+	28.06
5	T	40	KN8	+	30.10
6	T	40	Spiral	+	28.22
7	T	33	KN4	-	24.26
8	T	33	KN8	-	28.26
9	T	33	Spiral	-	24.21
10	T	33	KN4	+	22.28
11	T	33	KN8	+	30.41
12	T	33	Spiral	+	20.72
13	G	33	KN4	-	19.22
14	G	33	KN8	-	31.62
15	G	33	Spiral	-	19.85
16	G	33	KN4	+	23.65
17	G	33	KN8	+	28.00
18	G	33	Spiral	+	21.25

(+) Torque-stop was used, (-) Torque-stop was not used.

Table 3 – Results of ANOVA for MLR model in 95% significance level

Model	Sum of squares	Df	Mean square	F	Sig.
Regression	1342.45	4	335.61	22.98	0.000
Residual	2803.90	192	14.60	-	-
Total	4146.35	196	-	-	-

Table 4 – Results of correlation coefficients between parameters

Parameter	RT	RD	DTN	TS
RT	1.00	-	-	-
RD	-0.50	1.00	-	-
DTN	0.03	0.00	1.00	-
TS	0.01	0.00	-0.03	1.00

15 terms with constant, linear, interaction, and squared terms. The R-value of model is found to be 0.85. So, it can be said that the model parameters have nonlinear relationships. Quadratic model has acceptable performance, but due to existence of numerous terms in this model and calculation complexity, it is not an appropriate predictor tool.

3.2 Artificial Neural Network Model

In this study, beside regression model, the feed forward multilayer perceptron network with back propagation training algorithm was used to develop a model for prediction of yarn hairiness. One of the most important issues in generation of network is determination of number of hidden layer and number of neurons in each layer. There are few thumbs in this manner, but none of them is certain. Hence, networks were built with varying hidden layer from 1 to 5 and the number of neurons in each layer varied from 2 to 10 in steps of 2. Matlab software version R2011a was used for programming ANN models. For faster convergence in training step, the Levenberg-Marquardt (LM) algorithm was selected and also hyperbolic tangent sigmoid was considered as the transfer function for hidden layers. Maximum number of epochs to train was fixed to 1000 and linear function was used for output layer. As the weights and biases were chosen randomly, each network structure was trained 5 times and the information of the best network structure assessed by R-value was recorded. Total number of 3905 networks was trained and the results of models evaluation are given in Table 5.

According to Table 5, high R-values of all fitted ANN models to data indicate that ANN is an excellent tool for the prediction of yarn hairiness. The best result is achieved by the network with 5 hidden layers (NN5), but the accuracy of the best two hidden layer network (NN2) is almost the same and clearly the complexity of network with two hidden layer is less. Hence, NN2 is selected for further study. In order to investigate the effect of transfer functions and training

algorithms on NN2. The following options are considered:

- Back-propagation training algorithm:
 - Gradient descent with momentum (Traingdm)
 - Gradient descent with momentum and adaptive learning rate (Traingdx)
 - Conjugate gradient with Powell-Beale restarts (Traincgb)
 - One-step secant (Trainoss)
 - Levenberg-Marquardt (Trainlm)
- Transfer function of hidden layers:
 - Hyperbolic tangent sigmoid transfer function (Tansig)
 - Logistic sigmoid transfer function (Logsig)
 - Radial basis (Radbas)

The main criterions for selection between different groups of back-propagation algorithms are speed, consumed memory and time. It must be mentioned that for each case the created network is trained 5 times and the obtained results are assessed by R-value. Furthermore, consumed time of training is recorded for further investigation. The resultant information is presented in Table 6.

Referring to Table 6, the network using Taringdm and Traingdx were exempted from extra investigation due to their extremely poor performance. Networks using Trainlm not only have the maximum R-value between other algorithms (0.9649), but also the best mean R-value (0.9632). Trainoss and Traincgb are in the next places. It is important to note that the network using Trainoss and Traincgb has almost similar performance (assessed by R-value) comparing with network using Trainlm. But considering the required time for training, it is observed that consumed time for Trainoss and Traincgb is about three times more than that for Trainlm. So, Trainlm can be selected as the best training algorithm. After determination of the most effective training algorithms, the most appropriate activation functions in hidden layers should be determined. A closer look to the Trainlm column in Table 5 reveals that all combination of activation functions results almost the same accuracy, but the highest R-value is related to the Radbas and Logsig functions for the first and second hidden layer respectively. So it can be concluded that the network with two hidden layer with 8 neuron in each of them, Radbas and Logsig as the activation function in the first and second hidden layer using Trainlm can predict the yarn hairiness with the highest accuracy (R-value = 0.9649).

Table 5 – Best neural networks structure

ANN	R-value	Network structure
5 Hidden layers (NN5)	0.968	8 – 6 – 8 – 8 – 10
4 Hidden layers (NN4)	0.967	10 - 2 - 4 - 6
3 Hidden layers (NN3)	0.966	2 - 6 - 8
2 Hidden layers (NN2)	0.964	8 - 8
1 Hidden layer (NN1)	0.91	8

Table 6 – Obtained R-value of ANN models for evaluation of best training algorithms and activation functions

Network structure	Activation function hidden layer		Training algorithms					
	First	Second	Traingdm	Traingdx	Traincgb	Trainoss	Trainlm	
8 – 8 (NN2)	Radbas	Radbas	0.7337	0.2483	0.9646	0.9647	0.9626	
	Radbas	Tansig	0.8104	0.3560	0.9646	0.9622	0.9637	
	Radbas	Logsig	0.4749	0.5886	0.9632	0.9626	0.9649	
	Tansig	Radbas	0.5835	0.2617	0.9622	0.9633	0.9626	
	Tansig	Tansig	0.2803	0.2199	0.9632	0.9627	0.9641	
	Tansig	Logsig	0.3495	0.2484	0.9619	0.9623	0.9626	
	Logsig	Radbas	0.7608	0.4175	0.9631	0.9621	0.9628	
	Logsig	Tansig	0.7634	-0.0782	0.9625	0.9624	0.9630	
	Logsig	Logsig	0.1389	0.2260	0.9618	0.9639	0.9628	
	Mean R-value			0.5439	0.2765	0.9612	0.9629	0.9632

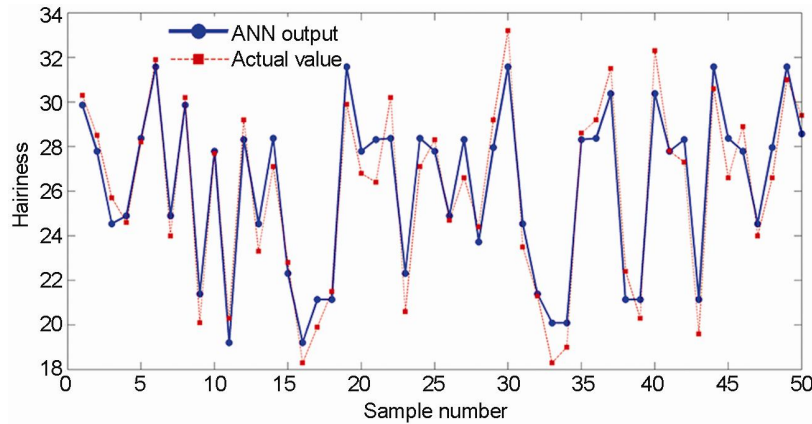


Fig. 1 – Predicted hairiness by NN2 and corresponding measured hairiness using Shirley tester (testing group)

The predicted values of the best network versus corresponding measured values (test data) are shown in Fig. 1.

3.3 Relative Effect of Machine Parameters on Yarn Hairiness

In order to determine the relative importance of each machine parameter on yarn hairiness, the obtained best network was considered. There are several methods that can give the relative contribution and/or the contribution profile of the input factors. Partial Derivative (PaD) is one of the most widely used methods which computes the partial derivatives for the ANN output with respect to the input neurons²⁵. For a network with n_i inputs, one hidden layer with k neurons, and one output ($n_o=1$), the partial derivatives of the output y_j with respect to input x_n (with $j=1 \dots N$ and N the total number of observations) are as follows:

$$d_{ji} = S_j \sum_{h=1}^{n_k} w_{ho} I_{hj} (1 - I_{hj}) w_{ih} \quad \dots(1)$$

where S_j is the derivative of output mode with respect to its input; I_{hj} , the response of the h^{th} hidden neuron; and w_{ho} and w_{ih} , the weights between the output neuron and h^{th} hidden neuron, and between the i^{th} input neuron and the h^{th} hidden neuron. The result of PaD concerns the relative contribution of the ANN output to the data set with respect to an input. It is calculated by a sum of the square partial derivatives obtained per input variable, as shown below:

$$SSD_i = \sum_{j=1}^N (d_{ji})^2 \quad \dots(2)$$

Classification of variables according to their relative importance to the output variable could be possible with the SSD values. The highest the SSD value, the more influential is the input variable on output variable. Normalized SSD values are calculated for the present study variables and the results are 0.42, 0.12, 0.28 and 0.18 for RT, RD, DTN and TS respectively. According to results of SSD ,

rotor type has the greatest effect on the hairiness followed by doffing-tube nozzle, torque-stop and rotor diameter.

Generally, the rotor with open and deeper groove offers better spinning stability but results in yarn with more hairiness. T-type rotor have wider and deeper groove than G-type rotor, hence T-type rotor leads to the yarn with more hairiness. Doffing-tube nozzle is the most important factor in increasing and also diffusing the false twist into the twist zone in rotor groove. It is known that more twist makes the yarn with less hairiness. The doffing-tube nozzle has two contradictory effects. First, more flutes lead to more vibration in yarn during passing from doffing-tube nozzle and it doesn't let the yarn flattened in its passing route, so friction results in more hairiness. Second, the diffused false twist will increase with the increase of flutes and more twist causes less hairiness. So, which of these contradictory effects will be dominant, it depends on the other parameters and also interactions between them. For example by considering *KN4* and spiral doffing-tube nozzles, in some cases using *KN4* results more hairiness in the same conditions. When the spinning stability is not perfectly satisfactory, the assistance of torque-stop is needed. With the aid of torque-stop, the twist in the yarn between torque-stop and rotor groove is increased. Yarn torsional moment is a contributing factor in producing belly bands and consequently for the hairiness in the rotor yarn. Generally, in a constant peripheral speed, decrease in rotor diameter results in reduction in yarn torsional moment and increase in overlapping fibres at the yarn peel-off point in the rotor groove. Due to the overlapping fibres, the almost spun yarn is covered by cross wrapping and it results in less hairiness. But when the spinning conditions vary considerably, since there are interactions between machine parameters, and existence of nonlinearity between phenomenon, as it was demonstrated with both linear and nonlinear regressions, each machine parts could influence other parts performance and create different impact upon resultant yarn properties. According to the results, it is of interest to mention that:

- The most yarn hairiness will be produced by using T-type rotor with 40mm diameter, *KN8* doffing-tube nozzle without the aid of torque-stop.
- Using G-type rotor with 33mm in diameter, *KN4* doffing-tube nozzle and without torque-stop

applied in the spinning machine, the yarn with the least hairiness will be produced.

4 Conclusion

In this paper, it was attempted to design a model for prediction of polyester/cotton blended rotor-spun yarns from machine parameters. Rotor type, rotor diameter, doffing-tube nozzle, and torque-stop were used as the input variables. Two models were built using ANN and MLR. Unacceptable R-value obtained from MLR indicates that linear model is not appropriate. Nonlinear regression indicates satisfactory performance, but due to numerous terms and computational complexity, it is not suitable. Furthermore, it is weaker than the worst developed neural network. The obtained results show that there is significant difference between prediction of network with different architectures and training algorithms. Regarding R-value, consumed time of training and complexity, the network with two hidden layers with Levenberg-Marquardt training function, radial basis and logistic sigmoid as the first and second hidden layer activation function have the best performance (R-value = 0.97). The study of the relative importance of input variables using Pad method based on the efficient network reveals that rotor type has the greatest impact on yarn hairiness and rotor diameter shows the least effect.

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