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Research Article

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Predicting the Hairiness and Coefficient of Variation of Elastic Core-spun Yarns Produced on Sirofil-Spinning System using Artificial Neural Network

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Abstract

This study aims to predict the hairiness (Number of hairs ≥ 3mm) and coefficient of variation (%CVm) of elastic core-spun yarns produced on Sirofil spinning system using artificial neural network method. Different controllable factors in Sirofil spinning system such as distance between two strands, twist level of produced yarns, draw ratio and feeding angle of the elastane and feeding position of elastane part between two strands were considered as input data. The effectiveness of each controllable factor on these two quality responses was also determined. The results showed that an artificial neural network model with two hidden layers with seven neurons and output layer with two neurons gives the best predictive power of the hairiness and %CVm of Sirofil spun yarns. The findings revealed that the feeding position of elastane part was the most dominant parameter on both yarn hairiness and %CVm. Also, the feeding angle of elastane part and yarn twist level showed the least impact on the mentioned quality responses, respectively.

Keywords

Elastic core-spun yarn; Hairiness; CVm%; Sirofil spinning; Artificial neural network

Introduction

Elastic core-spun yarns contain the hard sheath fiber and elastane filament as core part. The sheath part is often comprised of cotton or another staple fiber such as PET/Viscose, PET and etc. Core-spun yarns containing elastane filaments are commonly used for producing light-weight apparel fabrics, sportswear, underwear and outerwear [1,2]. These yarns, due to their stretch abilities, could be constructed with a wide range of properties using virtually any type of "hard" fibers as the cover yarn.

There are many methods for producing the elastic core-spun yarns, such as ring spinning, friction spinning, rotor spinning, Siro spinning, hollow spindle spinning and air entangling [1-8]. The basic requirement for producing an elastic core-spun yarn is to stretch an elastane filament before it enters the spinning unit, so that the elastane part is located in the center of the core-spun yarn and is covered completely by the staple fibers. Elastic core-spun yarns have been the subject of limited researches [9-13].

Zhang et al. [14] introduced a method to produce the cotton/spandex composite yarns on a modified rotor spinning system. They reported that the spandex draft ratio has great influence on the appearance and properties of rotor spun cotton/spandex composite yarns. The linear density of spandex filaments also has influence on the properties of composite yarns. Namiranian et al. [15] investigated the physical and mechanical properties of fine polyester/viscose elastic composite rotor-spun yarn.

Kakvan et al. [1] investigated the effects of draw ratio and feeding position of elastane part on physical properties of elastic wool/polyester core-spun ring yarns. They indicated that increasing the draw ratio of elastic yarn causes the increase of elastic core-spun yarn irregularity and fiber-covering factor. They found that positioning the elastane part positioning at the left edge of roving ribbon deteriorated core-spun yarn evenness while positioning it at the center of the roving ribbon improved the core-spun yarn hairiness. However, this controllable factor has no significant effect on elastic core-spun yarn tensile and fiber-covering properties.

Su et al. [11] investigated the effects of draw ratio and feeding angle of the elastane part on the structure and performance of core-spun yarns produced on the modified ring spinning frame. They reported that a higher feeding angle provides a better cover effect, and a draw ratio of 3.5 yields better dynamic elastic recovery. Babaarslan [12] showed that feeding position of elastane part has a direct effect on the properties, structure and performance of core-spun yarns produced on a modified ring spinning frame.

Two common problems in production of core-spun yarns on the ring spinning frame are sheath voids, which is characterized by length of elastane filament without covering, and the slippage of the staple sheath fibers relative to the core. Such defects cause the variation of physical properties of core-spun yarn.

An artificial neural network (ANN) is one of the intelligence technologies for data analysis which has been employed extensively in various textile disciplines ranging from yarn and fabric manufacturing to fabric properties [16-20]. This technique is useful when there are a large number of effective factors on the specific process. In the literature there are many researches in which the ANN algorithm has been Employed. Beltran et.al [17] investigated the pilling tendency of wool knits using ANN model. Tokarska [18] predicted the permeability features of woven fabrics. The performance of ANN model was compared with statistical regression and fuzzy regression to develop the predictive models for polyester dyeing [21]. ANN model has also been used to predict cotton yarn hairiness [22]. Hasani et al. [23] optimized the processing parameters of Siro spinning to produce elastic core-spun yarns using SOM neural network.

Different parameters in Sirofil spinning system such as distance between two strands, twist level of produced yarns, draw ratio and feeding angle of the elastane, and the elastane position between two strands can affect the physical and mechanical properties of core-spun yarns. This study focuses on the proposing a predictive model of

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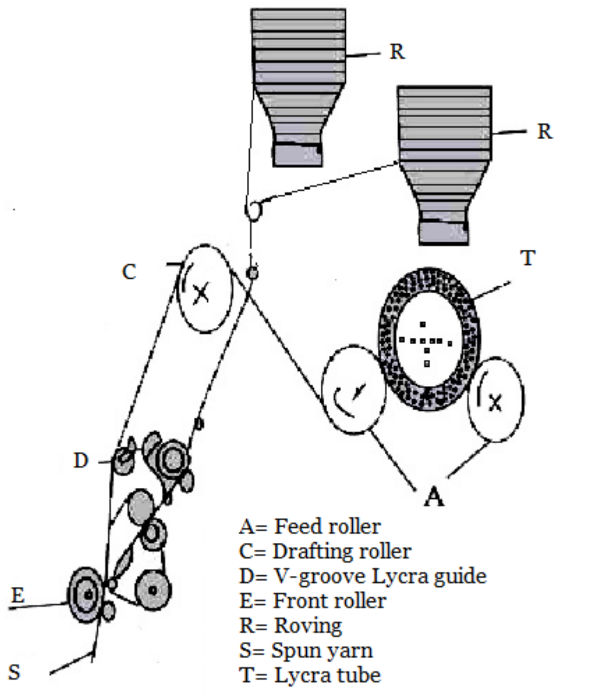

Figure 1: Sirofil spinning system.

Table 1: Setting parameters of Sirofil spinning system.

Setting parameters	Value of variable
Spindle speed (RPM)	7000
Total draft	22
Ring diameter(mm)	60
Traveler No. (ISO)	60
Elastane count (dtex)	40
Yarn count (Ne)	20

Table 2: Controllable factors and their levels.

Factors	Levels
Yarn twist (TPM)	450, 550, 650
Drawing ratio of elastane	2.2,3.2,4.2
Position of elastane between two strands	Left, middle, right
Distance between two strand (mm)	4, 8, 12
Feeding angle of elastane	tangential, 50°, 70°

hairiness and coefficient of variation of elastic Sirofil spinning system using an artificial neural network algorithm. The effectiveness of each processing parameters on these two quality responses was also determined.

Material and Methods

In this study, thirty-three different types of yarn samples were produced on a Sirofil spinning system equipped with a positive elastane feeding device. The cotton (3.5 µg/inch, 28 mm) and polyester (1.44 denier, 38 mm) fibers were blended together on a traditional short-staple carded system using standard mill procedures, adjustments and practices.

Two cotton/polyester rovings of 1.05 Ne were fed to the drafting system of the Sirofil spinning frame (Figure 1) in order to produce a 20-Ne core-spun yarn. Table 1 shows the machine settings for producing cotton/polyester core-spun yarn. Elastane filament (Lycra®) should be pre-drawn before entering the front roller. The velocity difference between elastane filament (Lycra®) positive feeding roller and front roller results in the pre-drawing of elastane part.

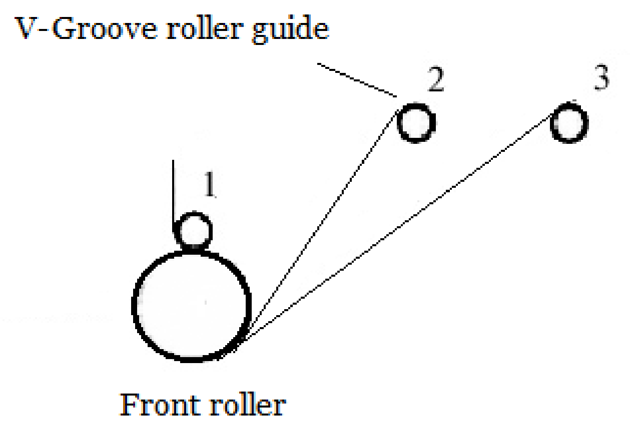

Figure 2: Feeding angle of the elastane: (1) tangential, (2) 50°, (3) 70°.

To produce elastic core-spun yarns, spinning frame must be modified with a "V" groove guide to feed elastane filament (Lycra®) yarn to the front roller under controlled and uniform stretch as well as correct position relative to the "hard" fiber roving. This guide were utilized in three different positions, as shown in figure 2, which prepare three feeding angle of elastane filament (tangential, 70° and 50°).

In order to determine the effects of controllable factors of Sirofil spinning system on the hairiness and coefficient of variation (%Cvm) of elastic core-spun yarns, three levels of yarn twist (450, 550 and 650 twist per meter), three levels of elastane drawing ratio (2.20, 3.20 and 4.20), three levels of elastane feeding angle (tangential, 70° and 50°), three levels of distance between two strand (4, 8, and 12 mm) and three levels of position of elastane between two strands (left, middle and right) were chosen as shown in table 2. The trials were run using a commercial spinning mill. The selected elastane count (40 dtex) is widely used in the industry for such core-spun yarns.

Ten cones of about 200 grams were prepared under each set of experimental conditions. In addition, the yarn samples were spun at the same spinning head to avoid any variations.

For measuring the yarn hairiness (number of hairs longer than or equal to 3 mm), a Shirley hairiness tester (model SDL096/8, UK) was utilized. Measurement was carried out on 25 m of each yarn sample with a speed of 60 m/min. Coefficient of variations (%CVm) of yarns were determined using an Uster tester III (model UT3-LG, Switzerland) on 1000 m of yarn at a test speed of 400 m/min. The experiments were conducted under standard conditions (22 ± 2 °C and 65 ± 2% RH). The list of the yarn samples and considered controllable factors is shown in table 3.

Artificial neural network parameters

Training process of models was carried out with back-propagation learning algorithm based on scaled conjugate gradient algorithm. This algorithm does not perform a line search at each iteration.

Table 3: List of the yarn samples and controllable factors.

Yarn No.	Distance Between Two Strand (mm)	Position of Elastane feeding	Sirofil Twist (TPM)	Draw Ratio	Feeding angle (Degree)
A1	12	Left	450	2.2	70
A2	12	Left	450	3.2	70
A3	12	Left	450	4.2	70
A4	12	Left	600	2.2	70
A5	12	Left	600	2.2	0
A6	12	Left	600	3.2	70
A7	12	Left	600	4.2	70
A8	12	Left	750	2.2	70
A9	12	Left	750	3.2	70
A10	12	Left	750	4.2	70
A11	12	Middle	600	2.2	0
A12	12	Right	600	2.2	0
A13	4	Left	600	2.2	0
A14	4	Middle	450	2.2	0
A15	4	Middle	450	3.2	0
A16	4	Middle	450	4.2	0
A17	4	Middle	600	2.2	0
A18	4	Middle	600	3.2	0
A19	4	Middle	600	4.2	0
A20	4	Middle	750	2.2	0
A21	4	Middle	750	3.2	0
A22	4	Middle	750	4.2	0
A23	4	Right	600	2.2	0
A24	8	Middle	600	2.2	0
A25	8	Right	450	2.2	50
A26	8	Right	450	3.2	50
A27	8	Right	450	4.2	50
A28	8	Right	600	2.2	50
A29	8	Right	600	2.2	0
A30	8	Right	600	3.2	50
A31	8	Right	600	4.2	50
A32	8	Right	750	2.2	50
A33	8	Right	750	4.2	50

Table 4: Code of each input unit for three position of feeding of elastane part.

Position of elastane part related to two strands	5th input unit	6th input unit
Middle	1	1
Left	1	0
Right	0	1

Scaled conjugate gradient substitutes the line search by a step scaling that depends on the success in error reduction and goodness of the quadratic approximation to the error. It is motivated by a desire to accelerate the typically slow convergence associated with the gradient descent method while avoiding the information requirements associated with the evaluation, storage and inversion of the Hessian matrix as required by the Newton method [24]. Experiments show that, scale conjugate gradient is considerably faster than Back-propagation gradient descent, conjugate gradient algorithm, conjugate gradient algorithm combined with the safeguard quadratic univariate minimization, and one-step broyden-fletcher-goldfarb-shanno memory-less quasi-newton method. The standard conjugate gradient method was originally developed by Hestenes and Stiefel and the scale conjugate gradient was developed by Moller [25,26].

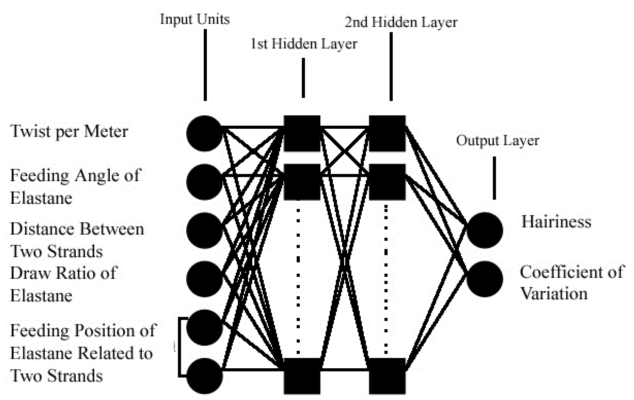

Figure 3: Schematic structure of artificial neural network models.

For predicting the Hairiness and %CVm of Sirofil spun yarns, one feed forward multilayer neural network models based on back propagation learning algorithm with two neurons as outputs and six input parameters in input layer was designed. The input parameters were draw ratio of elastane part, feeding angle of elastane part(degree), distance between two strands(mm), yarn twist (Twist per meter) and position of elastane part between two strands of Sirofil spun yarn. Regarding the qualitative input parameter namely position of elastane part between two strands, two input units were used and each position was coded as table 4, therefore six input units were selected. All of these parameters were expressed in a vector form. Figure 3 depicts the schematic of basic topology of ANN models.

In this study, due to the availability of only a small sample data, memorization or over fitting of networks was prevented using weight decay technique. This involves modifying the performance function. Therefore, mean square error regularization (*MSEREG*) performance function was used instead of common mean square error (*MSE*) function. This function is as follow [26]:

$$MSEREG = \gamma\,(MSE) + (1-\gamma)MSW \tag{1}$$

$$MSW = \frac{1}{n}\sum_{j=1}^{n} w_j^2 \tag{2}$$

where γ is the performance ratio and, n is the number of weighted connection.

Samples were divided randomly in training and testing sets. Twenty-eight and five sets of data were chosen for training the ANN models and testing the predictive power of developed models, respectively. To eliminate effect of different units of input and output parameters, data normalizing was carried out in such a way that they got zero mean and unit standard deviation [27]. After some trials, 300 epochs were selected as number of training cycle and according to table 5, tangent hyperbolic and linear transfer function was used for hidden neurons and output neurons, respectively. The tangent hyperbolic function can range between -1 and 1 and is differentiable.

The number of hidden neurons and the number of hidden layers are usually adjusted by trial and error because these are problem-dependent parameters. It is known that neural networks with one hidden layer are suitable for majority of applications [28] and the

Table 5: Effect of transfer function on performance of ANN models.

Topology	Transfer function of 1st hidden layer	Transfer function of 2nd hidden layer	Transfer function of output layer	MSE of training data	MSE of testing data
6-6-2	Logsig	------	Linear	0.03999	0.1718
6-6-6-2	Logsig	Logsig	Linear	0.0335	0.1829
6-6-2	Tansig	-------	Linear	0.0143	0.1360
6-6-6-2	Tansig	Tansig	Linear	0.0053	0.1358
6-2	Logsig	------	Logsig	0.1960	0.6864
6-2	Tansig	------	Tansig	0.0494	0.3493

Table 6: The Performance of ANN models.

Model No.	Network structure(input units-number of neurons in hidden layer(s)-output layer)	MSE (Training set)	MSE (Testing set)
1	6-6-2	0.0143	0.1360
2	6-7-2	0.0117	0.1400
3	6-8-2	0.0103	0.1108
4	6-9-2	0.0086	0.1569
5	6-10-2	0.0092	0.1129
6	6-11-2	0.0067	0.1182
7	6-12-2	0.0056	0.1452
8	6-6-6-2	0.0053	0.1358
9	6-6-5-2	0.0063	0.1702
10	6-6-4-2	0.0058	0.1482
11	**6-7-7-2**	**0.0041**	**0.0907**
12	6-7-6-2	0.0028	0.1465

second hidden layer can improve the performance of the network if there is a complex relationship between input and output parameters. Therefore, twelve topologies with one and two hidden layers and six to twelve neurons in hidden layers were considered. Our preliminary evaluations revealed that neural network models with more than two hidden layers containing twelve neurons were not suitable in this case. The mean square error of testing sets was considered getting the best topology. In programming the network architecture, training and testing the models the neural network toolbox of Matlab software was used.

Results and Discussion

Artificial neural network performance

Training results of twelve selected topologies is presented in table 6. Experimental results reveal that the number of neurons have a dominant effect on performance of the proposed model. Also, the results show that the model with two hidden layers containing seven neurons gives the best performance and the least MSE values for predicting the hairiness and %CVm after 300 epochs. The MSEs of prediction of testing data and training data were 0.0907 and 0.0041, respectively. According to table 7, the maximum and minimum error of prediction of hairiness was 8.59% and 0.00%, respectively while the predicted values of %CVm were 4.01% and 0.30% respectively. The average of prediction errors of hairiness and %CVm were 3.86% and 2.44% respectively. The results confirmed the excellent capability and predictive power of ANN algorithm to predict these two main parameters of Sirofil spun yarns.

Analyzing the impact of input parameters on hairiness and coefficient of variation of elastic sirofil spun yarns

In the second step, the relative contribution of each of the controllable factors was evaluated using ANN model. For ANN model, an effectiveness of each input parameter was determined by

Table 7: Predicted values of hairiness (Number of hairs ≥3mm) and coefficient of variation (%CVm) of testing data.

Hairiness(Number of hairs ≥3mm)			Coefficient of variation (%CVm)		
Target Value	Predicted Value	Error (%)	Target Value	Predicted Value	Error (%)
4.22	4.09	3.08	14.00	13.65	2.50
3.05	2.93	3.93	13.47	13.43	0.30
5.47	5.00	8.59	14.33	14.59	1.81
4.47	4.47	0.00	12.60	13.05	3.57
3.23	3.35	3.72	12.21	12.70	4.01

Table 8: Ranking of input parameters according to artificial neural network model.

Output Parameter	Hairiness(Number of hairs ≥3mm)		Coefficient of variation(%CVm)	
Input Parameter	Weights	Ranking	Weights	Ranking
Feeding Position of Elastane	+6.7854	1	+3.1980	1
Distance Between two strands	-1.0113	4	-2.8050	2
Feeding Angle of Elastane	+0.7604	5	-1.0333	3
Draw Ratio of Elastane	+2.6501	2	+0.8564	4
Twist per Meter	-2.1405	3	-0.3468	5

adding the connection weights which connect each input parameter to the output parameters. The sum of connection weights shows the significant of each input and the contribution of each input has the direct relationship with this value.

Ranking of input parameters according to ANN model is shown in table 8. Since two input unit was considered for position of elastic yarn feeding average value of its weight was calculated. According to this table, the position of feeding was the most dominant parameter on both hairiness and %CVm. Another side, the feeding angle of spandex and twist level showed the least impact on yarn hairiness and %CVm, respectively.

The findings show that the feeding position of elastane part plays the most important role in varying the irregularity and hairiness of elastic core-spun yarns. This result confirms the findings reported by Babaarslan [12] and Kakvan et al. [1]. They concluded that the effects of elastic core yarn positioning on yarn irregularity and hairiness are significant. They also pointed out that the elastane part positioned at the center of roving ribbon results the lowest hairiness value and irregularity than two other cases.

Conclusion

The results showed that an ANN model with two hidden layers each contains seven neurons and an output layer containing two neurones gives the best predictive power of the hairiness (Number of hairs ≥ 3mm) and coefficient of variation(%CVm) of Sirofil spun yarns. The R-square value of model was 0.9876. The mean square error of the proposed model was 0.0907 for predicting the testing data. The findings showed that the feeding position of elastane part was the most dominant parameter on both hairiness and coefficient of variation. In other side, the feeding angle of elastane part and twist value showed the least impact on hairiness and coefficient of variation of Sirofil spun yarns respectively.

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