Modeling the Properties of Core-Compact Spun Yarn Using Artificial Neural Network

Parvaneh Kheirkhah Barzoki, Morteza Vadood, and Majid Safar Johari

***Abstract*—In this research, the compact-core spun yarns have been produced using RoCoS roller and the effects of filament pre-tension, yarn count and type of sheath fibers were investigated on the physical and mechanical properties of produced yarns such as strength, elongation percentage, hairiness, and abrasion resistance. After statistically analysis on the obtained results, for modeling the core-compact yarn properties, the regression and artificial neural network (ANN) were used to predict the physical and mechanical properties. Trial and error method was considered for determining the best of ANN topology. For this aim, 1110 topologies of ANN (with different hidden layers and neurons in each hidden layer) were investigated for each property. Moreover, to evaluate the accuracy of the created ANN three indexes were used, namely mean absolute percentage error (MAPE), mean square error (MSE), and correlation coefficient (R-value). It was observed that the most accurate results were obtained based on MAPE and the best topology for predicting all properties is a two-hidden layer ANN (maximum MAPE < 0.10) except for the abrasion resistance which is a three-hidden layer ANN (MAPE < 0.17).**

***Keyword:* artificial neural network, compact-core yarn, modeling, physical and mechanical properties, RoCoS roller**

I. Introduction

In the past decades, core-spun spinning has been developed to achieve a better yarn quality and mechanical properties as well as higher production per spinning unit. The special structure of core-spun yarns, in which a filament core is covered by staple fibers, permits to ideally combine the advantages of filaments like high strength with those of the staple fibers like appearance or absorbency properties. Core-spun yarns are used in a wide spectrum of various applications such as military, industrial, technical textiles and sport clothing. Ring and Siro spinning systems are the most conventional systems for production of core-spun yarns. Some researchers [1,2] employed a novel method using ring spinning frame to produce core-spun yarns. Also, a modified ring spinning system has been introduced for producing core-spun yarns [3]. This system utilizes an air jet for better forming of the sheath fiber around the core. Jou and East [4] designed a filament charging device, which was based on the principle of a two–electrode system to separate a multi filament yarn. Embeddable and Locatable spinning (ELS) have been introduced in another work [5], in which locating technology is employed to locate filaments and staple fibers so that each staple strand could be reinforced by the filaments, and the staple fiber could be well embedded into the stem of the yarn. Pourahmad and Johari [6] investigated the physical and mechanical properties of Ring, Solo and Siro core–spun yarns at different controllable parameters. Compact spinning is another method for producing core-spun yarns. This system has two different types which are called Elicore and Elicore Twist. Brunk [7] reported that core-spun yarns produced by these systems have better evenness and abrasion resistant in comparison with Ring core-spun yarns.

The artificial neural network (ANN) is one of the intelligent techniques for data processing which has been employed extensively in various textile fields. This technique is useful when there are nonlinear relationships between parameters. There are many published work, in which ANN has been employed to predict the properties of different yarns and fabrics and many other characteristics of textile materials [8-15]. It seems there is a lack of research focused on the predicting properties of core-compact yarns based on the spinning parameters, therefore this paper presents the application of ANN models to predict the properties of core-compact yarns based on the statistically significant controllable factors such as filament pre-tension, yarn count and kind of sheath fibers.

II. Neural Network

ANN is a structure inspired from the human brain. ANN is very useful for modeling nonlinear problems and complex functions. ANN consists of three layers including input, hidden, and output layers. Neurons in each layer are connected by associated weights to other neurons in the next layer. The input data is received in input layer and the output is obtained in the output layer by a mathematical function through hidden layers [16]. In ANN there are three operations including training, validation and testing sets. Training is used to train the ANN. Validation is useful when the network begins to overfit the data, and testing group is used to control the error during the training process [17]. In this study for predicting mechanical and physical properties of compact-core yarns, a feed forward multilayer ANN model was used.

III. Materials and Methods

In this study, 56 different types of yarn samples were produced on a compact-core spinning system. A blended viscose/polyester and cotton fibers were used as the sheath fiber and multi filament nylon yarn with a count of 100

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denier was used as the core filament. The sheath fiber properties are shown in Table I.

TABLE I
THE PROPERTIES OF SHEATH FIBERS

Type of sheath fiber	Length (mm)	Denier	Percentage of fiber blending (%)	Tenacity (gf/tex)	Elongation (%)
Viscose	38	1.5	45	19	20
Polyester	34	1.4	55	41	45
Cotton	27	1.24	100	28	6

The cotton and viscose/polyester roving count were 0.72 and 1.09 Ne, respectively. To produce the compact-core yarns the RoCoS system was installed on SKF lab spinner instead of delivery top roller (Fig. 1), and each roving was fed to the drafting system of the compact-core spinning frame.

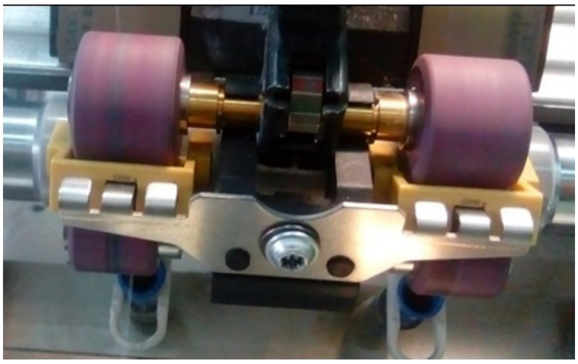

Fig. 1. Rotorcraft compact spinning roller (RoCoS).

In order to produce different types of compact-core yarns, the core filament should be pre-drawn before entering the front rollers (RoCoS roller). The filament also should be fed to compactor groove of RoCoS roller. For this aim, guide rod and pre tensioner were used. Fig. 2. shows the process of core-compact yarn production and Table II shows the machine settings for producing compact-core spun yarns.

TABLE II
MACHINE SETTINGS

Setting parameters	Value
Twist per meter	900
Spindel speed (rpm)	22000
Ring diameter (mm)	36

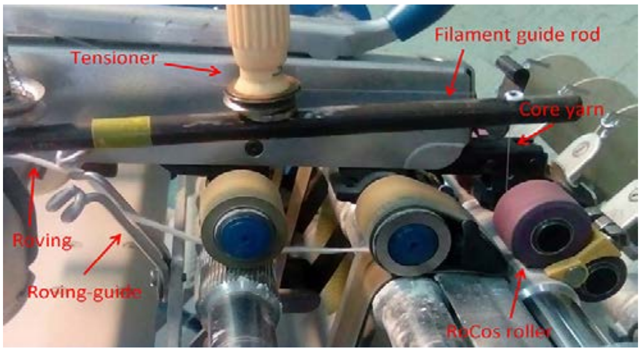

Fig. 2. Production of core-compact yarns.

In this study, the tenacity, elongation percentage, hairiness and abrasion resistance were considered as the physical and mechanical properties of compact-core yarns

TABLE III
LIST OF YARN SAMPLES AND CONTROLLABLE FACTORS

No.	Filament pre-tension	Yarn count	Type of fiber	No.	Filament pre-tension	Yarn count	Type of fiber
1	25	41.5	Viscose/polyester	29	25	48	Viscose/polyester
2	50	41.5	Viscose/polyester	30	50	48	Viscose/polyester
3	75	41.5	Viscose/polyester	31	75	48	Viscose/polyester
4	100	41.5	Viscose/polyester	32	100	48	Viscose/polyester
5	125	41.5	Viscose/polyester	33	125	48	Viscose/polyester
6	160	41.5	Viscose/polyester	34	160	48	Viscose/polyester
7	180	41.5	Viscose/polyester	35	180	48	Viscose/polyester
8	25	41.5	Cotton	36	25	48	Cotton
9	50	41.5	Cotton	37	50	48	Cotton
10	75	41.5	Cotton	38	75	48	Cotton
11	100	41.5	Cotton	39	100	48	Cotton
12	125	41.5	Cotton	40	125	48	Cotton
13	160	41.5	Cotton	41	160	48	Cotton
14	180	41.5	Cotton	42	180	48	Cotton
15	25	43.5	Viscose/polyester	43	25	59	Viscose/polyester
16	50	43.5	Viscose/polyester	44	50	59	Viscose/polyester
17	75	43.5	Viscose/polyester	45	75	59	Viscose/polyester
18	100	43.5	Viscose/polyester	46	100	59	Viscose/polyester
19	125	43.5	Viscose/polyester	47	125	59	Viscose/polyester
20	160	43.5	Viscose/polyester	48	160	59	Viscose/polyester
21	180	43.5	Viscose/polyester	49	180	59	Viscose/polyester
22	25	43.5	Cotton	50	25	59	Cotton
23	50	43.5	Cotton	51	50	59	Cotton
24	75	43.5	Cotton	52	75	59	Cotton
25	100	43.5	Cotton	53	100	59	Cotton
26	125	43.5	Cotton	54	125	59	Cotton
27	160	43.5	Cotton	55	160	59	Cotton
28	180	43.5	Cotton	56	180	59	Cotton

and to determine the effect of controllable factors on these properties, 7 levels of filament pre-tension (25, 50, 75, 100, 125, 160, and 180 g), 4 levels of yarn count (41.5, 43.5, 48 and 59 tex) and two kind of sheath fibers (cotton and polyester/viscose) were chosen. The list of yarn samples and considered controllable factors are shown in Table III.

Instron testing machine (Model M10-8201-1) was used to measure the tenacity and elongation at breakage of yarns with a gauge length of 25 cm. For measuring hairiness (number of hairs, longer than or equal to 3 mm), Shirley Hairiness Tester (Model SDL096/8) was used. The measurement was carried out on 20 m of each yarn sample at the speed of 60 m/min. Abrasion resistance was determined by Shirley Abrasion Tester (Model Y027). All experiments were conducted under the conditions of 22ºC and 65 RH%. In order to determine the tenacity and elongation, each test was repeated 10 times and for abrasion resistance and hairiness the tests were repeated 5 times, and the average values were considered for each measured property.

TABLE IV
THE STATISTICAL RESULTS OF MANOVA TEST WITH A %95 CONFIDENCE INTERVAL

Characteristic	source	SSE	df	MSE	F	P-value
Hairiness	Yarn count	295.8	3	98.62	7.29	0.00
	Filament pre-tension	603.39	6	100.57	7.43	0.00
	Type of sheath fiber	1874.11	1	1874.11	138.47	0.00
	Error	609.05	45	13.53	-	-
	total	3382.42	55	-	-	-
Tenacity	Yarn count	13.24	3	4.41	2.84	0.04
	Filament pre-tension	67.75	6	11.29	7.27	0.00
	Type of sheath fiber	1995.47	1	1995.47	1155.68	0.00
	Error	69.91	45	1.55	-	-
	total	1946.37	55	-	-	-
Abrasion resistance	Yarn count	73.03	3	24.34	4.64	0.00
	Filament pre-tension	64.38	6	10.73	2.05	0.04
	Type of sheath fiber	234.88	1	234.88	44.78	0.00
	Error	236.05	45	5.24	-	-
	total	608.36	55	-	-	-
Elongation	Yarn count	39.46	3	13.15	2.94	0.04
	Filament pre-tension	113.18	6	18.46	4.21	0.00
	Type of sheath fiber	2520.81	1	2520.81	563.01	0.00
	Error	201.48	45	4.48	-	-
	total	2874.93	55	-	-	-

IV. RESULTS AND DISCUSSION

To evaluate the effectiveness of considered parameters on the yarn properties, multivariate analysis of variance (MANOVA) was conducted on the obtained experimental data. The results of MANOVA test with a 95% confidence interval, for each property are shown in Table IV. This test compares the variance explained by factors to the left over variance that cannot be explained. If the calculated P-value is lower than 5%, it means that the effect of the corresponding factor is significant on the investigated property. The statistically analysis showed that the controllable factors have significant effects on all investigated properties.

Moreover, in this study, a multi compare test with a 95% confidence interval on the measured properties was conducted to determine whether the collected data are all the same, against the general alternative that they are not all the same. The obtained results are presented in Table V.

TABLE V
THE RESULTS OF MULTI COMPARE TEST WITH A %95 CONFIDENCE INTERVAL FOR EACH GROUP

Group 1	Group 2	Lower boundary for the true mean	Mean of group 1 minus the mean of group 2	Upper boundary for the true mean
Hairiness	Tenacity	-8.35	-4.38	-0.40
Hairiness	Abrasion resistance	-1.12	-0.97	-0.82
Hairiness	Elongation	-6.70	-4.47	-2.25
Tenacity	Abrasion resistance	3.26	7.23	11.21
Tenacity	Elongation	-2.32	-1.24	-0.15
Abrasion resistance	Elongation	-9.55	-5.58	-1.60

If the confidence interval contains 0, the difference would not be significant. As can be observed in Table V, for none of the pairs of investigated properties the confidence interval is 0, therefore the difference is significant. As a result, separate models were used to predict each property.

A. *Regression Model*

Linear multiple regression analysis was used to establish a relationship between the core-compact yarn properties and the investigated controllable factors. To this aim, all data were divided randomly into two groups; namely reg-train and test group. Reg-train group (44 data sets) was used to determine the regression coefficients and test group (12 data sets) was used to evaluate the accuracy of obtained regression equation in predicting measured properties. In this paper, three indexes were considered for measuring accuracy; namely mean absolute percentage error (MAPE, Eq. (1)), mean square error (MSE, Eq. (2)) and correlation coefficient (R-value).

$$\text{MAPE} = 100 \times \frac{1}{n} \times \sum_{i=1}^{n} \left| \frac{y_i - x_i}{x_i} \right| \tag{1}$$

$$\text{MSE} = \frac{1}{n} \times \sum_{i=1}^{n} (y_i - x_i)^2 \tag{2}$$

where x_i is the actual value and y_i is the corresponding predicted value. The range of R-value is between -1 to +1 and in prediction a higher R-value means higher accuracy. But for the other indexes such as MAPE and MSE, higher accuracy in modeling obtains when they are 0 or very close to 0. Eqs. (3) to (6) and Table VI present the obtained results for regression analysis.

$$Tenacity = -4.84 + 0.08 \times N + 0.01 \times T + 11.23 \times F \tag{3}$$

$$Elongation = -4.67 - 0.21 \times N + 0.02 \times T + 13.34 \times F \tag{4}$$

$$Hairiness = 37.66 - 0.8 \times N + 0.07 \times T - 11.36 \times F \tag{5}$$

$$Abrasion\ resistance = 3.65 - 0.04 \times N + 0.01 \times T - 2.14 \times F \tag{6}$$

where *N*, *T* and *F* are the yarn count, the filament pre-tension and the type of sheath fibers, respectively. Here, cotton and viscose/polyester types were considered 1 and 0, respectively. As can be seen in Table VI, the accuracy of regression model evaluated by R-value is high, but MSE and MAPE are not close to 0 which means the linear regression is not appropriate enough to model the measured properties. It should be mentioned that although using a higher order regression like quadratic leads to better results in prediction as shown in Table VI, this type of regression due to existence of numerous terms and calculation complexity is not easy to use. Hence, a more powerful model such as ANN is required for modeling.

TABLE VI
R-VALUE, MSE AND MAPE BETWEEN REGRESSION PREDICTION AND CORRESPONDING ACTUAL DATA (TEST GROUP)

Model type	Property	MAPE	MSE	R-value
Linear	Tenacity	1.29	2.18	0.97
	Elongation	1.57	10.42	0.66
	Hairiness	2.77	12.45	0.86
	Abrasion resistance	1.34	3.51	0.32
Quadratic	Tenacity	0.81	1.08	0.98
	Elongation	1.36	2.74	0.97
	Hairiness	1.19	2.30	0.64
	Abrasion resistance	1.72	4.93	0.24

B. ANN Model

ANN includes various parameters which influence directly the prediction accuracy, but the most effective ones are the number of hidden layers and the number of neurons in each hidden layer. In this study to find the best set of ANN parameters for each investigated property, the trial and error method was applied. Regarding the literature review, the number of hidden layers and neurons in each hidden layer were considered between 1 to 3 and 1 to 10, respectively. The activation functions for all the hidden and output layers were considered Tangent hyperbolic shown in Eq. (5), and linear functions, respectively.

$$Tanh = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{5}$$

ANNs were trained with the error back propagation algorithm using Trainlm function. To train ANN, the data sets in reg-train group were divided randomly into two groups; namely ANN-train (34 data sets) and validation (10 data sets) groups. As initial weights in ANN were selected randomly, each ANN topology was considered five times and the best result for that topology was considered. To evaluate the accuracy of ANN models, the same test group for regression analysis was used and all three mentioned indexes were calculated. The best topology of ANNs for each investigated property corresponding to different indexes are shown in Table VII.

TABLE VII
THE BEST TOPOLOGY OF ANN FOR EACH INVESTIGATED PROPERTIES BASED ON MAPE, MSE AND R-VALUE

Considered index to select the best ANN	Properties	Hidden layer (best topology of ANN)	Accuracy indexes between ANN output with best topology and corresponding actual values for testing group		
			MAPE	MSE	R-value
MAPE	Tenacity	{8 3}	0.0626	0.8500	0.9929
	Elongation	{9 9}	0.0600	0.4843	0.9942
	Hairiness	{6 6}	0.0997	0.3283	0.8374
	Abrasion resistance	{2 4 4}	0.1744	1.8600	0.7587
MSE	Tenacity	{8 4}	0.0629	0.8550	0.9800
	Elongation	{7 9}	0.0650	0.4840	0.9950
	Hairiness	{4 6}	0.0829	0.6400	0.9800
	Abrasion resistance	{2 5 5}	0.1754	1.8500	0.7540
R-value	Tenacity	{8 6}	0.0628	0.8850	0.9939
	Elongation	{9 7}	0.0630	0.4950	0.9990
	Hairiness	{6 8}	0.0815	0.6927	0.9946
	Abrasion resistance	{2 5 5}	0.1854	1.9400	0.7589

In Table VII, for example {2 4 4} in the hidden layer column means that ANN contains three hidden layers with 2, 4 and 4 neurons at first, second and third hidden layers, respectively, and this ANN can predict the abrasion resistance with the highest accuracy according to MAPE index. But in using MSE as the accuracy index, the best topology for predicting abrasion resistance is {2 5 5}. Besides the criteria index to select the best ANN topology, the other two indexes were calculated as shown in Table VII.

According to Table VII, the perfect prediction ability of ANN model is revealed, but a closer look indicates that considering the MAPE index for choosing the best ANN topology leads to higher accuracy in prediction. Fig. 3 illustrates the ANN outputs based on MAPE index to select ANN topology along with corresponding actual values for different properties.

Regarding the high accuracy of ANN, the physical and mechanical properties of compact-core spun yarns can be predicted instead of arduous task of experimental analysis. So the yarn parameters can be adjusted to produce compact-core yarn with desired physical and mechanical properties.

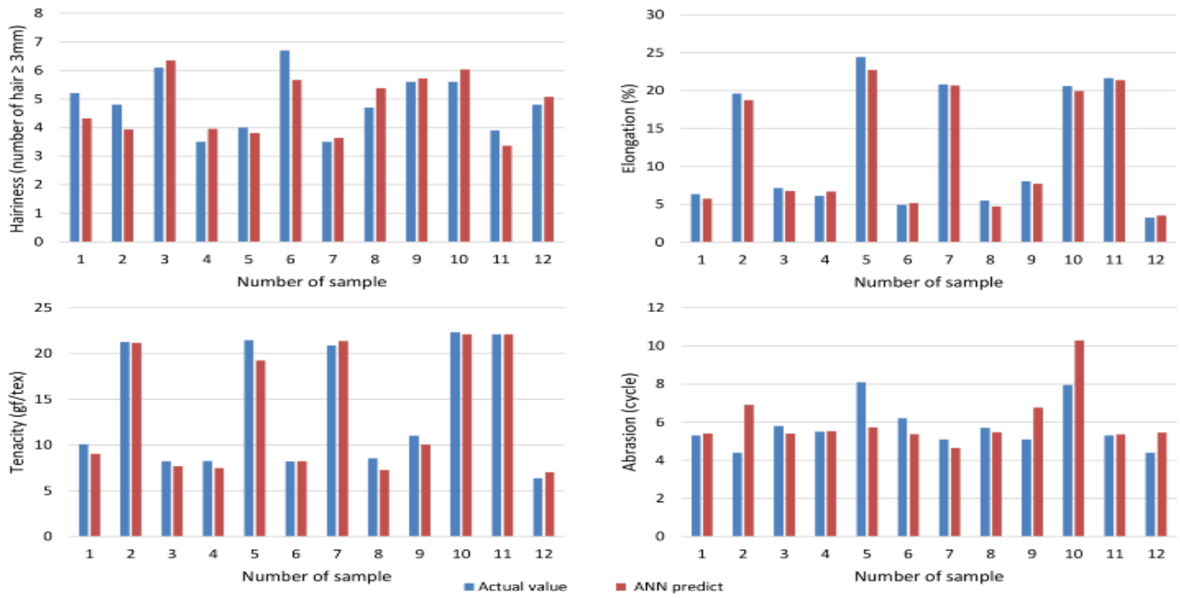

Fig. 3. The ANN output (selected based on the MAPE index shown in Table VI) along with the corresponding actual values for different properties (testing group).

V. Conclusion

Core-spun yarns are used in a wide spectrum of end-uses such as military textiles and industrial textiles. The yarn parameters such as filament pre-tension, yarn count and the type of sheath fiber have a significant influence on physical and mechanical properties of compact-core spun yarns such as tenacity, elongation, hairiness and abrasion resistance. Therefore, modeling these parameters can give in-depth information about yarn properties. In the first step, the significant effect of yarn parameters on the measured properties were investigated statistically. Regarding the results of multi compare test, to predict yarn properties separately, regression and ANN models were considered based on the yarn parameters. To achieve the best result for modeling, three indexes namely MAPE, MSE and R-value were evaluated and finally it was found that considering MAPE as a criterion for selecting the best ANN topology leads to the highest accuracy in prediction. Moreover, the results showed that the best topology for predicting tenacity, elongation and hairiness is a two-hidden layer ANN (maximum MAPE < 0.10) with {8 3}, {9 9} and {6 6} formats, respectively, while for the abrasion resistance the best one is {2 4 4} (MAPE < 0.17).

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