Predicting the Hairiness of Cotton Rotor Spinning Yarns by Artificial Intelligence

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***Abstract*- Hairiness is one of the most important parameters affecting fabric quality in textile industries. Up to now, many researchers have focused their studies on the hairiness and its related concepts. It is well known that fiber properties affect hairiness, nevertheless, spinning machine parameters which are also effective on hairiness are not well studied before. In this study, the prediction ability of hairiness by taking account of the variables including rotor type, rotor diameter, doffing-tube nozzle and torque-stop was studied using support vector machine (SVM) and adaptive neuro fuzzy interface system models. Moreover, the genetic algorithm was applied to ensure that the model parameters were optimized correctly. Then, the obtained results were compared with those provided by artificial neural network (ANN) and it was revealed that all models had the great potential to be used in hairiness prediction (mean absolute percentage error = 3.8-3.9). The performances of SVM and ANN models were almost the same, however, they were better than that of fuzzy model.**

***Keywords*: hairiness, machine parameter, support vector machine, adaptive neuro fuzzy interface system, genetic algorithm**

I. INTRODUCTION

Hairiness is one of the key features of yarn and refers to those fibers located outside of the yarn body and up to now many studies have been conducted in this field [1-4]. Generally, hairiness is considered as an undesired factor and researchers have always tried to minimize it as much as possible [5]. For instance, recently Abghary *et al.* have experimentally tried to minimize the hairiness of cotton rotor-spun yarns by taking account of the different influencing parameters [6]. Prediction of hairiness based on various parameters has always been an attractive field for researchers. The artificial intelligence models such as adaptive neuro fuzzy interface system (ANFIS) and support vector machine (SVM) present high-potential tools to be used in nonlinear and complicated engineering problems such as predicting properties of textile yarns. Hitherto, ANFIS has been used in many published works to predict yarn properties [5, 7-11]. For example, Majumdar used ANFIS to predict the cotton yarn hairiness based on fiber properties such as fiber mean length and the obtained model showed an average error about 2% in prediction [5].

Recently, Vadood *et al.* used ANFIS to model the elongation and hairiness for multi-objective optimization purpose [12]. Besides, some researchers used SVM model for textile subjects [13-18]. For example, Nurwaha and Wang employed SVM to predict the rotor spun yarn strength based on the information obtained from High Volume Instrument and Advanced Fiber Information System and the SVM accuracy was compared to that provided by ANFIS [14]. Ghosh and Chatterjee compared the performance of SVM and artificial neural network (ANN) models in prediction the properties of ring and rotor yarns [13]. Jin and Zhu used SVM and ANN to predict the performance of spun bonded filtration by the help of structural parameters [18]. Furthermore, Ghosh modeled the ring yarn properties such as hairiness based on the fiber properties by ANN, ANFIS and SVM [9]. According to the published works mentioned above, researchers generally have attempted to model hairiness by taking account of physical and mechanical fiber properties. However, lately, some researchers such as Ghorbani *et al.* have modeled hairiness based on the machine parameters and they found that the obtained results were satisfying [19].

Despite many studies on the yarn hairiness, to the best of authors' knowledge, hardly any trace of scientific work can be found that encompasses modeling hairiness by SVM based on the machine parameters. Therefore, in this study yarn hairiness is modeled by the help of SVM

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based on the machine parameters and ANFIS model is also used to complete the study. Because these models have various parameters affecting the results, an appropriate optimization algorithm is needed, and to this aim the genetic algorithm (GA) is used to ensure that all parameters are predicted correctly.

A. SVM

SVM is a statistical method which can be used for classification and regression [20]. In a linear regression method, the goal is to find f(x), given in Eq. 1, so that the absolute difference between f(x) and actual response becomes lower than epsilon (ε). Moreover, f(x) should be flat as much as possible; hence the Euclidean norm of ω should be minimized:

$$f(x) = \langle \omega, x \rangle + b \qquad \omega \in x, b \in \mathbb{R} \tag{1}$$

The symbol < > means dot product of vector variables. In nonlinear problems, the linear form of f(x) is not efficient and it should be updated to its nonlinear form conducted with kernel functions (KF) and Lagrange dual form. The nonlinear f(x) is given in Eq. 3 [21]:

$$f(x) = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) KF\left(x_i, x\right) + b \tag{2}$$

Where α and α* are the Lagrange multipliers. The other parameter affecting the SVM result is box constraint. Common KFs which are usually used in SVM model are also presented in Eqs. 3 to 5.

$$KF_{\text{Radial base}} = \exp\left(-\frac{\|x - z\|^2}{2\sigma^2}\right) \tag{3}$$

$$KF_{\text{Polynomial}} = \left(1 + \langle x.z \rangle\right)^P, \quad P \in \{\mathbb{N} \geq 2\} \tag{4}$$

$$KF_{\text{Linear}} = \langle x, z \rangle \tag{5}$$

B. ANFIS

As matter of fact, ANFIS is a tool based on the Sugeno fuzzy logic. In this method, at first, data are converted to the fuzzy sets and then inputs are assigned to the outputs by IF-THEN rules. At the end, the results are turned to real numbers [22]. The most effective parameters in ANFIS are the number of membership function (MF) and its kind. In this study three kinds of MF given in Eqs. 6 to 8 are considered as follow:

$$\text{Generalized bell\_shape} = \left(1 + \left|\frac{x - c}{a}\right|^{2b}\right)^{-1} \tag{6}$$

$$\text{Gaussian} = \exp\left(-\frac{(x - c)^2}{2\sigma^2}\right) \tag{7}$$

$$\Pi\_\text{shaped} = \begin{cases} 0, & x \leq a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \leq x \leq \frac{a+b}{2} \\ 1 - 2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \leq x \leq b \\ 1, & b \leq x \leq c \\ 1 - 2\left(\frac{x-c}{d-c}\right)^2, & c \leq x \leq \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \leq x \leq d \\ 0, & x \geq d \end{cases} \tag{8}$$

C. GA

Generally, in engineering design optimization problems there are many parameters which needed to be optimized to provide the best results. The optimization procedure can be developed by different algorithms, among which the GA algorithm is the best because of its special features. In this procedure, first, the structure of a solution is converted to a vector known as chromosome and then each chromosome is evaluated by the fitness function. By applying various mechanisms such as crossover, different chromosomes are established and once again the fitness value is measured. This cycle is continued until a desired criterion is satisfied [23].

II. DATA COLLECTION

The data used in this study were collected from the published literature [19]. The database includes 252 datasets of machine parameters and corresponding hairiness of cotton rotor spinning yarns. The considered machine parameters are the following: rotor type (T and G), rotor diameter (33 and 40 mm), doffing-tube nozzle (fluted (KN4, KN8) and spiral (KS) nozzles) and torque-stop (presence and absence). Therefore, the input and output of the SVM and ANFIS models are machine parameters and hairiness, respectively. A Shirley tester (Model SDL096/8) with the yarn length of 10 m and speed of 50 m/min was used for measuring the hairiness. It is noteworthy to mention that the output of the experiment was the number of hairs more than one millimeter. Some of the obtained data, shown in Table 1, are known as test group and will be explained in the later section.

A. Optimization by GA

As mentioned before, GA was used to optimize the SVM and ANFIS parameters. Therefore, in this study, the chromosome is a vector that contains the parameters of a model, as shown in Fig. 1.

TABLE I
EXPERIMENTAL DATA OF TEST GROUP

No.	Rotor type	Rotor diameter (mm)	Novel	Torque stop *	Hairiness (hairs/m)
1	T	40	KN8	1	30.3
2	T	40	Spiral	1	28.5
3	T	33	KN4	1	25.7
4	T	40	Spiral	0	24.6
5	T	40	KN4	1	28.2
6	G	33	KN8	0	31.9
7	T	40	Spiral	0	24
8	T	40	KN8	1	30.2
9	G	33	KN4	1	20.1
10	T	40	Spiral	1	27.7
11	G	33	KN4	0	20.3
12	T	33	KN8	1	29.2
13	T	33	KN4	1	23.3
14	T	40	KN4	1	27.1
15	T	33	Spiral	0	22.8
16	G	33	KN4	0	18.3
17	T	33	KN4	0	19.9
18	T	33	KN4	0	21.5
19	T	40	KN4	0	29.9
20	T	40	Spiral	1	26.8
21	T	33	KN8	1	26.4
22	T	40	KN4	1	30.2
23	T	33	Spiral	0	20.6
24	T	40	KN4	1	27.1
25	T	40	Spiral	1	28.3
26	T	40	Spiral	0	24.7
27	T	33	KN8	1	26.6
28	G	33	Spiral	1	24.4
29	G	33	KN8	1	29.2
30	G	33	KN8	0	33.2
31	T	33	KN4	1	23.5
32	G	33	KN4	1	21.3
33	G	33	Spiral	0	18.3
34	G	33	Spiral	0	19
35	T	33	KN8	1	28.6
36	T	40	KN4	1	29.2
37	T	33	KN8	0	31.5
38	T	33	KN4	0	22.4
39	T	33	KN4	0	20.3
40	T	33	KN8	0	32.3
41	T	40	Spiral	1	27.8
42	T	33	KN8	1	27.3
43	T	33	KN4	0	19.6
44	G	33	KN8	0	30.6
45	T	40	KN4	1	26.6
46	T	40	Spiral	1	28.9
47	T	33	KN4	1	24
48	G	33	KN8	1	26.6
49	G	33	KN8	0	31
50	G	33	KN8	1	29.4

*: 0 and 1 mean without and with torque stop, respectively.

As can be observed in Fig. 1a, each cell of chromosome specifies one parameter in SVM. The first cell (kind of KF) is encoded according to Table II.

The second cell (sigma value) in Fig. 1a is used if only the KF is radial base and if KF is polynomial, sigma value is ignored and the order of polynomial is read from the

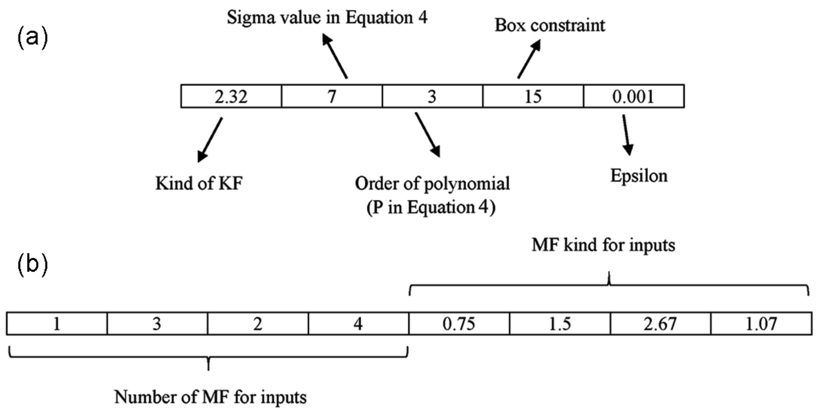

Fig. 1. Schematic of chromosome containing the parameters information for model: (a) SVM, and (b) ANFIS. Rounded values are considered for order of polynomial, box constraint and number of MF.

TABLE II
ENCODED TABLE FOR KF USED IN SVM MODEL

Code	Assigned function
$0 \le x < 1$	Radial base
$1 \le x < 2$	Polynomial
$2 \le x < 3$	Linear

TABLE III
ENCODED TABLE FOR MF USED IN ANFIS MODEL

Code	Assigned function
$0 \le x < 1$	Generalized bell-shaped
$1 \le x < 2$	Gaussian
$2 \le x < 3$	Π-shaped

third cell. Finally, if the KF is linear, the second and third cells are ignored. In Fig. 1b, the values of the four first cells (from the left side) indicate the number of MF for the rotor type, rotor diameter, doffing-tube nozzle and torque-stop, respectively, and 5th to 8th cells specify the kinds of MF for inputs with the same order according to Table III. For example, in Fig. 1b, 5th cell denotes the generalized bell-shaped for the rotor type.

Before starting the model processing, all data were divided randomly into three groups named train, validation and test sets with proportion of 60%, 20% and 20% of all data, respectively. To assess the accuracy of established models, the mean absolute percentage error (MAPE) was defined as the fitness function in GA according to Eq. 9. Therefore, when GA creates a model based on the information of a chromosome, the model is trained by the help of train and validation sets and after that the fitness value or in other words MAPE is measured for that model based on the test group. So, the lower MAPE means a model with higher accuracy in prediction. It should be mentioned that GA was run two times; once for SVM model and the other time for ANFIS model.

$$\text{Fitness\_function} = \frac{100}{n}\sum_{i=1}^{n}\frac{|y_i - t_i|}{t_i} \tag{9}$$

Where y and t are the predicted and actual values, respectively. GA was run with 30 random initial chromosomes and stopped at 30th generation. The lower and upper bounds for SVM chromosome are indicated in Table IV, and the number of MF for ANFIS model was considered to vary between 2 to 4. All programs were developed by MATLAB software.

RESULTS AND DISCUSSION

As initial chromosomes in GA are selected randomly, GA was run 10 times for each model and the best result obtained for each case was chosen. It should be mentioned that, the validation set was used in the ANFIS model to prevent overfitting error in the training step and for SVM model train and validation sets were used together to determine model parameters. The best chromosome obtained for each model is presented in Table V.

Referring to Table V, the SVM model with polynomial order of 3, box constraint of 9 and epsilon of 0.001 has

TABLE IV
ENCODED TABLE FOR KF USED IN SVM MODEL

Bound	KF kind	Sigma for radial base	Order for polynomial	Box constraint	Epsilon
Lower	0	0.1	2	5	0.000001
Upper	3	10	10	30	0.1

TABLE V
EXPERIMENTAL DATA OF TEST GROUP

Model	Cell (according to the order of chromosomes shown in Fig. 1)								MAPE
	1	2	3	4	5	6	7	8	
SVM	1.872	9.059	2.902	9.249	0.001	-	-	-	
ANFIS	3.948	3.419	2.502	2.831	0.908	0.225	2.526	1.433	3.92

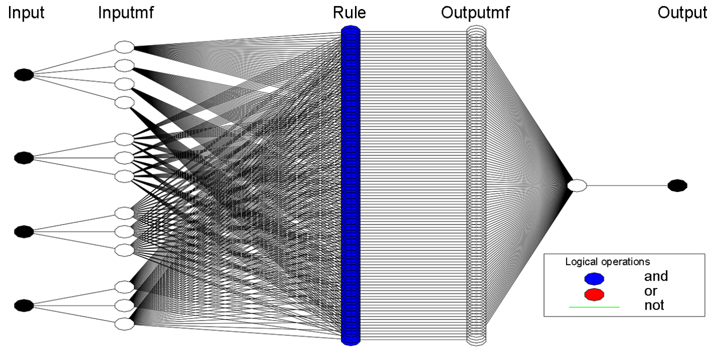

Fig. 2. The structure view of the best obtained ANFIS model.

the highest accuracy. On the other side, the ANFIS model with the combination of all considered MFs and 108 rules is the best obtained fuzzy model and Figs. 2 and 3 show its structure view and a part of its rule view, respectively.

According to the published work [19], the use of ANN for modeling of hairiness with the same data (train, validation and test groups) resulted in the MAPE of 3.87 and the R-square of 0.93. Fig. 4 indicates the actual and predicted values for different models. However, as can be observed in Fig. 4 and as well as Table V, all models almost benefit from the same accuracy.

Therefore, the question here is which model is more appropriate. To answer this question other parameters of models such as run time should be considered. So, the model takes lower run time is the best one and to this aim, the training step for the best obtained models was repeated 10 times and the average run times are as follows:

- SVM model: 0.087 s
- ANFIS model: 6.297 s
- ANN model: 0.011 s

It should be mentioned that all training steps were accomplished by the same computer with configuration of CPU: Core i7-4790 3.6 GHz and RAM: 8 GB. The obtained results revealed that ANFIS was the slowest model in operation and ANN and SVM were found to be the fastest models but with a little difference. Moreover, the average GA run time for the ANFIS model was about 190 min. Therefore, not only ANFIS was the slowest model, but also finding the optimum parameters for this model took too much time. By ignoring the difference between

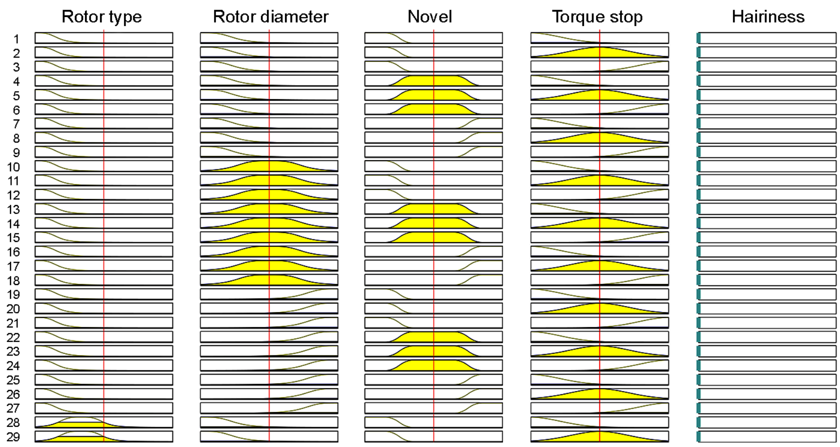

Fig. 3. A part of rule view from 108 rules of the best obtained ANFIS model.

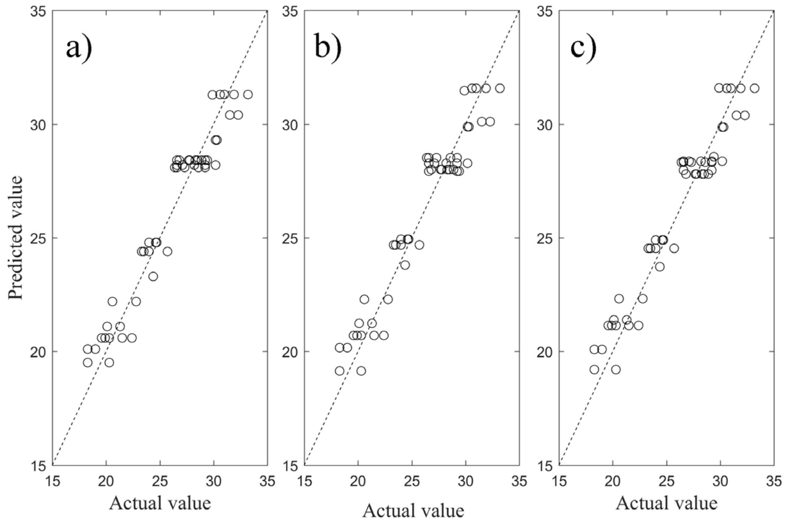

Fig. 4. Actual and predicted hairiness values (hair/m) for the test group: (a) SVM model with R-square=0.93 and MAPE=3.82, (b) ANFIS model with R-square=0.92 and MAPE=3.92, and (c) ANN model with R-square=0.93 and MAPE=3.87.

training times of SVM and ANN, it can be concluded that both these models are accurate and fast models for hairiness prediction. The presented approach can be used in the quality control of spinning processes to enhance the yarn quality.

V. CONCLUSION

In this study, rotor type, rotor diameter, doffing-tube nozzle and torque-stop were selected as the machine parameters and the hairiness of cotton rotor spinning yarns was measured against different levels of machine parameters. The SVM and ANFIS models were used to find the relation between the machine parameters and measured hairiness, and GA was implemented to optimize models parameters. The obtained results showed that the accuracies of SVM, ANFIS and ANN models are almost the same (MAPE was between 3.8 and 3.9). Besides, comparing the run times of the models revealed a little difference in performance between the SVM and ANN models but they were remarkably better than ANFIS model.

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