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Prediction of rotor-spun yarn quality using hybrid artificial neural network-fuzzy expert system model

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This study aims at developing a new approach to predict and determine the quality of rotor-spun yarn in terms of fibre characteristics as well as critical yarn properties. Hybrid modeling by combining two or more techniques has been demonstrated to give better performance than that of several single approaches over many research areas. Hence, in this study a hybrid model by combining two soft computing approaches, namely artificial neural network (ANN) and fuzzy expert system, has been developed. The ANN is used to predict three yarn characteristics, namely tenacity, breaking elongation and CVm. Then these three outputs are used to predict the new quality index by means of the fuzzy expert system. The accuracy of predicted model has been estimated using statistical performance criteria, such as correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE) and mean relative per cent error (MRPE). The results show the ability of model to predict the rotor-spun yarn quality and according to the analytical findings, the hybrid model gives accurate result.

Keywords: Artificial neural network, Fuzzy expert system, Global yarn quality, Hybrid model, Rotor-spun yarn

1 Introduction

Strength is recognized as the most important yarn quality parameter, which is significantly affected by other properties such as breaking elongation and unevenness. The relationship between fibre characteristics and yarn properties has been the focus of several researches. Indeed, mathematical, theoretical and statistical models have been developed to predict and understand this complex relationship[1-4]. However, the use of statistical approaches is not practical due to the inherent non-linear relationship that exists between fibre properties, process parameters and yarn properties.

Recently, there has been a rising utilization of many soft computing approaches. In fact, artificial neural network has been identified as an important tool to solve non-linear complex problems. For this reason, some researchers[5-8] have shown an interest on the use of ANN to predict yarn characteristics. Furthermore, Chattopadhyay and Guha[9] have reviewed textile application of artificial neural network in details. In fact neural network methods have been widely used for the prediction of CSP[6], tenacity and breaking elongation[10]. Although artificial neural networks are considered as a universal function approximator and they are able to learn from examples, they behave like a black box. In fact, they cannot give explicitly the relationship between input factors and output response.

Furthermore, fuzzy technique can be used in modeling yarn properties by discovering the linguistic rules relating the inputs and outputs. Besides, the development of fuzzy approach is relatively easier than ANN as it requires neither a training nor an important amount of input/output data for model parameter optimization. Also, as compared to other approaches such as regression, mathematical and neural network methods, the fuzzy logic method examines the possibility more than the probability. Thus, fuzzy method is more flexible in defining, evaluating constraints, predicting and in modeling complex and non-linear problems[11-14].

It is concluded that in literature, a large number of studies have been reported to predict several yarn properties. However, limited researches are available to predict an overall yarn quality that considers all yarn properties simultaneously[15]. For this reason, we carried out this study which deals with the prediction of a global quality index of a rotor-spun yarn using a hybrid model based on cascading artificial neural network models and fuzzy expert system.

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2 Materials and Methods

Five cotton blends were selected for the study. Before being processed, fibre properties of each blend were measured using Uster HVI testing machine system. Then, two second drawing slivers were obtained from each set of fibres with count numbers 0.12 and 0.13. Yarn tensile properties were evaluated on Uster Tensorapid 3 tensile testing machine. Unevenness was measured through Uster Tester 3. All experiments were performed at a temperature 20±2°C and relative humidity 65±4%. The statistics summary of measured fibre and yarn properties is given in Table 1. Table 2 shows in details the quality index and the properties of rotor-spun yarns as well as the different inputs of the hybrid model.

2.1 Determination of Overall Yarn Quality

Many attempts have been made to relate raw material characteristics to different yarn properties. However, it is desirable to predict an overall yarn quality that takes into consideration simultaneously all yarn characteristics. That is why, we introduced a new quality index which is based on expert opinions. These opinions themselves are based on Uster statistics. Indeed, Uster statistics are considered as a common quality language between producers and buyers. Spinners can trust Uster statistics signpost, better competitiveness, cost optimized quality disciplines and avoidance of expensive claim and rejects.

Thus, Uster statistics published in 2013 (ref. 16) were used as benchmarks. It provides graphs with percentile curves that indicate the range USP which refers to the percentage of the total world production. For example, the 5% limit line means that 5% of the spinning mills are producing yarn with better characteristics. The same applies for the other limits at 25%, 50%, 75% and 95%.

Table 1 — Fibre, sliver and yarn properties statistics summary

Factor	Minimum	Average	Maximum	Standard deviation
Short fibre index (SFI)	7.9	9.12	10.7	0.67
Fibre strength (Str)	25.5	28.100	31.2	1.27
Yarn count (Ne)	10	22.04	37	8.31
Twist level	400	598.46	1000	175.27
Sliver count (NeR)	0.12	0.126	0.13	0.006
Sliver unevenness (RgR)	2.52	2.94	2.65	0.16
Tenacity , cN/tex	7.7	12.87	16.92	2.01
Yarn elongation, %	5.79	7.57	9.39	0.9
CVm, %	11.47	12.74	15.65	1.11

In present study, three characteristics were taken into consideration to determine quality. So, we will calculate the overall quality range using the following equation:

$$USP_{Quality} = USP_{Tenacity} + USP_{Elongation} + USP_{CVm} \qquad ...(1)$$

The target of the spinner is that USP quality is 5%. However, the worst produced yarn quality is when USP= 95%. So, if USP quality is equal to 5%, the quality index would be 1, and if it is 95%, the quality index would be 0. Table 3 gives the relationship between USP quality and quality index for different ranges. So, it allows us to determine the linear relationship between them . Thus, we can deduce that

$$\text{Quality index} = -0.01\times USP_{Quality} + 1.042 \qquad ...(2)$$

2.2 Hybrid Model

Hybrid models are composed of two learning stages. The first stage is used for preprocessing data and the second one for the final prediction output[17]. Thus, they are considered as a combination of two approaches. Hybrid models are often associated with the use of artificial neural networks to facilitate construction and learning as far as the other approach is concerned. There exist many designs of hybrid models combining the two soft computing approaches ANN and fuzzy logic system. Indeed, ANFIS has been used frequently to model and predict yarn unevenness and CSP strength of rotor yarn[18, 19].

In hybrid artificial neural network- fuzzy expert structure, membership functions are adjusted by a hybrid model and expert opinions cannot be taken into consideration. Thus, we used a cooperative model in which the neural network occurs once to predict separately three yarn properties. Then, the obtained results are injected and used by the fuzzy system in order to predict the quality index.

2.3 ANN Model

An artificial neural network is defined by three kinds of parameters. They are the interconnection pattern among different layers of network, learning function that defines the way of updating the weights of interconnection and the activation function. Among several ANN structures existing in literature, multilayer perceptron has been successfully applied by Haykin[20].

The error is then minimized in iterative steps by adjusting the synoptic weights using a suitable training algorithm. Back propagation algorithm developed by Rumelhart *et al*.[21] is the most used one.

Table 2 — Fibre properties, yarn properties and corresponding index quality

Fibre and process parameters						Yarn properties			Quality index
SFI	Str, cN/tex	RgR	NeR	Ne	Twist, turns/m	Tenacity cN/tex	Elongation %	CVm, %	
10.7	29.8	2.94	0.12	8.85	400	9.6	7.66	11.64	0.63
10.7	29.8	2.94	0.12	8.85	500	11.7	7.8	12.14	0.84
10.7	29.8	2.94	0.12	8.85	600	12.75	9.39	11.76	0.84
10.7	29.8	2.94	0.12	8.85	700	12.9	8.53	11.99	0.84
10.7	29.8	2.86	0.13	10.62	400	9.54	7.39	12.66	0.56
10.7	29.8	2.86	0.13	10.62	500	11.7	7.32	13.11	0.71
10.7	29.8	2.86	0.13	10.62	600	13.14	7.91	12.8	0.78
10.7	29.8	2.86	0.13	10.62	700	13.5	8.14	12.99	0.78
10.7	29.8	2.86	0.13	12.98	400	7.7	6.56	13.54	0.39
10.7	29.8	2.86	0.13	12.98	500	11.66	7.93	12.05	0.84
10.7	29.8	2.86	0.13	12.98	600	12.98	8.45	12.12	0.84
10.7	29.8	2.86	0.13	12.98	700	13.64	8.96	11.82	0.84
10.7	29.8	2.86	0.13	17.7	600	10.5	6.47	13.55	0.39
10.7	29.8	2.86	0.13	17.7	700	11.4	6.61	14.03	0.39
10.7	29.8	2.86	0.13	17.7	1000	12.3	7.89	13.96	0.69
10.7	29.8	2.86	0.13	21.83	600	9.99	6.07	14.23	0.23
10.7	29.8	2.86	0.13	21.83	700	11.1	6.39	15.32	0.24
10.7	29.8	2.86	0.13	21.83	1000	12.95	7.55	14.73	0.54
9.4	28.1	2.64	0.12	8.85	400	10.05	7.39	11.47	0.63
9.4	28.1	2.64	0.12	8.85	500	11.7	7.29	12.06	0.78
9.4	28.1	2.64	0.12	8.85	600	12.75	7.79	11.63	0.84
9.4	28.1	2.64	0.12	8.85	700	12.9	8.24	11.56	0.84
9.4	28.1	2.52	0.13	10.62	400	10.8	7.06	11.86	0.63
9.4	28.1	2.52	0.13	10.62	500	12.78	7.22	12.63	0.78
9.4	28.1	2.52	0.13	10.62	600	13.68	7.77	12.31	0.84
9.4	28.1	2.52	0.13	10.62	700	14.04	8.02	13.13	0.93
9.4	28.1	2.52	0.13	12.98	500	11.44	7.33	12.36	0.63
9.4	28.1	2.52	0.13	12.98	600	13.2	7.06	12.48	0.78
9.4	28.1	2.52	0.13	12.98	700	13.42	8.54	12.26	0.84
9.4	28.1	2.52	0.13	17.7	700	10.8	6.15	14.85	0.23
9.4	28.1	2.52	0.13	17.7	1000	12.3	7.67	14.43	0.54
9.4	28.1	2.52	0.13	21.83	700	10.73	5.79	15.65	0.16
9.4	28.1	2.52	0.13	21.83	1000	12.58	7.27	15.45	0.48
9.2	31.2	2.53	0.12	8.85	400	12.3	7.44	11.6	0.78
9.2	31.2	2.53	0.12	8.85	500	14.1	7.44	12.05	0.93
9.2	31.2	2.53	0.12	8.85	600	14.85	7.99	12.01	0.99
9.2	31.2	2.53	0.12	8.85	700	14.7	7.9	11.85	0.99
9.2	31.2	2.54	0.13	10.62	400	14.04	7.42	11.85	0.93
9.2	31.2	2.54	0.13	10.62	500	16.2	7.47	12.17	0.93
9.2	31.2	2.54	0.13	10.62	600	16.92	8	11.55	0.99
9.2	31.2	2.54	0.13	10.62	700	16.92	8.44	12	0.99
9.2	31.2	2.54	0.13	12.98	500	13.86	7.48	12.5	0.93
9.2	31.2	2.54	0.13	12.98	600	14.96	8.15	12.48	0.99
9.2	31.2	2.54	0.13	12.98	700	15.4	8.66	12.08	0.99
9.2	31.2	2.54	0.13	17.7	600	12.3	6.1	12.83	0.54
9.2	31.2	2.54	0.13	17.7	700	13.5	6.46	12.99	0.63
9.2	31.2	2.54	0.13	17.7	1000	13.8	8.16	13.24	0.93
9.2	31.2	2.54	0.13	21.83	600	12.95	5.79	13.76	0.46
9.2	31.2	2.54	0.13	21.83	700	13.69	6.13	13.33	0.54
9.2	31.2	2.54	0.13	21.83	1000	14.43	7.75	13.58	0.84

Network weights are updated iteratively until satisfying the appropriate stopping criteria. Thus, the best generalization is accomplished.

Back propagation network is made up of several interconnected neurons. These neurons are arranged in layers: one or more hidden layers sandwiched between one input layer and one output layer. It was established that a single hidden layer feed-forward network can approximate any continuous mapping with arbitrary precision[22,23].

Determining the number of hidden neurons is an essential element for designing a neural network, as fewer neurons cannot learn the problem correctly and largely. It may lead to an over-fitting problem and increase the training time. Up to now, there exists no systematic rule allowing to calculate the optimal number of hidden neurons and this parameter is selected by trial and error. As activation functions, non linear tangent sigmoid activation function was used in the hidden layer and a linear function was used in the output layer**.** The program treats different numbers of neurons in the hidden layer until reaching the minimum root mean square errors generated by the training and testing data[24].

In this study, the input units are composed of fibres properties, and sliver & yarn construction parameters such as short fiber index (SFI), fibre strength (Str), yarn count (Nm), twist, sliver count (NmR) and sliver unevenness (RgR). The output unit is in each time, one of three yarn properties (tenacity, breaking elongation, Cvm) as given in Fig.1

Table 3 — Relationship between USP quality and quality index

USP quality, %	Quality index
5	1
25	0.75
50	0.5
75	0.25
95	0

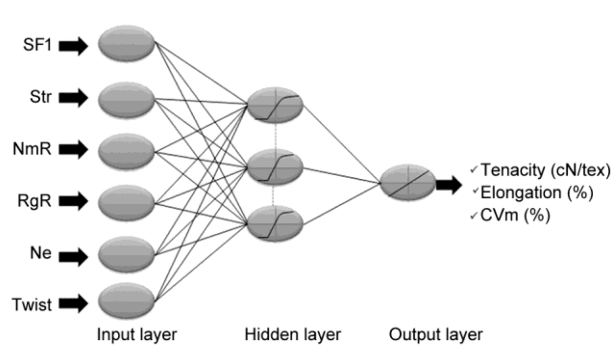

Fig.1 — Neural network architecture

When training, over-fitting phenomenon may happen i.e a neural network over learns. As a result, this network may not perform well when it is tested because of a lack of generalization capability. In fact, the fitted model is expected not only to recall the observed data with the required accuracy but also to give good predictions for unseen (test) data.

In literature, two approaches were suggested to overcome this phenomenon. These approaches were the early stopping technique and Bayesian regularization. In our study, we will use the Bayesian regularization technique

A commonly used cost function is the mean sum of squared error, which aims at minimizing the average squared error between the networks output and the target value over all example pairs. The Bayesian regularization approach helps in modifying this function by adding the sum of squares of the network weights. The objective of this modification is to improve the model's generalization capability.

2.4 Fuzzy Logic System

In fuzzy logic, a fuzzy set is an extension of a classical crisp set. A fuzzy set contains elements with only partial membership ranging from 0 to 1 to define uncertainty for classes that do not have clear defined boundary [25].

The first step in the fuzzy logic theory is the fuzzification. It converts each input in to the values belonging to [0 1], and so indicates the appurtenance of the input to the fuzzy set. Secondly, the fuzzified values are then inferred to give decisions by the inference engine with the support of the fuzzy rule list. As a result of this step, we obtained the fuzzy sets that would be converted to crisp values by defuzzification. And so, the defuzzified values represent the decision made by the fuzzy building model.

2.5 Model Evaluation and Interpretation

In order to evaluate the prediction performances of our neural models and our fuzzy expert system, four statistical criteria were investigated, namely root mean square error (RMSE), mean absolute error (MAE), mean relative per cent error (MRPE) and correlation coefficient (R), as given below:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - Y_i)^2} \quad \ldots(3)$$

$$R = \frac{\sum T_i Y_i - (\sum T_i Y_i / N)}{\sqrt{(\sum T_i^2 - (\sum T_i)^2/N) \times (\sum Y_i^2 - (\sum Y_i)^2/N)}} \quad \ldots(4)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|T_i - Y_i| \quad \ldots(5)$$

$$\mathrm{MRPE} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{|T_i - Y_i|}{T_i}\,100 \qquad \dots (6)$$

where N, Ti and Yi respectively refer to data number, experimental output and estimated output

3 Results and Discussion

3.1 Predicting Yarn Properties using ANN

Figure 2 shows the plots of both $RMSE_{train}$ and $RMSE_{test}$ as a function of hidden neurons for the three predicting yarn property models. The hidden neurons number that deals with the minimum of two measured errors is the most adequate one. Therefore, the neural network models are optimized at seven neurons in the hidden layer for tenacity, two for elongation and four for CVm.

To test the generalization behavior of the optimal ANN, we used the test database to validate processes. The main quality indicator of a neural network is its ability to predict accurately the output of unseen data. According to Table 4, the ANN model gives high coefficient values for both training and test subsets. Indeeed, the correlation coefficients are ranged between 0.88 and 0.99 for the three outputs. Furthermore, MRPE values are ranged from 0.58% to 3.7% which are considered low according to El-Ghezal *et al.*[26]. So, the predictibilty of ANN fits very well. This result is in harmony with the plots given in Figs 3 and 4. As a consequence, the built models have good learning and generalization performances.

3.2 Predicting Yarn Quality Index using Fuzzy Expert System

The development of the fuzzy expert system is carried out using Matlab Fuzzy logic toolbox. In fuzzy inference, the Mamdani method is used for calculating the output inferred by a set of n fuzzy rules[27]. Indeed, the Mamadani method is the most commonly applied fuzzy methodology. Then, the centroid methods are used for defuzzification.

In the present study, the “generalized bell- shaped” function has been chosen and used for yarn properties. However, for yarn quality index, we have used triangular membership function. This combination is found the most adequate one for our study (Fig. 5).

According to Majumdar *et al.* [19], if α is the number of membership functions for each input and β is the number of inputs, then there are α^β rules to be trained. In our study, we have 3 inputs and 4 membership functions. So, we can have 81 rules. However, we have only 51 data sets for training. So, the number of rules is kept at 21 to be trained properly using the

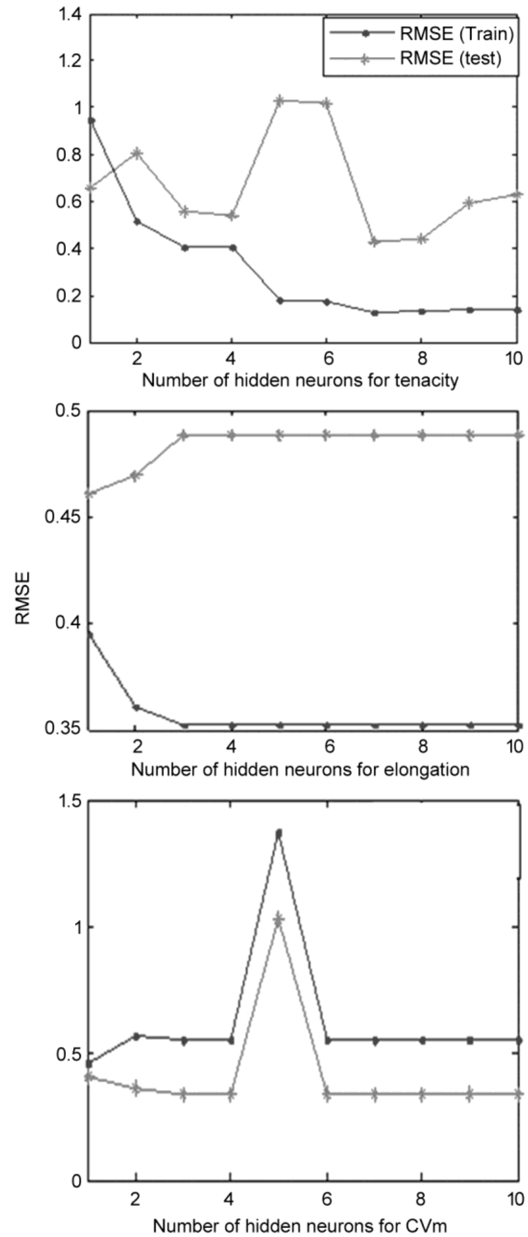

Fig. 2 — $RMSE_{train}$ and $RMSE_{test}$ versus number of hidden neurons

Table 4 — Prediction result summary of three neural models in training and testing data

Yarn property	Training performance				Testing performance			
	RMSE	MAE	MRPE	R	RMSE	MAE	MRPE	R
Tenacity	0.1	0.068	0.58	0.99	0.38	0.31	2.4	0.97
Elongation	0.36	0.29	3.8	0.9	0.49	0.35	3.7	0.88
CVm, %	0.33	0.27	2.1	0.94	0.55	0.44	2.8	0.92

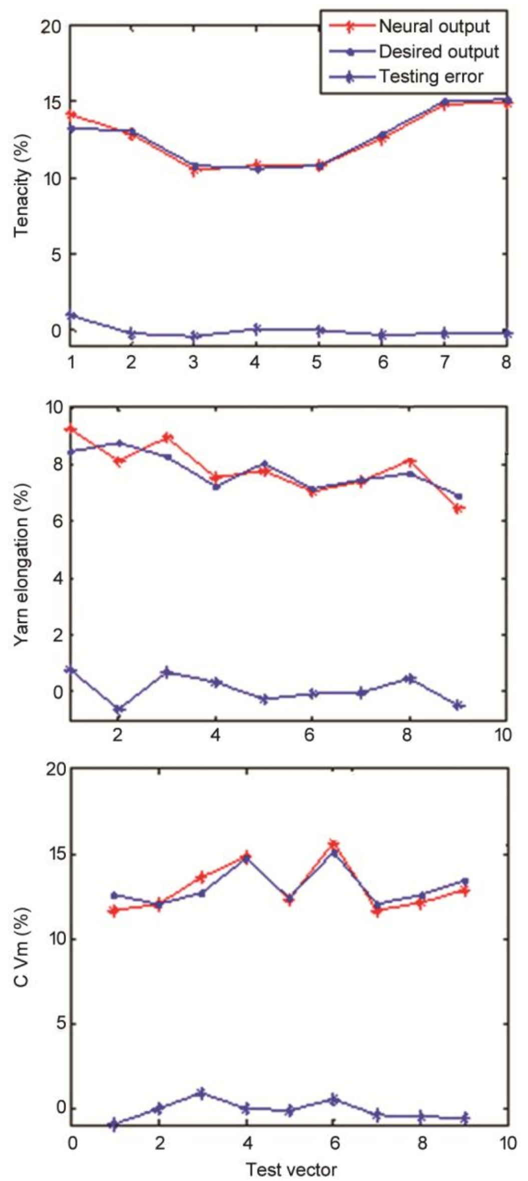

Fig. 3 — Predicted and measured values and predicting error over the test subsets for tenacity, elongation and CVm

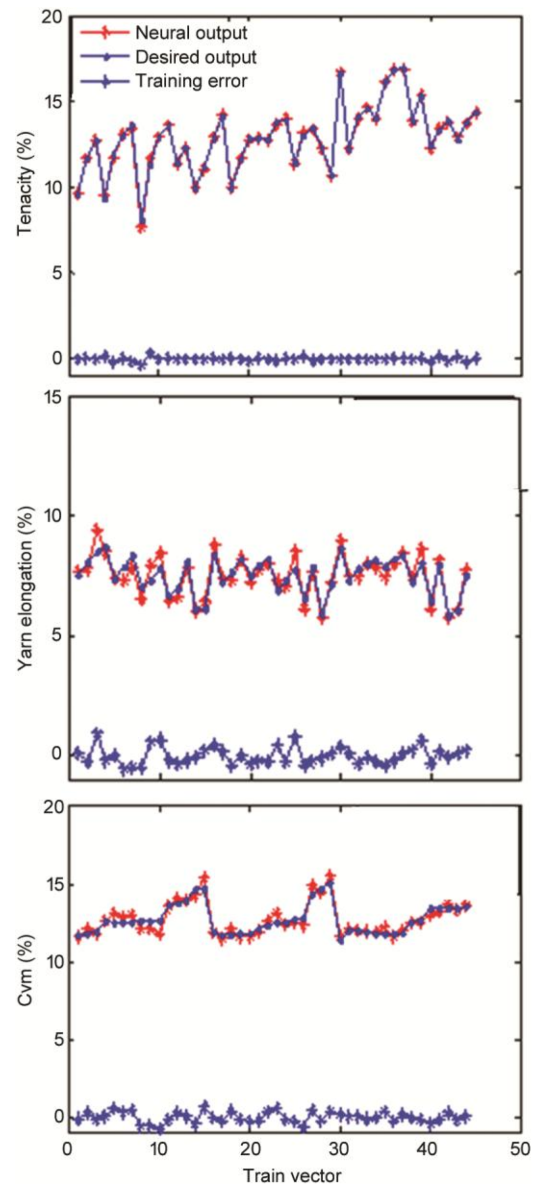

Fig. 4 — Predicted and measured values and predicting error over the training subsets for tenacity, elongation and CVm

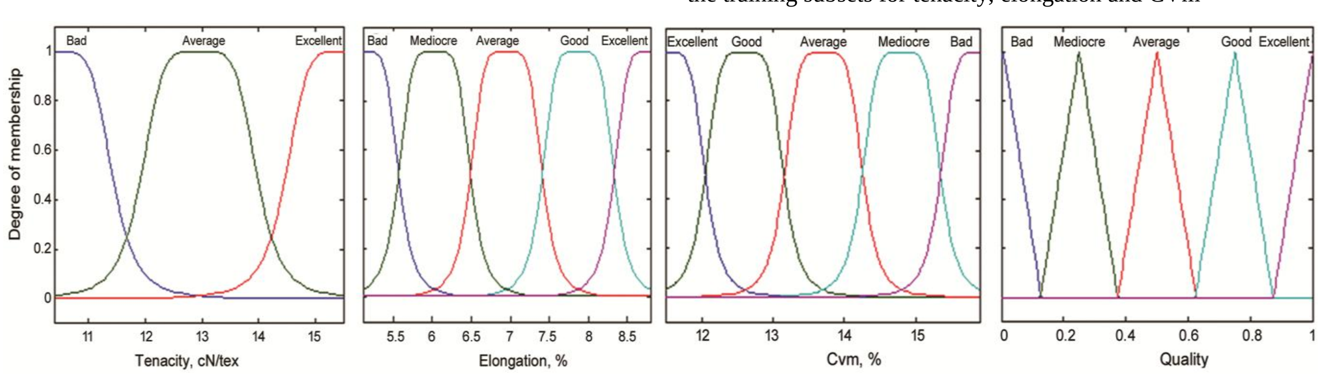

Fig. 5 — Generalized-bell membership function plots for yarn properties and triangular membership function plot for yarn quality

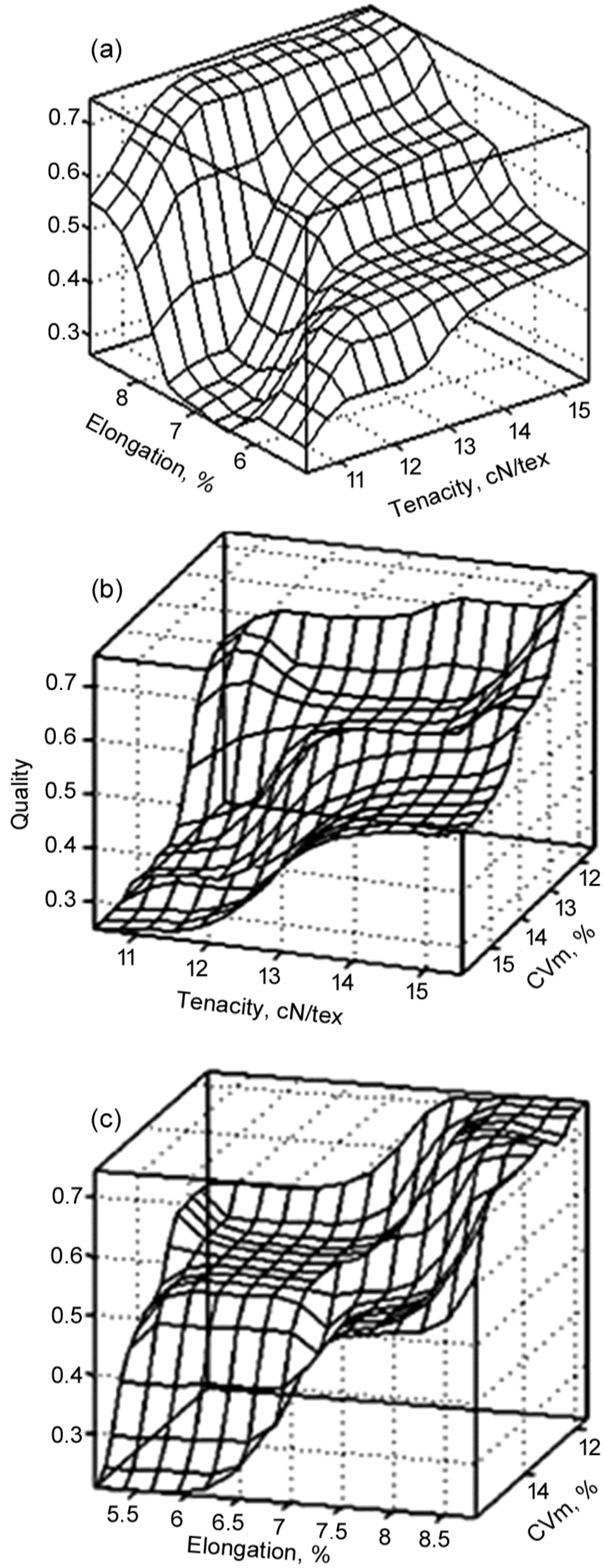

Fig. 6 — Surface plots showing the effect of several yarn properties on quality index variation (a) as function of tenacity and breaking elongation; (b) as function of CVm and tenacity; and (c) as function of CVm and breaking elongation

Table 5 — Fuzzy rules list

Rule	Tenacity	Elongation	CVm	Quality
1	Bad	Good	Excellent	Average
2	Average	Excellent	Excellent	Good
3	Bad	Good	Good	Average
4	Average	Good	Good	Good
5	Average	Excellent	Mediocre	Good
6	Bad	Average	Average	Mediocre
7	Average	Excellent	Excellent	Good
8	Average	Excellent	Average	Good
9	Bad	Mediocre	Mediocre	Mediocre
10	Bad	Average	Bad	Mediocre
11	Average	Good	Mediocre	Average
12	Average	Good	Excellent	Good
13	Excellent	Excellent	Good	Excellent
14	Bad	Mediocre	bad	Bad
15	Average	Good	Bad	Average
16	Excellent	Mediocre	Excellent	Excellent
17	Excellent	Excellent	Excellent	Excellent
18	Average	Mediocre	Good	Average
19	Average	Average	Good	Average
20	Average	Mediocre	Average	Average
21	Excellent	Excellent	Average	Good

available data. The overall rules we used and which are the core of the fuzzy expert system are shown in Table 5. These rules are fixed and then developed according the database constructed (Table 2).

The prediction acuracy of the fuzzy approach is studied using performance evaluation parameters. The obtained results are as follows. The root of mean square error RMSE is low (0.07). Also, the mean relative per cent error is equal to 10% which can be considered acceptable and significant according to El-Ghazel *et al.*[26]. Moreover, the correlation coefficient is found very close to 1 as it is equal to 0.98. As a consequence, the developed hybrid model is accurate.

Figure 6 shows the effect of various yarn properties on the quality index. Indeed, this figure shows that as tenacity increases, there is a concomitant increase in quality index. Breaking elongation also exhibits a similar impact. So, yarn quality attains the apex when yarn tenacity and breaking elongation are excellent. However, the CVm has a negative effect on quality index. In fact, if CVm decreases i.e yarn evenness becomes better, the quality increases.

These results are expected. If one of the four quality criteria, i.e yarn characteristics, becomes better, its USP becomes smaller and so USP quality decreases. Thus, quality index increases. These conclusions are in agreement with the studies of Yunus and Rhman[28], who proposed a yarn quality index expression, as shown below:

$$\text{Yarn quality} = \frac{\text{Breaking elonagtion} \times \text{Tenacity}}{\text{Unevenness}} \quad \ldots (7)$$

This expression proves that yarn quality increases by increasing yarn tensile properties or decreasing unevenness or through satisfying all these conditions.

4 Conclusion

The method used consists of hybrid model which captures both the high prediction of ANN and the ability to treat uncertain data of fuzzy logic. This model uses the fuzzy logic to translate the spinner experience into a set of expert system rules in order to predict an overall yarn quality index of rotor spun yarn. According to the analytical findings and the performance criteria, the proposed model gives high prediction accuracy.

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