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MODELING RING SPUN YARN TENSILE PROPERTIES USING FUZZY INFERENCE SYSTEM

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ABSTRACT

This paper aims to predict ring spun yarn tensile properties using non-correlated HVI fibers characteristics and some construction parameters. For this purpose, five different cotton blends were processed into yarns having different metric numbers (Nm13, Nm19, Nm21, Nm31 and Nm37). Each count was spun at different twist levels (450 trs/m, 500 trs/m, 650 trs/m, 750 trs/m and 850 trs/m).

To fulfill this goal, one of the soft computing approach tools is investigated namely fuzzy logic system. The prediction accuracy of this approach was estimated using four performance criteria specifically correlation coefficient, mean square error, mean absolute error and mean relative percent error. The model prediction accuracy was found to be very interesting.

Our study is very useful for industrial applications since it permits the quality management prediction based on input variables namely fiber characteristics and process parameters

KEYWORDS

Artificial neural network; Construction parameters; Fuzzy Inference;
HVI fibers characteristics System; Tensile properties.

1. INTRODUCTION

Yarn properties modeling is one of the most interesting fields of research in textile engineering. Among these properties, we have tensile characteristics. Indeed, yarn tenacity and breaking elongation have considerable effects on spinning process as well as on the subsequent manufacturing operations such as warping, knitting and weaving.

Several studies have been carried out about the effect of fibers properties and process parameters on yarn tenacity and breaking elongation. In fact, researchers have made relentless efforts to formulate mathematical, statistical and theoretical models to predict various yarn properties. The statistical approach has been the most popular method during the second half of the twentieth century. Indeed, it was the first technique used in the textile engineering field to explore the relationship between variables and yarn properties and optimize them (Erol, Sagbas, 2009). However, it is limited by the problem of nonlinearity. Besides, intelligent techniques such as fuzzy approach have been identified as important tool for modeling the nonlinear relationship between input variables and output responses. So, they are defined as a nonlinear processing system that is suitable for a large number of applications.

Recently, some researchers have shown an interest to many soft computer approaches such as fuzzy logic. This technique was used for predicting rotor spun yarn strength and CSP strength which is obtained

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through multiplying breaking strength by yarn count (Nurhawa, Wang, 2008; Nurhawa, Wang, 2010) and yarn strength (Majumdar, Ghosh, 2008).

Artificial neural network has been also identified as an important tool to solve nonlinear complex problems. For this reason some researchers (Ethridge, Zhu, 1996; Cheng, Adams, 1995; Ramesh et al., 1995; Zhu, Ethridge, 1997) have shown an interest to the use of the ANN to predict yarn characteristics. Furthermore, Chattopadhyay and Guha (Chattopadhyay, Guha, 2004) have reviewed textile application of artificial neural network in details. In fact neural network methods have been widely used for the prediction of CSP (Cheng, Adams, 1995), tenacity and breaking elongation (Sette et al., 1995). 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.

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.

In this study, we have to model yarn tensile properties using micronaire, upper half mean length, fiber strength and elongation, yarn count and twist level as input variables.

This paper is organized as follows. In the following part, we introduce the experiment and materials investigated to elaborate this work. The next part deals with the description of modeling procedure. In the third part, we will give the experimental results and we finish with a conclusion.

2. MATERIALS AND METHODS

2.1. Materials

In the scope of this study, different ring spun yarns were elaborated at several fineness and twist levels. These yarns are produced using five selected sets. The characteristics of different fibers were evaluated using Uster HVI testing system. Then, in order to reduce the number of parameters contributing in the models lately built, we used the principal component analysis (Ben Hassen et al., 2007; Hamdi et al., 2014).

The PCA results are shown in figure1. According to the PCA method, the HVI properties are arranged into groups A, B and C. The group A is composed of factors Elg and Mat. Therefore, these two parameters are positively correlated and one of them is chosen.

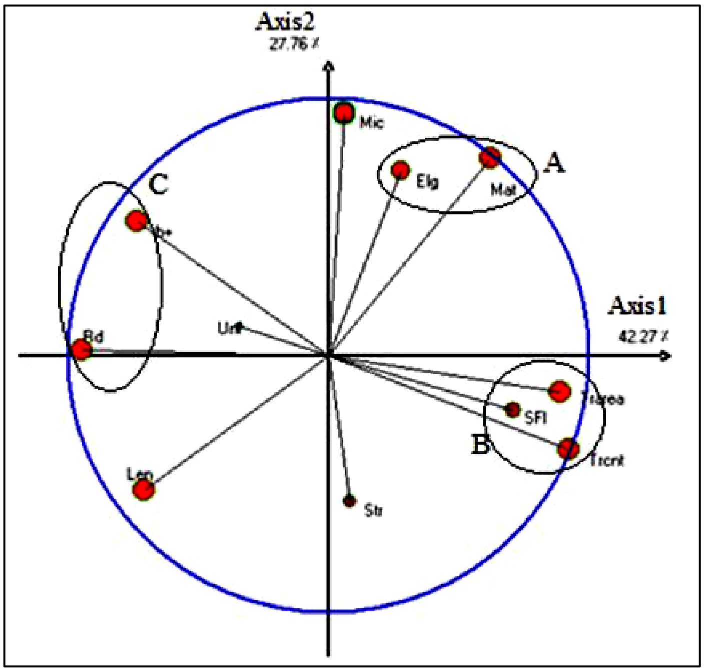

Figure 1: Principal component analysis applied to HVI fiber characteristics

The group B is composed of three factors: Trarea, SFI and Trcnt. The result indicates that these parameters are positively correlated. So, one of them is sufficient to be used in building models. The group C consists of two factors b+ and Rd. These two parameters are positively correlated but negatively correlated with group B.

The parameter Unf is situated close to the center and has no significant effect on yarn properties. Parameters Mic, Str, Len are not correlated to any other factors.

According to these results, only four HVI characteristics would participate in predicting yarn properties which are Len, mic, Elg and Str, in addition to process parameters, Nm and twist. Therefore, other parameters were neglected from the analysis.

Table 1 shows the statistics summary of these parameters in addition to process parameters. The whole of these parameters will be the input of all established models.

Table1: Input variables statistics summary

Fiber/Yarn Properties	Symbol	Minimum	Average	Maximum
Fiber fineness	Mic	3.95	4.04	5.08
Upper Half Mean Length	Len	27.81	28.77	30.67
Fiber Strength	Str	25.50	28.10	31.20
Fiber Elongation	Elg	8.40	8.86	9.90
Yarn count (m/10^{-3}Kg)		13	24.2	37
Twist level (turns/m)		450	640	850

After being conditioned in a standard atmosphere for at least 24 hours, yarns tensile properties were measured by Uster Tensorapid 3 according to NFG 07-002 which provides tenacity and breaking elongation. The statistics summary of measured tensile properties is given in table 2.

Table2: Ring spun yarn tensile properties statistics summary

Yarn property	Minimum	Average	Maximum
Tenacity (cN/tex)	11.47	16.61	21.73
Elongation (%)	5.04	7.07	11.39

2.2. Fuzzy logic approach

In the beginning, we have to define the fuzzy set which contains elements with partial membership ranging between 0 and 1 to define uncertainty for classes that do not have clear defined boundaries (Majumdar et al., 2008).

Once the fuzzy sets are chosen, a membership function of each set should be done. This membership function is a typical curve that converts the numerical values of input with a range from 0 to 1 showing the appurtenance of the input and the output to fuzzy set. This step is named fuzzification.

Membership function can have various forms. In our study, we will use two kinds of forms which are triangular and trapezoidal shapes as given in figure 2.

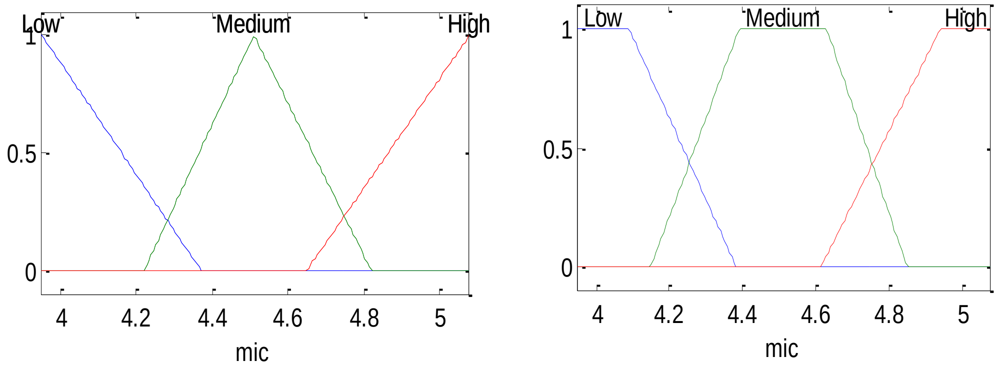

Figure 2: Triangular, trapezoidal-shaped membership used in our fuzzy models

The following step consists in building fuzzy rules which provide quantitative reasons that associate input fuzzy sets with output fuzzy sets. A fuzzy rule base consists of a number of fuzzy if-then rules. It can be expressed as follows:

If *input 1* is *high* and *input 2* is *low,* then *output* is *medium*

Where high, low and medium are the fuzzy sets of respectively input1, input2 and ouput.

For fuzzy modeling, the selection of the proper combination of inputs and the determination of the number of membership functions for each input are very important since they determine the number of rules to be obtained.

According to Majumdar et al. (Majumdar et al., 2008), 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 6 inputs and 3 membership functions. So we can have 216 rules. However, we have only 125 data sets for training. So, the number of rules was kept at 26 to be trained properly using the available data.

The overall rules used, shown in table3, are fixed and then developed in order to investigate the best to fit the collected experimental data.

The output of each rule is also a fuzzy set. Output sets are then aggregated into a single fuzzy set. Finally, this single set is converted into a single crisp number by defuzzification using the centroid method.

The prediction performances of fuzzy models were evaluated by means of four statistical performance criteria: root mean square error (RMSE), mean absolute error (MAE), Mean relative percent error (MRPE) and correlation coefficient (R) given by the following equations:

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

$$R = \frac{\sum T_i Y_i - (\sum T_i Y_i / N)}{\sqrt{(\sum T_i^2 - (\sum T_i)^2/N)/(\sum Y_i^2 - (\sum Y_i)^2/N)}} \qquad (2)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|T_i - Y_i| \qquad (3)$$

$$\mathrm{MRPE} = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{|T_i - Y_i|}{T_i} \times 100 \qquad (4)$$

Where N stands for data number, Ti: Experimental output, Yi: Estimated output

In our study, the fuzzy models development was performed by means of Matlab Fuzzy logic toolbox .

Table3: Fuzzy rule list

	Membership level							
Rules	Mic	Len	Str	Elg	Nm	Twist	Tenacity	Breaking elongation
1	M	L	L	L	L	L	M	L
2	M	L	L	L	L	M	M	M
3	M	L	L	L	L	H	M	H
4	M	L	L	L	H	M	L	L
5	M	L	L	L	H	H	M	L
6	L	L	L	L	L	L	M	M
7	L	L	L	L	L	M	M	H
8	L	L	L	L	L	H	M	H
9	L	L	L	L	H	M	L	L
10	L	L	L	L	H	H	M	L
11	L	L	H	M	L	L	M	M
12	L	L	H	M	L	M	M	M
13	L	L	H	M	L	H	M	H
14	L	L	H	M	H	M	L	L
15	L	L	H	M	H	H	M	L
16	H	L	M	H	L	L	M	M
17	H	L	M	H	L	M	M	M
18	H	L	M	H	L	H	M	L
19	H	L	M	H	H	M	L	L
20	H	L	M	H	H	H	M	L
21	L	H	H	L	L	L	H	M
22	L	H	H	L	L	M	H	M
23	L	H	H	L	L	M	H	M
24	L	H	H	L	L	H	H	M
25	L	H	H	L	H	M	H	L
26	L	H	H	L	H	H	H	L

L: Low, M: Medium, H: High, Weight associated with rule: 1, connective: and.

3. RESULTS AND DISCUSSION

Table 4 shows the prediction accuracy of the fuzzy approach for both triangular and trapezoidal membership functions. The mean relative error values (MRPE) are ranged from 4% and 7.5%. Furthermore, RMSE values are lower than the standard deviation of both ouput variables. These findings are considered significant and considerable according to El-ghezal et al (El-ghezal et al., 2011). Furthermore, the correlation coefficient R seems close to 1 (ranged between 0.77 and 0.907) for both fuzzy membership functions.

Besides, comparing MAE and RMSE values allows us to check if all individual errors are neighboring or not. Indeed, if RMSE and MAE are equal this means that individual errors have the same magnitude. However, when examining table 4, we note that RMSE values are greater than MAE one, the greater the difference between them, the greater the scatter of individual errors (Ureyen, Gurkan, 2008).

Thus, the fuzzy logic is an efficient approach to model and understand the relationship between the tensile properties and the HVI fiber properties.

However, trapezoidal membership function reveals a slightly better performance than the triangular one. In fact, fuzzy inference system based on trapezoidal function gave lower errors (RMSE and MAE) and bigger correlation coefficients than triangular membership function. This result could be due, perhaps, to the fact that trapezoidal membership function fits better with input variables.

Table 4: Fuzzy models prediction results summary

	Tenacity (cN/tex)		Breaking elongation (%)	
	Triangular membership function	Trapezoidal membership function	Triangular membership function	Trapezoidal membership function
R	0.907	0.903	0.77	0.77
RMSE	1.08	1.04	0.92	0.92
MAE	1.16	0.88	0.85	0.78
MRPE	7.5%	6%	6%	4%

Figure 3 shows also the accuracy of fuzzy models. It could be depicted that the fuzzy Inference System can respectively explain up to 81.6 % and 59.7% of total variability of yarn tenacity and breaking elongation.

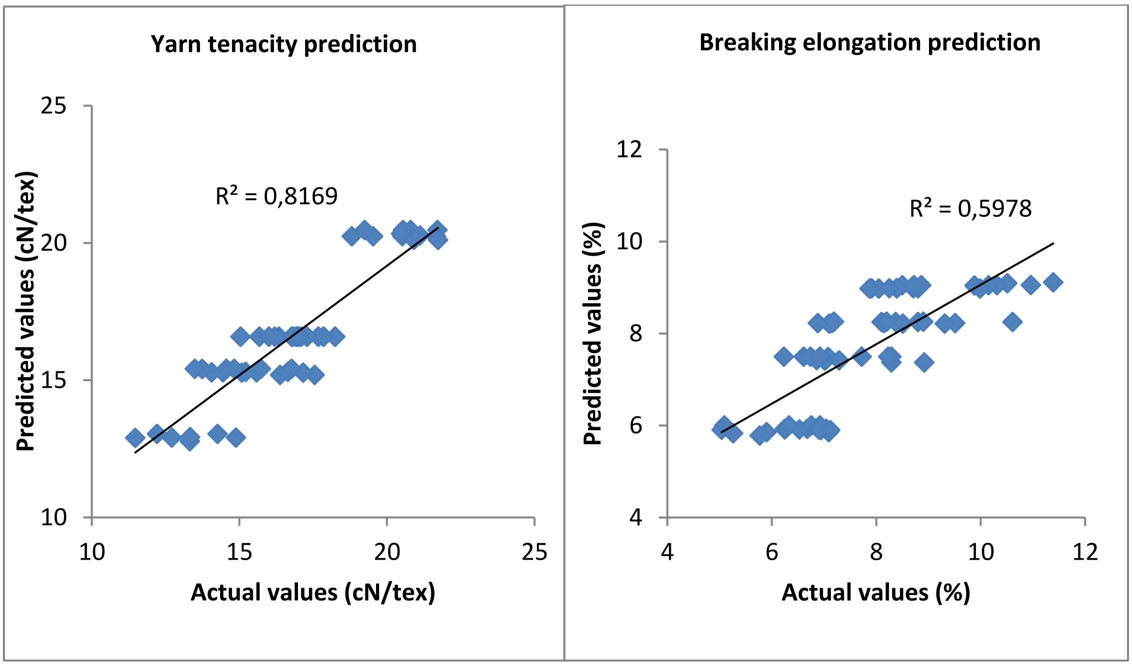

Figure 3: Experimental and predicted tensile properties using trapezoidal membership function.

Although, fuzzy logic method seems to be a good tool to model and predict ring spun yarn tensile properties, compared to results given by our previous studies (Ghanmi et al., 2014), we notice that ANN models are more powerful than fuzzy models with regards to root mean square error, mean absolute error. Figure 4 states the comparison between ANN and fuzzy models in predicting yarn tenacity and breaking elongation. As depicted from these graphics. In fact, these statistical criteria are bigger in fuzzy models compared to those of ANN models. These graphics reveal also that the regression coefficients of neural network models are more significant than fuzzy models.

As a consequence, we can enhance our results by considering the advantages of the two approaches and so using the Adaptive-Network-based Fuzzy Inference Systems (ANFIS).

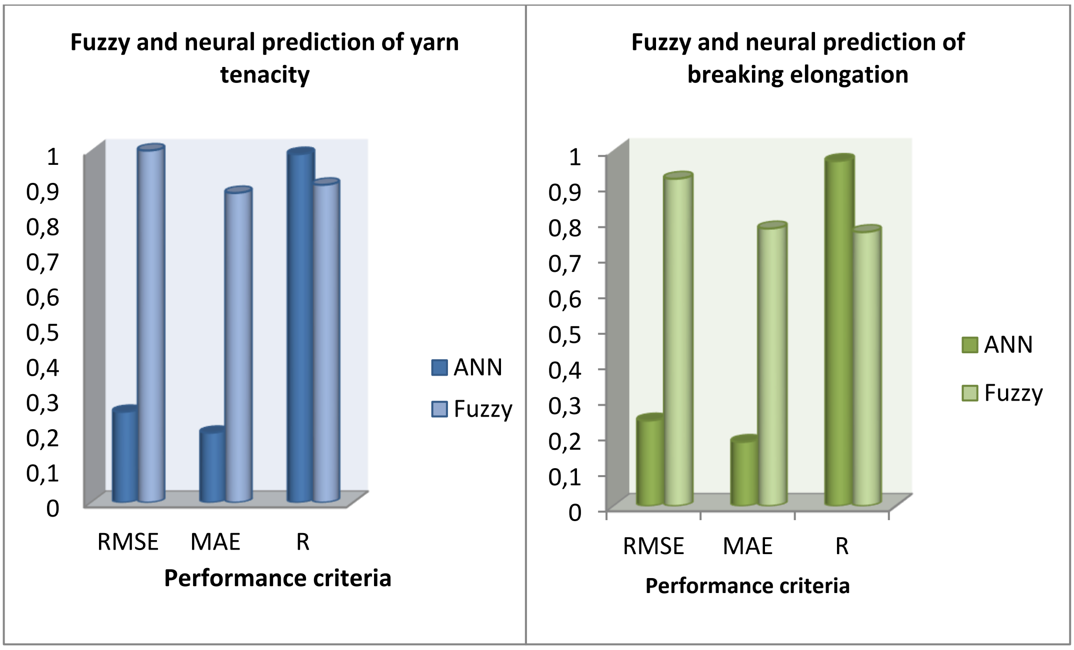

Figure 4: Comparison of fuzzy and neural prediction performances

4. CONCLUSION

This paper provided a study of the relationship between HVI fiber characteristics, construction parameters and tensile properties of ring spun yarn. In fact, we have developed models based on an intelligent approach which is Fuzzy logic to predict tenacity and breaking elongation.

The prediction accuracy of the fuzzy system is generally good since we have good RMSE and MAE values when comparing with other studies. The trapezoidal shape of membership function shows slight better results than the triangular one in terms of prediction error and correlation coefficient.

This study can further be smoother by taking into consideration experts' experiences and perceptions so that modeling accuracy will be improved.

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