Yarn Strength Modelling Using Fuzzy Expert System

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ABSTRACT
Yarn strength modelling and prediction has remained as the cynosure of research for the textile engineers although the investigation in this domain was first reported around one century ago. Several mathematical, statistical and empirical models have been developed in the past only to yield limited success in terms of prediction accuracy and general applicability. In recent years, soft computing tools like artificial neural networks and neural-fuzzy models have been developed, which have shown remarkable prediction accuracy. However, artificial neural network and neural-fuzzy models are trained using enormous amount of noise free input-output data, which are difficult to collect from the spinning industries. In contrast, fuzzy logic based models could be developed by using the experience of the spinner only and it gives good understanding about the roles played by various inputs on the outputs. This paper deals with the modelling of ring spun cotton yarn strength using a simple fuzzy expert system. The prediction accuracy of the model was found to be very encouraging.

INTRODUCTION
Modelling of yarn properties by deciphering the functional relationship between the fibre and yarn properties is one of the most fascinating topics in textile research. A large number of predictive models have been exercised to prognosticate the yarn properties like strength, elongation, evenness, hairiness etc. The prediction of yarn strength acquires a mammoth share among these models. By and large, there are three distinguished modelling methods for predicting the yarn properties, namely mathematical models, statistical regression models and intelligent models.

Mathematical models developed by Bogdan [1, 2], Subramanian, Ganesh and Bandyopadhyay [3], Zurek, Frydrych and Zakrzewski, [4] and Frydrych [5] are very appealing as they are based on the fundamental theories of basic sciences and give good understanding about the mechanics of the process. However, the prediction accuracy of mathematical models is not very encouraging due to the assumptions or simplifications used while building these models. Statistical regression models proposed by Hafez [6], Hunter [7], Mogahzy [8], and Smith and Waters [9] are very simple to understand and the beta coefficient analysis gives an indication of relative importance of various inputs on the yarn strength. However, foretelling the type of relationship (liner or non-linear) is essential for developing a regression model. The advent of artificial intelligence has provided a new impetus in the research on modelling of yarn properties. Cheng and Adams [10], Ramesh, Rajamanickam and Jayaraman, [11], Zhu and Ethridge [12, 13], Guha, Chattopadhyay and Jayadeva [14] and Majumdar and Majumdar [15] have successfully used the artificial neural network (ANN) and neural-fuzzy methods to predict various properties of spun yarns. The prediction accuracy of ANN has been acclaimed by most of these researchers. However, ANN modelling has also received criticisms galore for acting like a 'black box' without revealing much about the mechanics of the process.

Some lacunas of the ANN modelling could be overcome by using fuzzy logic, which can effectively translate the experience of a spinner into a set of expert system rules. The development of fuzzy expert system is also relatively easy than ANN as no training is required for model parameter optimization. Unlike ANN models, fuzzy logic do not require enormous amount of input-output data. Besides, fuzzy expert system can cope with the imprecision involved in cotton fibre property evaluation as well as with the inherent variability of fibre properties.

The concept of fuzzy logic relies on age-old skills of human reasoning which is based on natural language. Fuzzy logic and fuzzy set theory may be used to solve problems in which descriptions of activities and observations are imprecise, vague and uncertain. The term "fuzzy" refers to situation where there is no well defined boundary for the set of activities or observations. Fuzzy logic is focused on modes of reasoning which are approximate rather than exact. For example, a spinner often uses the terms such as low or high to assess the fibre fineness, yarn strength etc. However these terms do not constitute a well defined boundary. Further, a spinner may know the approximate interaction between fibre parameters and yarn strength from his knowledge and experience. For example, longer and finer fibres produce stronger yarns. Therefore, it is quite possible to devise a fuzzy logic based expert system which can predict yarn strength from the given input parameters.

In this work an effort has been made to develop a fuzzy expert system for the modelling of yarn tenacity using fibre tenacity, mean length, micronaire and short fibre content as input variables.

FUZZY LOGIC AND FUZZY SET THEORY

The foundation of fuzzy logic, which is an extension of crisp logic, was laid by Lotfi A. Zadeh [16] at University of California at Berkeley, USA. The theoretical aspects of fuzzy logic and fuzzy arithmetic have been explained in many standard textbooks authored by Zimmerman [17], Berkan and Trubatch [18], Kartalopoulos [19], Klir and Yuan [20] and Bector and Chandra [21]. In crisp logic, such as binary logic, variables are true or false, black or white, 1 or 0. If the set under investigation is A, testing of an element x using the characteristic function χ is expressed as follows.

$$\chi_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases}$$

In fuzzy logic, a fuzzy set contains elements with only partial membership ranging from 0 to 1 to define uncertainty of classes that do not have clearly defined boundaries. For each input and output variable of a fuzzy inference system (FIS), the fuzzy sets are created by dividing the universe of discourse into a number of sub-regions, named in linguistic terms (*high*, *medium*, *low* etc.). If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs as

$$A = \{x, \mu_A(x) | x \in X\},$$

where $\mu_A(x)$ is the membership function of x in A.

All properties of crisp set are also applicable for fuzzy sets except for the excluded-middle laws. In fuzzy set theory, the union of fuzzy set with its complement does not yield the universe and the intersection of fuzzy set and its complement is not null. This difference is shown below.

$$A \cup A^c = X \qquad A \cap A^c = \varnothing \qquad \text{Crisp sets}$$

$$A \cup A^c \neq X \qquad A \cap A^c \neq \varnothing \qquad \text{Fuzzy sets}$$

<u>Membership Functions and Fuzzification</u>

Once the fuzzy sets are chosen, a membership function for each set should be created. A membership function is a typical curve that converts the numerical value of input within a range from 0 to 1, indicating the belongingness of the input to a fuzzy set. This step is known as 'fuzzification'. Membership function can have various forms, such as triangle, trapezoid and Gaussian. Triangular membership function is the simplest one and it is a collection of three points forming a triangle. Dubois and Prade [22] defined triangular membership function as follows.

$$\mu_A(x) = \begin{cases} \dfrac{x-L}{m-L}, & \text{for } L < x < m \\ \dfrac{R-x}{R-m}, & \text{for } m < x < R \\ 0, & \text{otherwise} \end{cases}$$

where m is the most promising value, L and R are the left and right spread (the smallest and largest value that x can take).

The trapezoidal membership curve has a flat top and it is just a truncated triangle producing $\mu_A(x) = 1$ in large regions of universe of discourse. The trapezoidal curve is a function of a vector x and depends on four scalar parameters a, b, c, and d, as shown below.

$$\mu_A(x) = \begin{cases} 0, & \text{for } x \le a \text{ or } x \ge d \\ \dfrac{x-a}{b-a} & \text{for } a \le x \le b \\ 1, & \text{for } b \le x \le c \\ \dfrac{d-x}{d-c}, & \text{for } c \le x \le d \end{cases}$$

The Gaussian membership function depends on two parameters, namely standard deviation (σ) and mean (μ) and it is represented as shown below.

$$\mu_A(x) = e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

Fuzzy Linguistic Rules

Fuzzy linguistic rules provide quantitative reasoning that relates input fuzzy sets with output fuzzy sets. A fuzzy rule base consists of a number of fuzzy if-then rules. For example, in the case of two-input and single-output fuzzy system, it can be expressed as shown below.

If x is *high* and y is *medium* then z is *low*,

where x, y and z are variables representing two inputs and one output; *high, medium* and *low* are the fuzzy sets of x, y and z, respectively.

Defuzzification

The output of each rule is also a fuzzy set. Output fuzzy sets are then aggregated into a single fuzzy set. This step is known as 'aggregation'. Finally, the resulting set is resolved to a single crisp number by 'defuzzification'. There are several methods of defuzzification like centroid, centre of sums, mean of maxima and left-right maxima. However, centroid method of defuzzification is generally used in most of the cases and it is done as shown below.

$$x^* = \frac{\int \mu_A(x)x dx}{\int \mu_A(x) dx}$$

where x^* is the defuzzified output and $\mu_A(x)$ is the output fuzzy set after aggregation of individual implication results.

DEVELOPING FUZZY EXPERT SYSTEM

Four parameters of cotton fibres namely fibre bundle tenacity (cN/tex), HVI mean length (mm), micronaire and AFIS short fibre content (%) have been used as the input parameters to the fuzzy expert system. These fibre parameters have been exclusively selected since they influence the yarn tenacity significantly [23]. A MATLAB (version 7.0) based coding was used to execute the proposed fuzzy model of yarn strength. Three linguistic fuzzy sets namely *low*, *medium* and *high* were chosen for each of the input parameters in such a way that they are equally spaced and cover the whole input spaces. Two forms of membership functions (Gaussian and triangular) were tried for inputs as well as for the output. *Figures 1* and *2* depict the Gaussian and triangular membership curves, respectively, for fibre tenacity which is one of the inputs to fuzzy expert system. Nine output fuzzy sets (level 1 to 9) were considered for yarn tenacity, so that the expert system can map the small changes in yarn tenacity with the changes in input variables. *Figures 3* and *4* show the Gaussian and triangular membership curves, respectively, for tenacity of 16 Ne yarn. Similar membership curves for yarn tenacity were also developed for 22 Ne and 30 Ne yarns. However, the ranges of yarn tenacity covered by output membership curves were varied by a little, depending on the yarn count, as coarse yarns show higher yarn tenacity and vice versa when the input variables are at the same level. Theoretically there could be $3^4 = 81$ fuzzy rules, as there are four input variables and each one of them are having three linguistic levels. However, to simplify the expert system only 36 fuzzy rules were developed as shown in *Figure 5*. Here 'min' function was used to represent 'fuzzy and' operator and 'max' function was used to represent 'fuzzy or' operator between two fuzzy sets A and B as shown below.

$$\text{fuzzy and} = \min\{\mu_A(x), \mu_B(x)\}$$
$$\text{fuzzy or} = \max\{\mu_A(x), \mu_B(x)\}$$

RESULTS AND DISCUSSION

Operation of Fuzzy Expert System

Figure 6 schematically demonstrates the operation of the developed fuzzy expert system with an example. For the ease of illustration, out of thirty six rules only two fuzzy rules have been depicted in the diagram. According to the first rule, if all the input fibre parameters are having the *medium* level then output yarn tenacity will have the *level 6*. Besides, according to the second rule, if fibre strength is at *low* level and all the three remaining input parameters are at the *medium* level, then output yarn tenacity will have *level 4*, which means lower value than the *level 6*. For

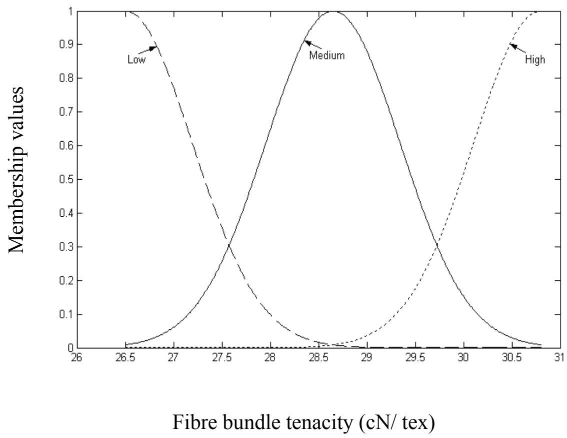

FIGURE 1. Gaussian membership function plots of fibre tenacity

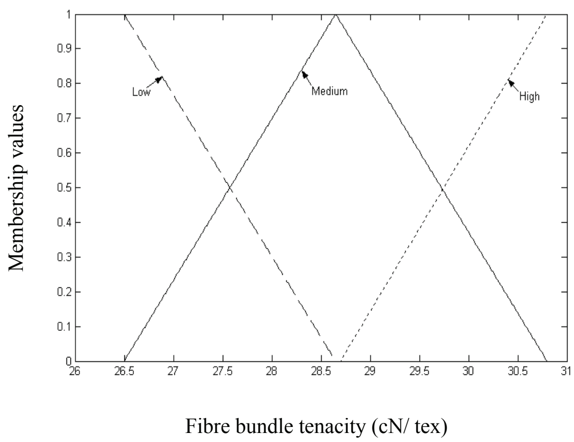

FIGURE 2. Triangular membership function plots of fibre tenacity

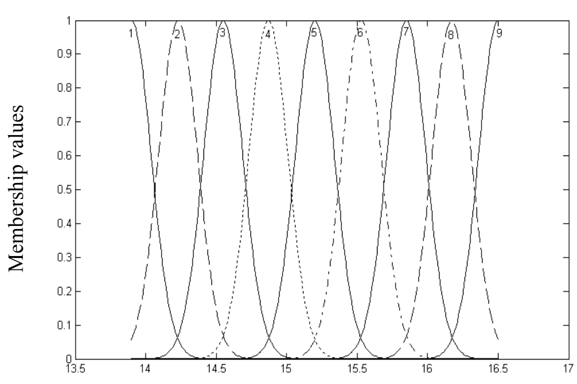

FIGURE 3. Gaussian membership function plot of tenacity for 16 Ne yarn

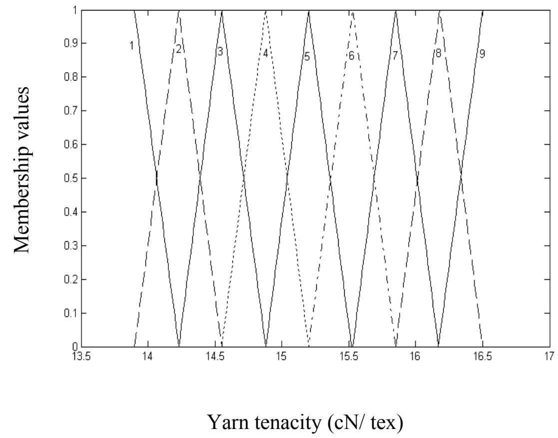

FIGURE 4. Triangular membership function plots of tenacity for 16 Ne yarn

example, if fibre tenacity is 27.8 cN/tex, HVI mean length is 20.7 mm, AFIS short fibre content is 15.7% and micronaire is 3.59, then all thirty six fuzzy rules are evaluated simultaneously to determine the yarn tenacity. However, some of the rules will remain defunct as ‘fuzzy and’ function has been used in the antecedent part of the fuzzy rules and they will not produce any output fuzzy set. Outputs of active fuzzy rules are then aggregated to get a final output fuzzy set, which is finally defuzzified using centroid method to produce the crisp output (yarn tenacity) of 15.2 cN/tex as shown in *Figure 6*.

Fuzzy rules, the heart of the fuzzy expert system, determine the input-output relationship of the model. *Table I* is showing the 36 fuzzy rules, which are self explanatory, in the matrix form. The surface plots shown in *Figures 7-9* depict the impacts of fibre parameters on the yarn tenacity. *Figure 7* shows that as fibre tenacity and mean length increase, there is concomitant increase in yarn tenacity as expected. The yarn tenacity reaches the apex when the fibre tenacity and mean length both reach their respective maximum level. *Figure 8* demonstrates that as the cotton fibre becomes finer the yarn tenacity increases, although the effect is less prominent at the higher level of fibre tenacity. *Figure 9* shows that as the short fibre content in cotton increases, especially at lower level of fibre tenacity, yarn tenacity diminishes. Short fibres do not contribute much towards yarn tenacity. Besides the short fibres also generate drafting waves during roller drafting operations in drawframe, speedframe and ringframe and deteriorates the evenness of the fibre strand, which in tern reduces the yarn tenacity.

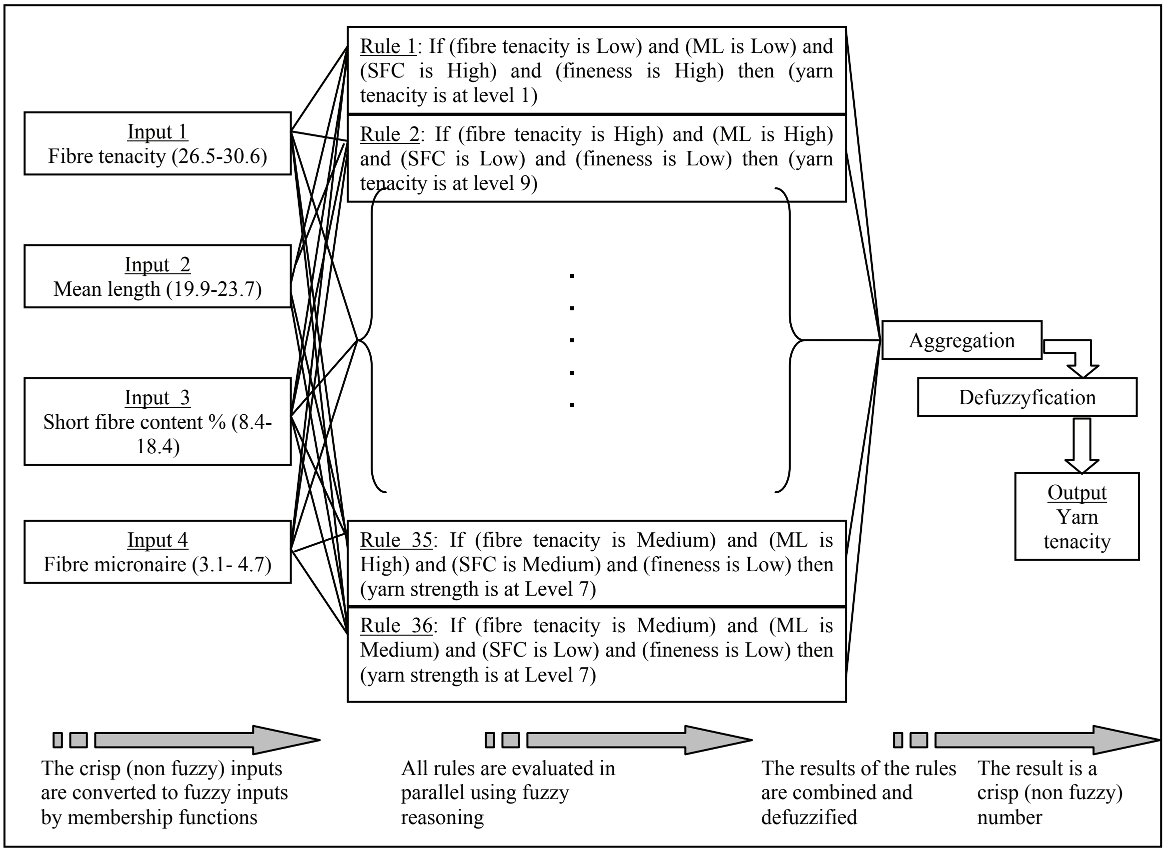

FIGURE 5: Schematic representation of fuzzy expert system for yarn tenacity modeling

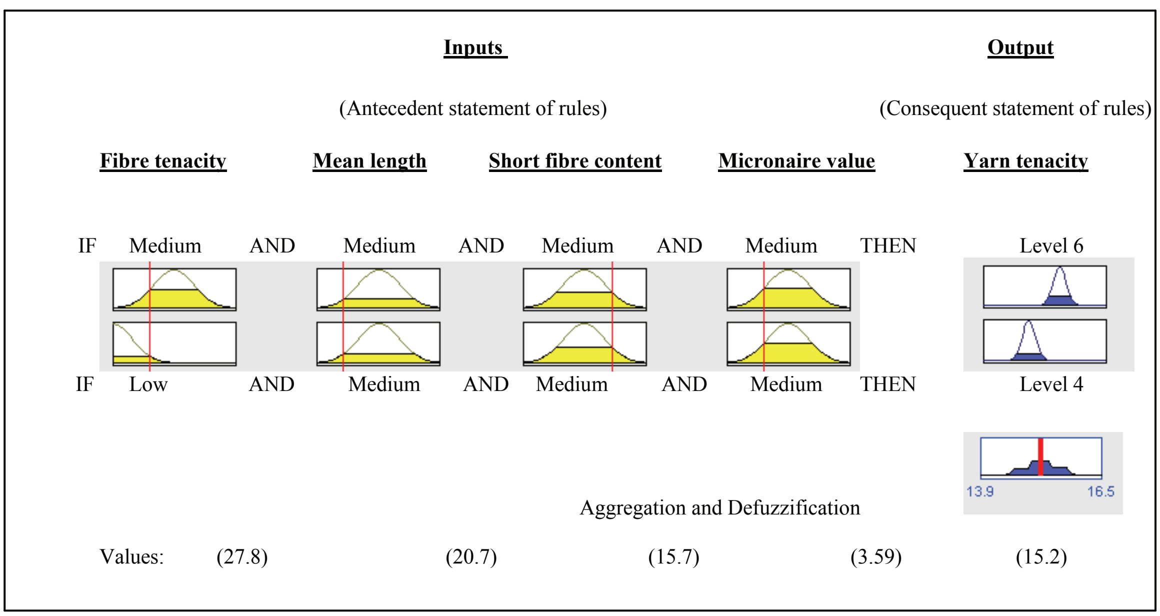

FIGURE 6. An example showing the operation of fuzzy expert system

TABLE I. Matrix of Fuzzy Rules

	Membership level				
Rule no	Fibre tenacity	Mean length	Short fibre content	Micronaire	Yarn tenacity
1	L	L	H	H	Level 1
2	H	H	L	L	Level 9
3	H	M	L	L	Level 7
4	H	L	L	L	Level 4
5	M	H	L	L	Level 6
6	L	H	L	L	Level 3
7	H	H	M	L	Level 7
8	H	H	H	L	Level 4
9	H	H	L	M	Level 8
10	H	H	L	H	Level 6
11	M	L	H	H	Level 3
12	H	L	H	H	Level 5
13	L	M	H	H	Level 2
14	L	H	H	H	Level 3
15	L	L	M	H	Level 3
16	L	L	L	H	Level 5
17	L	L	H	M	Level 2
18	L	L	H	L	Level 4
19	M	M	M	M	Level 6
20	L	M	M	M	Level 4
21	H	M	M	M	Level 8
22	M	L	M	M	Level 5
23	M	H	M	M	Level 7
24	M	M	L	M	Level 7
25	M	M	H	M	Level 4
26	M	M	M	L	Level 7
27	M	M	M	H	Level 5
28	H	H	M	M	Level 8
29	H	M	L	M	Level 8
30	H	M	M	L	Level 8
31	L	M	M	H	Level 2
32	L	L	M	M	Level 2
33	L	M	H	M	Level 2
34	M	H	L	M	Level 7
35	M	H	M	L	Level 7
36	M	M	L	L	Level 7

H: high; M: medium; L: low

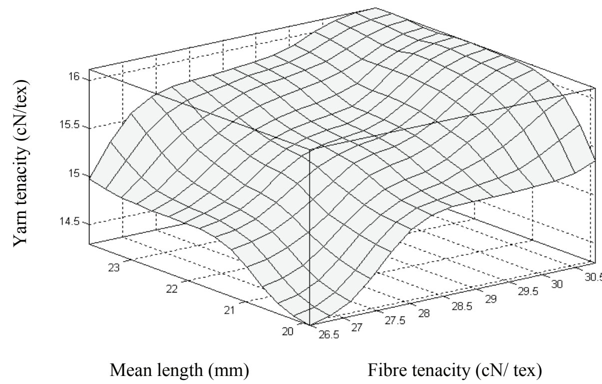

FIGURE 7. Surface plot showing the effect of fibre length and tenacity on yarn tenacity.

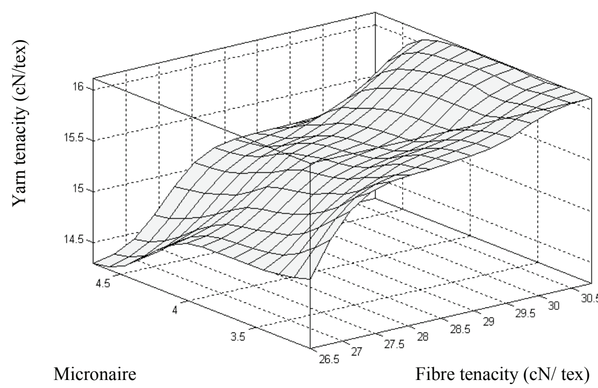

FIGURE 8. Surface plot showing the effect of fibre micronaire and tenacity on yarn tenacity

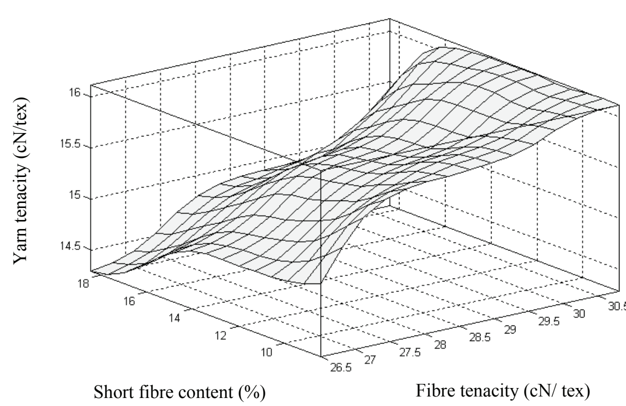

FIGURE 9. Surface plot showing the effect of short fibre content and fibre tenacity on yarn tenacity.

Validation of Fuzzy Expert System

Some fibre and corresponding yarn data for three different yarn counts (16, 22 and 30 Ne) were collected from published literature. The fibre tenacity, mean length, and micronaire were evaluated by using USTER HVI 900 system whereas the short fibre content was measured by the Advanced Fibre Information System (AFIS). Carded yarns were spun using ring spinning system with a twist multiplier of 4.1. The yarn tenacity was evaluated by using Uster Tensorapid III, keeping gauge length of 500 mm and rate of extension of 5000 mm/ min. The prediction accuracy of the fuzzy expert system was evaluated by calculating coefficient of determination (R^2) and mean absolute error% from the actual and predicted yarn tenacity. Results are shown in *Table II* and also depicted in *Figure 10*. It is observed that the coefficient of determination is 0.75 (R=0.87) for both the Gaussian and triangular membership functions. Therefore, it could be inferred that the proposed fuzzy expert system can explain up to 75% of the total variability of yarn tenacity. The mathematical model developed by Zurek, Frydrych and Zakrzewski [4] showed correlation coefficients (R) of 0.79 and 0.63 respectively for yarn strength and elongation. Frydrych [5] also reported a slightly lower correlation coefficient (0.85) while predicting yarn strain using mathematical modelling. Only four input parameters (fibre tenacity, mean length, micronaire and short fibre content) have been considered in this work for developing the expert system. Parameters like fibre maturity, length uniformity and fibre friction were not considered in this investigation which may have resulted in higher coefficient of determination. However, addition of more input variables will necessitate more fuzzy rules to be developed and the complexity of the expert system will be increased. Fuzzy expert system based on Gaussian membership function is showing lower mean error (4.04%) as compared to that of triangular membership function (4.26%). This could probably be attributed to the fact that Gaussian membership function fits better with most of the fibre properties. In this work, no attempt has been made to quantify the relative contribution of four input parameters.

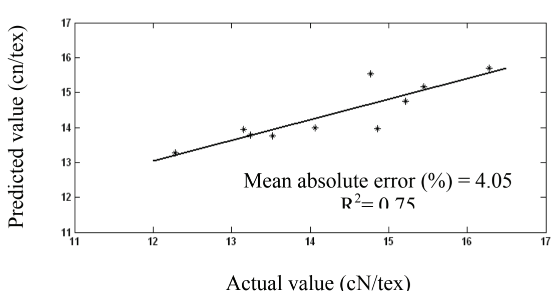

FIGURE 10. Actual and predicted yarn tenacity using Gaussian membership function

TABLE II. Prediction of Yarn Tenacity with Gaussian and Triangular Membership Functions

Yarn count (Ne)	Actual yarn tenacity (cN/tex)	Gaussian membership function		Triangular membership function	
		Predicted yarn tenacity (cN/tex)	Absolute error (%)	Predicted yarn tenacity (cN/tex)	Absolute error (%)
16	14.77	15.54	5.23	15.50	4.95
	16.28	15.71	3.53	15.77	3.14
	15.45	15.17	1.83	15.06	2.50
22	13.15	13.95	6.11	13.93	5.91
	15.21	14.74	3.09	14.75	3.02
	13.24	13.79	4.17	13.83	4.45
30	13.52	13.76	1.80	13.84	2.35
	12.28	13.28	8.16	13.26	8.02
	14.06	13.99	0.52	14.30	1.71
	14.86	13.97	6.01	13.89	6.55
Mean absolute error (%)		4.04		4.26	
R^2		0.75		0.75	

CONCLUSIONS

A fuzzy expert system has been developed to model the tenacity of ring spun cotton yarns. The expert system was developed by translating the perception and experience of a spinner into fuzzy inference system. The developed fuzzy rules give a very good understanding about the interaction between important fibre parameters and their influence on yarn tenacity. The prediction accuracy of the proposed fuzzy system is reasonably good as the mean error% of prediction was below 5% for Gaussian and triangular form of membership functions. The Gaussian form of membership functions show slight edge over the triangular membership functions in terms of prediction error%. The system is quite easy to develop and it could be modified easily if the spinning technology is changed. Further attempts are being made to incorporate more input variables in the expert system so that the modelling accuracy could be enhanced.

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JEFF Journal would like to recognize Seshadri S. Ramkumar, Ph.D., Associate Professor at Texas Tech University, Lubbock, Texas, USA, for encouraging the authors to submit their manuscripts to the Journal.