American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-6, Issue-1, pp-184-193
www.ajer.org
Research Paper Open Access

Comparison of Fuzzy Intelligent Model and Taguchi Mathematical Model for the Prediction of Bursting Strength of Viscose Plain Knitted Fabrics

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ABSTRACT: *The main objective of this research is to compare the Fuzzy intelligent model and Taguchi mathematical model for the prediction of bursting strength of viscose plain knitted fabrics. The prediction models have been developed based on yarn tenacity and knitting stitch length as input variables and fabric bursting strength as output variable. The models developed in this study have been verified by experimental data and then compared with each other's in terms of prediction accuracy. It was found that both the models have ability and accuracy to predict the fabric bursting strength effectively in non-linear domain. However, Fuzzy intelligent model showed higher prediction accuracy than that of Taguchi mathematical model.*

Keywords: *Fuzzy logic, Taguchi method, Bursting strength, Prediction*

I. INTRODUCTION

The knitted fabrics made of viscose are very popular in various casual wear, active wear and sportswear because of their excellent comfort, softness and easy-care properties due to their good air permeability, better stretch and recovery properties as compared to woven fabrics [1-4]. Apart from these properties, bursting strength is the most important physical and mechanical properties of knitted fabrics. The physical and mechanical properties of viscose knitted fabrics are very essential in many ways. The fabrics should have sufficient strength against forces acting on it during their different wet processing in the factory and their end-uses. Due to their distinct structural properties, testing tensile and tearing strength is not suitable for knitted fabrics. Consequently, the bursting strength test is executed to evaluate the fabric's ability to withstand multi axial stresses without breaking off [1, 5-7]. The different factors affecting on the bursting strength of knitted fabric have been studied in the past decade [1, 5-7]. However, the effects of different factors on the bursting strength of knitted fabrics are not linear. Due to the non-linearity and mutual interaction of these factors, it is very difficult to use conventional approach like mathematical or statistical models to predict the fabric bursting strength before manufacturing [2, 6, 8, 9].

Conversely, the intelligent approaches like ANN and ANFIS models have been applied by several investigators in the past research for predicting the bursting strength of knitted fabrics. Jamshaid et al. [1] applied ANFIS model to predict the bursting strength of plain knitted fabrics as a function of yarn tenacity, knitting stitch length and fabric GSM. Ertugrul and Ucar [6]revealed intelligent technique namely ANN and ANFIS models for the prediction of bursting strength of the knitted fabrics using yarn strength, yarn elongation and fabric GSM as input variables. Unal et al. [7] presented ANN model for the prediction of bursting strength as a function of yarn strength, yarn count, yarn evenness, yarn twist, yarn elongation and fabric wales and courses. Bahadir et al.[10] proposed ANN model to predict the bursting strength of knitted fabrics. Zeydan [11] developed ANN model to predict the woven fabric strength. However, ANN and ANFIS models need large amounts of noisy input-output data for model parameters optimization, which are challenging, labor intensive and time consuming process to collect from the knitting industries [8, 12].

In this background, fuzzy logic is the most well-organized modeling device compared to conventional, ANN and ANFIS models as fuzzy logic simulates the decision making activities like human expert and capable of mapping very non-linear complex fields with lowest amounts of test data [2, 9, 12, 13]. Unlike statistical regression model, fuzzy logic needs no information or aforementioned appraisal of any mathematical models in advance. Moreover, unlike ANN and ANFIS models, fuzzy logic does not require large amounts of input-output data [2, 8, 9, 13].The key purpose of this work is to construct fuzzy intelligent model and Taguchi mathematical model as well as compare them in terms of prediction accuracy for predicting the bursting strength of viscose plain knitted fabrics. The prediction models have been built as a function of yarn tenacity and stitch length. Taguchi method has been effectively applied in the previous research for modeling non-linear and complex relationship in textile [5, 14-16].

II. FUZZY INTELLIGENT MODELING

The fuzzy logic is an artificial intelligence derived from fuzzy set theory and is capable of capturing any kind of functional relationship from input-output data as well as mimics the behavior of biological system like human brain [12, 17]. A fundamental fuzzy logic unit comprises fuzzifier, membership function, fuzzy rule base, inference engine, and defuzzifier as shown in Figure 1.

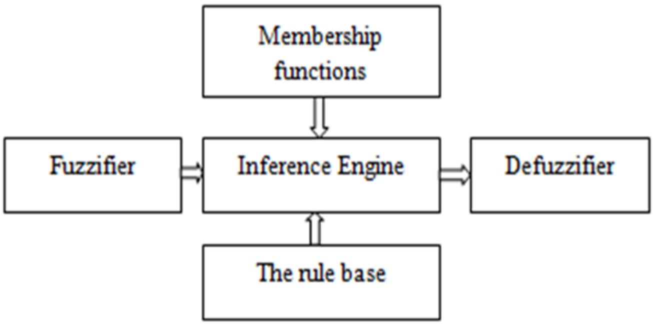

Figure 1: Fundamental unit of a fuzzy intelligent system [2,18]

Fuzzifier: Fuzzifier converts all the crisp numeric values of inputs-outputs into fuzzy sets such as low, medium, high and so on by using membership functions.

Membership function: The central concept of fuzzy set is a membership function which converts the numerical value of input –outputs into fuzzy number within a range from 0 to 1. Basically, membership functions for all input and output variables are created based on system knowledge, expert’s appraisals and experimental conditions. Among various membership functions, triangle membership function is the simplest and most often used which is defined as follows [2, 12, 19].

$$\mu_A(x) = \left\{ \begin{array}{ll} \dfrac{x-L}{m-L}; & L \le x \le m \\ \dfrac{R-x}{R-m}; & m \le x \le R \\ 0; & otherwise \end{array} \right\} \qquad (1)$$

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 fuzzy rule base: The fuzzy rules are the heart of fuzzy expert system which are formed based expert knowledge and previous experience and are usually expressed by if-then statements [2,12, 13]. As an expression, when a fuzzy model with two inputs and one output involves n fuzzy rules, then development of fuzzy rules can be presented as follows:

Rule 1: If x is A_i and y is $B_{i,}$ then z *is* C_i.

Rule 2: If x is A_2 and y is $B_{2,}$ then z is C_2.

……………..

Rule n: If x is A_n and y is $B_{n,}$ then z is $C_{n.}$

where *x*, *y*, and *z* is the linguistic variables representing the input variables and the output variable respectively, $A_{i,}B_{i,}$ and C_i (i=1, 2… ..n), are the fuzzy numbers that represent the linguistic states.

Fuzzy Inference engine: The Fuzzy inference engine performs a vital role in the fuzzy modeling owing to its ability to create human decision making and infer control actions by employing an inference mechanism. Mamdani suggested the application of a minimum operation rule as a fuzzy inference function. For two-inputs and single-output, fuzzy inference method is mathematically expressed as follows [9, 12]:

$\alpha_i = \mu_{Ai}(SL) \wedge \mu_{Bi}(YT)$ i =1, 2… n. (2)

and

$$\mu_C(BS) = \bigcup_{i=1}^{n} [\alpha_i \wedge \mu_{Ci}(BS)] \quad (3)$$

where α_i is the weighting factor as a measure of the contribution of ith rule to the fuzzy control action, and μ_{Ai}, μ_{Bi}, μ_{Ci} ,and μ_C are the membership functions associated with fuzzy sets A_i, B_i, C_i and C, respectively.

Defuzzifier: Defuzzifier is the last unit of fuzzy modelling. Fundamentally, the conclusion of the decision making logic is the fuzzy output. Finally, among different defuzzification methods, the centre of gravity method is adopted here to transform the fuzzy inference output into a non-fuzzy value z in the following form for the distinct case [2, 9, 12]:

$$z = \frac{\sum_{i=1}^{n} \mu_i(b_i)}{\sum_{i=1}^{n} \mu_i} \quad (4)$$

where bi is the position of the singleton in the i^{th} universe, and μ_i is the membership function of i rule.

For development of fuzzy intelligent model, two knitting variables such as knitting stitch length (SL) and yarn tenacity (YT) have been used as input variables and bursting strength of knitted fabrics as output variable. These knitting variables have been entirely chosen as they influence the fabric bursting strength considerably. A Fuzzy logic Toolbox from MATLAB (version 7.10) was used to develop the proposed fuzzy model of bursting strength. For fuzzification, nine possible linguistic subsets namely very very low (VVL), very low (VL), low (L), low medium (LM), medium (M), high medium (HM), high (H) and very high (VH), very very high (VVH) for input variable YT and six convenient linguistic subsets namely very low (VL), low (L), low medium (LM), medium (M), high (H) and very high (VH) for input variable SL were chosen in such a way that they are evenly spaced and cover up the entire input spaces. Fourteen output fuzzy sets (Level 1 to 14) (where, L=Level) were considered for fabric bursting strength (BS), so that the fuzzy logic system can map small changes in bursting strength with the changes in input variables. In this study, the triangular shaped membership functions are used for input-output variables because of their accuracy [2, 12]. Further, a Mamdani max-min inference approach and the center of gravity defuzzification method have been applied in this work. Fuzzifications of the used factors are made by aid follows functions:

$$SL(i_1) = \begin{Bmatrix} i_1; & 2.6 \le i_1 \le 3.1 \\ 0; & otherwise \end{Bmatrix} \quad (5)$$

$$YT(i_2) = \begin{Bmatrix} i_2; & 14 \le i_2 \le 16 \\ 0; & otherwise \end{Bmatrix} \quad (6)$$

$$BS(o_1) = \begin{Bmatrix} o_1; & 190 \le o_1 \le 460 \\ 0; & otherwise \end{Bmatrix} \quad (7)$$

wherei_1,and i_2 *are the* first (SL) and second (YT) input variables respectively and o_1 is the output variable (BS) showing in Eq. (5)-(7).

Prototype triangular fuzzy sets for the fuzzy variables, namely, stitch length (SL) and yarn tenacity (YT) and bursting strength (BS) are set up using Fuzzy Toolbox from MATLAB. The membership functions obtained from the above formula are shown in the Figures 2- 4.

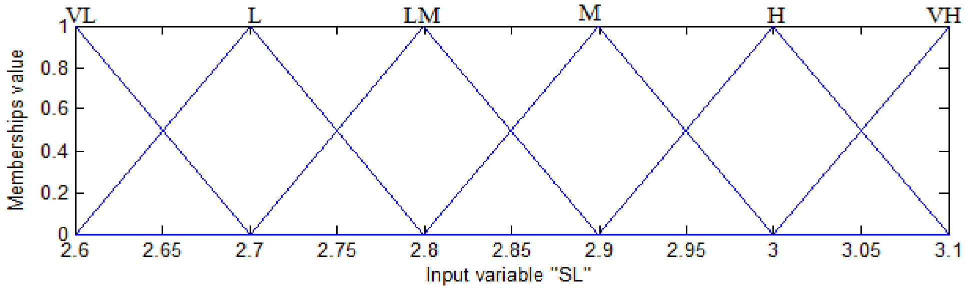

Figure 2: Membership functions of input variable “SL”

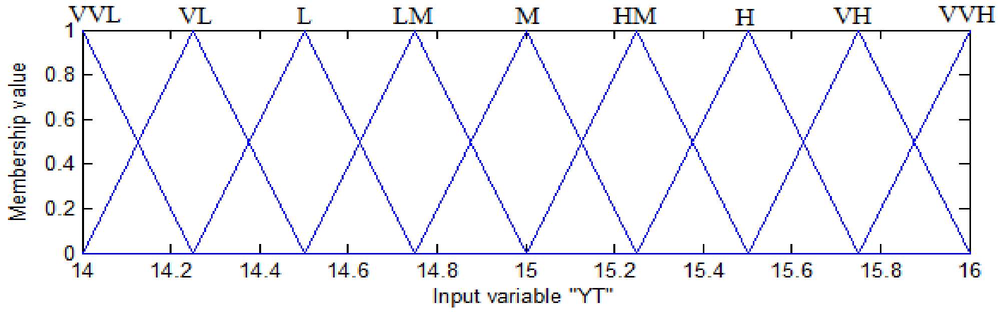

Figure 3: Membership functions of input variable "YT"

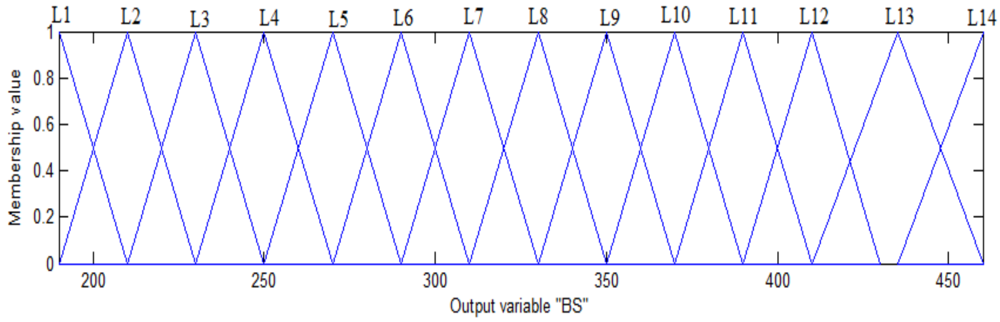

Figure 4: Membership functions of output variable "BS"

In this study, to make simpler the fuzzy logic system only 24 fuzzy rules have been formed based on expert knowledge and previous experience [2,13]. Some of the rules are presented in Table 1.

Table 1: Fuzzy rules

Rules no.	Input variables		Output variable
	SL	*YT*	*BS*
1	VL	VVL	Level 4
2	L	VVL	Level 3
…..	…..	…..	…..
10	M	HM	Level 8
11	H	HM	Level 7
…..	…..	…..	…..
23	H	VH	Level 11
24	VH	VH	Level 14

To demonstrate the fuzzification process, linguistic expressions and membership functions of stitch length (SL) and yarn tenacity (YT) obtained from the developed rules and above formula (Eq. 5-7) are presented as follows:

$$\mu_L(SL) = \begin{cases} \dfrac{i_1 - 2.6}{2.7 - 2.6}; & 2.6 \le i_1 \le 2.7 \\ \dfrac{2.8 - i_1}{2.8 - 2.7}; & 2.7 \le i_1 \le 2.8 \\ 0; & i_1 \ge 2.8 \end{cases} \tag{8}$$

$$\mu_L(SL) = \{0/2.6 + 0.05/2.65 + 1/2.7 + \ldots.. + 0.05/2.75 + 0/2.8\}$$

$$\mu_H(YT) = \begin{cases} \dfrac{i_2 - 15.25}{15.5 - 15.25}; & 15.25 \le i_2 \le 15.5 \\ \dfrac{15.75 - i_2}{15.75 - 15.5}; & 15.5 \le i_2 \le 15.75 \\ 0; & i_2 \ge 15.75 \end{cases} \tag{9}$$

$$\mu_H(YT) = \{0/15.25 + 0.2/15.35 + 1/15.5 + \ldots.. + 0.04/4 + 0/15.75\}$$

In defuzzification stage, the membership functions (μ) of the rules are calculated for each rule by Eq. (3). To comprehend fuzzification, an example is considered. For crisp input SL=2.7 mm and YT=15.5 g/tex, the rule 14 is fired. The firing weighting factorα of the one rule is calculated by Eq. (3) and found as:

$$\alpha_{14} = \min\{(\mu_L(SL), \mu_H(YT))\} = \min\ (1,1) = 1 \qquad (10)$$

Consequently, according to Eq. (3), the membership function for the conclusion reached by rule (14) is obtained as follows:

$$\mu_{14}(BS) = \min\{1, \mu_{L9}(BS)\} \qquad (11)$$

Finally, using Eq. (4), (10) and (11) with Figure 4, the crisp output of bursting strength is obtained as 350 kPa.

III. TAGUCHI MATHEMATICAL MODELING

Taguchi method is one of the most efficient tools in quality engineering in the world which uses a special design of orthogonal arrays (OA) to study the entire process parameter space with only a small number of experiments and provides reliable prediction outcome in a faster and economic way [5, 14-16]. Among various quality mode, larger is better mode has been chosen in this study. Mathematically, it can be expressed as bellow:

(i) Larger is better (strength, air permeability, efficiency etc.).

$$S/N = -10log\left(\frac{1}{n}\sum_{i=1}^{n} 1/y_i^2\right) \qquad (12)$$

where n is the number of repetitions for an experimental combination, i is a numerator, and y_i is the performance value of the i^{th} experiment.

In this study, two controllable factors namely, knitting stitch length and yarn tenacity and their four levels have been used for Taguchi mathematical model development as shown in Table 2. An L16 (4^2)Taguchi OA design has been selected as experimental design and presented with experimental results in Table 3.

Mathematical model development: Taguchi mathematical model has been developed based on yarn tenacity (*YT*) and stitch length (*SL*) as predictor variables and fabric busting strength (*BS*) as response variable. The regression equation for actual unit of measurement has been created using Minitab 16 software for the predictor variables are presented as below:

BS = - 962 + 97.1 x YT - 66.5 x SL (13)

IV. FABRIC PREPARATION AND BURSTING STRENGTH TESTING

As per Taguchi design of experiment (DOE), L16 orthogonal array design of experiment was conducted followed by validation experiments of 8 runs. In the experiment, a total of 24 viscose plain fabrics samples were knitted of which 16 are from Taguchi DOE and 8 for validation experiments. Pailung single jersey circular knitting machine, having 30 inches diameter, 20 gauges (needles/inch) and 90 yarn feeders was used for knitting.

Table 2: Knitted fabric variables and their level

Process Parameters	Level			
	1	2	3	4
Yarn tenacity (g/tex)	14	15.25	15.5	15.75
Stitch length (mm)	2.6	2.8	2.9	3.1

The fabrics samples were subjected to semi-bleached at 90^0C for 40 min in a sample dyeing machine using anti creasing agent (Kappavon CL 1g/l), sequestering agent (Sirrix 2UD 0.5g/l), wetting agent (Felosan NOF 1g/l), soda ash (2.5g/l), hydrogen peroxide 50% (1g/l), stabilizing agent (0.2g/l). Then the fabrics samples were washed with proper rinsing and finally treated with acetic acid (1g/l) followed by peroxide killing agent (0.2g/l). After bleaching, the fabric samples were dried in an open stenter and compacted properly. After production, all the fabrics samples were conditioned firstly on a flat surface for at least 24 hours prior to testing under standard atmospheric conditions at relative humidity (65 ± 2) % and temperature (20 ± 2)°C. Then the bursting strength (kPa) of each sample was tested using SDL ATLAS Pneumatic Bursting tester (Model 229P) with a specimen of 30 mm in diameter according to ISO-139388-1 test method. The experimental results are presented in Table 3.

Table 3: Taguchi L16 orthogonal array and results for bursting strength

No.	Stitch length (mm)	Yarn tenacity (g/tex)	Bursting strength (kPa)
1	2.6	14.00	248
2	2.8	14.00	219
3	2.9	14.00	221
4	3.1	14.00	185
5	2.6	15.25	330
6	2.8	15.25	290
7	2.9	15.25	324
8	3.1	15.25	259
9	2.6	15.50	356
10	2.8	15.50	342
11	2.9	15.50	329
12	3.1	15.50	286
13	2.6	15.75	468
14	2.8	15.75	458
15	2.9	15.75	403
16	3.1	15.75	440

V. RESULTS AND DISCUSSION

5.1 Operation of Fuzzy Logic Intelligent Model

The schematic operation of the fuzzy logic prediction model has been depicted with an example in *Figure 5*. For simple expression, only one fuzzy rule out of twenty four has been shown in the picture. As per this rule, if stitch length (SL) is low (L) and yarn tenacity (YT) is high (H) then output fabric bursting strength (BS) will be Level 9 (L9). For example, if input SL is 2.7 mm and YT is 15.5 g/tex, then fuzzy output BS is 350 kPa. Using MATLAB Fuzzy Toolbox the fuzzy control surfaces was developed as shown in *Figure 6.* The image shows the relationship between yarn tenacity (YT) and stitch length (SL) on input side and bursting strength (BS) on output side. The surface plot shown in *Figure 6* depicts the impact of stitch length and yarn tenacity on bursting strength.

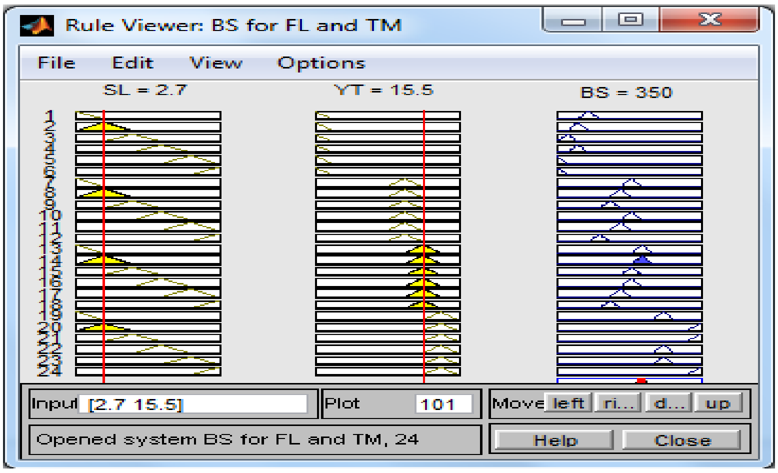

Figure 5: Operation of fuzzy intelligent model

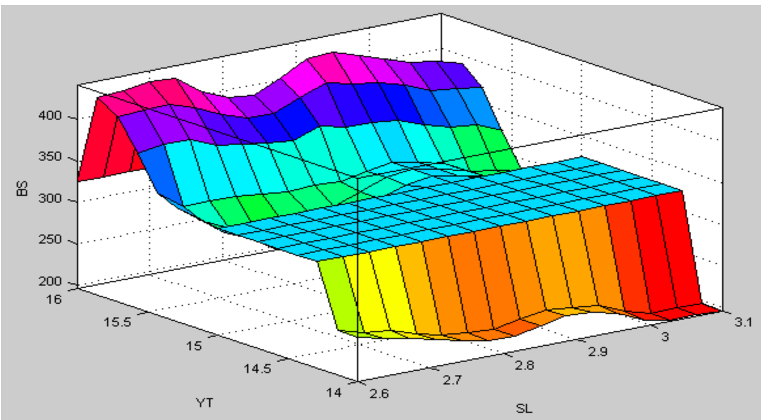

Figure 6: Control surface for FIS

5.2 Analysis of experimental results

Effects of stitch length and yarn tenacity on bursting strength have been depicted in *Figure 7*. It is obvious from Figure *8* that decrease in stitch length from 3.1 mm to 2.6 mm only slightly increases the fabric bursting strength. Approximately, bursting strength increases 20-25% with a decreasing of 16% in stitch length. The reason for an increase in bursting strength with decreasing in stitch length is probably due to increasing number of loops per unit area which bears the multidirectional forces. Conversely, the effect of decreasing the stitch length is not linear, as a consequence, while the stitch length decreases further than an optimal level, produced fabric turn into more stiffer and less extensible, hence resulting in fabric holes as well as poor bursting strength.

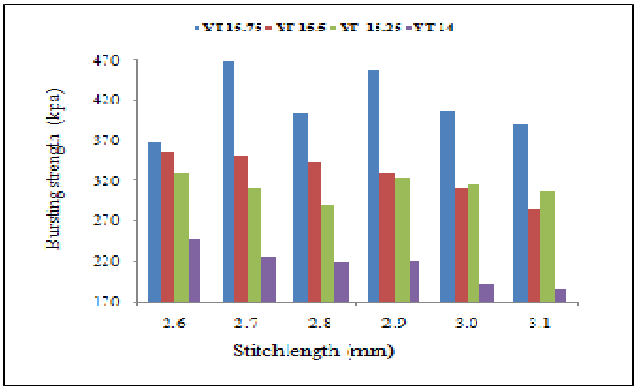

Figure 7: Effects of stitch length and yarn tenacity on bursting strength

In contrast, the effect of yarn tenacity on bursting strength is much more reflective as compared to stitch length as shown in *Figure 7*. Figure shows that bursting strength increases drastically with the increasing of yarn tenacity and vice versa. Approximately, the bursting strength increases 70-80% with an increasing of 12% in yarn tenacity. However, it was found from *Figure 7* that knitting stitch length and yarn tenacity has strong interaction on fabric bursting strength. The extensibility of the fabric decreases whilst the yarn tenacity is increased further at lower stitch length levels and as a result the bursting strength obtains a descending tendency. From this investigation, it is noticeably observed that yarn tenacity has the greatest and main effect on bursting strength when compared to knitting stitch length.

5.3 Taguchi Mathematical Model

Out of 24 data, sixteen data sets used for developing the Taguchi mathematical model are shown in Table 3. Regression coefficient and analysis of variance for bursting strength are shown in Table 4 and Table 5 respectively.

Table 4: Regression coefficient for fabric bursting strength

Term	Reg. Coef	Std.Er.Coef	T-value	P-value
Constant	-962.408	288.757	-3.333	0.005
Yarn Tenacity(*YT*)	97.069	15.604	6.221	0.000
Stitch length(*SL*)	-66.538	58.263	-1.142	0.274

Table 5: ANOVA for fabric bursting strength

Source	DF	SS	MS	F	P
Regression	2	70614.5	35307.3	20.0022	0.000*
YT	1	68312.3	68312.3	38.7001	0.000*
SL	1	2302.2	2302.2	1.3043	0.274
Error	13	22947.2	1765.2		
Total	15	93561.8			

SS = Sum of Square, DF = Degree of Freedom; *Significant at $p \leq 0.05$, MS = Mean square.

P-value for regression is 0.000 which means that the model is statistically significant with more than 99% confidence. Further, it has been observed through residual analysis for the developed model (*Figure 8*) that normal probability plots of the residuals are generally fall on a straight line; meaning that errors are distributed normally as well as the model is satisfactory in better predicting. According to ANOVA Table V, the yarn tenacity is found to be most significant ($p<0.05$) and stitch length insignificant ($p>0.05$) for bursting strength at 95% confidence level. The contribution of two factors to the bursting strength are given away as following order: yarn tenacity (73.01%)> stitch length (2.46%).

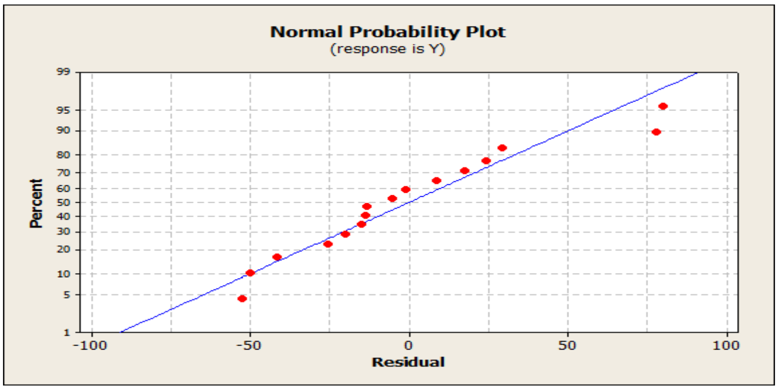

Figure 8: Normal probability plot of Residuals

5.4 Validation of the Prediction Models

The developed prediction models have been validated by experimental data. Prediction was done using the fuzzy intelligent model and Taguchi mathematical model. The data of 8 samples out of 24 knitted samples were used for the validation of the developed models. The results from the developed prediction models were then compared with the 8 validation samples results as shown in Table 6.

Table 6: Comparison of actual and predicted values of bursting strength

No.	Stitch length (mm)	Yarn tenacity (g/tex)	Actual bursting strength	Fuzzy intelligent model		Taguchi mathematical model	
				Predicted value	Relative error%	Predicted value	Relative error%
1	2.7	14.0	226	230	1.77	217.85	3.61
2	3.0	14.0	193	196	1.55	197.9	2.54
3	2.7	15.25	330	310	6.06	339.23	2.80
4	3.0	15.25	308	310	0.65	319.28	3.66
5	2.7	15.5	351	350	0.28	363.5	3.56
6	3.0	15.5	322	310	3.73	343.55	6.69
7	2.7	15.75	458	450	1.75	387.78	15.33
8	3.0	15.75	406	390	3.94	367.83	9.40
Mean relative Error (%)				**2.47**		**5.95**	
Correlation coefficient (*R*)				**0.995**		**0.94**	

The correlations between predicted values and experimental values of fabric bursting strength are also depicted in Figures 9 and 10. The correlation coefficient (*R*) and mean relative error between the actual bursting strength and that predicted by the Fuzzy intelligent model were found to be 0.995 and 2.47%, respectively. Conversely, the correlation coefficient (*R*) and mean relative error between the actual bursting strength and that predicted by the Taguchi mathematical model were found to be 0.94 and 5.95%, respectively. Taguchi mathematical model developed by Mavruz and Ogulata [5] showed slightly lower correlation coefficient (0.91) and higher mean relative error (6.08%) respectively, for predicting bursting of knitted fabrics. All the results demonstrated good prediction ability and accuracy of the developed models; however, fuzzy intelligent model exhibits better prediction performance than that of Taguchi mathematical model.

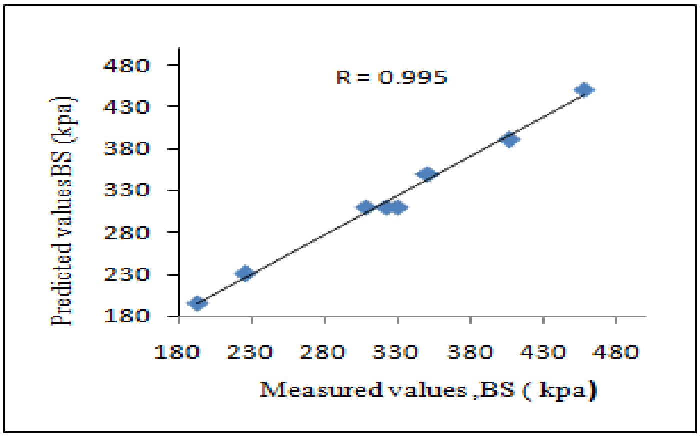

Figure 9: Correlation between actual and predicted values of bursting strength by fuzzy intelligent model

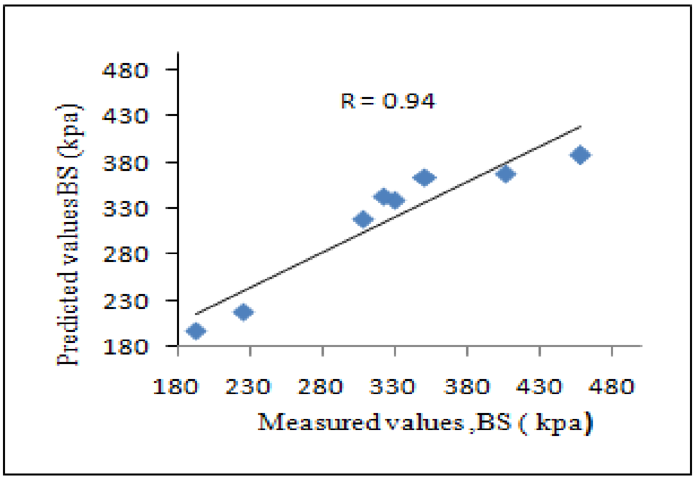

Figure 10: Correlation between actual and predicted values of bursting strength by Taguchi model

VI. CONCLUSIONS

In this study, Fuzzy intelligent model and Taguchi mathematical model have been developed and compared for predicting the bursting strength of viscose plain knitted fabric. The prediction models were constructed by taking the yarn tenacity and knitting stitch length as input variables and fabric bursting strength as output variable. The developed prediction models confer an excellent perceptive about the interaction between knitting process variables and their effects on the fabric bursting strength. It has been found that yarn tenacity has the greatest and main effects on the fabric bursting strength than that of knitting stitch length. Finally, the models derived in this research have been verified from the experiment. The correlation coefficient and mean relative error were found to be 0.995 and 2.47%, respectively, between the actual fabric bursting strength and that predicted by fuzzy intelligent model. Alternatively, the correlation coefficient and mean relative error were found to be 0.94 and 5.95%, respectively, between the actual fabric bursting strength and that predicted by Taguchi mathematical model. From this research investigation, it has been found that both the Fuzzy intelligent model and Taguchi mathematical model have the ability to predict fabric bursting strength. As, various non-linear and mutually dependent factors affect the fabric bursting strength; application of intelligent approach like fuzzy logic for prediction problems may be preferable due to its superior prediction performance than the Taguchi method.

ACKNOWLEDGEMENTS

The authors are thankful to the Department of Textile Engineering, Faculty of Engineering, Daffodil International University and the Management of APS Textile research laboratory, APS Group Bangladesh for providing the facilities for this research work.

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