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Comparison of Regression and Adaptive Neuro-fuzzy Models for Predicting the Bursting Strength of Plain Knitted Fabrics

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Abstract: The aim of this study was to compare the response surface regression and adaptive neuro-fuzzy models for predicting the bursting strength of plain knitted fabrics. The prediction models are based on the experimental data comprising yarn tenacity, knitting stitch length and fabric GSM as input variables and fabric bursting strength as output/response variable. The models quantitatively characterize the non-linear relationship and interactions between the input and output variables exhibiting very good prediction ability and accuracy, with ANFIS model being slightly better in performance than the regression model.

Keywords: Bursting strength, Knitted fabric, Prediction, Regression, ANFIS

Introduction

Knitting is one of the three major fabric production methods along with weaving and nonwovens. Knitted fabrics are distinguished from other types of fabrics because of their elasticity, drape, wrinkle resistance and easy-care properties. Due to their softness and comfort, knitted fabrics are usually preferred to woven fabrics in next-to-skin wear and their popular end uses include underwear, casual wear, active wear and sportswear [1,2].

Bursting strength is one of the most important mechanical properties of knitted fabrics. Knitted fabrics are exposed to multi-axial forces not only during their dry and wet processing in the factory but also during their end-use. Due to their distinct structural features, tensile and tear strength testing as applicable to woven fabrics, is not suitable for the knitted fabrics. Therefore, bursting strength of knitted fabrics is conducted to assess the fabric’s ability to withstand multi-axial stresses without breaking off.

Effect of different factors on the bursting strength of knitted fabrics have been studied in the past and it is known that the bursting strength increases by increasing the constituent yarn tenacity, decreasing knitting stitch length and increasing knitted fabric density (GSM) [3-7]. It has also been described that the effect of different variables on the bursting strength is not linear. However, the non-linearity of these factors and their mutual interactions have not been well elaborated using statistical techniques.

Because of their ability to model non-linear relationships, intelligent techniques such as artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) have been employed in the past for predicting the bursting strength of knitted fabrics. Ertugrul an Ucar developed intelligent models for predicting the bursting strength of knitted fabrics using yarn strength, yarn elongation and fabric GSM as input variables [8]. Unal, Ureyen and Armakan developed an ANN-based model for predicting the bursting strength using yarn strength, yarn count, yarn evenness, yarn twist, yarn elongation and fabric wales and courses as input variables [9].

One of the limitations of artificial neural networks is that they not only require a large amount of data for proper training but work like black-boxes and there is no explicit elaboration of the nature of non-linear relationships between the input and output variables. Statistical quadratic models on the other hand, give better explanation of the nature of non-linearity among the input and output variables. The purpose of this study was to develop statistical response surface regression model for predicting the bursting strength of knitted fabrics, which has not so far been reported in the literature. The model was developed by taking stitch length as one of the input variables, which has also not been used as a factor in previously reported prediction models. Other input variables taken for this study included yarn tenacity and fabric GSM. It could appear that the knitting stitch length and fabric GSM are correlated. However, it is known that GSM is not just controlled by the stitch length but also by controlling the yarn amount fed to the knitting needles, which is also the case in this study. The response surface regression model developed in this study is also compared with the adaptive neuro-fuzzy model (ANFIS) in terms of prediction accuracy. The ANFIS approach has been successfully used in the past for modeling non-linear relationships in textiles [10-15].

Materials and Methods

Twenty eight samples were knitted on FUKUHARA single jersey circular knitting machine (Model FXC-3S), having 30 inches diameter, 20 gauge (needles/inch) and 90 yarn feeders. Yarns of two different tenacities were used for knitting the samples. Two fabric knitting variables were employed,

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Table 1. Range of knitted fabric variables

Variables	Min.	Max.
Input variables		
Yarn tenacity (g/tex)	11	15
Stitch length (mm)	2.6	4.8
Fabric weight/GSM (g/m^2)	122	292
Output variable		
Fabric bursting strength (kg/cm^2)	2.25	10.5

i.e. fabric stitch length and fabric weight (GSM). Different fabric GSM levels were obtained not just by change in the stitch length but also by changing the amount of yarn fed to the knitting needles, as may be the case in industrial knitting.

All the samples were dry-relaxed before industrial-scale scouring, bleaching and drying. Then the samples were conditioned under standard atmospheric conditions at 20±2 °C and relative humidity of 65±2 %. The conditioned samples were tested for fabric GSM according to ASTM D-3776. The stitch length was measured by unraveling number of courses over 50 needles and measuring the total length of yarn and then dividing the total length by 50 to get the stitch length. Ten measurements were repeated to get the average stitch length. The fabric bursting strength was tested according to ISO-13938-1. The range of variables of the knitted samples is given in Table 1.

Out of the 28 data-sets corresponding to the same number of knitted samples, 20 were used for developing the models and 8 were used for validation of the models. Statistical modeling was done using response surface regression on MINITAB™ statistical software. Adaptive neuro-fuzzy modeling was done using MATLAB® Fuzzy Logic Toolbox (The MathWorks, Inc.) using triangular membership functions (MF) for input variables, linear membership functions for output variables, and Sugeno-type fuzzy inference system. The same input and output variables were used as were used for regression modeling. Fuzzy inference system (FIS) was generated using Grid partition method while training of the FIS was done using hybrid optimization method. Error tolerance and number of epochs were set at 0 and 6, respectively. The number and type of membership functions were determined by trial and error to get the model with good data fit and prediction accuracy.

Results and Discussion

The Regression Model

Twenty data sets used for developing the prediction models are given in Table 2. Yarn tenacity (g/tex), stitch/loop length (mm) and fabric weight in grams per square meter (GSM) were used as predictor variables and fabric bursting strength (kg/cm^2) was taken as response variable. Analysis of variance for response surface regression is given in Table 3.

P-value for regression is 0.000 which means that the model is statistically significant with more than 99 % confidence. P-values for linear effect, squared effect and interaction are also less than 0.05 indicating that not only the linear effect of predictor variables is significant but some predictor variable(s) do have curvilinear effect on the bursting strength and that there is significant interaction among some input variables. Interaction between any two variables means that the effect of one variable on the response is not independent but depends on the value of the other predictor variable. The contribution of linear effect in the total regression model is 97.6 % (i.e. 96.0667*100/98.4392), that of square or

Table 2. Data of knitted fabrics used for developing the prediction models

No.	Yarn tenacity (g/tex)	Stitch length (mm)	Fabric GSM (g/m^2)	Bursting strength (kg/cm^2)
1	15	4.2	146	3.25
2	15	4.1	156	4.00
3	15	4.0	166	4.50
4	15	4.0	184	5.25
5	15	3.8	196	6.00
6	15	3.5	216	7.50
7	15	3.4	218	7.75
8	15	3.3	220	8.00
9	15	3.0	244	9.25
10	15	2.6	292	10.50
11	11	4.8	122	2.25
12	11	4.1	144	3.00
13	11	3.8	170	3.75
14	11	3.5	178	4.00
15	11	3.3	188	4.50
16	11	3.1	204	5.25
17	11	2.9	224	6.75
18	11	2.8	234	7.25
19	11	2.7	237	7.50
20	11	2.7	248	8.25

Table 3. Response surface regression coefficients for fabric bursting strength

Term	Regression coefficient	Standard error coefficient	T-value	P-value
Constant	6.5480	0.2587	25.308	0.000*
Yarn Tenacity (T)	0.0953	0.1481	0.644	0.531
Loop length (L)	-3.4149	1.3898	-2.457	0.029*
Fabric GSM (W)	0.8058	1.3844	0.582	0.570
L^2	-9.1610	2.6296	-3.484	0.004*
W^2	-11.4501	2.7540	-4.158	0.001*
L*W	-20.3806	5.3045	-3.842	0.002*

*Statistically significant; R-Sq=98.97 %.

Table 4. Analysis of variance for fabric bursting strength

Source	DF	Seq SS	Adj SS	Adj MS	P-value
Regression	8	98.4392	98.4392	12.3049	0.000*
Linear	3	96.0667	35.4305	11.8102	0.000*
Square	2	0.5164	0.3173	0.1587	0.023*
Interaction	3	1.8561	1.8561	0.6187	0.000*
Residual error	11	0.3233	0.3233	0.0294	
Total	19	98.7625			

*Statistically significant.

curvilinear effect is 0.5 % (i.e. 0.5164*100/98.4392) and that of interaction effect is 1.9 % (i.e. 1.8561*100/98.4392).

The response surface regression coefficients for fabric bursting strength, including statistically significant squared effects and interactions, are given in Table 4. All analyses were done using standardized coded units of the predictor variables. It is clear that the effect of yarn tenacity, within the range used in the knitted samples, is not significant. The effect of loop length and fabric GSM is curvilinear as indicated by the significant p-values of their squared terms. The value of coefficient of determination (R-sq) is 98.97 %, which means that 98.97 % change in fabric bursting strength is explained by the terms included in the model, which is a quite good figure for the expected prediction accuracy of the regression model.

The response surface regression equation, using the standardized coded units of the predictor variables, is given as follows:

$$\text{Fabric bursting strength} = 6.5480 + 0.0953 \times T - 3.4149 \times L + 0.8058 \times W - 9.1610 \times L^2 - 11.4501 \times W^2 - 20.3806 \times LW \quad (1)$$

The response surface equation, using the actual units of measurement for the predictor variables is given as follows:

$$\text{Fabric bursting strength} = -323.049 + 0.0476628 \times T - 98.0420 \times L + 1.47209 \times W - 7.57103 \times L^2 - 0.00158479 \times W^2 - 0.217975 \times LW \quad (2)$$

The effect of different predictor variables on the fabric bursting strength is depicted in Figures 1-3. It is evident from Figure 1 that, increase in yarn tenacity from 11 to 15 g/tex only marginally increases the fabric bursting strength. However the effect of stitch length is much more profound. Bursting strength increases in the beginning by decreasing stitch length because of increasing number of loops per unit area. However, the effect of decreasing the stitch length is not linear. As the fabric becomes less and less extensible because of increasing number of loops per unit area, the effect of decreasing the stitch length becomes less pronounced and after a certain limit, the trend in reversed.

Figure 2 depicts that the effect of fabric GSM on the bursting strength is also not linear. Firstly, as GSM increases,

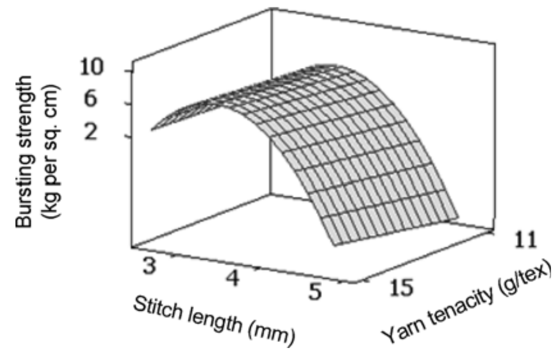

Figure 1. Effect of stitch length and yarn tenacity on fabric bursting strength (regression model).

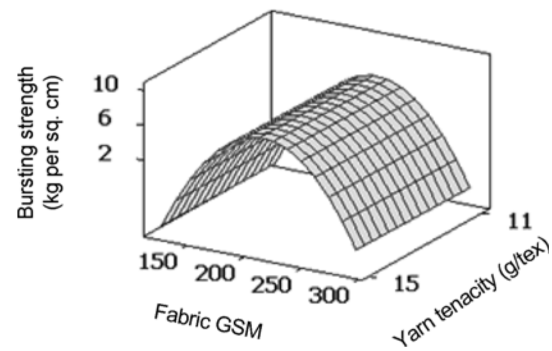

Figure 2. Effect of fabric GSM and yarn tenacity on fabric bursting strength.

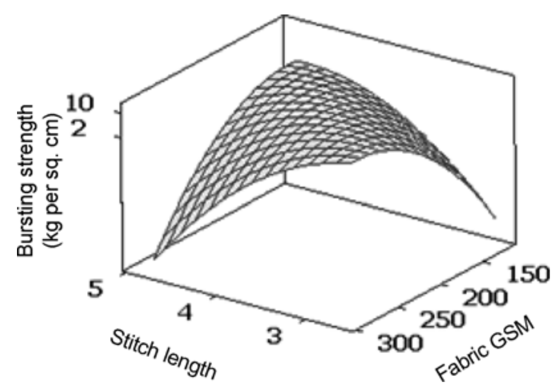

Figure 3. Effect of stitch length and fabric GSM on fabric busting strength.

bursting strength increases due to increase in number of loops per inch which bear the multidirectional forces. To bear multidirectional forces, fabric's extensibility is also very important. As GSM increases further than an optimum level, fabric become stiffer and less extensible, thus resulting in poor bursting strength.

Figure 3 shows a strong interaction between the fabric stitch length and the GSM. Bursting strength tends to be lower at lower stitch length and lower GSM because of lower number of loops per unit area. However, bursting strength increases at lower stitch length when the GSM is increased by increasing the amount of yarn fed to the knitting needles, thus increasing the amount of yarn per unit area. Bursting strength tends to be higher at higher stitch length and lower GSM because of greater fabric extensibility. However, when the GSM is increased at higher stitch length levels, the extensibility of the fabric decreases and thereby the bursting strength gets a downward trend.

After analyzing Figures 1-3, it would be rather simplistic to believe (as would the common sense be inclined to) that by simply increasing the fabric GSM or decreasing the fabric stitch length, fabric bursting strength may be improved. Actually, this is not the case and because the effect of stitch length and GSM is not linear on one hand and on the other hand these two factors have significant interaction between one another. Hence, in order to achieve maximum fabric bursting strength, an optimum combination of these factors is essential.

The ANFIS Model

The structure of the developed adaptive neuro-fuzzy inference system (ANFIS) is shown in Figure 4. The ANFIS structure consists of 3 input variables, viz., yarn tenacity with 2 triangular membership functions (MF), stitch length with 3 triangular MF and fabric GSM with 3 triangular MF. There is one output variable i.e., bursting strength, consisting of 18 linear membership functions. The whole model is based on 18 if-then rules of the form.

If x is A_1 and y is B_1 and z is C_1, then output $= k_1x + k_2y + k_3z + k_4$

where x, y and z are inputs, A, B and C, are fuzzy membership functions (MF) for corresponding inputs, and k_1, k_2, k_3 and k_4 are constants determined by training the model. The number and type of membership functions for different inputs were determined through trial and error to result in a model with good fit and prediction accuracy of unknown input values.

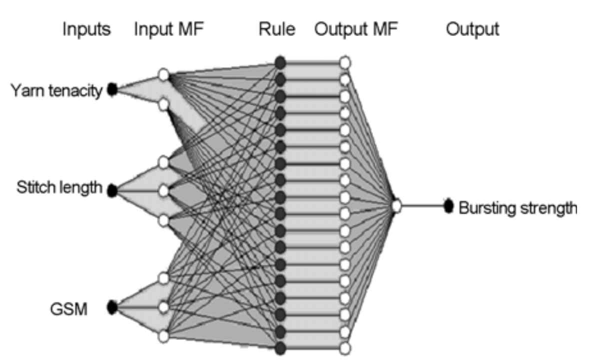

Figure 4. ANFIS structure.

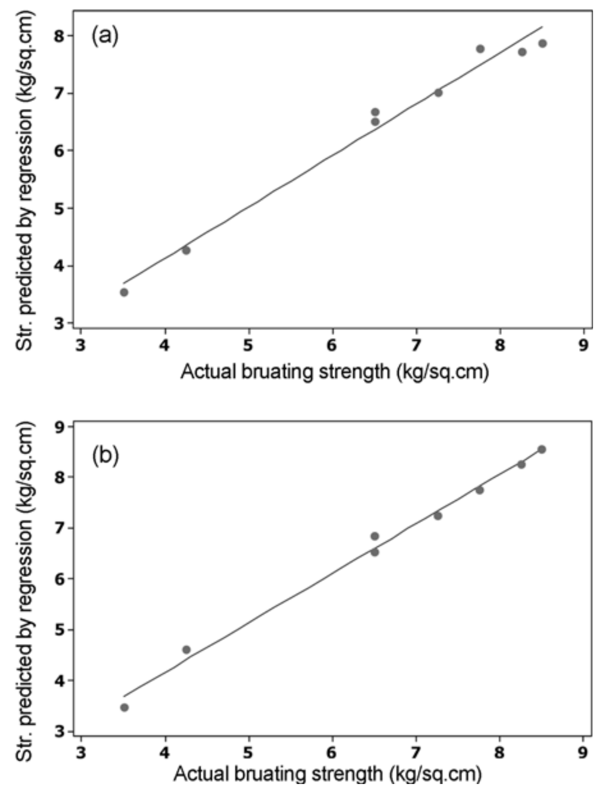

Figure 5. Fitted line plot for actual and predicted bursting strength by regression model.

Table 5. Comparison of actual and predicted bursting strength values

No.	Yarn tenacity (g/tex)	Stitch length (mm)	Fabric GSM	Actual bursting strength	Regression model		ANFIS model	
					Predicted values	% Diff. from actual	Predicted values	% Diff. from actual
1	15	4.20	148	3.50	3.46	1.14	3.55	-1.43
2	15	3.74	208	6.50	6.85	-5.38	6.51	-0.15
3	15	3.60	214	7.25	7.25	0.00	7.02	3.17
4	15	3.10	226	8.50	8.56	-0.71	7.87	7.41
5	15	3.20	222	8.25	8.25	0.00	7.72	6.42
6	11	2.91	223	6.50	6.52	-0.31	6.68	-2.77
7	11	2.70	240	7.75	7.75	0.00	7.77	-0.26
8	11	3.42	184	4.25	4.60	-8.24	4.27	-0.47

Validation of the Prediction Models

Out of total 28 knitted samples, 20 were used for the development of prediction models whereas data of 8 samples were used for the validation of the developed models. A comparison of the actual bursting strength of the 8 validation samples with the strength values predicted by using regression and ANFIS models is given in Table 5.

Figure 5(a), (b) show fitted line plots between actual bursting strength and that predicted by the regression model and the ANFIS model, respectively. The Pearson correlation between the actual bursting strength and that predicted by the regression model was found to be 0.991 with p-value of 0.000, and between the actual strength and that predicted by the ANFIS model was found to be 0.996 with a p-value of 0.000, indicating very good prediction ability and the accuracy of the developed models, ANFIS model being slightly better.

Conclusion

Response surface regression model and adaptive neuro-fuzzy inference model was developed for predicting the bursting strength of plain knitted fabrics by taking yarn tenacity, knitting stitch length and fabric GSM as predictor variables. It has been found that the effect of stitch length and fabric GSM is not linear on the fabric bursting strength and there is statistically significant interaction between the stitch length and the fabric GSM. It was further found that both the response surface and ANFIS models have the ability to predict fabric bursting strength with very good accuracy, with ANFIS model being slightly better in performance.

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