PREDICTING BURSTING STRENGTH OF PLAIN KNITTED FABRICS USING ANN

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Abstract: In this study, the effects of yarn parameters, on the bursting strength of the plain knitted fabrics were examined with the help of artificial neural networks. In order to obtain yarns having different properties such as tenacity, elongation, unevenness, the yarns were produced from six different types of cotton. In addition to cotton type, yarns were produced in four different counts having three different twist coefficients. Artificial neural network (ANN) was used to analyze the bursting strength of the plain knitted fabrics. As independent variables, yarn properties such as tenacity, elongation, unevenness, count, twists per inch together with the fabric property number of wales and courses per cm were chosen. For the determination of the best network architecture, three levels of number of neurons, number of epochs, learning rate and momentum coefficient were tried according to the orthogonal experimental design. After the best neural network for predicting the bursting strength of the plain knitted fabrics was obtained, statistical analysis of the obtained neural network was performed. Satisfactory results for the prediction of the bursting strength of the plain knitted fabrics were gained as a result of the study.

1 INTRODUCTION

Knitting is one of the fabric production methods other than weaving and non woven. In knitting, fabric surface is formed by loops connected to each other in wale and course directions. A knitted fabric is supposed to have some properties according to the fabric application area. For instance, a knitted fabric made for underwear must have high comfort properties. In addition to the application fields, mechanical characteristics of knitted fabrics are very essential in downstream processes. It will be a problem for a knitted fabric which has deficient mechanical properties to be processed in finishing treatments. Among the mechanical characteristics of knitted fabrics, bursting strength is of great importance. Fabrics are not only exposed to forces in the vertical and perpendicular directions but also they are exposed to multi axial forces during the usage. Therefore, breaking and tear strength analysis are not enough for the determination of strength properties of the fabrics against the multi axial forces. As a consequence, bursting strength is extremely important for especially knitted fabrics, parachutes, filtration fabrics and sacks. For this reason, estimating the bursting strength of knitted fabrics before manufacturing is very important.

A few studies have done about the prediction of properties of the knitted fabrics. Ertugrul and Ucar (2000) predicted the bursting strength of cotton plain knitted fabrics before manufacturing via using intelligent techniques of neural network and neuro-fuzzy approaches. Ju and Ryul (2006) examined the effects of the structural properties of plain knitted fabrics on the subjective perception of textures, sensibilities, and preference among consumers by

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using neural networks. The prediction of fuzz fibres on fabric surface was studied by using regression analysis and ANN and was found that neural networks gave better results than regression analysis (Ertugrul and Ucar, 2007). Park, Hwang and Kang (2001) concentrated on the objective evaluation of total hand value in knitted fabrics using the theory of neural networks.

In this work, it is aimed to predict the bursting strength of plain knitted fabrics using artificial neural networks before manufacturing the aforementioned fabrics with regard to the yarn properties and fabric properties.

2 MATERIAL AND METHOD

In this study, in order to predict the bursting strength of plain knitted fabrics, fabrics were produced in four different yarn counts (Ne 20, Ne 25, Ne 30, and Ne 35) having three different kinds of twist coefficients (α_e 3.8, α_e 4.2, and α_e 4.6). In order to obtain yarns having different tenacity, elongation and unevenness values, the yarns were produced from six different cotton types. Totally, seventy two different plain knitted fabrics were produced. For the yarn tenacity and breaking elongation tests Uster Tensorapid tensile tester was used. Yarn unevenness measurements were performed on Uster Tester 3. For fabric testing, the numbers of wales and courses per cm were counted and bursting strength properties of each plain knitted fabric were measured with James H. Heal TruBurst Tester.

2.1 Artificial Neural Network Design

For the prediction of bursting strength of the plain knitted fabrics, a multi layer feed forward network with one hidden layer was used. While bursting strength property of the plain knitted fabrics was used as an output, yarn count (Ne), twist (turns/inch), yarn tensile strength (cN/tex), yarn elongation (%), yarn unevenness (CVm%) and number of multiplication of wales and courses per cm^2 were used as inputs in the model. As an activation function, a hyperbolic function $f(x)=(e^x-e^{-x})/(e^x+e^{-x})$ was used in the hidden layer and a linear function $f(x)=x$ was used in the input and output layers. The training was performed in one stage via using the back propagation algorithm;

$$\Delta\omega_{ij}(t)=\eta\delta_j o_i+\alpha\Delta\omega_{ij}(t-1) \qquad (1)$$

where $\eta=$ the learning rate, $\delta=$ the local error gradient, $\alpha=$ the momentum coefficient, $o_i=$ the output of the ith unit.

As it is generally known, learning rate influences the speed of the neural network. Increasing the learning rate will cause the network either oscillate or diverge from the true solution. Giving a too low value for this parameter will make the network too slow and it will be time consuming to converge on the final outputs. The other parameter that affects the performance of the back propagation algorithm is the momentum coefficient. High values of momentum coefficient ensure high speed of convergence of the network. However, choosing too high momentum coefficients may sometimes cause missing the minimum error. On the other hand, setting this parameter to a low value guarantees the local minima and will slow down the training stage. In the constitution of the network, the first step was to determine the number of hidden layers and the number of neurons in each layer. In our study, one hidden layered network gave satisfactory results with regard to error standard deviation, absolute error mean and coefficient of regression. In the second step it was aimed to determine the number of neurons in the hidden layer. For this purpose, three levels of number of neurons such as 3, 6 and 9, three levels of number of epochs such as 5000, 10000 and 20000, three levels of learning rate and momentum coefficients 0.001, 0.01, 0.1 and 0.1, 0.3, 0.5 were tried respectively according to the orthogonal experimental design.

As there are four parameters of neural network, three different levels of each parameter make it difficult and time consuming to perform full factorial experimental design (3^4). Thus, an orthogonal experimental design was used. As a result, 16 different kinds of neural networks were tried.

3 RESULTS

According to the orthogonal experimental design, the number of neurons were changed and found that increasing the number of neurons increased the regression coefficient of training and testing (Figure 1). As a result, 9 neurons in the hidden layer were chosen.

In the back propagation, training was started at 5000 epochs and then it was increased up to 20000 epochs. However, increasing the number of epochs did not improve the results of testing, in fact it decreased the prediction power of testing (Figure 2).

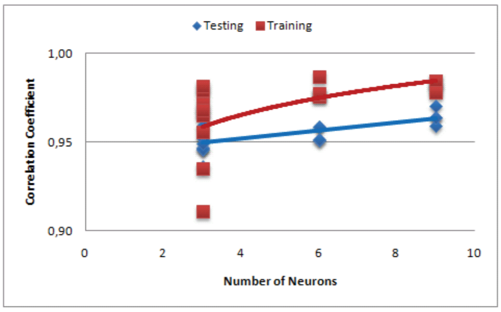

Figure 1: Change of correlation coefficient according to the number of neurons.

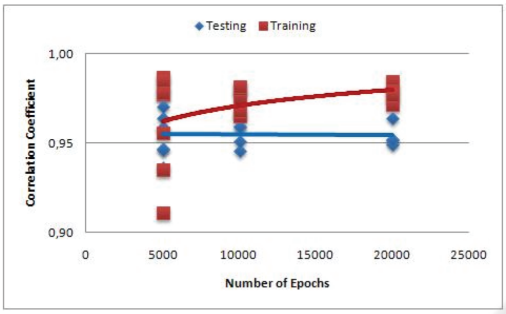

Figure 2: Change of correlation coefficient according to the number of epochs.

Learning rate of the algorithm was altered in three levels according to the experimental design. It was observed that increasing this parameter did not make any changes in the testing results. On the other hand, increasing this parameter increased correlation coefficient of the training (Figure 3).

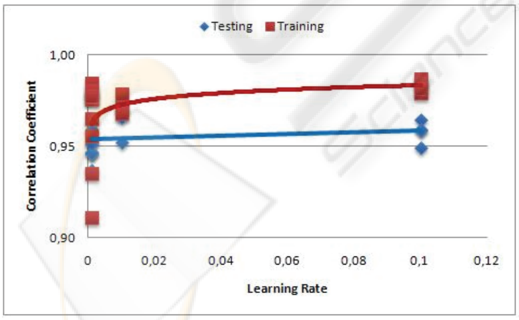

Figure 3: Change of correlation coefficient according to learning rate.

Altering the momentum neither improved the results of the testing nor changed the results of the training (Figure 4).

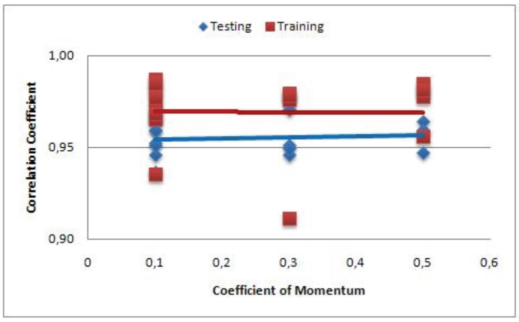

Figure 4: Change of correlation coefficient according to the coefficient of momentum.

According to Table 1, the best neural network which has the high correlation and regression coefficients and minimum mean absolute error and standard deviation ratio for the testing stage is the 14th neural network.

Table 1: Testing results of the neural networks according to the orthogonal experimental design.

N	MAE	S.D.R.	Corr.	Regr.
1	24.1260	0.3346	0.9459	0.89
2	27.2966	0.3162	0.9640	0.93
3	30.4082	0.3578	0.9366	0.88
4	26.6822	0.3365	0.9513	0.90
5	26.4993	0.3033	0.9588	0.92
6	28.2412	0.3323	0.9524	0.91
7	30.1326	0.3399	0.9592	0.92
8	23.4184	0.3306	0.9470	0.90
9	26.0238	0.3250	0.9462	0.90
10	29.5191	0.3347	0.9492	0.90
11	27.4834	0.3300	0.9515	0.91
12	29.9798	0.3102	0.9587	0.92
13	29.9740	0.3345	0.9643	0.93
14	20.2556	0.2639	0.9707	0.94
15	25.2005	0.3214	0.9594	0.92
16	26.2121	0.2696	0.9655	0.93

N: Networks; MAE: Mean Absolute Error; SDR: Standard Deviation Ratio; Corr: Correlation Coefficient; Regr: Regression Coefficient

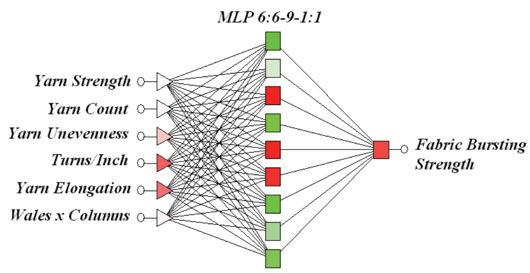

Figure 5: The best neural network obtained from the trials.

The best neural network after several trials is given in Figure 5. The inputs are given according to their impact coefficients. As a result of several trials, the number of neurons, number of epochs, learning rate and momentum coefficients were determined as 9, 5000, 0.01 and 0.3 respectively.

In order to observe the significance levels of each variable in the best neural network for fabric bursting strength, sensitivity analysis of the neural network were performed. In this analysis, the sensitivity is calculated as follows; the ratio of the error in the absence of values for each variable to total network error is calculated. This ratio means the significance level of that particular variable to the network. If the ratio is high, the deterioration will be high which means that the network is more sensitive to that particular variable. Once sensitivities have been calculated for all variables, they are ranked in order. Thus, the inputs are ranked according to the calculated ratios of each variable. Table 2 represents the sensitivity analysis results.

Table 2: Sensitivity analysis of the developed network.

	Ten.	Cnt	Uneven	Tpi	Elg.	WxC
Ratio	1.0010	1.0004	1.0003	1.0002	0.9999	0.9998
Rank	1	2	3	4	5	6

Ten: Yarn Strength; Cnt: Yarn Count; Uneven: Yarn Unevenness; Tpi: Turns per inch; Elg: Yarn Elongation; WxC: Wales x Courses

As it is seen in Table 3, all the ratios of each parameter are close to each other. However, the most important parameter which affects fabric bursting strength is yarn tenacity. The second parameter is the yarn count. As it is known, fabric bursting strength is mostly affected by the yarn strength. Thus, this result is as expected. In addition to yarn strength, the second parameter which affects mostly the fabric bursting strength is yarn count. As the yarn count changes, the properties such as yarn strength, yarn elongation and yarn unevenness will be changed.

The summary statistics of ANN is given in Table 3. It can be seen that even the error values of testing are lower and estimation coefficient values are higher. The RMSE of testing is 26.25. Since the range of bursting strength values is 300 to 700 kPa, this will lead a deviation in the predicted values 3.75-8.75 % of the target outputs. This result is a desired result since in prediction of textile materials' properties it is a difficult task to estimate the material property with a low deviation.

4 CONCLUSIONS

In this study, it was aimed to predict the bursting strength of the plain knitted fabrics regarding yarn properties. In order to determine the best neural network architecture, three levels of number of neurons, number of epochs, learning rate and momentum coefficient was used according to the orthogonal experimental design. As a result of several trials, the number of neurons, number of epochs, learning rate and momentum coefficients were determined as 9, 5000, 0.01 and 0.3 respectively.

It has been observed that the technique of neural networks showed better agreement with the prediction of the fabric bursting strength. The developed neural network revealed a good coincidence with the results of bursting strength. Therefore it can be stated that the neural network approach provides an effective skill for the prediction of bursting strength of the plain knitted fabrics only with a deviation of 3.75-8.75 %.

Table 3: Descriptive statistics of the best network.

	Training	Testing	Total
Data Mean	501.75	503.96	502.30
Data S.D.	96.90	97.60	97.08
Error Mean	14.81	5.06	12.37
Error S.D.	20.03	25.76	22.01
Abs E. Mean	21.32	20.26	21.05
Mean Sq. Error	194.23	689.18	204.01
Root Mean Sq. Er.	13.94	26.25	14.28
Correlation	0.98	0.97	0.97
Regression	0.96	0.94	0.95

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