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Evaluation of Bending Rigidity of Dressing Materials using Artificial Neural Networks

M. Chenganmal, Dept. of Textile Tech, K.S.R College of Technology,
H.L. Vijayakumar, Army Institute of Fashion & Design,
V. Subramaniam, Dept. of Textile Tech., Jaya Engineering College
India

ABSTRACT

In garment industries, the formability is one of the factors to construct the garment. Like the cuff and collar of a garment, the fabric is turned over on itself then the inner layer of fabric has to conform to smaller radius of curvature than the outer layer. In this regard, the outer layer has to stretch and inner layer has to contract. So, the fabric is unable to accommodate this change in length, the inner layer will get pucker. This ability to deform is known as "Formability". The measurement of formability is derived from the bending stiffness of the fabric and its modulus of compression. Hence, the bending rigidity is another important factor for the garment industries. It is necessary for the garment industries, to predict the flexural rigidities of 15 different varieties of Polyester with micro denier, polyester/viscose, and polyester/cotton plain woven dressing materials were used for designing the back-propagation network and a statistical regression analysis approaches. The optimum construction of neural network was investigated through the change of layer and neuron number. The results showed that the back-propagation network could predict the bending values of the above fabrics with a meaningful difference. In this study, neural network has been successfully applied to predict the bending properties of plain woven dressing materials with good reliability.

Keywords: Garment fitting, Back- propagation, Neural Network, neuron number, pure bending tester, Formability.

1. INTRODUCTION

An artificial neural network is a powerful, useful network and predicts the values in a very accurate rate, because the network is processed like the human brain. This tool is mainly used in various areas like biotechnology, biochemistry, textile industry etc. It forecasts the various properties of textile materials, classifications and analysis of defects, identification, and process optimization and planning. A great study and attention has been focused by many research scholars on various areas like yarn properties, dimensional properties, perception of fabric hand values, total hand values etc. Using neural network, Desai[7] stated to relate the yarn properties to fiber properties and to map the two properties easily without complex regression equations. Their statistical data analysis of few yarn properties will determine the suitability of neural networks for such textile applications. Hui[8]stated that identify reliable sensory fabric hand attributes with correlated attributes of fabric properties, and attempt a novel approach for predicting sensory hand based on fabric properties using a resilient back propagation neural network. Weishyr T[9] studied that take new approaches using a one-step transformation process to establish translation equations for the total hand evaluation of sixteen fabrics by employing a stepwise regression method and an artificial neural network. The key mechanical properties selected from sixteen fabric mechanical properties based on a KES system, using the stepwise regression selection method, are the parameters. Majumdar PK[10] has illustrated that three modeling methods for evaluating the breaking elongation of ring cotton yarns. Fiber properties and yarn count are the input values for these models. Beltran R[11] has been studied a method for predicting worsted spinning performance with an artificial neural network (ANN) trained with back propagation. The applicability of artificial neural networks for predicting spinning performance is first evaluated against a well-established prediction and benchmarking tool. Tokarska M[12] has studied the features of air permeability on woven fabrics using neural network. Behera B.K. and Guruprasad R[14] have studied to investigate the predictability of bending property of woven fabrics using artificial neural network (ANN) approach. In this study, the plain and satin weave construction under desized, scoured, and relaxed conditions. These fabrics tested for the bending properties of thread density, linear density, and twist per cm and weave construction were accounted as input data for this model whereas the output data of warp and weft way bending rigidities by an adaptive learning rate back-propagation. In this paper, the evaluation of bending properties based on the back propagation neural network and comparison of the KESF bending results are discussed.

2. MATERIALS AND METHODS

2.1. Yarn and fabric samples

In this study, a series of 15 specimens were developed totally to weave the plain woven dressing fabrics. The training set of fabric details and the first set of samples were produced from the possible range of fabric using polyester viscose blended yarns. The second set of fabrics developed was polyester cotton yarns in warp and weft which was produced from ring and open end spinning method,fromR37tex, R37tex/2with 4 levels of ends/cm and picks/cm.

2.2. Testing Methods

A series of specimens were tested with various geometrical properties like ends/cm, picks/cm, areal density, and thickness of the fabrics. The number of warp yarns (ends) per unit distance and filling yarns (picks) per unit distance were tested by magnifying counting glass as per the ASTM D3775.The determination of the aerial density of the specimen was tested as per the ASTM D3776. The thickness test for fabrics was measured as per the ASTM D 1777. The fabrics were tested for their bending properties by Kawabata Evaluation system of KES-FB2. The mechanical and dimensional properties of textiles depend on the temperature and the relative humidity under which the tests were made, and hence it was important to carry out the tests under standardized atmospheric conditions, defined as 25 ± 2^{o}C temperature and 65 ± 2% relative humidity. The flexural rigidity (B) was measured as the average slopes of the bending hysteresis curve, when the fabric is bent on its both sides (face and back) between the curvatures of ± 0.5-1.5cm^{-1}. Every sample was tested both n warp and weft direction and the average of four readings was taken. The average warp way and weft way bending rigidity were taken as fabric bending rigidity(B) and the bending moment (2HB) was calculated by the couple required to restore zero curvature, denoted the coercive couple is mentioned as half the intercept constitute the output parameters of the network.

Table 1. Training set of Fabric details

Fabric code	Weave type	Filament Denier	Yarn count in tex		Threads / Cm		Fabric weight in g/m^2	Fabric thickness in cm
			Warp	Weft	Warp	Weft		
F1	Plain	30tex/2	30tex/2	9	50	34	109.2	0.5
F2	Plain	30tex/2	30tex/2	17	50	34	135.1	0.53
F3	Plain	30tex/2	30tex/2	9	50	34	112.4	0.49
F4	Plain	30tex/2	30tex/2	9	50	34	113.8	0.50
F5	Plain	30tex/2	30tex/2	17	50	34	138.9	0.54
F6	Plain	37tex/2	37tex/2	37tex/2	32	24	169.8	0.69
F7	Plain	37tex/2	37tex/2	37tex/2	32	24	157.5	0.66
F8	Plain	37tex/2	37tex/2	37tex/2	32	24	176.7	0.68
F9	Plain	30tex/2	30tex/2	30tex/2	28	22	213.1	0.74
F10	Plain	30tex/2	30tex/2	30tex/2	28	22	196.0	0.72
F11	Plain	30tex/2	30tex/2	30tex/2	28	22	198.2	0.73
F12	Plain	25tex	25tex	25tex	31	24	138.7	0.69
F13	Plain	25tex	25tex	25tex	31	24	131.1	0.69
F14	Plain	25tex	25tex	25tex	31	24	131.7	0.72
F15	Plain	25tex	25tex	25tex	31	24	136.1	0.69

2.3. Artificial Neural Network (ANN)

Artificial neural networks are mathematical inventions inspired by observations made in the study of biological systems. An artificial neural network can be described as mapping an input space to an output space. The purpose of a neural network is to map an input into desired output. While patterned interconnections between neurons are found in biological systems, artificial neural networks are no more related to real neurons than feathers are related to modern aero-planes. Both biological systems neurons and feathers serve a useful purpose, but the implementation of the principals involved has resulted in man – made inventions that bear little resemblance to the biological systems that spawned the creative process.

As illustrated in figure 1, a back-propagation network of three layers, namely the vector input signal, summing junction, activation junction and output was used. A total of 15 samples were considered for training of the network. Of these, 7 physical factors shown in table 1 were regarded as the training input vector, with their bending rigidity and bending moment property producing the learning target data. The physical factors and sensory factor results pertaining to the last 15 samples served as query inputs and outputs respectively and were compared with KAWABATA bending test values as indicated in table:2.The values of the function vary between 0 and 1 for the input layer, while the tansig transfer function was used on the hidden layer. In order to attain output values greater than 1, a linear transfer function was used on the output layer. In computing the change in weight between the hidden and the output layers the generalized delta-learning rule was used. The aim of network learning is to reduce the delta between the target value and the predicted value. The quality of learning, which is the error vector evaluated by the following equation:

$$E = \frac{1}{2}\sum(Tj - Yj)^2 \text{----------------} (1)$$

Where E is the error vector; Tj is the output layer of target value; and Yj is the output layer of prediction value at node j. To minimize the value of the energy function, the steepest gradient descent entry point method was used. The optimal data convergence after network training was obtained under these conditions. In the supervised network learning process, the degree of convergence can be expressed in terms of the root-mean-square error (MSE) from the following relationship:

$$RMSE = \frac{1}{n}\sum(Tj - Yj)^2{}^{\frac{1}{2}} \text{---------}(2)$$

Where n is the number of units processed by the output. The MSE value varies from 0 to 1. If the MSE converges to less than 0.1, a good result is obtained. The average prediction error and the range of error were slightly high in case of prediction of bending rigidity in comparison to bending moment.

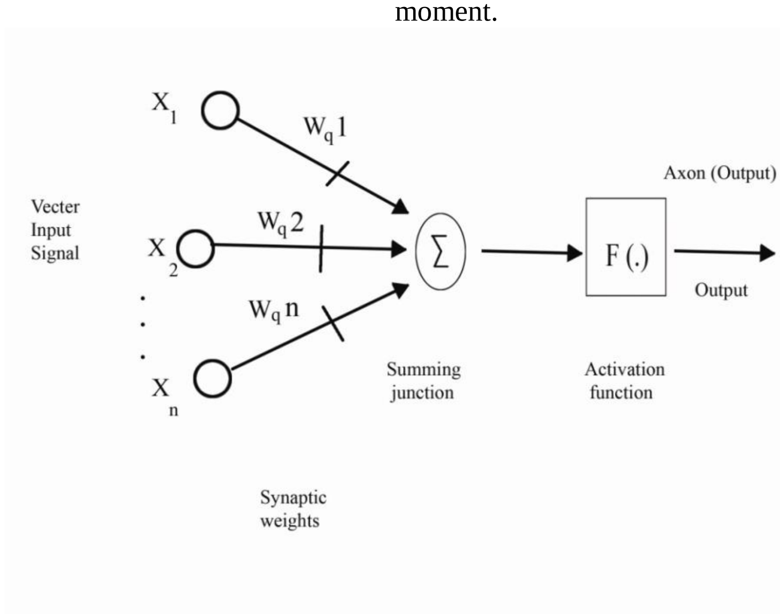

Figure 1. Simple Neuron network

Table 2. Predicted and actual values of bending rigidity, bending moment

S.No.	Fabric code	KESF Values		NN value		Average prediction error(%)	
		B	**2HB**	**B**	**2HB**	**B**	**2HB**
1.	F1	0.0531	0.0306	0.0530	0.0791	0.1883	0.3836
2.	F2	0.0797	0.0570	0.0308	0.0571	61.36	0.1751
3.	F3	0.0510	0.0388	0.0510	0.0386	0	0.5155
4.	F4	0.0465	0.0350	0.0544	0.0413	16.99	1.8
5.	F5	0.0824	0.0686	0.0830	0.0685	0.7282	0.1459
6.	F6	0.2674	0.3859	0.2479	0.3659	7.29	5.18
7.	F7	0.2095	0.3161	0.2096	0.3160	0.048	0.032
8.	F8	0.2686	0.3954	0.2685	0.3955	0.037	0.025
9.	F9	0.2935	0.3631	0.2938	0.3630	0.1022	0.028
10	F10	0.3174	0.4474	0.3172	0.4475	0.063	0.022
11.	F11	0.4177	0.6018	0.3416	0.4301	18.22	28.53
12.	F12	0.0589	0.0828	0.0557	0.0694	5.43	16.18
13.	F13	0.0547	0.0706	0.0565	0.0795	3.29	12.61
14.	F14	0.0568	0.0894	0.0567	0.0785	0.176	12.19
15.	F15	0.0572	0.0699	0.0556	0.0720	2.79	3.0
Average						7.7808	5.3878

2.4. Design and Training the network

Seven physical factors are used as the training input and two learning target data as the output data of bending rigidity B, bending moment 2HB for the training network as shown in figure 2. The training input (7 physical factors) data are used to train the network such as Filament denier, Warp count, Weft count, Ends / centimeter, Picks / centimeter, Weight (GSM), Thickness.

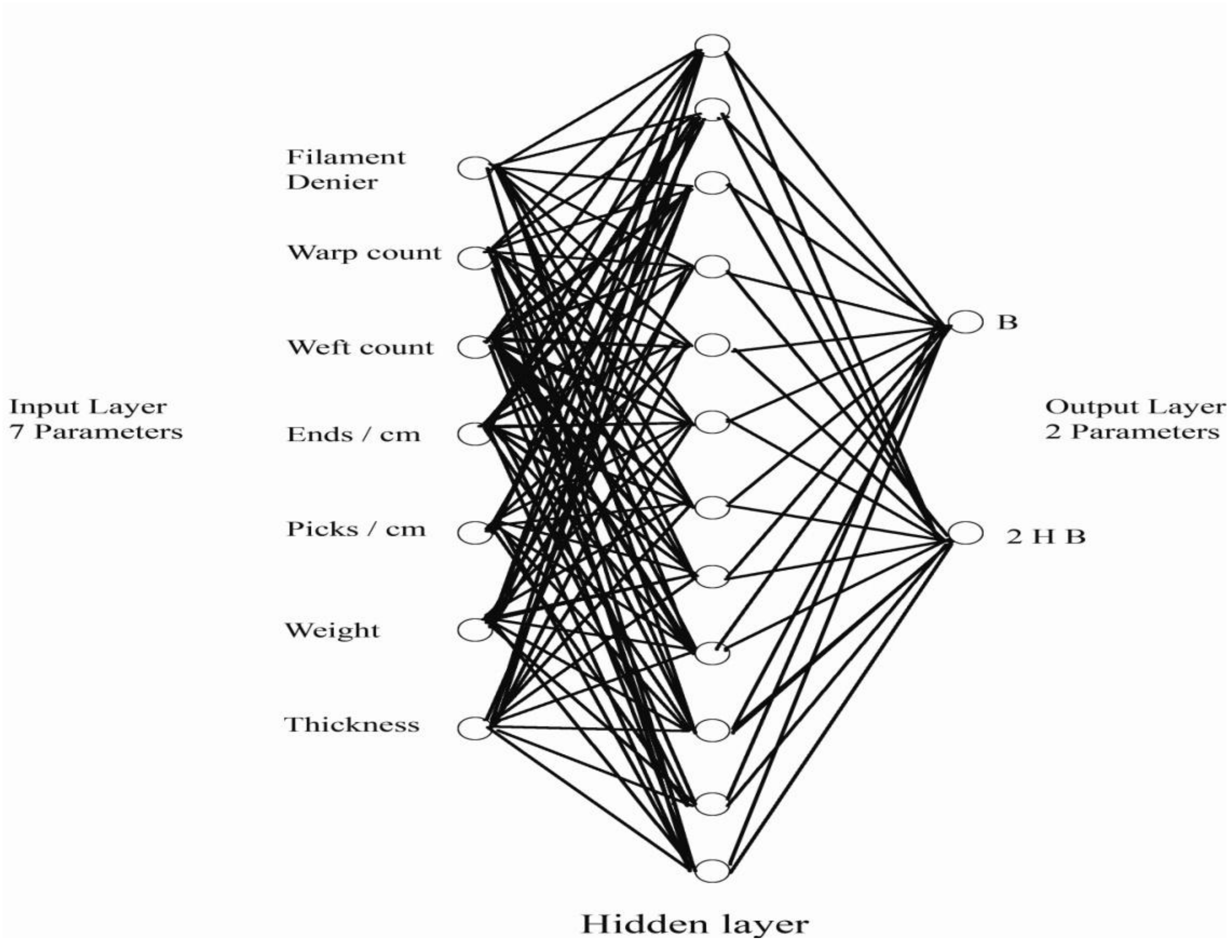

Figure 2. Training network

In this evaluation, the ANN toolbox of MATLAB ® is used for network development. Fifteen different plain woven fabrics are used as the training input and 15 x 02 matrixes of performance parameters is used as the output data for the network to be trained. The learning rate and momentum factors used, etc., are default value in Mat lab ANN toolbox, and the mean square error goal is kept as 0.001.The learning graph of the training set is shown in figure 3.

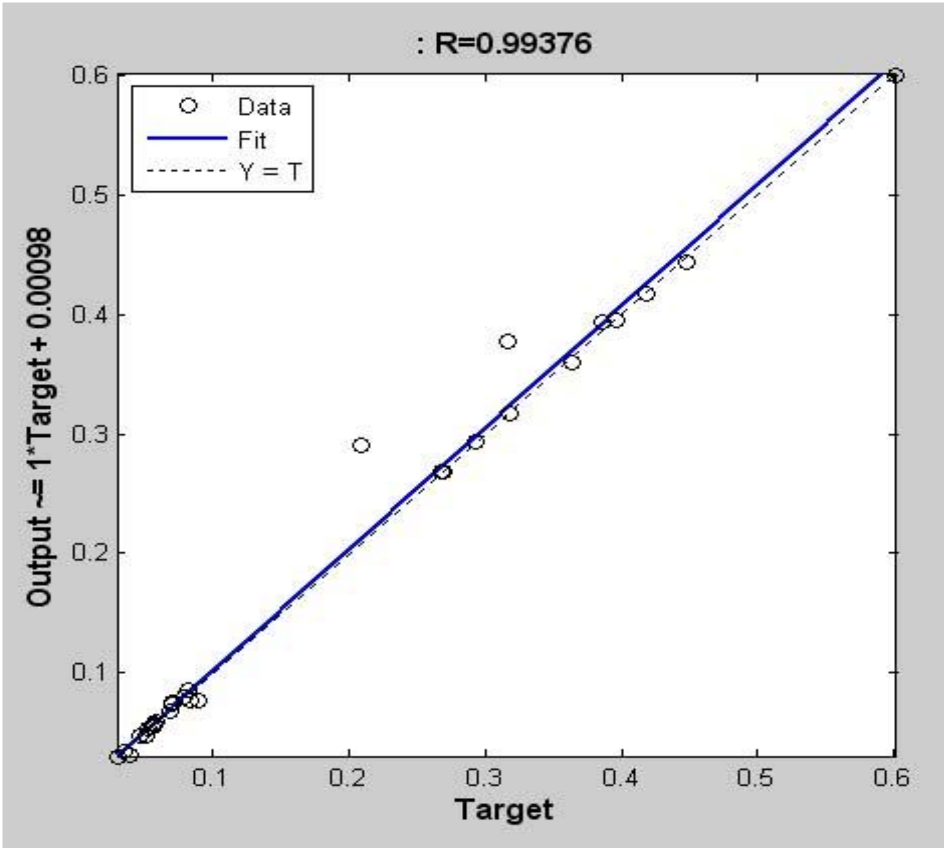

Figure 3. Learning graph

3. RESULTS AND DISCUSSION

The real performance of network was measured by the training and validation test sets. In this study of neural network, the system developed with 12 neuron of one hidden layers found the best prediction results with the R value of 0.99376 as shown in Figure 3. This was acieved at approximately 9 iterations of 9000 training cycles.In the test set,15 samples were considered covering the possible range of KESF bending and moment results.A coefficient of correlation was designed for fine results and more effectiveness of the network model. A graph of the neural network Vs KESF bending results is shown in Figure 4 between the predicted values of neural network value and actual values of KESF values which is highly judged as the predicted data with the R^2 value of 0.970. Bending moment of the coefficient of correlation values were very impressively agreed in between both the values with R^2 value of 0.951 as shown in Figure 5.The correlation coefficient between the bending rigidity and bending moment values of neural network model and KESF system were graphically represented in Figure 6 and Figure 7.And both of which have shown appreciable results. The MAPE (%) values of the best performing model were 7.7808 and 5.3878 of B and 2HB respectively.

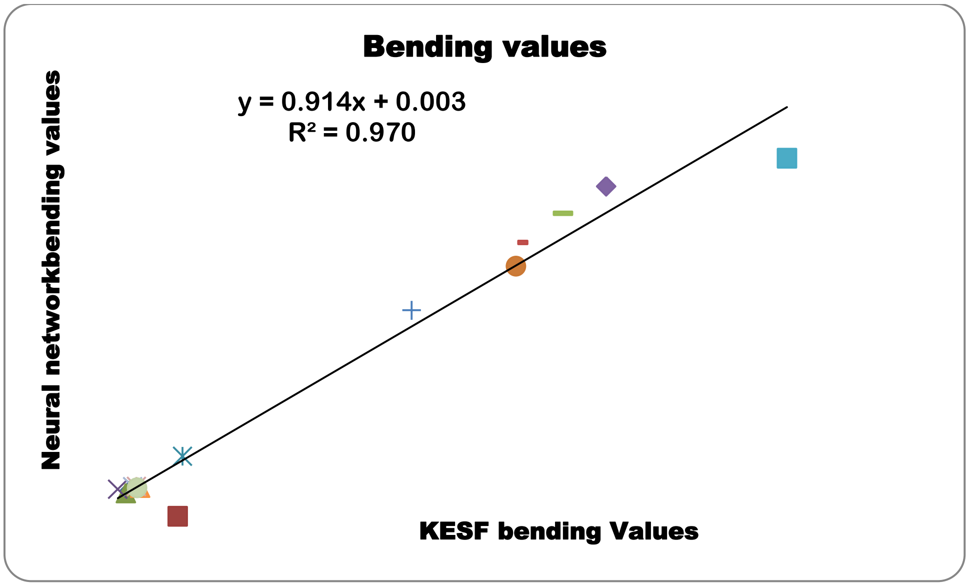

Figure 4. The coefficient of correlation between the bending values of neural network and KESF values

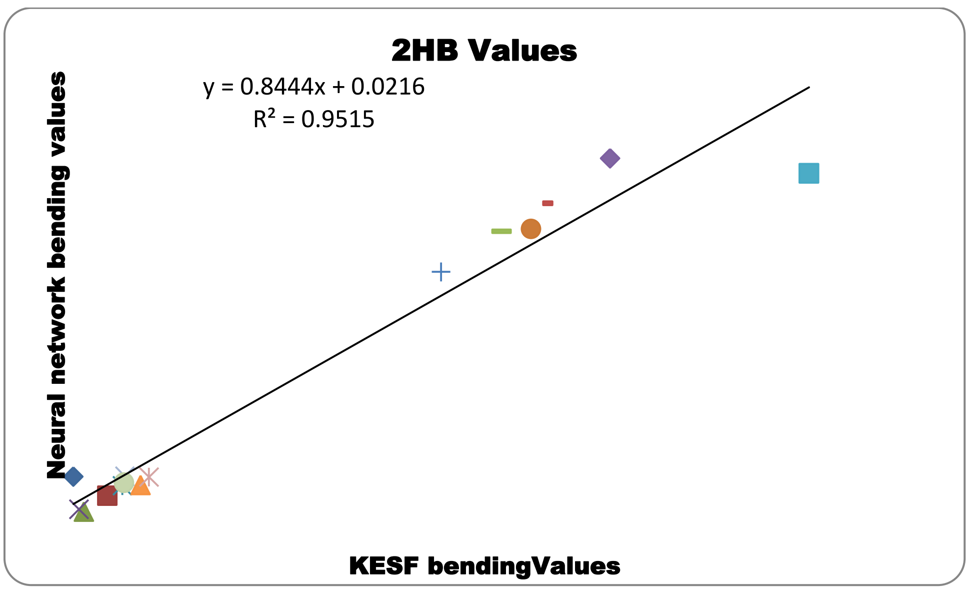

Figure 5. The coefficient of correlation between the 2HB values of predicted neural network and KESF values

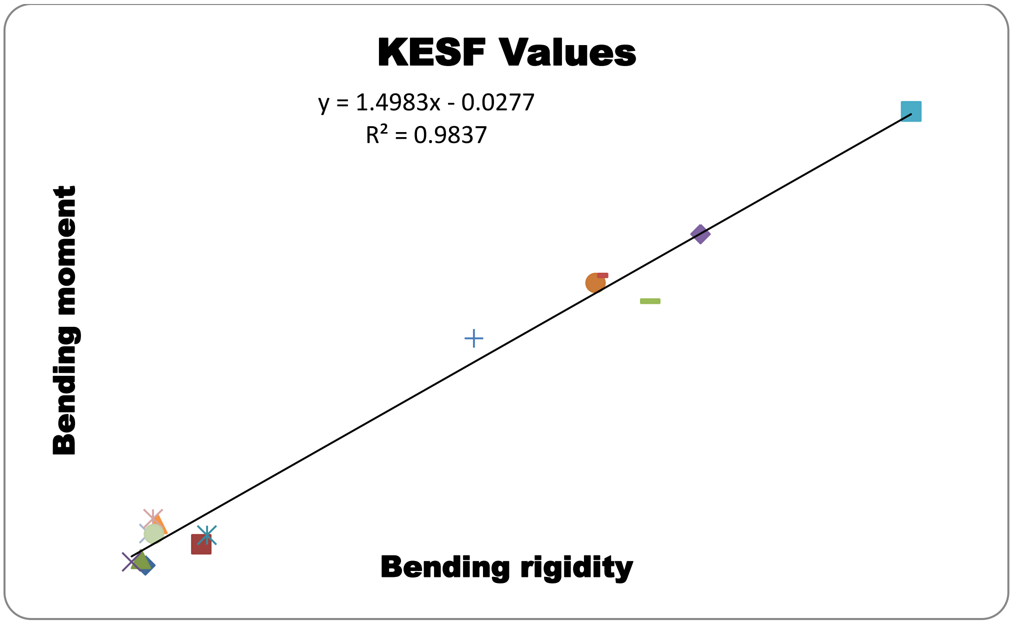

Figure 6. The coefficient of correlation between the bending rigidity values and bending moment values of KESF

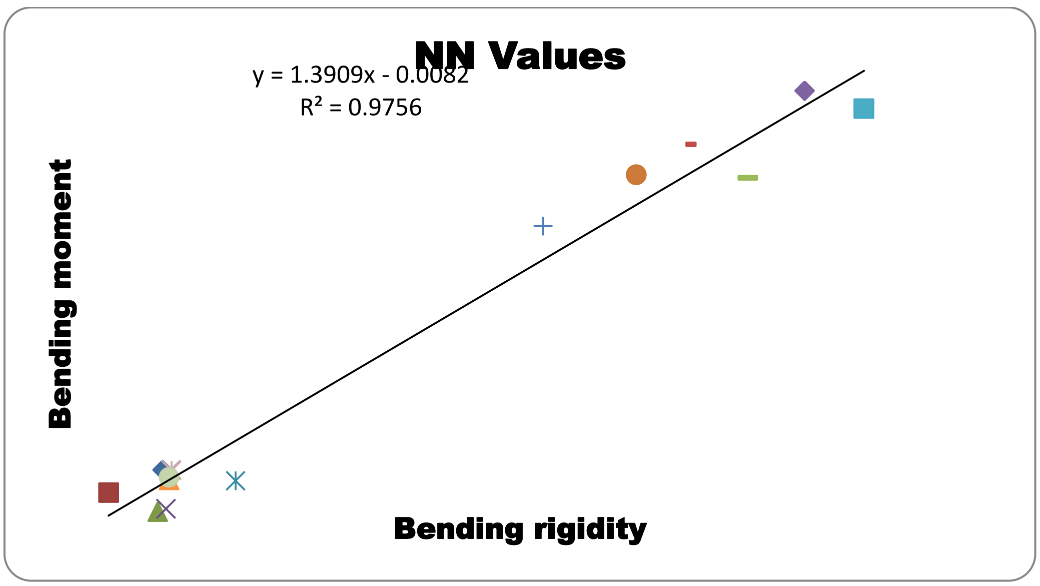

Figure 7. The coefficient of correlation between the bending rigidity values and bending moment values of neural network

4. CONCLUSIONS

Using neural network system, we investigated the fabric parameters of warp, weft count, ends/cm, picks/cm, filament denier, weight, thickness which are the input parameters. The output results of bending rigidity, bending moment have shown high correlation coefficient values ($R^2 < 0.9$). This research study shows that intelligent artificial neural network can be used to predict the bending rigidity, bending moment of the plain woven fabrics with highly satisfactory results. This method of determining the bending rigidity is very useful for the garment industries. A good predictability of the properties by the model has been observed was 7.7808% and 5.3878 of B and 2HB. The correlation coefficient of bending rigidity between the KESF values and predicted values was high at 0.97.An appreciable correlation of bending moment between the KESF values and predicted values was at 0.95.The coefficient correlation between the bending rigidity and bending moment of KESF value and NN values are very good appreciable results at 0.98 and 0.97 respectively.

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