World Applied Sciences Journal 9 (2): 167-177, 2010
ISSN 1818-4952

Application of Artificial Neural Nets in Carpet Thickness Loss Prediction

[1]A.R. Moghassem, [2]A.A. Gharehaghaji, [2]S. Shaikhzadeh Najar, [3]M. Palhang and [4]M. Shanbeh

[1]Faculty of Engineering, Islamic Azad University, Sciences and Research Branch (IAU), Tehran, Iran
[2]Department of Textile Engineering, Amirkabir University of Technology (AUT) Tehran, Iran
[3]Department of Electrical and computer Engineering, Isfahan University of Technology (IUT), Isfahan, Iran
[4]Department of Textile Engineering, Isfahan University of Technology (IUT), Isfahan, Iran

Abstract: Many factors such as constructional parameters and quality of the fibres affect carpet performance in thickness loss after dynamic loading. Therefore, developing a predicting model of the carpet properties before manufacturing will be helpful in obtaining quality product. In this regard, eighteen carpets were manufactured with different knot density (Persian knot), pile height and content of slipe wool and were tested under four cyclic impacts. Thickness reduction of the carpets was measured after loading. This parameter was predicted using back-propagation artificial neural network based on scale conjugate gradient (SCG) learning method and statistical regression. Results indicated that, the R-square of ANN and regression model for predicting testing data was 93.70 percent and 81.60 percent respectively. Based on the proposed ANN model, the dominant parameter on thickness loss found to be knot density. Also, according to the best regression equation, carpet thickness and knot density are the most effective factors on carpet thickness change.

Key words: Artificial neural network · Scale conjugate gradient · Statistical regression · Wool fibres · Carpet thickness loss

INTRODUCTION

Hand woven carpet is one of the most important products in the textile industry. There are many factors that, affect the quality and performance of a carpet [1]. The effect of these parameters on carpet properties has been studied by researchers. Studies showed that, the extent of thickness loss of carpet in the initial months of use was more in comparison with change occurred in later months. Besides, in previous works a linear relationship was found between the thickness and the logarithm of the number of impacts on the carpet or the number of people walking over the carpet [2-5].

By studying the effect of knot types, it is shown that, the percentage of thickness loss in carpet under a static load for the samples woven by symmetrical, asymmetrical and paired knots are 42%, 46% and 56% respectively [6].

Also, previous studies showed that, a dense carpet and short pile will result in less compression and less thickness loss after recovery. Also, previous works indicate that, change in pile height after recovery increased with increase in its height [2, 3]. The variation in pile height and knot density, results in a change in the amount of elastic recovery of the pile. Having more pile density, also improves the elastic recovery of piles, which in return reduces the thickness loss of the carpet [7, 8].

Since, interaction between effective factors and carpet performance is very complex, it is useful to know and model this relationship for further achievements in quality product. Artificial neural networks (ANN) have been employed extensively in various textile disciplines ranging from yarn manufacturing, fabric formation and fabric properties [9].

For example, Beltran *et al.* predicted the pilling tendency of wool knits using ANN model [10]. A study was carried out by Tokarska for predicting the permeability features of woven fabrics [11]. Artificial neural network model has also been used for predicting cotton yarn hairiness [12]. This algorithm was also used to predict the sewing performance of fabrics in apparel industry [13].

Corresponding Author: A.R. Moghassem, Faculty of Engineering, Islamic Azad University, Science and Research Branch (IAU), Tehran, Iran
E-mail: armogh@yahoo.com, Tel: 0098-021-44869726, Fax: 0098 – 21-44869728

Statistical approach for establishing a relationship between dependent and independent variables has been used frequently in various textile applications. Ureyen and Kadoglu used regression analysis to predict ring cotton yarn properties [14]. Many researchers have compared the capability of artificial neural network and regression [15-18].

In the present study two different methodologies, namely artificial neural network (ANN) and statistical regression were used to evaluate the relationship between thickness loss of the carpet and some structural and experimental factors. The predicting model was developed on the basis of carpet constructional parameters that are knot density, pile height, content of slipe wool and testing parameter which is number of cyclic impacts. These factors were chosen due to their importance and detrimental effects on the recovery behavior of pile yarns in carpet. Then, prediction performance of these models was assessed to get the best results.

MATERIALS AND METHODS

Several skins had been selected from an Iranian wool breed called Naini. Wool fibres were removed from parts of the skins as virgin wool. Then, tanning solution was applied on the other skins to remove slipe wool. Three yarn samples that are used as pile yarns were spun with 0%, 30% and 100% of slipe wool fibres content. Yarn count and yarn twist were chosen to be 152tex and 200turns/m that are conventional in hand woven carpet industry [19]. Characteristics of the extracted wool fibres have been shown in Table 1.

In order to investigate the effects of knot density, carpet thickness and percentage of slipe wool on the performance of hand woven carpet, 18 samples were prepared according to the specifications shown in Table 2. Warp yarn of the samples was from cotton fibres in accordance with the material that is used in hand woven carpet industry. Thick and thin weft yarns were from cotton-polyester blend fibres. Specifications of the pile yarns warp yarn, thin and thick weft yarns that are used in carpet weaving have been depicted in Table 3. A schematic of structrul elements in hand woven carpet has been shown in Figure 1.

In the present study, knot density and pile height were considered as variables in manufacturing of samples due to their great effect on pile recovery behavior. Since, carpet thickness is one of the input parameters for artificial neural networks and statistical regression modelling pile height was changed to get samples with different thickness values.

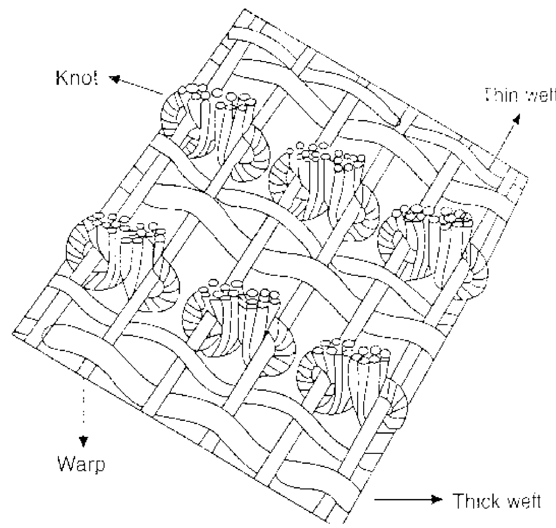

Fig. 1: A schematic of structural elements in hand woven carpet

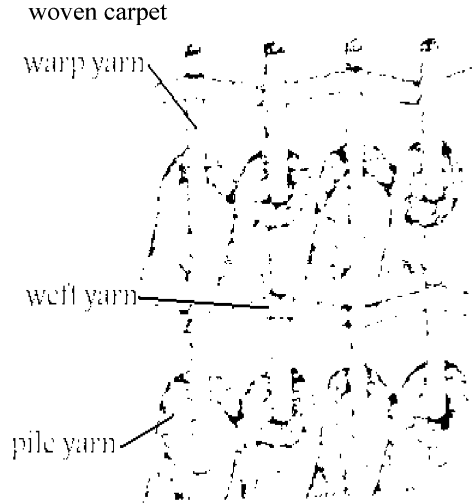

Fig. 2: A schematic of Persian knot

All the samples were woven using asymmetric knot (Persian knotting) which is conventional knotting method in Isfahan. A schematic of Persian knot has been shown in Figure 2. The only applicable method for changing knot density while other factors remain constant was changing knotting method that is adopted for this work to get carpet samples with different amount of knots per unit area.

Nevertheless, nowadays slipe wool is mixed with virgin wool and used as pile yarn in spite of the damaging effects of chemical process on the slipe wool which affect the quality of carpet [8, 19]. In this study, content of slipe wool is considered as one of the variables to further emphasis on destroying impact of the slipe wool on the quality of hand woven carpet.

Table 1: Characteristics of the virgin and slipe wool used in the structure of pile yarn

Swelling in diameter (%)	Drop in elongation (%)	Drop in tenacity (%)	Elongation (%)	Tenacity (cN/dtex)	Diameter (micron)	Crimps/2.5cm	Length (mm)	Breed of wool
				Virgin wool fibre			Naini	
----	-----	-----	39.11	1.40	28.22	2.90	109.54	Average value
------	-------	--------	3.76	3.45	33.66	7.05	24.55	CV%
				Slipe wool fibre			Naini	
5.74	7.31%	22.42%	36.37	1.04	29.84	2.70	105.54	Average value
15.23	8.55	13.43	4.11	3.78	32.11	6.75	23.22	CV%

Table 2: Specifications of hand woven carpets

		Carpet thickness(mm)		Knots/6.5cm	
Sample No	Content of pile yarn	Average value	CV%	Average value	CV%
1	100%slipe wool	16.50	2.12	20	1.43
2	100%virgin wool	16.50	3.01	20	1.56
3	30%slipe&70%virgin wool	16.50	2.26	20	1.23
4	100%slipe wool	13.50	2.45	20	1.95
5	100%virgin wool	13.50	2.89	20	1.37
6	30%slipe&70%virgin wool	13.50	2.76	20	1.11
7	100%slipe wool	9.00	2.73	20	1.75
8	100%virgin wool	9.00	2.35	20	1.82
9	30%slipe&70%virgin wool	9.00	2.85	20	1.40
10	100%slipe wool	16.50	2.54	40	1.29
11	100%virgin wool	16.50	3.13	40	1.74
12	30%slipe&70%virgin wool	16.50	2.92	40	1.94
13	100%slipe wool	13.50	2.67	40	1.37
14	100%virgin wool	13.50	3.41	40	1.95
15	30%slipe&70%virgin wool	13.50	2.34	40	1.53
16	100%slipe wool	9.00	2.11	40	1.66
17	100%virgin wool	9.00	2.37	40	1.31
18	30%slipe&70%virgin wool	9.00	2.59	40	1.12

Table 3: Specifications of pile yarn, warp yarn, thin and thick weft yarns used in carpet samples construction

	Linear density of ply yarn (tex)		Twist of ply yarn (twist/m)		Twist of single yarn (twist/m)		
No. Of. Plies	Average value	CV%	Average value	CV%	Average value	CV%	Pile yarn usage
2	363.94	2.56	85.00	4.11	165	2.36	100%Slipe wool
2	357.44	3.21	90.00	3.87	167	3.11	100%Virgin wool
2	405.20	3.72	75.00	4.67	160	2.14	30%Slipe&70%Virginl wool
2	40.03	2.18	400.00	3.79	----	----	Thin weft yarn
4Thread ×10 Ply	1551.90	3.49	280.00	2.57	124	2.73	Thick weft yarn
3Thread×3Ply	317.72	3.78	600.00	4.82	---	----	Warp yarn

After preparing of carpet samples, thickness loss which indicates the elastic recovery of pile yarns have been assessed under dynamic loading for 50, 100, 500, 1000 cyclic impacts by Shirley Dynamic Loading Machine according to British Standard 4052 (ISO 2094). Sample thickness measured before and after each test immediately for 10 random areas on the carpet by Shirley Digital Thickness Gauge according to British Standard 4051 (ISO 1765). Consequently, thickness loss of the samples was calculated after each test using these values.

All the tests were carried out in 65 percent RH and 20°C temperature. The results of the experiment have been shown in Table 4. A statistical analysis (one way ANOVA) was carried out to analyze the differences between the test results for different groups of samples at 95 percent level. Also, a multiple range test method (Tukey) was performed for a better analysis within groups. Details of the analysis have been reported in Table 5.

Artificial Neural Network Model: Artificial neural networks (ANN) have been inspired by the human brain. There are many different neural network (NN) structures and learning algorithms available in the literature [12, 13, 18], but among these, feed-forward multi-layer networks have been extensively and successfully applied to many function approximation and modelling problems. Therefore, the feed-forward multi-layer network was developed in the present study.

A typical multilayer neural network is shown in Figure 3. Here, one or more hidden layers can be sandwiched between the input and output layers.

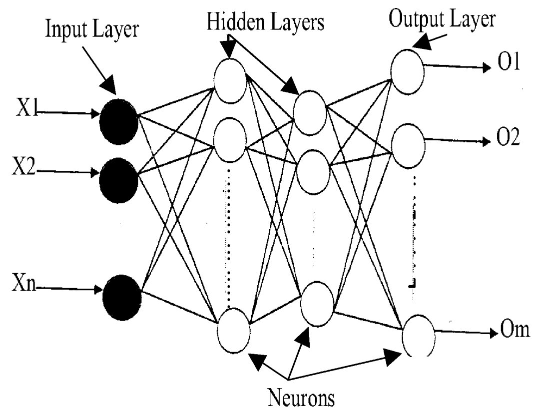

Fig. 3: A schematic of multilayer feed forward neural network with two hidden layers

Table 4: Thickness change of the carpet samples after dynamic loading

Number of impacts							
1000		500		100		50	
Samples code	Thickness change	Samples code	Thickness change	Samples code	Thickness change	Samples code	Thickness change
55	2.43	37	2.28	19	2.18	1	1.89
56	1.72	38	1.21	20	1.03	2	0.70
57	2.10	39	1.73	21	1.48	3	1.32
58	2.31	40	2.14	22	2.01	4	1.29
59	1.24	41	1.08	23	0.76	5	0.49
60	2.04	42	1.56	24	1.39	6	1.19
61	1.72	43	1.43	25	1.17	7	1.06
62	1.12	44	0.92	26	0.65	8	0.40
63	1.21	45	0.97	27	0.79	9	0.51
64	2.22	46	1.78	28	1.59	10	1.12
65	0.92	47	0.71	29	0.36	11	0.25
66	2.19	48	1.75	30	1.36	12	0.88
67	1.27	49	1.07	31	0.76	13	0.53
68	0.87	50	0.69	32	0.35	14	0.24
69	1.15	51	0.95	33	0.51	15	0.49
70	1.16	52	0.93	34	0.67	16	0.44
71	0.66	53	0.40	35	0.28	17	0.20
72	1.02	54	0.73	36	0.48	18	0.38

Table 5: Results of the statistical analysis (ANOVA test)

Dependent Variable: thickness loss

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	51.16[a]	71	0.72	3.77E3	.00
Intercept	181.73	1	181.73	9.51E5	.00
Content of slipe wool(CSW)	13.96	2	6.98	3.65E4	.00
Carpet thickness(CT)	10.57	2	5.28	2.76E4	.00
Knot density(KD)	9.15	1	9.15	4.79E4	.00
Number of impacts(NI)	11.94	3	3.98	2.08E4	.00
(CSW)*(CT)	1.75	4	0.43	2.30E3	.00
(CSW)*(KD)	0.70	2	0.35	1.84E3	.00
(CSW)*(NI)	0.14	6	0.02	126.06	.00
(CT)*(KD)	0.82	2	0.41	2.16E3	.00
(CT)*(NI)	0.22	6	0.03	192.50	.00
(KD)*(NI)	0.04	3	0.01	81.34	.00
(CSW)*(CT)*(KD)	0.98	4	0.24	1.293E3	.00
(CSW)*(KD)*(NI)	0.14	6	0.02	129.32	.00
(CT)*(KD)*(NI)	0.21	6	0.03	190.24	.00
(CSW)*(CT)*(KD)*(NI)	0.46	24	0.01	100.36	.00
Error	0.01	72	0.00		
Total	232.91	144			
Corrected Total	51.17	143			

a. R Squared = 1.00 (Adjusted R Squared =.99)

Each neuron receives a signal from the neurons of the previous layer and these signals are multiplied by separate synaptic weights. The weighted inputs are then summed up and passed through a transfer function, which converts the output to a fixed range of values. The output of the limiting function is then transmitted to the neurons of next layer.

Back-propagation algorithm is the most popular one among the existing neural network algorithms. According to this algorithm, training occurs in two phases, namely a forward pass and a backward pass. In the forward pass, a set of data is presented to the network as input and its effect is propagated, in stages, through different layers of the network. Finally a set of output is produced. The calculation of error vector is done from the difference between actual and predicted outputs according to the following relationships Equation 1 [9, 15].

$$E = \sum_{j=1}^{p} E_j \tag{1}$$

Where E is the error vector, E_j the error associated with the j the pattern; and P the total number of training patterns. The expression of E_j is given in the Equation 2.

$$E_j = 1/2 \sum_{r=1}^{s} (T_r - O_r)^2 \tag{2}$$

Where T_r and O_r are the target output and predicted output respectively at output neuron r; and s, the total number of output neurons. In the backward pass, this error signal is propagated backwards to the neural network and the synaptic weights are adjusted in such a manner that the error signal decreases with each iteration process [9, 15].

In this work, training was done with the back-propagation based on scaled conjugate gradient (SCG) learning algorithm. This algorithm does not perform a line search at each iteration. Scaled conjugate gradient substitutes the line search by a scaling of the step that depends on success in error reduction and goodness of the quadratic approximation to the error. It is motivated by the desire to accelerate the typically slow convergence associated with the gradient descent method while avoiding the information requirements associated with the evaluation, storage and inversion of the Hessian matrix as required by the Newton method [20].

Experiments show that, scale conjugate gradient is considerably faster than Back-propagation Gradient Descent, conjugate gradient algorithm(CG), conjugate gradient algorithm combined with the safeguard quadratic univariate minimization(CGL) and one-step broyden-fletcher-goldfarb-shanno memory-less quasi-newton method (BFGS).

The standard conjugate gradient method was originally developed by Hestenes and Stiefel [20] and the scale conjugate gradient was developed by Moller [21]. This algorithm is a variation of a standard conjugate gradient algorithm.

The core idea of conjugate gradient algorithm is that up to second order, it produces non-interfering directions of search. Minimization in one direction d_t followed by minimization in another direction d_{t+1} imply that the error has been minimized over the whole subspace spanned by d_t and d_{t+1}. The search directions are given by Equation 3.

$$d_{t+1} = -E'(w_{t+1}) + ß_t d_t \tag{3}$$

Where w_t is a vector containing all weight values at time step t and β_t is as following equation 4.

$$ß_t = \left|E'(w_{t+t})\right|^2 - E'(w_{t+1})^T E'(w_t) / \left|E'(w_t)\right|^2 \tag{4}$$

In the standard conjugate gradient algorithm the step size ε_t is found by a line search which can be very time consuming because this involves several calculations of the error or the first derivative. In the Scaled Conjugate Gradient algorithm the step size is estimated by a scaling mechanism thus avoiding the time consuming line search. The step size is given by Equation 5.

$$e_t = \frac{-d_t^T E'(w_t)}{d_t^T s_t + ?_t \left|d_t\right|^2} \tag{5}$$

Where S_t is:

$$s_t = \frac{E'(w_t + s_t d_t) - E'(w_t)}{s_t} \tag{6}$$

ε_t is the step size that minimizes the second order approximation to the error function. S_t is a one sided difference approximation of $E''(w_t)\, d_t$. Also, λ_t is a scaling parameter whose function is similar to the scaling parameter found in Levenberg-Marqurdt methods. λ_t is in each iteration raised or lowered according to how good the second order approximation is to the real error. The weight update formula is as follow [21] Equation 7.

$$\Delta w_t = e_t d_t \qquad (7)$$

The authors didn't find any research reporting the use of this algorithm in textile disciplines. That is while initial evaluations performed, clearly show the advantages of this algorithm compared with the conventional gradient descent with momentum and gradient descent with variable learning rate algorithms.

As stated in materials and methods section, four parameters were varied in 4, 3, 2 and 3 levels and by considering full factorial design 72 samples were tested. Therefore, 72 pairs of input-output patterns were available from the experiments. These patterns were randomly divided into training and testing sets. 57 data pairs were selected as training set out of 72 input-output data pairs and 15 data pairs as testing set. In the proposed neural network model, the input units were knot density, carpet thickness, content of slipe wool and number of cyclic impacts and the output unit was the thickness loss of the carpet under dynamic loading.

Artificial Neural Network Parameters: It is known that, a feed-forward neural network with only one hidden layer can approximate any function to an arbitrary degree of accuracy. However, some workers have used more than one hidden layer and have obtained better results [15].

In this work, 11 different network structures with one and two hidden layer(s) were assessed. The number of neurons in hidden layer(s) varied from 4 to 8. Data normalizing was carried out in such away that they had zero mean and unit standard deviation.

Tangent hyperbolic and sigmoid activation function was used in neurons of first and second hidden layers and linear activation function was used for single output neuron. In programming the network architecture, the neural network toolbox of MATLAB software was used for training and testing the models involve.

As mentioned above, 11 different network structures were selected. To get the best structure, after training, each of them with predetermined parameters was saved and then the network performance on training and testing sets was assessed. Two parameters, namely the Means Square Error (MSE) and R^2-value coefficient were used to characterize the model performance. Weight decay technique was used to prevent over fitting of networks. In this concern the mean square error regularization (MSEREG) performance function was used instead of common mean square error function [17].

Statistical Regression Models: The statistical modeling is the most popular method for duration second half of the twentieth century of period [14]. Statistical modeling has been used frequently in textile disciplines especially yarn properties [14-16].

In this study, three kinds of multiple linear regression models consisting of linear regression variables (Equation 8), linear and interaction regression variables (Equation 9) and linear and quadratic regression variables (Equation 10) were used to predict thickness loss of carpet. These equations were used to find the best predictive model because it was not clear which kind of relationships are between the mentioned parameters.

In these equations, Y is thickness loss of carpet (mm); X_1 is percentage of slipe wool; X_2 is carpet thickness (mm); X_3 is knot density (knots/6.5cm) and X_4 is numbers of cyclic impacts. Total of 57 samples, the same number that is used in ANN models, were used to develop the predicting model. Statistical analysis was performed using the SAS software.

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4 \qquad (8)$$

$$\begin{aligned} Y = \beta_0 &+ \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X \\ &+\beta_5X_1X_2+\beta_6X_1X_3+\beta_7X_1X_4 \\ &+ \beta_8X_2X_3 + \beta_9X_2X_4 + \beta_{10}X_3X_4 \end{aligned} \qquad (9)$$

$$\begin{aligned} Y = \beta_0 &+ \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X + \\ &\beta_5X_1^2 + \beta_6X_2^2 + \beta_7X_3^2 + \beta_8X_4^2 \end{aligned} \qquad (10)$$

RESULTS AND DISCUSSION

Artificial Neural Network Model: Results indicated that, the neural network model with two hidden layers, seven neurons in first and second hidden layers gives the best prediction results after 90 epochs. Figure 4 shows the schematic diagram of artificial neural network model developed for this work.

Statistical Regression Model: The developed equations from the training data using the backward method are given in equations 11-13. There are three broad categories i.e. forward selection, backward elimination and stepwise regression for evaluating regressors. According to the literature, backward elimination is often a very good variable selection procedure.

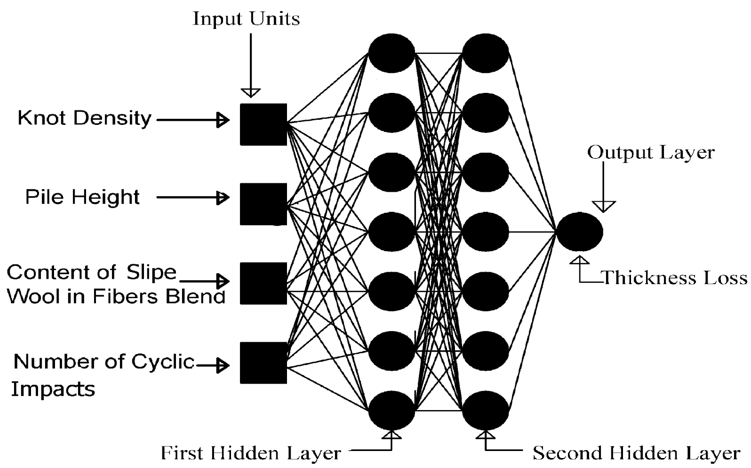

Fig. 4: A schematic diagram of proposed A.N.N model

Table 6: Analysis of variance for testing significance of first regression model

Source	Degree of Freedom (df)	Sum of Square	Mean Square	F_{value}	P_r>F
Model	4	92.57	23.14	327.90	<0.00
Error	53	3.74	0.07		
Corrected Total	57	96.31			

Table 7: Analysis of variance for testing significance of second regression model

Source	Degree of Freedom (df)	Sum of Square	Mean Square	F_{value}	P_r>F
Model	4	92.83	23.20	353.39	<0.00
Error	53	3.48	0.06		
Corrected Total	57	96.31			

Table 8: Analysis of variance for testing significance of third regression model

Source	Degree of Freedom(df)	Sum of Square	Mean Square	F_{value}	P_r>F
Model	5	92.92	18.58	285.37	<0.00
Error	52	3.38	0.06		
Corrected Total	57	96.31			

It is particularly favoured by analysts who like to see the effect of including all the candidate regressors (independent variables), just so that nothing 'obvious' will be missed. Besides, the backward elimination algorithm is often less adversely affected by the correlative structure of the regressors than is forward selection and thus backward elimination is preferred to use here.

$$Y = 100.28*10^{-3}X_2 + 0.49*10^{-3}X_1X_2 - 0.08*10^{-3}X_2X_3 + .05*10^{-3}X_2X_4 \quad (11)$$

$$Y = 100.28*10^{-3}X_2 + 0.49*10^{-3}X_1X_2 - 0.08*10^{-3}X_2X_3 + .05*10^{-3}X_2X_4 \quad (12)$$

$$Y = 14.11*10^{-3}X_1 + 94.45*10^{-3}X_2 + 1.07*10^{-3}X_3 + 0.72*10^{-3}X_4 - 0.07*10^{-3}X_1^2 \quad (13)$$

The analysis of variance of models has been brought in Tables 6 - 8 respectively. The F-value of all models clearly shows the significance of the obtained models at 5 percent of significance level. The performance of these models is given in Table 9. The results show that,

Table 9: The performance of three kinds of regression models

Regression models (regression variables)		R - square	M.S.E	Adj R-square
1	Linear	0.82	0.07	0.81
2	Linear, interaction	0.84	0.06	0.83
3	Linear, quadratic	0.84	0.06	0.83

Table 10: Comparison between the prediction powers of four models on training and testing data

			Training set					Testing set		
			Prediction Error (%)					Prediction Error (%)		
Models	M.S.E	R^2-Value	Min	Max	Mean	M.S.E	R^2-Value	Min	Max	Mean
Neural Network	0.015	0.96	0.002 (0.19)	0.37(29.00)	11.18	0.01	0.93	0.01(0.93)	0.22 (14.8)	11.88
Reg (Linear)	0.06	0.82	0.008 (0.87)	0.67 (56.7)	26.31	0.07	0.73	0.00(0.11)	0.45(48.91)	26.78
Reg (Linear, interaction)	0.05	0.84	0.001 (0.21)	0.70 (59.00)	19.72	0.07	0.74	0.01(2.15)	0.61 (45.59)	24.66
Reg (Linear, quaratic)	0.06	0.84	0.001 (0.08)	0.59 (50.00)	25.41	0.05	0.81	0.02(2.15)	0.34 (25.00)	23.80

the regression model consists of the linear and quadratic variables has the best performance among all of the three proposed models, but the difference between this model and a model containing linear and interaction variables is marginal.

Prediction Performance of Artificial Neural Network and Multiple Linear Regression Models: Table 10 shows the results of comparison of prediction performance of regression models and artificial neural network model. For comparison, all of the three regression models were also subjected to the testing and training data the same procedure that is carried out on ANN model as well.

It is resulted that, among regression equations, equation 3 that is the model with linear and quadratic regression variables results in the best performance. This model has the 0.81 and 0.84 R^2-value in predicting the test and trained data respectively. Nonlinearity between the independent variables and the dependent variable will lead to a reduction in the accuracy of the multiple linear regressions with linear components compared to other models.

Table 10 shows that, the prediction performance (R^2- value) of artificial neural network in training and testing data is 0.96 and 0.93 respectively. The predictive performance of the neural network compared with the best regression model revealed that, the ability of the neural network to predict the testing data is much better than regression model combined with this model.

The difference between the R^2-value and the MSE of two models that are Neural Network and Regression (linear, quadratic) in predicting testing data set is 12 percent and 0.03 respectively. Also, the predictive power of ANN model is much better in training data. The difference between R^2-values and MSE of two models is 11.10 percent and 0.04. This table reveals that, the minimum error for ANN model for testing data is as low as 0.93 percent and for the regression model with quadratic and linear components this error is 2.46 percent. The maximum error for ANN and the best regression model is 14.80 percent and 62.10 percent respectively. The property of testing samples and the predicting ability of all models has been shown in Table 11 and Table 12 respectively.

Analysis of the Impact of Input Parameters on Thickness Variation of Hand Woven Carpets: The relative contribution of each of the carpet constructional parameters and number of cyclic impacts has been evaluated using artificial neural network model and the best multiple linear regression model. The significance and direction of each input parameter is determined by considering the t-value associated with the estimated coefficients in statistical regression model.

However, for the ANN model, an input significance test was conducted by eliminating one designated input from the model at each time. The neural network was trained again and the prediction was made from the testing data. The increase in the mean squared error of prediction as compared to that parent network was considered as the indicator of importance of the eliminated input. Ranking of input parameters according to the regression and ANN models are shown in Tables 13 and 14 respectively.

Table 11: Specifications of samples selected for testing set

Sample number	Slipe wool (%)	Pile height (mm)	Knot density (knot/6.5cm)	Number of cyclic impacts
1	0	13.50	20	50
2	100	16.50	40	50
3	30	13.50	40	50
4	100	9.00	40	50
5	0	16.50	20	100
6	30	16.50	20	100
7	0	9.00	20	100
8	30	16.50	40	100
9	30	9.00	40	100
10	100	13.50	20	500
11	0	13.50	20	500
12	100	13.50	40	500
13	100	9.00	40	500
14	30	13.50	20	1000
15	0	16.50	40	1000

Table 12: The prediction error of testing samples

		Prediction error (mm)							
		Artificial Neural Network		Regression (Linear)		Regression (Linear, quadratic)		Regression (Linear, interaction)	
Sample	Thickness loss (mm) Experimental value	Absolute Error (%)	Predicted	Absolute Error (%)	Predicted	Absolute Error (%)	Predicted	Absolute Error (%)	Predicted
1	0.49	28.57	0.63	77.55	0.87	65.31	0.81	79.59	0.88
2	1.12	15.17	1.29	18.75	1.33	15.18	1.29	13.39	1.27
3	0.49	6.12	0.46	18.36	0.58	40.82	0.69	16.32	0.57
4	0.44	15.91	0.51	36.36	0.60	31.82	0.58	56.82	0.69
5	1.03	15.53	0.87	16.50	1.20	8.85	1.13	8.74	1.12
6	1.48	14.86	1.26	5.41	1.40	1.35	1.5	7.42	1.37
7	0.65	9.23	0.59	27.69	0.47	51.16	0.43	6.15	0.61
8	1.36	8.82	1.48	24.32	0.91	25.00	1.02	45.59	0.74
9	0.48	6.25	0.45	62.5	0.18	35.41	0.31	14.58	0.41
10	2.14	5.14	2.03	13.08	1.86	14.49	1.83	12.15	1.88
11	1.08	7.41	1.16	11.11	1.20	5.56	1.02	12.04	1.21
12	1.07	14.01	1.22	28.04	1.37	24.30	1.33	28.04	1.37
13	0.93	1.08	0.94	0.00	0.93	2.15	0.91	2.15	0.91
14	2.04	8.33	1.87	13.24	1.77	7.84	1.88	12.75	1.78
15	0.92	21.73	1.12	48.91	1.37	40.22	1.29	41.30	1.3
Mean Absolute Error (%)	-----	11.88	------	26.78	------	24.66	-----	23.80	-----

Table 13: Ranking of input parameters according to artificial neural network models

Model	Artificial Neural Network	
Input parameter	M.S.E (after eliminating)	Rank
Carpet thickness	0.09	4
The percentage of slipe wool	0.12	3
Knot density	0.16	1
Numbers of cyclic impacts	0.12	2

Table 14: Ranking of input parameters according to multiple linear regression involve linear and quadratic regression variables

Input parameters	t-value	Rank
Carpet thickness	+13.20	1
Knot density	-8.74	2
Numbers of cyclic impacts	+8.51	3
(The percentage of slipe wool)^1	+4.08	4
(The percentage of slipe wool)^2	-2.33	5

Table 13 indicates that, according to the ANN model knot density and numbers of cyclic impacts are the major contributing parameters to the thickness loss of carpet in the order of descending importance. Table 14 shows that, carpet thickness and knot density have the major effect on thickness loss of carpet in regression model.

Results of predictive regression models show that, the percentage of slipe wool in pile yarn at the level that is used in this work has the least impact on thickness loss but the ANN model show that, the carpet thickness has the least impact. This difference in ranking may attributed to the non-linear relationship between the input parameters and thickness loss of carpet. Furthermore, the regression model with non-linear parameters doesn't have any success in this subject.

The results clearly show that, the capability and performance of ANN method for developing the predictive models is due to intrinsic nonlinearity of this algorithm. The proposed regression models probably fail to discover this non-linear relationship, resulting in lack of predictive power and relative lower accurately. Finding one specific regression model that fits well is time consuming process specially when there is not any clear relationship between input and output parameters. This demonstrates the advantages of ANN when compared with regression modeling.

Effects of percentage of slipe wool, carpet thickness (pile height), knot density and number of cyclic impact have been predicted as well by two models (Table 13). Based on the experimental data, higher slipe wool content in the pile yarn leads to more reduction in pile height after applying compressive load and poor elastic recovery after removing the load. Dense carpet samples give less compression and less thickness loss after recovery.

This study shows that, an increase in pile height improves the compressibility of the carpet and decreases its elastic recovery. Consequently thickness loss of the carpet increases by increase in the number of impacts on carpet surface.

CONCLUSION

The thickness loss of hand woven carpet has been predicted using two methodologies, namely artificial neural network and multiple regressions. Knot density (Persian knot), carpet thickness, the percentage of slipe wool and numbers of cyclic impacts in testing were considered as inputs for predictive models. Multiple linear regression models were used in three different kinds of equations. One of them was consisted of linear regression variables and two of them were consisted of interaction-linear and quadratic-linear regression variables respectively. The results show that, the prediction performance of the statistical regression model with quadratic-linear components is the best followed by interaction-linear components and the linear models. The mean square error of the best regression model for prediction the testing set was 0.05. Based on the results, prediction performance of ANN model is much better than statistical model with quadratic components. The difference between the R^2-value and mean square error (MSE) of two models in predicting testing data was 11.10 and 0.04 percent respectively. The results suggested that scale conjugate learning algorithm of ANN model is a powerful algorithm in prediction of thickness loss of hand woven carpet.

REFERENCES

1. Tavassoli, M.S. and R. Rangbar Pazoki, 1997. Carpets and Non-Woven. Tehran, Amir Kabir Publishing Ltd.
2. Cusick, G.E. and S.R.K. Dawber, 1964. Loss of Thickness of Carpet in Floor Trials, J. Text. Inst., 55: 531-536.
3. Onions, W.J., 1967. An Assessment of Methods of Test of Carpets for Flattening; Change of Appearance and Long-term Wear. J. Text. Inst, 58(10): 487-516.
4. Noonan, K.K., W.J. Lewis, I.D. McFarlane and D.G. Palmer, 1975. The Use of Thickness Measurement During Wear as a Basis for Estimating Carpet Wear-Life. J. Text. Inst., 66(5): 175-179.
5. Ince, J. and M. L. Ryder, 1984. The Evaluation of Carpet Made from Experimental Wools. J. Text. Inst., 75(1): 47-59.
6. Bassam, J., M. Hamidi and B. Nasirirad, 2000. Investigation on the Physical and Mechanical Properties of Symmetric and Un-symmetric Knots and Comparison with Un-allowable Knots, Tehran. Iranian National Carpet Center.
7. Dunlop, J.I. and S. Jie, 1989. The Dynamic Mechanical Response of Carpets. J. Text. Inst., 80(4): 569-578.
8. Mirjalili, S.A. and M. Sharzehee, 2005. An Investigation on the Effect of Static and Dynamic Loading on the Physical Characteristics of Hand-Made Persian Carpets: Part1: The Effect of Static Loading. J. Text. Inst., 96(5): 287-293.
9. Chattopadhyay, R. and A. Guha, 2004. Artificial Neural Networks: Application to Textiles, The Textile Institute.

10. Beltran, R., I. Wang and X. Wang, 2006. Predicting the Pilling Tendency of Wool Knits. J. Text. Inst., 97(2): 129-136.
11. Tokarska, M., 2004. Neural Model of the Permeability Features of Woven Fabrics, Text. Res. J., 74(12): 1045-1048.
12. Babay, A., M. Cheikhrouhou, B. Vermeulen, B. Rabenasolo and J.M. Castelain, 2004. Selecting the Optimal Neural Network Architecture for Predicting Cotton Yarn Hairiness. J. Text. Inst, 96(3): 185-192.
13. Hui, C.L. and S.F. Ng, 2005. A New Approach for Predicting of Sewing Performance of Fabrics in Apparel Manufacturing Using Artificial Neural Networks. J. Text. Inst., 96(6): 401-405.
14. Ureyen, M.E. and H. Kadoglu, 2006. Regressional Estimation of Ring Cotton Yarn Performance From HVI Fiber Properties. Text. Res. J., 76(5): 360-366.
15. Kumar, P. and A. Majumadar, 2004. Predicting the Breaking Elongation of Ring Spun Cotton Yarns Using Mathematical, Statistical and Artificial Neural Network Models. Text. Res. J., 74(7): 652-655.
16. Majumdar, A., M. Kumar Majumdar and B. Sarkar, 2005. Application of Linear Regression, Artificial Neural Network and Neuro-Fuzzy Algorithms to Predict the Breaking Elongation of Rotor-Spun Yarns. Indian. J. Fib & Text. Res., pp: 19-25.
17. Nasiri, N., M. Shanbeh and H. Tavanai, 2005. Comparison of Statistical Regression, Fuzzy Regression and Artificial Neural Network Modeling Methodologies in Polyester Dyeing. In the proceedings of International Conference on Computional Intelligence for Modelling, Control & Automation(CIMCA) Jointly with International Conference on Intelligent Agents Web Technologies and International Commerce(IAWTIC), pp: 505-510.
18. Gharehaghaji, A.A., M. Shanbeh and M. Palhang, 2007. Analysis of Two Modeling Methodologies for Predicting the Tensile Properties of Cotton-Covered Nylon Core Yarns. Text. Res. J., 77(8): 565-571.
19. Hassan Pour, J., 2001. Study on the Chemical Damage of Wool Fibres due to Tanning in Hand Woven Persian Carpet. Isfahan University of Technology, Textile Department, M.Sc. Thesis.
20. Moller, M., 1993. Efficient Training of Feed-Forward Neural Networks. Daimi, Arhus University, Ph.D Thesis.
21. Hestenes, M.R. and S. Stiefel, 1952. Method of Conjugate Gradient for Solving Linear Systems. J. Res. Nat. Bur. Standards, 49: 409-436.