

Predicting the Tensile and Air Permeability Properties of Woven Fabrics Using Artificial Neural Network and Linear Regression Models

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Abstract

The objective of this paper is to investigate the predictability of some of woven fabric properties using artificial neural network (ANN) and regression models. For achieving this purpose, a neural network with three layers was adopted. The regression model was of type a multiple – linear regression one. The independent variables were weft yarn count, twist multiplier and weft density; and the dependent ones were tensile strength, breaking extension and air permeability of the woven fabrics. The ANN and regression models were assessed using the Root means square error (RMSE) and the coefficient of determination (R²-value). The findings of this study revealed that ANN is superior to regression model in predicting the woven fabric properties.

Keywords: Neural networks; Back-propagation; Woven fabrics properties; Tensile strength; Air permeability

Introduction

Artificial neural network

Artificial Neural Networks (ANNs) are algorithmic structures derived from a simplified concept of the human brain structure. They belong to the Soft Computing family of methods, along with fuzzy logic/fuzzy control algorithms and genetic algorithms [1]. They all share an iterative, non-linear search for optimal or suboptimal solutions to a given problem, without the presupposition of a model of any type for the underlying system or process [2]. Various different ANN types have already been successfully employed in a wide variety of application fields [3]. Major ANN functionalities are: function approximation which can be exploited in system input-output modeling and prediction, and pattern recognition and classification problems [4].

The structure or ‘architecture’ of an ANN contains a number of nodes, called neurons, organized in a number of layers and interconnected to form a network. Each neuron receives connections from other neurons and/or itself, each with an associated weight. The interconnectivity defines the topology of the ANN. The weights represent information being used by the neural network model to solve a problem. One of the central issues in neural network design is to utilize systematic procedures (a training algorithm) to modify the weights directly from the training data without any assumptions about the data’s statistical distribution [5].

There are different kinds of topologies and training algorithms but the multi-layered feed-forward neural network with back-propagation learning algorithms is more popular and commonly used [6]. In this structure, the neurons are located in layers and from one layer to another one connected with each other with links to carry the signals between them. There is a weight for each connection link which acts as a multiplication factor to the transmitted signal. An activation function such as linear or sigmoid is applied to each neuron’s input to determine the output signal. Usually a feed forward neural network consists of several layers of nodes, one input layer, one output layer and some hidden layers in between.

The training of a neural network by back-propagation involves three stages: The feed-forward of the input training pattern, the calculation and back-propagation of the associated error, and the adjustment of the weights. The calculation of error vector to adjust the weights is

done according to the calculated mean square error (MSE) form the difference between actual and predicted outputs according to the following relationship.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - x_i)^2 \quad (1)$$

Where N=the number of observations, y_i =the neural network predicted values, and x_i =the actual target values.

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. Thus, the neural network model approaches closer and closer to producing the desired output. The corrections necessary in the synaptic weights are carried out by a delta rule, which is expressed by the following equation.

$$\Delta W_{ji(n)} = -\eta \left[\frac{\partial(MSE)}{\partial W_{ji(n)}} \right] \quad (2)$$

Where $W_{ji(n)}$ is the weight connecting the neurons j and i at the nth iteration; $\Delta W_{ji(n)}$, the correction applied to $W_{ji(n)}$ at the nth iteration; and η , a constant known as learning rate [7,8].

Prediction of yarn and woven fabric properties

Generally, modeling and prediction of yarn and fabric properties based on fiber properties, fabric characteristics and process parameters have been considered by many researchers. Over the years, one of the first approaches has been the use of mechanistic models. In this category, some studies such as the work of Alsaid A Almetwally [9] and Pinar [10] to predict cotton yarn strength and spinning quality, Hearle, El-Beherly and Thakur [11] in relation to structural mechanics

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of fibers, yarns, and fabrics, the prediction of yarn strength by Frydrych [12], and works performed by Vitro et al., [13] Kim and El-sheikh [14] and Yong Ku Kim [15] and El-sheikh [16] can be mentioned. However, statistical regression models for this purpose have been used by some researchers, namely El-Mogahzy [17], Hunter [18] and Alsaïd Ahmed Almetwally [19,20] and M M Mourad [21].

The limitation of mechanistic and statistical regression models was described in previous works [22,23]. ANNs, genetic algorithm, and fuzzy set theory are presented as attractive alternatives for predictive modeling. ANN algorithms have been used by many researchers for modeling the different textile processes, especially for predicting different kinds of yarn and fabric properties. Alsaïd Ahmed Almetwally [5] compared between artificial neural networks and regression models in relation to the tensile properties of cotton/spandex core spun yarns. The results of his study revealed that ANN has better performance in predicting comparing with multiple linear regressions. ANNs were also used to predict the stress strain curve of the woven fabrics [24].

Fabric hand is a property that combines the mechanical properties of a fabric with the sensory perception of the fabric by the humans when they touch it. Fabric hand was predicted by using artificial neural networks by Youssefi and Faez [25], Hui et al. [26], and Matsudaira [27]. Drapability is far the most complex mechanical property of the fabrics and it is essential for many applications of the textile fabrics. The prediction of the drape has been made using ANNs [28].

Materials and Methods

In this study eighteen fabric samples were woven. All fabric samples were produced from Egyptian cotton of type Giza 80. The properties of cotton used to spin the weft and warp yarns from which the fabric samples are woven, were listed in Table 1. All warp yarns were made with the same English count, but the weft yarns were spun from three different counts. Each weft yarn also has two twist multipliers. Each fabric sample was woven with three different densities for the weft yarns. Generally, fabric samples used in this study were woven on Rapier weaving machine of model Picanol Gamamax with the following particulars:

Warp yarn count: 30/1 Ne

Weft yarn counts: 24/1 Ne, 30/1 Ne, and 36/1 Ne.

Warp yarn density: 108 ends/inch.

Weft yarn densities: 50, 60, and 70 ppi.

Twist multiplier of warp yarns: 4.

Twist multipliers of weft yarns: 3.8 and 4.2.

Weave structure: plain 1/1.

Warp width: 176.8 cm.

Number of harness: 6

Parameter	Value
Micronaire value	4.67
Mean length (mm)	28.7
Uniformity Index (%)	82.4
Strength (g/tex)	34.1
Elongation (%)	7.8
Maturity %	86
Fineness (mtex)	185

Table 1: Characteristics of cotton used to make the fabric samples.

Reed count: 20.5 dent/cm

Fabric width: 170 cm (Table 1).

Since the variation in the fabric samples were conducted in the weft direction, then testing the fabric properties were carried out in the same direction. Before testing, all fabric samples were conditioned and then tested under standard condition of $20 \pm 2^\circ\text{C}$ and $65 \pm 5\%$ relative humidity. Tensile strength and breaking extension measurements of the fabric samples were executed by standard strip method on an Instron 4411 Tester (Instron Inc., USA) in accordance with ASTM D1682; ten individual readings for each fabric sample were taken and averaged. The air permeability was measured by shierly Air permeability Tester according to ASTM D737-04; ten readings for each fabric sample were recorded and averaged.

Neural network design

Architecture: First, the size of the network must be determined by the number of hidden layers and the number of neurons in these layers. A network with three layers is sufficient for most practical applications. The number of input neurons normally corresponds to the number of input variables of the process to be modeled. In selecting the output neurons, note that it is generally inadvisable to train a network for several tasks simultaneously. In this study we have selected a network with three layers: an input layer with three neurons, hidden layer with 5 neurons, and an output layer with one neuron corresponding to one dependent variable subject to the analysis at a time.

Learning strategy and transfer functions: Before learning, the whole experimental data were segregated into training, validation, and testing patterns: 60% of the patterns were randomly selected for training, 20% were for testing the neural network, and the remaining 20% of patterns were for validating the model's performance [5]. Training is an important feature of neural networks. The objective of the training process is to minimize the squared error between the network output and the desired output. This is done by adjusting the connection weights across the network. The validation set is a part of the data used to tune network topology or network parameters other than weights. For example, it is used to define the number of units to detect the moment when the neural network performance started hidden to deteriorate. To choose the best network (i.e. by changing the number of units in the hidden layer), the validation set is used. Whereas, the test set is a part of the input data-set used to test how well the neural network will perform on new data. The test set is used after the network is ready (trained), to test what errors will occur during future network application. This set is not used during training and thus can be considered as consisting of new data entered by the user for the neural network application. The learning method is back-propagation with Levenberg-Marquardt algorithm. Three of the most commonly used transfer functions are linear, sigmoid, and tanh:

$$\text{Linear: } f(x)=x \quad (3)$$

$$\text{Sigmoid: } f(x)=\frac{1}{(1+e^{-x})} \quad (4)$$

$$\text{Tanh: } f(x)=\frac{(e^x - e^{-x})}{(e^x + e^{-x})} \quad (5)$$

The topology architecture of feed-forward three-layered back-propagation neural network is illustrated in Figure 1.

Performance of the neural network

The performance of the ANN was assessed using the root mean

square error (RMSE), and the coefficient of determination according the following formulas:

$$\text{Root mean square error: RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - x_i)^2} \quad (6)$$

$$\text{Coefficient of determination} = \frac{SS_{reg}}{SS_{total}} \quad (7)$$

Where N=the number of observations, y_i =the neural network predicted values of fabric properties, x_i =the actual values of fabric properties.

Statistical regression

In this study, multiple-linear regression was used for developing three predictive models of fabric tensile strength, fabric breaking extension, and fabric air permeability. In this concern, the same sets of data used for evaluating ANN model were used in a multiple linear regression algorithm. Independent variables were weft yarn count (Ne), weft density (ppi) and the twist multiplier of weft yarns. The following linear regression models correlate the fabric properties of woven fabrics with the independent variables, i.e. weft yarn count, weft density, and twist multiplier.

Tensile strength, kg=97.3 - 2.3 × weft yarn count + 5.3 × twist multiplier + 0.6 × weft density

Breaking extension, %=31.2- 0.2 × weft yarn count + 1.1 × twist multiplier - 0.14 × weft density

Air permeability, (cm³/cm².sec)=45.4 + 0.4 × weft yarn count + 5.2 × twist multiplier - 0.96 × weft density

As seen from the regression models above, twist multiplier of weft yarns affected all fabric properties positively. However, weft yarn density affected breaking extension and air permeability negatively and affected the fabric tensile strength positively. Whereas weft yarns count

influenced the tensile strength and breaking extension negatively; while air permeability is affected positively. The statistical analysis also revealed that yarn count accounts for 76% of the variability in fabric tensile strength and that twist multiplier accounted for 7%, while weft density accounted for 52% of the variability in fabric tensile strength. With respect to breaking extension, it was determined that weft yarn count, twist multiplier and weft density accounted for 50%, 11% and 55% respectively of the variability in fabric breaking extension. Finally, it was found that weft yarn count, twist multiplier and weft density accounted for 23%, 12% and 92%, respectively of the variability in fabric air permeability.

Results and Discussion

In this study, we have adopted a three-layer neural network consisting of a three-input layer, a 5-neuron hidden layer, and a one-neuron output layer at a time, focusing on fabric tensile strength (kg), breaking extension (%), and air permeability (cm³/cm².sec). The neural network learning model is in accordance with the experiment data of three inputs and three targets, which are listed in Table 2. The general view of the neural network used in this study is shown in Figure 1. The RMSE and coefficient of determination (R²) were used to judge the performance of ANN and regression models (Table 2).

Tensile strength

Tensile strength has been accepted as one of the most important attributes of woven fabrics. It is the main characteristic that distinguishes it from non-woven and knitted fabric. The strength of a woven fabric depends not only on the strength of constituent yarns, but also on the yarn and fabric structure and many other factors [29].

The actual and predicted tensile strength values of woven fabric samples, according to the variation of the independent variables, using ANN and regression models and its performance are presented in Tables 3 and 4 and in Figure 2, respectively. The results revealed that ANN model gives the best performance with the least RMSE and highest R² values. The values of the root mean square error were 3.1 and zero for regression and ANN models, respectively. The coefficient of determination values of regression and ANN models were found to equal 0.87 and 1, respectively. This signifies that an artificial neural network model fits the data very well and it is better than the regression model in predicting the tensile strength of the woven fabrics.

From Table 3, it can be seen that the minimum and maximum absolute errors for regression model are 1.6 and 15.5%, while the corresponding values for ANN model are zero and 6.1%. This confirms that ANN model has a better predictive performance than regression analysis to predict the tensile strength of woven fabrics under study.

Figure 2 compares the predicted outputs of the ANN model and

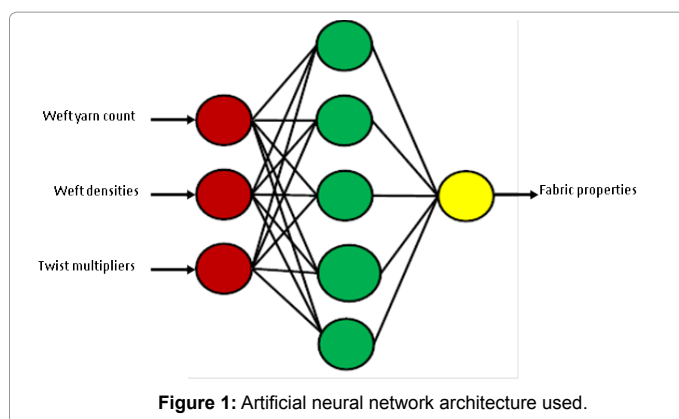


Figure 1: Artificial neural network architecture used.

Sample No.	Inputs			Targets		
	Yarn count (Ne)	Twist multiplier	Weft density (ppi)	Tensile strength (kg)	Breaking extension (%)	Air permeability (cm ³ /cm ² .sec)
1	24	4.2	50	39.33333	24.66667	30.33333
2	30	3.8	50	33	22.00000	28.66667
3	30	3.8	70	55.33333	19.33333	11.00000
4	30	4.2	60	41.66667	21.66667	22.00000
5	36	3.8	60	25	21.00000	19.66667
6	36	3.8	70	31.66667	17.66667	13.33333
7	36	4.2	70	36	18.33333	13.66667

Table 2: Learning data of the back-propagation neural network for fabric tensile properties and air permeability.

Actual values	Multi-linear regression		Artificial neural network	
	Predicted value	Absolute error (%)	Predicted value	Absolute error (%)
54.66667	56.83333	3.963402	54.55063	0.212268
39.33333	45.44444	15.53672	39.33333	0
51.33333	54.72222	6.601734	48.21225	6.080026
48.33333	47.55556	1.609179	48.33333	0

Table 3: Tensile strength predicted by multi-linear regression and neural network.

Statistical parameters	Regression	ANN
Coefficient of determination, R ²	0.87	1
Root mean square error, RMSE	3.072428	0.000

Table 4: Comparison of prediction performance of ANN and regression models for tensile strength.

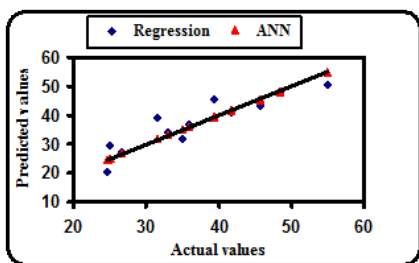


Figure 2: Actual against predicted values using ANN and regression models for tensile strength.

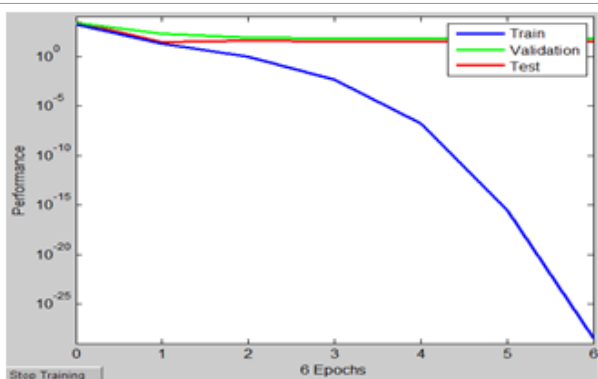


Figure 3: The performance plot of the ANN used to predict the fabric tensile strength.

multi-linear regression model with the experimentally actual tensile strength of woven fabrics. It is observed that ANN model reproduced the trend in the measured values better than regression model; and the ANN model has more capability of making quantitatively accurate tensile strength predictions. The correlation coefficient between actual and predicted yarn tensile strength using ANN and regression models were 1 and 0.94, respectively (Tables 3 and 4) (Figures 2 and 3).

Figure 3 describes the performance training algorithm for the ANN used to predict the tensile strength of the woven fabrics. This is a useful diagnostic tool to plot the training, validation, and test errors to check the progress of training. This figure describes that the test set error and the validation set error has similar characteristics, and it does not appear that any significant over fitting has occurred. The training stopped after 6 iterations because the validation error increased.

Breaking extension

Equally important to the fabric strength is its ability to extend under load. When the fabric is subjected to tension in one direction, the extension takes place in two main phases. The first phase is decrimping or crimp removal in the direction of the load. The removal of the crimp is accompanied by a slow rate of increase of the load. The second phase is the extension of the yarn during which the fabric becomes stiffer; the stiffness depends mainly on the character of the yarn. The more is the crimp in the yarn, the more extensible is the fabric [29,30].

Actual and predicted values of breaking extension of the woven fabrics under study and their predicted errors are listed in Table 5. A Comparison between the performances of the ANN and multiple linear-regression models on the data-sets is provided in Table 6.

It can be noticed that ANN model achieved an average RMSE of 0.0006. Comparing this value to the regression model with an average RMSE of 0.1.2, suggested that the ANN model highly superior to the regression one.

It is also observed that the artificial neural network model has a capability of achieving a very good fit to the measured breaking extension values as noticed by high R² value of 0.9999. While the R² value associated with the multi linear – regression model was lower to large extent (R²=0.67), which means that regression model failed to interpret 37% of the total variation in the breaking extension values of the woven fabric under study. The poor performance of the regression model in predicting the breaking extension values may be ascribed to this model may be nonlinear.

As seen from Table 5, the predicted errors associated with ANN models were all close to zero, while that associated with regression one range between 6 and 12%, which confirms the high-ability of ANN model to predict the breaking extension values of woven fabrics. Figure 4 illustrated the predicted breaking extension values of ANN and regression models. From this figure it can be seen that a good agreement between actual and predicted values for ANN model assuring that the predicted errors nonsexist. Whereas the predicted values in the regression model are randomly distributed around the regression line. This confirms that ANN model can perform good prediction with very minor errors.

The performance of the artificial neural network used to predict the breaking extension at the validation, test and training stages were depicted in Figure 5. It can be seen that validation and testing errors have nearly the same characteristics. This type of ANN attains their performance goal after five iterations (Table 6) (Figures 4 and 5).

Actual values	Multi-linear regression		Artificial neural network	
	Predicted value	Absolute error (%)	Predicted value	Absolute error (%)
18.33333	20.37963	11.16161	18.33342	0.000489
23	22.24074	3.301130	22.99990	0.000399
24.66667	23.15741	6.118608	24.66657	0.000382
20	21.29630	6.4815	20.00003	0.000156

Table 5: Breaking extension predicted by multi-linear regression and neural network.

Statistical parameters	Regression	ANN
Coefficient of determination, R ²	0.67	0.9999
Root mean square error, RMSE	1.2479	0.0006

Table 6: Comparison of prediction performance of ANN and regression models for breaking extension.

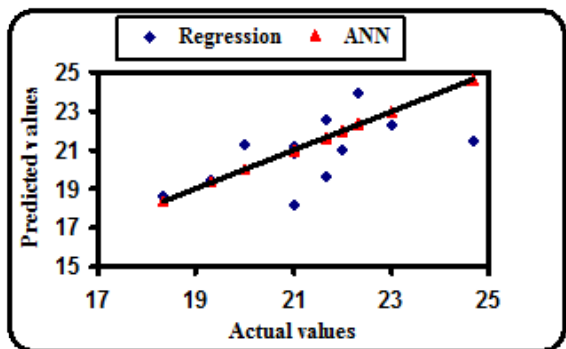


Figure 4: Actual against predicted values using ANN and regression models for breaking extension.

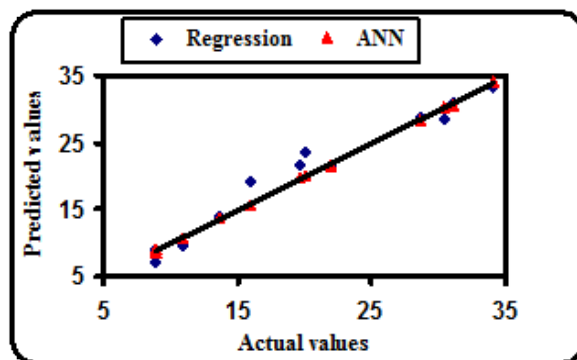


Figure 6: Actual against predicted values using ANN and regression models for air permeability.

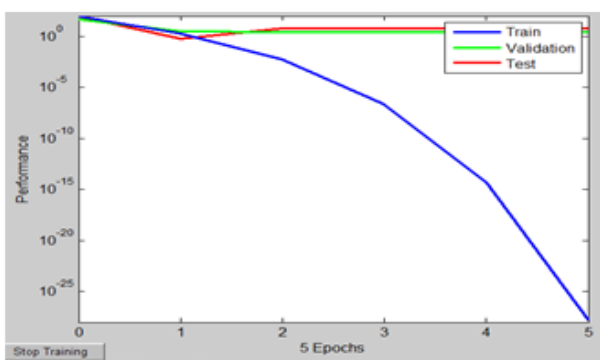


Figure 5: The performance plot of the ANN used to predict the fabric breaking extension.

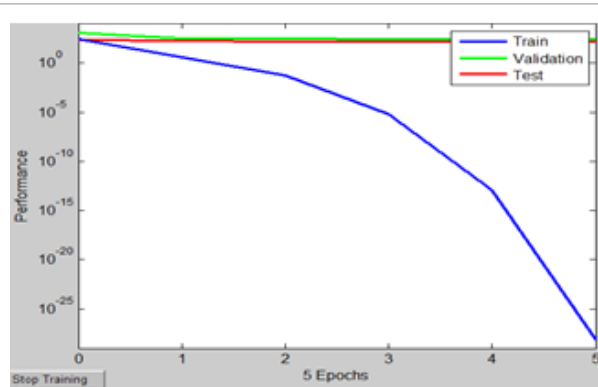


Figure 7: The performance plot of the ANN used to predict the fabric air permeability.

Actual values	Multi-linear regression		Artificial neural network	
	Predicted value	Absolute error (%)	Predicted value	Absolute error (%)
11	9.518518	13.46802	10.7	2.835158
22	21.25926	3.367	21.8	1.04382
30.3333	28.50926	6.013325	30.2	0.286504
34	33.34259	1.933559	34.1	0.29391

Table 7: Air permeability predicted by multi-linear regression and neural network.

Air permeability

The air permeability is a very important factor in the performance of some textile materials. Especially, it is taken into consideration for clothing, parachutes, sails, vacuum cleaner, fabrics for air bags and industrial filter fabrics. The air permeability is mainly dependent upon the fabric's weight and construction (thickness and porosity).

The actual and predicted values of air permeability of woven fabrics and their absolute errors for ANN and regression models were listed in Table 7. From this table, it can be observed that the absolute errors of the air permeability predicted by ANN model are highly lower compared to those predicted by regression model. The predicted errors of the air permeability associated by ANN model ranges between 0.3 and 3%, whereas the corresponding errors associated with regression model falls between 2 and 13%. The lower predicted errors accompanied by ANN model give a high degree of confidence in this type of prediction models.

Statistical parameters	Regression	ANN
Coefficient of determination, R^2	0.95	1
Root mean square error, RMSE	4.4776	1.08807

Table 8: Comparison of prediction performance of ANN and regression models for air permeability.

The R^2 and RMSE values of air permeability of the woven fabrics under study predicted by ANN and regression models are presented in Table 8. The average R^2 and RMSE values predicted via ANN model are 1 and 1.09, respectively. While such values predicted using regression model are 0.95 and 4.5 for R^2 and RMSE, respectively. The coefficient of determination values show that ANN model explained about 100% of the variations in the air permeability, whereas the variations explained by the regression model approaches 95%.

The air permeability values of the woven fabrics predicted by ANN and the regression models were depicted in Figure 6. From this figure it can be observed that the agreement between the actual values of air permeability and that predicted by ANN model is very high; while the agreement between the corresponding values predicted by the regression model is lower to some extent. The correlation coefficient between actual values of air permeability and that predicted by ANN model is approximately 1; while the correlation coefficient between the corresponding values for regression model equals to 0.95. Therefore, ANN model can perform good prediction with least error compared to regression one (Tables 7 and 8) (Figures 6 and 7).

Figure 7 depicts the plot of the performance of the ANN used to predict the fabric air permeability at training, validation and testing stages. It is shown that this neural network attains their optimum performance after 5 epochs, whereas the training and validation errors have the same characteristics.

Conclusion

In this study, tensile properties and air permeability of woven fabrics were predicted using ANN and regression models. The independent variables in the predicted models were weft yarn count (Ne), twist multiplier and weft density (ppi). Dependent variables which predicted by ANN and regression models were tensile strength, breaking extension and air permeability. The findings of this study revealed that R^2 values associated with ANN models for all fabric properties were very high compared to the R^2 values accompanied the regression models. Also, the RMSE values with ANN models are lower than those associated with regression ones. All absolute errors of the fabric properties predicted by ANN model were highly lower than that errors predicted by the regression model. Good agreement between predicted and actual values of tensile strength, breaking extension and air permeability of the woven fabrics proves that the neural network is an effective technique. With the help of the neural network, we can predict woven fabric properties easily, effectively and accurately.

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