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Research Article • DOI: 10.2478/ftee-2022-0036 FTEE • 30(4) • 2022 • 54–59

Prediction of Mechanical Properties of Woven Fabrics by ANN

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Abstract
This study aims to obtain an accurate prediction model of mechanical properties of woven fabric to achieve customer satisfaction. Samples of plain woven fabric were produced from different yarn counts and blend ratios of cotton and polyester of weft yarn at different weft densities. Mechanical properties such as tensile strength, bending stiffness and elongation% in both the warp and weft directions were tested. The prediction model was based on Artificial Neural Networks (ANNs). For each model, thirty-nine samples were used for training and fifteen for testing prediction performance. Findings indicated that the ANN achieved a perfect performance in predicting all properties.

Keywords
ANN, mechanical properties, prediction performance, modelling, woven fabric.

1. Introduction

Lately, fabric production operations have become nearly entirely automated in order to achieve high productivity and high quality while meeting consumer demands. Tensile strength, fabric stiffness, and elongation are the mechanical qualities of woven fabric which have a significant impact on the fabric's durability, comfort, lifetime, and overall quality. As a result, predicting fabric mechanical qualities like strength, elongation, and stiffness is a complicated relationship, which is influenced by fabric design, warp and weft densities [1, 2] , and customer satisfaction. Therefore, testing these properties should be done regularly to check the achievements of required specifications. On the other hand, more testing means high waste of material and money. Therefore, predicting the values of these properties saves testing time and, hence, cost. According to literature studies, regression analysis and artificial neural networks have been used to predict fabric properties. Numerous prediction models based on regression analysis have been introduced. Artificial neural networks (ANNs) are powerful in modeling complicated outcomes in textile processes. Recently, artificial neural networks have been used successfully to predict various properties of woven fabrics. Some studies predict the mechanical properties of woven fabrics using one or both of the prediction approaches.

Concerning tensile strength, Zeydan [3], for example, introduced a new computational modeling technique to the predict tensile strength of jacquard woven fabric based on TDOE (Taguchi Design of Experiment), ANN, GA-ANN (Genetic Algorithm Based Artificial Neural Network) hybrid structure and multiple regression methodology. The parameters studied were fiber type and counts of warp and weft yarns, as well as weft and warp densities. By comparing traditional techniques like multiple regression modeling and the computational modeling proposed, the GA-ANN hybrid technique was found as a suitable modeling approach. In addition, outcomes revealed that the most important factor affecting the fabric strength is warp density according to the S/N Ratio. Abou-Nassif [4] initiated two prediction models to predict tensile strength, extension and air permeability properties of woven fabrics using Linear Regression and Artificial Neural Network Models. Experimental parameters were the weft yarn count, twist multiplier and weft density. By comparing prediction results of the proposed models based on (R^2-value), it was found that ANN is more accurate than the regression model at predicting the characteristics of woven fabrics. Majumdar et al. [5] developed two empirical modeling methods based on an artificial neural network (ANN) and linear regression in order to predict woven fabric strength in the warp direction. Experimental variables were the weft count, strength and elongation of warp yarn, as well as warp and weft densities. Results showed that the two most significant factors affecting fabric strength in the warp direction were warp yarn strength and warp density. In addition, both prediction models were able to predict the fabric strength precisely, but the ANN model achieved higher prediction accuracy than that by the regression model. Malik and Arain [6] introduced an empirical regression models to predict the tensile strength of woven fabrics produced by different warp and weft yarn count densities. Prediction results revealed a very high accuracy of the models developed.

Regarding the prediction of woven fabric stiffness, Hedfi et al.[7] presented a simulation model to predict the fabric drape properties of woven fabric based on Artificial Neural Networks and the Finite Element Method, concluding that using the Finite Element Method increased the accuracy of predication of this model. Erenler and Oğulata[8] established different prediction models using a feed-forward and back propagation network to predict woven fabric stiffness by modeling the fabric construction, such as the weft yarn count, fabric design and weft density, in addition to finishing properties. The models varied from the properties of ANNs, such as the transfer function, numbers of neurons and number of hidden layers. The high accuracy model is selected from among ten models according to its high degree of correlation "R-value". Eman et al. [9] used bending stiffness as a regressor to predict the pilling of woven fabrics.

In addition, a number of studies have been conducted on the prediction of the elongation and extension of woven fabric. For example, Ogulata et al.[10] introduced prediction models of the elongation and recovery of polyester/ viscose/elastane blended woven fabric using both regression models and ANN. In this study, results showed that prediction by ANN was more accurate than by the regression model. In addition, elongation properties were predicted more precisely using both models than for recovery. Hadizadeh et al. [11] proposed prediction using an ANN back-propagation algorithm to predict the performance of the initial load-extension of plain weave, and accurate mapping results were generalised. Marasović and Penava [12] introduced three mathematical models based on nonlinear regression to determine the breaking force and elongation at break for samples of plain woven fabrics with various angles. From the previous literature, it is seen that there is a lack of studies which present a prediction model for all mechanical properties together in both the warp and weft directions. Thus, the main aim of this research work is to introduce a prediction model of woven fabric properties such as tensile strength, stiffness and elongation in both the warp and weft directions using artificial neural networks.

		Levels		
Factors		1	2	3
X1	Weft density (picks/m)	0.23	0.25	0.27
X2	Weft yarn count (Nm)	40/1	50/1	------
X3	Fiber blend ratio of weft yarn Polyester (PE %)	0%	50%	65%
X4	Fiber blend ratio of weft yarn Cotton (C%)	100%	50%	35%

Table 1. Factors and levels of weft yarns

Run	X1	X2	X3	X4
	Picks/m	Weft yarn count (Nm)	PE %	C %
1	1	1	1	1
2	1	1	2	2
3	1	1	3	3
4	1	2	1	1
5	1	2	2	2
6	1	2	3	3
7	2	1	1	1
8	2	1	2	2
9	2	1	3	3
10	2	2	1	1
11	2	2	2	2
12	2	2	3	3
13	3	1	1	1
14	3	1	2	2
15	3	1	3	3
16	3	2	1	1
17	3	2	2	2
18	3	2	3	3

Table 2. Experimental model

2. Experimental

2.1. Materials

Samples from plain woven fabric were produced on an air jet weaving loom. The fabric construction consisted of warp yarn of (50/1 Nm) from (65% Polyester /35% Cotton) and two levels of weft yarn (40/1 Nm and 50/1 Nm) from three levels of blend ratios (100% cotton, 50% Polyester /50% and 65% Polyester /35%) at warp density (0.30 ends/m) and three levels of weft densities (0.23, 0.25 and 0.27 picks/m). Table (1) shows the different factors and levels of weft yarns used in the manufacturing. Table (2) shows the experimental design of producing the test samples at the same warp and warp yarn density with different weft yarns and weft densities. Each experiment was repeated three times and fifty-four readings recorded.

2.2. Methodology

Before testing, all test samples were conditioned for 24 hours in the standard testing atmosphere: relative humidity 65%±2 and temperature 20±2ºC. The mechanical properties were tested according to the following procedures.

2.2.1. Tensile strength

Fabric strength is one of the most important properties for woven fabric performance, affecting its quality; therefore, it is an important feature to estimate the performance of woven fabrics in many applications [13-17]. Tensile strength is measured by the maximum force recorded in extending the sample tested to the moment of rupture at the breaking point. Consequently, this force breaks a large number of yarns simultaneously in either the warp or

-Train network using Levenberg-Maquardt back-propagation	
- Activation function: (trainlm).	-Hidden layer size =10
-Performance: Mean squared error (mse)	-Gradient: 1.00e-05

Table 3. ANN Training Algorithm

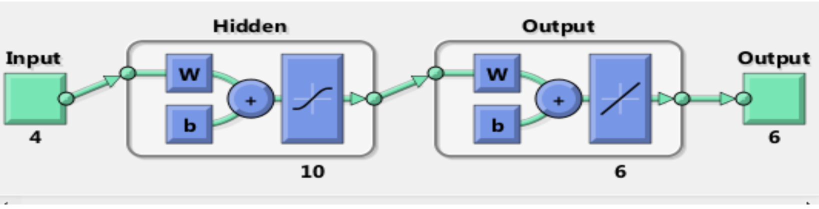

Fig. 1. Neural Network architecture for all mechanical properties

weft directions which cannot resist any more [18, 19]. The tensile was measured in both the warp and weft directions by measuring the breaking force according to the strip method (ASTM:D 5035) [20]. Specimens with dimensions(of 0.2 m) length and (0.025 m) raveled width were cut in the warp and weft directions. On the apparatus, the gauge length used was (0.075m), at a speed of (0.3 m/min).

2.2.2. Elongation

Elongation is the ratio of the increase in the length of the specimen to its starting length. Hence, elongation is usually defined as strain or percentage extension [18]. Therefore, it is one of the major features of woven fabrics which are especially made from elastane that affects fabric recovery and comfort, which, in turn, impacts fabric quality [10]. Breaking elongation is recorded at the rupture point of the breaking force. Thus, both the tensile strength (N) and elongation % were measured together in both warp wise and weft wise in accordance with (ASTM:D 5035-95) [20].

2.2.3. Fabric stiffness

Fabric stiffness is one of the most important properties of fabrics as the bending resistance of fabrics, which is one of the objective measurement methods, is an indicator of the fabric handle, drape, buckling behavior, wrinkle-resistance and crease resistance of textile products [21-23]. Stiffness was measured by measuring the bending length in both the warp and the weft directions. The bending length was measured by a cantilever bending tester, developed by the Shirley Institute, according to (ASTM:D 1388)[24]. Specimens with dimensions ($2.5*22*10^{-4}$ m^2) were cut in the warp and weft directions. Each specimen bends under its own weight to a fixed angle (41.5°) from the horizontal plane. The length of the sample overhang and the angle were then used to calculate the bending stiffness of the fabric samples.

2.3. Artificial Neural Network Prediction Model

Artificial neural networks (ANNs) have a wide range of application in the textile industry as they are powerful in many prediction-related problems in the textile sector, such as the prediction of textile properties like identification, pattern recognition, classification and defect analysis [8]. Figure 1 represents the network structure for the prediction of six mechanical properties: (tensile strength (N), bending length (m) and elongation %) in both the warp and weft directions. This ANN model consists of one input layer with four inputs (X1-X4), one hidden layer with ten neurons, and an output layer with six outputs. Table 3 shows the ANN training algorithm for a feed- forward back propagation neural network, for which MATLAB 2013 software was used. The prediction model for the mechanical properties of the woven fabrics tested was carried out by artificial neural networks. Thirty-nine samples were used for training and fifteen samples for testing the prediction model performance.

2.4. Prediction Accuracy

The prediction accuracy was evaluated according to statistical variables. **R-Squared** (coefficient of determination), **MSE** (mean squared error), **RMSE** (root mean squared error), **MAE** (mean absolute error) and **MAPE** (mean absolute percentage error) are calculated by the following equations 1-5[25]. Moreover, **MAPE** significantly indicates the prediction performance.

$$\mathbf{R^2} = 1 - \frac{\Sigma(y_i - \hat{y})^2}{\Sigma(y_i - \bar{y})^2} \quad (1)$$

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

$$\mathbf{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \quad (3)$$

$$\mathbf{MAE} = \frac{1}{N}\sum_{i=1}^{N} y_i - \hat{y} \vee \quad (4)$$

$$\mathbf{MAPE} = \frac{1}{N}\sum_{i=1}^{N} y_i - \hat{y} \vee \frac{}{y_i} x100\% \quad (5)$$

Where: $\mathbf{y}_{i:}$ *actual value of* y , $\bar{\mathbf{y}}$: *average of y,* and $\hat{\mathbf{y}}$: *predicted value of y*

3. Results and Discussion

3.1. Training Results

The best training performance results were obtained at the number of neurons (n=10). Results of the artificial neural network proposed are summarised as follows: the MSE "Mean squared error" for training, validation and testing are 0.023, 0.084 and 0.026, and R values -" coefficient of correlation " are 0.99 in each case. The overall MSE is 0.016, and the overall R is 1, which means that there is high correlation and close relationship between the measured and predicted values of the properties tested, as shown in Figure 2.

3.2. Testing Results

The testing data set contains fifteen samples; Tables 4 and 5 represent comparisons between actual and predicted values by the ANN model for mechanical properties in both the warp and weft directions in series. Furthermore, Table 6 compares the precision of the prediction

Run	Tensile strength (N)		"Stiffness" Bending length * 10^{-2} (m)		Elongation %	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	357.00	357.00	2.30	2.39	20.50	20.90
2	334.00	334.00	2.20	2.15	19.40	19.30
3	377.00	377.00	2.70	2.67	22.40	22.50
4	368.00	368.00	2.50	2.50	22.30	22.00
5	358.00	358.00	2.40	2.42	22.00	22.00
6	360.00	360.00	2.40	2.35	22.60	22.60
7	368.00	368.00	2.00	1.95	20.70	20.70
8	369.00	369.00	2.50	2.53	23.10	23.40
9	360.00	360.00	2.40	2.35	22.60	22.60
10	351.00	351.00	2.20	2.19	21.60	21.70
11	350.00	350.00	2.30	2.32	21.30	21.40
12	331.00	331.00	2.00	2.09	15.70	15.70
13	353.00	353.00	2.40	2.42	23.30	23.00
14	350.00	350.00	2.30	2.32	21.30	21.40
15	353.00	353.00	2.40	2.42	23.30	23.00

Table 4. Comparison between actual and predicted values of properties tested in the warp direction

Run	Tensile strength (N)		"Stiffness"Bending length * 10^{-2} (m)		Elongation %	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	258.00	258.00	2.10	2.15	17.70	17.60
2	234.00	234.00	2.00	1.95	13.70	13.50
3	321.00	321.00	2.40	2.37	21.80	21.20
4	307.00	307.00	2.20	2.20	21.20	21.20
5	251.00	251.00	2.10	2.11	13.50	13.30
6	290.00	290.00	2.10	2.09	20.50	20.50
7	241.00	241.00	2.00	2.01	15.10	14.60
8	312.00	312.00	2.30	2.31	20.70	21.10
9	290.00	290.00	2.10	2.09	20.50	20.50
10	228.00	228.00	2.00	1.99	13.10	13.50
11	284.00	284.00	2.00	2.00	19.20	19.20
12	207.00	207.00	1.90	1.92	13.20	13.40
13	290.00	290.00	2.20	2.22	21.70	21.60
14	284.00	284.00	2.00	2.00	19.20	19.20
15	290.00	290.00	2.20	2.22	21.70	21.60

Table 5. Comparison between actual and predicted values of properties tested in the weft direction

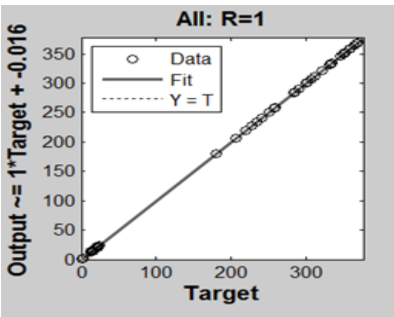

Fig. 2. Overall Training Performance of ANN model

model for the testing data set to express how well the model performs in its prediction using statistical indicators (R^2, MSE, RMSE, MAE and MAPE). First, the prediction performance in the warp direction is evaluated according to R^2 values, which are (1.00, 0.97 and 0.99) for the tensile strength, stiffness, and elongation % in series, which refer to satisfactory results and high correlation between actual and predicted values. In addition, low values of (MSE, RMSE and MAE) indicate the high accuracy of this model. Furthermore, MAPE values are (0.01%, 1.62% and 0.69%) for tensile strength, stiffness, and elongation % in series. Second, the performance of prediction in the weft direction is tested using R^2 values of (1.00, 0.98, and 0.99) for tensile strength, stiffness, and elongation % in series, indicating satisfactory results and a high correlation

Tested properties / Statistical factors	Tensile strength (N)		"Stiffness" Bending length * 10^{-2} (m)		Elongation %	
	warp	weft	warp	weft	warp	weft
R-squared :coefficient of determination	1.00	1.00	0.97	0.98	0.99	0.99
MSE :mean squared error	0.00	0.00	0.00	0.00	0.04	0.07
RMSE :root mean squared error	0.04	0.03	0.05	0.02	0.20	0.27
MAE :mean absolute error	0.03	0.02	0.04	0.02	0.15	0.19
MAPE: mean absolute percentage error	0.01%	0.01%	1.62%	0.88%	0.69%	1.14%

Table 6. Comparison between the prediction performance of all properties by ANNs

between actual and predicted values. Moreover, low values of (MSE, RMSE, and MAE) imply that this model is highly accurate. Furthermore, MAPE values for tensile strength, stiffness, and elongation % are (0.01%, 0.88%, and 1.14%) in series.

Finally, a comparison between prediction performances in warp and weft directions is shown by identical R^2 values (1.00 and 1.00), (0.97 and 0.98) and (0.99 and 0.99) for tensile strength, stiffness, and elongation % in the warp and weft directions, respectively, indicating no remarkable difference between them in both directions. Besides, MAPE values are (0.01% and 0.01%), (1.62%and 0.88%) and (0.69%and 1.14%) for tensile strength, stiffness, and elongation% in the warp and weft directions, respectively. Therefore, there is no significant difference between performance in the warp and weft directions because MAPE do not exceed 10% [26]. As a result of the low MAPE values, the high prediction accuracies are arranged from the most to the least accurate as follows: tensile strength in the weft direction, tensile strength in the warp direction, elongation % in the warp direction, stiffness in the weft direction, elongation % in the weft direction, and stiffness in the warp direction. Thus, this model can precisely predict all properties tested with the least error.

4. Conclusions

This work introduced a predictive approach to predict the mechanical properties of woven fabric such as tensile strength, fabric stiffness, and elongation % using artificial neural networks. An optimal neural network structure was developed by changing the number of neurons. The best one selected is 10 to obtain the best training performance results (R=1.00). In general, the ANN achieved a high performance in predicting all properties, with high values of R^2 (0.97 to1.00) with least values of MSE(0.00 to 0.07), RMSE (0.02 to 0.27), MAE (0.02 to 0.19) and MAPE (from 0.01% to 1.62%), which refer to the good fitting of this model and strong relation between actual and predicted outcomes. Besides, there is no significant difference between performance in the warp and weft directions. Because of its high accuracy, this model is recommended for precisely predicting the mechanical properties of plain woven fabrics, which will be helpful in weaving mills by estimating all the properties required simultaneously. Hence, the testing cost and material waste will be reduced. Thus, it will be beneficial in achieving high quality with less cost.

Declaration of Conflicting Interests

Author declares there is no conflict of interest.

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