(REFEREED RESEARCH)

A COMPARISON OF ARTIFICIAL NEURAL NETWORKS AND MULTIPLE LINEAR REGRESSION MODELS AS IN PREDICTORS OF FABRIC WEFT DEFECTS

KUMAŞ ATKI HATASI TAHMİNİNDE YAPAY SİNİR AĞLARI VE ÇOKLU DOĞRUSAL REGRESYON MODELLERİNİN KARŞILAŞTIRILMASI

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ABSTRACT

Predicting uncertainty is quite important for the reliability of decisions to be made by business managers. Contemporary problems are complex, and their solutions require scientific decision-making. The aim of this study is to predict weft defects in fabric production for a textile business using a multilayer perceptron model and multiple linear regression models. Matlab R2010b software was used for multilayer perceptron model solutions, and SPSS 13 packet software was used for multiple linear regression model solutions. The results of the two models were compared, and the multilayer perceptron model was identified as the best predictive model. This study shows that in operational research both artificial neural networks and the multiple linear regression model can be successfully used to predict fabric weft errors.

Key Words: Artificial neural network, Multilayer perceptron model, Multiple linear regression model, Fabric weft defect, Prediction.

ÖZET

Firmalar için belirsizliğin tahmini yöneticiler tarafından alınan kararların güvenilirliği için oldukça önemlidir. Günümüz problemleri karmaşık ve çözümü de bilimsel karar vermeyi gerektirir. Bu çalışmanın amacı bir tekstil firmasının kumaş üretiminde ortaya çıkan atkı hatalarını önceden tahmin etmektir. Bu tahmin için çok katmanlı algılayıcı model ve çoklu doğrusal regresyon model teknikleri kullanılmıştır. Çalışmada çok katmanlı algılayıcı model çözümleri için Matlab R2010b programı, çoklu doğrusal regresyon model çözümü için SPSS 13 paket programı kullanılmıştır. Firmanın kumaş atkı hata tahmininde bu iki model kıyaslanmış ve en uygun modelin çok katmanlı algılayıcı model olduğu belirlenmiştir. Bu çalışma yöneylem araştırması tekniklerinden yapay sinir ağ ve çok değişkenli regresyon modellerinin kumaş atkı hatalarının tahmininde faydalı bir araç olarak kullanılabileceğini göstermektedir.

Anahtar Kelimeler: Yapay Sinir Ağları, Çok Katmanlı Algılayıcı Model, Çoklu Doğrusal Regresyon Model, Kumaş Atkı Hatası, Tahmin.

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1. INTRODUCTION

The fierce demand-side competition in global markets forces businesses to produce with as few defects as possible. Today, lean manufacturing, six sigma, benchmarking, total quality management and just-in-time inventory systems are used as the business methods providing the minimum defect production. Growing global markets and intense competition have increased the importance of operations research because it can be used to make rational decisions in these business methods. Operations research uses artificial neural networks and multiple linear regression models to determine the minimum level of defects in the production process of businesses. Today's problems are more complex, so their solutions require scientific decision-making. Furthermore, the increasing problems of businesses and researchers' differing viewpoints concerning them indicate the need for artificial neural networks in business life. Therefore, artificial neural network models have begun to be used in a variety of business fields in the twenty-first century.

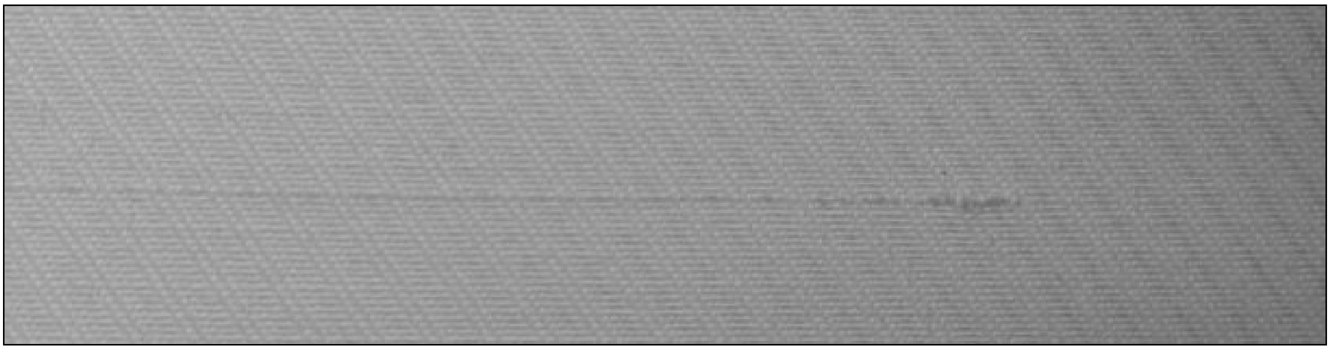
Our study is related to the textile field, so let's briefly describe the previous studies of artificial neural networks associated with this topic in the literature. *Gong and Chen* investigated the effects of the input and interlayer neurons of the artificial neural network (ANN) they used to predict fabric properties on prediction accuracy, and claimed that ANN was a valid and reliable tool for predicting fabric properties (1). *Ertuğrul and Uçar* tried to predict the bursting strength of flat woven cotton fabric before the production phase using ANN and fuzzy logic (2). *Fan et al.* examined predictions for drapery made using ANNs (3). *Zhang, Friedrich and Velten* used a multilayer feed-forward network and predicted the specific resistance ratio and friction coefficient based on the database of short fiber reinforced polyamide 4.6 (4). *Jeon et al.* showed that the detection and recognition of a fabric's patterns is a single class of problems, and thus a candidate for the use of ANNs (5). *Kuo, Lee and Tsai* used a vision processing system and ANN to analyze dynamic movements and errors on a white fabric, so they were able to determine fabric defects and errors (6). *Kumar* developed a new approach for the segmentation of local textile defects using a feed forward neural network. Principal component analysis is used to reduce the dimension of feature vectors for fabric defects. The experimental results obtained from real fabric defects by the two approaches proposed in his study confirmed their usefulness (7). *Zeng, Wang and Yu* used numeric simulation and artificial neural network model methods and predicted the strength properties of yarns produced in an air jet spinning machine (8). *Beltran, Wang and Wang* predicted the pilling tendencies of thread, yarn and fabric. In their study, a multilayer perceptron model was used as an artificial neural network to determine the effects of thread, yarn and fabric properties in all wool single jersey and rib knitted fabrics on pilling tendency. They compared the multilayer perceptron model with multiple linear regression models, and they concluded that the multilayer perceptron model performed best (9). *Oğulata et al.* predicted the elasticity and elongation properties of stretch-woven fabrics using a multilayer perceptron artificial neural network and multiple linear regression models. Their results was found the artificial neural network model to be better than the multiple linear regression model, despite the high predictive power of both models (10). *Islam et al.* claimed that reducing errors when identifying fabric defects requires an automated, accurate inspection process. This study determined that the multilayer neural network classifies specific problems best. To feed the neural network, digital fabric images taken by a digital camera and converted to RGB images are first converted into binary images by a restoration process and local threshold techniques. Then three different features are determined for the actual input to the neural network. This system is able to identify holes, scratches, and other types of minor defects (11). *Gharehaghaji, Shanbeh and Palhang* used multiple linear regression models and a multilayer perceptron artificial neural network model and investigated the resistance properties of cotton-coated nylon threads (12). *Furferi and Gelli* tried to predict yarn strength with a back-propagation neural network model, and they compared their findings with the results of multiple linear regression models (13). *Guruprasad and Behera* examined the probabilistic estimation of bending properties of cotton woven fabrics using artificial neural networks and genetic algorithms. They initially established a feed-forward neural network method. Then a hybrid learning strategy was adopted. The prediction performances of both models were compared, and the hybrid model provided better outcomes than the back-propagation neural network model (14). *Vassiliadis et al.* noted that the inspection of fabrics for faults is a very important operation traditionally carried out by skilled operators. Many attempts have been made to automate this inspection. So the task of automated defects detection is popular, and research teams have focused their interest on it, many of them using ANN to support the fault detection task (15). *Bahadır, Bahadır and Kalaoğlu* predicted the bursting strength of knitted fabrics with a back-propagation artificial neural network model (16).

The paper is directly related to weft defects in a textile factory. First, we met with its owner who asked us to minimize the number of weft defects in the production process. To solve the problem we decided to use the multiple linear regression model and the multilayer perceptron model. So the main purpose of this study was to predict fabric weft defects before production using the two models and, subsequently, to determine which model solves the problem more efficiently.

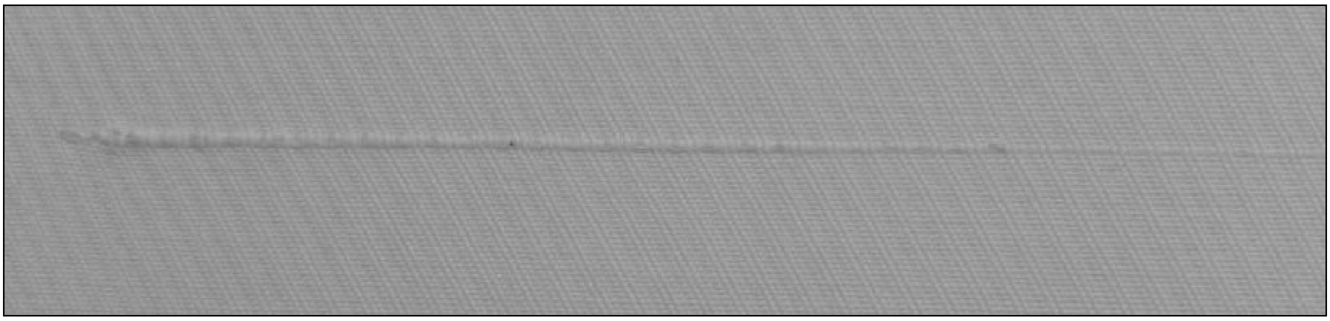
2. MATERIAL AND METHOD

The study collected 320 data from the textile company between July 2010 and April 2012. The data concern weft defects in woven fabric batches and the main causes of these defects. There are three types of weft defects in our study. These are *missing pick*, *filling bar* and *double pick*.

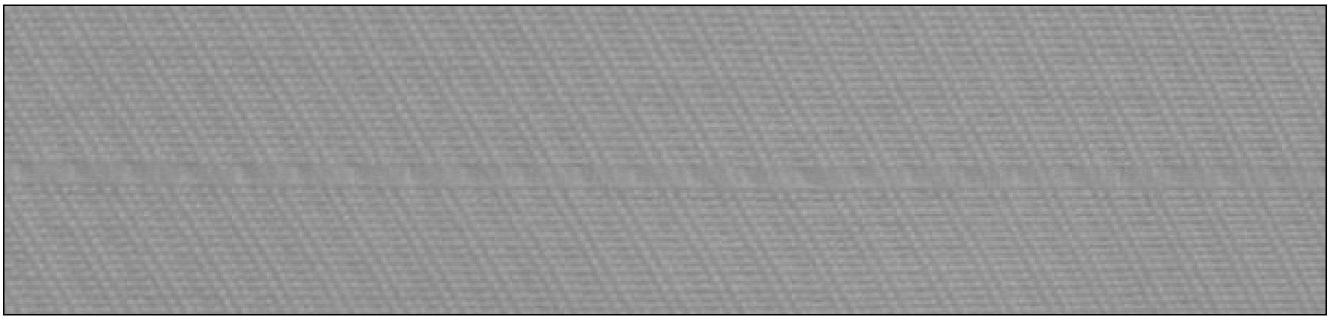
Missing pick is where the weave design is broken by the absence of a pick.



Filling bar is a visual defect across the width which contains a limited number of picks with an irregular appearance.



Double pick is one of the most common defects. It occurs when, instead of taking a single thread, the machine mistakenly takes two.



Our study identified 13 input variables. In order to reduce these variables to a smaller size, principal components analysis was applied using the SPSS package program. However, the number of input variables remained the same due to the low correlation between the data. These input variables are fabric length, machine speed (revolutions per minute), fabric width, warp density, efficiency, yarn strength, weft yarn number, warp yarn number, weft density, weft yarn type, warp yarn type, loom type and weave type. The output variable is the number of weft defects which occurred in fabrics.

In this study weft yarn type, warp yarn type, loom type and weave type are categorical input and are classified by numeration. Weft yarn type used in fabric production includes cotton, %20 polycotton, %25 polyester cotton and %25 polyester yarns. Two types of warp yarn, %55 polyester cotton and polyester were used in production.

The loom types used for fabric production are CTP, Somet Alpha, Somet Excel and Sulzer. There are nine weave types which are plain weave, 2/1 twill, 2/1 herringbone, 2/2 twill, 2/2 weft rib, double 2/2 twill, double 2/2 oxford, 3/1 twill and armure. These weave patterns is given in Appendixes.

This study used the multilayer perceptron and multiple linear regression methods to estimate weft defects in fabric production.

2.1. Artificial Neural Network Models

Artificial neural networks offer a new information processing approach based on computer simulation of the behavior of the human brain and nerve system. A neural network is an intensively parallel distributed processor consisting of simple processing units that have a natural tendency to store and use experiential knowledge (17). McCulloch and Pitts first advanced its theory in 1943. Later Hebb, Rosenblatt, Widrow and Hoff, and Paul Werbos developed successful applications of it (18).

Artificial neural networks simulating the performance of the human brain have many features such as learning from data, generalizing, tolerating errors and working with an unlimited number of variables. The smallest units forming the basis of ANN are called artificial neurons or computing elements. As Figure 1 shows, the simplest artificial neuron consists of five main components: inputs, weights, the combination function, the transfer function and output.

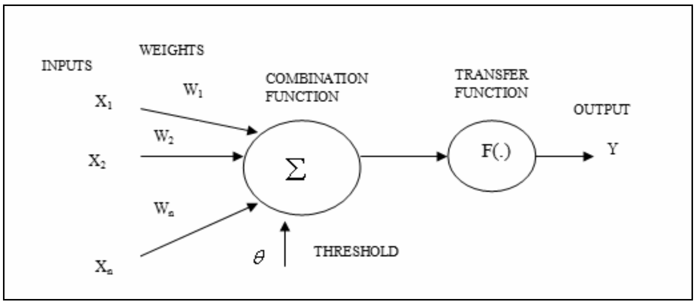


Figure 1. Functional Structure of Artificial Neuron

Figure 1 shows that inputs ($x_1, x_2, ..., x_n$) are obtained from outside the artificial neuron. These data can be provided by samples which the network will use to learn using another neuron or the neuron itself. The weights ($w_1, w_2, ..., w_n$) are values indicating the effects on a set of inputs or a computing element of previous layers. Each input is combined by the combination function by multiplication of the weights connecting input to the computing element. The output (v) is determined by processing the result of the combination function through a linear or nonlinear derivative transfer function.

$$y = f\left(\sum_{i}^{n} x_i w_i + \theta\right) \quad (1)$$

At present, a great number of artificial neural network models have been developed for various purposes and use in many different fields. Among these network models, the multilayer feed-forward artificial neural networks (MLP) is the most commonly used, and it is used in our study.

2.1.1. The Multilayer Perceptron Model

The multilayer perceptron (MLP) is an artificial neural network type which uses at least one layer between the input and output layers. Unlike the single layer perceptron, MLPs can solve non-linear problems, so they are the most popular type of artificial neural network in widespread use. The structure of an artificial neural network using one hidden layer between its input and output layers is shown in Figure 2 (19).

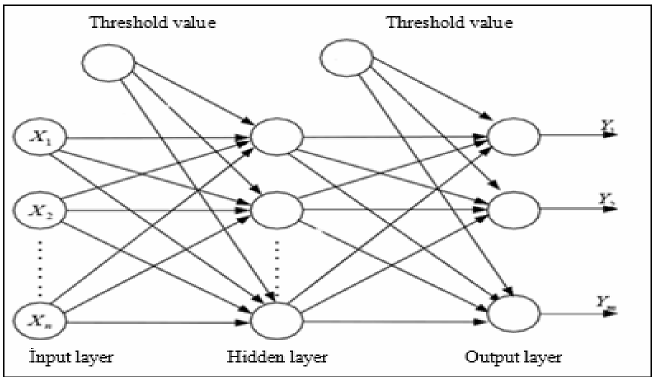


Figure 2. Structure of Multilayer Perceptron Artificial Neural Network

An artificial neural network learns from training samples and acquires the ability to generalize from sample data. The power of a neural network is closely dependent on how well it can generalize from the sample data set. The learning process of artificial neural network is determined by the weight values of neurons between layers. Change of weight values is determined by the choice of learning algorithm. In the learning phase of MLP networks, a back-propagation algorithm is used. The algorithm aims to reduce and distribute errors from the output to the input layers and is therefore known as back-propagation algorithm. This algorithm has a supervised learning structure, and it is the most commonly used learning algorithm. In a supervised learning algorithm, a sample data set consisting of input and target values trains the network. In the learning phase of a supervised learning algorithm, weights are updated with the minimize error function (20).

(Total error) $$TE = \frac{1}{2}\sum_{m=1}^{n}(B_m - y_m)^2 \quad (2)$$

In equation 2, B_m is the output produced by the network, and y_m is the actual (target) output. Link weights are updated to minimize the total error. The network is thus expected to produce the outputs closest to the target output values. When weights are correctly updated, a neural network correctly predicts the desired outputs for new inputs.

2.2 The Multiple Linear Regression Model

Multiple linear regression is a method for investigating the linear relation between one dependent variable and two or more independent variables. It is generally shown as a model demonstrating the relation between a dependent variable (output) and *n*-independent variables (input) (21).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ...\beta_n x_n + u \quad (3)$$

In the Equation 3, y signifies the output variable, x_i (i=1,2..n) stands for input variables, β_0 is a constant parameter of regression, β_i (i=1,2..n) are partial regression coefficients of x_i variable and u is the random error term.

The least-squares method is generally used for estimation purposes in the multiple-regression model. Once regression coefficients are obtained, a prediction equation can then be used to predict the value of a continuous output as a linear function of one or more independent inputs. The popularity of the regression models can be attributed to the interpretability of its model parameters and its ease of use.

To compare artificial neural networks and multiple linear regression models, following criteria such as corrected determination coefficient (R^2), mean square error (MSE), square root of the mean squared error (RMSE) and mean absolute error (MAE) are used. According to these criteria, high R^2 and low MSE, RMSE and MAE values indicate the best model. Equations 4,5,6,7 and their terms are shown below.

$$\bar{R}^2 = 1 - \left(1 - R^2\right)\frac{n-1}{n-k} \quad (4)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \quad (7)$$

In this equation, y_i is the target value (actual), $\hat{y}_i$ is the output produced by the network (predicted), n is the number of data and k is the number of variables in the model.

3. THE CONSTRUCTION OF THE MODELS AND THEIR RESULTS

In this section, we will discuss our models' results for fabric weft defects in the textile business.

Multilayer Perceptron Model and Results

The 320 data used in our study was collected between July 2010 and April 2012. Matlab R2010b was used for the models' development and solutions. Of the data, 80% was used as training data, and the rest was test data. Of the training data, 25% was set aside for verification data. Thus, the total data set was divided into 3 groups: 60% for the training set (192 units), 20% for the verification set (64 units) and 20% for the test data set (64 units). The data was divided randomly.

The multilayer perceptron model was constructed for data training. There are a total of 13 neurons in input layer (fabric length, machine speed, fabric width, warp density, efficiency, yarn strength, weft yarn number, warp yarn number, weft density, weft yarn type, warp yarn type, loom type and weave type), while the single neuron in the output layer shows the number of weft defects. The hidden layer and the number of neurons in this layer were determined through trial and error. In this regard, one hidden layer was included in the model. In order to determine how many neurons would be included in the hidden layer, to this layer was given from 1 to 50 neurons and each model was tested 10 times to determine the best model for our study. The *hyperbolic tangent sigmoid* (tansig) transfer function was used between the input and hidden layers in the model. A *linear* (pureline) transfer function was used between the hidden and output layers. To determine the most suitable model, the back-propagation algorithm known as the *Levenberg-Marquardt* (LM) algorithm was used for data training. In the training phase, the maximum *iteration* (epoch) numbers was 1000, and there was no time constraint. The performance criteria were MSE, RMSE and MAE. The learning coefficient was set at 0.001 at the beginning. In case of any worsening in the training process, the program intervenes and changes this coefficient either by increasing or decreasing it.

After an appropriate model was constructed and trained for the parameters, the results of the model were tested, and the most convenient model is identified. The model thus obtained was observed to comply with the criteria by yielding the smallest MSE, RMSE and MAE values and the highest R^2 with 6 hidden neurons. Therefore, the most suitable model was identified as the model with a 13-6-1 network structure. In this network topology, MSE was 4.21, RMSE was 2.05, MAE was 1.63, and R^2 was 0.93. The high determination coefficient R^2 indicates the success and accuracy of the prediction. The relation between actual outputs (number of weft defects) of 64 data separated for test set and the outputs of MLP network (predicted number of weft errors) is shown in Figure 3.

The Multiple Linear Regression Model and Results

After concluding that the data obtained from the textile business showed a normal distribution, and that there were no multicollinearity problems among the independent variables, the multiple linear regression model was applied to the firm's weft defect problems. Independent variables including fabric length, machine speed, fabric width, warp density, efficiency, yarn strength, weft yarn number, warp yarn number, weft density, weft yarn type, warp yarn type, loom type and weave type accounted for 71% of the weft defects. With the F table value obtained from variance analysis table, the model was deemed to be significant in its entirety. Afterwards, the coefficients of independent variables were determined by making prediction with model, and the t-test was performed. In this test, the effect of each variable on the number of weft errors was investigated. The significance level was set to 0.05, and 8 out of 13 variables were found to have significant effects in the analysis. Therefore, the multiple linear regression model for the firm included in the study was determined to be equation 8:

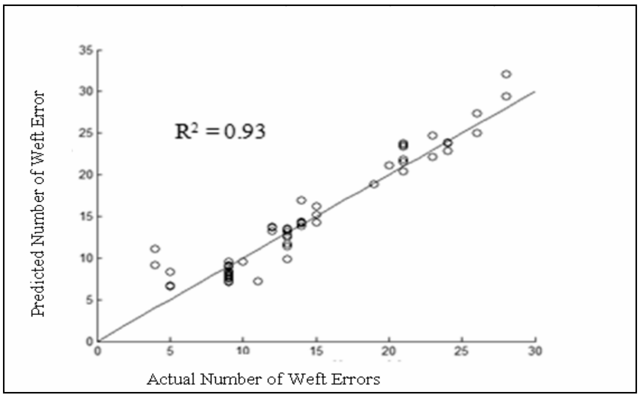


Figure 3. The Actual and Predicted Number of Weft Errors for Test Data Set

The parameters fabric length (X_1), machine speed (X_2), efficiency (X_5), yarn strength(X_6), weft yarn number (X_7), weft yarn type (X_{10}), loom type (X_{12}) and weave type(X_{13}) were found to affect the number of weft defects. In this regard, a 1 cm increase in fabric length reduces weft defects by 0.008. Similarly, a 1 rpm of increase in machine speed (faster than normal speed) increases the weft defects by 0.13 and a 1% of increase in efficiency reduces weft defects by 24.007. One unit of increase in yarn strength reduces weft defects by 0.019. 1 denier of increase in weft yarn number reduces weft errors by 0.189.

The comparison of the prediction performance of the MLP and MLR models found, that the MLP model produced the best results for the firm. This is because, the highest determination coefficient (R^2) as well as the smallest error performance criteria were yielded by the MLP, as Table 1 shows. The firm can thus achieve a 93% success rate by using MLP in its planning of fabric production.

$$\hat{Y} = -71{,}526 - 0{,}008\,x_1 + 0{,}13\,x_2 - 24{,}366\,x_5 - 0{,}019\,x_6 - 0{,}189\,x_7 - 0{,}732\,x_{10} - 0{,}438\,x_{12} - 0{,}375\,x_{13} \quad (8)$$

Table 1. A Comparison of the MLP and MLR Models

Model	**R^2**	**MSE**	**RMSE**	**MAE**
MLP	0.93	4.21	2.05	1,63
MLR	0.71	13.52	3.68	2.72

4. CONCLUSION AND RECOMMENDATIONS

Our study aims to predict the weft defects that occur during fabric production. To do this we used the SPSS package program with the multiple linear regression model and the Matlab program with the multilayer perception model. As a result, it was determined that the most suitable model was the multilayer perception model. Accordingly, the production and planning department and quality department experts will be able to predict the number of weft defects as output data, using the MLP model we suggest for the firm and entering the pre-production data in the Matlab program.

The study's results clearly indicate that firms can predict the properties of products and number of errors prior to production of customer orders by using artificial neural networks as prediction tools. In this way, managers can take correct decisions of production with necessary measures, channel the resources in the right direction and determine provision of the required raw materials in advance. Thus, business's can reduce the costs of errors caused by production and inventories.

This study developed two models to determine how many weft errors will occur in a fabric batch by altering some input variables in planning stages of fabric production. MLP was found to be the most appropriate model for determining weft errors. Therefore, this study makes an important contribution to increasing the efficiency of fabric production, product quality and customer satisfaction.

REFERENCES

1. Gong, R., H. and Chen, Y.(1999). Predicting the Performance of Fabrics in Garment Manufacturing with Artificial Neural Network, *Textile Research Journal*, 69(7): 477-482.
2. Ertuğrul, S., Uçar, N.(2000). Predicting Bursting Strength of Cotton Plain Knitted Fabrics Using Intelligent Techniques, *Textile Research Journal*, 70 (10): 845-851
3. Fan J., Newton E., Au R. and Chan S.C.F. (2001). Predicting Garment Drape with a Fuzzy-Neural Network, *Text. Res. J.*, 71(7), pp 605-608.
4. Zhang, Z., Friedrich K. and Velten, K.(2002). "Prediction on Tribological Properties of Short Fibre Composites Using Artificial Neural Networks", *Wear Journal*, 252: 668 672.
5. Jeon B. S., Bae J. H. and Suh M. W. (2003). Automatic Recognition of Woven Fabric Patterns by an Artificial Neural Network, *Text. Res. J.*, 73(7), pp 645-650.
6. Kuo, C., J., Lee, C., Tsai, C.(2003a), Using a Neural Network to Identify Fabric Defects in Dynamic Cloth Inspection, *Textile Research Journal*, 73 (3): 238-244.
7. Kumar A. (2003). Neural Network Based Detection of Local Textile Defects, *Pattern Recognition,* 36: 1645 – 1659.
8. Zeng, Y.,Wang, K. And Yu, C.(2005). "Predicting the Tensile Properties of Air-Jet Spun Yarns", *Textile Research Journal*, 74(8): 689-694.
9. Beltran, R.,Wang, L. and Wang X.(2006). Predicting the Pilling Tendency of Wool Knits**,** *The Journal of the Textile Institute*, 97(2): 129-136.
10. Oğulata, S. N. ve diğerleri.(2006). "The Prediction of Elongation and Recovery of Woven Bi-Stretch Fabric Using Artificial Neural Network and Linear Regression Models", *Fibres and Textiles in Eastern Europe*, 14(2): 46-49.
11. Islam M.A., Akhter S., Mursalin T.E. & Amin M.A. (2006). A Suitable Neural Network to Detect Textile Defects, King et al. (Eds.): *ICONIP 2006*, Part II, LNCS 4233: 430 – 438, Springer.
12. Gharehaghaji, A. A., Shanbeh, Mohsen and Palhang, M.(2007)."Analysis of Two Methodologies for Predicting the Tensile Properties of Cotton-Covered Nylon Core Yarns", *Textile Research Journal*, 77: 565-571.
13. Furferi, R. and Gelli, M.(2010) "Yarn Strength Prediction: A Practical Model Based on Artificial Neural Networks", *Advances in Mechanical Engineering*, doi:10.1155/2010/640103
14. Guruprasad, R. and Behera, B.K.(2010)."Prediction of Bending of Woven Fabrics By Soft Computing", 7th International Conference TEXSCI, Liberec.
15. Vassiliadis S., Rangoussi, M., Cay A. and Provatidis, C. (2010). Artificial NeuralNetworks and Their Applications in the Engineering of Fabrics, Woven Fabric Engineering, Polona Dobnik Dubrovski.
16. Bahadır, M. Ç.,Bahadır, S. K.and Kaloğlu, F.(2012). An Artificial Neural Network Model for Prediction of Bursting Strength of Knitted Fabrics, International Conference on Machine Learning and Computer Science, Puket, 11-12 August.
17. Haykın, S.(1999). Neural Networks: A Comprehensive Foundation, New Jersey.
18. Krycha K. A. and Wagner U. (1999), "Applications of Artificial Neural Networks in Management Science: A Survey", *Journal of Retailing and Consumer Services*, Vol. 6, p. 185 – 203.
19. Lippmann, R. P.(1987). An Introduction to Computing with Neural Nets, IEEE ASSP Magazine.
20. Öztemel, E.(2003). Yapay Sinir Ağları, Papatya Yayıncılık, İstanbul.
21. Tso GK, Yau KK (2007). Predicting Electricity Energy Consumption: A Comparision of Regression Analysis, Decision Tree and Neural Networks. *Energy*, 32: 1761-1768.

Appendixes

1. The Weave Patterns

x	
	x

Plain weave

	x	x
x	x	
x		x

2/1 twill

		x	x
	x	x	
x	x		
x			x

2/2 twill

		x	x
x	x		

2/2 weft rib

				x	x	x	x
		x	x	x	x		
x	x	x	x				
x	x					x	x

Double 2/2 twill

	x	x	x
x	x	x	
x	x		x
x		x	x

3/1 twill

	x	x	x		x
x	x		x	x	
x		x		x	x

2/1 herringbone

				x	x	x	x
				x	x	x	x
x	x	x	x				
x	x	x	x				

Double 2/2 oxford

2.Intervals of Input Parameters

Fabric length	Machine speed	Width of fabric	Warp density	Efficiency	Yarn strength	Weft yarn number	Warp yarn number	Weft density
12-412	220-460	154-175	27-54	76-94	10-38	10-150	30-150	21-36

3. Determining the Most Appropriate MLP Model

Hidden Layer Neurons Number	R	R^2	MSE	RMSE	MAE
1	0,89	0,79	10,84	3,29	2,50
2	0,91	0,82	10,61	3,26	2,47
3	0,91	0,83	8,98	3,00	2,25
4	0,90	0,81	9,45	3,07	2,32
5	0,95	0,90	5,49	2,34	1,89
6	0,96	0,93	4,21	2,05	1,63
7	0,95	0,90	5,69	2,39	1,90
8	0,96	0,92	5,91	2,43	1,98
9	0,95	0,90	5,76	2,40	1,96
10	0,93	0,87	7,02	2,65	2,09
11	0,91	0,84	8,34	2,89	2,46
12	0,94	0,88	6,53	2,56	2,04
13	0,95	0,90	6,21	2,49	1,85
14	0,95	0,90	5,86	2,42	1,85
15	0,90	0,81	10,90	3,30	2,71
16	0,92	0,85	8,00	2,83	2,40
17	0,94	0,88	7,05	2,66	2,21
18	0,93	0,87	7,17	2,68	2,27
19	0,91	0,83	8,72	2,95	2,50
20	0,94	0,88	6,53	2,56	2,07
21	0,95	0,90	6,15	2,48	2,12
22	0,94	0,89	6,52	2,55	2,08
23	0,94	0,88	7,37	2,72	2,03
24	0,91	0,83	11,53	3,40	2,56
25	0,91	0,83	8,69	2,95	2,42
26	0,93	0,87	7,31	2,70	2,08
27	0,91	0,83	9,31	3,05	2,55
28	0,88	0,78	11,64	3,41	2,97
29	0,91	0,83	11,84	3,44	2,93
30	0,87	0,75	14,79	3,85	3,17
31	0,86	0,73	15,34	3,92	3,33
32	0,90	0,81	12,26	3,50	2,84
33	0,89	0,79	12,12	3,48	3,05
34	0,82	0,67	18,70	4,32	3,70
35	0,87	0,76	15,57	3,95	3,17
36	0,86	0,74	14,93	3,86	3,15
37	0,86	0,74	15,48	3,93	3,27
38	0,84	0,71	19,88	4,46	3,75
39	0,84	0,70	17,96	4,24	3,25
40	0,81	0,66	20,28	4,50	3,71
41	0,82	0,67	19,19	4,38	3,33
42	0,77	0,60	21,88	4,68	3,73
43	0,85	0,73	16,99	4,12	3,38
44	0,88	0,78	15,65	3,96	3,28
45	0,88	0,77	16,36	4,04	3,17
46	0,82	0,67	21,03	4,59	3,60
47	0,84	0,71	22,76	4,77	4,02
48	0,85	0,72	20,64	4,54	4,07
49	0,84	0,70	21,96	4,69	3,74
50	0,81	0,65	23,06	4,80	4,00