(REFEREED RESEARCH)

# A RESEARCH ON ESTIMATION OF THE WEAVE FABRIC PROPERTIES WITH THE ARTIFICIAL NEURAL NETWORKS

# DOKUMA KUMAŞ ÖZELLİKLERİNİN YAPAY SİNİR AĞLARI İLE TAHMİN EDİLMESİ ÜZERİNE BİR ARAŞTIRMA

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**ABSTRACT**

In this study, a feedforward backpropagation artificial neural network (ANN) software was developed and it was tested with two different fabric group. While the former was consisted of 29 cotton samples produced under different conditions, the latter was consisted of 49 polyester samples produced under the same conditions. Each group is divided into training and control groups. The result values of the control groups produced by the trained neural network were obtained. The results of the linear regression for both groups with the same method were also obtained. While the fabric weight, thickness, warp and weft tensile strength for the cotton samples are being examined, the air and water permeability values for the polyester samples were examined. Artificial neural network values for all samples showed better fit than linear regression values. ANN and linear regression results were produced closer results for the polyester samples produced under controlled conditions. While ANN results on cotton samples produced under uncontrolled conditions showed good agreement, the fit of the linear regression results deteriorated. This study was supported by the BAP unit of Uşak University.

**Keywords:** Artificial neural network, Weaving, regression, database

**ÖZET**

Bu çalışmada ileri yayılımlı geri beslemeli yapay sinir ağı (YSA) yazılımı geliştirilerek iki farklı kumaş gurubu ile test edilmiştir. Birinci gurup farklı koşullarda üretilmiş 29 pamuklu numuneden, ikinci gurup aynı koşullarda üretilmiş 49 polyester numuneden oluşturulmuştur. Her gurup kendi içinde eğitim ve kontrol guruplarına ayrılmıştır. Eğitilmiş sinir ağı tarafından üretilen kontrol gruplarının sonuç değerleri elde edilmiştir. Aynı yöntemle her iki gurup için lineer regresyon sonuçları da elde edilmiştir. Pamuk numuneler için kumaş ağırlığı, kalınlığı, atkı ve çözgü kopma mukavemeti incelenirken, polyester numuneler için hava ve su geçirgenliği değerleri incelenmiştir. Tüm numunelerde yapay sinir ağı değerleri lineer regresyon değerlerinden daha iyi uyum göstermiştir. Kontrollü şartlar altında üretilen polyester numunelerde YSA ve lineer regresyon sonuçları birbirine daha yakın sonuçlar üretmiştir. Kontrolsüz şartlarda üretilmiş pamuklu numunelerde YSA sonuçları iyi uyum gösterirken regresyon sonuçlarının uyumu kötüleşmiştir. Bu çalışma Uşak Üniversitesi BAP birimi tarafından desteklenmiştir.

**Anahtar Kelimeler:** Yapay sinir ağı, Dokuma, regresyon, veri tabanı

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## 1. INTRODUCTION

Increasingly difficult competitive conditions in the textile industry have brought to the fore the quality and production speed. Manufacturers which can respond faster to customer needs are preferred by the customers. The weaving preparation procedures are time-consuming processes. Various trials that are made during the productions of the new fabrics to ensure the desired properties cause waste of time. In small weaving mills, the large part of the trial processes are made with the machines used for fabric manufacturing, so the production losses occur. In these type factories, production losses arising from the trials can be minimized by using a high-precision estimation system.

The artificial neural networks can be successfully used for estimation process of the relationships among the parameters.

## 2. ARTIFICIAL NEURAL NETWORKS

The human brain consists of approximately $1,3 \times 10^{10}$ nerve cells called neuron. Each biological neuron consists of a core, a body and the two different extensions. While short branched extensions of the neurons are called dendrite, long and single ones are called axon. Dendrites transmit to the cell body the signals collected from other nerve cells. The output signal produced in the body is transmitted to other nerve cells by means of axons. Every nerve cells has a threshold value (1,15,17).

Artificial neural networks (ANN) consist of artificial neural cells are bound to each other on various ways. Neural cells are placed in different layers. It can be realized as electronic circuit or software. ANN which is suitable for the brain data processing method is a paralel processor that has storing and generalization ability of any information after a learning process (2).

As shown Fig 1. An artificial neural cell consists of p unit entry signal (x1,...xp), a weight value for each entry signal (wk1,..wkp), summing unit, activation function unit,threshold signal and output units.

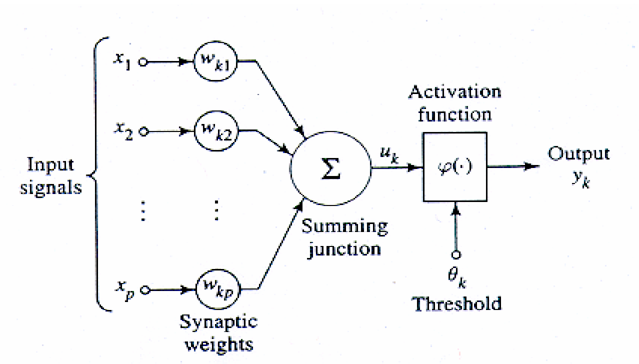


**Figure 1.** An artificial neural neuron structure

Weighted input signals ($x_p.w_p$) are obtained via input signals and weight values of the nerve cell are multiplied by each other. Summing unit of the nerve cell is used to sum weighted input signals. Different functions are used as activation function. In written sources, sigmoid is the most used activation function. Weight values of the input signals ($w_1…w_p$) are determined in [-1, 1] range by fully casual way. Total input values of the neuron are required different from zero. Therefore, a threshold value different (bias, ) from zero for every neuron is randomly selected (2, 17).

The mathematical model of an artificial neural network was shown in Eq. 1,2,3.

$$Y_k = \varphi(U_k + \theta_k) \qquad U_k = \sum_{i=1}^{p} x_i \times w_i \qquad \text{Equation (1)}$$

$$Y_k = \varphi\left(\theta_k + \sum_{i=1}^{p} x_i \times w_i\right) \qquad \text{Equation (2)}$$

$$Y_k = \frac{1}{1 + e^{-(\theta_k + \sum_{i=1}^{p} x_i x w_i)}} \qquad \text{Equation (3)}$$

Artificial neural networks are composed of at least two layers that contain one or more neurons. These are input and output layers. The others between input and output layers are called intermediate layers. Input and output neuron number is bound to respectively dependent and independent variable number.

A neural Network's structure is shown Fig. 2. Output values ($Ç_{O1}$, $Ç_{O2}$) which start from input layer for every neuron is calculated by equation 3. This process is called "feed forward" (1, 2, 15, 17).

There are different methods that provide learning of the artificial neural network. The most prevalent method is known as the supervised learning. In this method, input and desired output values are given to the network for the training.

Backward propagation algorithm is used to reduce the error of the supervised learning method. The calculated output value with feed forward method is compared with desired value. The difference between calculated and desired output values gives error value of the network (Eq. 4). In case of multiple network output the total error expression of the network is given with Equation 5.

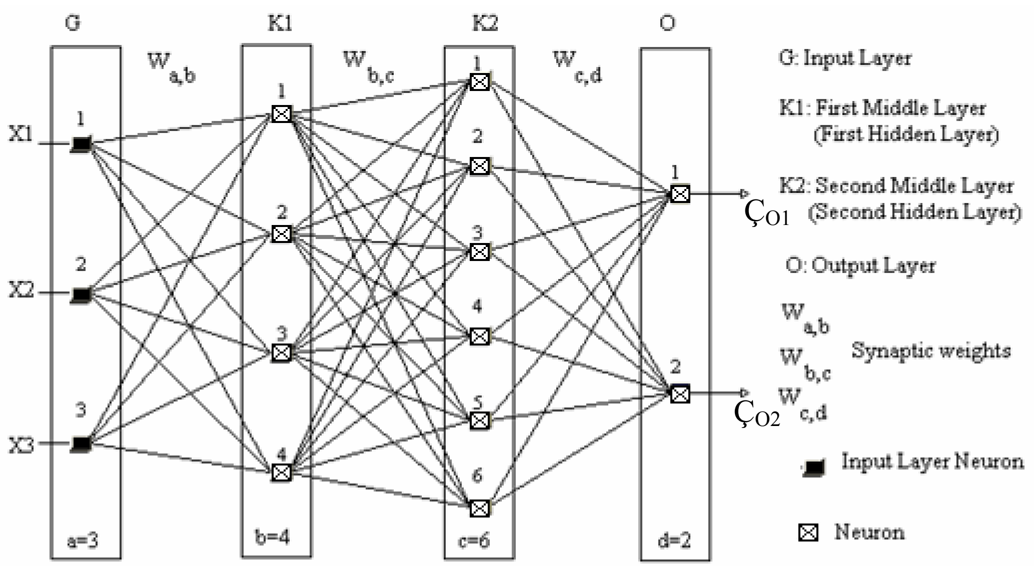


**Figure 2.** The schematic structure of an artificial neural network

$$E_m = B_m - Ç_m \qquad \text{Equation (4)}$$

$$TH = \sqrt[2]{\sum_{m=1}^{n} E_m^{2}} \qquad \text{Equation (5)}$$

The purpose of the backpropagation method is to minimize the total error. To minimize the error amount, total error is distributed on all process elements and weight values are calculated. These processes are repeatedly performed for each value that submitted to network during the training. The amount of weight change between the output and the intermediate layer equations are given in 6,7,8 (1,2,15,17).

$$\Delta A^{o}_{jm}(t) = \lambda \delta_m Ç^{a}_{j} + \alpha \Delta A^{o}_{jm}(t-1) \qquad \text{Equation (6)}$$

$$\delta_m - Ç_m(1 - Ç_m)E_m \qquad \text{Equation (7)}$$

$$A^{o}_{jm}(t) = A^{o}_{jm}(t-1) + \Delta A^{o}_{jm}(t) \qquad \text{Equation (8)}$$

Error value of the output layer should be spread towards the intermediate and input layers. These expressions are given in equations 9,10,11 (1,2,15,17).

$$\Delta A^{i}_{kj}(t) = \lambda \delta^{a}_{j} Ç^{i}_{k} + \alpha \Delta A^{i}_{kj}(t-1) \qquad \text{Equation (9)}$$

$$\delta^{a}_{j} = Ç^{a}_{j}\left(1 - Ç^{a}_{j}\right)\sum_{m} \delta_m A^{o}_{jm} \qquad \text{Equation (10)}$$

$$A^{i}_{kj}(t) = A^{i}_{kj}(t-1) + \Delta A^{i}_{kj}(t) \qquad \text{Equation (11)}$$

Because of the transfer functions used in the neural networks, all data are converted to the values in [0,1] range. After the calculation process, normalized data are converted to their original values.

### Using Artificial Neural Networks in Textiles

Ertuğrul and Uçar (2000) estimated the burst strength of knitted fabrics that depend on the fabric weight, the yarn breakage strength and elongation with normal and fuzzy neural network. In this paper, both the neural network obtained by the estimation results showed satisfactory results (3).

Feng et al. (2003) took the error photos consisting of holes, oil stains, and loose warp and weft yarns on white fabrics. These images were transformed to the gray level images. Then, the gray level images were used to train the artificial neural networks (4).

Boong and Ji (2003) used a neural network and image processing technology for classifying woven fabric patterns. The reflected fabric image was captured and digitized by the computer system. The LVQ algorithm as a learning rule of the artificial neural network enabled recognition of woven fabric types more effectively. As a result, three basic weave types were classified accurately, and the structural parameters such as the yarn spacing and weft spacing were measured (5).

Majumdar et al. (2004) evaluated the elongation at break of the cotton ring-spun yarns with help of ANN, lineer regression and mathematical models. The most accurate evaluation results are obtained by using the artificial neural network (6).

Lin (2007) estimated the warp and weft shrinkage values of the finished woven fabrics by using artificial neural network. In this study, the neural nets were used to find the relationships between the shrinkage of yarns and the cover factors of yarns and fabrics. The prediction of yarn shrinkage in the off-loomed fabrics can thus be fulfilled through a prediction model constructed with neural net. The prediction of yarn shrinkage before production process of the fabrics was realized by the ANN (7).

Uçar and Ertugrul (2007) used ANN for estimation of the knitted fabrics hairiness. In this study, 43 samples of plain knitted fabrics produced with different cotton yarns and on different knitting machines were used. Yarn hairiness, the yarn count and the fabric tightness factor were considered as affecting parameters. Before measuring the stitch length and taking a photo of the fuzz on the fabric surface, all fabrics were placed on a fat surface for one week in standard atmospheric conditions. To be able to compare the results of all models, the sum of square of errors was calculated for both the testing and checking data. Furthermore, the correlation coefficients between fabric fuzz and results obtained from models (linear regression, second-power regression and ANN) were calculated by using all 43 samples.When the values of the sum square total error (SSE) and the correlation coefficient (CC) are examined, it appears that the ANN gave better results (8).

Gurkan and Ureyen (2008) produced 180 different cotton ring spun yarns by using 15 different blends. The four yarn counts and three twist multipliers were chosen within the range of Ne 20–35 and $\alpha_e$ 3.8–4.6 respectively. After measuring yarn tenacity and breaking elongation, evaluations of data were performed by using ANN. Afterwards, sensitivity analysis results and coefficient of multiple determination ($R^2$) values of ANN and regression models were compared. The results showed that ANN is more powerful tool than the regression models (9).

Halizadeh et al. (2009) guessed tensile strength of the plain woven fabrics with four inputs and one output neural network. They showed that the estimation results are compatible with the real measurement results (10).

Balcı and Oğulata (2009) investigated the finishing process influence onto CIELab color values. They used in this research six different woven and colored fabrics. Values were estimated by using ANN in different topologies. In this study it was shown that the ANN models can be used to estimate color change of dyed fabrics (12).

Rocco and Maurizio (2010) measured the different sliver properties to train the network. The different strip values used for fifty yarns were tested with trained network. The error in the test results was lower than 4% (13).

Yaman et al. (2011) analysed textile diapers comfort subjectively with a group of experts. They also tested the properties of diapers. Practical measurements, neural network values and multiple regression values were compared with subjective measurement values. Evaluation results showed that artificial neural networks and subjective estimation results are more compatible (14).

Bahadır et al. (2012) estimated the bursting strength of single jersey fabrics knitted with the cotton yarns and the elastomeric yarns. Input parameters of the network were cotton yarn count, elastomeric yarn count and composition ratio of elastomeric yarns. Estimation results showed very good agreement with real bursting strength of the fabrics (16).

Özdemir (2013) used artificial neural networks for determination of woven fabric errors. He digitized the gray level images in error detection work. Fabrics were randomly separated into two groups. While first group was used for training, the other group was used to test the network. In this research, the ANN was trained with 97 fabric sample. After the training, ANN classified the control group samples according to the raw materials of the fabrics. The classification process was performed by the ANN in a very successful manner except polyester fabrics (19).

Arıkan Kargı V. S. (2014) predicted weft defects in fabric production using a multilayer perceptron model and multiple linear regression models. 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 and three different type polyester cotton mixture yarns. Two types of warp yarn, %55/45 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. At the end of the process, ANN model has shown better compliance ($R^2$=0,93) than the multiple linear regression model ($R^2$=0,71) (20).

Utkun E. (2015) investigated the use of artificial neural networks for the assessment of clothing comfort. According to this research, the compound systems are the best models for evaluating of the clothing comfort. Especially, the models of the “Statistic + ANN + ANN” or “Statistics + ANN + Fuzzy Logic” are the most successful estimators and the former model is better than the latter model (21).

Yamin J. (2015) determined the thermal properties of textiles using artificial neural network. In this study, thermal conductivity (W/m.K) of the yarns and weight (gr/m$^2$), air permeability (L/m$^2$.s), porosity (%) values of the fabrics were used as input parameters of the ANN. Thermal conductivity values of fabrics were estimated with high compliance (22).

## 3. MATERIAL AND METHOD

### 3.1. MATERIAL

In this study, polyester and cotton samples were used. Cotton fabric samples were got from different textile mills. Polyester fabric samples were woven in the same conditions (11). The cotton and polyester samples were divided into two different sections as control and training groups. Fabric weights, thicknesses, warp and weft tensile strengths of the cotton samples, with air permeability and constant pressure water permeability values of the polyester samples were measured. Fabric properties used in this study are shown in Table 1, 2 and Table 3, 4.

At the end of training process, input parameters in the control groups were offered to the network and the corresponding output values were calculated by the network. The standards used to determine the fabric sample properties are shown in table 5.

**Table 1.** Polyester fabrics properties in training group. (11)

| Sample | Warp Dens. (Wrp/cm) | Weft Density (Weft/cm) | Weft count (Den) | Weave Factor | Reynolds | Warp Type * | Weft Type * | Weight ($gr/m^2$) | Air Perm. (mm/sn) | Sample | Warp Dens. (Wrp/cm) | Weft Density (Weft/cm) | Weft count (Den) | Weave Factor | Reynolds | Warp Type * | Weft Type * | Weight ($gr/m^2$) | Air Perm. (mm/sn) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 34.1 | 58.4 | 75 | 0.67 | 3463.05 | 2 | 1 | 79.95 | 495.8 | 21 | 33.6 | 32.2 | 75 | 0.5 | 3433.68 | 2 | 2 | 59.92 | 423.2 |
| 2 | 34.4 | 58.3 | 75 | 0.67 | 3587.17 | 1 | 2 | 81.14 | 546.6 | 22 | 34 | 32.2 | 75 | 0.5 | 3054.13 | 1 | 2 | 61.65 | 436.8 |
| 3 | 34.3 | 58 | 75 | 0.67 | 4646.58 | 1 | 1 | 81.67 | 679 | 23 | 32.3 | 32 | 300 | 0.67 | 1872.18 | 2 | 1 | 146.91 | 277.6 |
| 4 | 34.6 | 57.8 | 75 | 0.67 | 2931.12 | 2 | 2 | 85.52 | 444.6 | 24 | 33.5 | 31.6 | 75 | 0.5 | 3793.84 | 2 | 1 | 59.11 | 480.8 |
| 5 | 34.3 | 51.1 | 75 | 0.67 | 3334.5 | 2 | 2 | 78.4 | 509.8 | 25 | 33.8 | 31.6 | 75 | 0.5 | 4204.41 | 1 | 1 | 57.97 | 653.4 |
| 6 | 34.2 | 50.8 | 75 | 0.67 | 4262.04 | 2 | 1 | 79.48 | 829.4 | 26 | 32.4 | 31.2 | 300 | 0.67 | 2314.98 | 1 | 1 | 144.8 | 330.4 |
| 7 | 34.5 | 50 | 75 | 0.67 | 4426.02 | 1 | 2 | 72.8 | 631.8 | 27 | 32.6 | 30.5 | 150 | 0.5 | 2116.61 | 2 | 1 | 83.97 | 350 |
| 8 | 34 | 49.6 | 75 | 0.67 | 5089.85 | 1 | 1 | 72.63 | 792.6 | 28 | 32.6 | 30.1 | 150 | 0.5 | 2806.45 | 1 | 1 | 82.32 | 351.2 |
| 9 | 33.52 | 44.9 | 150 | 0.67 | 2749.38 | 2 | 1 | 110.18 | 383.4 | 29 | 32.3 | 29.3 | 300 | 0.67 | 3487.43 | 2 | 1 | 133.57 | 455.4 |
| 10 | 33.8 | 43.8 | 75 | 0.67 | 4010.48 | 2 | 2 | 69.93 | 638.2 | 30 | 32.2 | 28.4 | 300 | 0.67 | 3362.20 | 1 | 1 | 130.65 | 510.6 |
| 11 | 33.9 | 43.1 | 75 | 0.67 | 4382.83 | 2 | 1 | 68.12 | 708.2 | 31 | 32.5 | 26.4 | 150 | 0.5 | 3546.16 | 2 | 1 | 77.04 | 507.8 |
| 12 | 34 | 41.6 | 75 | 0.5 | 1630.13 | 2 | 1 | 66.32 | 226 | 32 | 32.3 | 25.3 | 150 | 0.5 | 5658.34 | 1 | 1 | 78.32 | 707 |
| 13 | 34.1 | 40.9 | 75 | 0.5 | 1711.46 | 1 | 1 | 66.63 | 275.8 | 33 | 32 | 24.6 | 300 | 0.5 | 1179.10 | 2 | 1 | 118.7 | 161.4 |
| 14 | 33.45 | 40.4 | 150 | 0.67 | 3815.45 | 2 | 1 | 103.04 | 573.2 | 34 | 32.1 | 23.8 | 300 | 0.67 | 5745.89 | 1 | 1 | 114.96 | 874 |
| 15 | 34.2 | 37.08 | 75 | 0.5 | 1670.25 | 1 | 2 | 65.12 | 254.8 | 35 | 32 | 23.6 | 300 | 0.5 | 1799.68 | 1 | 1 | 117.2 | 232.2 |
| 16 | 33.76 | 37 | 75 | 0.5 | 2388.17 | 2 | 1 | 61.47 | 361 | 36 | 32 | 23.2 | 300 | 0.5 | 2374.82 | 1 | 1 | 114.94 | 228 |
| 17 | 33.9 | 36.5 | 75 | 0.5 | 2576.51 | 1 | 1 | 61.21 | 436.4 | 37 | 32.2 | 20.9 | 300 | 0.5 | 2996.50 | 2 | 1 | 108.77 | 403.1 |
| 18 | 32.8 | 34.5 | 150 | 0.5 | 975.19 | 2 | 1 | 90 | 134.4 | 38 | 32.3 | 17.6 | 300 | 0.5 | 5302.02 | 2 | 1 | 94.49 | 775.8 |
| 19 | 33 | 34 | 150 | 0.67 | 5923.19 | 1 | 1 | 89.58 | 903.2 | 39 | 32.2 | 17 | 300 | 0.5 | 6857.13 | 1 | 1 | 91.79 | 1020 |
| 20 | 32.8 | 34 | 150 | 0.5 | 1135.88 | 1 | 1 | 89.45 | 187 | | | | | | | | | | |

* : 1: circular fiber cross-section 2: hexagon fiber cross-section

**Table 2.** Polyester fabrics properties in control group. (11)

| Sample | Warp Dens. (Wrp/cm) | Weft Density (Weft/cm) | Weft count (Den) | Weave Factor | Reynolds | Warp Type * | Weft Type * | Weight ($gr/m^2$) | Air Perm. (mm/sn) | Sample | Warp Dens. (Wrp/cm) | Weft Density (Weft/cm) | Weft count (Den) | Weave Factor | Reynolds | Warp Type | Weft Type | Weight ($gr/m^2$) | Air Perm. (mm/sn) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 33,9 | 32,2 | 75 | 0,5 | 3263,57 | 2 | 2 | 60,01 | 392.8 | 6 | 32,5 | 24,5 | 300 | 0,67 | 5473,27 | 2 | 1 | 118,01 | 777,8 |
| 2 | 33,06 | 38,8 | 150 | 0,67 | 4245 | 1 | 1 | 100,77 | 620 | 7 | 34,1 | 43 | 75 | 0,67 | 4503,1 | 1 | 2 | 66,47 | 731,4 |
| 3 | 34 | 37,5 | 75 | 0,5 | 1461,68 | 2 | 2 | 64,5 | 210,4 | 8 | 34,3 | 41,6 | 75 | 0,5 | 915,35 | 1 | 2 | 71,2 | 181,8 |
| 4 | 33,9 | 42,8 | 75 | 0,67 | 5417,86 | 1 | 1 | 66,47 | 920,6 | 9 | 32,1 | 20,5 | 300 | 0,5 | 4049,27 | 1 | 1 | 100,7 | 422,4 |
| 5 | 33,25 | 35,1 | 150 | 0,67 | 4714,125 | 2 | 1 | 93,54 | 768,4 | 10 | 33,6 | 44,3 | 150 | 0,67 | 3227 | 1 | 1 | 105,5 | 498,4 |

* : 1: circular fiber cross-section 2: hexagon fiber cross-section

**Table 3.** Cotton fabrics properties in training group.

| Sample | Weave Factor | Warp Density (Warp/cm) | Warp Count (Ne) | Warp Crimp (%) | Weft Density (Weft/cm) | Weft Count (Ne) | Weft Crimp (%) | Production method 1: Ring 2: O.E. | | Thickness (mm) | Weft Tens. Strength (N) | Warp Tens. Strength (N) | Fabric Weight (gr/m$^2$) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Warp | Weft | | | | |
| 1 | 0.5 | 27.7 | 24.30 | 8.70 | 30.3 | 31.02 | 7.5 | 1 | 2 | 0.63 | 328.5 | 415.05 | 134.40 |
| 2 | 0.5 | 29 | 27.80 | 9.20 | 26 | 30.2 | 4 | 1 | 1 | 0.57 | 320.5 | 403.7 | 120.00 |
| 3 | 0.5 | 30 | 30.20 | 5.08 | 22.6 | 27.8 | 9.47 | 1 | 1 | 0.53 | 275.5 | 384.6 | 115.07 |
| 4 | 0.5 | 29 | 28.10 | 7.80 | 24 | 30 | 3.3 | 1 | 1 | 0.56 | 298.8 | 433.8 | 115.50 |
| 5 | 0.5 | 28.7 | 28.37 | 6.80 | 23.3 | 30.2 | 5 | 1 | 1 | 0.5 | 261.6 | 404 | 112.90 |
| 6 | 0.5 | 27 | 27.80 | 11.00 | 25 | 29.2 | 5.2 | 1 | 1 | 0.49 | 302.03 | 376 | 116.10 |
| 7 | 0.5 | 29.7 | 27.60 | 10.10 | 22 | 30 | 3.9 | 1 | 1 | 0.5 | 233.03 | 433.3 | 115.20 |
| 8 | 0.5 | 29.3 | 21.80 | 13.60 | 22.6 | 25.2 | 5.9 | 1 | 1 | 0.45 | 437.67 | 523.4 | 143.80 |
| 9 | 0.5 | 29 | 29.05 | 7.10 | 23 | 30.5 | 4.8 | 1 | 1 | 0.46 | 264.17 | 385.53 | 112.65 |
| 10 | 0.5 | 29.3 | 26.50 | 6.90 | 25 | 30.3 | 5.7 | 1 | 1 | 0.46 | 324 | 458 | 119.25 |
| 11 | 0.5 | 29 | 27.70 | 3.30 | 24 | 29 | 5.3 | 1 | 1 | 0.49 | 294.6 | 432.7 | 114.30 |
| 12 | 0.5 | 29 | 28.20 | 7.10 | 22 | 29.05 | 5.3 | 1 | 1 | 0.47 | 251 | 382.3 | 112.70 |
| 13 | 0.5 | 28.7 | 32.08 | 7.70 | 23.3 | 32.12 | 5.6 | 2 | 2 | 0.45 | 256 | 320 | 113.00 |
| 14 | 0.5 | 28.7 | 27.01 | 8.70 | 23 | 30 | 4.2 | 1 | 1 | 0.56 | 282.7 | 424.3 | 115.70 |
| 15 | 0.6 | 49 | 27.80 | 8.70 | 28 | 30.26 | 3.2 | 1 | 1 | 0.49 | 365.3 | 987.4 | 168.26 |
| 16 | 0.5 | 27.5 | 44.30 | 7.50 | 19 | 16.9 | 5.7 | 2 | 1 | 0.42 | 309 | 406.5 | 109.00 |
| 17 | 0.5 | 28.2 | 43.80 | 5.90 | 20 | 17 | 2.35 | 2 | 1 | 0.41 | 334 | 474.4 | 113.20 |
| 18 | 0.5 | 29.5 | 47.40 | 10.70 | 19.5 | 19.3 | 4.85 | 2 | 1 | 0.49 | 261 | 346 | 102.50 |
| 19 | 0.6 | 65.5 | 43.05 | 13.46 | 40 | 43.04 | 3 | 2 | 2 | 0.44 | 460 | 691.7 | 159.20 |
| 20 | 0.6 | 56.5 | 32.10 | 10.00 | 30.3 | 32 | 6.7 | 2 | 2 | 0.46 | 554 | 948 | 174.90 |
| 21 | 0.5 | 30 | 21.50 | 4.20 | 18 | 19.3 | 14.5 | 1 | 1 | 0.38 | 246 | 494 | 152.5 |
| 22 | 0.6 | 30 | 12.60 | 11.50 | 20.7 | 16.7 | 4 | 1 | 1 | 0.59 | 632.3 | 838 | 233.00 |
| 23 | 0.67 | 44 | 13.00 | 18.20 | 23.3 | 12.4 | 3.5 | 1 | 1 | 0.87 | 690 | 580 | 345.90 |

**Table 4.** Cotton fabric properties in control group.

| Sample | Weave Factor | Warp Density (Warp/cm) | Warp Count (Ne) | Warp Crimp (%) | Weft Density (Weft/cm) | Weft Count (Ne) | Weft Crimp (%) | Warp Prod. Method * | Weft Prod. Method * | Thickness (mm) | Weft Tens. Strength (N) | Warp Tens. Strength (N) | Fabric Weight (gr/m$^2$) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.5 | 33 | 26.80 | 9.90 | 28.3 | 30 | 6.5 | 1 | 1 | 0.57 | 372.6 | 429.95 | 137.05 |
| 2 | 0.5 | 28 | 27.00 | 9.10 | 23 | 29.7 | 4 | 1 | 1 | 0.56 | 250 | 360 | 113.60 |
| 3 | 0.5 | 30.3 | 30.4 | 5 | 30 | 26 | 8 | 1 | 1 | 0.48 | 355 | 425.5 | 137.50 |
| 4 | 0.5 | 35 | 32.05 | 5 | 21.7 | 30.4 | 12 | 2 | 2 | 0.57 | 249 | 335.3 | 116.20 |
| 5 | 0.6 | 40 | 28 | 8.7 | 27 | 30 | 4.3 | 1 | 1 | 0.55 | 328.33 | 586.6 | 146.66 |
| 6 | 0.67 | 56 | 32.4 | 11.8 | 27 | 9.8 | 5.5 | 2 | 1 | 0.72 | 694 | 1109 | 279.40 |

*: 1: O.E 2: Ring

**Table 5.** Used test standards in the study.

| Used Standards | | | |
|---|---|---|---|
| **Parameter** | **Standard No** | **Parameter** | **Standard No** |
| Yarn count | TS 255 | Warp/Weft Tensile strength | TS 245 |
| Warp/Weft density | TS 250 EN 1049-2 | Fabric weight | TS EN 12127 |
| Air permeability | TS 391 EN ISO 9237 | Fabric thickness | TS 7128 EN ISO 5084 |

## 3.2 METHOD

### 3.2.1 The structure and properties of artificial neural network program

The software was designed as feedforward and back propagation neural network program and written with Microsoft Visual Basic programming language. It was designed to take data from a database such as Microsoft Excel or Microsoft Access. In the program, number of input neuron, intermediate layers and output neuron were designed to be adjusted optionally. The ANN has the sigmoid transfer function. Initial values of the neurons can be saved. The learning and momentum coefficients of the network can be adjusted in the beginning period of the training. In this study these coefficients were accepted as 0.5 and 0.8 respectively. Feed-forward and back propagation algorithm of neural network can be seen in Figure 10.

Before the training period, input and output parameters of the network were selected from the database. If necessary, the data can be filtered from the database.During the training period all data were offered to the network. The average error between the network output values and the actual values is calculated. The calculated average error value is fed back to the network. The error value is distributed in proportion to the weight values of the neurons to the network. This process continues until the error value reaches the minimum average. During the training process, the change of the mean error value is drawn according to the number of transactions (Fig. 3.A).

In the training process to determine the appropriate cycle number error graph is drawn (Fig.3.B). Thanks to the error graph, the deviation between the target value of each data in the training data set and the output value calculated by the network can be seen (Fig. 3.B). The erroneous data among the data set can also be determined by the error graph. The network whose training phase was completed can be saved with a special name and called back. It can be used for single or a lot of data prediction.

The properties and input-output parameters of the networks that were used for prediction process were shown in Table 6. For each prediction process, a different network was used. In order to compare the results calculated by the network, the values of the sample using the same parameters were calculated with linear regression method. The results of the linear regression are shown in table 7.

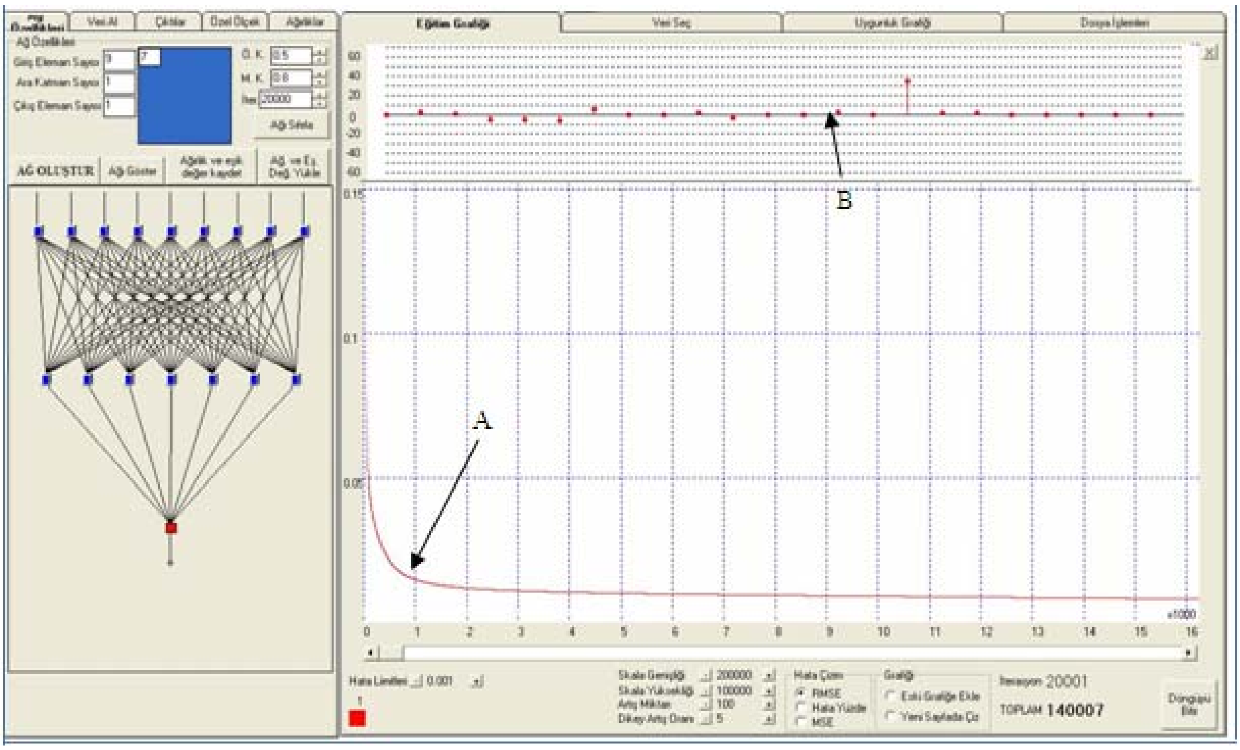


**Figure 3.** Network structure, network training screen and the error chart.

**Table 6.** Properties of the network used in the study, input and output parameters

| **Network properties of the cotton samples** | | | | |
|---|---|---|---|---|
| **ANN Properties** | **(1)** | **(2)** | **Input layer parameters (1)** | **Input layer parameters (2)** |
| The Number Of Neurons In The Input Layer | 9 | 11 | **1)**Warp count **2)**Warp density **3)**Warp crimp **4)** Warp prod. Meth. **5)** Weft prod. Meth. **6)**Weft count **7)**Weft density **8)**Weft crimp **9)**Weave factor | **1)**Warp count **2)**Warp density **3)**Warp crimp **4)** Warp prod. Meth. **5)** Weft prod. Meth. **6)**Weft count **7)**Weft density **8)**Weft crimp **9)**Weave factor **10)** Fabric Thickness **11)** Fabric Weight |
| Middle Layer Count | 1 | 1 | | |
| Middle Layer’s Neuron Count | 7 | 9 | | |
| Output layer Neuron Count | 1 | 1 | | |
| Learning Coefficient | 0.5 | 0.5 | | |
| Momentum Coefficient | 0.8 | 0.8 | **Output layer parameters (1)** | **Output layer param. (2)** |
| (1): ANN used for fabric weight and fabric thickness<br>(2): ANN used for warp and weft tensile strength | | | **1)** Weight<br>**2)** Thickness | **1)** Warp tensile strength<br>**2)** Weft tensile strenght |
| **Network properties of the polyester samples** | | | | |
| **ANN Properties** | | **Input layer parameters** | | |
| The Number Of Neurons In The Input Layer | 7 | **1)** Weft count **2)** Warp type **3)** Warp density **4)** Weft density **5)** Weave factor **6)** Fabric Weight **7)** Weft type | | |
| Middle Layer Count | 1 | | | |
| Middle Layer’s Neuron Count | 5 | | | |
| Output layer Neuron Count | 1 | **Output layer parameters** | | |
| Learning Coefficient | 0.5 | **1)** Air permeability | | |
| Momentum Coefficient | 0.8 | **2)** Reynolds | | |

**Table 7.** The linear regression models obtained from cotton and polyester fabric samples.

| | | |
|---|---|---|
| Polyester | $R^2$=0.815 | $R = 84428,46 - 1042,99 \times CS - 50,84 \times AS + 1,886 \times ANo + 22721,02 \times OF - 559,68 \times CT - 281,784 \times AT - 79,187 \times AG$ |
| | $R^2$=0.865 | $HG = 8091,88 - 95,85 \times CS - 8,29 \times AS + 0,547 \times ANo + 8590,96 \times OF - 76,61 \times CT - 87,99 \times AT - 12,72 \times AG$ |
| Cotton | $R^2$=0.972 | $AG = -153,669 - 0,2577 \times CS + 694,8 \times OF - 0,7926 \times CNo + 3,042 \times CK + 0,269 \times AS - 2,64 \times ANo - 0,443 \times AK - 26,89 \times CUY + 28,31 \times AUY$ |
| | $R^2$=0.778 | $K = -0,467 - 0,0078 \times CS + 2,302 \times OF - 0,0069 \times CNo + 0,0058 \times CK + 0,0016 \times AS - 0,0056 \times ANo - 0,0005 \times AK - 0,215 \times CUY + 0,142 \times AUY$ |
| | $R^2$=0.924 | $CKM = 413,374 - 15,95 \times CS + 3934,54 \times OF - 9,109 \times CNo - 10,26 \times CK - 1,766 \times AS - 29,836 \times ANo - 19,023 \times AK - 376,912 \times CUY + 335,509 \times AUY - 1202,69 \times KL - 4,164 \times AG$ |
| | $R^2$=0.968 | $AKM = 726,486 + 5,068 \times CS - 712,988 \times OF - 17,71 \times CNo + 0,91 \times CK + 28,013 \times AS - 18,08 \times ANo + 6,577 \times AK + 260,82 \times CUY - 150,17 \times AUY - 94,68 \times KL + 0,07 \times AG$ |
| R:Reynolds CS: Warp Density AS: Weft Density AN: Weft Count OF: Weave Factor CT: Warp Type AT: Weft Type AG: Weight<br>HG: Air Permeability CNo: Warp count CK: Warp Crimp AK: weft Crimp CUY: Warp production method AUY: Weft production method<br>CKM: Warp Tensile strength AKM: Weft tensile strength KL: Fabric thickness | | |

## 4. EVALUATION AND CONCLUSION

A Comparison of the air permeability and Reynolds number values for polyester control group fabrics were shown in Table 8. According to the table, the calculated results by the ANN showed better compliance than from the linear regression results.

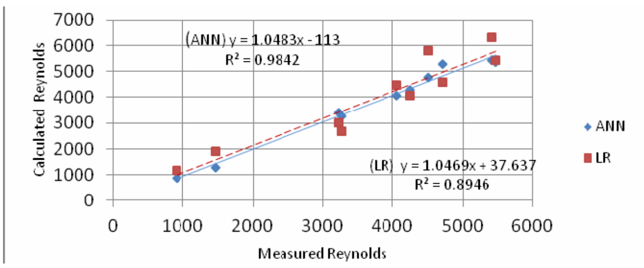


Figure 4. The relationship between measured and calculated values of the Reynolds number used for water permeability of polyester weave fabrics.

The relationship between measured and calculated values of Reynolds number and air permeability are linear according to both methods. This situation can be seen in fig.4 and fig.5.

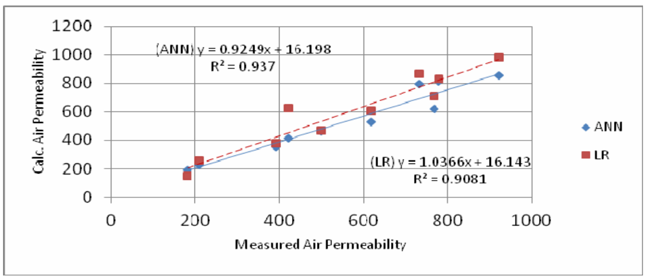


**Figure 5.** The relationship between air permeability values of polyester weave fabrics calculated by two different methods.

According to the table, while linear regression analysis results of the Reynolds values showed distribution between -17,8 and 29,96 per cent, ANN results showed distribution between -12.83 and 11,82 per cent. As a result, the distribution of the linear regression analyzes showed results in the range of about twice the size of the ANN.

The deviation values of air permeability analysis of the ANN are bigger than deviation of the Reynolds analysis values. The same situation is valid for the linear regression results too.

**Table 8.** Measured and calculated values of the air permeability and Reynolds number properties of the polyester control group fabrics.

| Sample No | Reynolds Value | | | | | Air Permeability | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Artificial N.N. | | Lineer Regression | | | Artificial N. N. | | Lineer Regression | |
| | Measured Value | Calculated Value | Difference (%) | Calculated Value | Difference (%) | Measured Value | Calculated Value | Difference (%) | Calculated Value | Difference (%) |
| 1 | 3263.57 | 3265.56 | 0.061 | 2682.49 | -17.8 | 392.8 | 356.11 | -9.34 | 378.07 | -3.75 |
| 2 | 4245 | 4280.29 | 0.83 | 4064.92 | -4.24 | 620 | 529.83 | -14.54 | 606.95 | -2.11 |
| 3 | 1461.68 | 1274.11 | -12.83 | 1899.54 | 29.96 | 210.4 | 226.93 | 7.86 | 256.72 | 22.02 |
| 4 | 5417.86 | 5412.2 | -0.10 | 6290.26 | 16.10 | 920.6 | 858.35 | -6.76 | 982.14 | 6.68 |
| 5 | 4714.125 | 5271.22 | 11.82 | 4596.11 | -2.50 | 768.4 | 620.41 | -19.26 | 713.54 | -7.14 |
| 6 | 5473.27 | 5342.36 | -2.39 | 5434.07 | -0.72 | 777.8 | 810.68 | 4.23 | 832.80 | 7.07 |
| 7 | 4503.1 | 4778.51 | 6.12 | 5781.5 | 28.39 | 731.4 | 797.08 | 8.98 | 870.29 | 18.99 |
| 8 | 915.35 | 862.5 | -5.77 | 1166.48 | 27.43 | 181.8 | 192.08 | 5.65 | 148.28 | -18.44 |
| 9 | 4049.27 | 4055.58 | 0.16 | 4467.66 | 10.33 | 443.4 | 416.89 | -5.98 | 628.28 | 48.74 |
| 10 | 3227 | 3399.16 | 5.34 | 3012.59 | -6.64 | 498.4 | 462.57 | -7.19 | 470.69 | -5.56 |
| | MEAN | | 4.54 | | 14,41 | MEAN | | 8.98 | | 14.05 |

**Table 9.** Measured and calculated values of the cotton fabrics.

| | No | Weight (gr/m2) | | | Thickness (mm) | | | Warp Tensile Strenght(N) | | | Weft Tensile Strenght (N) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Msrd. | Calc. | Diff. (%) | Msrd. | Calc. | Diff. (%) | Msrd. | Calc. | Diff. (%) | Msrd. | Calc. | Diff. (%) |
| Artificial N. N. | 1 | 137.05 | 138.216 | 0.85 | 0.57 | 0.4688 | -17.75 | 429.95 | 440.82 | -2.53 | 372.6 | 377.34 | -1.27 |
| | 2 | 113.6 | 114.568 | 0.85 | 0.56 | 0.5780 | 3.21 | 360 | 384.57 | -6.82 | 250 | 237.92 | 4.83 |
| | 3 | 137.5 | 137.66 | 0.12 | 0.48 | 0.4927 | 2.65 | 425.5 | 401.16 | 5.72 | 355 | 356.57 | -0.44 |
| | 4 | 116.2 | 115.026 | -1.01 | 0.57 | 0.551 | -3.33 | 335.3 | 339.38 | -1.2 | 249 | 241.03 | 3.2 |
| | 5 | 146.66 | 153.655 | 4.77 | 0.55 | 0.5485 | -0.27 | 586.6 | 589.29 | 0.46 | 328.3 | 351.32 | -7.01 |
| | 6 | 279.4 | 293.66 | 5.1 | 0.72 | 0.7056 | -2.00 | 1109 | 973.8 | 12.2 | 694 | 719.89 | -3.73 |
| Lin.Regression | 1 | 137.05 | 121.034 | -11.69 | 0.57 | 0.4685 | -17.81 | 429.95 | 282.183 | 34.368 | 372.6 | 433.205 | -16.265 |
| | 2 | 113.6 | 120.21 | 5.82 | 0.56 | 0.4989 | -10.91 | 360 | 376.109 | -4.475 | 250 | 270.95 | -8.379 |
| | 3 | 137.5 | 114.32 | -16.86 | 0.48 | 0.5108 | 6.43 | 425.5 | 402.858 | 5.321 | 355 | 459.47 | -29.429 |
| | 4 | 116.2 | 97.60 | -16.01 | 0.57 | 0.3722 | -34.70 | 335.3 | 211.784 | 36.837 | 249 | 328.68 | -32.001 |
| | 5 | 146.66 | 184.73 | 25.96 | 0.55 | 0.6444 | 17.17 | 586.6 | 795.395 | -35.594 | 328.3 | 335.37 | -2.146 |
| | 6 | 279.4 | 261.10 | -6.55 | 0.72 | 0.6269 | -12.93 | 1109 | 730.940 | 34.090 | 694 | 815.12 | -17.452 |
| MEAN | | A.N.N | | 2.12 | A.N.N. | | 4.87 | A.N.N | | 4.82 | A.N.N | | 3.41 |
| | | Linear Reg. | | 13.81 | Linear Reg | | 16.66 | Linear Reg | | 25.114 | Linear Reg | | 17.61 |

Msrd: Measured values, Calc: Calculated values, Diff: Difference

According to Table 9, the values calculated by artificial neural network gave more accurate results than the linear regression values. According to Figure 6-9, there are linear relationship between the ANN results and measured values of the examined parameters. The compliance is high between them.

Linear regression results of the cotton fabrics are worse than the ANN results. Calculated and measured values of fabric weight and weft tensile strength show linear relationship. But regression values of fabric thickness parameter are not appropriate. Calculated thickness values of four samples are quite different from each other although these measured values are nearly same. As a result of this situation, the regression results of thickness values don't show a meaningful relation.

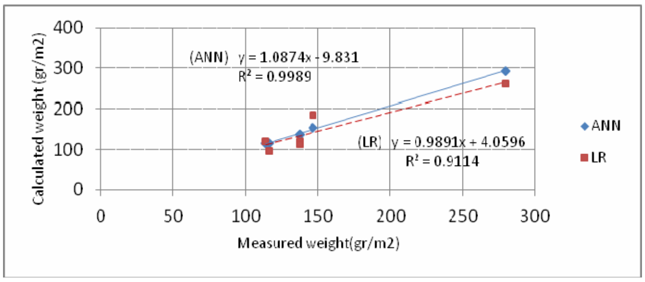


**Figure 6.** The relationship between weight values and calculated values measured by two different methods of cotton sample fabrics.

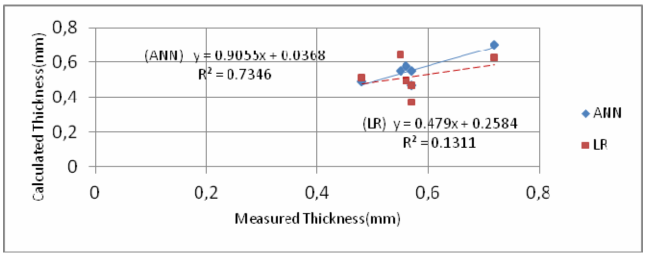


**Figure 7.** The relationship between thickness values and calculated values measured by two different methods of cotton sample fabrics.

Although the relation between measured and calculated warp tensile strength values seems to a quadratic equation, it is possible that this result is misleading. While warp tensile strength values of five cotton fabric samples show the linear relationship, only one sample value deviation causes to the quadratic relationship (Fig 8). This situation may result from measuring error of the fifth fabric sample. Linear regression equation of this group is *y=0,64153x +133, 64* ($R^2$=0,557). When the suspicious value (sample No: 5) is excluded in this group, linear regression equation is *y=0,5764x +94,149 ($R^2$=0, 8816)* and quadratic regression equation is *y= -0, 0004.x2 + 1, 1933.x - 81, 01* ($R^2$=0, 8854). According to these results, the relationship between warp strength and fabric parameters is bound to linear.

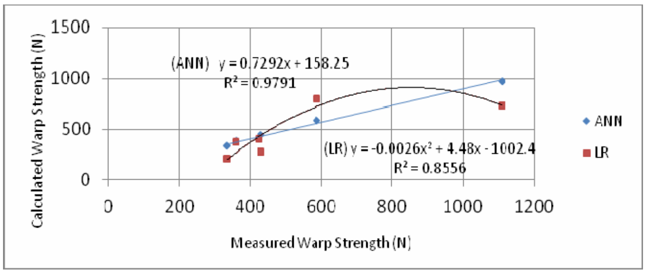


**Figure 8.** The relationship between warp strength values and calculated values measured by two different methods of cotton sample fabrics.

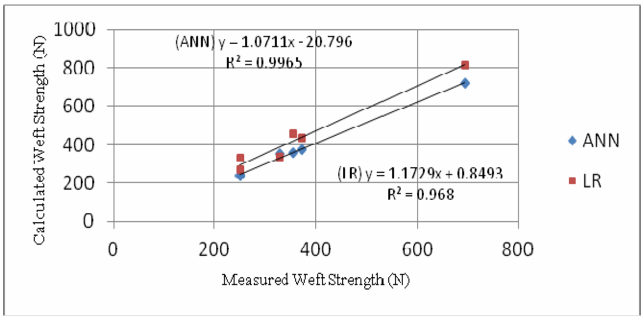


**Figure 9.** The relationship between weft strength values and calculated values measured by two different methods of cotton sample fabrics.

## 5. RESULTS

All cotton fabric samples used in this study were obtained from businesses which have different working conditions. Polyester fabrics were woven with the same yarns on the same weaving machine.

Artificial neural network prediction results yielded more accurate results in both cotton and polyester samples according to the linear regression results. According to these values, the results of the linear regression are closer to the neural network results for the polyester samples. The regression results of cotton samples showed more variance.

The production of the polyester samples was carried out under more homogeneous conditions. Uncontrollable parameter count of the cotton samples is higher than the polyester samples since they are picked up from different factories. Therefore linear regression results showed more deviation than the real results.

According to the results obtained, artificial neural networks provided the possibility of more flexible and accurate prediction results compared to the linear regression method. It can be confidently used in the situations in which the count of uncontrollable parameters is high.

Due to the nature of the program, it can communicate directly with the database that is used in the enterprise. In the case of selecting the appropriate data in the database, it is possible to predict the fabric properties for special circumstances and make custom queries like time, staff, climate, machine adjustments effects on fabric properties.

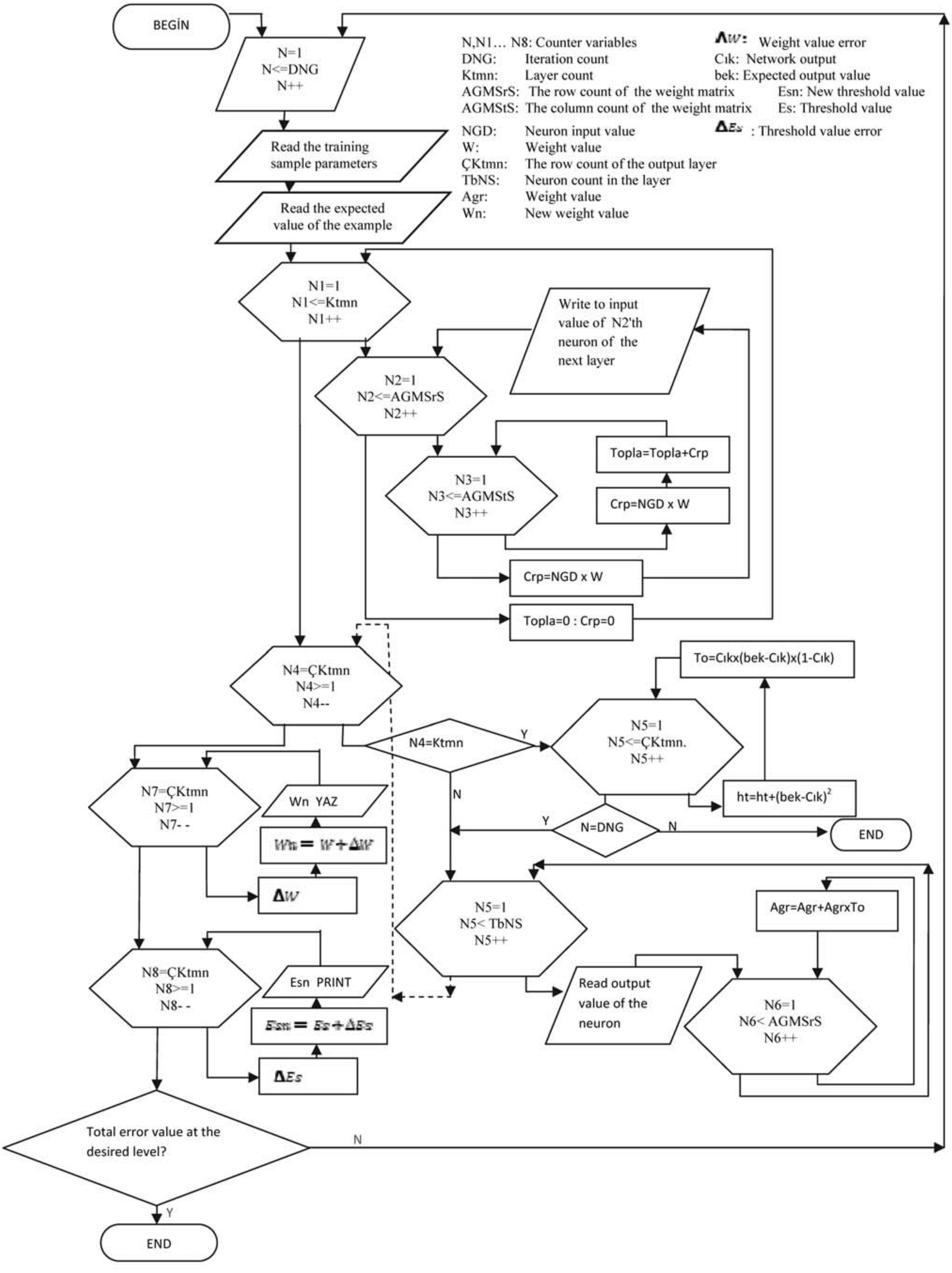


**Figure 10.** The artificial neural network algorithm.

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