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Prediction of Ultimate Tensile Strength of Prestressed Concrete Strand Using Artificial Neural Network Model

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Abstract

The iron and steel industry is one of the essential sector for the industrial and economic development of a country. The most common problem in iron and steel industry is to determine the ultimate tensile strength of the product. The raw materials that are used in the Prestressed Concrete (PC) strand product are deformed under force and their shape and size are changed since the characteristics of them are not constant. To understand the material properties of the product such as the yield and the ultimate tensile strength, some mechanical tests are carried out. The product, the time and the labor loss occured in these mechanical tests reveal the need to develop a prediction method based on non-destructive measurement. In this study, the mechanical properties of PC strand product is predicted by using artificial neural networks (ANN). 'Feed-Forward Backpropagation (FFBP)' has been preferred since it is the most accurate network type for the current process. To determine the ultimate tensile strength, the data such as the load applied to the material (loadcell output), the DC voltage and the DC current of the induction furnace, the speed of the PC strand line, the temperature of the induction furnace, the temperature of the quench tank and the diamater of the PC strand product are collected from a real production line and are utilized as the input parameters of the ANN in the simulation environment. The study illustrates that the ANN model give a very good prediction of the ultimate tensile strength of PC strand.

Keywords: Prestressed concrete strand, Tensile test, Artificial neural networks, Feed-forward backpropagation

Yapay Sinir Ağ Modeli Kullanılarak Ön Germeli Beton Demeti Maksimum Çekme Mukavemetinin Tahmini

Öz

Demir ve çelik endüstrisi, bir ülkenin endüstriyel ve ekonomik kalkınması için vazgeçilmez sektörlerden biridir. Demir ve çelik endüstrisindeki en yaygın sorun, ürünün maksimum çekme mukavemetini belirlemektir. Ön germeli beton demeti (ÖGBD) ürününde kullanılan hammaddeler kuvvet altında

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deforme olmakta ve karakteristikleri sabit olmadığından şekilleri ve boyutları değişmektedir. Ürünün, akma ve maksimum çekme mukavemeti gibi malzeme özelliklerini anlamak için bazı mekanik testler gerçekleştirilir. Bu mekanik testlerde ortaya çıkan ürün, zaman ve iş gücü kaybı, tahribatsız ölçümlere dayanan bir tahmin metodu geliştirme ihtiyacını ortaya koymaktadır. Bu çalışmada, ön germeli beton demeti ürününün mekanik özellikleri yapay sinir ağları (YSA) kullanılarak tahmin edilmiştir. Mevcut işlem için en doğru ağ tipi olduğundan 'İleri Beslemeli Geri Yayılım (İBGY)' tercih edilmiştir. Maksimum çekme mukavemetini belirlemek için, malzeme üzerine uygulanılan yük (yük hücresi çıkışı), indüksiyon fırınının DC gerilimi ve DC akımı, ÖGBD hattının hızı, indüksiyon fırınının sıcaklığı, soğutma tankının sıcaklığı ve ÖGBD ürününün çapı gibi veriler gerçek bir üretim hattından toplanmakta ve simülasyon ortamında YSA'nın girdi parametreleri olarak kullanılmaktadır. Çalışma, ANN modelinin, ön gerilmeli beton demetinin maksimum çekme mukavemetine dair çok iyi tahminde bulunulduğunu göstermektedir.

Anahtar Kelimeler: Öngermeli beton demeti, Çekme testi, Yapay sinir ağları, İleri beslemeli geri yayılım

1. INTRODUCTION

The iron and steel industry, one of the most important heavy industry sectors, supplies raw materials to many important industries such as construction, transportation, automotive and machinery. Determining the tensile strength of the raw materials is one of the most commonly encountered problem in iron and steel industry. In the present industrial conditions, the tensile strength of steel materials is determined by the tensile test, which is widely used method to determine the mechanical properties of materials. With this test, it is tried to determine the resistance of a material towards a static and slowly applied load. The amount of elongation of the material is measured using an extensometer; the applied load (force) is measured using a load cell and a stress-strain diagramme, which gives information about the strength, ductility, and rigidity of the material, is obtained [1].

The tensile test process is incredibly long, inconvenient and costly due to the operator must take the PC strand specimens and test them continuously. As an alternative to the traditional tensile test, non-destructive measurement based prediction methods have arisen. With the prediction of properties of materials, the time spent for testing is avoided and the cost of the product is reduced remarkably.

In recent years, a significant amount of research has been carried out in the area of non-destructive estimation of mechanical properties of the raw materials used in the iron and steel industry. In a majority of these studies, researchers have attempted the Artificial Neural Network (ANN) approach in the estimation of the mechanical properties of the materials. In [2], the fatigue crack growth rate of nickel base superalloys has been modelled by using ANN model within a Bayesian framework. Cool et al. [3] implemented ANN to model the yield and ultimate tensile strengths of weld deposits as a function of the chemical composition, welding conditions and heat treatment parameters. In [4], fatigue behavior of unidirectional glass fiber/epoxy composite laminae is predicted with training ANN by using the input data of maximum stress, stress ratio and fiber orientation angle. Akbari et al. [5] proposed four ANN based models to predict the features of the nanoparticle reinforced composites. Malinov et al. [6] developed a model for the analysis and prediction of the correlation between processing (heat treatment) parameters and mechanical properties in titanium alloys by applying ANN. In [7], a model is developed for the prediction of the correlation between alloy composition and microstructure and its tensile properties in gamma-based titanium aluminide alloys through the ANN by using the inputs of alloy composition, microstructure type and work (test) temperature. In [8], a three-dimensional finite element model (FEM) along with establishing the ANN is used for the evaluation of ultimate torsional strength of reinforcement concrete beams. Jeyasehar et al. [9] carried out a study for the assessment of damage in prestressed concrete (PC) beams using its present stiffness and natural frequency as the test inputs of the feed-forward ANN trained by back propagation (BP) algorithm. In [10], the effects of chemical composition and process parameters on the tensile strength of hot strip mill products have been researched by using ANN. In [11], feed-forward back-propagation (FFBP) ANN has been used for the prediction of the mechanical properties of galvanized coils from its chemistry and key galvanizing process parameters. In [12], the optimized ANN model with Levenberg–Marquardt algorithm is presented for the estimation of mechanical properties of carbon fiber through high temperature furnace.

Although ANNs have been used to determine the various mechanical properties for different steel materials and industrial products, the prediction of the ultimate tensile strength of the PC strand product has not been studied before. In this paper, the ultimate tensile strength of the PC strand, which is considered as the highest value-added product in the metal sector, is estimated by using ANN. Thus, it is aimed to avoid labor and production losses with the prediction of the ultimate tensile strength non-destructively. The input data taken from the production line such as the loadcell output, the DC voltage and the DC current of the induction furnace, the speed of the PC strand line, the temperature of the induction furnace, the temperature of the quench tank and the diamater of the PC strand product are used to train the FFBP based ANN model.

The remainder of the paper is organized as follows. Section 2 presents the brief information about the PC Strand line and the key procedures of the tensile test. Section 3 provides the description of the FFBP ANN based estimation method. The simulation results are given and discussed in Section 4. Finally, conclusions of the study are highlighted in Section 5.

2. PC STRAND PRODUCTION LINE

PC strand, consisting of seven wires, six of which are helically wrapped around one center wire, are used in the areas such as bridge girder production, prefabricated construction elements, ground and mine anchorages and nuclear power stations. The production flow of the PC strand is given in Figure 1.

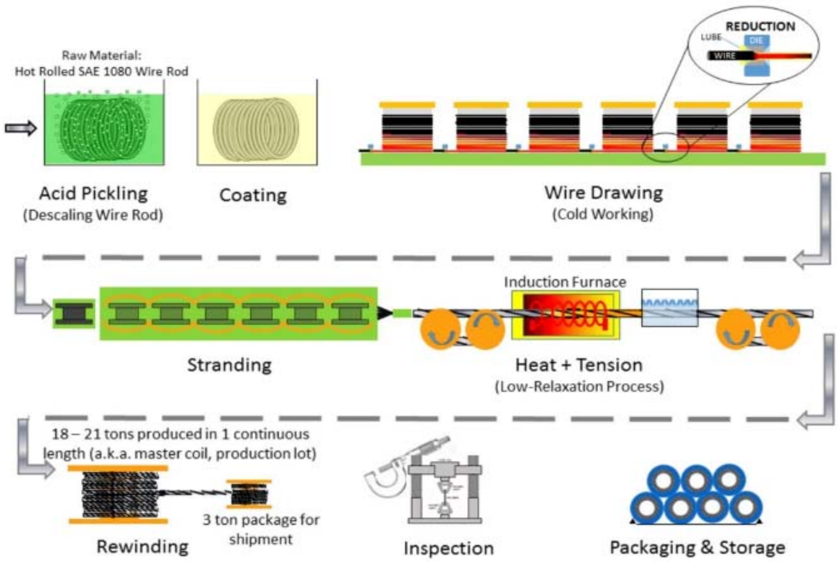

Figure 1. PC Strand production flow [13]

The wire is made by a rod or bar which is sunk in acid pickling bath and then is coated with a chemical substance to roll it easily in drawing machine. Coated raw material (a rod or bar) passes through drawing machine and thereby is lubricated in die boxes and is cooled on the drawing blocks which are revolved by electric motors.

High tensile strength, excellent prestressing in small edges and less labour for anchorage and other applications are the core benefits of the PC strand product. The PC strand products are produced in accordance with the ASTM, BS, EN, TSE and JIS standards.

2.1. Tension Tests and Procedures

Tension test is an approval test for the specification of materials and is extensively utilized to provide a basic design information on the strength of materials. The main parameters that describe the stress-strain curve obtained during the tension test are the ultimate tensile strength (UTS), the yield strength (σy), elastic modulus (E), percent elongation (ΔL%) and the reduction in area (RA%). Toughness, resilience, Poisson's ratio(ν) can also be gained by the use of this testing technique.

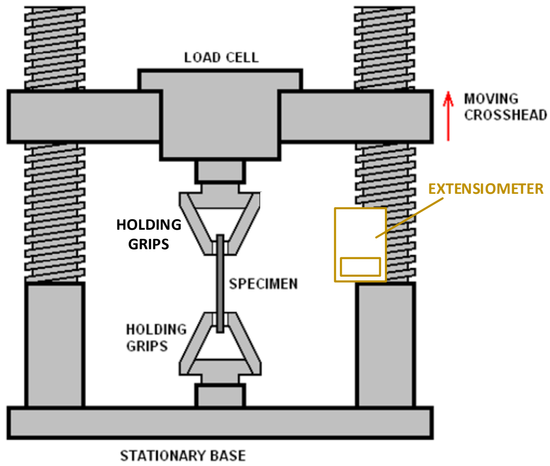

Figure 2. Tension test procedure

The tension test procedure is displayed in Figure 2. A test piece of the strand is located in the serrated teeth of the tension test machine. The testing speed is regularly adjusted to approximately 5 kips per minute. The extensometer is located on the strand before the test begins. The extensometer measures displacements at mid-length of the test specimen. The knife-edges of the extensometer have a tendency to slip on the twisting strand. To reduce this matter, two-sided tape and multiple rubber bands are used to keep the extensometer vertical and tight against the strand. The data acquisition system saves data automatically every second during testing.

2.1.1. Ultimate Tensile Strength

The ultimate tensile strength (UTS) is computed by dividing the maximum load by the initial cross-sectional area of the test sample and is expressed in megapascals (MPa) (Eq. 1). The diagram of the UTS is illustrated in Figure 3.

$$UTS = \frac{(Load\ at\ Break)}{(Original\ Width)*(Original\ Thickness)} \tag{1}$$

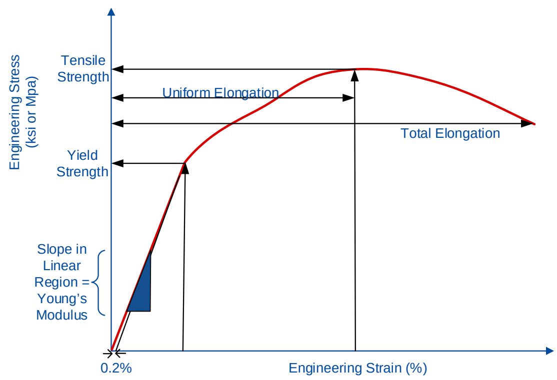

Figure 3. Stress-strain graph

3. PREDICTION OF UTS WITH ANN

ANN is a statistical method used for mapping the non-linear correlation. ANN structure is commonly used for many applications to create the relationships in data [15]. In this study, ANN is used to predict the relationship between the ultimate tensile strength of the Grade 270, which is the raw material of the PC strand, and the various input data digitally received via the sensors from a real production line.

The duration of a single charge of the PC strand line varies from approximately 6 to 8 hours, when there is no fault on the line. An average of two hours is required for a new charge. Thus, this cycle can continue up to three times in a day. At the end of each charge, samples are taken from the product and mechanical tests are carried out. Every single test result is used to construct the training data for the ANN output. During the charging period, the input data is stored in the database.

The input data is comprised of the load applied to the material (LDCLL), the DC voltage of the induction furnace (INDVDC), the DC current of the induction furnace (INDIDC), the speed of the PC strand line (SPEED), the temperature of the induction furnace (INDTPR), the temperature of the quench tank (TNKTPR) and the diameter of the PC strand product (DMTR). The ultimate tensile strength (UTS) is predicted by using the FFBP algorithm.

FFBP model is as shown in Figure 4 has three layers named as input layer, hidden layer and output layer. The training examples are received from experimental data. The network generates an output by processing the input and compares the output with the target. The difference between the target and the output determines the error. Then the synaptic weights of the network are modified by the training algorithm proportional to the error. The goal of the training process is to reduce the error below a predetermined value on an iterative basis. This requires a presentation of many training examples, which constitutes a training set. This form of administered learning is called error correction learning [16]. A schematic representation of the error-correction learning is shown in Figure 5.

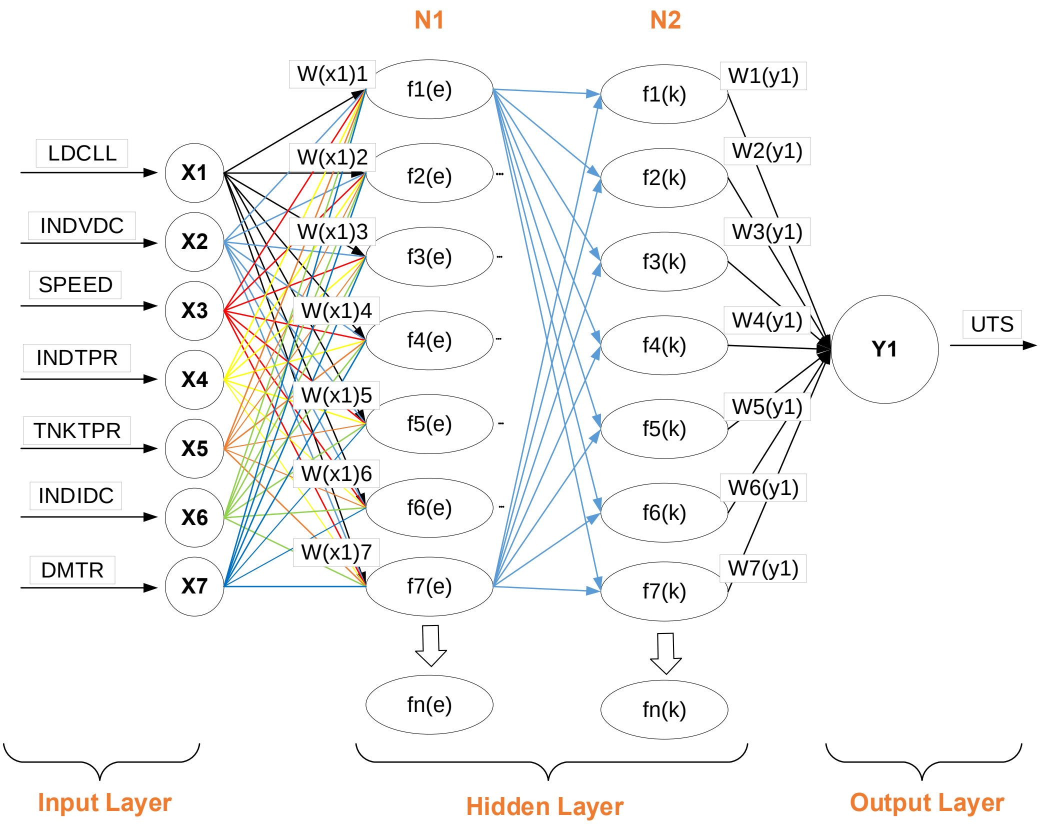

Figure 4. FFBP ANN model

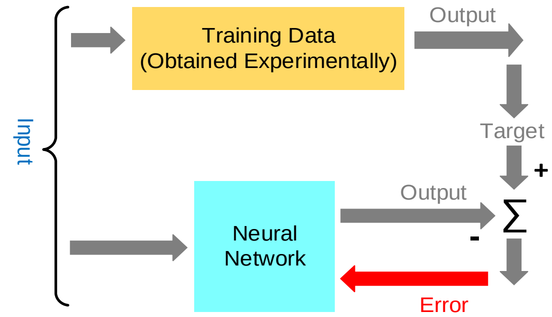

Figure 5. Schematic of error-correction learning

3.1. Training Functions

There are several training functions related to ANN in MATLAB library. Generally, the Levenberg-Marquardt (trainlm) algorithm provides the fastest convergence for a few hundred weights. This advantage is especially noticeable if very accurate training is required. In many cases, 'trainlm' is able to obtain lower mean square errors (MSE) than any of the other algorithms tested. However, when the number of weights in the network increases, the advantage of 'trainlm' decreases. In addition, 'trainlm' performance is relatively poor in pattern recognition. Besides, the storage requirements of 'trainlm' are larger than the other functions. The Resilient Backpropagation (trainrp) function is the fastest algorithm on pattern recognition problems. However, it does not perform well on function approximation problems. Its performance also degrades as the error goal is reduced. The memory requirements for this algorithm are relatively small in comparison to the other algorithms considered. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) Quasi-Newton (trainbfg) function is similar to that of 'trainlm'. It does not require as much storage as 'trainlm', but the required computation increases geometrically with the size of the network, because the equivalent of a matrix inverse must be computed at each iteration. The Variable Learning Rate Backpropagation (traingdx) function is usually much slower than the other methods and has the same storage requirements as 'trainrp' but it can still be useful for some problems. There are certain situations in which it is better to converge more slowly. The Scaled Conjugate Gradient (trainscg) function notably, seem to perform well over a wide variety of problems, especially for networks with a large number of weights. The 'trainscg' algorithm is almost as fast as the LM algorithm on function approximation problems (faster for large networks) and is almost as fast as 'trainrp' on pattern recognition problems. Its performance does not degrade as quickly as 'trainrp' performance does when the error is reduced. The conjugate gradient function have relatively modest memory requirements and the most accurate, significant and interpretable results of our study are revealed by it [17].

3.2. Performance Functions

Mean square error (MSE) is a network performance function that is probably the most commonly used error metric. It penalizes larger errors because squaring larger numbers has a greater impact than squaring smaller numbers. The *MSE* is the sum of the squared errors divided by the number of observations. A_t is the actual value (target), F_t is the forecasted value (output) and n is the number of testing data. The equation of *MSE* is presented in Eq. 2.

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n} \tag{2}$$

The root mean square error (RMSE) is the square root of the MSE. The equation of *RMSE* is presented in Eq. 3.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{3}$$

Mean Absolute Percentage Error (MAPE) is the average of absolute errors divided by actual observation values. *MAPE* is the average absolute percent error for each time period or forecast minus actuals divided by actuals. The equation of *MAPE* is expressed in Eq. 4.

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} * 100 \tag{4}$$

The coefficient of determination (R^2) is one measure of how well a model can predict the data and falls between 0 and 1. The higher the value of R^2, the better the model is at predicting the data. The equation of R^2 is given in Eq. 5.

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - mean(A_t))^2} \quad (5)$$

MAPE and R^2 performance functions have been used at the end of this study to compare the performance of the training algorithms.

3.3. Training the Neural Network

The training data, consisting of 119 rows, is gathered from a real PC strand production line. This data consists of 7 input variables and 1 output variable. Six of the input variables (LDCLL, INDVDC, INDIDC, SPEED, INDTPR and TNKTPR) are taken from the line using a software developed on a programmable logic controller (PLC) automatically. The last input variable 'DMTR' and output variable 'UTS' are obtained from the tensile test results. Table 1 summarizes the ranges of training data used to train the ANNs.

Table 1. The ranges of training data used to train the ANN

	INPUT VARIABLES							OUTPUT V.
	LDCLL	INDVDC	INDIDC	SPEED	INDTPR	TNKTPR	DMTR	UTS
MIN.	76.368	437.056	90.007	398.902	51.07	693.008	12.58	1850.4
MAX.	126.434	530.088	129.819	399.763	76.172	933.377	15.76	1989.2

The flowchart used in the study is given in Figure 6. Training data must be splitted into "inputs" and "targets" matrices. For the present study, as there are 7 input variables, "inputs" matrix will consist of 7 columns. "targets" matrix is composed of 'UTS' output variable. After selection of input and target matrices, training, validation and testing percentages are determined. In addition, number of hidden neurons, training rate, learning rate and training function must be selected. In the next stage, neural network is created with the selected parameters and trained using training data supplied to it. Validation and testing data are used to measure the performance of the trained network. R^2 is used for performance evaluation. If the R^2 is in the range of 0 and 1, then the actual data and neural network output is compared with a ±25 MPa in accuracy. If the neural network output is close to the actual data, the network is considered as successful. Otherwise, number of neurons, training rate, learning rate parameters are changed and same procedure is applied. The same flowchart is used for each of the training algorithms mentioned in the section title 3.1.

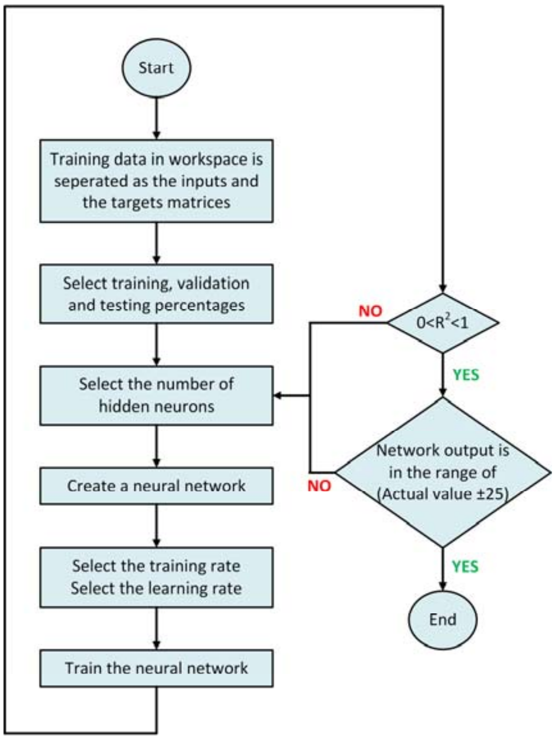

Figure 6. Flowchart of the algorithm

4. RESULTS AND DISCUSSION

Using the procedure explained in the above section, several ANNs are trained for different parameters (number of neurons in first hidden layer (N1), number of neurons in second hidden layer (N2), learning rate, training rate and training function). The first 9 rows of Table 2 is used to compare the performances of different training algortihms. As it can be seen from the table, “trainscg” gives the best performance for current problem.

After many trials and literature search, the parameters are chosen as follows:

- Neuron 1 (N1) = 30
- Neuron 2 (N2) = 30
- Learning Rate (l_{rate}) = 0.70
- Training Rate (trate) = 0.70
- Training Function = trainscg

The results using to the parameters given above are displayed in Figure 7 and Figure 8 respectively. Also, MAPE and R^2 for this parameters are given in the last row of Table 2.

Table 2. The pivot table of all the tests performed

Test Number	N1	N2	Learning Rate	Training Rate	Training Function	MAPE	R^2
T1	10	10	0.70	0.70	‘trainlm’	0,6817	0,7966
T2	10	10	0.70	0.70	‘trainbfg’	0,7089	0,7594
T3	10	10	0.70	0.70	‘trainbrp’	0,8934	0,7839
T4	10	10	0.70	0.70	‘traincgb’	0,8339	0,3226
T5	10	10	0.70	0.70	‘traincgf’	0,8707	0,2932
T6	10	10	0.70	0.70	‘traincgp’	0,8693	0,0045
T7	10	10	0.70	0.70	‘trainoss’	0,5925	0,6774
T8	10	10	0.70	0.70	‘traingdx’	1,0594	-0,6076
T9	10	10	0.70	0.70	‘trainscg’	0,665	0,8166
T10	30	30	0.70	0.70	‘trainscg’	0,5551	0,8567

The performance is evaluated by considering the MAPE and R^2 values. Calculation of the MAPE and R^2 have been given in Eq. 4 and Eq. 5 respectively. The MAPE is one of the most popular measure for forecasting error and is desired to be close to zero. The R^2 is another commonly used statistical measure of how close the data are to the fitted regression line. The R^2 simply explains how good is the developed model when compared to the baseline model. The R^2 can take value between 0 and 1 where values closer to ‘0’ represent a poor fit while values closer to ‘1’ represent a perfect fit. Figure 7 shows the MAPE and R^2 values for the case (Test number 10) as 0.5551 and 0.8567 respectively.

The correlation between target (actual data) and output (forecasted data) is represented in Figure 8. It is seen that R=0.932 that means there is a positive relation between target and output. Minimum limit of the estimated value is obtained as 1866.7 MPa when the actual value is 1888.7 MPa. The difference between the estimated and actual value is found to be 22 MPa. When the prediction performance is evaluated, it can be said that the result is quite well since the output is estimated within ±25 MPa range.

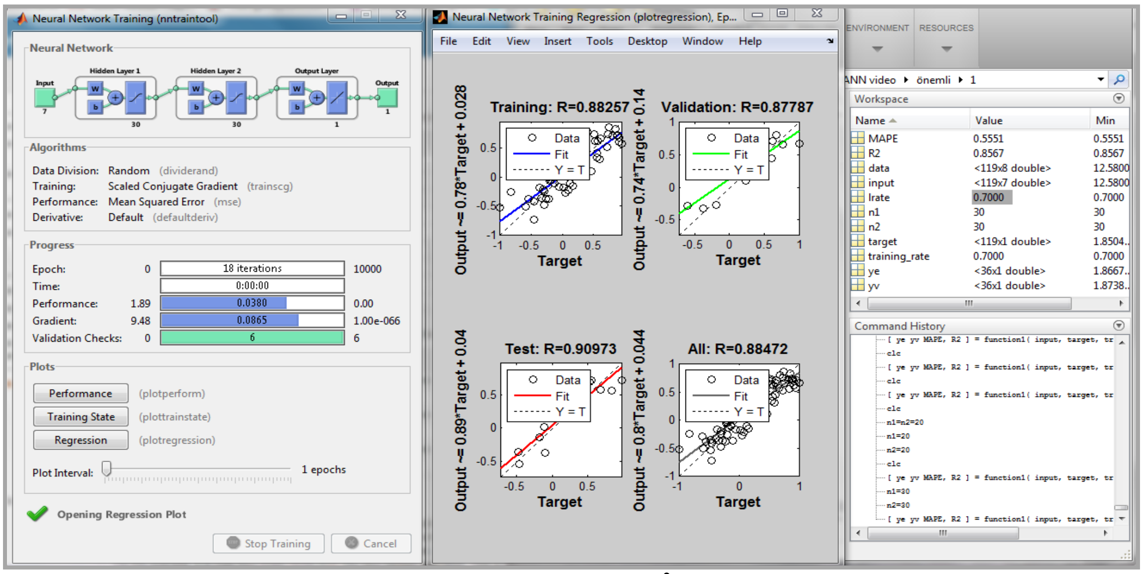

Figure 7. Training with scaled conjugate gradient function: R^2=0.8567, MAPE=0.5551

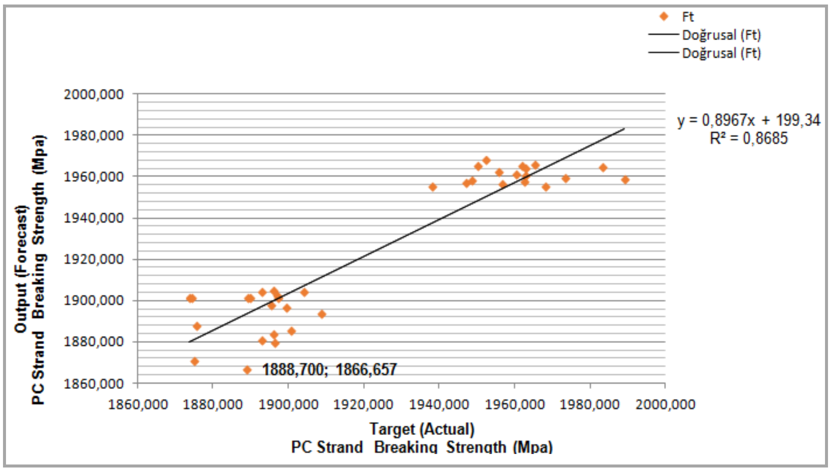

Figure 8. Target-output graph

5. CONCLUSION

It has been shown that in today's industrial conditions, the ultimate tensile strength of the PC strand product can be predicted by ANNs in a non-destructive way and without losses.

As specified in ASTM A416/A416M-17 standard, the tensile strength for grade 270 raw material of the PC strand product must be higher than the value of 270 ksi (1860 MPa). In this study, the lowest estimated value of the tensile strength is obtained as 1866.7 MPa with the ANN while the actual value is recorded as 1888.7 MPa. The ANN model provides a very good prediction of the ultimate tensile strength of PC strand with a sensitivity of ± 25 MPa.

In this study, 83 training data and 36 test and verification data were used by the neural network and it can be interpreted that the network has very few data samples. If more data are collected from

PC strand line, more accurate, sensitive and reliable results can be obtained. By incorporating different inputs into the neural network, such as expansion of the data set and chemical composition, predicted values can be realized much more precisely.

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