CUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Hayrullah ÖZEL

PREDICTION OF ULTIMATE TENSILE STRENGTH OF PRESTRESSED CONCRETE STRAND USING ARTIFICIAL NEURAL NETWORS

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on 23/07/2018.

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ABSTRACT

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PREDICTION OF ULTIMATE TENSILE STRENGTH OF PRESTRESSED CONCRETE STRAND USING ARTIFICIAL NEURAL NETWORS

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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 fixed. To understand the material properties of the product such as the yield and the ultimate tensile strength, some mechanical tests are carried out by the manufacturers.

The literature survey clearly shows that the easiest and the most important mechanical test applied to the seven steel wire strand concrete (PC Strand) is the 'Tensile Test'. Even in the simplest experiment, the product, the time and the labor loss reveal the need of the non-destructive measurement. This thesis study is focused on the prediction of mechanical properties of PC strand product by using artificial neural networks (ANN). 'Feed-Forward Backpropagation (FFBP)' has been preferred since it is the most accurate network type for the current problem.

The data such as the loadcell, 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 production line. These data are utilized as the input parameters of the ANN in the simulation environment. Eventually, the ultimate tensile strength of the PC strand is determined at the output of the ANN.

Key Words: PC Strand, Tensile Test, ANN, FFBP

ÖZ

YÜKSEK LİSANS TEZİ

YAPAY SİNİR AĞLARI KULLANILARAK ÖN GERMELİ BETON DEMETİ MAKSİMUM ÇEKME MUKAVEMETİNİN TAHMİNİ

Hayrullah ÖZEL

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Demir çelik endüstrisi, bir ülkenin endüstriyel ve ekonomik kalkınması için vazgeçilmez sektörlerden biridir. Demir çelik endüstrisindeki en yaygın sorun, ürünün üst çekme mukavemetini belirlemektir. Ön germeli beton demeti (ÖGBD) ürününde kullanılan hammaddeler kuvvet altında deforme olurlar ve karakteristikleri sabit olmadığından şekilleri ve boyutları değişir. Ürünün, akma ve üst çekme mukavemeti gibi malzeme özelliklerini anlamak için operatörler tarafından bazı mekanik testler gerçekleştirilir.

Literatür araştırması, yedi çelik telli beton demetine uygulanan en kolay ve en önemli mekanik testin 'Çekme Testi' olduğunu açıkça göstermektedir. En basit deneyde bile, ürün, zaman ve iş gücü kaybı, tahribatsız ölçüm ihtiyacını ortaya çıkarmaktadır. Bu tez çalışması, yapay sinir ağları (YSA) kullanılarak öngermeli beton demeti ürününün mekanik özelliklerinin tahminine odaklanmıştır. Mevcut sorun için en doğru ağ tipi olduğundan 'İleri Beslemeli Geri Yayılım (İBGY)' tercih edilmiştir.

Yük hücresi, indüksiyon fırınının DC gerilimi ve DC akımı, ÖGBD hattının hızı, indüksiyon fırınının sıcaklığı, soğutma tankının sıcaklığı ve ÖGBD ürününün çapı gibi veriler üretim hattından toplanır. Bu veriler, simülasyon ortamında YSA'ın girdi parametreleri olarak kullanılmaktadır. Sonuç olarak, ÖGBD' nin üst çekme mukavemeti, YSA'nın çıkışında belirlenmektedir.

Anahtar Kelimeler: ÖGBD, Çekme Testi, YSA, İBGY

EXTENDED SUMMARY

Factors such as the variability of customer needs, developing technology and competition among firms have made the development of the iron and steel industry inevitable. 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. Improvement of the iron and steel sector is inevitable in terms of the integration of industries and the development of the national economy.

The most common problem in iron and steel industry products is to determine the breaking strength of the material. Non-destructive determination of the breaking strength is not possible with current technology. In the present industrial conditions, the tensile strength of steel materials is determined by the tensile test. The tensile test is one of the most widely used methods in the industry to determine the mechanical properties of materials. With this experiment, it is tried to determine the resistance of a material towards a static and slowly applied load. In this experiment, 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 is obtained by using these values. The Stress-Strain diagramme gives information about the strength, ductility, and rigidity of the material. A standard has been set for the strength, the ductility and the rigidity due to these mechanical properties in the stress strain diagramme are important in terms of the sector to be used.(Malinov, S., and Sha, W., 2004)

In this thesis study, with the help of data which are taken from the PC (Prestressed Concrete) strand line, the ultimate tensile strength have been tried to be estimated by ANNs. Thus, it is aimed to avoid labor and production losses with non-destructively estimated tensile test values. Since ANNs work successfully in many applications and there has been some studies in the metal sector realized with this method has been an inspiration for the thesis work. Although the ANNs were

used for different steel materials and industrial products, the methodology of prediction with ANNs by specifying parameters of PC strand has not been used before.

Tensile test results used in ANN training were obtained by analyzing grade 270 material (raw material) in mechanical testing laboratory. The data that constitute the input variables of ANNs are determined by information obtained from material analysis and literature search. The input variables are the load on the material (loadcell), induction furnace current and voltage value, induction furnace temperature, velocity of PC strand line, cooling water temperature at induction furnace outlet and PC wire diameter. This data, digitally taken from the sensors, was instantaneously recorded in the database after being multiplied by previously determined coefficients in the production line and made physically meaningful. A single charge cycle of the PC strand line is approximately 6-8 hours, provided there is no fault. After the charge is finished, it takes about two hours to load the line with the new wire. Therefore, this cycle can be continued up to three times a day. At the end of each charge, samples are taken from the product and mechanical tests are carried out. A test made corresponds to an output (sampling) for ANNs. During the charging period, the input data is recorded in the database once in a second. When the values of the line become unstable, such as stopping or malfunctioning, this data has been deleted from the database. Then the recorded data are transferred to an excel file and after taking the arithmetic mean inputs for a single output was determined. 119 input and output (target) data for use in ANNs were obtained by the specified method.

In this study, Matlab / Simulink software was used to train ANNs. The input and target data in the excel file are transferred in the Matlab workspace and are also divided into input and target files. The reason for doing this is to train the network and to be able to test and verify afterwards. There are two ways to run ANNs in Matlab after the files have been shredded. One of them is to write 'nftool' on the command screen and to confirm. The user can not change the desired variable with this method. The values that may affect the result when the training function, training rate, learning rate, neuron number, etc., are preset by the program designer as the initial values. In order to remove this dependency, a new function has been created and the control of the variables are left to the user.

First, 119 dataset was introduced to Matlab using the 'nftool' method. 70% (83 data set) are assigned as unchangeable by the program for training. The remaining data are randomly determined by Matlab as test and verification data and can be changed by the user. The program fixes the training function as a backpropagation Levenberg Marquardt. In addition, the number of hidden neurons can be changed optionally. As a result of the analysis, the actual values (target) and the estimated value (output) of the neural network are compared. Matlab calculates Mean Square Error (MSE) and coefficient of determination (R^2). MSE value does not give meaningful results because the units of the data and the scaling (normalization) are not done. Alternatively, as long as R^2 approaches 1, the prediction errors are reduced.

Although the above method gives a specific idea, a function has been written in Matlab for changing variables and for more detailed and accurate analysis. The variables to be changed for the ANN are the training function, the training rate, the learning rate, and the number of neurons for two hidden layers. They were left in user control and their values are hanged to find the best results. Although output values can be used in other methods for accuracy comparison, Mean Absolute Percentage Error (MAPE) and coefficient of determination (R^2) which give the most accurate and meaningful result are used. MAPE expresses the error as a percentage of its true value that means the accuracy is increased when zero is approached. Variables used for the most accurate values in many neural network experiments are as follows; Training function is Scaled Conjugate Gradient (trainscg), training rate is 0.70, learning rate is 0.70, number of neurons in layers are 30.

As specified in ASTM A416 / A416M-17 standard, the minimum breaking strength for grade 270 product of the PC strand is 1860 MPa. The lowest estimated value of the ANN output was 1866.7 MPa. actual value for this value is 1888.7 MPa. 36 test data have been estimated with a sensitivity of ± 25 MPa.

It has been shown that in today's industrial conditions, the breaking point value measured by destructive, can be predicted by ANNs in a non-destructive way and without losses. By incorporating different inputs into the network, such as expansion of the data set and chemical composition, predicted values can be realized much more precisely and accurately.

GENİŞLETİLMİŞ ÖZET

Tüketici ihtiyacının değişkenlik göstermesi, gelişen teknoloji ve firmalar arası rekabet gibi etmenler demir çelik sektörünün de gelişmesini kaçınılmaz kılmıştır. En önemli ağır sanayi sektörlerinden biri olan demir çelik sektörü; inşaat, köprü, yüksek hızlı tren, otomotiv ve makina gibi birçok önemli endüstriye hammadde sağlamaktadır. Sanayi kollarının entegrasyonu ve ülke ekonomisinin gelişimi açısından demir çelik sektörünün iyileştirilmesi kaçınılmaz hale gelmiştir.

Demir çelik sanayisi ürünlerinde en sık karşılaşılan problem, malzemenin kopma mukavemetinin belirlenmesidir. Tahribatsız olarak kopma mukavemetinin tayin edilmesi günümüz teknolojisi cihazları ile mümkün değildir. Mevcut sanayi şartlarında çelik malzemelerin kopma mukavemetleri, çekme deneyi yardımıyla tayin edilmektedir. Çekme deneyi, malzemelerin mekanik özelliklerinin belirlenmesi amacıyla mevcut endüstri şartlarında en çok kullanılan test yöntemlerinden biridir. Bu deney yardımıyla bir malzemenin statik ve yavaş olarak uygulanan bir yüke karşı dayanımı tespit edilmeye çalışılmaktadır. Bahsi geçen deneyde malzemenin uzama miktarı bir ekstensometre ile uygulanan yük (kuvvet) ise bir yük hücresi ile ölçülür ve bu ölçülen uzama ve yük değerleri kullanılarak Gerilim-Gerinim eğrisi grafiği elde edilmektedir. Gerilim-Gerinim eğrisi ise malzemenin mukavemeti, sünekliği, ve esnemezliği (katılığı) hakkında bilgi vermektedir. Gerilim-Gerinim eğrisindeki mukavemet, süneklik ve esnemezlik gibi mekanik özellikler, kullanılacağı sektör açısından önemli olmasından dolayı bunlarla ilgili standart belirlenmiştir.

Bu tezde ön germeli beton demeti hattından alınan numunelerin, kopma mukavemeti değerinin yapay sinir ağları ile tahmin edilmesi konusuna çalışılmıştır. Böylece tahribatsız olarak tahmin edilen çekme test değerleri ile işçilik ve üretim kayıplarının önüne geçilmesi hedeflenmiştir. YSA birçok uygulamada başarılı bir şekilde çalıştığı ve bu yöntemle metal sektöründe bazı çalışmalar yapıldığından tez çalışması için bir ilham kaynağı olmuştur. Farklı çelik malzemeler ve sanayi

ürünleri hakkında yapay sinir ağları kullanılmış olmasına rağmen, ön germeli beton demeti konusunda parametreler belirlenip yapay sinir ağlarıyla tahmin metodolojisi daha önceden kullanılmamıştır.

Yapay sinir ağları eğitiminde kullanılan çekme deney sonuçları, mekanik test laboratuvarında grade 270 malzemelerin (hammadde olarak kullanılan ürün) analizi yapılarak elde edilmiştir. Yapay sinir ağlarının girdi değişkenlerini oluşturan veriler, malzeme analizleriyle ve literatür araştırmasından elde edilen bilgilerle belirlenmiştir. Girdi değişkenleri, malzeme üzerindeki yük (loadcell), indüksiyon fırını akım ve voltaj değeri, indüksiyon fırınının sıcaklığı, ön germeli beton demeti hattının hızı, indüksiyon fırını çıkışındaki soğutma suyu sıcaklığı ve ön germeli beton demeti çapı olarak belirlenmiştir. Sensörlerden dijital olarak alınan bu veriler üretim hattında daha önce belirlenen katsayılarla çarpılıp fiziksel olarak anlamlı hale getirildikten sonra veritabanına anlık olarak kaydedilmiştir. Ön germeli beton demeti hattının tek bir şarj süresi herhangi bir arıza olmaması kaydıyla yaklaşık olarak 6-8 saat olarak değişmektedir. Şarj bittikten sonra hattın yeni tel ile yüklenmesi için yaklaşık iki saat gerekmektedir. Dolayısıyla günde en fazla üç kere bu döngü devam edebilmektedir. Her şarj sonunda üründen numune alınmakta ve mekanik testleri yapılmaktadır. Yapılan bir test yapay sinir ağları için bir çıktı (örnekleme) anlamına denk gelmektedir. Şarj süresi boyunca girdi verileri saniyede bir kere olmak üzere veri tabanına kaydedilmiştir. Hattın durması veya arıza gibi sebeplerde değerler anlamsızlaştığında veritabanından bu veriler silinmiş ve sadece hattın çalışma süresi boyunca anlık olarak kayıt alınmıştır. Daha sonra kaydedilen veriler excel dosyasına aktarılmış ve bunların aritmetik ortalaması alındıktan sonra tek bir çıktı için girdiler belirlenmiştir. Yapay sinir ağlarında kullanılmak üzere 119 adet girdi ve çıktı (hedef) verisi belirtilen yöntemle elde edilmiştir.

Bu çalışmada yapay sinir ağlarını eğitmek için Matlab/Simulink yazılımından faydalanılmıştır. Excel dosyasında bulunan girdi ve hedef verileri Matlab çalışma sayfasında tanımlanmış ayrıca girdi ve hedef dosyaları olarak ikiye ayrılmıştır. Bu işlemin yapılma sebebi ağı eğitmek ve sonrasında test ve doğrulama işlemleri yapabilmektir. Dosyalar parçalandıktan sonra Matlab' da yapay sinir ağlarını çalıştırmanın iki yolu vardır. Bunlarda biri komut ekranına 'nftool' yazıp onaylamaktır. Bu yöntemle kullanıcı istediği değişkeni değiştirememektedir. Önemli değişkenlerden olan eğitim fonksiyonu, eğitim oranı, öğrenme oranı, nöron sayısı gibi, değiştirildiğinde sonucu ciddi ölçüde etkileyecek değerler ilk değer olarak program tasarımcısı tarafından önceden belirlenmiştir. Bu bağımlılığı ortadan kaldırmak için yeni bir fonksiyon oluşturulmuş ve bu değişkenler kullanıcı kontrolüne bırakılmıştır.

Öncelikli olarak 119 tane veri kümesi 'nftool' yöntemiyle Matlab'a tanıtılmıştır. Eğitim için %70 (83 adet veri kümesi) program tarafından değiştirilemez olarak atanmaktadır. Geriye kalan veriler ise test ve doğrulama verileri olarak Matlab tarafından rastgele belirlenmekte ve kullanıcı kontolünde değiştirilebilmektedir. Program eğitim fonksiyonunu geri yayılımlı Levenberg Marquardt olarak sabitlemektedir. Ayrıca isteğe bağlı olarak gizli nöron sayısı değiştirilebilmektedir. Analiz sonucunda gerçek değerler (hedef) ve sinir ağının tahmin değeri (çıktı) karşılaştırılmaktadır. Matlab ortalama hata karesi (MSE:Mean Square Error) ve belirlilik katsayılarını (R^2:coefficient of determination) hesaplamaktadır. MSE değeri verilerin birimleri ve ölçeklendirilmesi (normalizasyonu) yapılmadığı için çok anlamlı sonuç vermemektedir. Bunun yerine R^2 değeri 1' e yaklaştıkça tahmin hataları azalır.

Yukarıdaki yöntem belirli bir fikir vermesine rağmen değişkenleri değiştirmek ve daha detaylı ve doğru analiz için Matlab' da bir fonksiyon yazılmıştır. YSA için değiştirilecek değişkenler eğitim fonksiyonu, eğitim oranı, öğrenme oranı ve iki gizli katman için nöron sayısıdır. Bunlar kullanıcı kontolüne bırakılmış ve en iyi sonuçları bulmak için değerleri değiştirilmiştir. Çıktı değerlerinin doğruluk karşılaştırmasında başka yöntemlerde kullanılabilecek olmasına rağmen en doğru ve anlamlı sonucu veren ortalama mutlak hata yüzdesi (MAPE:Mean Absolute Percentage Error) ve belirlilik katsayılası (R^2:coefficient of determination) kullanılmıştır. Ortalama mutlak hata yüzdesi, hatayı gerçek değerinin yüzdesi olarak ifade etmekte ve ne kadar sıfıra yakın ise o kadar doğruluğun arttığı anlamına gelmektedir. Sinir ağında yapılan birçok deneme sonucunda en doğru değerler için kullanılan değişkenler; Eğitim fonksiyonu Scaled Conjugate Gradient (trainscg), eğitim oranı 0.70, öğrenme oranı 0.70, 2 katmanlı sinir ağında katmanlardaki nöron sayıları 30 olarak belirlenmiştir.

ASTM A416/A416M-17 standardında belirtildiği üzere ön germeli beton demetinin grade 270 ürün için minimum kopma mukavemeti 1860 MPa olarak belirtilmiştir. Yapay sinir ağı çıkışımızın en düşük tahmin değeri 1866,7 MPa olmuştur. Bu değere karşılık gerçek değerimiz 1888,7 MPa 'dır. 36 tane test verisi ±25 MPa hassasiyette tahmin edilmiştir.

Günümüz sanayi şartlarında tahribatlı olarak ölçülen kopma noktası değeri yapay sinir ağları vasıtasıyla tahribatsız bir şekilde ve kayıplar olmadan tahmin edilebileceği ortaya konulmuştur. Veri kümesinin genişletilmesi ve kimyasal kompozisyon gibi farklı girdilerin ağa dahil edilmesi ile tahmin değerleri çok daha hassas ve doğru şekilde gerçekleştirilebilecektir.

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σy	: Yield Strength or Yield Point
E	: Elastic Modulus
R2	: Coefficient of Determination
ν	: Toughness, Resilience, Poisson's Ratio
x^*	: Normalized Data
μi	: The average of the Input Set
σ	: Standard Deviation of Input Set
Xi	: Input Value
e	: Natural Logarithm Value

LIST OF ABBREVIATIONS

PC	: Prestressed Concrete
ANN	: Artificial Neural Network
MLP	: Multilayer Perceptron
FFBP	: Feed-Forward Backpropagation
MLPNN	: Multilayer Perception Neural Network
logsig	: Logarithmic Sigmoid Transfer Function
tansig	: Symmetric Sigmoid Transfer Function
purelin	: Linear Transfer Function
learngdm	: Gradient Descent with Momentum Weight and Bias Learning Function
learngd	: Gradient Descent Weight and Bias Learning Function
UTS	: Ultimate Tensile Strength
MSE	: Mean of Squared Errors
TTT	: Time-Temperature-Transformation
CCT	: Continuous Cooling Transformation
PVP	: Polyvinylpyrrolidone
MWCNTs	: Multiwalled Carbon Nanotubes
HMI	: Human-Machine Interface
ODBC	: Open Database Connectivity
SQL	: Structured Query Language
MPI	: Multi-Point Interface
MLA	: Machine Learning Algorithm
R&D	: Research and development
UCTEA	: The Union of Chambers of Turkish Engineers and Architects
ΔL%	: Percent Elongation
RA%	: Reduction in Area

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1. INTRODUCTION

The Industrial Revolution has caused enormous growth in many areas of the industry, such as mining, transportation and construction. This growth created a demand for new products with more raw materials and better properties. Some countries that are aware of this situation have prepared their infrastructures. The iron and steel industry is possibly one of the most important area of a nation's industrial economic infrastructure, and the consumption of steel per head of population is an indicative index of industrialization and headway.

The steelmaking process starts with the processing of iron ore. The iron ore is removed from the rock ground using magnetic rollers. The iron ore is transformed into various types of iron through several processes. Some of these iron species are raw materials used in Prestressed Concrete (PC) strand. The PC strand raw material becomes available on line after acid pickling and diameter reduction processes. In this process, the experience in making mechanical, electrical, metallurgical and chemical tests of the materials (wire products) have been obtained in accordance with customer requirements and standards. All tests should be done without interruption and is informed to the customer. The time and the product losses occur during these tests. With current technology conditions, the tensile test is used to determine the properties of the products.

The tensile test is one of the most used test methods for determining the mechanical properties of PC strand materials. With the aid of this experiment are studied to determine the resistance of a material. Besides, the amount of elongation of the material is measured by an extensometer and then the applied load is measured by loadcell and Stress-Strain graph is obtained with these data. The strength, the ductility, and the rigidity of the material can be determined by this experiment. Therefore, these values are standardized because of their importance.

According to the tensile test method, the operator must take the PC strand specimens and test them continuously. This process is incredibly long and inconvenient. Since the tensile testing method is rather inconvenient and costly, the need for an alternative method has arisen. Neural network analysis is a form of regression or classification modeling which can help resolve these difficulties whilst striving for longer-term solutions (Bhadeshia, 1999).

In this thesis, it is focused on the PC Strand product which is considered as the highest value-added product in the metal sector. From the mechanical properties obtained after the tensile test of the PC strand, the most important value for the customer is the ultimate tensile strength. The ANNs have been worked successfully in many applications so far and also some studies have been done in the metal sector as it will be detailed in the literature survey section. On this basis, it is thought that the ultimate tensile strength can be estimated with the ANNs. Thus, it is aimed to avoid labour and production losses with non-destructive tensile test values.

Initially, the tensile test results of Grade 270 material which is raw material of PC strand are started to be recorded in the mechanical testing laboratory. At the same time, the input data set is stated with the help of literature search and then the data is recorded in the database. The input variables are loadcell, 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 respectively. These data, digitally received from the sensors, is recorded in the database after being multiplied with coefficients and made physically meaningful. The duration of a single charge of the PC Strand line varies from approximately 6-8 hours, provided there is no failure on the line. The average two hours is required for the 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 is an output (sampling) for ANNs. During the charging period, the input data is stored in the database once in a second. This value is deleted from the database when the values are lost for some reason such as a line stop or malfunction and only the data is recorded during the operating time of the line. Then, the recorded data is transferred to excel file and their arithmetic mean value is taken. Inputs for output are specified by this way. Input and output (target) data for use in ANNs is obtained by this method. In this thesis, Matlab/Simulink software is used for simulation. As a result of the analysis, the actual values (target) and the estimated value (output) of the neural network are compared. Matlab calculates Mean Square Error (MSE) and Coefficient of Determination (R^2). MSE does not give meaningful results because the units of the value data and scaling (normalization) are not done. Alternatively, as long as R^2 approaches to 1, the prediction errors are reduced.

Even though the above method gives an idea, a function is written in Matlab for changing variables and for more detailed and accurate analysis. The variables which are desired to be changed for the ANN are the training function, the training rate, the learning rate and the number of neurons for two hidden layers. They are left in user control and their values are changed to find the best results. The mean absolute error percentage (MAPE) and the coefficient of determination (R^2) are used to compare the accuracy of the output values. MAPE expresses the error as percentage of actual value. Accuracy increases as long as MAPE close to zero.

In the last part of the thesis, the input data of the ANN are subtracted from the network, respectively, and the results are compared. As a result, the effect of each input data on the output (the ultimate breaking strength) is shown in the graph by percentages.

Because industrial systems are influenced by too many variables, it leads to the complexity of the parameters affecting the final product. One of the most convenient ways to make sense of this situation is to use neural networks. In this study, the ultimate breaking strength of the PC strand product which has not been investigated before is estimated by using gathered input datas by means of ANN. It is expected that this thesis creates an approach to the identification of input data for this product. By incorporating different inputs into the network, such as expansion of the data set and chemical composition, predicted values can be realized much more precisely and accurately.

Last but not least, in the first chapter of the thesis general information is given and the methods are mentioned shallowly. The main application areas of ANNs are listed and the studies on the estimation of mechanical properties of the material are introduced briefly in the second chapter. The third chapter is about the history of artificial neural networks. The main architectures of ANNs and the multilayer perceptrons are illustrated under the third chapter. The PC strand line, raw material and product are presented in fourth chapter of the thesis and also the conventional test method of the PC strand is explained by the help of mathematical equations. The data acquisition from the PC strand line and the interpretation of the data with Matlab are depicted in the fifth chapter of the thesis and the data normalization methods are given in this part. The conclusions and future works are the last part of the thesis. The results of the simulations are interpreted and the ideas about future work are organized in the last chapter.

2. LITERATURE REVIEW

2.1. The Main Application Areas of Artificial Neural Networks

The Artificial Neural Networks (ANNs) are models of prediction that is inspired by biological nervous systems in the human brain. They are composed of a great number of notably interconnected neurons (nonlinear computational elements or nodes) working in unison to solve private problems. ANNs are structured for private applications, such as pattern recognition or data classification, through a learning process. These nodes are connected via weights that are characteristically adapted during use to enhance performance. This thesis focuses on data classification for the prediction of the ultimate tensile strength of the PC strand product. The main application areas of artificial neural networks are focused on primarily in this section and then estimation of the mechanical properties of the material is given. Some of the studies related to ANN are given below in detail.

A metaheuristic algorithm and hybrid neural network (NN) are recommended for a forecast method to predict solar power. The metaheuristic algorithm optimizes the free parameters of the NN. To illustrate the efficiency of the proposed forecast method, it is performed on a real-world engineering test case. Retrieved results represent the superiority of the proposed method in comparison with other prediction techniques (Abedinia et al, 2017).

The atomic features which bond dissociation energy, equilibrium bond length and equilibrium stretching frequency properties used in consideration new materials are enquired by T.R.Cundari and E.W. Moody. Three molecular properties are predicted more accurately by using ANN. The advantage of the neural network approach applies whether the simulation is used to predict a single property or to predict several properties contemporaneously (Cundari and Moody, 1997).

Popoola et al. improved the accuracy of path loss prediction for rural environments while protection simplicity using an ANNs. Field measurement data gathered along three different ways are used for neural network training, validation, and testing. A single layered, Feed Forward Backpropagation neural network is trained with varying neurons (10-100) using the Scaled Conjugate Gradient (trainscg) function (Popoola et al, 2017).

The engine velocity, mass flow rate, combustion efficiency, maximum pressure developed, Brake Specific Fuel Consumption (BSFC) and exhaust gas temperature values are measured and the data is stored throughout the experiment. Using the experimental data, a Levenberg Marquardt ANN algorithm and logistic sigmoid activation transfer function is developed to predict the BSFC, maximum pressure and combustion efficiency of G200 IMEX spark ignition engine (Nwufo et al, 2017).

A model is developed by Gavard et al. to estimate the austenite start and finish temperatures. A feedforward backpropagation network is used to be able of estimating the conversion temperatures and chemical composition. The aim of the model is to estimate the austenite start and finish temperatures(Gavard et al, 1996).

Asada et al. have created an artifical neural network which is comprised of three layers. In order to predict the superconducting transition temperature (Tc) of a material reinforced with calcium. They analyzed 28 fundamental elements and their concentration in the input layer to supply Tc in the output layer. The neural network is trained by the error back propagation technique utilizing data from the database (Asada et al, 1997).

Khan et al. introduced that multilayer perception neural network is used to predict thermal conductivity of polyvinylpyrrolidone electrospun nanocomposite fibers with multiwalled carbon nanotubes and nickel zinc ferrites. The prey-predator algorithm is operated to train the neural networks to find the best models. It should be had the minimal of sum squared error (SSE) between the experimental testing data and the output of the NN (Khan et al, 2017).

Zhang et al. preferred multilayer Feed Forward Backpropagation function to predict specific wear rate and friction coefficient of short fiber reinforced composites. In the following study, the autors research ANNs to predict the erosive wear rate of a few polymers as a function of testing situations and material features. In the different study of Zhang and Friedrich is observed the use of neural networks in polymer composites modeling and they have been investigated the influence of input parameters, the number of neurons in hidden layers and the size of the training set on neural network performance. They also highlight correct and incorrect exercises of neural networks and give suggestions on developing the models (Zhang et al, 2002; 2003).

S.J.Joyce et al. illustrated their ability to predict the glass-transition temperature (Tg) of linear homopolymers. A variety of multilayer feed forward backpropagation ANN is trained to predict the Tg values of the polymers from monomer structures applying the error back-propagation technique. The networks are created with the PlaNet and Aspirin/Migraines software. The networks are trained utilizing monomer structures and tested on an independent set of different monomer structures (S.J.Joyce et al, 1995).

Rumelhart et al. studied a different training procedure regularly adjusts the weights of the connections in the network in order to reduce a measure of the difference between the target and the forecasted data of the network. The multilayer perceptron-convergence method is used to make it real (Rumelhart et al, 1986).

MacKay developed a Bayesian framework by using Feed Forward Backpropagation networks that provides an opportunity calculation of error bars for model foresight and measures the significance of each input parameter automatically. This approach has advantages in analyzing the influence of several input parameters on a definite output parameter (Mackay, 1992).

Continuous Cooling Transformation (CCT) diagram and austenitizing temperature are predicted with the help of chemical composition in ANN suggested by Vermeulen et al. The amount of hidden nodes do not change the accuracy of the prediction~~s~~ results. Five hidden nodes are utilized to evaluate the performance of the ANN design (Vermeulen et al, 1997).

Time-Temperature-Transformation (TTT) diagram inform about the phase alteration and improvement of the steel material. Malinov et al. investigate to identify a convenient composition able of yielding an ultrafine bainitic microstructure by isothermal holding of austenite at low homologous temperature. To accomplish this, TTT diagram of varying compositions have been predicted a priori to reduce the required experimental trials (Malinov et al, 2000).

2.2. Estimation of Mechanical Properties of Material

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. Literature studies have been carried out on steel materials and details are given below.

Fujii et al. used an Feed Forward Backpropagation ANN to predict the fatigue crack growth rate in Ni-based superalloys. Neural networks is shown to enable studying the effects of unique input parameters on the outputs in isolation in cases where variables quintessentially depend on each other (Fujii et al, 1996).

Yoshitake et al. worked on Ni based superalloys using a neural networks within a Bayesian framework (Yoshitake et al, 1998). Ichikawa et al. also used a Bayesian framework to predict an appearance of solidification cracking in low alloy steel welds (Ichikawa et al, 1996).

Cool et al. implemented neural network to foresee the strength of steel welds. This method has been found to improve quality of prediction in the input areas where data is rare and stability is low (Cool et al, 1997).

Fatigue performance of unidirectional glass fiber/epoxy composite laminae is predicted applying ANN by Al-Assaf et al. The Feed Forward Backpropagation network is used and the count of the defect is determined with input parameters such as maximum stress, R-ratio, fiber orientation angle. Even though in small quantities of experimental data points are used for training the neural network, the results received are comparable to other current fatigue life-prediction methods (Al-Assaf et al, 2001).

To predict mechanical features of the nanocomposite, neural network models are designed and cross-validated by Akbari et al. The best results of mechanical properties for nanocomposite are obtained by using Bayesian regularization. The results reveal that the ANN has a great potential to be used as a practical tool for prediction of mechanical properties of metal to avoid loss of lots materials and energy (Akbari et al, 2017).

Khayyam et al. performed tests under different temperatures, fiber tensions and gas flow rates. Throughout these experiments, tensile strength of fibers is measured and the data is examined using proper characterization and surrogate modeling methods. Levenberg-Marquardt Neural Network algorithm is used for this application (Khayyam et al, 2017).

Jominy hardenability of steels is predicted quite correctly by W. G. Vermeulen et al. from chemical composition using FFBP ANN. About 800 sets of data are used to build an accurate model. Alloying element concentrations are introduced to the system as input parameters. The effect of boron on hardenability has been evaluated in detail. (Vermeulen et al, 1996).

Bhadeshia et al. utilized a Bayesian framework to analyze the influence of welding process, alloying elements, microstructure and test temperature on the Charpy toughness of steel welds (Bhadeshia et al, 1995).

An ANN model is developed by W.G. Vermeulen et al. for predicting the martensite start temperature from the chemical composition for a range of vanadium containing steels. Many neural networks with different numbers of hidden nodes are trained (Vermeulen et al, 1996).

Malinov et al. used ANN for modeling TTT diagrams for phase transformation in titanyum (Ti) alloys, the relationship between processing and working conditions and mechanical properties of Ti alloys. The productivity of several learning algorithms are examined in this study (Malinov et al, 2004).

A model is developed by Malinov et al. for the investigation and prediction of the correlation between processing parameters and mechanical properties in titanium alloys by using ANN. The input parameters of the neural network are the composition of alloy, heat treatment parameters and test temperature. The outputs of the neural network model are mechanical properties namely the ultimate tensile strength, the tensile yield strength~~,~~ the elongation. The model is based on multilayer FFBP. The neural network is trained with extensive dataset collected from literature (Malinov et al, 2001).

A model is developed by Mcbride et al. alloy composition, microstructure and its tensile properties in gamma-based titanium aluminide alloys using of ANN. The inputs of the neural network are alloy composition, microstructure type and test temperature. The outputs of the model are tensile properties, ultimate strength, elongation, reduction of area and elastic modulus. The model is based on FFBP ANN, trained with data collected from several sources of literature. It can be used to optimise processing parameters to attain desirable tensile properties (Mcbride et al, 2004).

Jeyasehar et al. 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. (Jeyasehar, 2006)

The effects of chemical composition and process parameters on the tensile strength of hot strip mill products have been researched by Esfahani at al. by using ANN. (Esfahani, 2009)

The 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 by Lalam at al.

As it is clearly seen from literature survey, industrial systems are affected from too many parameters such as the heat treatment temperature, the cooling water temperature and the microstructure of product. This leads to the complexity of the factors that influence the final product. One of the most convenient ways to make sense of this situation is to use neural networks. This thesis work focuses on the prediction of ultimate tensile strength of the PC Strand product using ANNs which has not been investigated before.

3. ARTIFICIAL NEURAL NETWORKS

3.1. Fundamentals

3.1.1. Introduction

ANNs are computer systems developed with the intention of automatically generating the ability to derive new information, learn and discover new information through learning from the characteristics of the human brain without any help.

ANNs; inspired by the human brain, mathematical modeling of the learning process has emerged as the end result. For this reason, studies on this subject began with the modeling of neurons, the biological units that make up the brain and their application in computer systems and later on, in parallel with the development of computer systems, many areas have become available. A contemporary description of ANNs is adapted from (Lau, 1992) as follows:

“*Any computing architecture consisting of massively parallel interconnected simple neural processors is called an ANN.*”

3.1.2. Mathematical Model of a Neuron

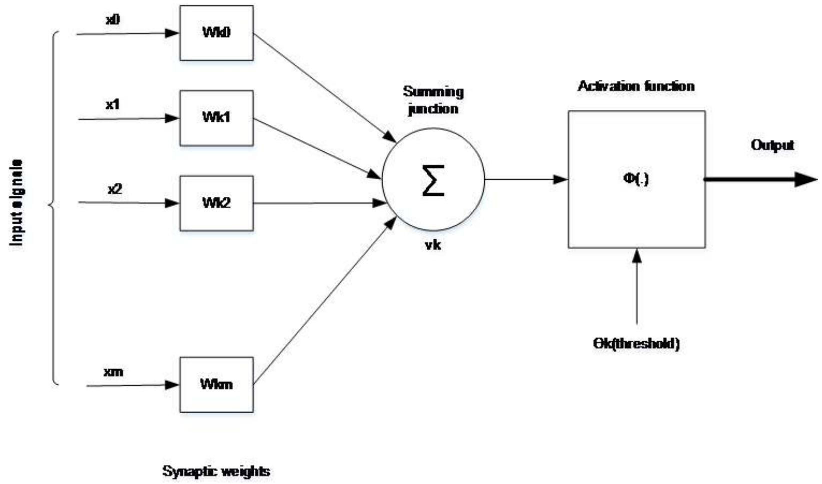

Figure 3.1. Signal flow graph of a neuron (McCulloch, 1943)

Fig. 3.1. shows a model of a neuron in the form of a directed graph. The neuron is stimulated with with the n number of inputs through its synaptic connections. Each synaptic connection has a weight, which is a positive or a negative number showing the strength of that connection. Each input is multiplied with the weight of the synaptic connection and the weighted inputs are summed together with an externally applied bias to give the induced local field v_k. On a directed graph the bias can be represented as a synaptic weight whose input is always set to +1. Then, an activation or squashing function φ_k (.) is applied to the induced local field of the neuron, which gives the output y_k of neuron k. The activation function squashes the range of the output to a certain interval. These concepts can be explained in mathematical terms as follows:

The input vector x_i is defined as

$$x_i = \left[x_1, x_2 \cdots x_m\right] \tag{3.1}$$

and the weight vector w_{ki} is defined as

$$w_{ki} = \left[w_{k1}, w_{k2} \cdots w_{km}\right] \tag{3.2}$$

The induced local field v_k is obtained by

$$v_k = \sum_{i=0}^{m} w_{ki} \cdot x_i \tag{3.3}$$

where m is the number of inputs and the bias b_k is given by

$$b_k = w_{k0} \tag{3.4}$$

Finally, the output y_k is obtained by

$$y_k = \varphi_k(.) * v_k \text{ (Francisco, 2015)} \tag{3.5}$$

3.2. Main Architectures of ANNs

Generally, an ANN can be divided into three parts, called layers, which are known as following:

1. Input Layer: This layer is responsible for receiving data, signals, features, or measurements from the external environment. These samples are usually normalized to the limit values produced by activation functions. This normalization results in better numerical precision for the mathematical operations performed by the network. (Beale, 2017)

2. Hidden Layers: These layers are comprised of neurons which are responsible for extracting patterns related to the process or system being analyzed. These layers perform most of the internal processing from a network. (Beale, 2017)

3. Output Layer: This layer is also composed of neurons and thus is responsible for creating and displaying the final network output, which results from the processing performed by the neurons in the prior layers. (Beale, 2017)

3.2.1. Feed-Forward Neural Networks

In feed-forward neural networks, the signal moves in one way between the layers and there is no connection between the neurons in the same layer (Lau,1992).

3.2.2. Recurrent Neural Networks

In recurrent neural networks, there is at least one feedback loop, which can comprise a unit delay operator resulting in a dynamical system and both kinds of connections are allowed (Lau,1992).

3.3. Multilayer Perceptrons

3.3.1. Architecture of a Multilayer Perceptron

A multilayer feed-forward network, or multilayer perceptron (MLP) as commonly referred in literature, consists of an input layer, one or more hidden layers and an output layer.

Fig. 3.2. demonstrates a multilayer perceptron with nodes in the input layer, neurons in the first hidden layer, neurons in the second hidden layer and neurons in the output layer. Take into consideration that the network shown here is entirely connected, which means each neuron in the network is connected to a node/neuron in the former layer. In addition to this, there are no connections between the nodes/neurons within the same layer of the network.

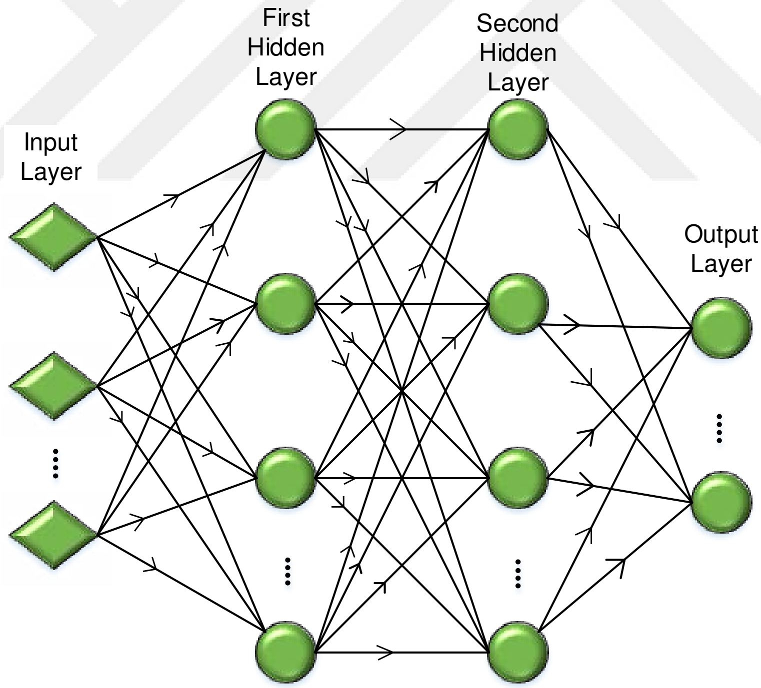

Figure 3.2. Architectural graph of a multilayer perceptron with two hidden (Haykin, 1999)

3.3.2. Error-Correction Learning

At the starting of the training operation, synaptic weights of the network are allotted random values. Then the network is presented with a training example at each iteration. A training example consists of an input and a corresponding target. The training examples are received from experimental or simulation 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. The presentation of a complete training set is called an epoch. This form of administered learning is called error correction learning. Fig. 3.3. shows a schematic representation of the error-correction learning (Denizer, 2008).

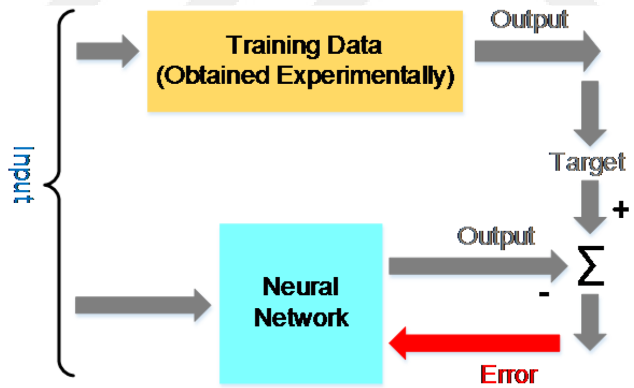

Figure 3.3. Schematic representation of error-correction learning (Denizer, 2008)

3.3.3. Feed Forward Back Propagation Algorithm

The output values can be traced back to the input values in networks with feedback. Nevertheless, there are networks wherein for every input vector laid on the network, an output vector is computed and this can be read from the output neurons that's why there is no feedback and so a forward flow of data is present.

Networks having this structure are called as feedforward networks (Sivanandam and co-workers, 2006).

A multilayer FFBP network with one layer of z-hidden units is shown in the Fig 3.4. The “y” output unit has w_{ok} bias and Z hidden unit has v_{ok} as bias. The output and the hidden units have the bias. The bias behaves like weights on the connection from units whose output is always. As it is understood Fig. 3.4. the network has one input layer, two hidden layer, and one output layer. There can be a large number of hidden layers. The input layer is connected to the hidden layer and the hidden layer is connected to the output layer by means of interconnection weights. In Fig. 3.4., only the feed forward phase of operation is shown. However during the back propagation phase of learning, the signals are sent in the reverse direction. The increase in the number of hidden layers results in the computational complexity of the network. As a result, the time taken for convergence and to minimize the error may be very high. The bias is provided for both the hidden and the output layer, to act upon the net input to be calculated (Sivanandam and co-workers, 2006).

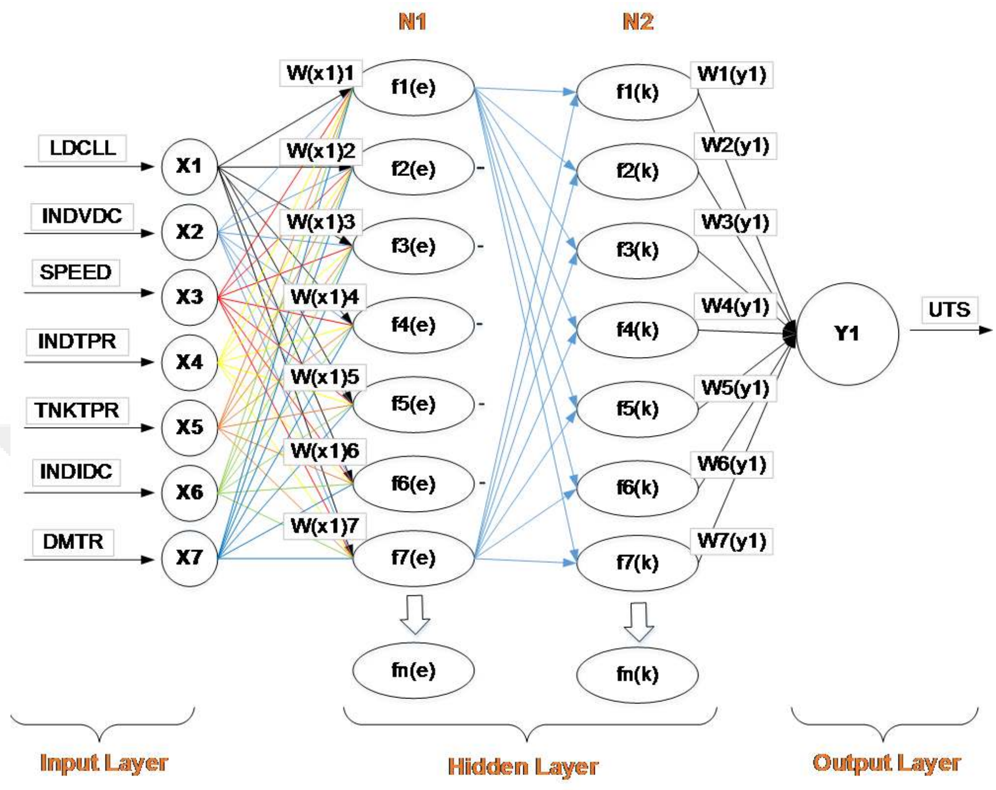

Figure 3.4. Architecture of back propagation network

3.3.4. Training Functions

There are several training functions in Matlab library. Generally, the Levenberg-Marquardt (trainlm) algorithm have 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. But, when the number of weights in the network increases, the advantage of trainlm decreases. In addition, trainlm performance is relatively poor in pattern recognition problems. The storage requirements of trainlm are larger than the other functions. The storage requirements can be reduced by means of some parameters yet at the cost of increased execution time.

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 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 increase 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 SCG 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 (Beale and co-workers, 2017).

3.3.5. Adaption Learning Functions

'learngdm' is gradient descent with momentum weight and bias learning function.

'learngdm' calculates the weight change dW for a given neuron from the neuron’s input P and error E, the weight (or bias) W, learning rate LR, and momentum constant MC, according to gradient descent with momentum: (Mathworks, 1998)

$$dW = MC * dW_{prev} + (1 - MC) * LR * gW \tag{3.6}$$

'learngd' is gradient descent weight and bias learning function.

'learngd' calculates the weight change dW for a given neuron from the neuron's input P and error E, and the weight (or bias) learning rate LR, according to the gradient descent:
(Mathworks, 1998)

$$dW = LR * gW \tag{3.7}$$

3.3.6. 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 below.

$$MSE = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n} \tag{3.8}$$

The root mean square error (RMSE) is the square root of the MSE. The equation of RMSE is below.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n}} \tag{3.9}$$

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 below.

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} * 100 \tag{3.10}$$

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 below.

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - mean(A_t))^2} \tag{3.11}$$

MAPE and R^2 performance functions have been used at the end of this thesis study to compare all the results.

3.3.7. Transfer Functions

The transfer function takes the measured input 'n' and produces the output 'a'. The transfer functions can be defined depend on users necessity. The frequently used transfer functions are described in detail below:

Fig. 3.5. demonstrates *the linear transfer function*. Neurons of this type are used in the final layer of multilayer networks that are used as function approximators.

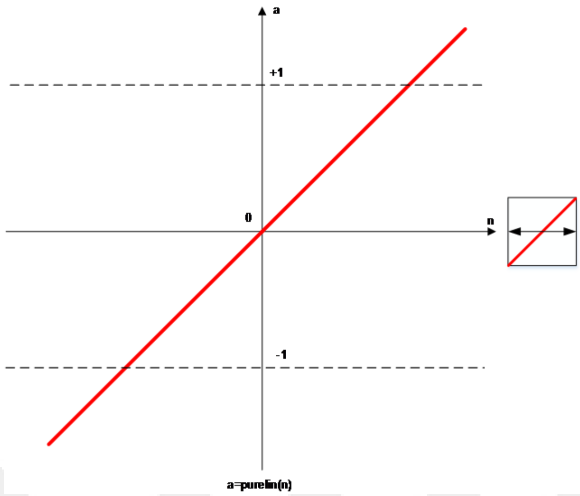

Figure 3.5. Linear transfer function (Beale and co-workers, 2017)

Fig. 3.6. *the sigmoid transfer function* is usually used to develop non-linear relationships. The tan sigmoid transfer function, shown in Figure 3.6. takes the input, which can have any value between plus and minus infinity and squeezes the output into the range -1 to 1. This transfer function is commonly used in backpropagation networks because it is differentiable and runs pretty quick (Demuth and co-workers, 2007).

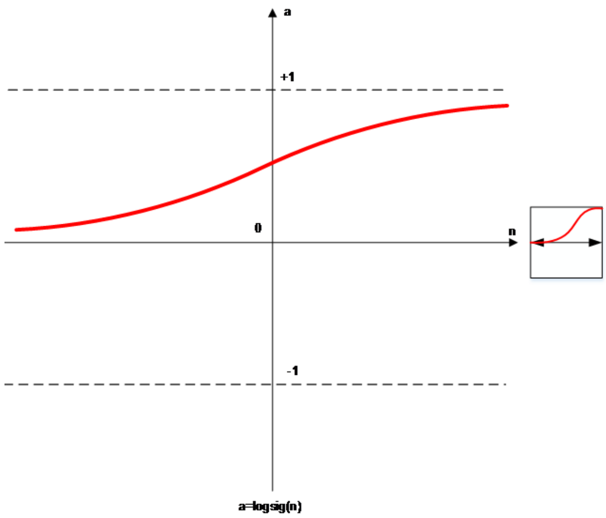

Figure 3.6. Log sigmoid transfer function (Beale and co-workers, 2017)

The activation functions and multi-layered ANN properties are changed and effects on ANN training are investigated by Altun, H. et al.. Tansig-Purelin activation functions have been shown to perform best in terms of average number of iterations and the number of networks that can be taught. To show the effect of the statistical values of the input data set on the training, experimental studies are carried out. (Altun and co-workers, unpublished).

The output of the neuron using the tan sigmoid transfer function is given by:

$$a = \frac{2}{(1 + exp^{(-2*n)})^{-1}} \tag{3.12}$$

In this thesis sigmoid transfer function is used as a default parameter and defined with blank curly braces in software.

4. PRESTRESSED CONCRETE STRAND LINE

4.1. Introduction of PC Strand

The PC strand with seven wires which is shown in Fig. 4.1. are used in the areas such as bridge girder production, prefabricated construction elements, ground and mine anchorages, nuclear power stations, silo constructions, housing constructions are produced in accordance with the ASTM, BS, EN, TSE ve JIS standards.

Core benefits of PC Strand:

- ✓ High tensile strength,
- ✓ Excellent prestressing in small edges,
- ✓ Less labour for anchorage and other application,

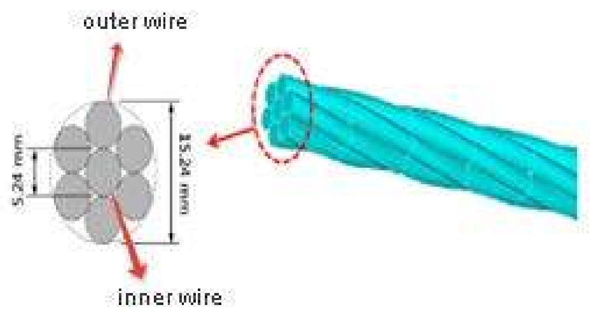

Figure 4.1. Seven wire strand

Generally, a wire is made by a rod or bar. Raw material (rod or bar) is sunk in acid pickling bath then it is coated with a chemical substance to roll it easily in drawing machine called cold drawing operation. Coated raw material pass through drawing machine thereby lubricating in die boxes and cooling on the drawing blocks. The block is revolved by an electric motor. The output of the drawing machine, diameter reduced and got longer wire is wraped on reel. A fine wire is made by a multiple-block machine as given in Fig.4.2. and Fig. 4.3. because the reduction cannot be achieved in a single draft.

Prestressing strand for concrete consists of seven wires, six of which are helically wrapped around one center wire. Each wire is drawn through nine tapered dies, which reduces the area of the wire by approximately 20 percent and gives the individual steel rod its appropriate diameter. Carbon, manganese, phosphorus, sulfur and silicon rate almost is the same with ordinary rebar. However, there is insignificantly less iron (98 to 99 percent) and more carbon (four to five times) in the strand (Godfrey, 1956).

The center wire of the seven-wire strand has an insignificantly (nearly 0.2 mm) larger diameter than the other six that surround it. To stop slip of the helically wrapped rods, the outer wires are wrapped extremely tightly around the four percent thicker center wire (Hill, 2006).

Just before the stress relieving treatment, the strand passes through machines to straighten the strand, making it easier to finally place it into tension. The stress relieving treatment burns away residual stresses generated by the cold drawing process gives uniform stress within all seven wires and above all makes the strand much more ductile. This process is executed by an electrical induction furnace at about 800 °F (400 °C), although the strand normally reaches about 600 °F (300 °C). Another significant case during the stress relieving treatment is stabilization. This thermo-mechanical process includes tensioning the strand between capstans as illustrated in Fig. 4.4. The hot and strained strand is water-cooled then it is dried and it is ready for use.

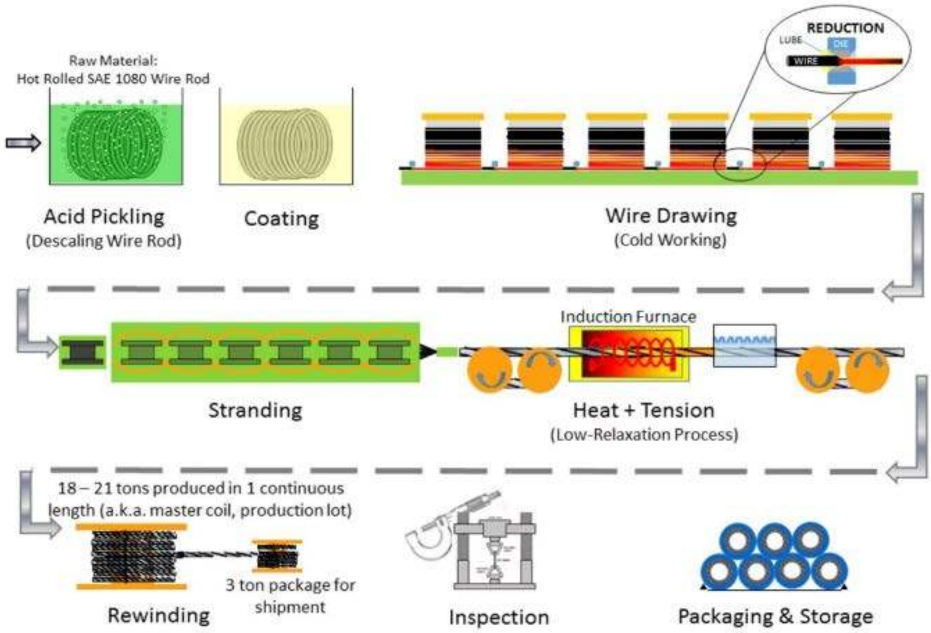

Figure 4.2. PC Strand production flow (Strongwill, 2007)

Figure 4.3. Wire drawing machine (Kemtech, 2014)

Figure 4.4. Capstan blocks (Kemtech, 2014)

4.2. Tension Tests, Test Specifications, Instrumentation and Procedure

Mechanical testing performs an important function in consideration basic properties of engineering materials as well as in developing new materials and in controlling the quality of materials for use in design and construction. If a material is to be used as part of an engineering structure that will be exposed to a load, it is important to know that the material is rigid and strong enough to resist the loads that it will experience in service. As a result, engineers have developed several experimental techniques for mechanical testing of engineering materials subjected to tension, pressurization, bending or torsion loading. The most popular type of test used to measure the mechanical properties of a PC strand material is the “Tension Test” (Gurbuz and Cevik, unpublished).

Tension test is extensively utilized to provide a basic design information on the strength of materials. Moreover, it is an approval test for the specification of materials. The main parameters that describe the stress-strain curve obtained during the tension test are the tensile strength (UTS), 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.

A test piece of the strand is located in the serrated teeth of the hydraulic tension test machine. The crosshead is adjusted to guarantee that the strand was vertical. The testing speed can be adjusted but is regularly set at approximately 5 kips per minute.

So as to pioneer the testing, ASTM A416/416M (2017) is the primary guidelines use to conduct all of the testings. One of the most critical features of the tension tests is to guarantee that the extensometer is calibrated. ASTM A416/416M declares that the calibration must be done with the smallest division less than or equal to 0.0001 in./in. of gage length.

The extensometer is located on the strand before the test began. The extensometer measure 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 as displayed in Fig. 4.5. The measurement machine has hydraulically controlled grips in both the upper and lower crossheads. Machine controller enables the crosshead to move at a constant rate until the specimen fractured or the test was stopped by the touch of the push-button. Within this period, the data acquisition system saves data automatically every second. The data saved includes time, load (kips), crosshead movement (in.) and extensometer displacement (in.). An example of a performed test with a clear break is given in Fig. 4.6.

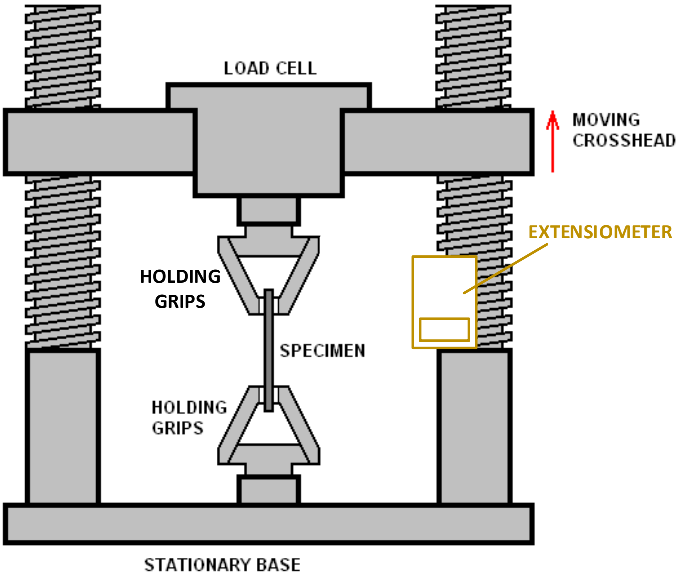

Figure 4.5. Tension test mechanism


Figure 4.6. PC Strand specimen (ANONYMOUS)

4.2.1. Ultimate Tensile Strength (UTS)

The maximum stress of the material will support just before fracture. The tensile strength is computed by dividing the maximum load by the initial cross-sectional area of the test sample. The result is declared in megapascals (MPa). The diagram of the UTS is illustrated in the Fig. 4.7.

$$\textit{Tensile Strenght} = \frac{\textit{(Load at Break)}}{\textit{(Original Width)*(Original Thickness)}} \tag{4.1}$$

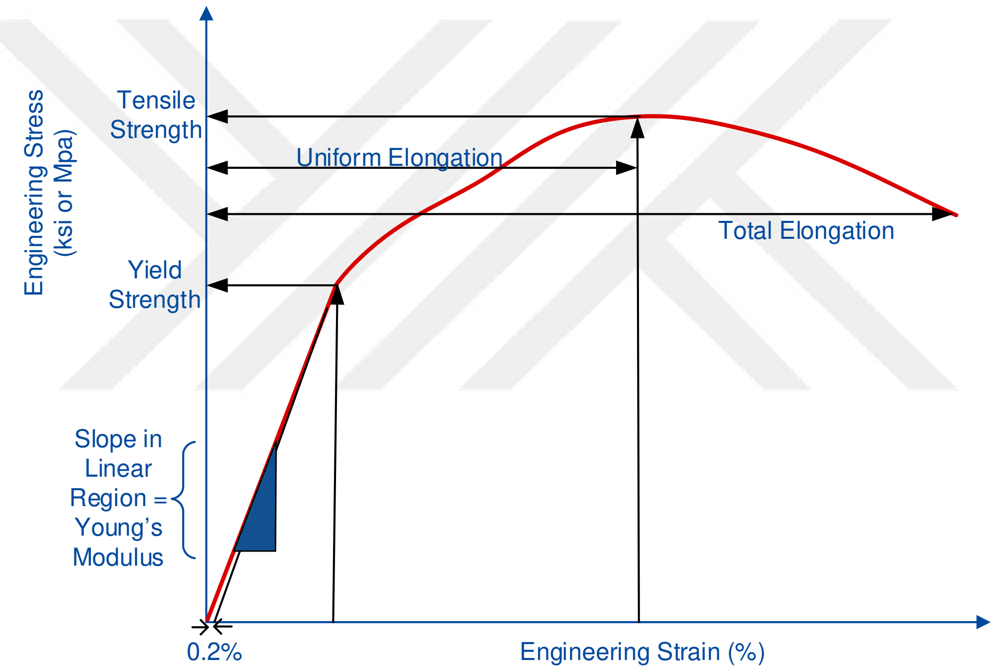

Figure 4.7. Stress-strain graph

4.2.2. Yield Strength

Stress and strain are directly linked to each other: as one of them rises, the other rises as well. The graph of stress-strain is demonstrated in Fig. 4.7.

A material begins enduring elastic deformation but once the stress on the material exceeds a determined amount, it exposes plastic deformation. When that switch occurs, the object has reached its yield stress.

4.2.3. Percent Elongation

A form of physical deformation is called elongation. Brittle materials (glass or ceramics) have low elongation, some plastics have very high elongation and metals slope to have the low and intermediate capability. It is calculated by dividing the elongation at the moment of rupture by the initial gauge length and multiplying by 100.

$$\text{Percent Elongation} = \frac{\text{(Elongation at Rupture) x 100}}{\text{(Initial Gage Length)}} \tag{4.2}$$

4.2.4. Young’s Modulus

The Young's Modulus (Elastic Modulus) is the stiffness of a material. To be more exact, the physics values are worked out as defined in the formula given below:

$$\text{Young's Modulus} = \frac{\dfrac{\text{(Load at Point on Tangent)}}{\text{(Original Width)*(Original Thickness)}}}{\dfrac{\text{(Elongation at Point on Tangent)}}{\text{(Initial Gage Length)}}} \tag{4.3}$$

In this thesis work, the output of the ANN will be the PC strand breaking strengh (tensile strength) (ultimate tensile strength). The network have been tried to estimate output with the help of input parameters. The calculation of UTS (Ultimate Tensile Strength) is in equation (4.1).

5. PREDICTION OF ULTIMATE TENSILE STRENGTH OF PC STRAND

5.1. Data Acquisition from PC Strand Production Line

Data acquisition is used to obtain data from industrial machines. The collected data can be analyzed to extract technical information regarding the operational state of the machine. The data can be managed to analyze faults. Consequently analyzing data can be utilized to allow to optimize maintenance periods, enhance product quality and make certain that quality standards are met.

In this thesis work, a Siemens S7-300 PLC has been prefered to collect data from the line. The PLC is utilized to gather the loadcell data, 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 is measured in the mechanical test laboratory and it is saved to the database. These data are used to train network and predict the output of the network (PC strand ultimate tensile strength). Some of the data such as PC strand diameter and PC strand ultimate tensile strength have been saved to database manually.

The detection system consists of the dependent computer, PLC and the host PC WinCC. The real-time monitoring and control function is implemented by this system. As the host computer of the monitoring system, WinCC not only performs the configuration of observation and control but also shows real-time the dynamic data in the interface and realize the function of alarming, data archiving and exporting online reports, display dynamic tendency of different parameters, etc (Siemens, 2008).

The slave computer of the monitoring system consists of PLC S7-300, current and voltage transducers, temperature sensors, pressure sensors, etc. The slave computer of the monitoring system is used to execute the function that collects data and automatic control and switch the operational mode. The structural component is shown in Fig. 5.1 (Siemens, 2008).

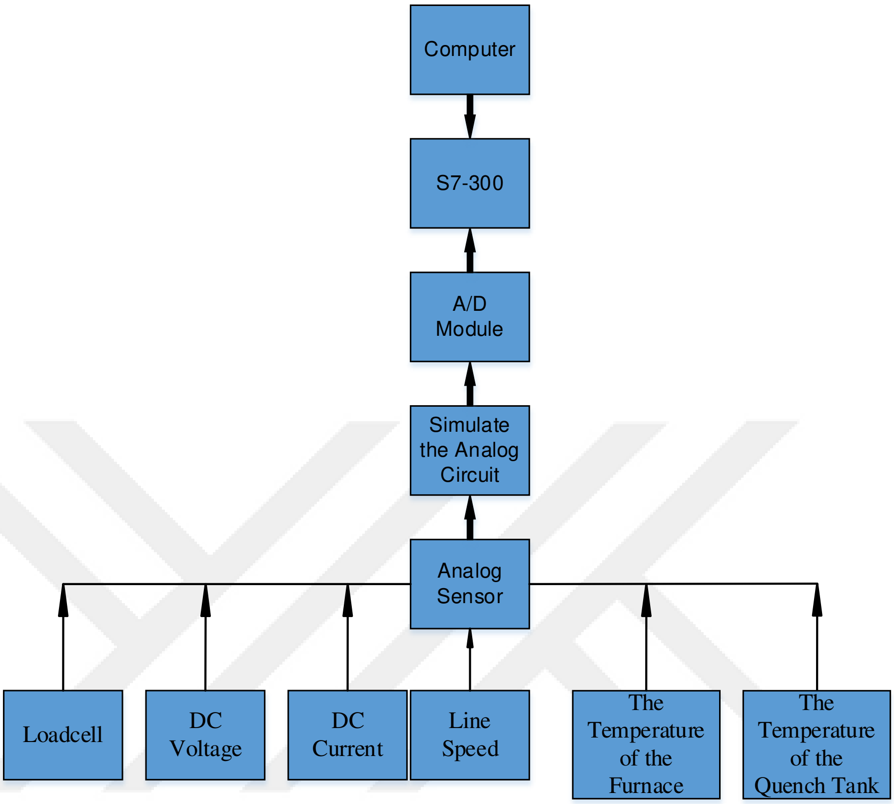

Figure 5.1. Structure of monitoring system

According to control requirements a type of DCS7-300 CPU3142DP (8DI/4DO) is selected in this system. The PLC have communicated the protocol of profibus. The data is transferred to PLC and then the computer have connected to the slave computer PLC by means of MPI/PC Cable (MPI: Multi-Point Interface) to achieve the real-time data transfer. The output of the instruments are (e.g.temperature sensor) 4~20 mA and also these values are analog signals. These analog signals have been converted to digital signals with the help of the A/D modul and transfered to the computer. The system can be switched between automatic mode and manual mode while running. The automatic mode can largely save labor, decrease additional mistakes in the process of artificial operation and perform the unattended monitoring system.

Data logging is succeeded via cycles and events. Logging cycles are used to guarantee continuous acquisition and storage of the tag values. Notwithstanding, data logging can also be triggered by events. These settings can be made for each tag individually. The tag values which are to be logged are captured, processed and stored in an ODBC, SQL, MySqual database or a file. The databases have been created on SQL Server or another database server data entry, deletion or update to be in progress these resources need to be reached. It can be used ODBC (Open Data Base Connectivity) to access database management systems. For this reason, data can be transferred directly to MS Office programs. In this regard, the thesis work have fulfilled by this method. The data have been transfered to in an excel file. It is shown in Fig. 5.2. and Fig. 5.3.

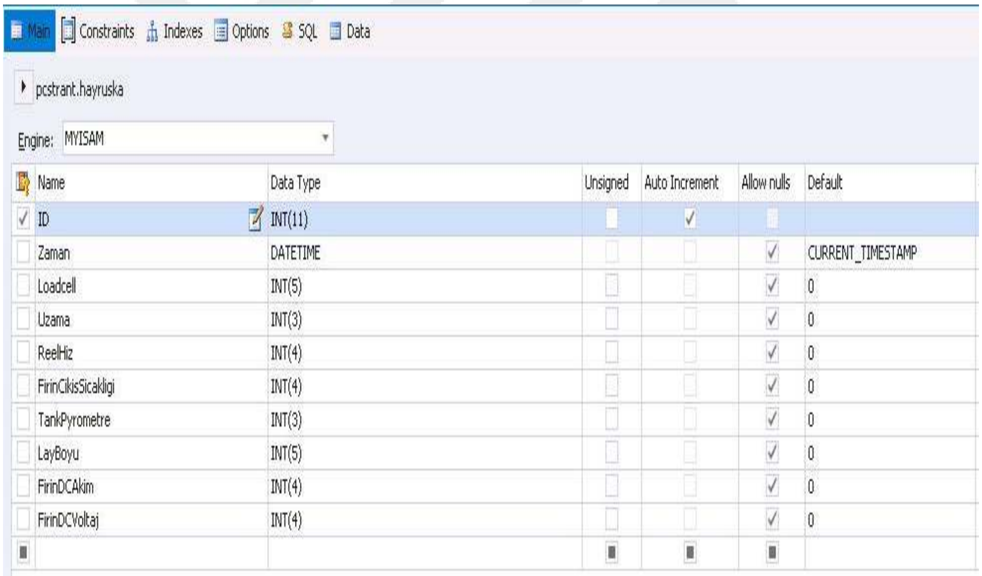

Figure 5.2. Database

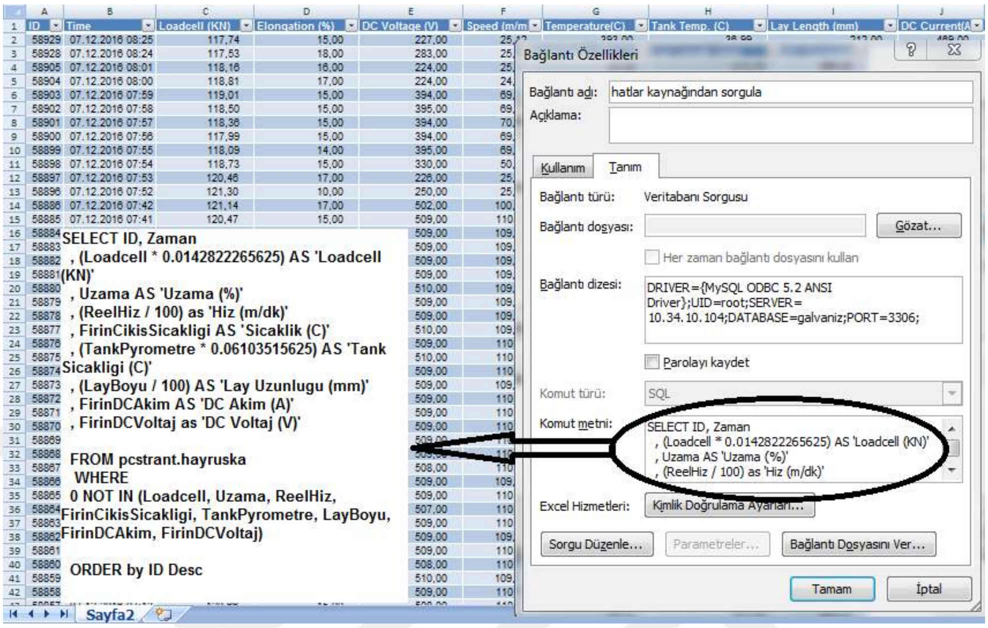

Figure 5.3. Connection string and command text

5.2. Data Interpretation in an Excel File

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 (Saravanakumar, 2012). In this study, some of the input data like the loadcell, the DC voltage and current of the induction furnace, the speed of the PC strand line, the temperature of the induction furnace, the temperature of the quench tank etc. data are retrieved from the database after making some modification. The others PC strand diameter and PC strand ultimate tensile strength are measured by the operator regularly in laboratory. The tension tests are made by an operator to determine PC strand ultimate tensile strength and other quality requirements. 6 outer and 1 inner wire are tested and breaking strength is calculated. At the same time diameter of the strand are measured with a caliper and both of them are saved in the database as well and then they are transferred to excel file.

By the help of literature search and metallurgical engineering knowledge the loadcell, the DC voltage and 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 assigned as ANN input parameters. The output of the network will be PC strand ultimate tensile strength. Training data sample is given in Fig. 5.4. The columns are colored with yellow represent some of inputs and red represent output of NN. The ANN input and target data are listed accurately in APPENDIX A.

The seven-wires are also tested in metallurgy laboratory one by one to determine the chemical composition of wires. Chemical composition has been used by some of the researchers. But in this thesis, it won't be used as we can get logical and useable results. Some of chemical test results are given in Fig. 5.5.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1–3	Wire Diameter	Breaking Strength (Mpa)	Avarage Wire Dia(mm)	Avarage Breaking Strength (Mpa)	Loadcell (KN)	Elognation (%)	DC Voltage (V)	Speed (m/min)	Temperature (C)	Tank Temperature (C)	Lay Length (mm)	DC Current (A)	Kopma (Mpa)	Yield Strength (Mpa)	Elastic Module (Mpa)	PC Strand Diameter (mm)
4	5,23	1886,60	5,13	1924,20	115,66	14,30	512,93	115,01	399,41	54,69	212,00	906,54	1861,30	1746,40	204210,22	15,30
5	5,02	1961,80														
6	5,23	1879,80	5,14	1964,45	115,59	14,46	500,47	109,99	399,57	54,70	212,00	889,73	1899,20	1756,00	209729,52	15,25
7	5,04	2049,10														
8	5,23	1959,70	5,12	1973,80	117,95	14,86	527,78	120,05	399,28	56,43	212,00	924,08	1885,00	1772,60	196802,00	15,30
9	5,01	1987,90														
10	5,24	1881,20	5,13	1912,65	115,27	14,47	500,20	110,01	399,56	56,13	212,00	888,74	1896,20	1763,20	204749,54	15,25
11	5,01	1944,10														
12	5,24	1897,10	5,13	1886,50	115,83	14,31	500,03	110,00	399,45	53,42	212,00	891,40	1894,60	1744,00	198758,00	15,28
13	5,01	1875,90														
14	5,23	1853,30	5,12	1867,05	115,76	14,25	502,62	110,01	399,57	52,05	212,00	890,85	1895,80	1792,20	211732,57	15,25
15	5,01	1880,80														
16	5,24	1902,80	5,13	1902,30	116,43	14,72	503,17	110,00	399,28	53,07	212,00	891,70	1894,00	1751,00	194884,00	15,28
17	5,02	1901,80														
18	5,24	1951,40	5,13	1965,55	117,34	14,88	518,94	115,01	399,52	72,43	212,00	914,77	1896,90	1791,00	200000,00	15,27
19	5,01	1979,70														
20	5,24	1839,40	5,13	1869,15	116,07	14,20	504,70	110,03	399,34	51,24	212,00	894,07	1914,50	1805,10	204210,22	15,25
21	5,02	1898,90														
22	5,24	1935,10	5,13	1927,68	115,56	14,14	515,33	115,03	399,15	75,70	212,00	908,27	1900,60	1830,00	196704,36	15,27
23	5,03	1920,25														
24	5,24	1918,20	5,14	1958,40	115,57	14,00	515,00	115,04	399,00	76,17	212,00	908,00	1896,50	1787,60	205563,37	15,28
25	5,04	1998,60														
26	5,24	1880,40	5,13	1901,95	115,57	14,00	515,00	115,04	399,00	76,17	212,00	908,00	1897,20	1789,10	194647,00	15,29
27	5,02	1923,50														
28	5,24	1900,00	5,13	1910,85	115,57	14,00	515,00	115,04	399,00	76,17	212,00	908,00	1906,70	1748,70	194242,50	15,28
29	5,02	1921,70														
30	5,25	1836,80	5,14	1875,00	115,57	14,00	515,00	115,04	399,00	76,17	212,00	908,00	1889,70	1776,60	207209,46	15,30
31	5,02	1913,20														

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Figure 5.4. Input and output data

	A	B	C	D	E	F	G	H	I	J	K
2	Wire Diameter (mm)	Breaking Strength (Mpa)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
3			Fe	c	Si	Mn	P	S	Cr	Co	Cu
4	5,23	1886,6	98,1000	0,7520	0,2420	0,4920	0,0051	0,0113	0,3020	0,0039	0,0498
5	5,02	1961,8	97,9000	0,8650	0,1570	0,6520	0,0082	0,0120	0,3260	0,0050	0,0361
6	5,23	1879,8	98,1000	0,7520	0,2420	0,4920	0,0051	0,0113	0,3020	0,0039	0,0498
7	5,04	2049,1	97,9000	0,8520	0,1670	0,6480	0,0071	0,0105	0,3140	0,0058	0,0696
8	5,23	1959,7	97,8000	0,8620	0,2760	0,6190	0,0077	0,0127	0,3460	0,0035	0,0489
9	5,01	1987,9	97,9000	0,8740	0,1550	0,6120	0,0071	0,0180	0,3290	0,0035	0,0450
10	5,24	1881,2	97,9000	0,8650	0,1570	0,6520	0,0082	0,0120	0,3260	0,0050	0,0361
11	5,01	1944,1	97,9000	0,8590	0,1670	0,6480	0,0070	0,0144	0,3260	0,0045	0,0459
12	5,24	1897,1	97,9000	0,8720	0,1620	0,6400	0,0075	0,0130	0,3220	0,0046	0,0349
13	5,01	1875,9	98,1000	0,7520	0,2420	0,4920	0,0051	0,0113	0,3020	0,0039	0,0498
14	5,23	1853,3	97,9000	0,8720	0,1620	0,6400	0,0075	0,0130	0,3220	0,0046	0,0349
15	5,01	1880,8	97,8000	0,8460	0,1930	0,6510	0,0078	0,0138	0,3450	0,0046	0,0563
16	5,24	1902,8	98,1000	0,7520	0,2420	0,4920	0,0051	0,0113	0,3020	0,0039	0,0498
17	5,02	1901,8	97,8000	0,8460	0,1930	0,6510	0,0078	0,0138	0,3450	0,0046	0,0563
18	5,24	1951,4	97,8000	0,9460	0,1590	0,6350	0,0115	0,0105	0,3400	0,0040	0,0459
19	5,01	1979,7	97,8000	0,9460	0,1590	0,6350	0,0115	0,0105	0,3400	0,0040	0,0459
20	5,24	1839,4	97,9000	0,8650	0,1630	0,6520	0,0086	0,0149	0,3260	0,0044	0,0548
21	5,02	1898,9	97,9000	0,8650	0,1630	0,6520	0,0086	0,0149	0,3260	0,0044	0,0548
22	5,24	1935,1	97,8000	0,8620	0,2760	0,6190	0,0077	0,0127	0,3460	0,0035	0,0489
23	5,025	1920,25	97,9000	0,8290	0,1610	0,6580	0,0112	0,0153	0,3250	0,0046	0,0553
24	5,24	1918,2	97,9000	0,8290	0,1610	0,6580	0,0112	0,0153	0,3250	0,0046	0,0553
25	5,04	1998,6	97,9000	0,8290	0,1610	0,6580	0,0112	0,0153	0,3250	0,0046	0,0553
26	5,24	1880,4	97,9000	0,8750	0,1600	0,6450	0,0085	0,0151	0,3260	0,0045	0,0583

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Figure 5.5. Chemical composition

5.3. Data Normalization

In ANNs, training data of ANN can be made more efficient by applying some pre-processing steps to network inputs and outputs. Network entry processing functions convert network use into a better form. Normalization is implemented to the raw data and this data have an influence on the preparation of the proper data set for training. Training of ANNs may be very slow without applying the normalization method to the raw data set. Different techniques can be used for normalization processes. There are many data normalization types in the literature. These can be listed: min-max rule, median, sigmoid, and Z-score (Jayalakshmi, 2011).

The input and output normalization of the Multi Layer Network (MLA) model have closely influenced the performance of the network. Because normalization have made the distribution of values in the data set regular. Extremely large or small values can be seen at ANN inputs. They may have unintentionally entered the input set. While the inputs are being calculated, these values can lead to misalignment of the network by causing extremely large or small values. The normalization of all inputs within a certain range (usually from 0 to 1) allows information from different environments to be reduced on the same scale. Some researchers have generated own normalization methods to solve their problems. A different normalization method can be used for each problem. MLA (Machine Learning Algorithm) designers can determine their own approach to normalizing data on their own. It would not be right to set a standard in this regard (Oztemel, 2012).

5.3.1. Min-Max Normalization

In this method, the largest and smallest values in a group are processed. All other data are normalized to these values. The aim here is to normalize the minimum value 0 and maximum value of 1 and all other data are spread to the range 0-1. The formula can be written as follow.

$$x^* = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{4.4}$$

x^*: normalized data

x_i: input value

Table 5.1. shows an example set of min-max normalization.

Table 5.1. Min-Max Normalization

Data	Normalization	Result
20	=(20-10)/(80-10)	0,142857
35	=(35-10)/(80-10)	0,357143
40	=(40-10)/(80-10)	0,428571
80	= (80-10)/(80-10)	1,000000
10	= (20-10)/(80-10)	0,000000
65	= (65-10)/(80-10)	0,785714
50	= (50-10)/(80-10)	0,571429

5.3.2. Median Normalization

The median means the middle value of a dataset. The median normalization method is used for each sample. The median is not affected by extreme deviations. The formula can be written as follow.

$$x^* = \frac{x_i}{Median} \tag{4.5}$$

x^*: normalized data

x_i: input value

5.3.3. Statistical or Z-Score Normalization

In this method, mean value and standard deviation values are considered. The formula can be written as follow.

$$x^* = \frac{x_i - \mu_i}{\sigma_i} \tag{4.6}$$

x^*: normalized data

x_i: input value

μ_i: the average of the input set

σ_i: standard deviation of input set

5.3.4. Sigmoid Normalization

The sigmoid normalization function classifies data between 0 and 1 or between -1 and 1. There are several non-linear sigmoid function types. Tangential sigmoid function may be a good choice for accelerating processes (Jayalakshmi, 2011). The formula can be written as follow.

$$x^* = \frac{e^{X_i} - e^{-X_i}}{e^{X_i} + e^{-X_i}} \tag{4.7}$$

x^*: normalized data

X_i: input value

e: natural logarithm value

Min-max normalization method will be used in this study. The goal is to normalize the minimum value 0 and maximum value of 1 and all other data are spread to the range 0-1.

5.4. Simulation Results

The flow chart of the system is demonstrated in Figure 5.6.

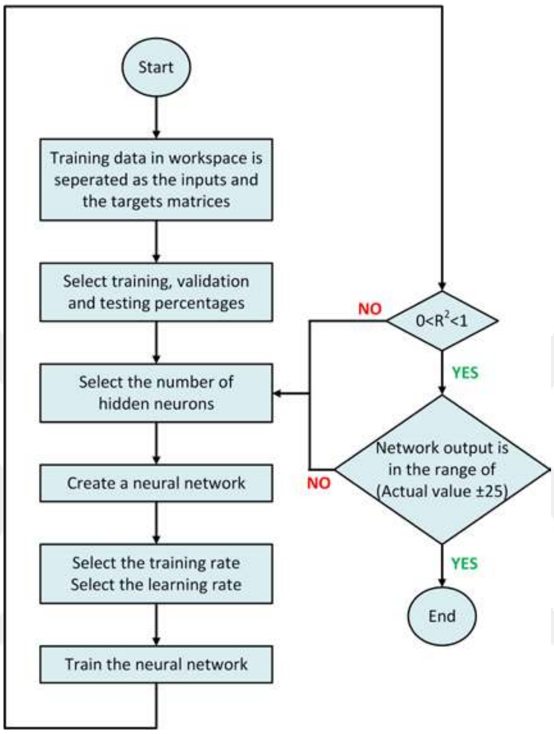

Figure 5.6. The flow chart

The input and target data (APPENDIX A) are defined in Matlab workspace. The data in excel file can be read by following Matlab code. The names of the columns as shown in Fig. 5.7. are the loadcell, the DC voltage and 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 and PC strand ultimate tensile strength (target), respectively.

```
>> data=xlsread('data.xlsx','Sayfa1');
```

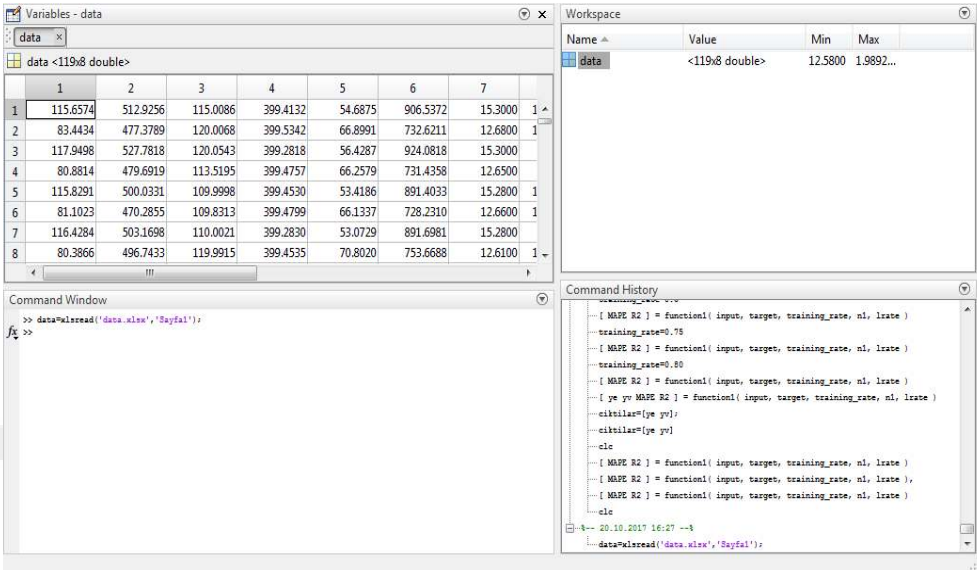

Figure 5.7. Data transfer

The data variable in Matlab workspace is seperated as input and target variables as illustrated in Fig. 5.8. by the following code.

```
>> input=data(:,1:7);
>> target=data(:,end);
```

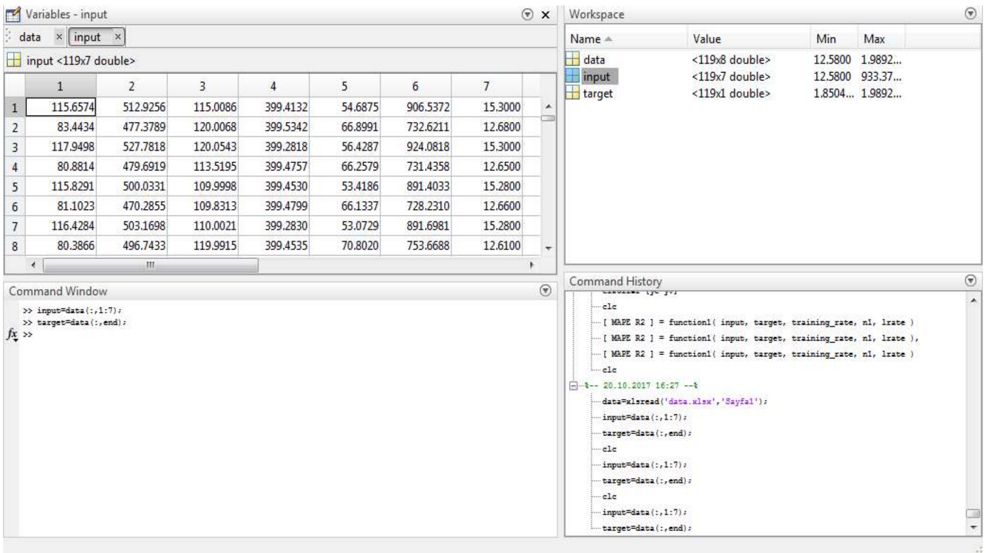

Figure 5.8. Input and target files

After the variables are created, there are two options to activate neural network. In the first option, 'nftool' command is given in command window and neural network fitting tool which is reached as given in Fig. 5.9. Second, a function is written to interface in neural network parameters like neurons, hidden layers, learning rate so on. Otherwise, neural network fitting tool doesn't allow to change all parameters.

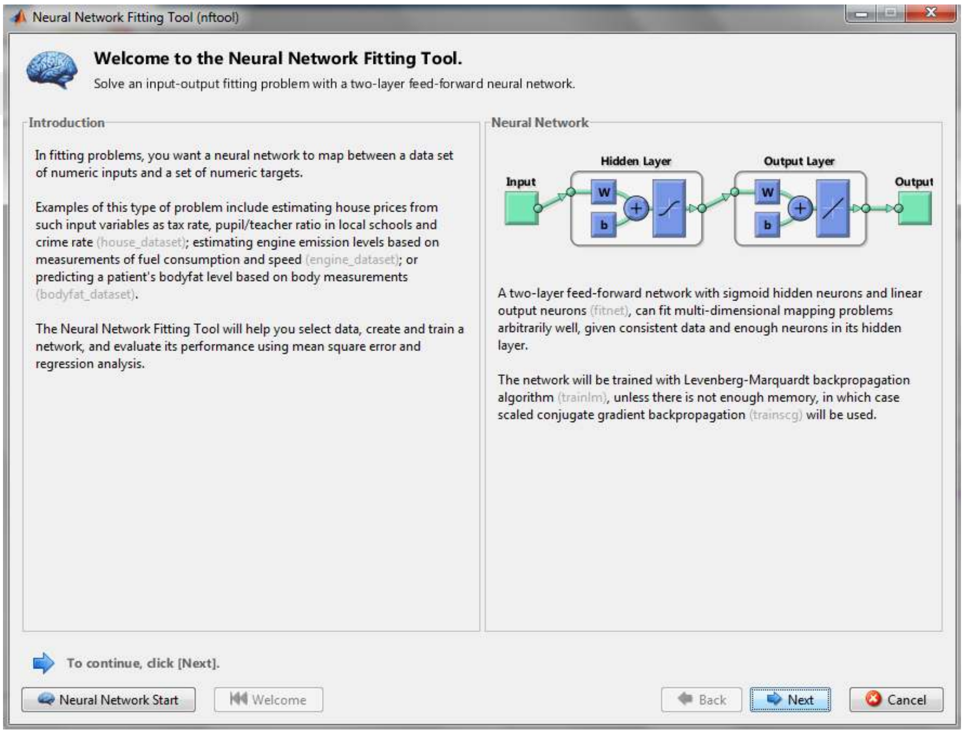

Figure 5.9. Neural network fitting tool

Later input and target values is imported to neural network fitting tool which is shown in Fig. 5.10. The data are got from workspace. “Input” matrice is selected from the inputs menu, “target” matrice is selected from the target menu.

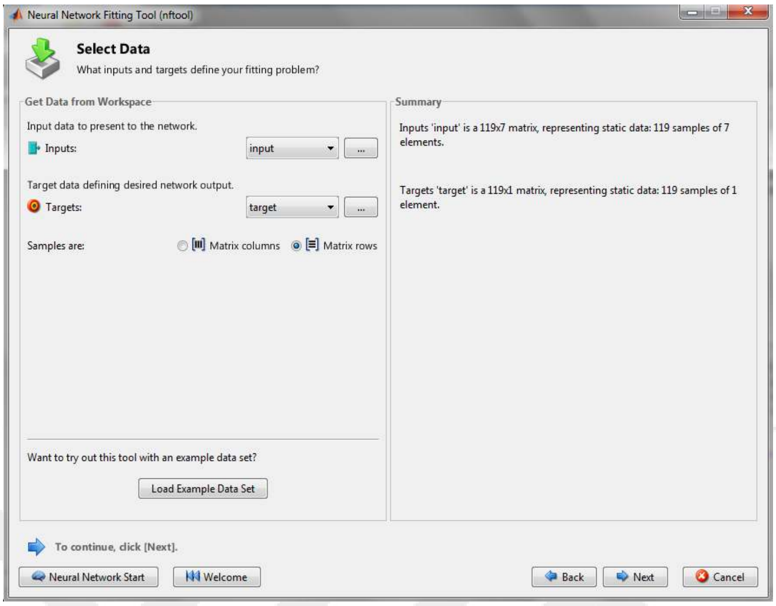

Figure 5.10. Importing of input and target data

In the next step, the percentages of validation and test data can be changed but training data is default as 70 % in Fig. 5.11. They can be changed in the range of 5 percent.

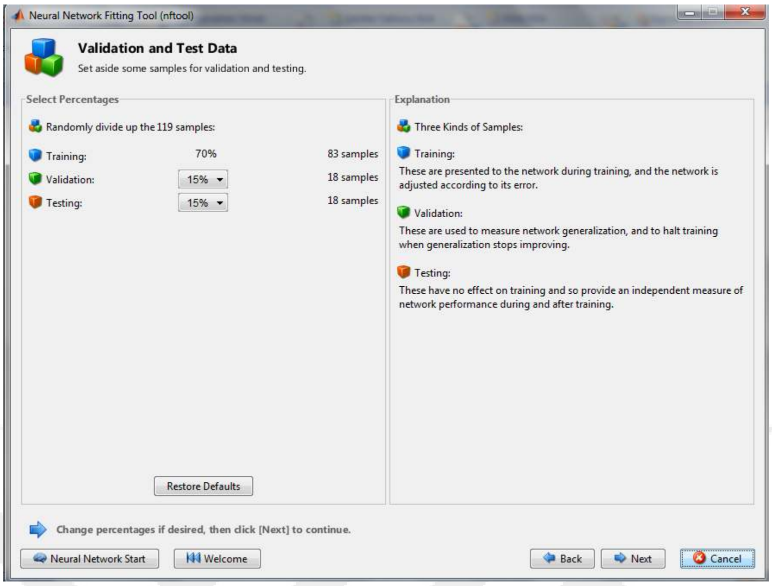

Figure 5.11. Validation and testing data

The network architecture is displayed in Fig. 5.12. If the network doesn't perform well, it is possible to change 'The Number of Hidden Neurons' from this page.

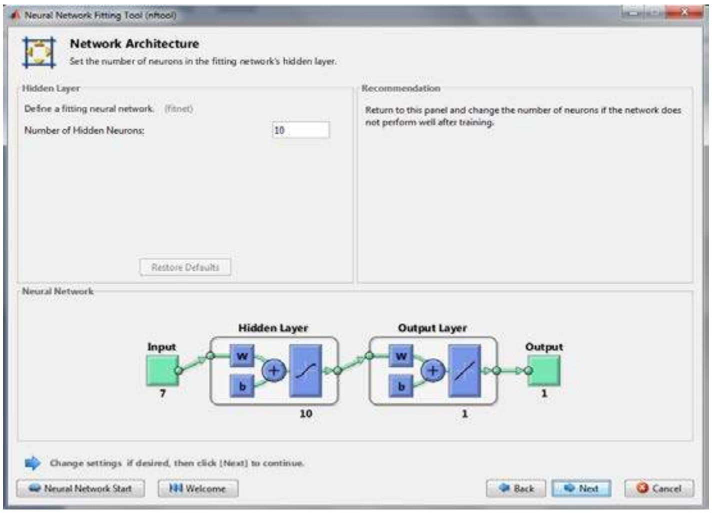

Figure 5.12. Network architecture

Pressing 'Neural Network Start' button will show a selection page as shown in Fig. 5.13. In this page, the problem type is selected. The problem in the study belongs to fitting tool scope.

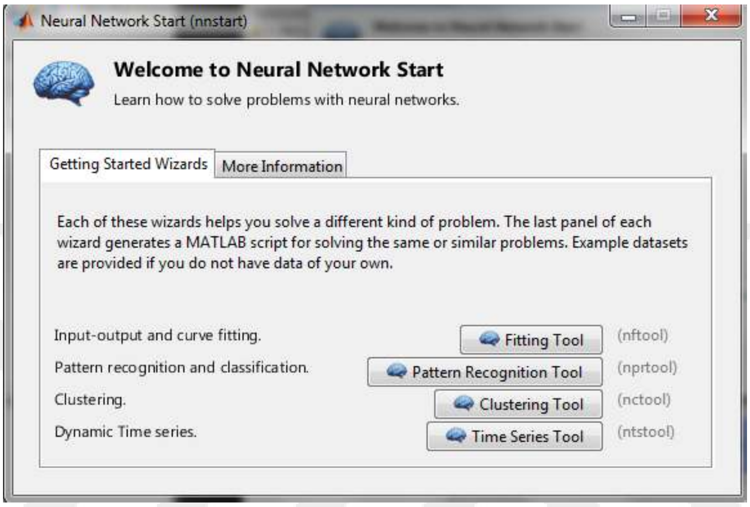

Figure 5.13. Fitting tool

Using the Levenberg-Marquardt back propagation algorithm, the neural network can be trained as given in Fig. 5.14.

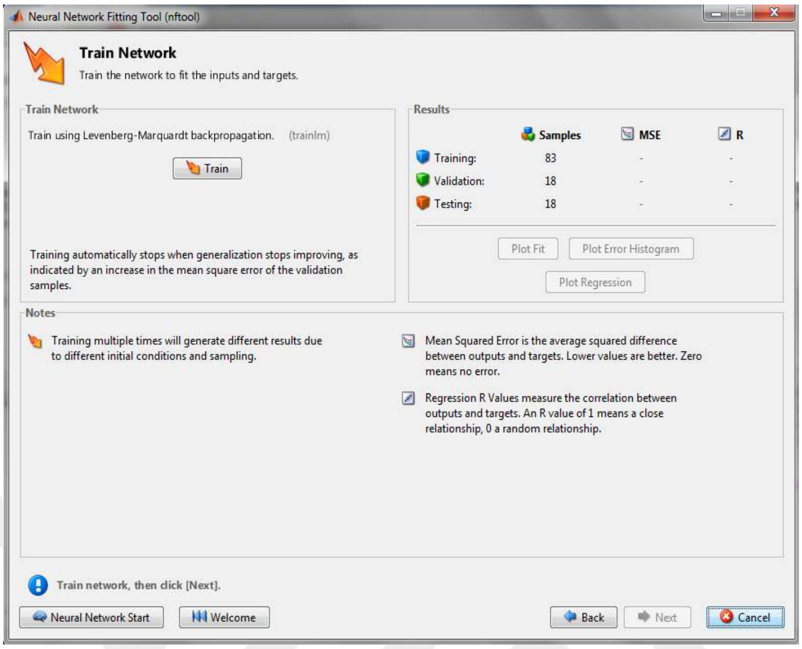

Figure 5.14. Train the network

When the 'Train' button is clicked, the results of MSE (mean of squared error) and R^2 (coefficient of determination) are calculated and shown in Fig. 5.15. MSE varies according to the scale. When the scale is unknown, R^2 gives more accurate results. When the R^2 approaches '1', it means that estimation errors are decreasing. The calculation of MSE is given in equation (2.1). Difference between 'Targets' and 'Outputs' is shown in error histogram as depicted in Fig. 5.16.

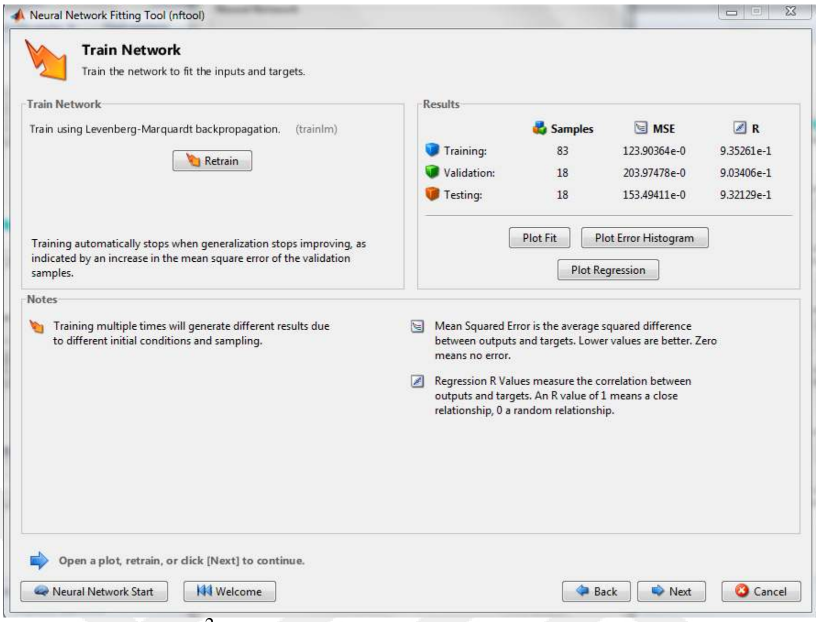

Figure 5.15. MSE and R^2

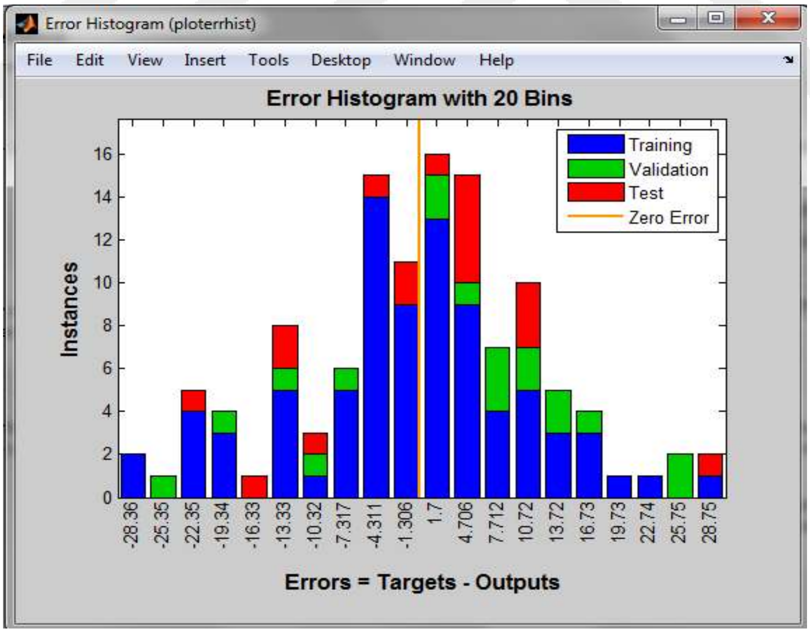

Figure 5.16. Error histogram

X-axis represents the target (real datas) and Y-axis represents the output (prediction datas) as shown in Fig. 5.17. It is desired that the data spread on the dashed line (Y=T). The relationship can be modeled 'Fit' lines as shown in Fig. 5.17. Training, validation and test results of the network is converging accurately.

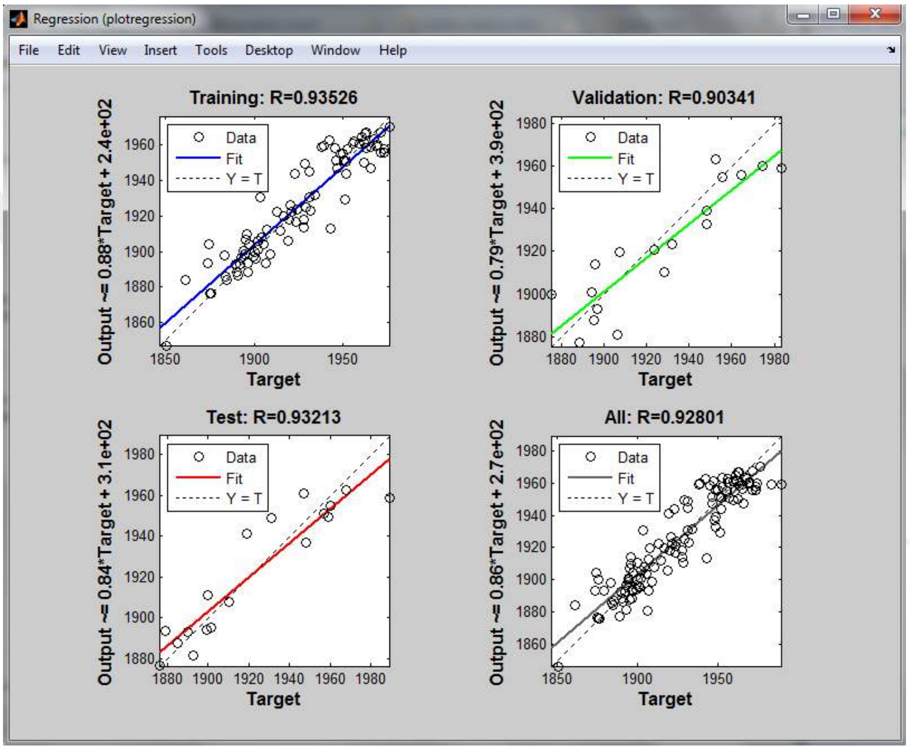

Figure 5.17. Regression

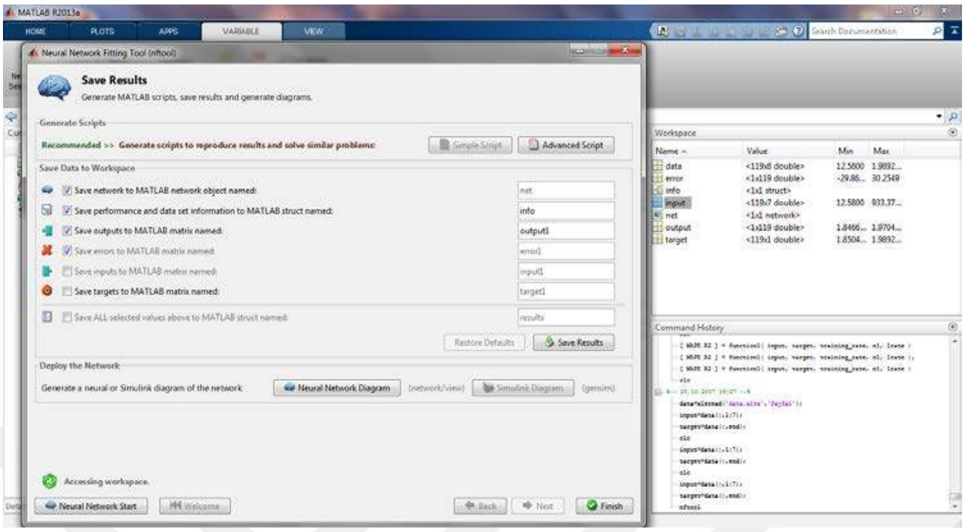

Figure 5.18. Save results

The 'output' values are transposed and written to the adjacent column to 'target' values to compare the two variables as illustrated in Fig. 5.19. The target and the output data are given in APPENDIX B.

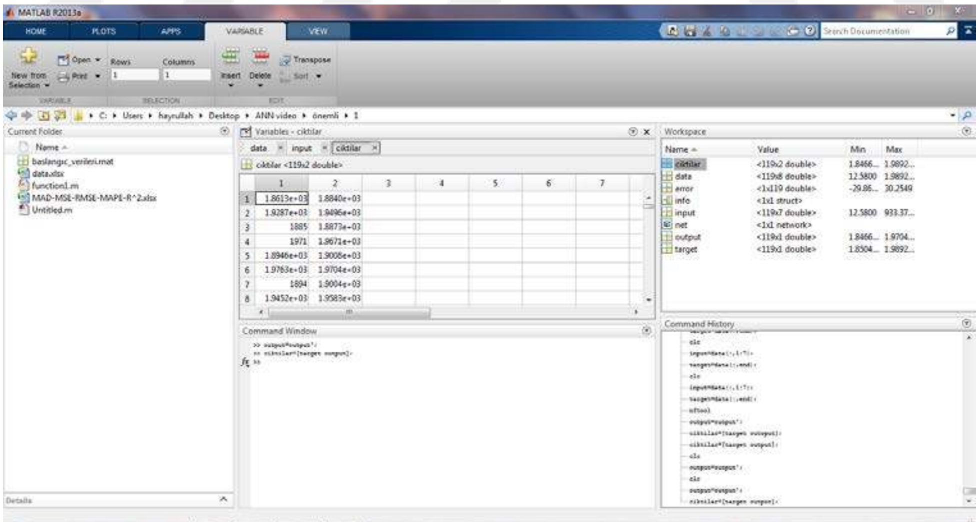

Figure 5.19. Target-output

The total correlation between target and output column are calculated as shown in Fig. 5.20.

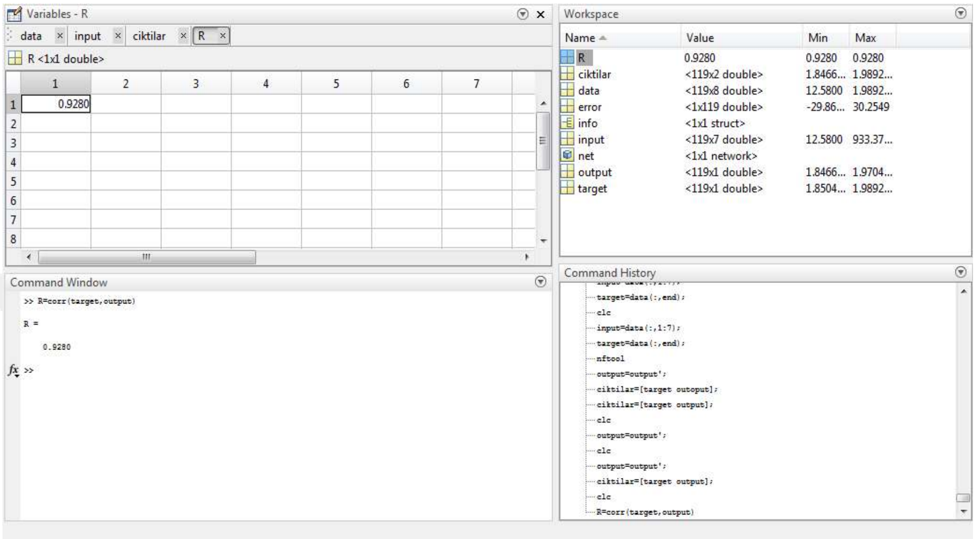

Figure 5.20. Correlation between target-output

The neural network parameters like neurons, hidden layers, learning rate, training rate so on are changed to determine the best result. The software codes are given in APPENDIX D.

Some variables (neurons=n_1,n_2, learning rate=lrate, training rate=training_rate, train function=trainlm) are entered by the keyboard and compared eachother. Performance analysis is performed by changing these parameters. The performance is measured by the MAPE and R^2 values. The MAPE and the R^2 are written on command window in Matlab. The MAPE is the most common measure of forecast error. Roughly the value is asked to be near zero. Calculation of the MAPE is given in equation (2.3). The R^2 is one measure of how well a model can predict the data and falls between 0 and 1. Higher value of R^2 is signed of a better predicting model. Calculation of R^2 is given in equation (2.4).

The neuron numbers, the learning rate, the training rate and training function have been changed in ANN software. So the performance analysis of data is done and compared. The performance analysis results of network are listed as below.

1. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, trainlm (Levenberg-Marquardt) produce the output as shown in Fig. 5.21. The performance of the network is MAPE=0.6817 and R^2=0.7966. The correlation between target and output is not bad. But the minimum value of the output is 1821 MPa. It is a non-standard prediction according to ASTM standard and also the output range is estimated with the ±40 MPa difference.

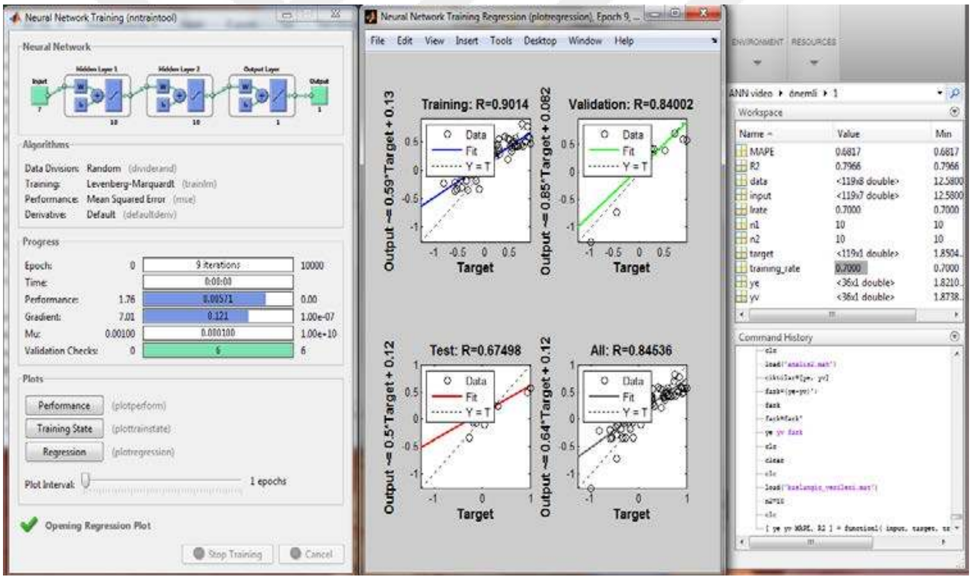

Figure 5.21. Levenberg-Marquardt

2. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, trainbfg (BFGS Quasi-Newton) produce the output as shown in Fig. 5.22. The performance of the network is MAPE=0.7089 and R^2=0.7594. The correlation between target and output is not bad. The minimum value of the output is 1871 MPa. It is a standard prediction

according to ASTM standard and also the output range is estimated with the ±30 MPa difference.

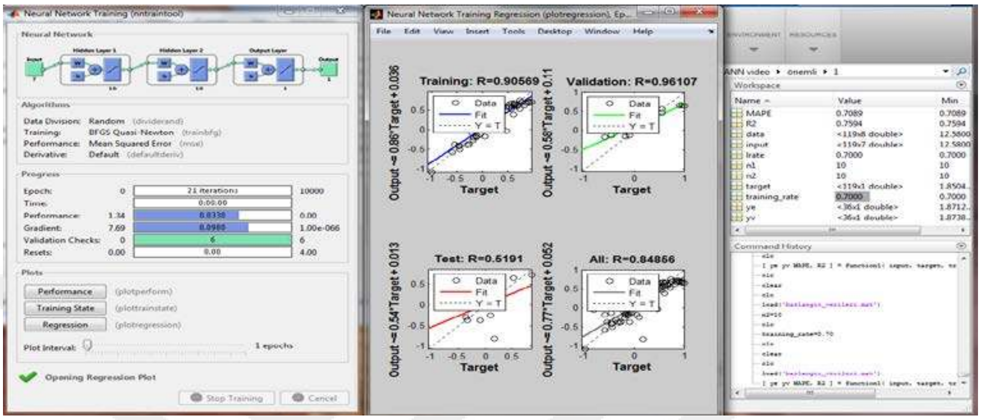

Figure 5.22. BFGS Quasi-Newton

3. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, trainbrp (Resilient Backpropagation) produce the output as given in Fig. 5.23. The performance of the network is MAPE=0.8934 and R^2=0.7836. The correlation between target and output is not bad. The minimum value of the output is 1872 MPa. It is a standard prediction according to ASTM standard and also the output range is estimated with the ±30 MPa difference.

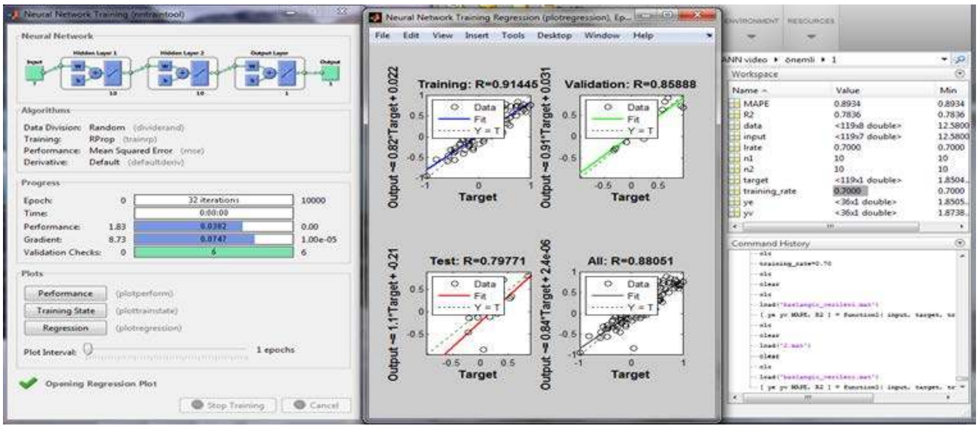

Figure 5.23. Resilient Backpropagation

4. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, traincgb (Conjugate Gradient with Powell/Beale Restarts) produce the output as given in Fig. 5.24. The performance of the network is MAPE=0.8339 and R^2=0.3226. The correlation between target and output is bad.

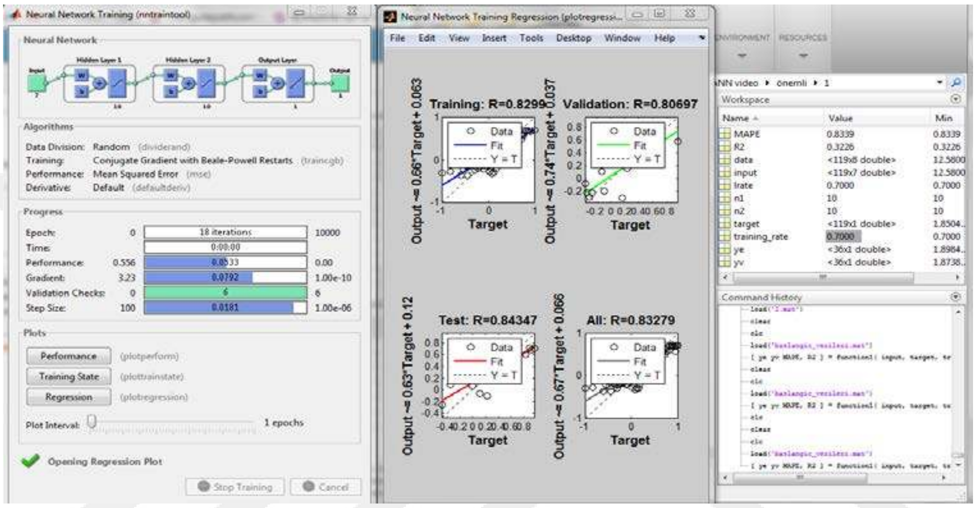

Figure 5.24. Conjugate Gradient with Powell/Beale Restarts

5. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, traincgf (Fletcher-Powell Conjugate Gradient) produce the output as presented in Fig. 5.25. The performance of the network is MAPE=0.8707 and R^2=0.2932. The correlation between target and output is not acceptable.

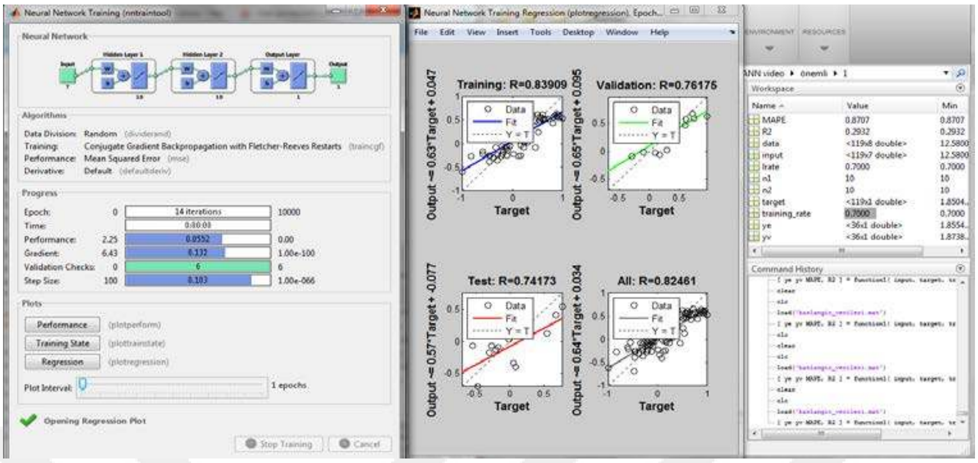

Figure 5.25. Fletcher-Powell Conjugate Gradient

6. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, traincgp (Polak-Ribiére Conjugate Gradient) produce the output as presented in Fig. 5.26. The performance of the network is MAPE=0.8693 and R^2=0.0045. The correlation between target and output is very bad.

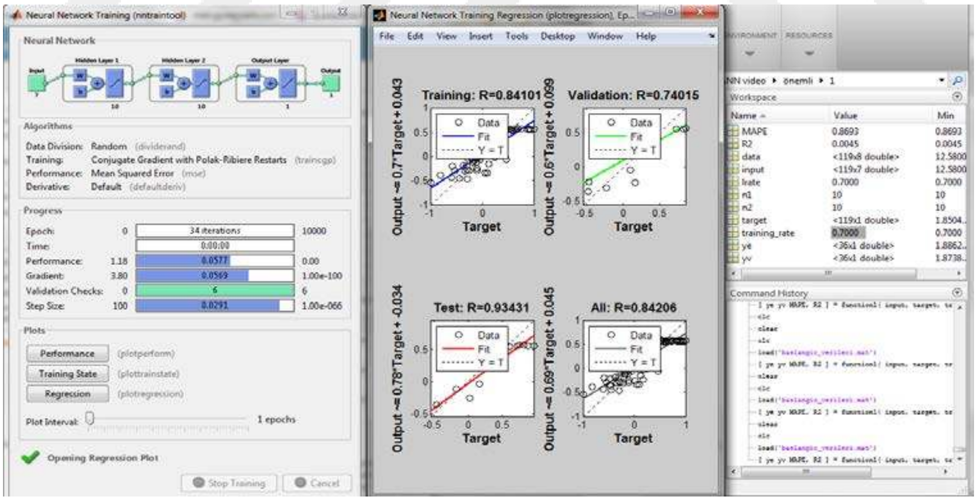

Figure 5.26. Polak-Ribiére Conjugate Gradient

7. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, trainoss (One Step Secant) produce the output as depicted in Fig. 5.27. The performance of the network is

MAPE=0.5925 and R^2=0.6774. The correlation between target and output is not acceptable.

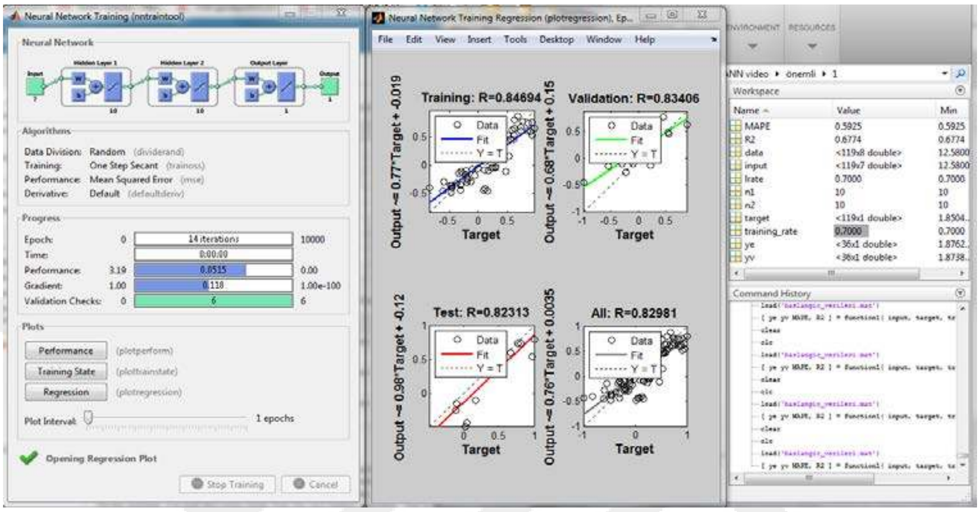

Figure 5.27. One Step Secant

8. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, traingdx (Variable Learning Rate Backpropagation) produce the output as depicted in Fig. 5.28. The performance of the network is MAPE=1.0594 and R^2= -0.6076. The correlation between target and output is very bad. The R^2 value can't be negative.

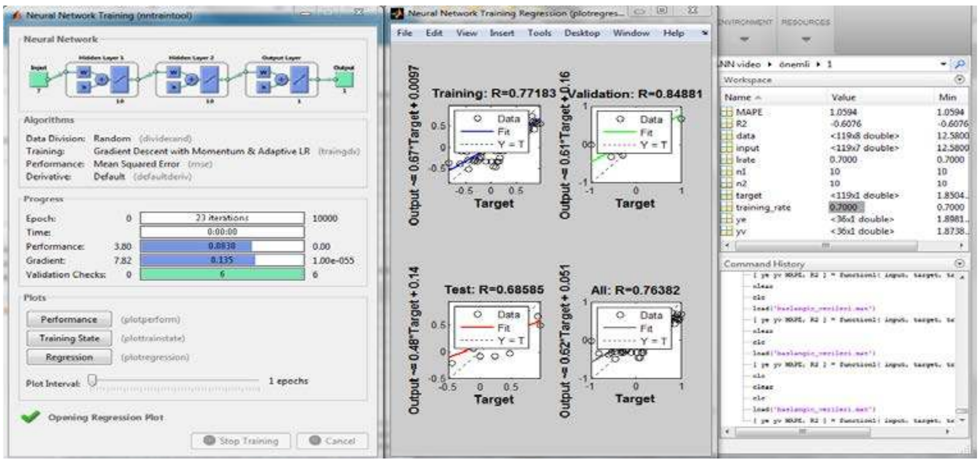

Figure 5.28. Gradient Descent with Momentum & Adaptive LR

9. n_1=10, n_2=10, l_{rate}=0.70, training_rate=0.70, trainscg (Scaled Conjugate Gradient) produce the output as shown in Fig. 5.29. The performance of the network is MAPE=0.6650 and R^2=0.8166. The correlation between target and output is good. The minimum value of the output is 1880 MPa. It is a standard prediction according to ASTM standard and also the output range is estimated with the ±35 MPa difference.

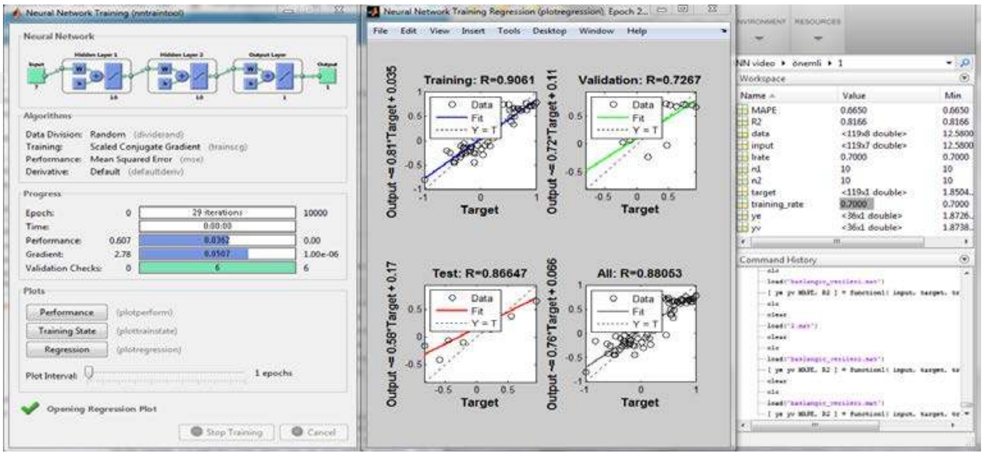

Figure 5.29. Scaled Conjugate Gradient

10. Training function algorithm which is listed above to confirm the best one and Scaled Conjugate Gradient is the most effective for this dataset. After many trials and literature search, the parameters are chosen by following and also the results and instructions are as given in Fig. 5.30., Fig. 5.31., Fig. 5.32. and below.

Parameters: n_1=30, n_2=30, l_{rate}=0.70, training_rate=0.70, trainscg

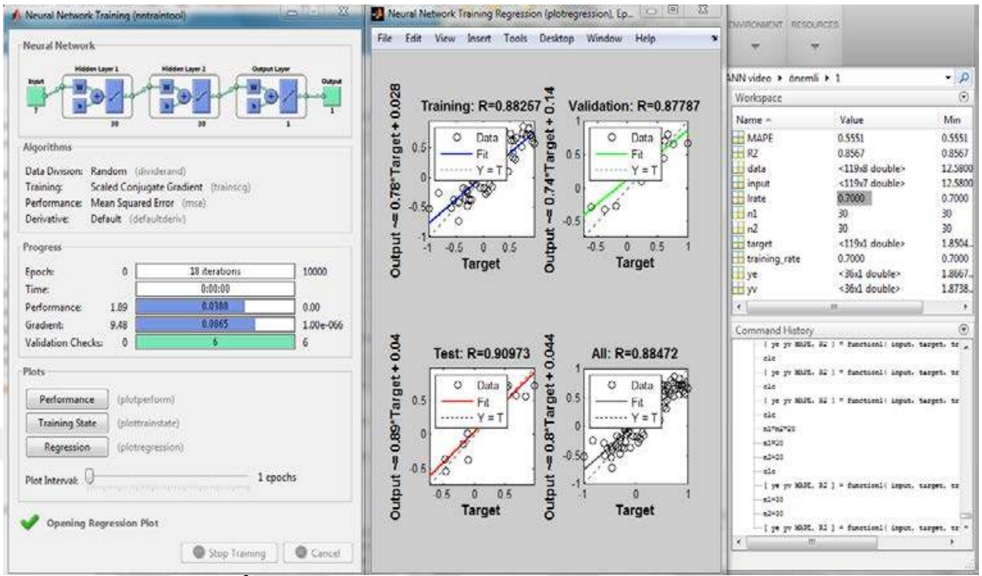

Figure 5.30. SCG: R^2=0.8567, MAPE=0.5551

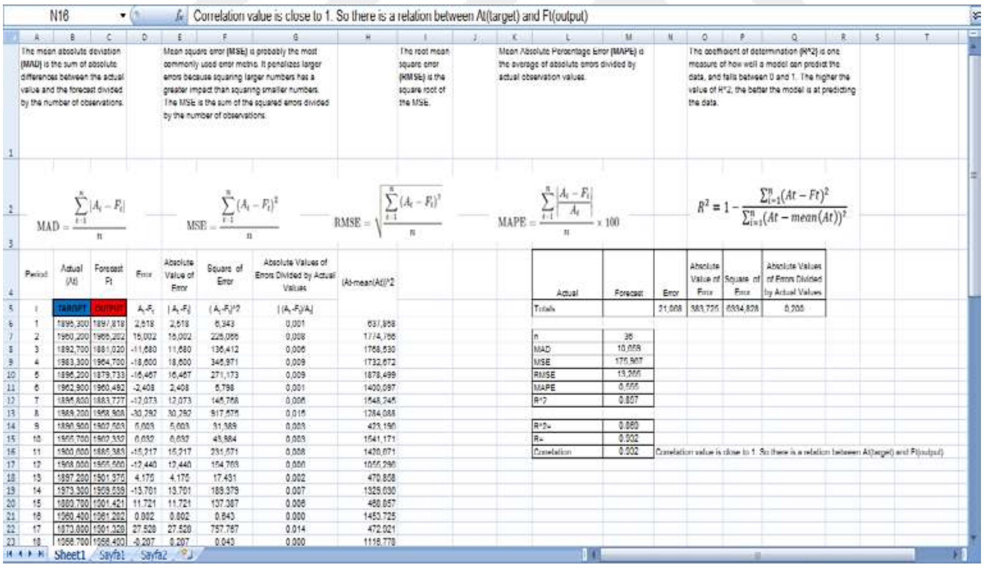

Figure 5.31. Forecasting performance

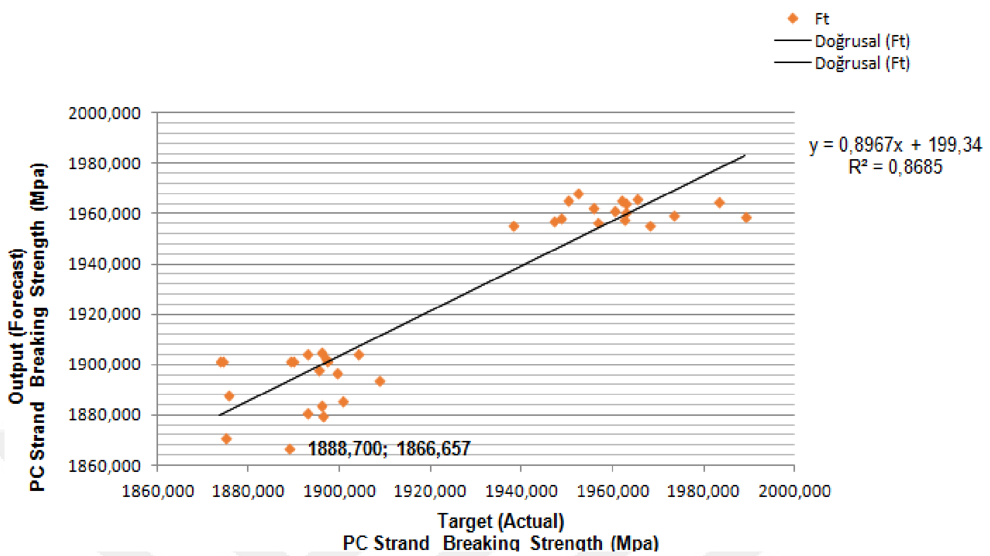

Figure 5.32. Target-output graph

Fig. 5.33. represents the percentage change on the output (PC strand ultimate tensile strength) of the input variables. One by one input data delete from dataset. And the network is trained with the 6 inputs. Consequently, the bars on the graph below shows change of output as percentage.

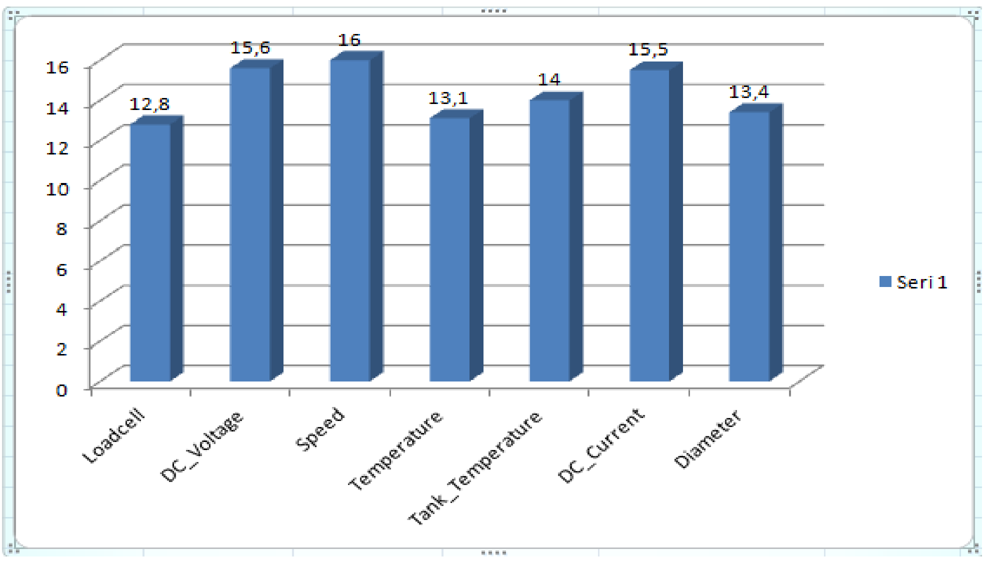

Figure 5.33. Percentage change

The correlation between target (actual data)-output (forecasted data) is very close to 1. It is R=0.932. As you can see in Fig. 5.30. It means that there is a positive relation between target and output. Minimum limit of the estimated value is 1866.7 MPa as you can see in Fig. 5.31. Minimum estimated value' actual value is 1888.7 MPa. The value is estimated with a difference of 22 MPa. Besides other results of network training is added APPENDIX C. 36 number of testing and validation data and 83 number of training data are used by neural network. When these data which are used testing and validation are analyzed as target and output, it is clear that the outputs are estimated with the ±25 MPa difference. It is quite well result. The pivottable of all the tests is demonstrated on Table 5.2.

Table 5.2. The Pivottable

Test Number	**Neuron 1**	**Neuron 2**	**Learning Rate**	**Training Rate**	**Train Function**	**MAPE**	**R^2**
1	10	10	0.70	0.70	trainlm	0,6817	0,7966
2	10	10	0.70	0.70	trainbfg	0,7089	0,7594
3	10	10	0.70	0.70	trainrp	0,8934	0,7839
4	10	10	0.70	0.70	traincgb	0,8339	0,3226
5	10	10	0.70	0.70	traincgf	0,8707	0,2932
6	10	10	0.70	0.70	traincgp	0,8693	0,0045
7	10	10	0.70	0.70	trainoss	0,5925	0,6774
8	10	10	0.70	0.70	traingdx	1,0594	-0,6076
9	10	10	0.70	0.70	trainscg	0,665	0,8166
10	20	20	0.70	0.70	trainlm	1,0933	0,4541
11	20	20	0.70	0.70	trainbfg	0,8935	0,1553
12	20	20	0.70	0.70	trainrp	0,9378	0,6522
13	20	20	0.70	0.70	trainoss	1,2916	-0,4251
14	20	20	0.70	0.70	trainscg	1,0732	0,7041
15	30	30	0.70	0.70	trainlm	1,0507	0,7661
16	30	30	0.70	0.70	trainbfg	0,9810	0,3891
17	30	30	0.70	0.70	trainrp	0,8737	0,5021
18	30	30	0.70	0.70	trainoss	0,9618	0,6472
19	**30**	**30**	**0.70**	**0.70**	**trainscg**	**0,5551**	**0,8567**
20	40	20	0.70	0.70	trainlm	1,7186	0,3413
21	40	20	0.70	0.70	trainbfg	1,0750	0,3293
22	40	20	0.70	0.70	trainrp	0,7060	0,4368
23	40	20	0.70	0.70	trainoss	1,3713	0,5991

Table 5.2. (Continue)

24	40	20	0.70	0.70	trainscg	1,0355	-0,3488
25	10	10	0.60	0.60	trainlm	1,7835	0,4040
26	10	10	0.60	0.60	trainbfg	0,6096	0,7256
27	10	10	0.60	0.60	trainrp	0,6743	0,6661
28	10	10	0.60	0.60	trainoss	2,2088	-15,295
29	10	10	0.60	0.60	trainscg	0,8297	0,3816
30	20	20	0.60	0.60	trainlm	1,0621	0,7588
31	20	20	0.60	0.60	trainbfg	0,6301	0,7822
32	20	20	0.60	0.60	trainrp	1,9383	-2,4747
33	20	20	0.60	0.60	trainoss	0,6035	0,6983
34	20	20	0.60	0.60	trainscg	0,7400	0,7922
35	30	30	0.60	0.60	trainlm	1,3246	0,7062
36	30	30	0.60	0.60	trainbfg	0,7990	0,4440
37	30	30	0.60	0.60	trainrp	0,8478	0,7509
38	30	30	0.60	0.60	trainoss	0,6950	0,6293
39	30	30	0.60	0.60	trainscg	1,0477	-0,1362
40	40	40	0.60	0.60	trainlm	1,9906	0,5992
41	40	40	0.60	0.60	trainbfg	1,1993	0,2124
42	40	40	0.60	0.60	trainrp	0,7267	0,6734
44	40	40	0.60	0.60	trainoss	0,8009	0,3934
45	40	40	0.60	0.60	trainscg	0,7980	0,6208
46	10	10	0.80	0.80	trainlm	1,1836	0,7074
47	10	10	0.80	0.80	trainbfg	0,8744	0,5223
48	10	10	0.80	0.80	trainrp	1,5462	-1,5649
49	10	10	0.80	0.80	trainoss	0,8043	0,6123
50	10	10	0.80	0.80	trainscg	0,6667	0,6127
51	20	20	0.80	0.80	trainlm	1,0592	0,7461
52	20	20	0.80	0.80	trainbfg	0,6258	0,7627
53	20	20	0.80	0.80	trainrp	0,6798	0,7965
54	20	20	0.80	0.80	trainoss	0,9434	0,0986
55	20	20	0.80	0.80	trainscg	0,6581	0,8105
56	30	30	0.80	0.80	trainlm	0,7463	0,7340
57	30	30	0.80	0.80	trainbfg	0,7292	0,7596
58	30	30	0.80	0.80	trainrp	1,4082	-0,0182
59	30	30	0.80	0.80	trainoss	0,8912	0,6729
60	30	30	0.80	0.80	trainscg	1,1142	0,2767
61	40	40	0.80	0.80	trainlm	1,7355	0,6567
62	40	40	0.80	0.80	trainbfg	2,1378	-0,6662
63	40	40	0.80	0.80	trainrp	0,8447	0,5763
64	40	40	0.80	0.80	trainoss	0,9634	0,5834
65	40	40	0.80	0.80	trainscg	0,7751	0,7941

Test material Grade 270 (Cousins, 2006) is used during this study as mentioned earlier. Minimum tensile strengths of Grade 270 is 270 ksi (1860 MPa). So the outputs are predicted also in accordance with the ASTM standard.

An approach is created to identify input data for this product and then the outputs are estimated with ANNs. The dataset of the network has very few samples. And another parameters like chemical composition are dramatically effect the result. This situation is pointed out in literature studies as well. If more data are collected from PC strand line, more accurate, sensitive and reliable results can be obtained.

Malinov and coworkers investigated how they would estimate mechanical properties of titanium alloys in 2001 and 2004. They trained the network with the composition of alloy, heat treatment and test temperature data. The output of the network was obtained the mechanical properties of the titanium alloy which are UTS, yield strenght, elongation so on. And they used Levenberg_Marquardt training function algorithm and used some of the dataset from the Russian literature. So they fed the network more data. Nevertheless, when we compare UTS results of grade 270 and titanium alloy, they are fairly accurate and close.

6. CONCLUSIONS AND FUTURE WORK

In this study it is discussed data acquisition, logging, transfer, normalization, interpretation and neural network training, testing using of influencing factors and examined to the application of ANN in PC Strand line.

As the characteristics of the materials are not fixed, they distort under force and show form and volume changes. Tensile test which is one of the most important mechanical test is carried out by the operators to understand the material properties. This brings about lost labor, time and product loss.

For this reason, it is decided to solve this problem by the help of ANN in MATLAB. The DC voltage and 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 data are collected in pre-stressed concrete strand line to utilize as input parameters in ANN. PC strand ultimate tensile strength is determined as the output parameter of the ANN. As a result of the literature survey, FFBP is determined as the most accurate network type for the current problem. Training function, training rate, learning rate, performance function, transfer function, number of hidden layers and number of neurons are changed with the help of a software to train network. Finally, them is identified by means of comparing the output of ANN. Training function is selected 'trainscg'. It performs well over the dataset. Training rate (training_rate) parameter is selected 0.70 and learning rate of the network is stated 0.70 as well. The last parameter which is changed the number of neurons (n_1, n_2). Even so, these values don't affect as well as the other parameters, both of them are preferred 30 neurons. 119 number of input data are used in the network. %70 of the data (83 pcs) are assigned training function and rest of them (36 pcs) are used for testing and validation. Just single input data takes at least 6-8 hours. This data set take about 2 months.

The ASTM standard (the specification for low relaxation seven-wire steel strand for prestressed concrete) says that minimum limit of PC strand must be above 270ksi [1860 MPa] for grade 270 material. As it is mentioned before, the company produces just grade 270 material. With this information, it can be interpretted the performance of the network. The minimum limit of the estimated value of NN is 1866.7 MPa. This value follows the standard specification. The outputs of the network are estimated with the ±25 MPa difference. And also R^2 equal to 0.8685. The correlation between the target (actual data) and the output of network (forecasted data) is very close to '1'. It is obviously seen that, %87 of the output of the network is determined by the input parameters. It is noticed that there is a remarkable relationship between input and output. The effect of input parameters on output is the loadcell (%12.8), the DC voltage of the induction furnace (%15.6), the speed of the PC strand line (%16), the temperature of the induction furnace (%13.1), the temperature of the quench tank (%14), the DC current of the induction furnace (%15,5), the diamater of the PC strand product (%13,4).

Besides, the dataset of the network have very few samples. Other parameters like chemical composition etc. are dramatically affected the result. If more data are collected from PC strand line, more accurate, sensitive and reliable results can be obtained. Furthermore, the other mechanical properties of PC strand which are yield strength, elastic modulus, elongation and reduction of area can be estimated with proper and sufficient number of data. The model is open for constant upgrade and improvement. So, this product with many application areas can be produced most properly at a lower cost with a different way. And last, a significant contribution will be made primarily to the firm and indirectly to the economy of the country.

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BIOGRAPHY

Hayrullah ÖZEL was born in Adana, Turkey in 1989. He graduated from Adana Borsa Anatolian High School in 2006. He received his BSc degree in Electrical and Electronics Engineering from Erciyes University in 2012. After graduation, he joined the army as a Third-Lieutenant in Cyprus during one year. After military service, he has specialized on Iron and Steel Industry Research And Development Department in private sector for 4-years. In 2014, he started his MSc education in charge of Assoc. Prof. Dr. Mehmet Uğraş Cuma in Electrical and Electronics Engineering in Cukurova University.

He is certificated by Turkish Republic Ministry of Labor and Social Security as B Class Occupational Safety Specialist, also by Turkish Republic Ministry of Energy and Natural Resources as Energy Manager.

His research areas are iron and steel research and development projects, process improvements, maintain and repair services and also energy efficiency applications like burning system modernization in the open flame annealing furnace and burning system modernization in the galvanizing bath on the galvanizing production line.

He is a member of The Union of Chambers of Turkish Engineers and Architects (UCTEA).

APPENDIXES

APPENDIX A

A) Inputs-Target Data Table

INPUT							TARGET
(KN)	(V)	(m/min)	(℃)	(℃)	(A)	(mm)	(MPa)
Loadcell	DC Voltage	Speed	Temp.	Tank Temp.	DC Current	PC Strand Diameter	PC Strand Ultimate Tensile Strength
115,657	512,926	115,009	399,413	54,688	906,537	15,300	1861,300
83,443	477,379	120,007	399,534	66,899	732,621	12,680	1928,700
117,950	527,782	120,054	399,282	56,429	924,082	15,300	1885,000
80,881	479,692	113,520	399,476	66,258	731,436	12,650	1971,000
115,829	500,033	110,000	399,453	53,419	891,403	15,280	1894,600
81,102	470,285	109,831	399,480	66,134	728,231	12,660	1976,300
116,428	503,170	110,002	399,283	53,073	891,698	15,280	1894,000
80,387	496,743	119,992	399,454	70,802	753,669	12,610	1945,200
116,072	504,704	110,029	399,338	51,244	894,070	15,250	1914,500
80,582	494,559	119,998	399,464	68,349	751,399	12,720	1971,100
115,572	515,000	115,040	399,000	76,172	908,000	15,280	1896,500
81,652	494,486	119,843	399,467	69,986	749,169	12,710	1974,200
115,572	515,000	115,040	399,000	76,172	908,000	15,280	1906,700
80,965	491,812	119,129	399,446	68,818	747,037	12,610	1969,400
115,572	515,000	115,040	399,000	76,172	908,000	15,300	1892,100
76,686	498,062	119,628	399,496	68,678	754,357	12,600	1931,200
115,572	515,000	115,040	399,000	76,172	908,000	15,270	1878,800
80,752	437,056	98,843	399,460	64,819	693,008	12,600	1952,000
116,790	519,763	115,033	399,763	55,601	912,461	15,360	1884,000
80,707	495,772	119,826	399,470	71,785	750,921	12,610	1939,000
115,708	524,571	115,015	399,333	74,585	910,905	15,290	1884,500
115,588	500,472	109,994	399,565	54,697	889,733	15,250	1899,200
83,558	476,760	120,027	399,407	66,330	732,348	12,670	1946,100
119,146	525,327	109,944	399,474	62,928	931,871	15,760	1850,400
119,408	511,627	108,584	399,661	71,609	900,305	15,270	1905,200
81,317	482,558	120,019	399,448	64,172	741,602	12,730	1919,100
121,438	512,756	110,007	399,349	73,178	909,837	15,200	1901,700
115,843	525,289	115,011	399,322	51,865	916,760	15,290	1875,400

118,617	502,092	109,999	399,534	74,648	903,176	15,170	1912,800
118,891	501,098	108,185	399,390	72,464	894,366	15,190	1927,900
121,381	492,321	105,456	399,482	69,739	878,286	15,220	1920,500
117,802	511,244	109,986	399,610	70,585	904,561	15,170	1902,200
119,838	502,628	109,254	399,262	71,247	898,183	15,300	1907,300
80,712	468,301	110,009	399,466	64,686	726,027	12,600	1942,400
113,575	516,877	110,002	399,420	72,712	906,123	15,270	1876,200
82,452	487,532	120,017	399,390	57,014	745,149	12,720	1933,900
120,445	504,753	109,993	399,432	72,675	903,993	15,190	1919,700
80,567	486,503	119,523	399,456	59,997	741,895	12,670	1903,500
126,201	484,242	99,174	399,484	73,182	891,110	15,660	1890,700
79,906	488,511	119,987	399,538	61,006	744,584	12,680	1951,100
120,894	501,863	110,084	399,432	72,084	901,781	15,210	1929,000
79,661	489,946	120,004	399,506	60,656	746,083	12,700	1931,100
126,434	513,467	109,402	399,356	74,857	928,800	15,620	1906,300
79,222	488,775	120,014	399,450	65,496	744,541	12,720	1931,000
120,659	505,541	110,008	399,541	73,083	900,324	15,190	1923,600
80,459	464,078	110,049	399,383	59,108	724,262	12,590	1947,900
119,780	508,047	110,171	399,256	74,890	903,384	15,270	1910,000
82,076	487,977	120,025	399,605	64,568	745,826	12,590	1922,500
119,452	529,869	118,036	399,672	51,070	933,377	15,200	1916,300
79,935	474,809	115,005	399,397	66,261	734,723	12,600	1964,700
119,854	506,864	110,018	399,321	52,533	902,926	15,300	1923,700
80,956	486,062	120,019	399,498	65,890	740,921	12,600	1965,900
121,216	523,683	117,949	399,396	57,251	927,683	15,210	1918,900
83,142	486,652	120,015	399,448	63,230	740,886	12,610	1959,100
117,215	505,143	109,682	399,516	74,903	902,155	15,230	1907,000
82,173	488,073	119,995	399,425	65,714	740,955	12,650	1949,800
119,525	507,877	109,997	399,580	74,996	903,840	15,290	1942,700
82,920	486,978	120,008	399,398	64,626	741,925	12,670	1955,600
125,848	512,763	110,026	399,553	60,903	929,316	15,600	1883,400
83,391	486,505	120,009	399,486	66,273	740,117	12,690	1973,300
124,343	461,344	90,007	399,344	54,733	852,656	15,690	1894,500
81,883	487,506	120,002	399,457	69,077	740,136	12,670	1969,000
119,655	508,521	110,008	399,545	74,930	904,306	15,150	1927,900
80,640	489,915	120,010	399,528	64,009	742,953	12,660	1951,800
120,102	501,773	109,262	399,397	74,752	897,085	15,170	1932,000
77,857	473,705	112,740	399,124	62,060	724,504	12,680	1946,400
120,728	503,679	110,004	399,305	53,372	902,412	15,300	1921,100
78,564	492,066	119,884	399,527	63,564	745,604	12,690	1948,500
121,312	501,955	108,178	399,439	71,352	894,121	15,170	1931,700

79,025	489,545	120,006	399,506	62,371	746,827	12,690	1948,100
120,925	503,451	108,843	398,902	72,443	899,078	15,170	1924,200
120,586	480,970	100,114	399,535	73,397	869,089	15,250	1928,200
86,611	473,053	118,021	399,496	66,562	731,807	12,620	1952,300
120,196	512,163	110,005	399,478	74,958	909,990	15,180	1900,200
85,529	479,385	119,795	399,460	66,699	738,144	12,660	1961,600
121,027	508,803	109,201	399,516	74,761	905,534	15,210	1894,800
85,913	488,884	124,963	399,460	72,550	748,202	12,620	1960,800
119,953	523,890	114,735	399,476	75,034	923,353	15,350	1889,900
86,022	488,835	125,005	399,450	71,539	749,573	12,620	1967,300
120,278	508,103	110,009	399,449	74,989	904,400	15,190	1900,000
86,501	464,238	115,954	399,472	66,903	722,356	12,660	1956,100
120,673	521,620	114,096	399,454	74,815	918,242	15,240	1901,300
86,572	489,802	124,956	399,483	69,457	748,417	12,620	1959,400
120,720	524,563	114,928	399,448	75,067	924,748	15,310	1895,300
79,871	507,398	125,009	399,448	71,993	763,920	12,620	1950,200
125,172	488,934	99,914	399,489	74,878	892,234	15,600	1892,700
82,641	482,412	114,083	399,501	60,283	731,020	12,610	1983,300
115,267	500,198	110,008	399,560	56,126	888,736	15,250	1896,200
80,688	497,624	120,020	399,475	70,420	751,261	12,650	1962,900
115,756	502,622	110,007	399,568	52,055	890,847	15,250	1895,800
81,365	496,373	119,902	399,464	70,098	752,402	12,740	1989,200
117,342	518,942	115,015	399,521	72,432	914,769	15,270	1896,900
81,699	494,266	120,002	399,467	70,180	749,853	12,630	1955,700
115,559	515,333	115,030	399,148	75,698	908,272	15,270	1900,600
79,842	463,694	107,662	399,500	64,576	720,216	12,640	1968,000
115,572	515,000	115,040	399,000	76,172	908,000	15,290	1897,200
79,898	493,925	119,992	399,454	69,758	751,446	12,650	1973,300
115,572	515,000	115,040	399,000	76,172	908,000	15,300	1889,700
78,970	497,778	120,008	399,440	69,447	753,027	12,580	1960,400
115,572	515,000	115,040	399,000	76,172	908,000	15,280	1873,800
76,368	503,374	119,887	399,469	69,944	756,343	12,580	1956,700
115,572	515,000	115,040	399,000	76,172	908,000	15,300	1889,200
81,257	497,678	119,967	399,531	71,880	752,605	12,620	1938,000
116,136	530,088	117,883	399,659	57,326	916,308	15,290	1875,000
79,966	469,247	109,999	399,444	66,163	729,871	12,620	1962,500
115,727	505,161	107,396	399,411	72,855	888,214	15,270	1875,500
79,508	480,262	115,006	399,488	68,117	739,524	12,610	1947,100
125,231	490,661	99,660	399,489	72,226	890,664	15,690	1888,700
79,689	493,830	120,008	399,468	70,055	751,722	12,630	1948,650
119,459	483,684	100,212	399,492	74,619	871,890	15,200	1904,100

86,890	504,098	129,819	399,474	70,911	758,283	12,660	1952,300
121,015	523,446	115,008	399,497	75,053	920,498	15,240	1892,800
85,869	453,338	110,570	399,463	64,280	717,672	12,630	1961,900
120,246	509,008	109,680	399,484	74,969	901,831	15,200	1896,000
85,926	484,459	121,789	399,493	70,332	743,350	12,630	1962,800
120,116	510,419	109,324	399,504	74,888	903,941	15,210	1874,400
85,148	476,256	119,487	399,473	66,978	733,930	12,700	1965,300
122,936	514,995	109,912	399,504	74,689	909,920	15,250	1899,200
120,306	513,577	110,022	399,468	73,245	908,207	15,220	1908,600

APPENDIX B

A) Target-Output Data Table

TARGET (MPa)	OUTPUT (MPa)
1861,3	1883,976085
1928,7	1949,613081
1885	1887,306192
1971	1967,148108
1894,6	1900,765923
1976,3	1970,388998
1894	1900,39347
1945,2	1958,341097
1914,5	1911,696516
1971,1	1955,66721
1896,5	1893,305582
1974,2	1960,090701
1906,7	1893,305582
1969,4	1960,119931
1892,1	1892,831388
1931,2	1949,01205
1878,8	1893,544011
1952	1950,983618
1884	1885,726155
1939	1959,759981
1884,5	1884,135056
1899,2	1894,216383
1946,1	1951,405372
1850,4	1846,567731
1905,2	1903,927625
1919,1	1941,000579
1901,7	1900,885466
1875,4	1876,167497

1912,8	1922,292186
1927,9	1917,919516
1920,5	1926,413274
1902,2	1905,903506
1907,3	1919,654669
1942,4	1962,457731
1876,2	1876,287356
1933,9	1931,647018
1919,7	1918,024563
1903,5	1930,690026
1890,7	1886,253597
1951,1	1929,08445
1929	1925,134283
1931,1	1930,554442
1906,3	1880,945628
1931	1944,865283
1923,6	1920,860722
1947,9	1936,786454
1910	1907,710027
1922,5	1943,974562
1916,3	1919,669846
1964,7	1956,022495
1923,7	1916,971994
1965,9	1947,065583
1918,9	1905,840642
1959,1	1949,221366
1907	1912,578926
1949,8	1955,500188
1942,7	1913,154552
1955,6	1954,901213
1883,4	1898,18005
1973,3	1957,544629
1894,5	1898,532226
1969	1959,537785
1927,9	1913,794369

1951,8	1944,045028
1932	1923,155883
1946,4	1947,147598
1921,1	1922,43441
1948,5	1938,889015
1931,7	1922,862728
1948,1	1933,022052
1924,2	1923,554818
1928,2	1910,546597
1952,3	1963,181751
1900,2	1900,093784
1961,6	1961,320189
1894,8	1906,822783
1960,8	1964,677446
1889,9	1888,654388
1967,3	1963,395282
1900	1910,789464
1956,1	1962,265926
1901,3	1895,221647
1959,4	1960,86672
1895,3	1887,704165
1950,2	1951,512948
1892,7	1881,655501
1983,3	1958,800883
1896,2	1888,306266
1962,9	1958,243977
1895,8	1913,90412
1989,2	1958,94513
1896,9	1904,387234
1955,7	1960,689052
1900,6	1896,108068
1968	1962,332525
1897,2	1893,068043
1973,3	1955,873609
1889,7	1892,831388

1960,4	1954,959259
1873,8	1893,305582
1956,7	1951,044005
1889,2	1892,831388
1938	1959,278787
1875	1876,371863
1962,5	1966,447648
1875,5	1899,960425
1947,1	1961,167121
1888,7	1877,44633
1948,65	1955,4005
1904,1	1908,045322
1952,3	1957,910641
1892,8	1896,841378
1961,9	1949,871724
1896	1910,04474
1962,8	1966,93535
1874,4	1904,260358
1965,3	1959,127813
1899,2	1897,001048
1908,6	1898,576285

APPENDIX C

A) Target-Output Estimation Results

TARGET (MPa)	OUTPUT (MPa)
1895,300	1897,818
1950,200	1965,202
1892,700	1881,020
1983,300	1964,700
1896,200	1879,733
1962,900	1960,492
1895,800	1883,727
1989,200	1958,908
1896,900	1902,503
1955,700	1962,332
1900,600	1885,383
1968,000	1955,560
1897,200	1901,375
1973,300	1959,539
1889,700	1901,421
1960,400	1961,202
1873,800	1901,328
1956,700	1956,493
1889,200	1901,421
1938,000	1955,258
1875,000	1871,022
1962,500	1957,612
1875,500	1887,669
1947,100	1957,022
1888,700	**1866,657**
1948,650	1958,111
1904,100	1904,002
1952,300	1967,933
1892,800	1904,175
1961,900	1965,059
1896,000	1904,786
1962,800	1963,987
1874,400	1901,297

1965,300	1965,648
1899,200	1896,700
1908,600	1893,925

APPENDIX D

```
function [ ye yv MAPE, R2 ] = function1( input, target, training_rate, n1, n2, lrate )
%The summary of neural network is following below.
%   Function structure terminates with 'end' command.
%   The output arguments are written in square bracket and the input arguments are
%   written in round bracket.
%  The 'input' variable is the input of the neural network and the 'target' variable is
the actual values(PC strand ultimate tensile strength).
%   1) The input matrix is seperated as 'training' and 'validation' data.
%   2) The output matrix is seperated as 'training' and 'validation' data.
%   3) Next, the neural network is created.
%   4) The neural network is trained using the training input and the training
output.
%   5) The validation input and outputs are sent the main network structure. And
then the actual outputs and the trained outputs are compared.
%   The input data is separated as %70 traing and %30 validation data or it could
be changed. So the number of data (noofdata) is found. And training_rate is an
input parameter and may vary between 0-1.
%   The ndt(number of training data) variable must be an integer value because of
that 'round' command is used.
noofdata=size(input,1);
ntd=round(noofdata*training_rate);
%   xt:training input
%   xv:validation input
%   The input is separated for training(xt) and validation(xv).
xt=input(1:ntd,:);
xv=input(ntd+1:end,:);
%The input is a matrix for this reason columns and raws info is defined.
%   yt:training target
%   yv:validation target
%   The target (PC strand ultimate tensile strength) is separated for training (xt) and
validation (xv).
yt=target(1:ntd);
yv=target(ntd+1:end);
%The target vector is only one column for this reason it is doesn’t use column info.
%   The Matlab accepts the data in colums. But our data are in raws. So the data
(xt,xv,yt,yv) need to transpose.
xt=xt';
xv=xv';
yt=yt';
yv=yv';
```

```
%   The data are varing different units.So the data is normilized.
%   xtn:Normalized training input
%   xvn:Normalized validation input
xtn=mapminmax(xt);
xvn=mapminmax(xv);
%   The training target is normalized.
%   ytn: Normalized training target
%   yvn:Normalized validation target
[ytn,ps]=mapminmax(yt);
%   ps (parameter setting) variable keeps normalization infos inside.
%   The network is created by means of 'newff' (new feed forward) command.
%   newff(input, target, number of neurons in hidden layer, transfer function,
training algorithm)
%   n1: neuron number of 1. hidden layer
%   n2: neuron number of 2. hidden layer
net=newff(xtn, ytn, [n1,n2], {}, 'trainscg' );
%   lrate: The learning rate of NN is defined and entered with keyboard.
net.trainParam.lr=lrate;
net.trainParam.epochs=10000;
net.trainParam.goal=1e-10000000000;
net.trainParam.show=NaN;
%   The network which is created above is trained.
net=train(net,xtn,ytn);
%  Next, the validation inputs are entered and obtained the validation output.
%   yen:normalized (0-1) validation output
yen=sim(net,xvn);
%   yvn, don't have normalized validation target.
%   yv: have non-normalized validation target.
%   yen: have normalized validation target.
%   ye: non-normalized validation target.
ye=mapminmax('reverse',yen, ps);
ye=ye'; %target
yv=yv'; %output
%MAPE: Mean absolute percentage error
MAPE=mean((abs(ye-yv))./ye)*100;
%SStotal:summing daviation of output
%SSerror:summing daviation of error( error=target-output
SSerror=sum((ye-yv).^2);
SStotal=sum((ye-mean(ye)).^2);
R2=1-SSerror/SStotal;
end
```