Düzce Üniversitesi
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Araştırma Makalesi

Prediction Of Compressive Strength Of Normal Weight Concrete Including Fly Ash By Using Artificial Neural Network

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ABSTRACT

The compressive strength of normal weight concretes which include fly ash have been predicted by artificial neural network (ANN) model. For the model 103 experimental results were used and trained. Cement content, water content, fly ash amount and slump values were used as inputs and compressive strength (MPa) was used as output while developing ANN model. Some of the architectures with different number of neurons studied here in hidden layer and their correlations with experimental results investigated. One hidden layer with seven neurons was the best model because of its high correlation with experimental results for testing set. Results have shown that ANN has strong potential for predicting compressive strength of concretes containing fly ash.

Keywords: *Concrete, Compressive strength, Fly ash, Artificial neural networks*

Uçucu kül içeren normal ağırlıklı betonların basınç dayanımının yapay sinir ağları metodu ile tahmini

ÖZET

Bu çalışmada uçucu kül içeren normal ağırlıklı betonların basınç dayanımı yapay sinir ağları metodu ile tahmin edilmiştir. Modelde 103 adet deney verisi kullanılmış ve model eğitilmiştir. Modeli eğitirken çimento içeriği, su içeriği, uçucu kül miktarı ve slump değerleri girdi olarak ve basınç dayanımı ise çıktı olarak kullanılmıştır. Çalışmada farklı gizli tabaka nöronları farklı ağ yapıları ile çalışılmış ve bunların deney sonuçları ile korelasyonları incelenmiştir. Bir gizli tabaka ve 7 nöron en iyi sonucu vermiştir. Sonuçlar yapay sinir ağlarının uçucu kül içeren betonların basınç dayanımını tahmin etme potansiyelinin olduğunu göstermiştir.

Anahtar Kelimeler: *Beton, Basınç dayanımı, Uçucu kül, Yapay sinir ağları*

I. INTRODUCTION

Compressive strength of the hardened concrete is the most important property that describes its quality and suitability for construction works. Most often, an ultimate target in the mixture design is the 28-day compressive strength. This strength is usually determined based on a Standard uniaxial compression test, and is accepted universally as a general index of concrete strength [1]. In view of the global sustainable development, it is imperative that supplementary cementing materials be used

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inreplace of cement in the concrete industry. One of the most worldwide available supplementary cementing material fly ash (FA), a by-product of thermal powder stations.

It is estimated that approximately 600 million tons of FA are available worldwide now, but at present, the current worldwide utilization rate of FA in concrete is about 10% [2-3]. Nowadays researchers focused on the new approaches to predict mechanical parameters of concretes. Artificial Neural Networks (ANN) is one of these new approaches has been widely used in concrete technology.

In recent years, the ANNs have been extended extensively and applied to many civil engineering applications [4] such as concrete durability, workability of concrete, mechanical behavior of concrete, and the effect puzzolans on concrete compressive strength [5-13].

In this paper, the back-propagation neural network was used to predict the concrete compressive strength based on the water, cement, fly ash content and slump values. Different models were studied to find the which has the best potantial to predict compressive strength.

II. Artificial Neural Networks

Recently, ANNs are developed as powerful computing tools for the problems where the rules which govern the results are either not defined properly or difficult to discover. No priori function is required before an ANN model can be developed. ANNs adapt solutions and are capable of capturing the interrelationships among multiple variables by simply feeding them with data. Due to this capability of ANNs, applications to civil engineering have increased recently. In several research, ANN modeling has been applied in the prediction cement and concrete strength [14].

Artificial neural networks (ANNs) mimic human brains to learn the relationships between certain inputs and outputs from experience. They are considered as information processing systems that have the abilities to learn, recall and generalize from training data. An ANN consists of several layers of a large of highly interconnected computational units called neurons. Fig. 1 shows the general structure of a three-layer feed-forward ANN. The neural network contains one input layer, one or two hidden layers, and one output layer. Process parameters that are normalized in the interval of [0, 1] are fed to the nodes of the input layer [5].

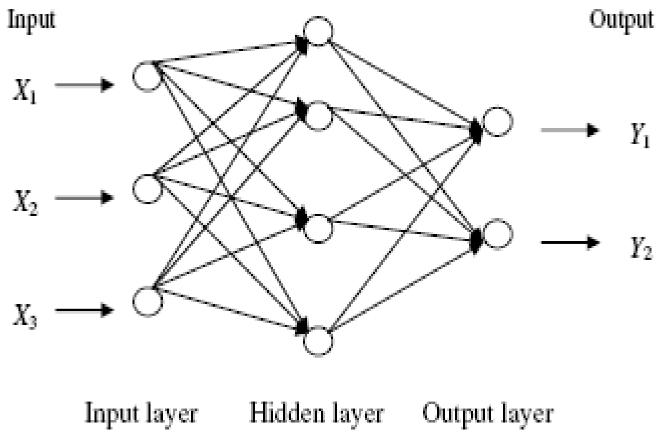

Figure 1. *A three-layer feed-forward neural network structure (Başyiğit et al., 2010).*

III. MATERIALS and METHOD

In this study, different mixing design have taken from ready mixed concrete factory to find applicability of ann on ready mixed concrete production. For this purpose 117 different concrete design used for developing ANN model. 103 samples of all mixing design selected for training set and residual data were selected for testing set (14 samples). The range of components of all mix design which were used for ANN model is given in Table 1.

Table 1. *Mixing parameters and data used for ANN*

Input variables	Data used in training and testing the models	
	Minimum	Maximum
Cement amount range (kg/m3)	260	345
Water range (lt/m3)	160	185
Slump value range (cm)	10	18
Replaced fly ash range (kg/m3)	0	70
Other parameters		
Sand	456	515
4-12 (kg/m3)	388	508
12-22 (kg/m3)	425	544
Stone dust (kg/m3)	285	508

IV. DEVELOPED ANN MODEL AND RESULTS

ANN model developed in this research has four neurons (variables) in the input layer and one neuron in the output layer. Some of the architectures with different number of neurons studied here in hidden layer and their correlations with experimental results investigated. One hidden layer with seven neurons was the best model because of its high correlation with experimental results for testing set. Cement rate, water rate, fly ash amount and slump values were used as inputs and compressive strength (MPa) was used as output while developing ANN models. For training set 103 samples were selected and the residual data were selected as test set (14 samples). All experimental variables were normalized between 0 and 1 using equation 1.

$$F = (F_i - F_{\min})/(F_{\max} - F_{\min}) \qquad (1)$$

In this equation F represents normalized value, Fi represents i. value of measured values and Fmax and Fmin represent maximum and minimum values of measured values. The back-propagation learning algorithm was used in feed-forward with one hidden layer. Logarithmic sigmoid transfer function was used as the activation function for hidden layers and output layers. Learning rate and momentum rate values were determined and the model was trained through iterations. The values of parameters used in the multilayer feed-forward neural network model are given in Table 2.

Table 2. The values of parameters used in the multilayer neural network model

Parameters ANN	
Number of input layer neurons	4
Number of hidden layer	1
Number of hidden layer	7
Number of output layer neuron	1
Momentum rate	0,1
Learning rate	0,001

Learning cycle	3000

The trained networks were used to run a set of test data. All of the developed networks (431-441-451-461-471-481-491) were compared with experimental results and R2 values of testing results are shown in Figure 2 – a,b,c,d,e,f and matching figure for all models is given in Figure 3. except the ANN 471.

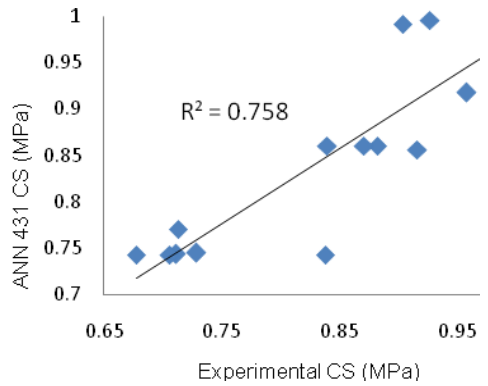

Figure 2a

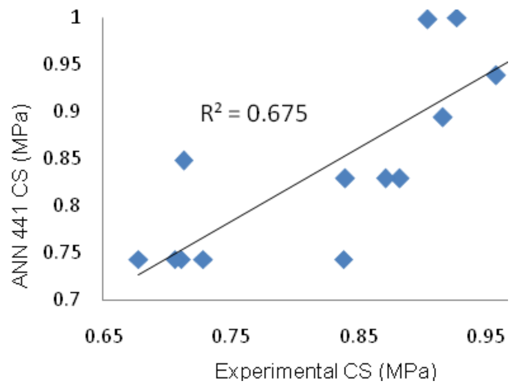

Figure 2b

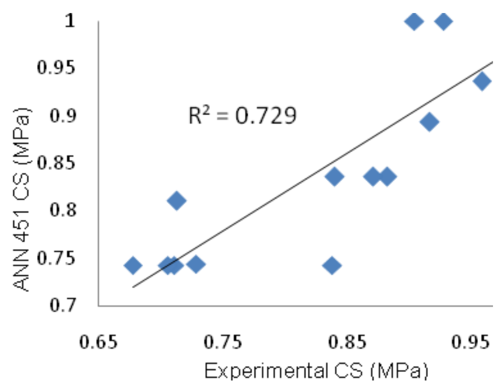

Figure 2c

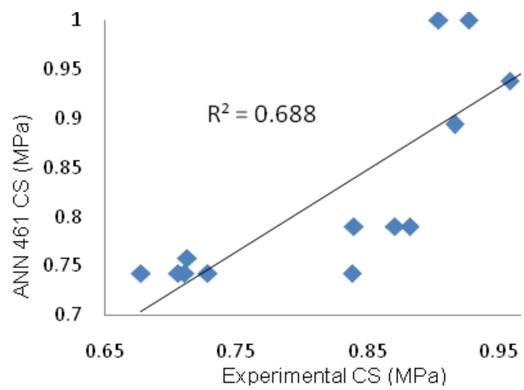

Figure 2d

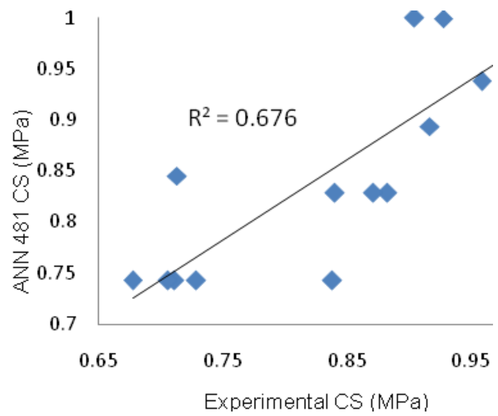

Figure 2e

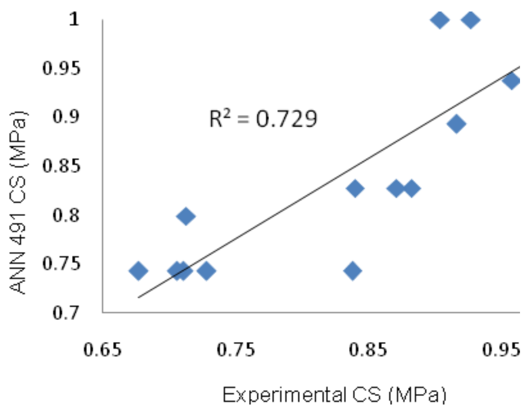

Figure 2f

***Figure 2**. a,b,c,d,e,f. Comparision of the experimental values with all developed models.*

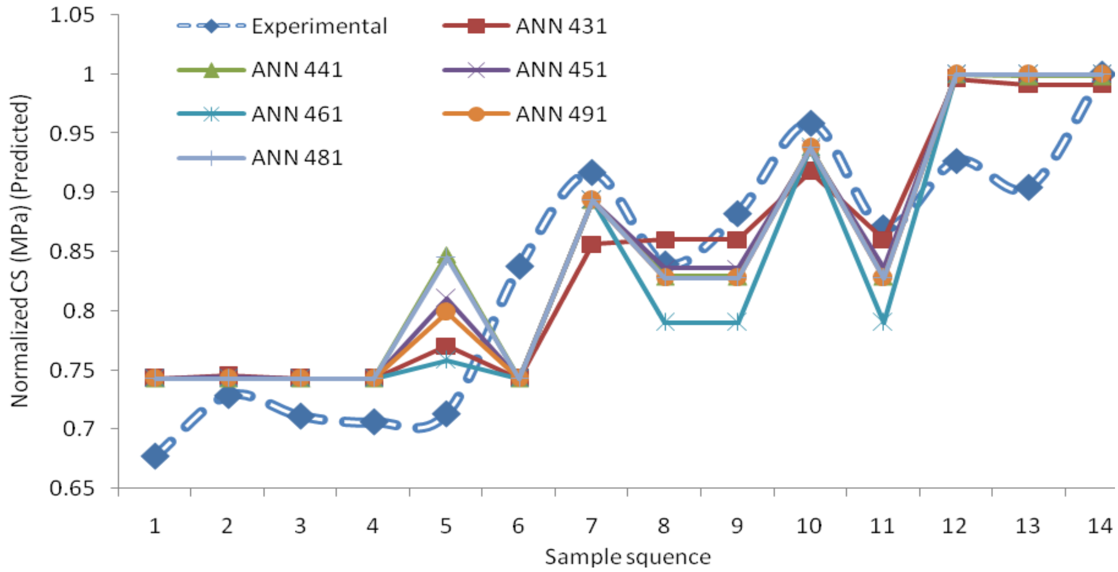

Figure 3*. Matching figure of all worked ANN models*

The representation of the network is as follow: in the model of 431, first number (4) represents the number of neuron in input layer, middle number (3) represents the number of neuron in hidden layer and last number (1) represents the number of neuron in output layer. The ANN (471) has the best correlation with experimental results for testing sets. ANN 471 details are given Fig. 4. When compared ANN 471 with experimental results at test stage R^2 found 0,76 (Fig. 5) and Figure 6 shows matching figure of the measured results with the results obtained from developed ANN 471 model.

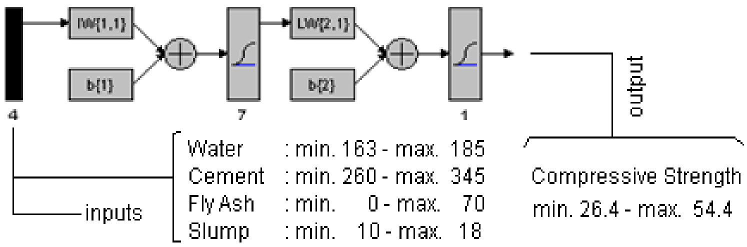

Figure 4*. ANN 471 details*

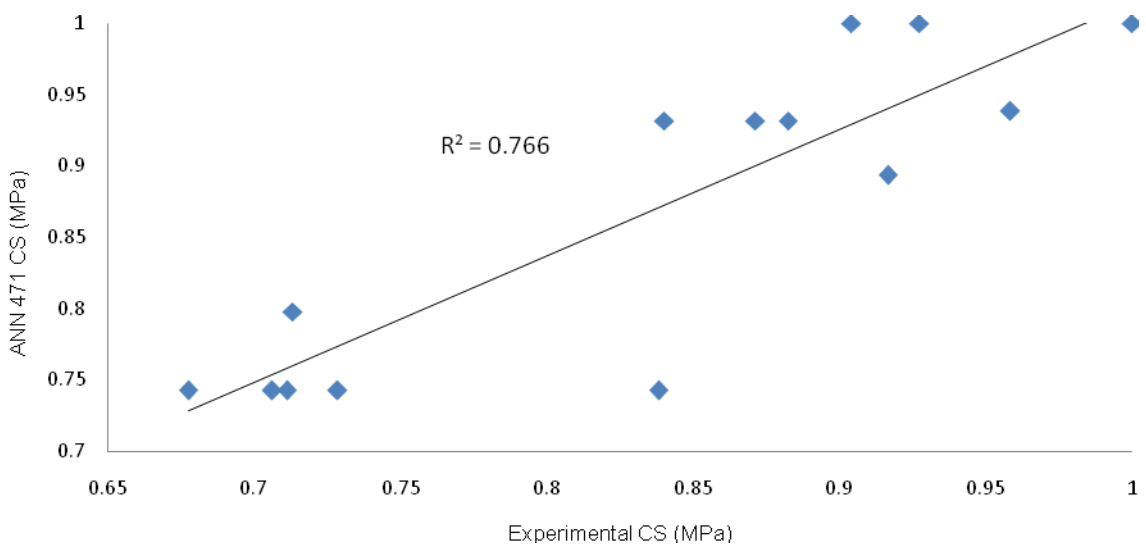

Figure 5. *Comparison of experimental values with the predicted values (ANN 471)*

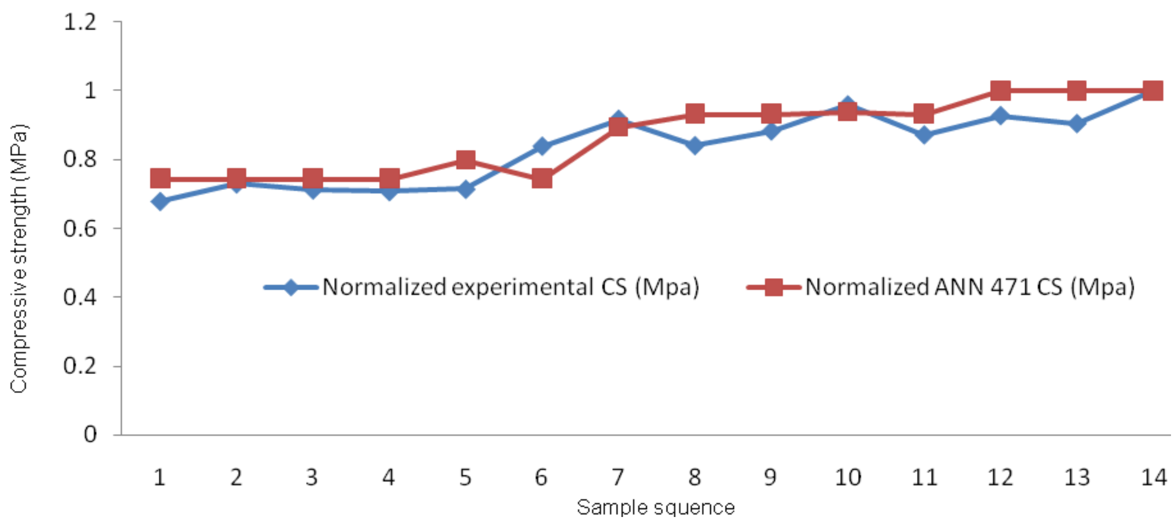

Figure 6. *Matching figure of experimental results and developed ANFIS model results*

V. CONCLUSIONS

In the presented study, an artificial neural network developed for the prediction the compressive strength values of mortars containing fly ash. In the model a multilayered feed-forward neural network with a back-propagation algorithm was used. In study different neurons were experimented in hidden layer and 7 models studied. These models were trained with input and output data. After experimenting different models, all models were tested only using input data set. Correlations between experimental values and ANN 431 - ANN 441 - ANN 451 - ANN 461 - ANN 471 - ANN 481 ANN 491 were found by using coefficient of determination (R2) and the coefficient of determination (R^2) values found 0,75 – 0,67 – 0,72 – 0,68 – 0,76 – 0,67 and 0,72 respectively. It is clearly seen from the coefficient of determination (R^2) results, ANN 471 has the best correlation with the experimental results. As a result, compressive values of mortars containing various amount fly ash can be predicted in a quite short period of time by using the multilayer feed-forward neural network models. The results have demonstrated that artificial neural networks are practicable methods for predicting compressive values of mortars containing fly ash.

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