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Estimating the Compressive Strength of Fly Ash Added Concrete Using Artificial Neural Networks

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Abstract

The aim of this study is to develop an artificial intelligence that predicts the compressive strength of fly ash substituted concretes using material mixing ratios. Within the scope of the study, 5 different fly ash mixed concrete samples were estimated. The strength values were estimated using artificial neural networks before the produced samples were subjected to the pressure test. In order to develop the artificial neural network, it is introduced as a dataset of 1030 different mixing ratios consisting of experimental results in the existing literature. In order to estimate the compressive strength, varying ratios of 8 different materials such as water, cement, fly ash entering the mixture are analyzed. As a result of the study, it has been observed that the predictions made using artificial neural networks are very close to the strength values obtained from the experiments.

Keywords: Artificial Intelligence, artificial neural networks, fly ash substituted concretes

1. Introduction

With the increasing population in the world, the rate of construction is also increasing. The need for more buildings increases the demand for useful, practical and economical building materials day by day. In this context, the most preferred building material is concrete with the ease of application it provides [1]. Due to its intensive use, concrete has been studied and continues to be studied by many researchers[2]. Concrete has an inhomogeneous structure due to the different materials entering the mixture. In addition, it is known that many parameters such as the type of materials entering the mixture, mixing ratios, and ambient conditions have an effect on concrete strength [3,4]). The parameter that affects the strength the most is the amount of material in the mix. It is necessary to carry out a series of experiments to examine the effect of the amount of material in the concrete mix on the strength. The realization of these experiments means a large amount of cost, labor and time loss. This situation allows researchers to predict the strength value of the mix. A solution to this problem is sought by using algorithms that emerged with the developing computer technology [5].In recent years, many studies have been carried out to predict concrete strengths in this direction. According to Subaşı and Beycioğlu (2008) [6], who studied the strength of concrete produced using crushed limestone aggregate, the artificial neural network method gives approximately 15% more accurate results than the multiple regression technique. Demirel (2008), investigating the effect of pumice and silica fume added to concrete on the compressive strength [7]. He proposed back propagation neural networks using the Matlab ANN toolbox as a modeling method. According to Demirel (2008), there is a 98% agreement between the data of the experimental results and the data of the trained model [7]. Yaprak and Karacı (2009), who tried to estimate the compressive strength of the concrete to which they added polypropylene fiber, stated that there was a 96.5%-100% agreement between the experimental and simulated compressive strength values of the concretes exposed to the high temperature effect [8]. Şahin et al., who investigated the fracture parameters by modeling the concrete to which they added steel wire, with artificial neural networks states that the model they created produces predictions with approximately 96% accuracy [9]. Using artificial neural networks, Açıkgenç et al., (2012) obtained results with similar accuracy [10]. Trying to estimate the ultrasound transmission velocity and compressive strength of the concretes with which they replace waste rubber, Topçu et al., (2007) compared artificial neural networks and fuzzy logic methods [11]. According to Topçu et al., (2007), it is possible to predict experimental results very close to reality with both artificial neural networks and

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fuzzy logic. Modeling the effect of plasticizer additives on concrete compressive strength using artificial neural networks, Uysal (2007) emphasized that the model he trained learned with a margin of error of about 2% and that artificial neural networks would be beneficial in the selection of building materials [12]. Şamandar, (2013), who tried to estimate the strength of fly ash substituted mortars, showed that artificial neural networks, like other researchers, were very successful in predicting mortar strength [13].

As can be understood from the studies in the literature, it is possible to estimate the compressive strengths close to reality by using artificial intelligence. On the other hand, efforts to reduce the amount of cement in concrete are gaining momentum due to environmental concerns Concretes with fly ash are also highly preferred mixtures in this context.

There are many prediction studies with artificial neural networks in the literature. However, the number of studies estimating the compressive strength of fly ash substituted concrete is insufficient. In this study, the data set published by the University of California is used [14]. The data set includes data obtained by different researchers who carried out different experimental studies in the field. In addition, the data set has 8 different material variables and includes 1030 compressive strengths. Strength estimates were made for 5 different samples selected from the data set.

2. Materials and Methods

Artificial neural networks are one of the artificial intelligence methods developed considering the human nervous system. The axon shown in Figure 1 uses the working principle of nerve cells consisting of dendrites. Electrical signals are processed between these cells and transferred to other neurons. The fulfillment of biological activities of human beings is realized by processing the electrical signal between these nerve cells [15].

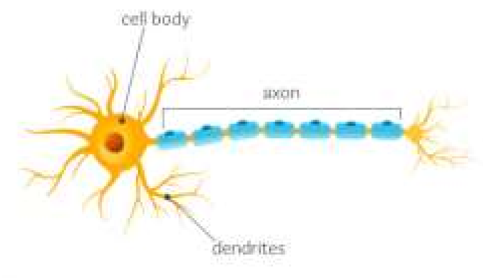

Figure 1. Nerve cell [15].

2.1 Artificial neural networks

A developed artificial neuron generally consists of inputs, input weights, summation function, activation function and outputs. The inputs represent the variables that provide information to the cells, the weights represent the effect of each input on the function, and the aggregation function represents the total effect of all the inputs with their weights. The outputs are the activation function that processes the net input obtained from the aggregation function on the network [16].

Artificial nerve cells are gathered together in 3 main layers (input layer, hidden layer, output layer) to form the artificial neural network. Figure 2 expresses the relationship between the layers [17].

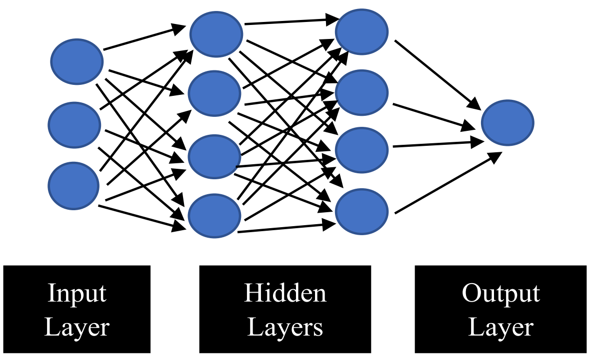

Figure 2: Neural network layers.

2.2. Backpropagation Neural Networks

Back propagation neural network algorithm is frequently used especially in engineering fields due to its high learning capacity and easy structure. Generally, this algorithm has an input layer, a minimum hidden layer, and an output layer. The number of hidden layers in neural networks and the number of nerve cells they contain can be found by experimenting [18, 19].

This process in which the neural network processes information is called "backward propagation". The neural network improves its predictive ability with each learning. The error function between its prediction and the actual value is transferred backwards. In each layer of the neural network, the effect of the weight function is transmitted forwards and backwards. Thus, the error is minimized. This process is called the "epoch". There are different methods to determine the errors that occur at each step. Examples are the mean of the square of the errors and the mean absolute error. There are also methods used to reduce errors in this process. Newton's method and Bayesian arrangement can be given as examples [20].

Matlab nnstart and nntoolbox were used to learn the dataset used in this study. Of 1030 pieces of data, 1025 were input data and 5 were estimated. Back propagation neural network was used as the method. 80% of the data was used as training, 10% as validation and 10% as test data. Bayesian Regulation was preferred as the algorithm. The first 5 rows of the data set containing the variables are given in Table 1.

Table 1. First five rows of data set used.

Cement (kg/m3)	Blast-Furnace Slag (kg/m3)	Fly Ash (kg/m3)	Water (kg/m3)	Plasticizer (kg/m3)	Coarse Aggregate (kg/m3)	Fine Aggregate (kg/m3)	Crashing Day	Compressive strength (MPa)
500	0	40	162	2,5	1040	676	28	79,986
460	0	80	162	2,5	1055	676	28	61,887
332,5	0	142,5	228	0	932	594	270	40,269
332,5	0	142,5	228	0	932	594	365	41,053
198,6	0	132,4	192	0	978,4	825,5	360	44,296

Normalization is required to accelerate the learning of artificial neural networks. Equation (2.1) of the normalization process has been solved with Matlab software [23]. “LEARNGDM” function for learning function of artificial neural networks, “TRAINLM” for t raining function, “MSE” for performance function and “logarithm-sigmoid (logsig)” transfer function as normalization function in Matlab software. The selected network structure is a network structure with 8 inputs, function, “MSE” for performance function and “logarithm-sigmoid (logsig)” transfer function as normalization function in Matlab software.The selected parameters, the maximum number of errors was selected as 1000, and the model was trained many times for minimum error [21,22]. The first 5 rows of values normalized using (1) are given in Table 2.

$$x' = \text{logsig}\,(x) = \frac{x - \min(x)}{\text{mak}(x) - \min(x)}$$

(2.1)

Table 2. First 5 rows of normalized input values.

Cement (kg/m^3)	Blast-Furnace Slag (kg/m^3)	Fly Ash (kg/m3)	Water (kg/m^3)	Plasticizer (kg/m^3)	Coarse Aggregat e (kg/m^3)	Fine Aggregat e (kg/m^3)	Crashin g Day	compressiv e strength (MPa)
1,000	0,000	0,134	0,321	0,078	0,695	0,206	0,074	0,967
1,000	0,000	0,268	0,321	0,078	0,738	0,206	0,074	0,742
0,526	0,000	0,396	0,848	0,000	0,381	0,000	0,739	0,473
0,526	0,000	0,396	0,848	0,000	0,381	0,000	1,000	0,482
0,221	0,000	0,368	0,561	0,000	0,516	0,581	0,986	0,523

While defining the relationship between the inputs, the correlation coefficient “r” is calculated using Equation (2.2) includes the expression of the R coefficient depending on the estimated and actual [24].

$$R = 1 - \frac{\sum_{i=1}^{N}(oi - ti)^2}{\sum_{i=1}^{N}(oi - oi')^2} \qquad \textbf{(2.2)}$$

If the “R” value calculated based on the estimated values and actual values is in the range of 0-0.25, it is very weak, between 0.26-0.49 weak, 0.50-0.69 moderate, 0.70-0.89 high , 0.90-1 is considered to be very high accuracy [5]. The artificial neural network model in this study was established as in Figure 3 and the correlation coefficient was obtained as 0.96692. This value is expressed as “very high accuracy correlation”.

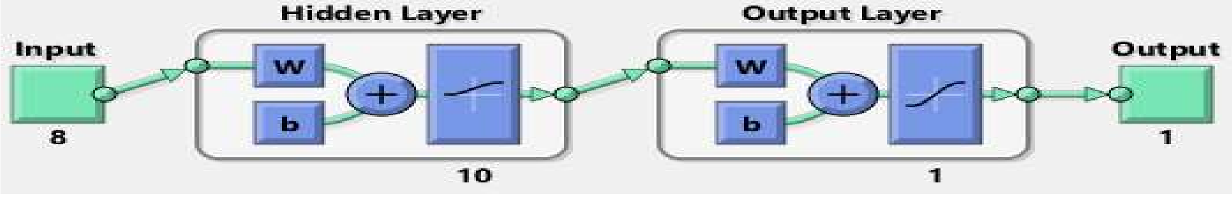

Figure 3. Selected network model.

Inputs

1- Cement component (kg/ m^3)
2- Blast Furnace Slag (kg/ m^3)
3- Fly Ash (kg/ m^3)
4- Water (kg/ m^3)
5- Superplasticizer (kg/ m^3)
6- Coarse Aggregate (kg/ m^3)
7- Fine Aggregate (kg/ m^3)
8- Age (day)

Outputs

1- Concrete compressive strength(MPa)

Figure 4. Inputs and outputs data.

3. Results and Discussion

Obtaining the correlation coefficient is as seen in the graph in Figure 4.

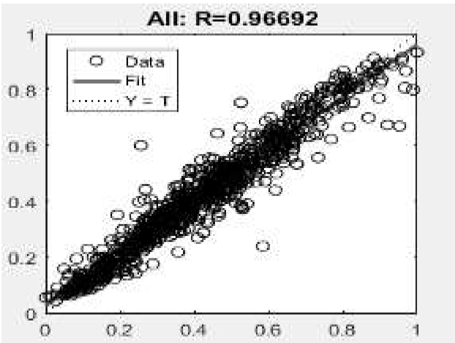

Figure 5. Total correlation coefficient of artificial neural network (nondimensional).

Table 3. Real, predicted and error values.

Data No	Actual Compressive Strength (MPa)	Estimated Compressive Strength (MPa)	Absolute Error (%)
1	44,28	44,69	0,91
2	31,18	35,96	15,32
3	23,70	24,28	2,47
4	32,77	29,74	9,23
5	32,40	34,98	7,96
		∑(Average Absolute Error)	**7,18**

Table 4. Corelation coefficients from literatüre.

Erdal[5]	0,859
Yeh [14]	0,914
Chou [24]	0,909
Model	0,967

4. Conclusion

When the correlation coefficient of the studies conducted with the same data set in the literature is examined, it is observed that the model obtained has a very high coefficient. In Table 3, the R coefficients obtained in other studies are given. To be estimated by modeling a public data set with artificial neural networks. The dataset has 8 variables and 1030 data. 80% of the data set in question was used for training, 10% for validation and 10% for testing. The correlation coefficient obtained in the model has a higher value than the correlation coefficients obtained using the same data set in the literature review. The 5 concrete pressure values selected in the study were estimated with an absolute average of approximately 7% error. The aim of the study is to help the sectors that experimentally obtain concrete strength

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Ethics

There are no ethical issues after the publication of this manuscript.

Author's Contributions

Zafer Kurt: Artificial intelligence calculations
Talip Çakmak: Experimental Studies
Ali Gürbüz: Drafted and wrote the manuscript, performed the experiment and result analysis.
İlker Ustabaş: Determination of concrete mix ratios

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