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Prediction of Splitting Tensile Strength of Concrete Containing Zeolite and Diatomite by ANN

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Abstract: This study was designed to investigate with two different artificial neural network (ANN) prediction model for the behavior of concrete containing zeolite and diatomite. For purpose of constructing this model, 7 different mixes with 63 specimens of the 28, 56 and 90 days splitting tensile strength experimental results of concrete containing zeolite, diatomite, both zeolite and diatomite used in training and testing for ANN systems was gathered from the tests. The data used in the ANN models are arranged in a format of seven input parameters that cover the age of samples, Portland cement, zeolite, diatomite, aggregate, water and hyper plasticizer and an output parameter which is splitting tensile strength of concrete. In the model, the training and testing results have shown that two different ANN systems have strong potential as a feasible tool for predicting 28, 56 and 90 days the splitting tensile strength of concrete containing zeolite and diatomite.

Introduction

Concrete, which is one of the most widely used artificial construction materials, has an important role to play in building technology in the world. Concrete is a composite material that consists homogenous mixtures of cement, aggregate (fine and coarse aggregate), water and sometimes chemical admixture and mineral additives (Erdoğan, 2007, Neville, 1999). Cement and aggregate are two most important components of concrete.

The aggregate is a granular material, natural such as sand, gravel, crushed stone, or artifical such as iron-blast furnace slag (Laserna and Montero, 2016, Afshinnia and Rangaraju, 2016, Binici, et al., 2010). The aggregate constitutes typically 75% of the concrete volume, or more, and therefore its properties largely determine the properties of the concrete (Erdoğan, 2007). For the concrete to be of good quality, the aggregate has to be strong, durable and free of silts, organic matter and so on (Kuyumcu, 2006).

There are many different kinds of cements. In concrete, the most commonly used is Portland cement. Portland cement is made by heating a mixture of limestone and clay ultimately to a temperature of about 1450°C (Neville, 1999). Due to economic and ecological factors like trass (Kocak et al., 2010), zeolite (Kocak et al., 2013), diatomite (Kocak and Savas, 2016, Gerengi et al., 2013), metakaolin (Keleştemur and Demirel, 2015, Subası and Emiroglu, 2015), pumice (Yildiz et al., 2010), fly ash (Kocak and Nas, 2014, Zhengqi, 2016), blast furnace slag (Zhao et al., 2015), and silica fume (Okoye et al., 2016, Kocak, 2010) are intensely used in the cement and concrete technology. Some characteristics such as strength, durability and low permeability expected from good concrete are closely related not only to mix proportions but also to cement properties. Zeolite and diatomite are natural mineral material and are abundant in our country.

Zeolite is defined as allophones that consist of alkali and alkaline–earth cations and have the crystal structure. Zeolites have water molecules in their canals which is one of the most significant properties setting them apart from other mineral groups (Canpolat, 2002, Serbest, 1999). Diatomite is a mineral described as consisting of the fossilized siliceous shell of the microscopic single–celled alga and possessing the structural properties of amorphous silica. There are nearly fifteen thousand types of diatomite in the nature. Diatomites generally have the shape of a round tray or a long fish. They contain 70–90% of SiO_2 and are cellular materials with high water absorption rate (Aruntas and Tokyay, 1996).

Nowadays, expert systems, which are Adaptive Network-based Fuzzy Inference Systems (ANFIS), fuzzy system, and so on, have been used by many researchers to solve a wide variety of problems in civil engineering applications. Artificial neural network (ANN) one of them can be alternative approaches for predicting such as mechanical behavior and physical properties of concrete and cement mortars (Beycioglu et al., 2015, Ashrafi et al., 2010, Atici, 2011, Yaprak et al., 2013, Subasi, 2009). The aim of this study is to build model in ANN system to evaluate the effect of splitting tensile strength of concrete containing zeolite and diatomite. In the study, 7 different cements are used, which are PC, 10–20% diatomite, 10–20% zeolite, 5+5–10+10% diatomite and zeolite are substituted for Portland cement. For purpose of constructing this model, 7 different mixes with 63 specimens of the 28, 56 and 90 days splitting tensile strength experimental results of concrete containing zeolite, diatomite, both zeolite and diatomite used in training and testing for ANN system were gathered from the concrete tests. The model was trained with 63 data of experimental results. The ANN model had seven input parameters that cover the age of samples, Portland cement, zeolite, diatomite, aggregate, water and hyper plasticizer and an output parameter, which is splitting tensile strength of concrete. The obtained results from splitting tensile strength of concrete were compared with predicted results.

Materials and Methods

Cement

The cement is CEM I 42.5 R (PC) which is provided from Bolu Cement Plant. The chemical properties of PC are given in Table 1 and physical and mechanical properties of PC are given in Table 2.

Pozzolan

Diatomite from Kutahya region and zeolite from Balikesir–Bigadic region are used as a pozzolan. Diatomite is supplied from ASU Chemistry and Mining Firm and zeolite from a Turkish Zeolite Firm. The chemical properties of zeolite and diatomite are given at the Table 1, and physical and mechanical properties of zeolite and diatomite are given in the Table 2.

Aggregate

In this study, Asar River aggregates in Duzce region as aggregate (crashed sand and crushed stone) are used. The physical properties of the aggregates are given in the Table 3.

In the study, seven different cements, which are PC, 10–20% diatomite, 10–20% zeolite, 5+5–10+10% diatomite and zeolite are substituted for Portland cement, are used. For concrete mixture design, materials' amounts to be put into the mixture are determined within the framework of the method stated in TS 802 standards (TSE, 2009). According to the type and rate of mineral additive, which is substituted for the concrete, seven types of concrete are produced. They are encoded as R, 10D, 20D, 10Z, 20Z 5D5Z and 10D10Z according to the addition rate and the used mineral additive. According to TS EN 12350–2, consistency of concrete in fresh concrete is stated for each mixing group individually (TSE, TS EN 12350, 2010). The materials amount of the samples in concrete mixture of $1m^3$ and the characteristics of fresh concrete are given in the Table 4.

Hyper plasticizer and mixing water

In this study, the type of fluid 70 produced by AYDOS Construction Chemicals Factory and new generation hyper plasticizer with solid matter content of 34.32%, intensity of 1.184 (20^{o}C), pH value of 7.26 (20^{o}C) are applied as admixture for concrete. Well water from Doganli village in Duzce as mixing water is used.

Table 1. The chemical properties of PC.

Materials	PC	Diatomite	Zeolite
Chemical composition, wt.%			
SiO_2	18.68	79.56	68.85
Al_2O_3	4.67	6.54	11.71
Fe_2O_3	3.53	2.76	1.29
CaO	64.56	2.45	3.97
MgO	0.98	0.79	1.06
SO_3	3.00	0.48	0.18
Na_2O	0.14	2.63	0.29
K_2O	0.73	0.69	2.19
S+A+F	-	88.86	81.85
Loss on ignition	3.92	3.88	10.00
Insoluble residue	0.50	75.98	37.32
Free CaO	1.74	-	-

Table 2. The physical and mechanical properties of PC.

Materials	Compressive strength, MPa		Setting time, minute		Blaine, cm^2/g	Specific gravity
	7 days	28 days	Initial	Final		
PC	29.6	52.8	118	-	4249	3.17
Diatomite	-	-	-	-	13640	2.28
Zeolite	-	-	-	-	5740	2.18

Table 3. The physical properties of the aggregates.

Test		Result			Standards
Unit weight, g/cm^3	Loose Unit Weight	1.48			TS EN 1097-3
	Dense Unit Weight	1.66			
Specific gravity and Water absorption		Aggregate grading			TS EN 1097-6
		0-5, mm	5-19, mm	19-30, mm	
	Dry weight	2.63	2.62	2.66	
	Saturated and surface-dry weight	2.64	2.65	2.69	
	Water absorption, %	0.61	1.16	1	
Moisture content, %		1.25	1.32	1.41	
Determination of organic impurities		The color of the liquid is light yellow color than colorless (Organic matter is harmless).			TS EN 1744-1

Table 4. Material quantity in the 1 m^3 for each concrete group.

Materials		Specific gravity	R, kg	10D, kg	20D, kg	10Z, kg	20Z, kg	5D5Z, kg	10D10Z, kg
Aggregate	0-5	2.66	822	831	822	843	855	849	855
	5-19	2.69	586	593	586	602	611	606	611
	19-30	2.70	428	433	428	439	446	442	445
Total			1836	1857	1836	1884	1912	1897	1911
PC		3.17	400	360	320	360	320	360	320
Diatomite		2.28	-	40	80	-	-	20	40
Zeolite		2.18	-	-	-	40	80	20	40
Hyper plasticizer		1.184	4.800	4.320	4.800	4.320	4.800	4.320	3.840
Water		1	139.7	139.7	123.3	139.7	123.2	139.7	124.2

The produced concretes are poured into 15x15x15 cm cubic molds without segregation. These concretes are retained for 24 hours in the molds and harden, then, they are cured in 23±2°C water for 28, 56 and 90 days. Splitting tensile strength experiments of concretes have been done according to TS EN 12390–6 (TSE, 2010).

Artificial Neural Network

Artificial neural network **(**ANN) consisted of an arbitrary number of simple elements called neurons. Neurons in ANN are, as similar in human brains, interconnected (Adhikary and Mutsuyoshi, 2006). ANN represents simplified methods of a human brain and uses new methods to solve problems rather than conventional methods with traditional computations which have difficult solution procedures (Trtnik et al., 2009). Generally, ANN is consisted of an input layer of neurons, one or more hidden layers of neurons and output layer of neurons. The neighboring layers are fully interconnected by weight. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units. All problems, which can be solved by a perceptron can be solved with only one hidden layer, but it is sometimes more efficient to use two hidden layers. Finally, the output layer neurons produce the network predictions to the outside world (Demir, 2008).

Figure 1 clearly illustrates the typical neural network, which is composed of five main parts such as inputs, weights, sum function, activation function and outputs (Topcu, et al., 2008, Parichatprecha and Nimityongskul, 2009). The input of a neuron comes from another neuron and it is obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them. The weighted sums of the input components $(net)_j$ are calculated by using Eq. (1) below:

$$(net)_j = \sum_{i=1}^{n} w_{ij} o_i + b \qquad (1)$$

where (net)j is the weighted sum of the j_{th} neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the j_{th} neuron in the preceding layer, o_i is the output of the i_{th} neuron in the preceding layer and b is a fix value as an internal addition (Topcu et al., 2008). Activation function is a function that processes the net input obtained from sum function and determines the neuron output. In general for multilayer feed forward models as the activation function (f $(net)_j$) sigmoid activation function is used. The output of the j_{th} neuron $(out)_j$ is computed using Eq. (2) with a sigmoid activation function as follows: (Parichatprecha and Nimityongskul, 2009).

$$o_j = f(net)_j = \frac{1}{1+e^{-\alpha(net)_j}} \qquad (2)$$

where α is constant used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except in the input layer. The sigmoid function represented by Eq. (2) gives outputs in (0, 1). If it desired, the outputs of this function can be adjusted to (-1, 1) interval. As the sigmoid processor represents a continuous function, it is particularly used in non-linear descriptions. Because its derivatives can be determined easily with regard to the parameters within $(net)_j$ variable (Parichatprecha and Nimityongskul, 2009).

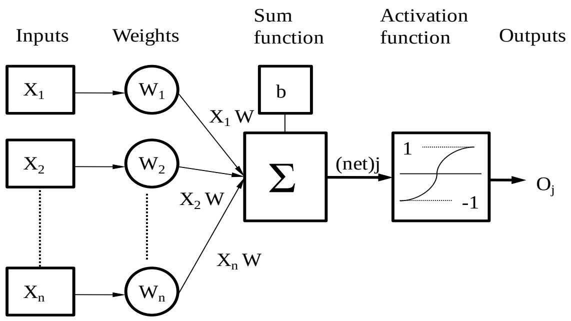

Fig 1. The artificial neuron model.

Artificial Neural Network Models and Parameters

In training and testing of the ANN model the age of samples, PC, zeolite, diatomite, aggregate, water and hyper plasticizer were entered as input, while splitting tensile strength of concrete were used as output (Table 5).

For the training of the model were used 63 of the experimental data and 21 data as the average of these test results were used for testing the trained model. The designed ANN-1 consisted of feed-forward back propagation, two hidden layers, training function (Levenberg-Marquardt), adaptation learning function (learngdm), transfer function (tansig) and performance function (MSE-mean squared error) as demonstrated

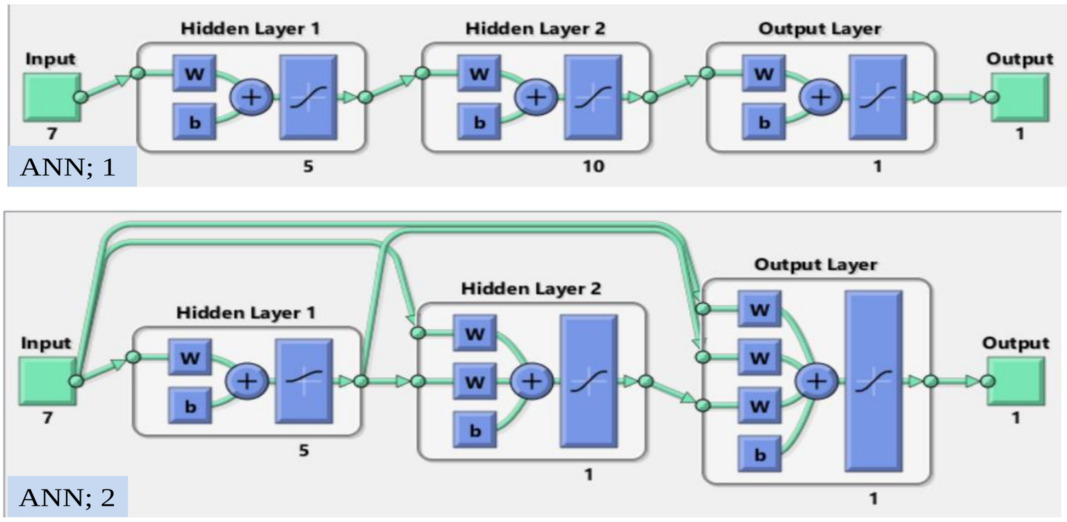

Fig.2 The architectures used in the ANN for splitting tensile strength.

in Figure 2-a. The designed ANN-2 consisted of same structure as demonstrated in Figure 2-b. The main difference, the input values of each layer is sum multiplied by weights of the outputs of all previous layers.

Table 5. The input and output quantities used in ANN model

		Data used in training and testing the model	
		Minimum	Maximum
Input variable	Age of samples, days	28	90
	PC, g	320	400
	Zeolite, g	0	80
	Diatomite, g	0	80
	Aggregate	1836	1912
	Water	123.2	139.7
	Hyper plasticizer	3.840	4.800
Output variable	Splitting tensile strength, MPa	5	10.4

Momentum rate and learning rate values were determined and the models were trained through iterations. The parameter values obtained from the multilayer feed-forward neural network models were given in Table 6. The trained models were tasted only with the input values and the predicted results were close to the experimental results.

Table 6. The values of parameters used in model.

Parameters	ANN-1	ANN-2
Number of input layer neurons	7	7
Number of hidden layer	2	2
Number of first hidden layer neurons	10	5
Number of second hidden layer neurons	5	1
Number of output layer neuron	1	1
Error after learning	$1x10^{-4}$	$1x10^{-6}$
Learning cycle	6	6

Results and Discussion

Multilayer feed forward network models that contain two hidden layers are used in order to find more reliable solutions. Determination of optimum number of the hidden layers neurons are very important to accurately predict the parameters used by ANN. Starting with a few numbers of neurons and then slightly increasing the number of neurons gives the best approach for finding the optimum number of hidden neurons. The performance of the ANN model is monitored according to chosen performance criteria during this process for each hidden neuron number. This process is repeated until the error becomes acceptably small or no significant improvement is observed.

This study uses different neurons in the two hidden layers at the beginning of the process then the neuron number was increased step-by-step adding 1 neuron until no significant improvement is noted. The ANN models tried to be compared according to the absolute fraction of variance (R^2), mean absolute percentage error (MAPE) and a root-mean squared (RMS) error criteria. These criteria are defined by Eqs. (3), (4) and (5) respectively (Ozcan et al., 2009).

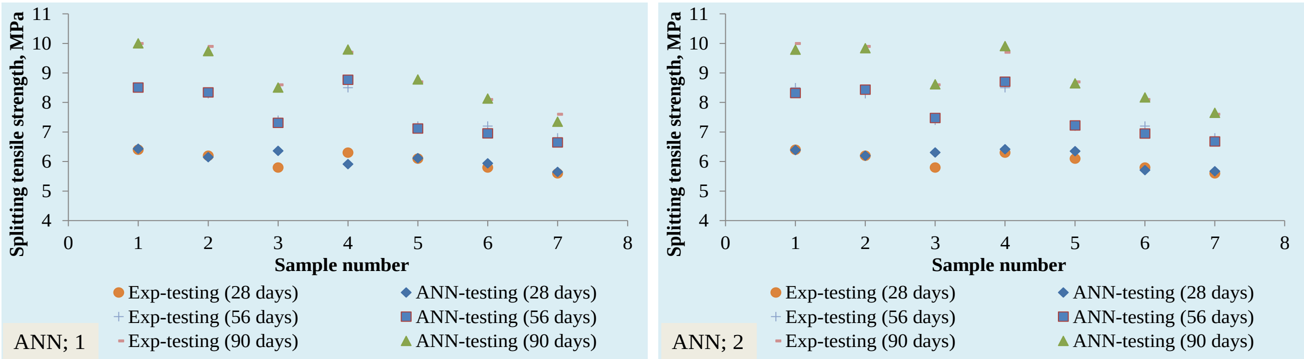

Fig 3. Comparison of splitting tensile strength experimental and training results with sample number.

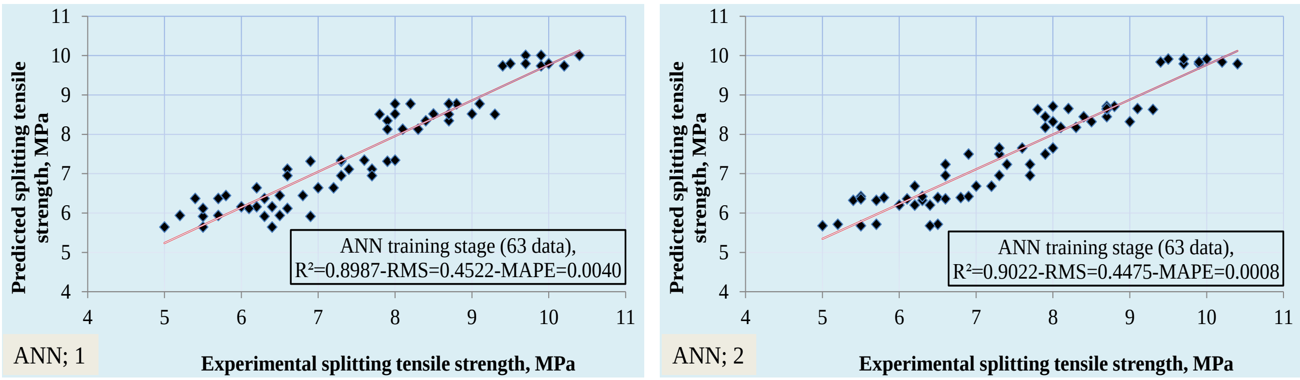

Fig 4. Comparison of splitting tensile strength average of test results and testing results with sample number.

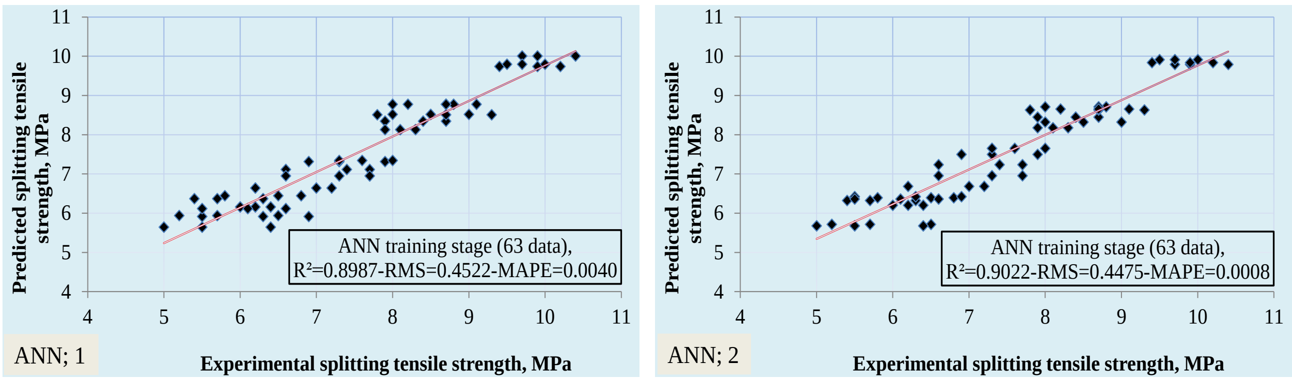

Fig 5. Comparison of splitting tensile strength experimental results with training results of model.

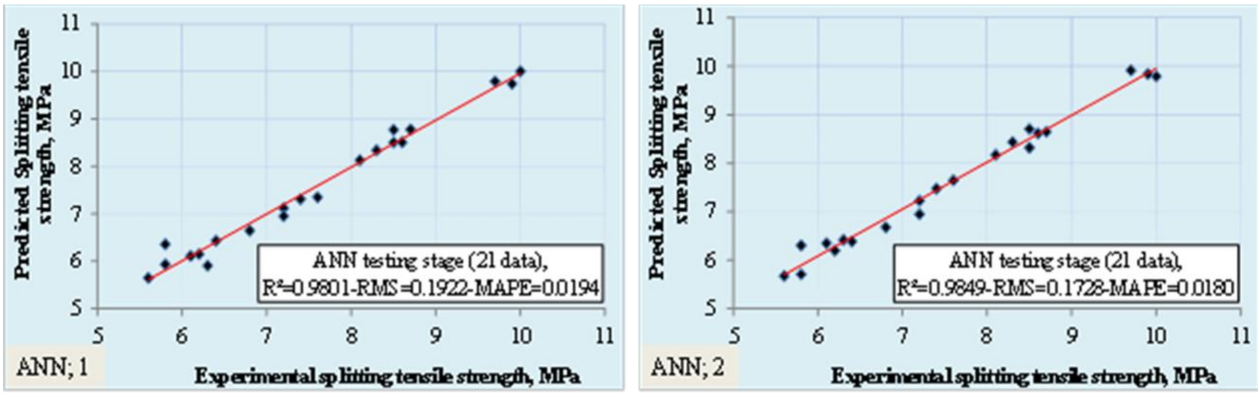

Fig 6. Comparison of splitting tensile strength average of experimental results with testing results of model.

Table 7. Comparison of splitting tensile strength average of test results with testing results obtained from ANN.

Data used in the model construction							Splitting tensile strength, MPa		
As, days	PC, kg	Zeolite, kg	Diatomite, kg	Aggregate, kg	Water, kg	Hyper plasticizer, kg	Exp.	ANN,1	ANN, 2
28	400	0	0	1836	139.7	4.80	**6.4**	6.4	6.4
28	360	0	40	1857	139.10	4.32	**6.2**	6.2	6.2
28	320	0	80	1836	123.3	4.80	**5.8**	6.4	6.3
28	360	40	0	1884	139.7	4.32	**6.3**	5.9	6.4
28	320	80	0	1912	123.2	4.80	**6.1**	6.1	6.4
28	360	20	20	1897	139.7	4.32	**5.8**	5.9	5.7
28	320	40	40	1911	124.2	3.84	**5.6**	5.6	5.7
56	400	0	0	1836	139.7	4.80	**8.5**	8.5	8.3
56	360	0	40	1857	139.10	4.32	**8.3**	8.3	8.4
56	320	0	80	1836	123.3	4.80	**7.4**	7.3	7.5
56	360	40	0	1884	139.7	4.32	**8.5**	8.8	8.7
56	320	80	0	1912	123.2	4.80	**7.2**	7.1	7.2
56	360	20	20	1897	139.7	4.32	**7.2**	7.0	7.0
56	320	40	40	1911	124.2	3.84	**6.8**	6.6	6.7
90	400	0	0	1836	139.7	4.80	**10**	10.0	9.8
90	360	0	40	1857	139.10	4.32	**9.9**	9.7	9.8
90	320	0	80	1836	123.3	4.80	**8.6**	8.5	8.6
90	360	40	0	1884	139.7	4.32	**9.7**	9.8	9.9
90	320	80	0	1912	123.2	4.80	**8.7**	8.8	8.6
90	360	20	20	1897	139.7	4.32	**8.1**	8.1	8.2
90	320	40	40	1911	124.2	3.84	**7.6**	7.4	7.6

Table 8. The splitting tensile strength statistical values of proposed ANN models.

Statistical parameters	ANN-1		ANN-2	
	Training set	Testing set	Training set	Testing set
RMS	0.4522	0.1922	0.4475	0.1728
R^2	0.8987	0.9801	0.9022	0.9849
MAPE	0.0040	0.0194	0.0008	0.0180

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|t_i - o_i\right|^2} \quad (3)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(o_i)^2}\right) \quad (4)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \quad (5)$$

Here ***t*** is the target value, ***o*** is the network output value, ***N*** is the total number of pattern. In the training and testing of ANN model from experimental data and average of these test results are used.

In the ANN models, 63 data of experiment results were used for training, whereas 21 data as average of these test results for testing. Sample number and experimental results with training and testing results obtained from ANN models were given in Figures 3 and 4 respectively. All results obtained from the studies and predicted by using the training and testing results of ANN model for 28, 56 and 90 days splitting tensile strength were given in Figures 5 and 6, respectively. Also, inputs values and experimental results with testing results obtained from ANN models were given in Table 7.

The linear least square fit line, its equation and the R^2 values were shown in these figures for the training and testing data. As it is visible in Fig. 5 and 6 the values obtained from the training and testing in ANN model are very closer to the experimental results. The result of testing phase in Figures 5 and 6 shows that the ANN models is capable of generalizing between input and output variables with reasonably good predictions. The statistical values for all the stations such as RMS, R^2 and MAPE were given in Table 8. While the statistical values of RMS, R^2 and MAPE from training in the ANN-1 model were found as 0.4522, 0.8987 and 0.0040, respectively. These values were found in testing as 0.1922, 0.9801 and 0.0194, respectively (Table 8). Similarly, for training of ANN-2 model were found as 0.4475, 0.9022 and 0.0008 and these values for testing were found 0.1728, 0.9849 and 0.018. All of the statistical values show that the proposed ANN model is suitable and predicts the 28, 56 and 90 days splitting tensile strength values very close to the experimental values.

Conclusion

In this study, ANN was used for the prediction the 28, 56 and 90 days splitting tensile strength values of concrete containing zeolite, diatomite, both zeolite and diatomite. In the model developed in ANN-1 system, a multilayered feed-forward neural network with a back-propagation algorithm was used. In the multilayer feed-forward neural network model, two hidden layers were selected. In the first hidden layer 10 neurons and in the second hidden layer 5 neurons were determined. This model was trained with input and output experimental data. Using only the input data in trained models the 28, 56 and 90 days splitting tensile strength values of concrete containing zeolite, diatomite, both zeolite and diatomite were found for testing the model. The splitting tensile strength values are very closer to the experimental data obtained from training and testing for ANN-1 model. ANN-2 model are prepared according to the designed model. The statistical parameter values of RMS, R2 and MAPE that calculated for comparing experimental data with two ANN models results have shown obviously this situation.

As a result, splitting tensile strength values of concrete containing zeolite, dolomite, both zeolite and diatomitecan be predicted in the multilayer feed-forwarded neural network model in a quite short period of time with tiny error rates. The conclusions have shown that ANN systems are predictable methods for containing zeolite, dolomite, both zeolite and diatomite.

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