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Predicting the strength development of cements produced with different pozzolans by neural network and fuzzy logic

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ABSTRACT

This study is based on the determination of optimum usage of pozzolans as supplementary cementing material for blended cement production. Blended cements were produced with natural zeolite (clinoptilolite), Eskişehir trass, Nevşehir trass, fly ash and ground granulated blast furnace slag at 10, 20, 30, 35, 40 and 45% replacement ratios. Experimental results were also obtained by building models according to artificial neural network and fuzzy logic systems. It is concluded that the strength development of cement mortars containing different pozzolans can be obtained according to neural network and fuzzy logic model test results without any experimental study.

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1. Introduction

Under the new specification, various materials can be used freely, but the material design methods of various cementitious materials must be established to satisfy the performance requirements of concrete [1]. Pozzolanic materials have been widely used as substitutes for Portland cement in many applications because of their advantageous properties which include cost decrease, reduction in heat evaluation, decreased permeability, alkali aggregate-expansion control, decreased chemical resistance, reduced concrete drying shrinkage and the improvement in the properties of fresh concrete [2]. Amorphous silica present in the pozzolanic materials combines with lime and forms cementitious materials. These materials improve the durability of concrete and the rate of gain in strength and can also reduce the rate of liberation of heat that is beneficial for mass concrete [3]. Nevertheless, the use of natural and artificial pozzolans as blend materials for cement has been constantly increasing in order to reduce energy consumption and CO_2 emission without causing any degradation to cement properties.

Zeolitic tuffs and amorphous silicate tuffs are the main natural pozzolans in the cement industry. The pozzolanic activity of zeolites depends on their chemical and mineralogical composition. The pozzolanic properties of zeolites are due to their reactive SiO_2 and Al_2O_3, which react with the $Ca(OH)_2$ liberated during the hydration of cement and convert it into C–S–H gels and aluminates. As a result, the micro-structure of hardened cement concrete is improved and the concrete becomes more impervious [4]. On the other hand, some waste materials such as fly ash (FA) and ground granulated blast furnace slag (BFS) can be used as supplementary cementing material, or artificial pozzolan, in concrete industry. The reactivity of FA and BFS is supposed to be particularly influenced by the glass content and its composition.

In this study, three different types of natural pozzolan (Eskişehir trass, Nevşehir trass and clinoptilolite) and two different types of artificial pozzolan (FA and BFS) were used with 10, 20, 30, 40 and 45% replacement ratios of clinker for blended cement production. The strength development of mortar specimens was determined according to the 2, 7, 28 and 180 days experimental compressive strength results. Besides, the strength development of different pozzolan blended cements was predicted with building models in the artificial neural network and fuzzy logic systems. For building these models, the 2, 7, 28 and 180 days compressive strength results of 244 mortar specimens produced with 61 different cements were used for training and testing of the multilayer feed-forward neural network and Sugeno-type fuzzy inference models. In training and testing of the models, the age of specimen (AS), clinker (C), zeolite (Z), Eskişehir trass (ET), Nevşehir trass (NT), FA and BFS were used as the experimental input variables while the experimental compressive strength (f_c) results were used as output. After training the models, tests were performed by using these experimental input variables as mentioned above. At the end of testing of the models, f_c values similar to the experimental results were predicted.

2. Experimental study

The raw materials of blended cement compositions were obtained from different sources. Clinker, gypsum, limestone and Eskişehir trass were obtained from Çimsa cement factory. F-type FA and BFS were obtained from Kütahya Tunçbilek

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Table 1
Chemical composition of raw materials

Chemical composition	Clinker (%)	Clinoptilolite (%)	Eskişehir tras (%)	Nevşehir tras (%)	Fly ash (%)	BFS[a] (%)
SiO_2	20.98	62.78	61.12	59.37	46.26	35.11
Al_2O_3	5.55	10.66	12.32	14.46	21.24	17.63
Fe_2O_3	3.85	4.20	6.51	6.99	4.29	0.35
CaO	65.85	2.37	4.28	5.82	9.82	37.56
MgO	1.12	1.10	5.88	4.99	2.62	5.52
K_2O	0.53	0.74	1.73	2.66	0.95	–
Na_2O	0.14	0.35	2.44	2.52	0.72	0.32
SO_3	0.97	–	0.1	–	2.11	–

[a] Granulated blast furnace slag.

Table 2
Mix proportions of blended cements

Cement type	Clinker (%)	Pozzolan (%)	Limestone (%)	Gypsum[a] (%)
CEM I 42.5	100	–	–	3
CODE 10	85	10	5	3
CODE 20	75	20	5	3
CODE 30	65	30	5	3
CODE 40	55	40	5	3
CODE 45	50	45	5	3

[a] Gypsum is used by weight of clinker.

thermal power plant and Zonguldak-Ereğli steel factory, respectively. Natural zeolite in clinoptilolite form was provided from Manisa Gördes region and Nevşehir Trass was obtained from Nevşehir-İnli region. Chemical analyses of the materials were performed by means of X-ray fluorescence (XRF) and the test results are given in Table 1.

In this study, 25 different types of blended cement mixes were prepared. For this purpose Z, ET, NT, FA and BFS were used by replacing cement clinker individually at the ratios of 10, 20, 30, 40 and 45% by weight. Besides, 5% limestone for particle size arrangement and 3% gypsum were also used for all series. Finally, each type of these 25 different blended cements was produced by intergrinding each mentioned material in a ball mill and defined as the first group. According to f_c results of the first group blended cements, the optimum replacement ratio of additives was found to be as 20 and 30% of clinker. Then the second group mixes with 30 different blended cements were designed through 20 and 30% replacement ratio as binary compositions. In addition, the third group mixes with 5 different blended cements were prepared with three different pozzolans of 30% replacement ratio. The properties of these blended cements were compared to reference CEM I 42.5 ordinary Portland cement in the experimental studies. The mix designs of ordinary and blended cements with different pozzolans are given in Table 2. The CODE expressions in Table 2 define the blended cement codes dependent upon pozzolan type and replacement ratio. The prepared cement mortars with the produced cements were cast in 40 × 40 × 160 mm prismatic moulds according to TS EN 196-1. The mortar specimens were removed from the moulds after 1 day and were then cured in lime saturated water at 20 ± 1 °C until the age of considering strength test. At the end of the curing period (2, 7, 28 and 180 days), mortar specimens were subjected to compressive strength test.

3. Artificial neural network

Artificial neural network (ANN) is an information processing technique that is inspired by the way biological nervous systems, such as the brain, process information [5]. ANN can show a surprising number of human brain's characteristics, e.g., learning from experience and generalizing from previous sample to solve new problems [6]. The technique is particularly suited to problems that involve the manipulation of multiple parameters and nonlinear interpolation, and as a consequence are not easily amenable to conventional theoretical and mathematical approaches [7]. In the recent years, ANN has been applied to many civil engineering problems with some degree of success. In particular, neural network has been applied to the determination of structural damage, structural system identification, modeling of material behavior, structural optimization, structural control, ground water monitoring, prediction of experimental results, and concrete and mortar mix ratios [8].

An artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. Inputs are information that enters the neuron from other neurons or from the external world. Weights are values that express the effect of an input set or another process element in the previous layer on this process element. Sum function is a function that calculates the effect of inputs and weights totally on this process element. This function calculates the net input that comes to a cell [9–13]. The weighted sums of the input components $(\text{net})_j$ are calculated by using Eq. (1) as follows:

$$(\text{net})_j = \sum_{i=1}^{n} w_{ij} x_i + b \tag{1}$$

where $(\text{net})_j$ is the weighted sum of the *j.* neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the *j.* Neuron in the preceding layer, x_i is the output of the *i.* neuron in the preceding layer [12–14] and b is a fix value as an internal addition. Activation function is a function that processes the net input obtained from sum function and determines the cell output. In general, for multilayer receptive models, sigmoid function is used as the activation function ($f(\cdot)$). The output of the *j.* neuron $(\text{out})_j$ is calculated employing Eq. (2) with a sigmoid function as follows [10–14]:

$$(\text{out})_j = f(\text{net})_j = \frac{1}{1 + e^{-\alpha(\text{net})_j}} \tag{2}$$

where α is a constant used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except in the input layer [12–14]. The sigmoid function represented by Eq. (2) gives outputs in (0,1). More details on the artificial neural network can be obtained from Refs. [6–18].

3.1. Neural network model structure and parameters

In this study, a multilayered feed-forward neural network with a back-propagation algorithm was adopted. Feed-forward neural networks are composed of layers of neurons, in which the output of each layer of neurons is connected to the input of the next layer. They are known by many different names, such as multilayer perceptrons [6]. Feed-forward neural networks have become increasingly popular in feature recognition and function approximation problems in a wide area of applications. Due to the largely used learning algorithm, these types of neural networks are sometimes referred to as back-propagation or back-propagation neural networks. Back-propagation algorithm, as one of the most well-known training algorithms for the multilayer perceptron, is a gradient descent technique to minimize the error for a particular training pattern in which it adapts the weights by a small amount at a time [7,12–14].

In training and testing of the neural network model AS, C, Z, ET, NT, FA and BFS were entered as input; while f_c values of cement mortars containing different pozzolans were used as output. Here-

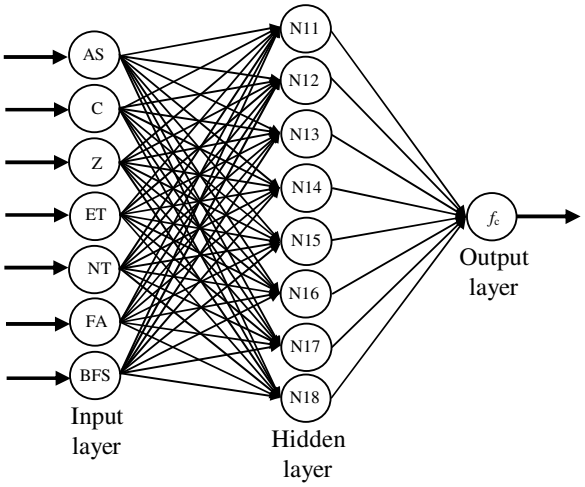


Fig. 1. The architecture used in the neural network model.

Table 3
The values of parameters used in the neural network model

Parameters	ANN
Number of input layer neurons	7
Number of hidden layer	1
Number of hidden layer neurons	8
Number of output layer neuron	1
Momentum rate	0.9
Learning rate	0.7
Error after learning	0.0005
Learning cycle	15.000

in, 163 of the experimental data were used for the training of the model and other 81 experimental data were used for testing the trained model. A multilayer neural network model developed in this research has seven neurons in the input layer and one neuron in the output layer as demonstrated in Fig. 1. One hidden layer was used in the architecture of multilayer neural network due to its minimum absolute percentage error values for training and testing sets. In the hidden layer eight neurons were determined. The neurons of neighboring layers were fully interconnected by weights. Momentum rate and learning rate values were determined and the model was trained through iterations. The trained model was tested only with the input values and the predicted results were close to the experimental results. The parameter values obtained from the multilayer feed-forward neural network model are given in Table 3.

4. Fuzzy logic inference systems

Fuzzy inference systems, which are also called fuzzy rule-based systems or fuzzy models, comprise four basic components. *Fuzzification* transforms the crisp inputs into fuzzy inputs by membership functions that represent fuzzy sets of input variables. *Fuzzy rule base* is composed of fuzzy if-then rules. *Fuzzy inference* takes into consideration all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. *Defuzzification* transforms the fuzzy output into crisp output. Defuzzification procedure requires the most computational complexity in fuzzy inference system, and center of gravity or height defuzzification method is common. In Sugeno-type fuzzy inference system, the final outputs are a weighted average of each rule output; thus, it does not require defuzzification procedure [12,19,20]. Fuzzy inference systems are powerful tools for the simulation of nonlinear behaviors with the help of fuzzy logic and linguistic fuzzy rules [12]. There are various fuzzy inference systems methodologies, such as Mamdani and Assilian [21] and Sugeno [22,23]. The fuzzy modeling or fuzzy identification, first explored systematically by Takagi, Sugeno and Kang, has found numerous practical applications in control, prediction and fuzzy inference systems [22,23]. Considering a first-order Sugeno-type fuzzy inference system, a fuzzy model contains two rules [12,16]:

- Rule$_1$: If x is A_1 and y is B_1, then $z_1 = p_1x + q_1y + r_1$.
- Rule$_2$: If x is A_2 and y is B_2, then $z_2 = p_2x + q_2y + r_2$.

If z_1 and z_2 are constants instead of linear equations, then we have a first-order Takagi, Sugeno and Kang fuzzy model [12,22,23]. In the Sugeno-type fuzzy inference system, outcomes of fuzzy rules are characterized by function crisp outputs [12]. In Fig. 2, the fuzzy inference methodology of a first-order Sugeno-type fuzzy inference system is denoted [24]. More details on the fuzzy logic can be obtained from Refs. [19–24].

4.1. Fuzzy logic inference system model

Fuzzy modeling is a system identification task, which includes two phases: structure identification and parameter prediction. Structure identification contains issues like selecting pertinent input variables, choosing a specific type of fuzzy inference system, determining the number of fuzzy rules, their antecedents and consequents, and determining the type and number of membership functions [12]. Parameter prediction is the determination of aimed values response to evident input values of the constituted model. For this purpose, 7 properties: AS, C, S, Z, ET, NT, FA and BFS amounts were used in the input layer, and f_c values of cement mortars containing different pozzolans were used in the output layer. In this study, 163 of the experimental data were used for the training of the model and other 81 experimental data were used for testing the trained model. Triangular-type membership functions were used, so as to run Sugeno-type fuzzy inference model. These membership functions were constructed with seven input variables and one output variable. The membership function plots of input variables used in the training of Sugeno-type fuzzy inference model are shown in Fig. 3. In the rule base, fuzzy variables were

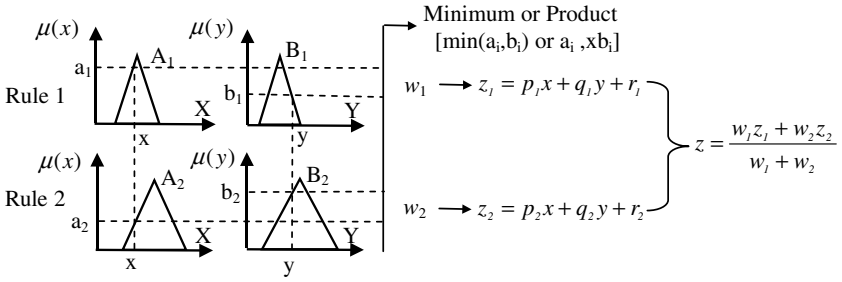


Fig. 2. Inference methodology of a first-order Sugeno-type model with two fuzzy rules.

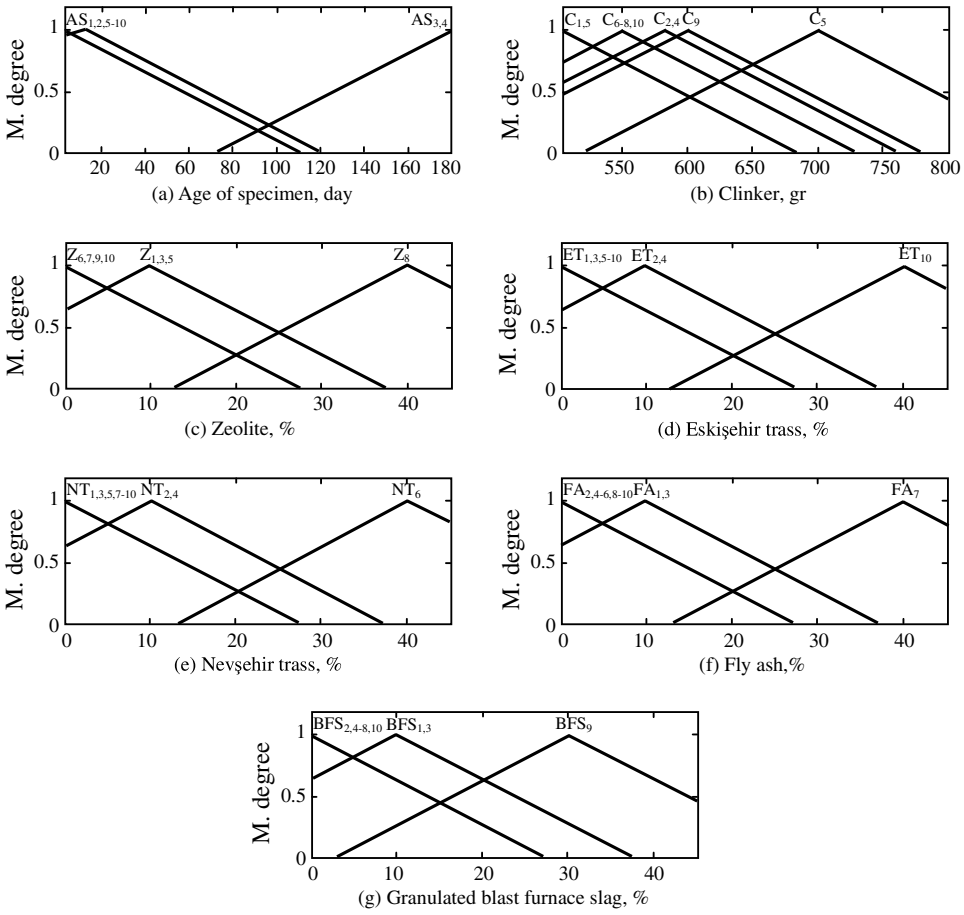


Fig. 3. Triangular-type membership functions of input variables for f_c: (a) age of specimen, (b) clinker, (c) zeolite, (d) Eskişehir trass, (e) Nevşehir trass, (f) fly ash and (g) granulated blast furnace slag.

connected with "prod" (fuzzy) operators and the implication of each rule was calculated using "wtaver" (weighted average) defuzzification method. Thus, for the f_c 10 rules are obtained as in the following:

R_i: If (AG is $AGmf_i$) and (C is Cmf_i) and (Z is Zmf_i) and (ET is $ETmf_i$) and (NT is $NTmf_i$) and (FA is $FAmf_i$) and (BFS is $BFSmf_i$) Then (f_c is $f_c mf_i$) $i = 1, 2 \ldots 10$.

5. Results and discussion

5.1. Experimental results

The aim of this study is to predict the strength development of different pozzolan blended cements with ANN and FL models. The data used in the models were obtained from the 2, 7, 28 and 180 days experimental f_c results of cement mortar specimens. The experimental results showed different behaviors depending upon the replacement ratio of pozzolans and age of the mortar specimens. In the early stage of cement hydration, $Ca(OH)_2$ from the hydrating paste was incorporated into the pozzolan structure and led to the formation of hydration product type C–S–H and hydrated aluminate phases. According to f_c results the early age strengths of blended cements were reduced with increasing amounts of replacement ratio. FA and BFS blended cements showed a good early age strength performance at the ages of 2 and 7 days compared to trass and zeolite blended cements. At the age of 28 days, the f_c values of BFS and zeolite blended cements were higher than reference CEM I 42.5 cement up to 40% replacement ratios. Moreover at 180 days, the f_c of BFS, FA and zeolite blended cements

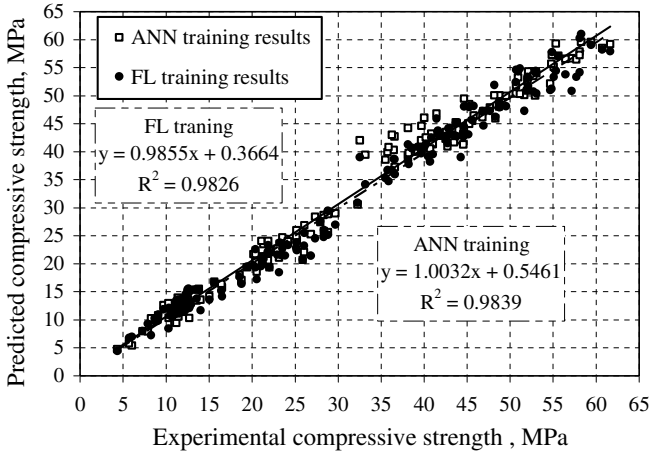


Fig. 4. Comparison of f_c experimental results with the training results of ANN and FL.

Table 4
The f_c statistical values of proposed ANN and FL models

Statistical parameters	ANN		FL	
	Training set	Testing set	Training set	Testing set
RMS	2.1867	3.1372	2.1508	3.2324
R^2	0.9962	0.9922	0.9963	0.9916
MAPE	5.7751	7.3929	6.8194	9.7037

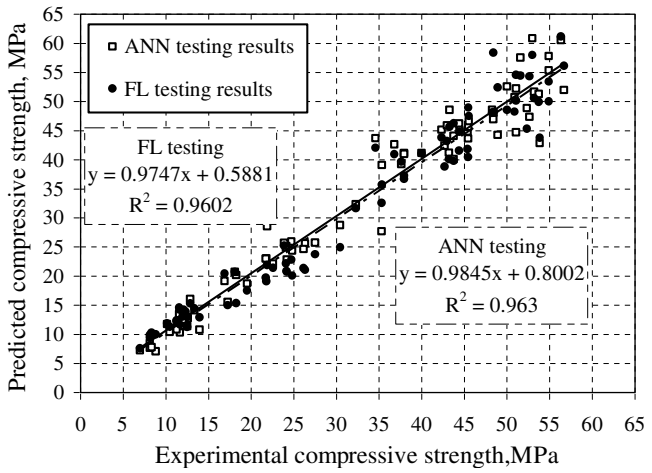


Fig. 5. Comparison of f_c experimental results with the testing results of ANN and FL.

reached approximately 58 MPa depending on the pozzolanic reaction of the considered mineral additive. This result was higher than the reference ordinary Portland cement mortars f_c (50 MPa). According to the mechanical testing results, it may be stated that the long-term strength performances of FA, BFS and natural zeolite (clinoptilolite) blended cements were better than reference CEM I 42.5 type cement. A comparison based on strength development indicates that the replacement of BFS, FA and zeolite is the most effective method in blended cement production.

5.2. Models results

In this study, the error that arose during the training and testing in the multilayer feed-forward neural network and Sugeno-type inference system can be expressed as a root-mean-squared (RMS) error and calculated [7,12,13] by

$$\mathrm{RMS} = \sqrt{\frac{1}{p}\sum_i |t_i - o_i|^2} \tag{3}$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are calculated [12,13] by Eqs. (4) and (5), respectively

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right) \tag{4}$$

Table 5
Comparison of experimental results with testing results obtained from ANN and FL models

Cement code	2 days f_c (MPa)			Cement code	28 days f_c (MPa)		
	Exp.	ANN	FL		Exp.	ANN	FL
ZC 10	11.60	13.81	14.23	ZC 20	42.31	45.18	43.85
ZC40	8.80	7.08	10.02	ZC 45	35.34	39.10	35.75
ETC 20	11.23	11.13	12.28	ETC 30	45.37	44.85	41.82
ETC 45	6.95	7.26	7.63	NTC 10	42.96	45.90	43.21
NTC 30	8.13	7.70	9.94	NTC 40	32.28	32.37	31.67
FAC 10	11.56	13.52	14.60	FAC 20	45.43	43.68	40.47
FAC 40	8.12	8.50	9.45	FAC 45	37.59	39.26	39.65
BFSC 20	12.84	16.07	15.33	BFSC 30	48.25	48.57	48.02
BFSC 45	8.31	7.80	10.30	FABFSC 10	43.25	48.56	45.66
FANTC 10	12.06	11.47	14.26	FANTC 20	37.92	41.19	37.30
FAETC 20	11.64	10.33	11.71	FAZC 10	45.46	45.63	48.97
ETFAC 20	11.24	10.87	12.42	ETNTC 10	34.56	43.72	42.05
ETBFSC 10	12.31	12.84	13.89	ETBFSC 20	37.93	40.99	36.70
ETZC 20	10.12	11.79	11.92	NTFAC 20	42.68	42.40	38.82
NTZC 10	12.56	12.73	13.02	NTZC 20	40.00	41.16	41.07
NTBFSC 20	12.07	11.94	13.64	ZFAC 20	43.75	44.12	46.25
ZNTC 20	10.45	10.40	11.33	ZBFSC 10	45.53	46.61	47.51
YFFAC 20	13.34	14.14	14.47	BFSZC 20	36.78	42.66	40.98
YFETC 20	13.94	10.81	12.93	BFSFAET	43.18	41.21	40.13
ZBFSET	11.96	12.17	13.05	ZFABFS	48.90	44.27	52.42
Cement code	7 days f_c (MPa)			Cement code	180 days f_c (MPa)		
	Exp.	ANN	FL		Exp.	ANN	FL
CEMI42.5	30.43	28.77	24.95	ZC 10	51.06	52.26	54.60
ZC30	24.18	22.84	20.78	ZC40	44.38	46.23	41.59
ETC 10	22.56	22.12	21.42	ETC 20	54.89	55.33	50.02
ETC 40	17.25	15.56	15.00	ETC 45	48.38	46.97	58.39
NTC 20	16.87	19.17	20.44	NTC 30	43.74	40.12	39.81
NTC 45	12.50	11.40	11.28	FAC 10	52.96	60.86	58.00
FAC 30	19.50	18.74	17.52	FAC 40	50.88	50.76	48.25
BFSC 10	35.31	27.70	32.61	BFSC 20	56.31	60.56	61.18
BFSC 40	24.81	24.41	20.09	BFSC 45	53.18	51.65	50.63
FABFSC 20	21.88	28.56	21.90	FANTC 10	54.91	57.82	53.45
FAETC 10	26.31	25.64	21.08	FAETC 20	48.41	48.11	48.22
FAZC 20	24.71	25.95	22.83	ETFAC 20	51.07	44.73	50.16
ETNTC 20	18.25	20.21	15.39	ETBFSC 10	51.58	57.54	54.45
ETZC 10	26.12	24.67	21.38	ETZC 20	52.32	48.88	45.36
NTETC 20	18.09	20.71	20.75	NTZC 10	53.72	51.33	49.96
NTBFSC 10	27.50	25.78	23.76	NTBFSC 20	52.64	47.36	54.33
ZETC 20	21.78	23.08	19.14	ZNTC 20	44.43	45.11	44.82
ZBFSC 20	24.13	25.15	20.91	YFFAC 20	56.67	51.98	56.16
BFSNTC 20	21.72	23.01	19.75	YFETC 20	53.84	42.85	43.81
FAZNT	24.09	24.98	22.19	ZBFSET	50.00	52.62	48.56
BFSNTFA	23.87	25.71	25.25				

$$\text{MAPE} = \left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \quad (5)$$

where t is the target value, o is the output value, and p is the pattern. The performances of the multilayer feed-forward neural network and Sugeno-type inference system models were determined according to the statistical parameters (Eqs. ((3)–(5)) given above.

The 2, 7, 28 and 180 days f_c results of the experimental studies and the training results which were obtained by ANN and FL models are given in Fig. 4. Also, the linear least square fit line, its equation and the R^2 values are shown in Fig. 4 for the training data. As shown in Fig. 4, the training results obtained from ANN and FL models are very close to the experimental results. This situation is demonstrated clearly by the statistical parameters shown in Table 4 (RMS, R^2 and MAPE). Nevertheless, after training the models, tests were performed using only the experimental input variables. The 2, 7, 28 and 180 days f_c results of the experimental studies and the testing results developed by ANN and FL models are given in Fig. 5 and Table 5, respectively. Also, the linear least square fit line, its equation and the R^2 values are shown in Fig. 5 for the testing data. As shown in Fig. 5 and Table 5, the testing results obtained from ANN and FL models are very close to the experimental results. The test results revealed that ANN and FL models were trained appropriately.

According to the statistical parameter values obtained from RMS, R^2 and MAPE, it is obviously possible to use the models constructed from ANN and FL systems for predicting the f_c development of different pozzolan blended cements. As the statistical values of RMS, R^2 and MAPE from training in ANN model were determined to be 2.0465, 99.89% and 2.8302%, respectively, these values were determined from testing as 2.3948, 99.84% and 3.3699%, respectively. Similarly, as the statistical values of RMS, R^2 and MAPE from training in FL model were determined to be 2.6557, 99.91 and 3.3699%, respectively, these values were determined from testing as 3.8655, 99.59 and 5.5245%, respectively. Also, the statistical values for f_c values found from training and testing in ANN and FL models as RMS, R^2 and MAPE are also given in Table 4. All the statistical values in Table 4 demonstrate that the proposed ANN and FL models are suitable and predict that the f_c values are very close to the experimental values.

6. Conclusion

In this study, the strength development of different mineral admixtures, which were prepared from trasses, zeolite (clinoptilolite), fly ash and ground granulated blast furnace slag was investigated. According to the experimental results, the early age compressive strength of blended cements reduced with increasing replacement ratios. However, when compared with the reference CEM I 42.5 cement, at the ages of 28 and 180 days, zeolite (clinoptilolite), blast furnace slag and fly ash replacements increased the compressive strengths depending on the pozzolanic reaction between $Ca(OH)_2$ and mineral additive. When compressive strength results were considered, the optimum replacement ratio was determined to be 20 and 30% for all pozzolan blended cement mixes. Furthermore, to predict the strength development of different blended cement mortars ANN and FL system models were constructed with the experimental results. The multilayer feed-forward neural network and Sugeno-type fuzzy inference models were trained with the input and output data. Using only the input data in the trained models, compressive strength values of different pozzolan cement mortars were predicted. The values obtained from both the models were close to the experimental results. Besides, the statistical values (RMS, R^2 and MAPE) obtained from ANN model were very closer to the experimental results compared to FL model. However, this case cannot be valid for other studies.

As a result, it was shown that compressive strength values of the different blended cement mortars can be predicted in ANN and FL models in a relatively short period of time with tiny error rates. A comparison based on strength development and cost per unit strength indicates that the addition of pozzolans to cement is the most economical and environmental effective production method in the cement industry.

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