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Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic

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Abstract

In this study, artificial neural networks and fuzzy logic models for predicting the 7, 28 and 90 days compressive strength of concretes containing high-lime and low-lime fly ashes have been developed. For purpose of constructing these models, 52 different mixes with 180 specimens were gathered from the literature. The data used in the artificial neural networks and fuzzy logic models are arranged in a format of nine input parameters that cover the day, Portland cement, water, sand, crushed stone I (4–8 mm), crushed stone II (8–16 mm), high range water reducing agent replacement ratio, fly ash replacement ratio and CaO, and an output parameter which is compressive strength of concrete. In the models of the training and testing results have shown that artificial neural networks and fuzzy logic systems have strong potential for predicting 7, 28 and 90 days compressive strength of concretes containing fly ash.

Keywords: Compressive strength; Fly ash; Artificial neural networks; Fuzzy logic

1. Introduction

New trends in environmental regulations related to disposal of wastes such as fly ash (FA) or ground granulated blast furnace slag have initiated increasing interests in using the wastes as construction materials partially replacing Portland cement in concrete [1]. FA has been commonly used to replace part of cement in concrete, and the percentage of replacement ranges from about 20% (low volume FA) to more than 50% (high volume FA) of the total cementitious materials [2]. Furthermore, if the early strength is not an important factor, FA as high as 60% can be used. It is a known fact that fly ashes generally have negative effects on the concrete strength, particularly at the early ages [3,4]. Especially, FA, the ash precipitated electrostatically or mechanically from the exhaust gases of coal-fired power stations, has been used in mass concrete to reduce the heat of hydration and cracking at early ages. Also, FA concrete increases long-term compressive strength and durability of concrete structures [1]. FA concretes may have better strength and durability performance when they are prepared at lower water to binder ratios.

For the last two decades, the different modeling methods based on artificial neural networks (ANN) and fuzzy logic (FL) systems have become popular and has been used by many researchers for a variety of engineering applications. The basic strategy for developing ANN and FL systems based models for material behavior is to train ANN and FL systems on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained ANN and FL systems will contain sufficient information about material's behavior to qualify as a material model. Such a trained ANN and FL systems not only would be able to reproduce the experimental results, but also they would be able to approximate the results in other experiments trough their generalization capability [5].

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The aim of this study is to build models in ANN and FL systems to evaluate the effect of FA on compressive strength of concrete. For purpose of constructing these models, 52 different mixes with 180 specimens of the 7, 28 and 90 days compressive strength experimental results of concretes containing FA used in training and testing for ANN and FL systems were gathered from the technical literature [6]. These concretes obtained from 52 different mixes, containing Portland cement and FA, were manufactured with three different partial FA replacement ratios (10%, 20% and 40%) using two different high-lime and two different low-lime fly ashes. In training of the models; day (D), Portland cement (PC), water (W), sand (S), crushed stone I (CS-I), crushed stone II (CS-II), high range water reducing agent (WRA), fly ash (FA) and CaO were entered as input; while compressive strength (f_c) values were used as outputs. The models were trained with 120 data of experimental results and then remainders were used as only experimental input values for testing and values similar to the experimental results were obtained.

2. Artificial neural networks

Artificial neural networks (ANN) were developed to model the human brain. Even an ANN fairly simple and small in size when compared to the human brain, has some powerful characteristics in knowledge and information processing due to its similarity to the human brain. Therefore, an ANN can be a powerful tool for engineering applications. The first studies on ANN are supposed to have started in 1943. Afterwards, as a second hit, in 1958 Rosenblatt [7] devised a machine called the perceptron that operated much in the same way as the human mind. Rosenblatt's perceptrons consist of "sensory" units connected to a single layer of McCulloch and Pitts [8] neurons. Rumelhardt et al. [9] derived a learning algorithm for perceptron networks with constituted hidden units. Their learning algorithm is called back-propagation and is now the most widely used learning algorithm. As a result of these studies, together with the developments in computer technology, use of ANN has become more efficient after 1980 [10–12]. In recent years, ANN has been applied to many civil engineering problems with some degree of success. In civil engineering, neural networks have been applied to the detection of structural damage, structural system identification, modeling of material behavior, structural optimization, structural control, ground water monitoring, prediction of settlement of shallow foundation, and concrete mix proportions [13].

An artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. Inputs are information that enters the cell from other cells of from 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 [12–16]. The weighted sums of the input components $(\text{net})_j$ are calculated by using the following equation:

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

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 [5,11]. b a fix value as internal addition and $\sum$ represents sum function. 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 as the activation function ($f(\cdot)$) sigmoid function is used. The output of the j. neuron $(\text{out})_j$ is calculated employing Eq. (2) with a sigmoid function as follows [5,11]:

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

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 [11,13]. The sigmoid function represented by Eq. (2) gives outputs in (0, 1). As the sigmoid processor represents a continuous function it is especially used in non-linear descriptions. Because its derivatives can be determined easily with regard to the parameters within $(\text{net})_j$ variable [5,11–13].

2.1. Neural network model structure and parameters

ANN model developed in this research has nine neurons in the input layer and one neurons in the output layer as

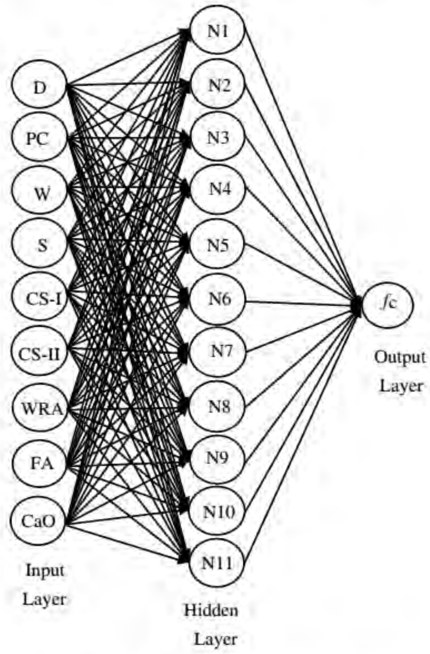

Fig. 1. The system used in the ANN model.

Table 1
The input and output quantities used in models

Input/output variables	Data used in training and testing the models	
	Minimum	Maximum
Cement (kg/m^3)	232.20	512.00
Water (kg/m^3)	115.00	184.00
Sand (kg/m^3)	500.00	551.00
Crushed stone I (kg/m^3)	256.00	282.00
Crushed stone II (kg/m^3)	877.00	964.00
WRA (kg/m^3)	30.00	35.80
Fly ash (kg/m^3)	0.00	204.80
CaO (%)	2.00	20.30
Compressive strength (MPa)	7.10	87.10

demonstrated in Fig. 1. The limit values of input and output variables used in ANN model are listed in Table 1. One hidden layer with 11 neurons was used in the architecture of multilayer neural network due to its minimum absolute percentage error values for training and testing sets. The neurons of neighboring layers are fully interconnected by weights. Finally, the output layer neurons produce the network prediction as a result. In this study, the back-propagation training algorithm has been utilized in feed-forward one hidden layers. 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 adjust the weights by a small amount at a time [5]. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by other computer techniques due to adaptive learning. Therefore, ANN can be used for a particular problem when deviation in the available data is expected and accepted and also when a defined methodology is not available, as in the case of present study [13]. The non-linear sigmoid function was used in the hidden layer and the cell outputs at the output layer. Momentum rate and learning rate values were determined and the model was trained through iterations. The trained model was only tested with the input values and the results found were close to experiment results. The values of parameters used in this research are as follows:

- Number of input layer units = 9
- Number of hidden layer = 1
- Number of hidden layer units = 11
- Number of output layer units = 1
- Momentum rate = 0.90
- Learning rate = 0.75
- Error after learning = 0.000163
- Learning cycle = 10.000

3. Fuzzy logic

The concept of "fuzzy set" was preliminarily introduced by Zadeh [17], who pioneered the development of fuzzy logic (FL) replacing Aristotelian logic which has two possibilities only. FL concept provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables [18,19]. Herein, uncertainties do not mean random, probabilistic and stochastic variations, all of which are based on the numerical data. Fuzzy set theory provides a systematic calculus to deal with such information linguistically. Fuzzy approach performs numerical computation by using linguistic labels stimulated by membership functions. Therefore, Zadeh [17] introduced linguistic variables as variables whose values are sentences in a natural or artificial language [19]. Although FL was brought forward by Zadeh [17] in 1965, fuzzy concepts and systems attracted attention after a real control application in 1975 conducted by Mamdani and Assilian [20–22].

The key idea in FL is the allowance of partial belongings of any object to different subsets of the universal set instead of belonging to a single set totally. Partial belonging to set can be described numerically by a membership function which assumes values between 0 and 1 contain. For instance, Fig. 2 shows a typical membership function for small, medium and large class sizes in a universe, U. Hence, these verbal assignments are fuzzy subsets of the universal set. In this figure, set values less than 2 are definitely "small"; those between 4 and 6 are certainly "medium"; while values larger than 8 are definitely "large". However, intermediate values such as 2.2 partially belong to the subsets "small" and "medium". In fuzzy terminology 2.2 has a membership value of 0.9 in "small" and 0.1 in "medium", but 0.0 in "large" subsets [18,19,23].

3.1. Fuzzy logic inference system

A general fuzzy inference system (FIS) has basically four components: these fuzzification, fuzzy rule base, fuzzy output engine and defuzzification [12,24]. Moreover, input and output data can be added. *Fuzzification* converts each piece of input data to degrees of membership by a lookup in one or more several membership functions [24]. *Fuzzy rule base* contains rules that include all possible fuzzy relation between inputs and outputs. These rules are expressed in the IF–THEN format. There are basically two kinds of fuzzy rules. In this study, the Sugeno-type fuzzy rules were constituted. *Fuzzy inference engine* takes into consideration all the fuzzy rules in the fuzzy rule base and learns how to

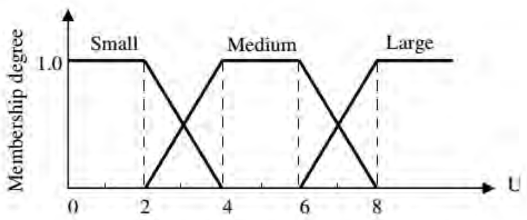

Fig. 2. Fuzzy subsets.

transform a set of inputs to corresponding outputs. There are basically two kinds of inference operators: minimization (min) and product (prod) [12,24]. In this study, the prod method was employed because of its better performance. *Defuzzification* converts the resulting fuzzy outputs from the fuzzy inference engine to a number [24]. There are many defuzzification methods such as weighted average (wtaver) or weighted sum (wtsum). In this study, the weighted average method was employed.

Fuzzy inference systems are powerful tools for the simulation of non-linear behaviors with the help of FL and linguistic fuzzy rules [25]. A FIS employing fuzzy "IF–THEN rules" can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses [21–29]. There are various FIS methodologies, such as Mamdani and Sugeno [20–27]. The fuzzy modeling or fuzzy identification, first explored systematically by Sugeno and Kang [26] and Takagi and Sugeno [27], has found numerous practical applications in control, prediction and FIS [26–29]. In the Sugeno FIS, outcomes of fuzzy rules are characterized by function crisp outputs. From mathematical viewpoint, if F denotes a real continuous mapping within a closed interval, then the parameterized non-linear mapping of a Sugeno-type FIS may be given in the following equation:

$$F = \frac{\sum_{i=1}^{m} w_i \Pi_{J=1}^{n} \mu_{A_j^i}(x_j)}{\sum_{i=1}^{m} \Pi_{J=1}^{n} \mu_{A_j^i}(x_j)} \tag{3}$$

where m denotes number of rules, n defines number of data points, and μ_A is the membership function of fuzzy set A. Another important issue affecting the performance of a FIS is the partitioning of input space. In this context, there are several partitioning techniques, such as grid partitioning and tree partitioning [12,25,28]. Considering a first-order Sugeno-type FIS, a fuzzy model contains two rules [26,29]:

Rule1 : IF x is A_1 and y is B_1, THEN $z_1 = p_1x + q_1y + r_1$
Rule2 : 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 first-order Takagi, Sugeno and Kang fuzzy model [25–29]. The basic learning rule of adaptive neuro-fuzzy inference system is the back-propagation gradient descent, which calculates error signals recursively from

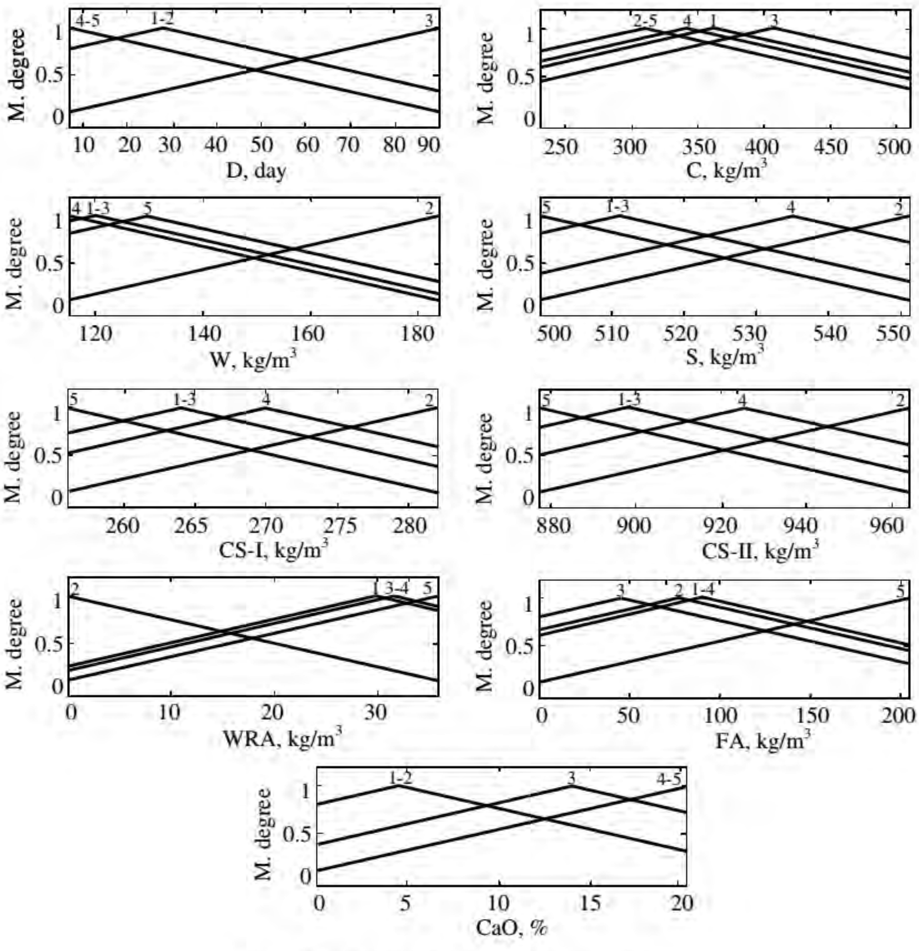

Fig. 3. Membership functions of input variables.

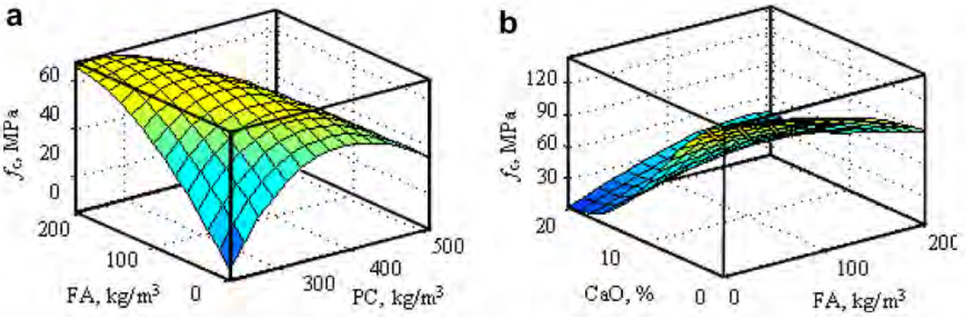

Fig. 4. Some inputs with f_c surface, (a) combined effects PC and FA on f_c, (b) combined effects FA and CaO on f_c.

the output layer backward to the input nodes. This learning rule is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks [12,25–29].

3.2. Fuzzy logic inference system model

Fuzzy modeling is a system identification task, which involves two phases: structure identification and parameter prediction. Structure identification contains the issues like selecting relevant input variables, choosing a specific type of FIS, determining the number of fuzzy rules, their antecedents and consequents, and determining the type and number of membership functions [29]. Parameter prediction is determination of aimed values response to evident input values of constituted model. For this aim, in the study 180 data experiment results were used in the processes of Sugeno-type fuzzy inference model in FL system. The limit values of input and output variables used in Sugeno-type fuzzy inference model are listed in Table 1.

The compact graphical form, which represents a fuzzy rule based system, is named fuzzy associate memory table. In the rule base, fuzzy variables were connected with "prod" (fuzzy and) operators and rules were associated using "max–min" decomposition technique. Moreover, training continued for over 1000 epochs and process terminated by the observation of the stability in error reduction. The membership functions of the training data set for the input variables of f_c are of the triangular type and premise parameter sub-spaces were determined by using clustering of the training data set. Thus, five rules being obtained as in the following:

R_i: IF (D is Dmf$_i$) and (PC is PCmf$_i$) and (W is Wmf$_i$) and (S is Smf$_i$) and (CS-I is CS-Imf$_i$) and (CS-II is CS-IImf$_i$) and (WRA is WRAmf$_i$) and (FA is FAmf$_i$) and (CaO is CaOmf$_i$) THEN (f_c is $f_c$mf$_i$) $(i = 1, 2, \ldots, 5)$

In order to apply for the Sugeno-type FIS in FL system, f_c results determined from literature were divided into the training and testing parts. Herein, 120 data of experiment results were used for training whereas 60 ones were employed for testing. All of the proposed membership functions in this study consist of nine inputs and one output. The membership function plots of input variables used in the training are shown in Fig. 3. In Fig. 4, based on the results of prediction runs of the model; shows the effects of two factors at a time on each surface plot of the f_c. The effects of PC, FA and CaO on f_c are shown in Fig. 4a and b. As can be seen in Fig. 4a and b, increasing of FA leads to a gradual increase of f_c.

4. Results and discussion

In this study, the error arose during the training and testing in ANN and FL models can be expressed as a root-mean-squared (RMS) error and is calculated [5,17] by using the following equation:

$$\mathrm{RMS} = \sqrt{\frac{1}{p}\sum_i |t_i - o_i|^2} \tag{4}$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are calculated [5,12] by using the following equations:

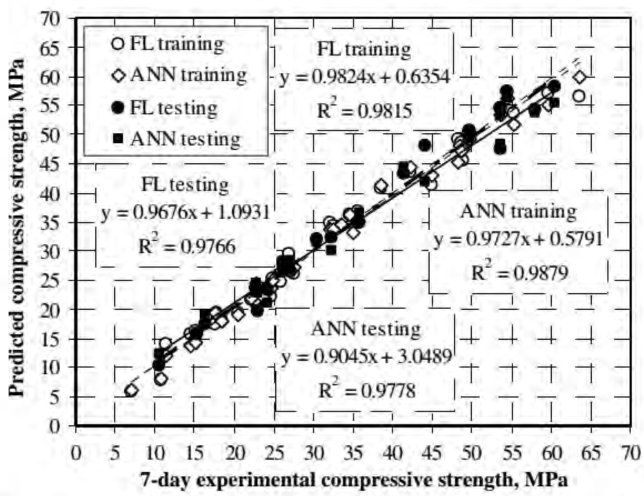

Fig. 5. Comparison of 7-day f_c exp. results with ANN and FL results.

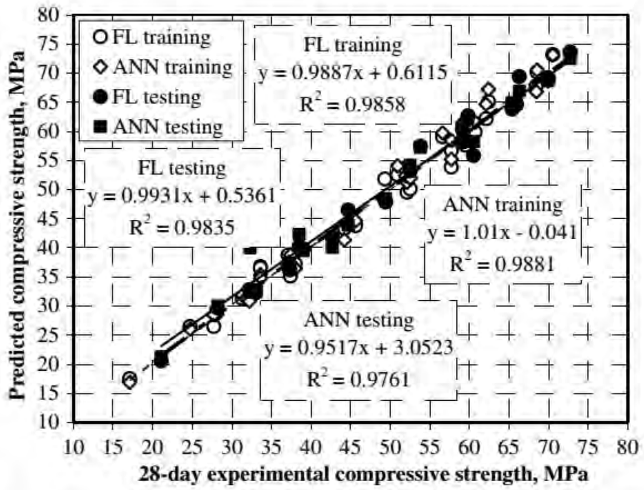

Fig. 6. Comparison of 28-day f_c exp. results with ANN and FL results.

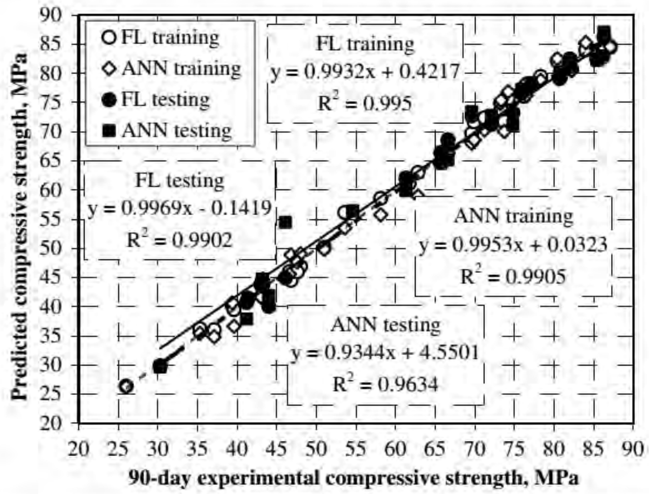

Fig. 7. Comparison of 90-day f_c exp. results with ANN and FL results.

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right) \quad (5)$$

$$\text{MAPE} = \left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \quad (6)$$

where t is the target value, o is the output value, p is the pattern.

Both experimental studies [6] and training and testing results developed by ANN and FL models for 7, 28 and 90 days f_c results were given in Figs. 5–7. The linear least square fit line, its equation and the R^2 values are shown in these figures for the training and testing data. Also, experimental results [6] and testing results obtained from ANN and FL models were given in Table 2. As it is visible in Figs. 5–7 with Table 2, the values obtained from the training and testing in ANN and FL models are very closer to the experimental results. This case proves that the experimental results with ANN and FL models results are all in harmony.

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 3. While the statistical values RMS, R^2 and MAPE from training in ANN model were found as 1.7099, 99.90% and 3.3325%, respectively, these values were found in testing as 2.8109, 99.72% and 5.0672%, respectively. Similarly, while the statistical values RMS, R^2 and MAPE from training in FL model were found as 1.7221, 99.89% and 3.6044%, respectively, these values were found in testing as 2.0206, 99.86% and 3.3772%, respectively. All of the statistical values in Table

Table 2
Comparison of f_c experimental results with testing results obtained from ANN and FL

7-day compressive strength			28-day compressive strength			90-day compressive strength		
Experimental	ANN model	FL model	Experimental	ANN model	FL model	Experimental	ANN model	FL model
22.70	24.47	23.70	38.50	42.32	40.20	46.10	54.47	44.96
22.90	22.77	19.63	32.30	40.00	32.51	41.40	50.19	41.48
44.20	41.82	48.13	53.80	57.28	57.44	69.60	73.41	72.74
53.70	53.51	54.41	65.90	64.76	64.64	80.70	79.68	79.18
58.00	53.72	54.17	66.30	66.96	69.42	86.10	82.98	82.80
60.50	55.37	58.12	72.70	72.48	73.67	86.30	87.07	86.26
53.70	48.22	47.55	59.80	62.24	62.69	77.10	78.39	78.20
15.30	15.99	15.69	33.00	32.49	32.62	41.20	37.92	40.73
49.80	49.23	50.63	59.20	60.02	58.21	75.90	77.22	76.71
30.50	31.62	31.96	44.70	43.91	46.52	66.60	65.17	68.65
41.50	44.46	43.24	65.40	64.96	63.83	85.40	82.29	82.39
27.20	28.52	26.41	42.70	40.08	41.81	61.30	59.91	62.06
35.80	36.65	34.99	60.50	58.27	55.85	74.80	71.21	73.27
22.70	24.47	23.70	37.30	37.40	36.28	43.20	44.73	43.76
10.50	12.49	10.44	21.10	21.29	20.59	30.30	29.67	29.92
32.40	30.15	32.43	52.50	54.19	53.25	72.10	72.78	71.24
16.40	19.22	17.40	28.20	30.00	29.65	44.00	41.93	40.05
26.00	26.51	28.12	49.40	48.45	47.87	65.70	64.56	66.41
54.40	56.20	57.46	69.90	68.71	69.16	82.00	81.12	82.46
24.30	21.01	23.38	39.00	39.53	39.82	54.60	56.41	55.83

Table 3
The f_c statistical values of proposed ANN and FL models

Statistical parameters	ANN		FL	
	Training set	Testing set	Training set	Testing set
RMS	1.7099	2.8109	1.7221	2.0206
R^2	0.9990	0.9972	0.9989	0.9986
MAPE	3.3325	5.0672	3.6044	3.3772

3 demonstrate that the proposed ANN and FL models are suitable and predict the f_c values very close to experimental values. A small perceptible deviation was observed for the calculated values.

5. Conclusions

In order to predict the 7, 28 and 90 days compressive strength values of concrete containing high-lime and low-lime FA without attempting any experiments were constructed models in artificial neural networks and fuzzy logic methods. The models were trained with input and output data. Using only the input data in trained models the 7, 28 and 90 days compressive strength values of concrete containing fly ash was predicted. The values are very closer to the experimental results obtained from training and testing for artificial neural networks and fuzzy logic models. RMS, R^2 and MAPE statistical values that calculated for comparing experimental results with YSA and BM model results have shown this situation.

As a result, compressive strength values of the fly ash concretes can be predicted in artificial neural networks and fuzzy logic models without attempting any experiments in a quite short period of time with tiny error rates. These conclusions have shown that artificial neural networks and fuzzy logic are practicable methods for predicting compressive strength values of concrete.

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