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PREDICTION OF COMPRESSIVE STRENGTH AND DURABILITY OF HIGH PERFORMANCE CONCRETE BY ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Neural networks have recently been widely used to model some of the human activities in many areas of civil engineering applications. In the present paper, artificial neural networks (ANN) for predicting compressive strength of cubes and durability of concrete containing metakaolin with fly ash and silica fume with fly ash are developed at the age of 3, 7, 28, 56 and 90 days. For building these models, training and testing using the available experimental results for 140 specimens produced with 7 different mixture proportions are used. The data used in the multi-layer feed forward neural networks models are designed in a format of eight input parameters covering the age of specimen, cement, metakaolin (MK), fly ash (FA), water, sand, aggregate and superplasticizer and in another set of specimen which contain SF instead of MK. According to these input parameters, in the multi-layer feed forward neural networks models are used to predict the compressive strength and durability values of concrete. It shown that neural networks have high potential for predicting the compressive strength and durability values of the concretes containing metakaolin, silica fume and fly ash.

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KEY WORDS: artificial neural networks, high performance concrete, metakaolin, silica fume

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1. INTRODUCTION

In recent years, in many countries, kaolin and clay are used for producing active pozzolanic materials. These pozzolanic admixtures are utilized for reducing the cement content in mortar and concrete production [1]. Also, the use of pozzolanic materials such as silica fume (SF), fly ash and MK is necessary for producing high performance concrete. These materials, when used as mineral admixtures in high performance concrete, can improve either or both the strength and durability properties of the concrete [2,3]. MK is a thermally activated alumino-silicate materials obtained by calcining kaolin clay within the temperature range 650–800°C [2]. SF is a by-product of the manufacture of silicon and ferrosilicon alloys [4]. Both MK and SF exhibit high pozzolanic activity and similar micro filler properties. They increase the water demand of the concrete mixes and produce dense and impermeable concrete [5]. The combination of MK and SF with superplasticizer produces high strength concrete. Many studies indicate that the presence of MK and SF in concrete seems to increase the compressive strength as compared to that of conventional concrete. An artificial neural network models for concrete mixtures is developed and found compressive strength of concrete can be predicted with ANN with minimum percentage of error [6].

In this study, the two groups of specimen with 7 different mixes have been obtained. It has been designed that the water-binder ratio are 0.3 and 0.32 for the first and second group of mixes, respectively. Each group included 7 mixes with 0%, 5%, 7.5% and 10% replacement by weight of cement with SF and another set of specimens with 0%,5%,7.5% and 10% , along with 10% constant replacement of fly ash. In the second set, MK is used instead of SF.

In the last years, ANN technology, a sub-field of artificial intelligence, are being used to solve a wide variety of problems in civil engineering applications [7-14] .The most important property of ANN in civil engineering problems are their capability of learning directly from examples. The other important properties of ANN are their correct or nearly correct response to incomplete tasks, their extraction of information from noisy or poor data, and their production of generalized results from the novel cases. The above-mentioned capabilities make ANN a very powerful tool to solve many civil engineering problems, particularly problems, where data may be complex or in an insufficient amount [13]. The basic strategy for developing an ANN system based models for material behavior is to train an ANN system on the results of a series of experiments using that material [8-12]. If the experimental results include the relevant information about the material behavior, then the trained ANN system will contain enough information about material's behavior to qualify as a material model [9-12]. Such a trained ANN system not only would be able to reproduce the experimental results, but also they would be able to approximate the results in other experiments through their generalization capability [8-12].

The aim of this study is to build models which have two different architectures in ANN system to evaluate the effect of MK with fly ash and SF with fly ash on compressive strength and durability of concrete. For purpose of constructing this models, 7 different mixtures with 140 specimens of the 3, 7, 28, 56 and 90 days compressive strength results of concretes containing MK and SF is used in training and testing [2-6]. In training and testing of the models constituted with two different architectures the age of specimen (AS), cement (C), silica fume

(SF), fly ash (FA), water (W), sand (S), aggregate (A) and superplasticizer (SP) and also used metakaolin instead of silica fume were entered as second set of inputs; while compressive strength (fc) and ultimate load values were used as output. The models were trained with 70% 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

ANNs are computing systems made up of a number of simple, highly interconnected processing elements, which processes information by their dynamic state response to external inputs [15]. The fundamental concept of neural networks is the structure of the information processing system [12]. Generally, an ANN are made of an input layer of neurons, sometimes referred to as nodes or processing units, one or several hidden layer 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 [16,17]. Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units [14]. 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 or three hidden layers. Finally, the output layer neurons produce the network predictions to the outside world [16,17]. Each neuron of a layer other than the input layer computes first a linear combination of the outputs of the neurons of the previous layer, plus a bias. The coefficients of the linear combinations plus the biases are called weights. Neurons in the hidden layer then compute a nonlinear function of their input. Generally, the nonlinear function is the sigmoid function [12].

According to the information mentioned above, an artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. Figure 1 shows a typical neural network with input, sum function, sigmoid activation function and output. The input to a neuron from another neuron is obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them [18]. The weighted sums of the input components $(net)_j$ are calculated by Eq. (1):

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

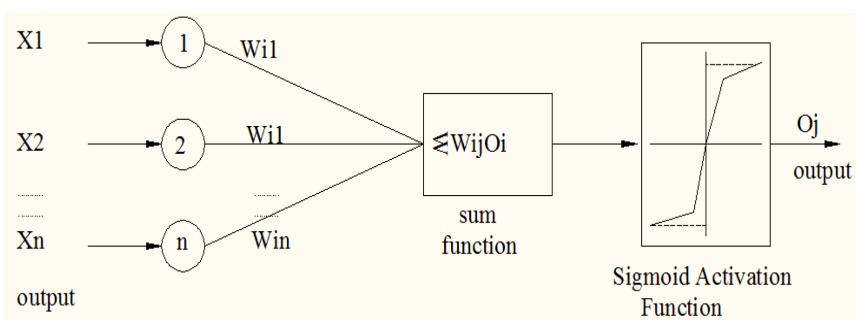

Figure 1. Artificial neuron model

Here $(net)_j$ is the weighted sum of the jth neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the jth neuron in the preceding layer, o_i is the output of the ith neuron in the preceding layer [9-11]. The quantity b is called the bias and is used to model the threshold. The output signal of the neuron, denoted by o_j in Figure 1, is related to the network input $(net)_j$ via a transformation function called the activation function [18]. The most common activation functions are ramp, sigmoid, and Gaussian function. In general for multilayer receptive models as the activation function $(f(net)_j)$ sigmoid function is used. The output of the jth neuron o_j is calculated by Eq. (2) with a sigmoid function as follows [9-11]:

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

Here oj is the output of neuron, a is constant used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except in the input layer [10, 11,18]. The sigmoid function represented by Eq. (2) gives outputs in (0, 1) [9-11].

In recent years, ANN have 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 experimental studies, and concrete mix proportions [14].The neural network based modeling process determination: (a)data acquisition, analysis and problem representation; (b) architecture determination; (c) learning process determination; (d) training of the networks; and (e) testing of the trained network for generalization evaluation[11,19]. After these processes are carried out, ANN can supply meaningful answers even when the data to be processed include errors or are incomplete and can process information extremely rapidly when applied to solve engineering problems [11,20].

3. FEED FORWARD NETWORKS

In a feed forward neural network, the artificial neurons are arranged in layers, and all the neurons in each layer have connections to all the neurons in the next layer [12]. However, there is no connection between neurons of the same layer or the neurons which are not in successive layers. The feed forward network consists of one input layer, one or two hidden layers and one output layer of neurons [18]. Associated with each connection between these artificial neurons, a weight value is defined to represent the connection weight [12]. Figure 2. shows a typical architecture of a multilayer feed forward neural network with an input layer, two hidden layer, and an output layer. The input layer receives input information and passes it onto the neurons of the hidden layer(s), which in turn pass the information to the output layer.

The output from the output layer is the prediction of the net for the corresponding input supplied at the input nodes. Each neuron in the network behaves in the same way as discussed in Eqs. (1) and (2). There is no reliable method for deciding the number of neural units required for a particular problem. This is decided based on experience and a few trials are required to determine the best configuration of the network[18]. In this study, the multilayer feed forward type of ANN, as shown in Figure 2 is considered. In a feed forward network, the inputs and output variables are normalized within the range of 0–1.

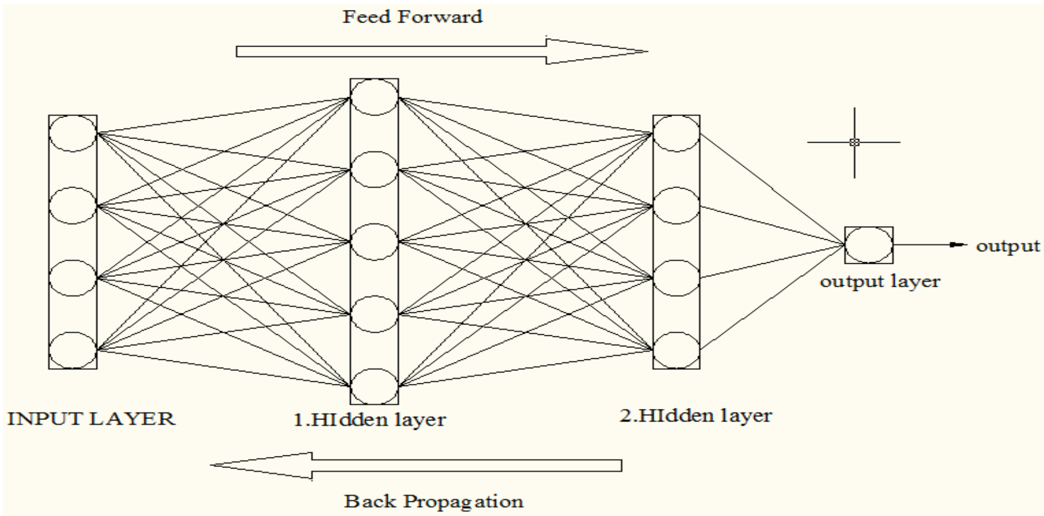

Figure 2. Typiacl architecture of a multilayer feed forward neural network

4. THE BACK PROPAGATION ALGORITHM

Back propagation algorithm, as one of the most well-known training algorithms for the multilayer perception, is a gradient descent technique to minimize the error for a particular training pattern in which it adjusts the weights by a small amount at a time [9-11].

The network error is passed backwards from the output layer to the input layer, and the weights are adjusted based on some learning strategies so as to reduce the network error to an Table acceptable level[16]. The error for rth example is calculated by Eq. (3):

$$E_r = ½ \Sigma (t_j-o_j)^2 \tag{3}$$

Here t_j is the output desired at neuron j and o_j is the output predicted at neuron j. As presented in Eqs. (1) and (2) the output o_j is a function of synaptic strength and outputs of the previous layer [18].

The learning consists of changing the weights in order to minimize this error function in a gradient descent technique. In the back propagation phase, the error between the network output and the desired output values is calculated using the so-called generalized delta rule [21], and weights between neurons are updated from the output layer to the input layer by Eq. (4) [13]

$$W_{ij} (m+1) = w_{ij}(m) + \eta (\delta_j o_j) + \beta w_{ij} (t) \tag{4}$$

Here, δ_j is the error signal at a neuron j, o_j is the output of neuron j, m is the number of iteration, and g, b are called learning rate and momentum rate, respectively. δ_j in Eq. (4) can be calculated using the partial derivative of the error function Er in the output layer and other layer, respectively, by Eqs. (5) and (6) [13,18]

$$\delta j = o_j\, (t_j - o_j)\, (1 - o_j) \tag{5}$$

$$\delta j = o_j\, (1 - o_j)\, \Sigma \delta_k w_{kj} \tag{6}$$

Here, the kth layer means the upper layer of the jth layer [13]. The above operations are repeated for each example and for all the neurons until a satisfactory convergence is achieved for all the examples present in the training set [18]. The training process is successfully completed, when the iterative process has converged. The connection weights are captured from the trained network, in order to use them in the recall phase [13]. For the present study, a multilayer feed forward network is adopted for training purpose. The error is reduced using a back propagation algorithm.

5. NEURAL NETWORK MODEL

In this study, a multilayered feed forward neural network with a back propagation algorithm was adopted. The nonlinear sigmoid function was used in the hidden layer and the cell outputs at the output layer. As shown in Figures 3(a), 3(b), 4(a) and 4(b), two different multilayer artificial neural network architectures namely ANN-I and ANN-II were built. In training and testing of the ANN-I and ANN-II models constituted with two different architectures AS, C, MK & SF, FA, W, S, A, and SP were entered as input; while fc value was used as output. In the ANN-I and ANN-II, 195 data of experiment results were used for training whereas 70% of these data were employed for testing. In ANN-I model, as shown Figure 3(a); one hidden layer was selected. In the hidden layer 10 neurons were determined due to its minimum absolute percentage error values for training and testing sets. In ANN-II model, as shown Figure 4 (a); two hidden layers were selected. In the first hidden layer ten neurons and in the second hidden layer ten neurons were determined due to its minimum absolute percentage error values for training and testing sets. The limit values of input and output variables used in ANN-I and ANN-II models are listed in Table 1 [2,6]. In the ANN-I and ANN-II models, the neurons of neighboring layers are fully interconnected by weights. Finally, the output layer neuron produces the network prediction as a result. Momentum rate and learning rate values were determined for both to modes and the models were trained through iterations. The values of parameters used in ANN-I and ANN-II are given in Table 2. The trained models were only tested with the input values and the results found were close to experiment results.

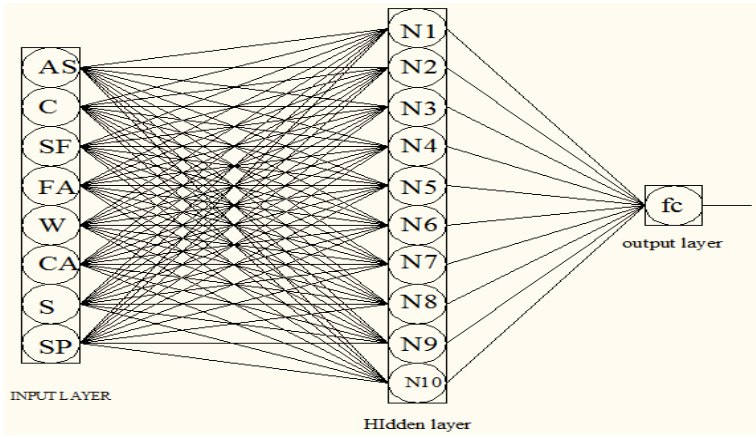

Figure 3(a). The system used in the ANN-I model

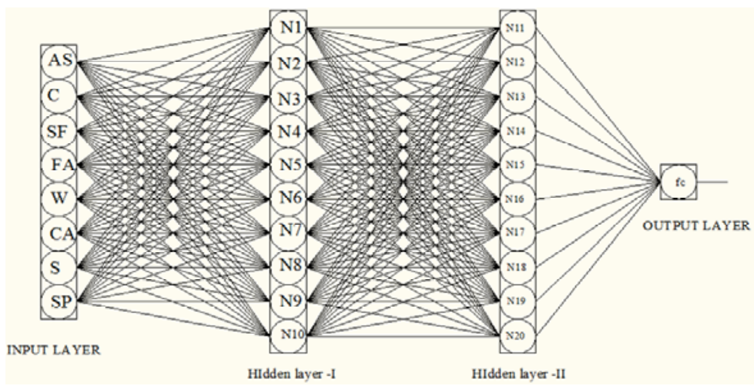

Figure 3(b). The system used in the ANN-II model

Table 1. The input and output quantities used in ANN models

Input variables	Data used in training and testing the models	
	Minimum	**Maximum**
Age of specimen (day)	3	90
Cement (kg/m^3)	457.53	571.91
Silica fume (kg/m^3) & Metakaolin	0	57.16
Fly ash (kg/m^3)	0	57.16
Water (l)	171.47	171.47
Sand (kg/m^3)	566.82	609.72
Aggregate (kg/m^3)	1171.80	1171.80
Superplasticizer (l/m^3)	6.97	17.19
Output variable		
Compressive strength (MPa) for SF	30.8534	75.8197
Compressive strength for Mk	30.6992	79.7649

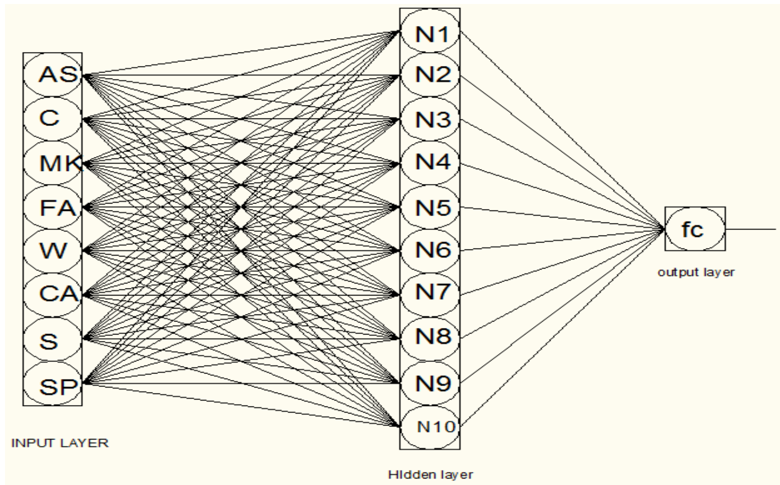

Figure 4(a). The system used in the ANN-II model

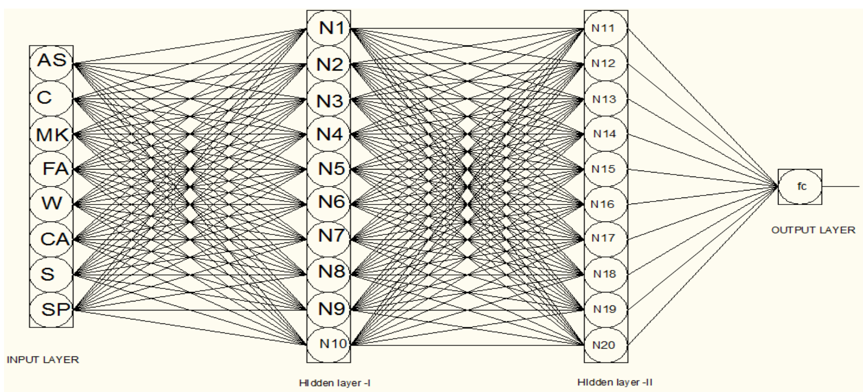

Figure 4(b). The system used in the ANN-II model

Table 2. The values of parameters used in models

Parameters	ANN-I	ANN-II
Number of input layer neurons	8	8
Number of hidden layer	1	2
Number of first hidden layer neurons	10	10
Number of second hidden layer neurons	20	20
Number of output layer neurons	1	1
Momentum rate	0.7	0.7
Learning rate	0.3	0.3
Error after learning	0.00100	0.000125
Learning cycle	5000	5000

6. RESULTS AND DISCUSSION

In this study, the error arose during the training and testing in ANN-I and ANN-II models can be expressed as a root-meansquared (RMS) error and is calculated by Eq. (7) [10,11]

$$\text{RMS}=\sqrt{\frac{1}{p}\sum_i \left|t_i - o_i\right|^2} \tag{7}$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are calculated by Eqs. (8) and (9), respectively [10,11,22,23]

$$R^2=1-\left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right), \tag{8}$$

$$\text{MAPE}=\left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \tag{9}$$

Here t is the target value, o is the output value, p is the pattern. In the training and testing of ANN-I and ANN-II models, various experimental data from two different sources are used. In the ANN-I and ANN-II models, 70% data of experiment results were used for training whereas 15% ones were employed for testing. All results, obtained from experimental studies and predicted by using the training and testing results of ANN I and ANN II models, for 3, 7, 28, 56, and 90 days f_c were given in Figures 5 and 6 respectively. The linear least square fit line, its equation and the R^2 values were shown in these figures for the training and testing data. Also, inputs values and experimental results with testing results obtained from ANN-I and ANN-II models were given in Table 3,4,5 and 6. The results obtained for durability studies are presented in Tables 7 to 16. From the Figures 5 and 6, it is found that the values obtained from the training and testing in ANN-I and ANN-II models are very closer to the experimental results. The result of testing phase in Figures 5 and 6 shows that the ANN-I and ANN-II models are capable of generalizing between input and output variables with reasonably good predictions. The performance of the ANN-I and ANN-II models for fc is shown in Figures 5 and 6, respectively. The statistical values for all the station such as RMS, R^2 and MAPE, both training and testing, are given in Table 17 to 20. While the statistical values of RMS, R^2 and MAPE from training in the ANN-I model were found as 2.1422, 99.12% and 1.8514%, respectively, these values were found in testing as 2.2551, 99.01% and 0.4287%, respectively. Similarly, while the statistical values of RMS, R^2 and MAPE from training in the ANN-II model were found as 4.4043, 99.65% and 3.7135%, respectively, these values were found in testing as 4.7382, 94.99% and 3.3920%, respectively. The best value of R^2 is 99.65% for training set in the ANN-II model. The minimum value of R^2 is 99.01% for testing set in the ANN-I model. All of the statistical values in Tables 17 to 20. shows that the proposed ANN-I and ANN-II models are suitable and predict the 3, 7, 28, 56, and 90 days fc values very close to the experimental values.

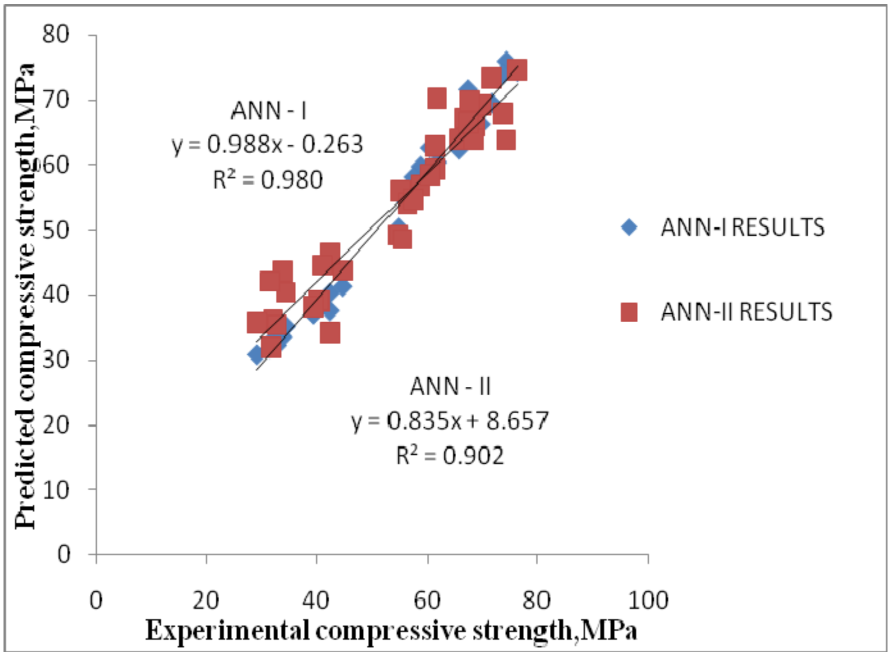

Figure 5. Comparison of f_c experimental results with predicted results

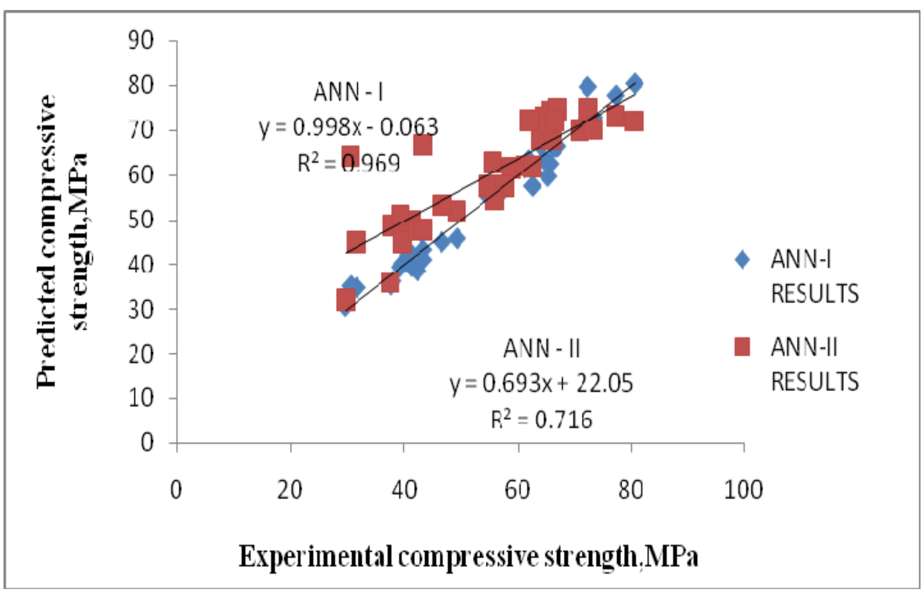

Figure 6. Comparison of f_c experimental results with predicted results

Table 3. Testing data sets for comparison of experimental results with testing results predicted from models (0.3w/b)

Data used in models construction								Compressive strength (MPa)			
AS (day)	C (kg/m^3)	SF (kg/m^3)	FA (kg/m^3)	W (kg/m^3)	CA (kg/m^3)	S (kg/m^3)	SP (l/m^3)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	171.47	1171.8	609.72	6.97	35.67	37.1806	35.6700	-4.23493
3	543.31	28.58	0	171.47	1171.8	599.81	8.83	32	35.1726	32.0000	-9.91438
3	529.01	42.87	0	171.47	1171.8	594.58	9.23	34.33	36.5486	38.1858	-6.46257
3	514.72	57.16	0	171.47	1171.8	589.35	9.75	32.67	32.3999	32.6700	0.826752
3	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	33.67	33.1987	33.6700	1.399762
3	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	31.33	32.7407	31.3300	-4.50271
3	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	29	30.6062	29.0000	-5.53862
7	571.19	0	0	171.47	1171.8	609.72	6.97	42.33	40.5497	42.3300	4.205764
7	543.31	28.58	0	171.47	1171.8	599.81	8.83	40.67	39.9614	38.0635	1.742316
7	529.01	42.87	0	171.47	1171.8	594.58	9.23	44.67	42.1719	44.6700	5.592344
7	514.72	57.16	0	171.47	1171.8	589.35	9.75	40.33	38.2956	38.7379	5.044384
7	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	42.33	38.2867	42.3300	9.551854
7	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	41	38.2146	40.7288	6.793659
7	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	39.33	36.1621	39.3300	8.054666
28	571.19	0	0	171.47	1171.8	609.72	6.97	54.67	55.3674	54.6700	-1.27565
28	543.31	28.58	0	171.47	1171.8	599.81	8.83	55	57.9681	55.0000	-5.39655
28	529.01	42.87	0	171.47	1171.8	594.58	9.23	61.33	61.8237	61.3300	-0.80499
28	514.72	57.16	0	171.47	1171.8	589.35	9.75	56.33	55.8945	54.2256	0.773123
28	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	58.67	59.8254	58.6700	-1.96932
28	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	57.33	58.0191	57.3300	-1.20199
28	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	55.33	55.0602	55.3300	0.48762
56	571.19	0	0	171.47	1171.8	609.72	6.97	61.33	61.2641	61.3300	0.107451
56	543.31	28.58	0	171.47	1171.8	599.81	8.83	61.67	62.4786	67.8248	-1.31117
56	529.01	42.87	0	171.47	1171.8	594.58	9.23	69.67	68.4972	69.6700	1.683364
56	514.72	57.16	0	171.47	1171.8	589.35	9.75	65.67	65.6221	62.0506	0.07294
56	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	68.67	67.1433	68.6700	2.223242
56	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	68.33	61.2353	67.5019	10.38299
56	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	60.33	60.8411	60.3300	-0.84717
90	571.19	0	0	171.47	1171.8	609.72	6.97	66.67	66.5322	66.6700	0.20669
90	543.31	28.58	0	171.47	1171.8	599.81	8.83	67.67	67.9173	67.6700	-0.36545
90	529.01	42.87	0	171.47	1171.8	594.58	9.23	76.33	71.4487	76.3300	6.394995
90	514.72	57.16	0	171.47	1171.8	589.35	9.75	71.67	72.0549	71.6700	-0.53704
90	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	74.33	74.3562	78.7473	-0.03525
90	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	73.67	73.4628	76.8461	0.281254
90	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	67.33	75.5732	67.3300	-12.243

Table 4. Testing data sets for comparison of experimental results with testing results predicted from models (0.3w/b)

Data used in models construction								Compressive strength (MPa)			
AS (day)	C (kg/m^3)	MK (kg/m^3)	FA (kg/m^3)	W (kg/m^3)	CA (kg/m^3)	S (kg/m^3)	SP (l/m^3)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	171.47	1171.8	609.72	6.97	31.67	34.7699	44.9089	-9.78813
3	543.31	28.58	0	171.47	1171.8	599.81	8.83	38	36.1983	48.5502	4.741316
3	529.01	42.87	0	171.47	1171.8	594.58	9.23	41	42.6622	49.7599	-4.05415
3	514.72	57.16	0	171.47	1171.8	589.35	9.75	39.67	40.2548	44.8524	-1.47416
3	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	29.67	30.6992	31.9423	-3.46882
3	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	41.33	39.5046	49.6930	4.416647
3	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	30.67	35.1654	64.2075	-14.6573
7	571.19	0	0	171.47	1171.8	609.72	6.97	42.33	38.5616	47.7150	8.902433
7	543.31	28.58	0	171.47	1171.8	599.81	8.83	39.33	39.4298	50.9818	-0.25375
7	529.01	42.87	0	171.47	1171.8	594.58	9.23	49.33	45.7944	51.9690	7.167241
7	514.72	57.16	0	171.47	1171.8	589.35	9.75	43.33	43.3153	47.7649	0.033926
7	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	37.67	35.4088	35.8681	6.002655
7	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	46.67	44.9872	53.2351	3.605742
7	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	43.33	41.0843	66.6270	5.182783
28	571.19	0	0	171.47	1171.8	609.72	6.97	54.67	55.6254	57.4813	-1.74758
28	543.31	28.58	0	171.47	1171.8	599.81	8.83	55.67	56.5992	62.7938	-1.66912
28	529.01	42.87	0	171.47	1171.8	594.58	9.23	59	61.4769	61.5164	-4.19814
28	514.72	57.16	0	171.47	1171.8	589.35	9.75	57.67	56.8890	57.4781	1.354257
28	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	56	57.6097	54.5571	-2.87446
28	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	64	66.7489	68.0191	-4.29516
28	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	55.67	52.6241	64.0402	4.638191
56	571.19	0	0	171.47	1171.8	609.72	6.97	61.33	61.5902	61.9474	-0.42426
56	543.31	28.58	0	171.47	1171.8	599.81	8.83	64.67	63.6546	72.8006	1.570125
56	529.01	42.87	0	171.47	1171.8	594.58	9.23	66.33	66.4007	67.8888	-0.10659
56	514.72	57.16	0	171.47	1171.8	589.35	9.75	62.67	57.5247	61.7325	8.210148
56	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	65.33	59.6996	71.5947	8.618399
56	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	67	66.5104	74.7460	0.730746
56	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	62	63.4232	72.2025	-2.29548
90	571.19	0	0	171.47	1171.8	609.72	6.97	66.67	66.3562	72.0829	0.470676
90	543.31	28.58	0	171.47	1171.8	599.81	8.83	72.33	72.5650	70.3067	-0.3249
90	529.01	42.87	0	171.47	1171.8	594.58	9.23	77.33	77.8410	73.1089	-0.6608
90	514.72	57.16	0	171.47	1171.8	589.35	9.75	71	70.8850	69.9708	0.161972
90	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	73.33	72.9947	70.1241	0.457248
90	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	80.67	80.5015	72.0714	0.208876
90	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	72.33	79.7649	74.6988	-0.1027

Table 5. Testing data sets for comparison of experimental results with testing results predicted from models (0.32w/b)

Data used in models construction								Compressive strength (MPa)			
AS (day)	C (kg/m^3)	SF (kg/m^3)	FA (kg/m^3)	W (kg/m^3)	CA (kg/m^3)	S (kg/m^3)	SP (l/m^3)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	182.90	1171.8	609.72	6.97	41	39.8121	40.9077	2.897317
3	543.31	28.58	0	182.90	1171.8	599.81	8.83	42	40.9684	41.9668	2.45619
3	529.01	42.87	0	182.90	1171.8	594.58	9.23	43	48.5766	40.2898	-12.9688
3	514.72	57.16	0	182.90	1171.8	589.35	9.75	39	41.1020	39.0706	-5.38974
3	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	38	41.3959	38.0398	-8.93658
3	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	36.5	41.0693	36.4176	-12.5186
3	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	34.5	39.5496	34.1566	-14.6365
7	571.19	0	0	182.90	1171.8	609.72	6.97	42.33	41.1472	43.3135	2.794236
7	543.31	28.58	0	182.90	1171.8	599.81	8.83	40.67	42.3729	44.7696	-4.18712
7	529.01	42.87	0	182.90	1171.8	594.58	9.23	44.67	49.3674	44.6781	-10.5158
7	514.72	57.16	0	182.90	1171.8	589.35	9.75	44.33	42.2562	44.3331	4.678096
7	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	42.33	46.1976	38.9734	-9.13678
7	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	41	45.8415	41.5603	-11.8085
7	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	39.33	44.2249	40.7892	-12.4457
28	571.19	0	0	182.90	1171.8	609.72	6.97	61	59.7935	60.4818	1.977869
28	543.31	28.58	0	182.90	1171.8	599.81	8.83	63	60.8687	63.0685	3.383016
28	529.01	42.87	0	182.90	1171.8	594.58	9.23	66	66.0386	67.5261	-0.05848
28	514.72	57.16	0	182.90	1171.8	589.35	9.75	60	61.2055	63.6606	-2.00917
28	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	57	61.8216	49.9294	-8.45895
28	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	64	61.7973	63.3652	3.441719
28	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	67	61.9203	66.2662	7.581642
56	571.19	0	0	182.90	1171.8	609.72	6.97	66	70.6058	65.9877	-6.97848
56	543.31	28.58	0	182.90	1171.8	599.81	8.83	68	67.5857	72.5078	0.609265
56	529.01	42.87	0	182.90	1171.8	594.58	9.23	73.5	73.2627	76.5833	0.322857
56	514.72	57.16	0	182.90	1171.8	589.35	9.75	65	71.3565	64.9618	-9.77923
56	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	64	69.7872	63.9073	-9.0425
56	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	69	69.9256	69.4009	-1.34145
56	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	72.5	70.0845	72.2466	3.331724
90	571.19	0	0	182.90	1171.8	609.72	6.97	66.67	67.3017	66.8701	-0.9475
90	543.31	28.58	0	182.90	1171.8	599.81	8.83	67.67	70.8083	66.9610	-4.63765
90	529.01	42.87	0	182.90	1171.8	594.58	9.23	76.33	76.0160	75.8728	0.411372
90	514.72	57.16	0	182.90	1171.8	589.35	9.75	71.67	73.3761	71.5011	-2.38049
90	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	74.33	73.6580	68.8911	0.904076
90	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	73.67	73.6901	73.0228	-0.02728
90	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	67.33	73.2255	72.0396	-8.75613

Table 6. Testing data sets for comparison of experimental results with testing results predicted from models (0.32w/b)

Data used in models construction								Compressive strength (MPa)			
AS (day)	**C (kg/m^3)**	**MK (kg/m^3)**	**FA (kg/m^3)**	**W (kg/m^3)**	**CA (kg/m^3)**	**S (kg/m^3)**	**SP (l/m^3)**	**Experimental results**	**ANN-I**	**ANN-II**	**% Error**
3	571.19	0	0	182.90	1171.8	609.72	6.97	41	39.5607	38.5920	3.510488
3	543.31	28.58	0	182.90	1171.8	599.81	8.83	42.4	48.9336	45.8287	-15.4094
3	529.01	42.87	0	182.90	1171.8	594.58	9.23	46	50.8648	49.4082	-10.5757
3	514.72	57.16	0	182.90	1171.8	589.35	9.75	44.5	44.8786	40.6819	-0.85079
3	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	43	43.9120	44.7331	-2.12093
3	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	47.5	50.3154	44.5809	-5.92716
3	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	46.2	48.4570	45.5674	-4.88528
7	571.19	0	0	182.90	1171.8	609.72	6.97	42.33	43.1016	41.9701	-1.82282
7	543.31	28.58	0	182.90	1171.8	599.81	8.83	55.35	52.6207	48.9622	4.930985
7	529.01	42.87	0	182.90	1171.8	594.58	9.23	57.5	54.8136	53.0566	4.672
7	514.72	57.16	0	182.90	1171.8	589.35	9.75	56.63	47.8480	46.0619	15.50768
7	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	54.5	46.6720	49.2148	14.3633
7	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	58.1	53.8550	48.2915	7.306368
7	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	54.05	51.3431	47.8876	5.008141
28	571.19	0	0	182.90	1171.8	609.72	6.97	61	59.7119	56.6797	2.111639
28	543.31	28.58	0	182.90	1171.8	599.81	8.83	63.7	65.1722	60.2211	-2.31115
28	529.01	42.87	0	182.90	1171.8	594.58	9.23	67	66.5070	65.4213	0.735821
28	514.72	57.16	0	182.90	1171.8	589.35	9.75	65.2	62.2260	63.3655	4.56135
28	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	66	59.9868	67.1228	9.110909
28	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	68.5	67.3223	65.6470	1.71927
28	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	64.8	64.5692	59.1054	0.356173
56	571.19	0	0	182.90	1171.8	609.72	6.97	66	66.5495	67.4413	-0.83258
56	543.31	28.58	0	182.90	1171.8	599.81	8.83	70	71.0091	68.4202	-1.44157
56	529.01	42.87	0	182.90	1171.8	594.58	9.23	72.95	74.2301	74.1683	-1.75476
56	514.72	57.16	0	182.90	1171.8	589.35	9.75	69	74.5866	72.0435	-8.09652
56	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	70.42	71.5630	68.4062	-1.62312
56	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	74	72.5775	70.8677	1.922297
56	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	71.5	71.9113	71.9234	-0.57524
90	571.19	0	0	182.90	1171.8	609.72	6.97	66.67	66.7330	66.4152	-0.0945
90	543.31	28.58	0	182.90	1171.8	599.81	8.83	72.33	70.4433	69.8030	2.608461
90	529.01	42.87	0	182.90	1171.8	594.58	9.23	77.33	71.7324	74.5534	7.238588
90	514.72	57.16	0	182.90	1171.8	589.35	9.75	71	72.5326	72.0904	-2.15859
90	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	73.33	74.8022	73.2528	-2.00764
90	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	80.67	79.2472	67.9087	1.763729
90	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	72.33	85.9765	67.8394	-18.867

Table 7. Results of saturated water absorption for silica fume with fly ash

Data used in models construction								Water absorption			
AS (day)	C (kg/m^3)	SF (kg/m^3)	FA (kg/m^3)	W (kg/m^3)	CA (kg/m^3)	S (kg/m^3)	SP (l/m^3)	Water absorption % in 24 Hrs	ANN-I	ANN-II	%Error
28	571.19	0	0	171.47	1171.8	609.72	6.97	3.36	3.3600	3.4815	0
28	543.31	28.58	0	171.47	1171.8	599.81	8.83	3.18	3.1800	3.2644	0
28	529.01	42.87	0	171.47	1171.8	594.58	9.23	1.63	1.7561	2.8811	-7.7362
28	514.72	57.16	0	171.47	1171.8	589.35	9.75	2.78	2.5837	2.7330	7.0611
28	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	3.53	3.5300	3.4701	0
28	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	1.72	1.7200	2.7810	0
28	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	2.27	2.2700	2.3090	0

Table 8. Results of saturated water absorption for metakaolin with fly ash

Data used in models construction								Water absorption			
AS (day)	C (kg/m^3)	SF (kg/m^3)	FA (kg/m^3)	W (kg/m^3)	CA (kg/m^3)	S (kg/m^3)	SP (l/m^3)	Water absorption % in 24 Hrs	ANN-I	ANN-II	% Error
28	571.19	0	0	171.47	1171.8	609.72	6.97	3.41	3.1957	5.1155	6.284457
28	543.31	28.58	0	171.47	1171.8	599.81	8.83	3.17	2.7009	3.3805	14.79811
28	529.01	42.87	0	171.47	1171.8	594.58	9.23	1.25	2.5000	2.6688	0
28	514.72	57.16	0	171.47	1171.8	589.35	9.75	1.61	1.9233	2.0215	-19.4596
28	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	3.18	3.2458	0.7152	-2.06918
28	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	1.43	1.7142	0.6967	-19.8741
28	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	3.93	3.4068	1.0705	13.31298

Table 9. Results of saturated water absorption for silica fume with fly ash

Data used in models construction				Water absorption			
Replacement percentage of silica fume (%)	Replacement percentage of fly ash (%)	Wet weight (kg)	Dry weight (kg)	Water absorption (%)	ANN-I	ANN-II	% Error
0	0	2.520	2.438	3.36	2.8637	2.9159	14.77083
5	0	2.525	2.447	3.18	3.2307	3.2646	-1.59434
7.5	0	2.561	2.520	1.63	1.5483	3.0382	5.01227
10	0	2.591	2.521	2.78	2.2360	3.4780	13.56835
5	10	2.575	2.487	3.53	1.5896	3.2781	14.96884
7.5	10	2.538	2.495	1.72	1.7279	3.1579	-0.4593
10	10	2.479	2.424	2.27	2.3091	2.2779	-1.72247

Table 10. Results of saturated water absorption for metakaolin with fly ash

Data used in models construction				Water absorption			
Replacement percentage of silica fume (%)	**Replacement percentage of fly ash (%)**	**Wet weight (kg)**	**Dry weight (kg)**	**Water absorption (%)**	**ANN-I**	**ANN-II**	**%Error**
0	0	2.516	2.433	3.41	3.5381	2.4648	-3.7566
5	0	2.533	2.455	3.17	2.9061	3.0562	8.324921
7.5	0	2.597	2.565	1.25	1.5027	1.2350	-20.216
10	0	2.583	2.542	1.61	1.6786	1.6312	-4.26087
5	10	2.565	2.486	3.18	3.9440	3.2883	-24.0252
7.5	10	2.625	2.588	1.43	2.2752	1.4137	-59.1049
10	10	2.587	2.489	3.93	3.4728	3.9435	11.63359

Table 11. Results of porosity for silica fume

Data used in models construction					Water absorption			
Replacement percentage of silica fume (%)	**Replacement percentage of fly ash (%)**	**Dry weight (kg)**	**Saturated weight (kg)**	**Submerged weight (kg)**	**Porosity at 28 days (%)**	**ANN-I**	**ANN-II**	**%Error**
0	0	2.483	2.516	1.3	2.71	2.5807	2.1734	4.771218
5	0	2.497	2.525	1.3	2.29	2.3861	2.1636	-4.19651
7.5	0	2.530	2.561	1.3	2.46	2.3367	2.2673	5.012195
10	0	2.561	2.591	1.3	2.33	2.3036	2.0819	1.133047
5	10	2.546	2.586	1.3	3.11	2.7028	3.1154	13.09325
7.5	10	2.556	2.594	1.3	2.93	2.7763	2.9940	5.245734
10	10	2.596	2.635	1.3	2.92	2.8026	2.9352	4.020548

Table 12. Results of porosity for metakaolin

Data used in models construction					Water absorption			
Replacement percentage of metakaolin (%)	**Replacement percentage of fly ash (%)**	**Dry weight (kg)**	**Saturated weight (kg)**	**Submerged weight (kg)**	**Porosity at 28 days (%)**	**ANN-I**	**ANN-II**	**%Error**
0	0	2.483	2.516	1.3	2.71	3.1233	2.3880	-15.2509
5	0	2.497	2.533	1.3	2.91	2.9318	2.9132	-0.74914
7.5	0	2.565	2.597	1.3	2.47	2.8157	2.4701	-13.996
10	0	2.542	2.583	1.3	3.20	2.9774	3.1992	6.95625
5	10	2.486	2.518	1.3	2.63	2.4371	2.6288	7.334601
7.5	10	2.548	2.598	1.3	3.85	3.6200	3.3315	5.974026
10	10	2.552	2.596	1.3	3.39	3.6146	3.3907	-6.62537

Table 13. Results of acid attack for silica fume

Data used in models construction				Water absorption			
Replacement percentage of silica fume (%)	Replacement percentage of Fly ash (%)	Dry weight (kg)	weight after immersed in acid (kg)	Weight loss (%)	ANN-I	ANN-II	%Error
0	0	2.483	2.395	3.67	3.7881	3.8335	-3.21798
5	0	2.497	2.406	3.78	3.7774	3.7800	0.068783
7.5	0	2.530	2.439	3.73	3.7756	3.7300	-1.22252
10	0	2.561	2.467	3.81	3.8060	3.8100	0.104987
5	10	2.494	2.406	3.65	3.4031	3.6500	6.764384
7.5	10	2.528	2.445	3.39	3.3824	3.3886	0.224189
10	10	2.578	2.492	3.45	3.4369	3.4500	0.37971

Table 14. Results of acid attack for metakaolin

Data used in models construction				Water absorption			
Replacement percentage of metakaolin (%)	Replacement percentage of fly ash (%)	Dry weight (kg)	weight after immersed in acid (kg)	Weight loss (%)	ANN-I	ANN-II	% Error
0	0	2.483	2.395	3.67	3.9136	3.5002	-6.6376
5	0	2.497	2.409	3.65	3.7424	3.6571	-2.53151
7.5	0	2.565	2.494	2.84	3.4389	3.2577	-21.088
10	0	2.542	2.447	3.88	3.3776	3.7775	12.94845
5	10	2.568	2.486	3.29	2.8522	3.2323	13.30699
7.5	10	2.592	2.526	2.61	3.1531	3.6270	-20.8084
10	10	2.496	2.417	3.26	2.5743	3.2783	11.03374

Table 15 Results of permeability coefficient for concrete with mineral admixtures

Replacement percentage (%)	Silica Fume	Silica Fume & 10%Fly ash	Permeability coefficient x 10^{-7} cm/sec ANN-I	Permeability coefficient x 10^{-7} cm/sec ANN-II	% Error
	Permeability coefficient x 10^{-7} cm/sec				
0	7.90	7.90	7.024	7.024	0
5	7.30	7.50	7.2515	7.2515	0
7.5	6.90	7.10	7.3002	7.3002	0
10	6.50	6.60	7.5201	7.5201	0

Table 16. Results of permeability coefficient for concrete with mineral admixtures

Replacement Percentage (%)	**Metakaolin**	**Metakaolin & 10%Fly ash**	**Permeability coefficient x 10^{-7} cm/sec ANN-I**	**Permeability coefficient x 10^{-7} cm/sec ANN-II**	**%EEROR**
	Permeability coefficient x 10^{-7} cm/sec				
0	7.90	7.90	6.9915	7.5352	-0.0777
5	7.30	7.50	7.1926	7.1008	0.0127
7.5	6.90	7.10	7.2100	7.2400	-.00416
10	6.50	6.60	7.3500	7.3600	-0.00136

Table 17. The f_c statistical values of proposed ANN-I and ANN-II models for SF&FA (0.3w/b)

Statistical parameters	**ANN-I**		**ANN-II**	
	Training set	**Testing set**	**Training set**	**Testing set**
RMS	2.1422	2.2551	4.4043	4.7382
R^2	0.9912	0.9901	0.9965	0.9959
MAPE(%)	1.8514	0.4287	3.7135	3.3920

Table 18. The f_c statistical values of proposed ANN-I and ANN-II models for MK & FA (0.3w/b)

Statistical parameters	**ANN-I**		**ANN-II**	
	Training set	**Testing set**	**Training set**	**Testing set**
RMS	1.9982	3.5819	4.4923	3.6969
R^2	0.9904	0.9741	0.8287	0.9796
MAPE(%)	0.0581	1.4067	-17.3529	-2.0698

Table 19. The f_c statistical values of proposed ANN-I and ANN-II models for SF & FA (0.32w/b)

Statistical parameters	ANN-I		ANN-II	
	Training set	Testing set	Training set	Testing set
RMS	6.3148	5.8829	2.1040	2.7107
R^2	0.7534	0.8670	0.9870	0.9916
MAPE(%)	-25.7597	-3.2539	0.4105	4.4001

Table 20. The f_c statistical values of proposed ANN-I and ANN-II models for MK & FA (0.32w/b)

Statistical parameters	**ANN-I**		**ANN-II**	
	Training set	**Testing set**	**Training set**	**Testing set**
RMS	3.2829	4.7340	2.3729	5.1073
R^2	0.9429	0.9820	0.9724	0.8537
MAPE(%)	-11.6970	-2.2939	-1.1138	-9.2574

7. CONCLUSIONS

Artificial neural networks are capable of learning and generalizing from examples and experiences. This makes artificial neural networks a powerful tool for solving some of the complicated civil engineering problems. In this study, using these beneficial properties of artificial neural networks in order to predict the 3, 7, 14, 28, 56, and 90 compressive strength and durability of concretes containing metakaolin and silica fume along with fly ash without attempting any experiments were developed with two different multilayer artificial neural network architectures namely ANN-I and ANN-II. In the two models developed in ANN method, a multilayered feed forward neural network with a back propagation algorithm was used. In ANN-I model, one hidden layer was selected. In the hidden layer 10 neurons were determined. In ANN-II model, two hidden layers were selected. In the first hidden layer ten neurons and in the second hidden layer ten neurons were determined. The models were trained with input and output data. Using only the input data in trained models the 3, 7, 28, 56, and 90 days compressive strength and durability of concretes containing metakaolin and silica fume were found. The compressive strength and durability of concrete values predicted from training and testing, for ANN-I and ANN-II models are very close to the experimental results. Furthermore, according to the compressive strength and durability of concrete results predicted by using ANN-I and ANN-II models, the results of ANN-II model are closer to the experimental results. RMS, R^2 and MAPE statistical values that are calculated for comparing experimental results with ANN-I and ANN-II model results have shown this situation.

As a result, compressive strength values of concretes containing metakaolin and silica fume can be predicted in the multilayer feed forward artificial neural networks models without attempting any experiments in a quite short period of time with tiny error rates. The obtained conclusions have demonstrated that multilayer feed forward artificial neural networks are practicable methods for predicting compressive strength and durability properties like saturated water absorption, porosity, acid resistance and permeability values of concretes containing metakaolin and silica fume.

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