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Predicting the compressive strength of cement mortars containing FA and SF by MLPNN

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Abstract. In this study, a multi-layer perceptron neural network (MLPNN) prediction model for compressive strength of the cement mortars has been developed. For purpose of constructing this model, 8 different mixes with 240 specimens of the 2, 7, 28, 56 and 90 days compressive strength experimental results of cement mortars containing fly ash (FA), silica fume (SF) and FA+SF used in training and testing for MLPNN system was gathered from the standard cement tests. The data used in the MLPNN model are arranged in a format of four input parameters that cover the FA, SF, FA+SF and age of samples and an output parameter which is compressive strength of cement mortars. In the model, the training and testing results have shown that MLPNN system has strong potential as a feasible tool for predicting 2, 7, 28, 56 and 90 days compressive strength of cement mortars.

Keywords: multi-layer perceptron neural network; cement; silica fume; fly ash; compressive strength

1. Introduction

During the previous decades, enormous researchers evaluated the effects of the partial replacement of cement by various types of additions that improve cement properties have been used in the cement. The most frequently used additions are fly ash, silica fume, blast furnace slag, trass, burned clay, zeolite, volcanic tuff and metakaolin (Behnood and Ziari 2008, Kocak 2010). Because of economic, technical and environmental considerations, additional cementitious materials have become very common usage in cement and concrete technology (Fu *et al.* 2002, Subasi 2009, Worrell *et al.* 2000). These cement materials consist of silica fume and fly ash.

Silica fume is produced from the reduction of high-purity quartz with coal in electric arc furnaces in the manufacture of ferrosilicon alloys and silicon metal (Neville 2006). Silica fume is used in two different ways as a cement replacement in order to reduce the cement and an additive to improve concrete properties (Nochaiya *et al.* 2010). The silica fume can result in matrix expansion due to the alkali–silicate reactions (Maas *et al.* 2007). While the resistance of concrete

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against corrosion is increasing, the permeability of silica fume is decreasing (Jo *et al.* 2007, Qing *et al.* 2007). Furthermore, contributes to cement and concrete mortars compressive strength and durability (Song *et al.* 2010).

Fly ash is a by-product of coal-fired electric power plants. It is separated from the flue gas of the power station burning pulverized coal. According to ASTM C618, two general classes of fly ash can be defined: low-calcium fly ash (class F) and high-calcium fly ash (class C). Its physical and chemical properties rely on the used coal quality and on burning conditions (Behnood and Ziari 2008). Fly ash is added to Portland cement or directly to mortars or concretes. There are a number of purposes to use of fly ash as a replacement addition to cement in production (Aruntas 2006). It lowers the heat of hydration and improves the durability and blocks the alkali-silicate reactions when used in concrete as a cement replacement. It also contributes to cement and concrete mortars compressive strength by filler effects and pozzolanic (Saraswathy *et al.* 2003, Neville 2006). In addition, fly ash use partially displaces production of other concrete ingredients, resulting in significant energy savings, reductions in CO_2 emission, conserving resources (Saridemir 2009). Moreover, fly ash makes substantial contributions to workability and chemical resistance (Garces *et al.* 2010, Wang *et al.* 2008).

Over the last two decades, artificial neural network (ANN) has become popular and has been used by many researchers to solve a wide variety of problems in civil engineering applications. Saridemir (2009) build models two different architectures in ANN system. This model evaluated the effect of metakaolin and silica fume on compressive strength of concrete. In training and testing of ANN system are used 33 different mixtures with 195 specimens of the 1, 3, 7, 28, 56, 90 and 180 days compressive strength results of concretes containing metakaolin and silica fume. Input variables are the age of specimen, cement, metakaolin, silica fume, water, sand, aggregate and super plasticizer; output variable is compressive strength values. The models were trained with 130 data of experimental results and the rest of them were used for testing. The results in the neural network models have shown strong potential for predicting (Saridemir 2009). Ozcan *et al.* (2009) were studied both an ANN and fuzzy logic model for prediction the compressive strength of silica fume concrete. The ANN model consists of one hidden layer which performed using the available test data of 240 different concrete mix-designs. The ANN and fuzzy logic models had six input variables and one output variable. Both ANN and fuzzy logic model results can be used alternative methods for the predicting of compressive strength of silica fume concrete (Ozcan *et al.* 2009). The ANN model generally focused on concrete and cement mortars properties such as workability, mechanical behavior and physical properties in civil engineering application (Ahmaruzzaman 2010, Subasi 2009, Yaprak *et al.* 2013, Topcu *et al.* 2009, Topcu and Saridemir 2008, Atici 2011, Ashrafi Jalal and Garmsiri 2010).

The aim of this study is to build model in a multi-layer perceptron neural network (MLPNN) system to evaluate the effect of FA and SF on compressive strength of cement mortars. The MLPNN is selected which is a special form of ANN with multiple layers. For purpose of constructing this model, 8 different mixes with 240 specimens of the 2, 7, 28, 56 and 90 days compressive strength experimental results of cement mortars containing FA, SF and FA+SF used in training and testing for MLPNN system were gathered from the standard cement tests. The model was trained with 180 data of experimental results. The MLPNN model had four input parameters and one output parameter. The obtained results from compressive strength tests were compared with predicted results.

2. Experimental study

In this study, the PC, FA, SF standard aggregate and water were used as raw materials. The PC was CEM I 42.5 R in accordance with TS EN 197-1. The PC was provided by Bursa Cement Plant; (Turkey). The FA was participated in the production of this cement as minor additional components. The FA and the SF were obtained from Seyitomer Thermal power plant in Kutahya (Turkey) and Antalya Etibank (Turkey) elektro-ferrochrome business, respectively. The CEN standard aggregate that was prepared by SET Trakya Cement industry with TS EN 196-1 and Bursa-Kestel province tap water were prepared in the cement mortars.

The PC being the reference is prepared a total of eight different mixtures in the study. By keeping constant weight, the amount of PC is reduced amount of FA by 10, 20 and 30% of the total weight. Similarly for SF, the amount of PC is reduced by 5 and 10% of the total weight. By investigating the properties of ternary mixtures, the amount of PC is reduced by 10 and 20% of the total weight. On the other hand, the amounts of FA and SF are substituted equally.

The samples used in the experiments are analysed for chemical and physical properties. Chemical analyses are achieved on ARL 9900 X-ray workstation (XRF+XRD). Surface areas are evaluated as Blaine values by Toni Technik 6565 Blaine and specific weights are measured by Quantachrome MVP-3. The chemical composition of PC, FA and SF were shown in Table 1. The physical properties of PC, FA, SF and cements were presented in Table 2.

In the preparation of cement mortar mixtures for compressive strength experiments, 450 g of PC, 1350 g of standard sand and 225 ml of water are used in each mortar mixture according to TS EN 196-1 and mixed in mortar mixer machine. Prepared cement mortars are poured into three-segmented rectangular prism moulds of size 40x40x160 mm. Prepared samples are waited in the laboratory for 24 hours. At the end of 24-hour period, the samples are taken out of the moulds and waited in water pools to get cured and prepared for the compressive strength experiments. Compressive strength of each cement mortar is measured at the end of 2, 7, 28, 56 and 90 days using Atom Technik device.

Table 1 Chemical composition of PC, FA and SF

Materials	PC, %	FA, %	SF, %
Chemical composition: wt.%			
SiO_2	21.82	53.39	78.50
Al_2O_3	6.49	16.07	1.22
Fe_2O_3	1.93	13.05	1.27
CaO	60.74	6.33	2.13
MgO	1.08	5.48	5.32
SO_3	2.62	1.06	0.15
Na_2O	0.14	1.59	1.78
K_2O	0.65	1.71	4.11
Cl^-	0.012	0.005	0.036
Loss on ignition (LOI)	1.65	1.15	4.93
Free CaO	0.84	0.11	-
Reactive SiO_2	-	45.18	76.2

Table 2 Physical properties of PC, FA, SF and cements

Mixtures	Range dimension (over sieve), %		Specific gravity, g/cm^3	Blaine, cm^2/g
	> 90 μm	> 45 μm		
PC	1.0	8.6	3.09	3830
FA	7.0	32	2.02	4890
SF	-	0.7	2.43	22310
10FA	1.6	10	2.88	3880
20FA	2.4	11.4	2.73	3900
30FA	3.4	14.8	2.59	4050
5SF	1.0	8.5	3.00	4700
10SF	0.9	8.2	2.98	5740
5FA5SF	1.5	10	2.93	4790
10FA10SF	1.4	12.6	2.85	5650

3. Artificial neural network

Artificial neural network **(**ANN) consisted of an arbitrary number of simple elements called neurons. Neurons in ANN are, as similar in human brains, interconnected (Adhikary and Mutsuyoshi 2006). ANN represents simplified methods of a human brain and uses new methods to solve problems rather than conventional methods with traditional computations which have difficult solution procedures (Trtnik *et al.* 2009). The simple ANN model layers are contained an input layer, one or more hidden layers and output layer. The two layers are fully interconnected by weight. The input layer neurons collect information from the outside environment and this information transfers to the neurons of first hidden layer without carrying out any calculation. Layers between the input and output layers are named hidden layers and may consist of a large number of hidden layer units. For some problems, which can be solved by a perceptron, it can be used with only one hidden layer. But it is sometimes more efficient to use two hidden layers. The output layer is generated the network predictions to the outside world (Demir 2008).

The typical neural network is consisted of blocks scheme such as inputs, weights, sum function, activation function and outputs (Fig. 1) (Topcu *et al.* 2008, Parichatprecha and Nimityongskul 2009).

Then, every input is multiplied by the corresponding weight of the neuron connection. The bias (b) is defined as a type of connection weight with a constant nonzero value. It is added to the summation of inputs. The weighted sums of the input components $(net)_j$ are calculated by using Eq. (1)

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

where (net)j is the weighted sum of the j_{th} neuron for the input received from the proceeding layer with n neurons, w_{ij} is the weight between the j_{th} neuron in the proceeding layer, o_i is the output of the i_{th} neuron in the proceeding layer (Topcu *et al.* 2008). Activation function is a function that processes the net input obtained from sum function and determines the neuron output. In general, the activation function for multilayer feed forward models is determined as the $(f\,(net)_j)$ sigmoid activation function. The output of the j_{th} neuron $(out)_j$ is computed by using Eq. (2) with a sigmoid activation function (Topcu *et al.* 2009)

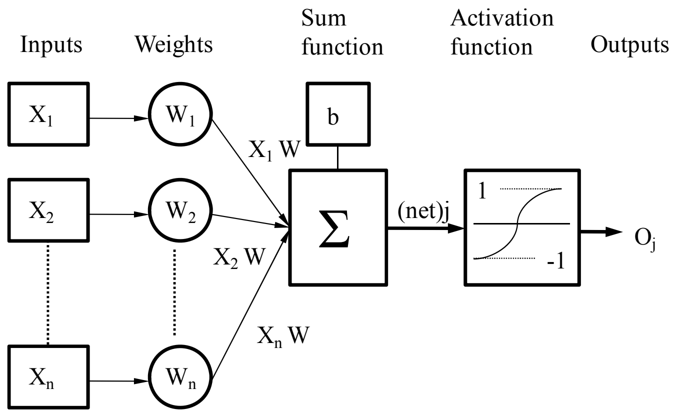

Fig. 1 The artificial neuron model

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

where α is constant which is used to control the slope of the semi-linear region. The sigmoid activates nonlinearity in every layer except in the input layer. The sigmoid function is represented by Eq. (2) and gives outputs between 0 and 1. When it is desired, the outputs of this function can be adjusted to between -1 and 1. If the sigmoid function represents a continuous function, it is specially used non-linear descriptions. Thus, derivatives can be determined easily with respect to the parameters within $(net)_j$ variable (Topcu *et al.* 2009).

4. Multi-layer perceptron neural network model and parameters

For training and testing of the neural network model, input variables were selected the age of samples, Portland cement (PC), fly ash (FA) and silica fume (SF). Similarly, output variable was selected compressive strength values of cement mortars (Table 3). In this study, it was used 180 and 60 of the experimental specimens for the training and the testing of ANN model, respectively.

The input and output variables are normalized between 0.1 and 0.9 by using Eq. (3).

$$x'' = \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right)0.8 + 0.1 \tag{3}$$

where x'' is normalized value, x is value to be normalized, $x_{\min}$ and $x_{\max}$ values minimum and maximum value in the data set, respectively.

The ANN model consists of feed-forward back propagation, two hidden layers, training function (Levenberg-Marquardt), adaptation learning function (learngdm), transfer function (tansig) and performance function (MSE-mean squared error) as demonstrated in Fig. 2.

This ANN model is called as a multi-layer perceptron (MLPNN). The neurons are 10 and 1 at the first and the second layers in the system, respectively. Momentum and learning rate values were determined and the MLPNN model was trained according to the MSE through iterations. The parameter values obtained from the MLPNN model were given in Table 4.

The trained model was tested only with the input values and the predicted results were close to the experimental results. The weights and bias values for our developed model were given in Table 5.

Table 3 The input and output quantities used in MLPNN model

		Data used in training and testing the model	
		Minimum	Maximum
Input variables	Age of samples (days)	2	90
	PC, g	315	450
	FA, g	0	135
	SF, g	0	45
Output variable	Compressive strength (MPa)	11.4	63

Table 4 The values of parameters used in models

Parameters	MLPNN
Number of input layer neurons	4
Number of hidden layer	2
Number of first hidden layer neurons	10
Number of second hidden layer neurons	10
Number of output layer neuron	1
Error after learning	$2.54x10^{-3}$
Learning cycle	32

Table 5 Weight and bias values for model

For hidden layer 1 to input layer										
Weights	1.785	1.848	-1.540	1.681	1.671	-1.348	-1.608	-0.499	2.064	2.281
	-1.953	1.143	1.280	0.119	0.983	-1.268	-0.680	2.213	0.878	0.968
	1.128	-1.146	1.345	1.268	1.116	1.117	1.588	-0.399	0.534	-0.608
	0.500	-1.422	-0.646	-1.990	-1.669	1.161	0.974	-1.492	1.551	-1.274
Bias	-2.172	-1.714	1.734	-0.320	-0.230	-0.905	-0.206	1.325	1.675	2.454
For hidden layer 2 to hidden layer 1										
Weights	0.009	-0.811	0.779	0.591	-0.496	0.649	0.448	0.002	0.551	0.677
	-0.208	0.078	0.043	-0.901	-0.627	-0.431	1.559	-0.524	-0.311	-0.784
	0.098	-0.045	0.275	0.879	0.626	1.283	-0.118	-0.334	-0.686	-0.485
	0.856	0.822	0.758	-0.305	0.465	-1.197	-0.672	0.058	0.958	-0.686
	-0.466	1.183	0.246	0.818	0.604	-1.084	0.489	1.176	0.572	-0.348
	-1.236	-0.829	0.045	0.770	0.772	-0.062	0.175	0.238	-0.843	-0.224
	-0.805	0.867	-0.415	0.321	-0.417	0.659	-0.647	0.337	-0.182	0.501
	-0.588	-0.860	-0.535	0.998	-0.513	0.278	-0.261	1.068	-1.257	-0.299
	-0.782	1.395	-0.831	-0.341	0.378	0.631	-0.773	-0.553	-1.971	0.560
	-0.102	1.677	-0.928	-0.248	-0.506	-1.122	0.657	0.260	0.024	-0.809
Bias	1.402	1.619	-0.775	-0.163	0.223	-0.074	-0.552	1.210	1.822	1.875
For output layer to hidden layer 2										
Weights	0.340									
	1.474									
	-0.664									
	0.246									
	-0.421									
	-1.163									
	0.016									
	-1.071									
	-1.107									
	-0.195									
Bias	-0.986									

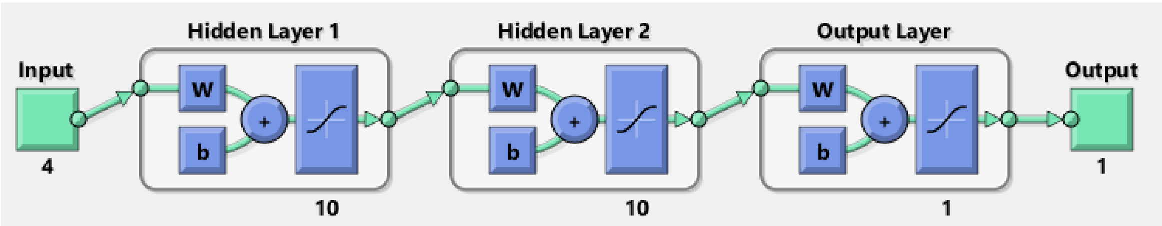

Fig. 2 The architecture used in the neural network model for compressive strength

5. Results and discussion

Multilayer feedforward network models which contain one and two hidden layers are used in order to find more reliable solutions. Determination of optimum number of the hidden layers neurons are very important to accurately predict the parameters used by MLPNN. To find an optimum number of hidden layers, one of the best approaches starts a few numbers of neurons and then slightly increases the number of neurons. This process continues until the selected performance a criterion is observed for each hidden layer neurons.

In this study, this model uses different neurons in the two hidden layers at the beginning of the process. Then, the neuron number was increased step-by-step adding 1 neuron until no significant improvement is noticed. The MLPNN models and experimental data compared to calculating the absolute fraction of variance (R^2), mean absolute percentage error (MAPE) and a root-mean squared (RMS) error criteria. These criteria are defined by Eqs. (4)-(6) (Ozcan *et al.* 2009).

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|t_{i\_}o_i\right|^2} \tag{4}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(o_i)^2}\right) \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \tag{6}$$

where ***t*** is the target value, ***o*** is the network output value and ***N*** is the total number of pattern.

In the MLPNN model, 180 data of experiment results were used for training whereas 60 ones were employed for testing. The experimental results and results obtained from MLPNN model for training were given in Fig. 3. Similarly, the experimental results and results obtained from MLPNN model for testing were seen in Fig. 4.

The inputs values, experimental results and results which were obtained from MLPNN model for testing were given in Table 6.

For 2, 7, 28, 56 and 90 days compressive strength, the results of the compared values from the experimental studies and predicted values of MLPNN model for the training were given in Fig. 5. Similarly, testing process results were shown in Fig. 6.

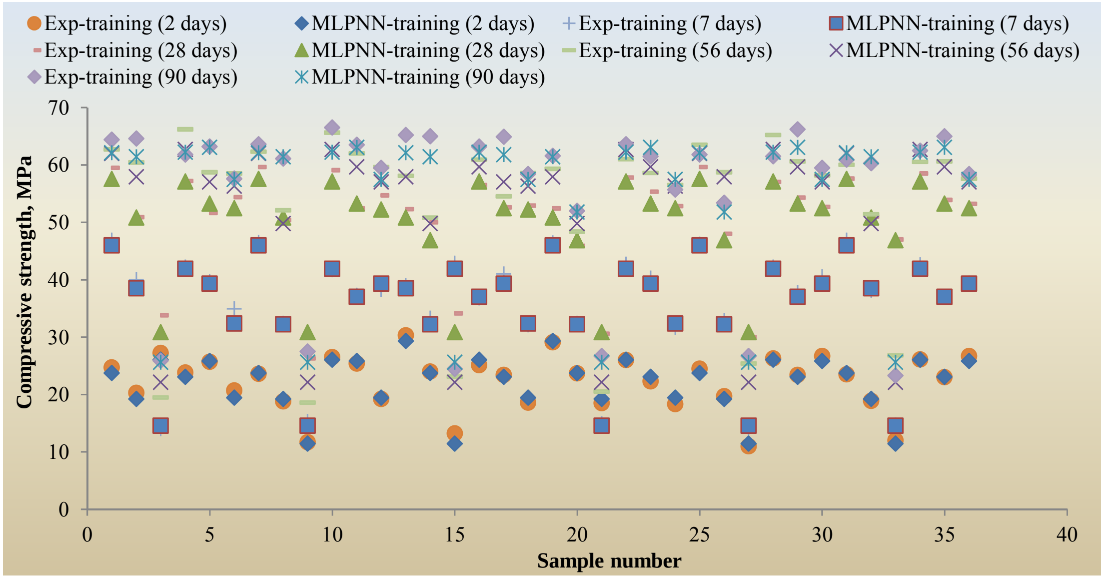

Fig. 3 Comparison of compressive strength experimental and training results with sample number

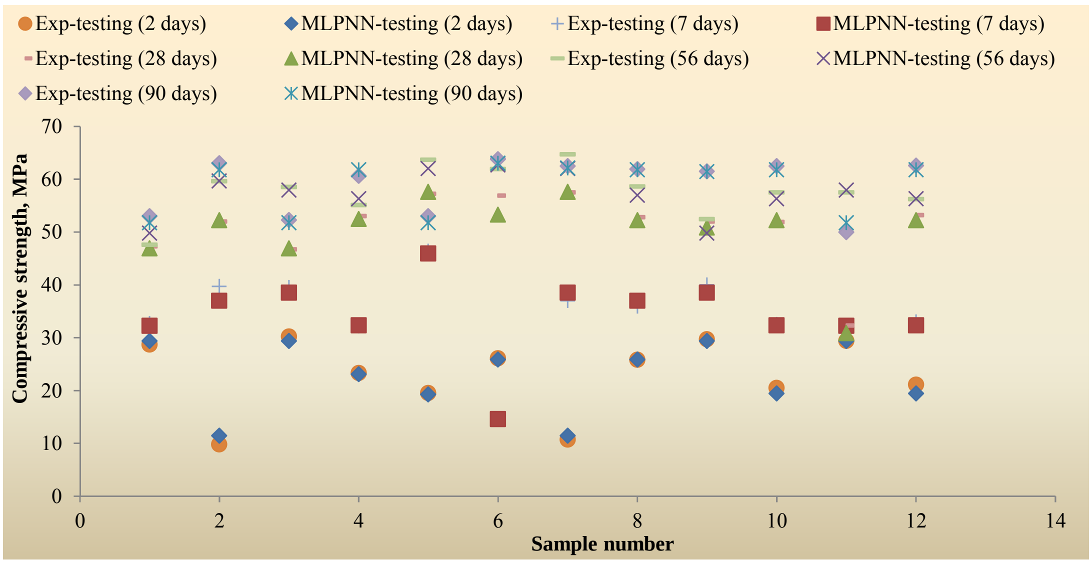

Fig. 4 Comparison of compressive strength experimental and testing results with sample number

Table 6 Comparison of compressive strength experimental results with testing results obtained from MLPNN

Data used in the model construction				Compressive strength, MPa		Data used in the model construction				Compressive strength, MPa	
As, days	PC, g	FA, g	SF, g	Exp.	MLPNN	As, days	PC, g	FA, g	SF, g	Exp.	MLPNN
2	450	0	0	28.7	29.3	28	450	0	0	57.5	57.6
2	315	135	0	9.8	11.4	28	360	45	45	52.8	52.2
2	450	0	0	30.2	29.3	28	405	45	0	52.0	50.8
2	405	0	45	23.3	23.1	28	360	45	45	51.9	52.2
2	360	90	0	19.5	19.2	28	315	135	0	32.3	30.8
2	405	22.5	22.5	26.1	25.8	28	360	45	45	53.2	52.2
2	315	135	0	10.7	11.4	56	360	90	0	47.6	49.8
2	405	22.5	22.5	25.8	25.8	56	405	0	45	59.6	59.7
2	450	0	0	29.7	29.3	56	405	45	0	58.5	57.9
2	360	45	45	20.5	19.4	56	360	45	45	55.1	56.3
2	450	0	0	29.4	29.3	56	450	0	0	63.7	62.0
2	360	45	45	21.1	19.4	56	427.5	0	22.5	61.9	62.7
7	360	90	0	32.7	32.2	56	450	0	0	64.7	62.0
7	405	0	45	39.7	37.0	56	405	22.5	22.5	58.6	57.0
7	405	45	0	39.5	38.5	56	360	90	0	52.4	49.8
7	360	45	45	32.2	32.4	56	360	45	45	57.5	56.3
7	450	0	0	46.4	46.0	56	405	45	0	57.5	57.9
7	315	135	0	14.5	14.6	56	360	45	45	56.2	56.3
7	405	45	0	37.0	38.5	90	360	90	0	53.0	51.8
7	405	0	45	35.9	37.0	90	405	0	45	63.0	61.8
7	405	45	0	40.0	38.5	90	360	90	0	52.3	51.8
7	360	45	45	32.5	32.4	90	405	0	45	60.6	61.8
7	360	90	0	32.0	32.2	90	360	90	0	53.0	51.8
7	360	45	45	33.0	32.4	90	405	22.5	22.5	63.8	63.0
28	360	90	0	47.3	46.9	90	450	0	0	62.5	62.1
28	360	45	45	52.0	52.2	90	405	0	45	61.9	61.8
28	360	90	0	46.7	46.9	90	405	45	0	61.5	61.4
28	405	22.5	22.5	53.0	52.5	90	405	0	45	62.5	61.8
28	450	0	0	57.2	57.6	90	360	90	0	50.0	51.8
28	405	0	45	56.9	53.3	90	405	0	45	62.6	61.8

The linear least square fit line, its equation and the R^2 values were shown in these figures for the training and testing data. As it is visible in Fig. 5 and 6, the values obtained from the training and testing in MLPNN model are very close to the experimental results. The result of testing in Fig. 5 and 6 shows that the MLPNN model is capable of generalizing between input and output variables with reasonably good predictions.

For both training and testing results, the statistical values such as RMS, R^2 and MAPE were given in Table 7. While the statistical values of RMS, R^2 and MAPE from the training in the MLPNN model were calculated as 1.2259, 0.9932 and 0.0266, respectively. Also, these values were found in testing as 1.5001, 0.9921 and 0.0293, respectively. All the statistical values in Table 7 show that the proposed MLPNN model is suitable. And the 2, 7, 28, 56 and 90 day’s compressive strength values are very close to the experimental values.

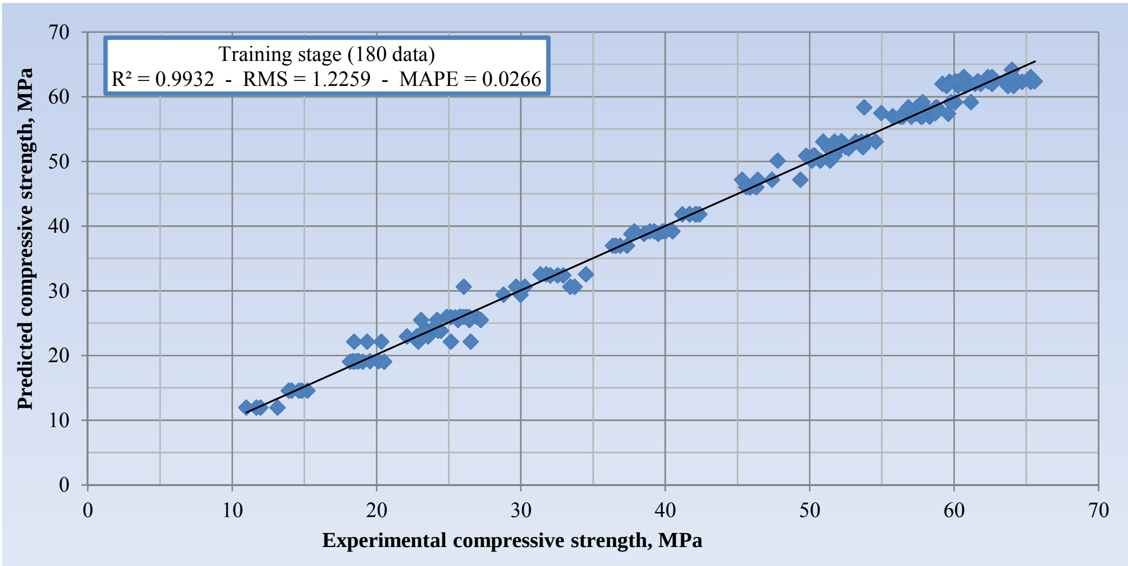

Fig. 5 Comparison of compressive strength experimental results with training results of model comparison

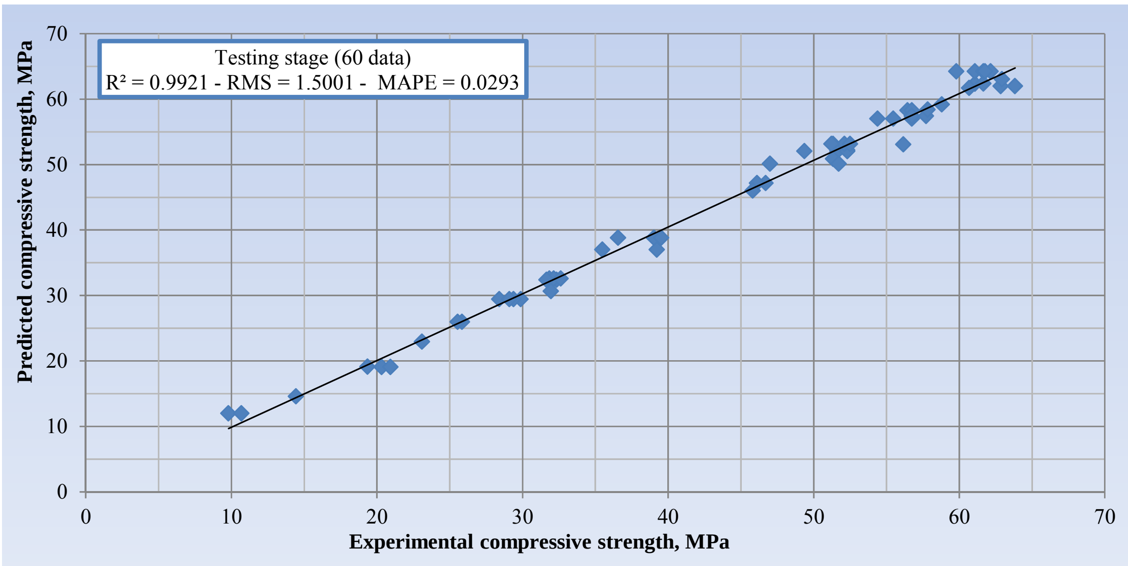

Fig. 6 Comparison of compressive strength experimental results with testing results of model

Table 7 The compressive strength statistical values of proposed MLPNN model

Statistical parameters	MLPNN	
	Training set	Testing set
RMS	1.2259	1.5001
R^2	0.9932	0.9921
MAPE	0.0266	0.0293

6. Conclusions

In this study, MLPNN model can be used for the prediction the 2, 7, 28, 56 and 90 day's compressive strength values of cement mortars containing FA, SF and FA+SF. The back-propagation algorithm was used in MLPNN model. This model consists of two hidden layers. There are 10 neurons in the first hidden layer and 10 neurons in the second hidden layer. This model was trained by using experimental data for input and output. After the model was trained the 2, 7, 28, 56 and 90 day's compressive strength values of cement mortars containing FA, SF and FA+SF, using only the test input data were predicted compressive strength values of cement mortars. The compressive strength values are correlated to the experimental data with data obtained from MLPNN model both for training and testing. The statistical parameter values of RMS, R^2 and MAPE which are calculated for comparing experimental data with MLPNN model results have shown statistically significantly related.

As a result, compressive strength values of cement mortars containing FA, SF and FA+SF can be predicted in the multilayer feed-forward neural network model in a quite short period of time with tiny error rates. The conclusions have shown that MLPNN system is practicable methods for predicting compressive strength values of cement mortars containing FA, SF and FA+SF.

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