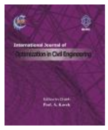
iINTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2016; 6(3):423-432



EVALUATION OF CONCRETE COMPRESSIVE STRENGTH USING ARTIFICIAL NEURAL NETWORK AND MULTIPLE LINEAR REGRESSION MODELS

F. Khademi[1] and K. Behfarnia[2*, †]
[1]*Structural Engineering, Illinois Institute of Technology, Chicago, IL, USA*
[2]*Department of Civil Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran*

ABSTRACT

In the present study, two different data-driven models, artificial neural network (ANN) and multiple linear regression (MLR) models, have been developed to predict the 28 days compressive strength of concrete. Seven different parameters namely 3/4 mm sand, 3/8 mm sand, cement content, gravel, maximums size of aggregate, fineness modulus, and water-cement ratio were considered as input variables. For each set of these input variables, the 28 days compressive strength of concrete were determined. A total number of 140 input-target pairs were gathered, divided into 70%, 15%, and 15% for training, validation, and testing steps in artificial neural network model, respectively, and divided into 85% and 15% for training and testing steps in multiple linear regression model, respectively. Comparing the testing steps of both of the models, it can be concluded that the artificial neural network model is more capable in predicting the compressive strength of concrete in compare to multiple linear regression model. In other words, multiple linear regression model is better to be used for preliminary mix design of concrete, and artificial neural network model is recommended in the mix design optimization and in the case of higher accuracy requirements.

Keywords: concrete; compressive strength; artificial neural network; multiple linear regression.

Received: 20 December 2015; Accepted: 15 February 2016

---

*Corresponding author: Department of Civil Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran
†E-mail address: kia@cc.iut.ac.ir (K. Behfarnia)

1. INTRODUCTION

Concrete compressive strength is assumed as one of the most important mechanical properties of concrete since it usually shows the overall quality of concrete. Although concrete compressive strength can be measured at different ages, codes generally specify standard 28-day testing [1,2]. This standard test needs curing time of 28 days which this time can be saved in the investigated model in this study. Data-driven models, which are studied in this paper, are easy to be used, fast, economical and are recommended by many scientists [3-6]. Therefore, having particular concrete characteristics and an appropriate choice of one of these data-driven models which applies to prepared specific dataset, the compressive strength of concrete can be properly estimated.

Researchers have used these data-driven models in different fields of concrete technologies. Nikoo et al. used self-organization feature map to estimate the compressive strength of concrete and concluded that it is an accurate model for predicting the concrete compressive strength [7]. Sadowski et al. utilized principal component analysis combined with a self-organization feature map to evaluate the pull-off adhesion between concrete layers. They concluded that this model is a suitable one for the prediction purposes [8]. Trtnik et al. predicted the compressive strength of concrete by artificial neural network and ultrasonic pulse velocity which the results were satisfactory [9]. In this study two different data driven models namely multiple linear regression and artificial neural network are applied in MATLAB software environment and the results are compared with each other.

2. ESTIMATION TECHNIQUES

The estimation models which are also called estimators utilize measured data as input variables for their estimation purposes. In any estimation models such as supervised prediction models the training step is involved which helps the model to learn from a set of training examples [10]. In this paper, multiple linear regression and artificial neural network models are used as the estimation models. Following, is a short description of each model.

2.1 Multiple linear regression model

Regression models are used to estimate the level of correlation between the predictors and criterion variables and explore the forms of relationships between them. Linear regression model is categorized into two types of simple linear regression and multiple linear regression. The simple linear regression examines the linear relationship between one response and one predictor variable, however, if the number of predictor variables becomes two or more, the model is called multiple linear regression.

Multiple linear regression (MLR) is used to evaluate the correlation between one dependent variable (response variable) from two or more independent ones (explanatory variables). MLR produces a relationship in terms of a straight line that best estimates all the individual data points including target and output variables. The general form of a multiple linear regression model is presented in Equation 1 below [10, 11]:

$$\hat{Y}= a_0 + \sum_{j=1}^{m} a_j X_j \quad (1)$$

where $\hat{Y}$ is the model`s output, $X_j$ `s are the independant input variables to the model, and $a_0, a_1, a_2, \ldots, a_m$ are partial regression coefficients.

2.2 Artificial neural network model

Artificial neural network (ANN) is a collection of neural and weighted nodes which each of them represents a brain neuron. ANN contains information-processing units which is so similar to human brain neurons, except that the neurons in ANN are in fact artificial neurons [10,12]. ANN model is superior in comparison to other methods due to its enormous advantages. Some of these superiorities are described in the following: (1) In ANN model, the field and experimental data sets are used directly and without any simplified assumptions, in other words, the advantage of ANN can be described as its capability in learning directly from examples, (2) ANN is able to provide correct or nearly correct response to incomplete tasks, also it is able to extract information from poor data [13].

Generally, ANN is comprised of three steps of training, validation, and test. In the training step, the connection between biases and weights in the ANN model are adapted through a continuous process of simulation by the situation where the network is embedded. Basically, the main purpose of training step is to minimize an error function such as the mean square error (MSE), shown in Equation (2), by investigating the connections which makes ANN to generate outputs as close as possible to target values [12,14].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad (2)$$

where "N" is the number of data, t_i are the output values, and a_i are the target value values.

The validation step is used to construct the model, however, it acts independent from the training set. In the test data set, the accuracy of the machine learning algorithm can be evaluated.

The neural network is formed in three layers, namely input layer, hidden layer, and output layer which in each of them one or more nodes exists.

3. DATASET DESCRIPTION AND PREPARATION

In order to get into objective of this study, different concrete specimens were constructed in the laboratory and cured for 28 days. Totally, 140 records of concrete mix design were selected to construct the training-testing database [6,7]. The concrete specimens were in cylindrical shape with a height of 300 mm and a diameter of 150 mm. The input parameters affecting the 28 days compressive strength of concrete were selected as 3/4 mm sand, 3/8 mm sand, cement content, gravel amount, maximums size of aggregate (MSA), fineness modulus(FM), and water-cement ratio(w/c). The characteristics of selected data are shown in Table 1:

Table 1: Characteristics of samples

Number	Parameters	Unit	Maximum	Minimum
1	Compressive strength of concrete	MPa	39.40	17.30
2	w/c	_	0.50	0.24
3	MSA	mm	50.00	5.12
4	Gravel	kg	1050.00	559.00
5	Cement	kg	549.00	243.00
6	Sand 3/8	kg	523.00	303.00
7	Sand 3/4	kg	693.00	365.00
8	FM	_	9.20	2.40

4. RESULTS AND DISCUSSION

In this study, 140 different concrete mix designs were utilized to evaluate the 28 days compressive strength of concrete. In the next step, the Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) models were chosen as the estimation models and the approximation for the concrete compressive strength have been achieved. In ANN model the data were divided into three subsets of training, validation (check), and test and the concrete compressive strength was predicted based on these three subsets. Next, in the multiple linear regression model the dataset were divided into two categorization of training and testing and the concrete compressive strength was determined. Both the ANN and MLR modeling have been performed in MATLAB software environment [15]. Thereafter, the performance of ANN and MLR models in predicting the 28 days compressive strength of concrete were compared with each other for the test dataset. The performance criteria for comparing the results is chosen as coefficient of determination (R^2), given in Equation (3) [16]:

$$R^2 = \frac{[\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})]^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2} \tag{3}$$

where "y_i" is the experimental strength of "i^{th}" specimen, "$\bar{y}$" is the averaged experimental strength, "$\hat{y}_i$" is the calculated compressive strength of "i" th specimen, and "$\bar{\hat{y}}$" is the averaged calculated compressive strength.

4.1 Multiple linear regression

In the multiple linear regression model, the number of input variables was chosen as 7 parameters and the number of output variables was selected as 1. The total number of specimens was chosen as 140 which out of all of them, 85% namely 119 samples were selected for training step, and 15% namely 21 samples were selected for the testing step. Fig. 1 shows the comparison between the measured compressive strength and predicted compressive strength for the training step in MLR model.

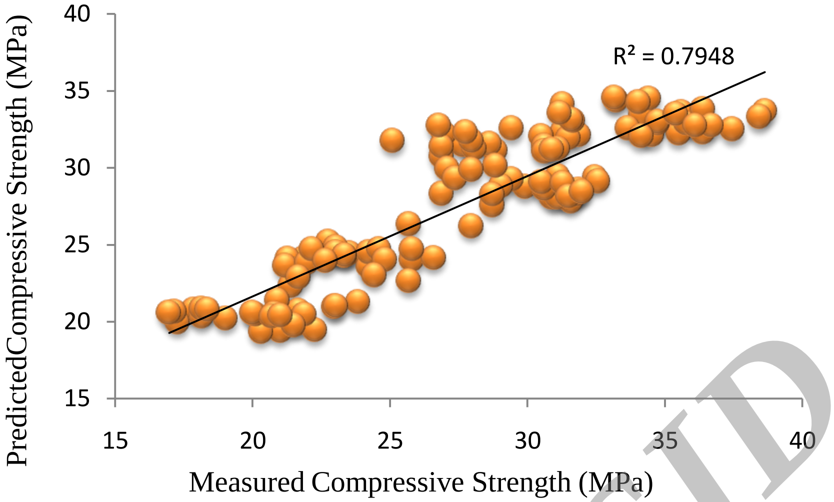


Figure 1. Comparison between the "Measured" and "Predicted" parameters for "Training" data in MLR model

According to training step, the weight parameters shown in Equation (1) are determined as α_0 =-0.0658, α_1 =0.7122, α_2 =0.073, α_3 =0.3058, α_4 =0.4704, α_5 =0.1093, α_6 =0.0362, and α_7 =-3.2428 for the constant parameter, the fineness modulus, the amount of sand ¾, the amount of sand 3/8, cement content, gravel, the maximum size of aggregate, and w/c, respectively. As it is illustrated in the Fig. 1, the MLR model with the coefficient of determination of R^2=0.7948 in the training step is not performed strong enough.

4.2 Artificial neural network

In the Artificial neural network model also the number of input variables was chosen as seven and the number of output variables was chosen as one, which means out of the total selected number of 140 specimens, 80% namely 98 specimens were assigned to training step, 15% namely 21 specimens were assigned to validation (check) step, and 15% namely 21 specimens were assigned to test step. Various training algorithms namely Delta Bar Delta, Momentum, Levenberg Marquardt, and Quickprop have been tried and among all of them, the Levenberg Marquardt (LM) was desired as the superlative one. In addition, in order to estimate the number of hidden nodes in hidden layer, the experimental formula presented in Equation (4) was used [6]:

$$N_H \leq 2N_1 + 1 \tag{4}$$

In which N_H is the maximum number of nodes in the hidden layer and N_1 is the number of inputs. Therefore, in this study, based on the number of input variables which was equal to 7, the maximum number of nodes in the hidden layer was selected as 15.

Fig. 2 shows the validation performance established in MATLAB software for the training, validation, and test steps. This figure demonstrates the mean squared error (MSE) of the network for the three steps of training, validation, and test which indicates the fact that the network is learning. According to this figure, the best validation performance is occurred at epoch 7 which has the least mean squared error (MSE). In other words, training in the training step continues as long as the network error on the validation vectors is decreasing. In addition, according to this figure, it is demonstrated that the analysis stop point is equal to 13, namely considering 6 error repetitions after the best validation performance (epoch 7).

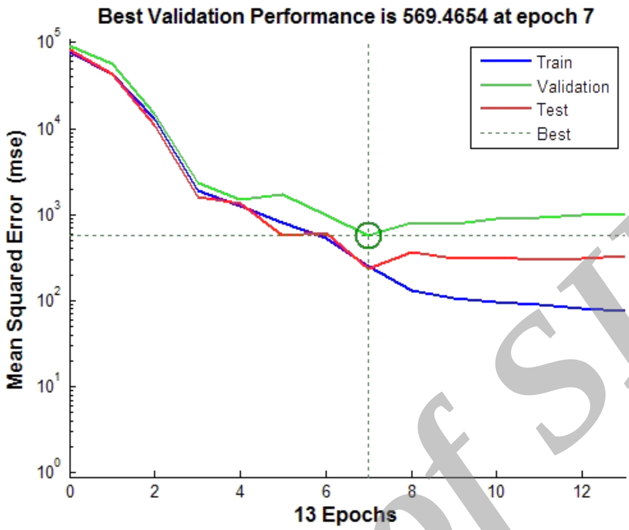


Figure 2. Best validation performance in ANN model

Fig. 3 illustrates the training state of artificial neural network. According to this figure, the errors are repeated 6 times after epoch number 7 and the acting is stopped at epoch 13. In other words, the last epoch before the error repetitions, namely epoch 7, is considered as the best performance and its related weights are assumed as the final model weights. Furthermore, the validation check is equal to 6 since it is based on the number of repetitions.

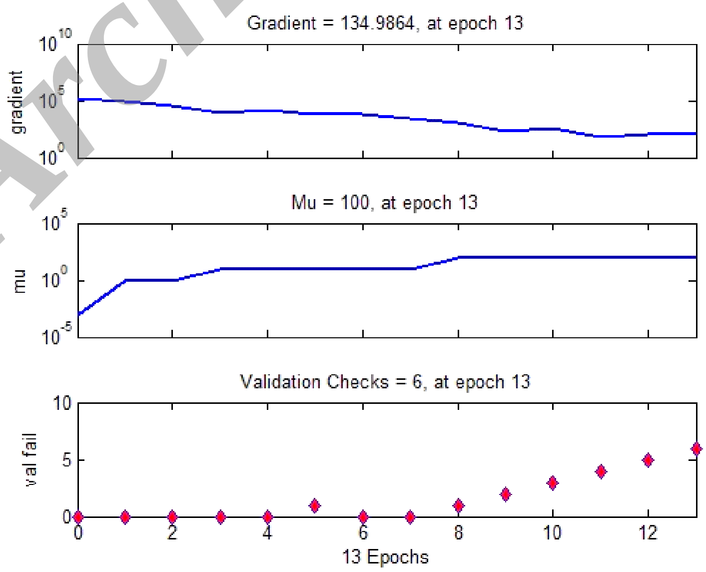


Figure 3. Training state of artificial neural network model

Fig. 4 illustrates the error histogram including 20 bins in the ANN model for the training, validation (check), and test. The errors are calculated based on reducing the predicted compressive strength from the measured compressive strength for each specific specimen. According to this figure, the yellow line indicates the zero error with 14 instances in the training step.

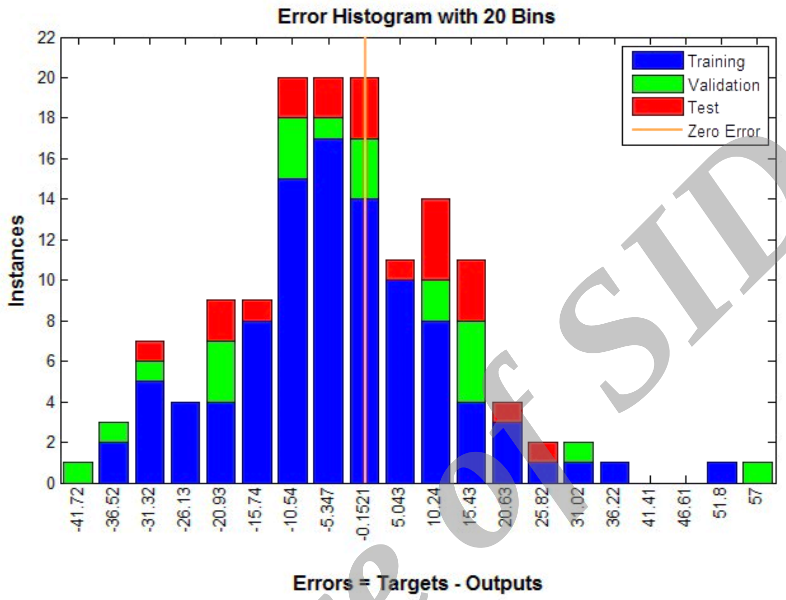


Figure 4. Error histogram with 20 bins for the three steps of training, validation, and test

Figs. 5 and 6 show the relationship between the measured compressive strength (target values) and predicted compressive strength (output values) for the training and validation steps, respectively. R^2 is a statistical measure of how close the data are to the fitted regression line. In both of the figures the model presents good results in the case of R-values.

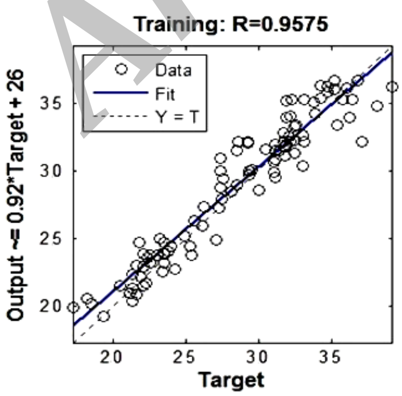


Figure 5. Regression of training subset simulated by ANN model

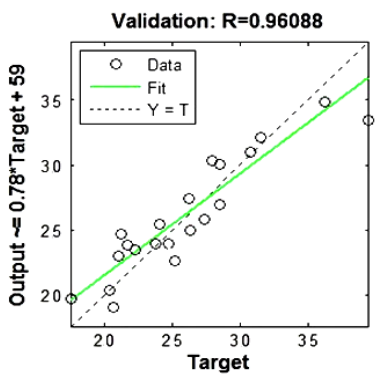


Figure 6. Regression of validation subset simulated by ANN model

4.3 Comparison of MLR & ANN models

In order to evaluate the performance of the model and also to determine the best model, the coefficient of determination (R^2) of each model is compared with the other one. Concerning the equal situations in the comparison of the models, the same data set is selected for the test step. Figs. 7 and 8 show the regression of test subset simulated by MLR and ANN model, respectively.

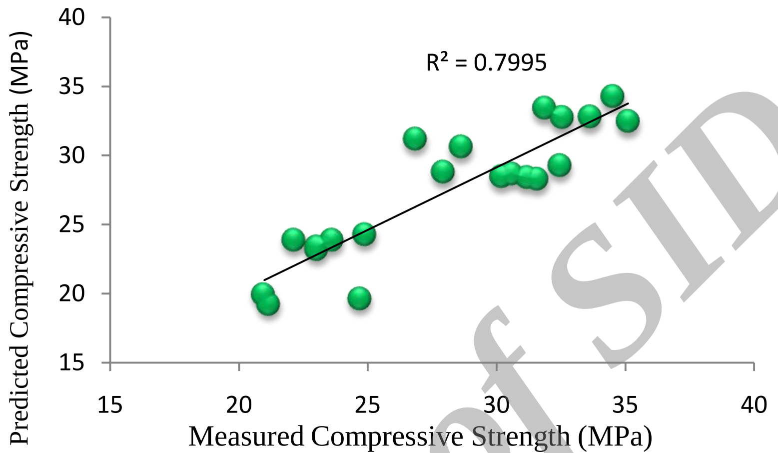


Figure 7. Comparison between the "Measured" and "Predicted" parameters for "Test" data in MLR model

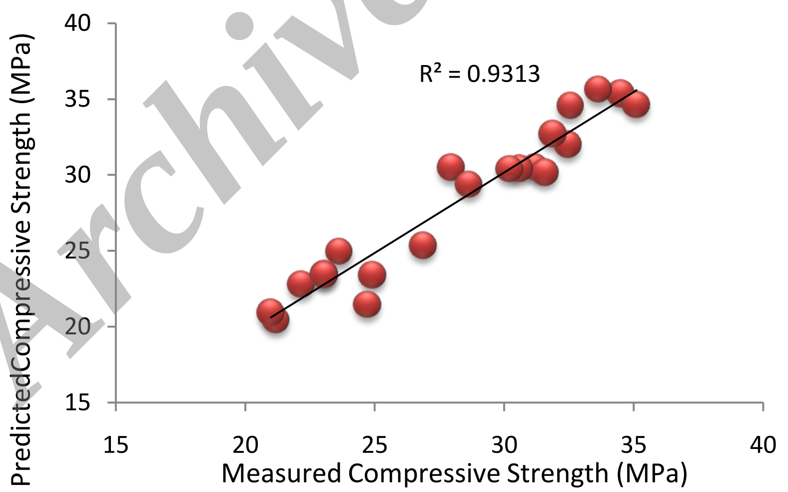


Figure 8**.** Comparison between the "Measured" and "Predicted" parameters for "Test" data in ANN model

According to Figs. 7 and 8, the ANN model with the coefficient of determination of R^2=0.9313 is better qualified for predicting the compressive strength of concrete in comparison to MLR model with the coefficient of determination of R^2=0.7995. Multiple linear regression model showed weak performance for both the training and testing steps, therefore, it is not reliable enough for prediction purposes. However, artificial neural network showed good performance not only in the training and validation steps, but also in test step. Hence, it can be concluded that the ANN model is a suitable model for predicting the compressive strength of concrete.

5. CONCLUSION

The objective of this study was to apply data-driven models, i.e. artificial neural network and multiple linear regression models for prediction of compressive strength of concrete, and compare their results with each other. In artificial neural network model one hidden layer with 15 neurons was selected. The modelling were carried out for the data from the literature for the 28 days compressive strength using ANN and MLR with a correlation coefficient above 0.9 and under 0.9, respectively. Results demonstrate that artificial neural network has better predictions of the experimental compressive strength values than those of multiple linear regression model. In other words, results from establishing an artificial neural network illustrates a good degree of coherency between the target and output values. Therefore, using ANN model, the 28 days compressive strength of concrete can be predicted both accurately and easily. It is worth mentioning that this model does not require a particular equation which differs from traditional prediction techniques. Additionally, in order to expand the suitability range of artificial neural network model, this model is able to re-train new data which makes the ANN to be superior in comparison to other models.

REFERENCES

1. Ozturan M, Ozturan T. Comparison of concrete strength prediction techniques with artificial neural network approach, *Build Res J* 2008; **56**(1): 23-36.
2. Khademi F, Akbari M, Jamal SM. Measuring compressive strength of puzzolan concrete by ultrasonic pulse velocity method, *i-Manag J Civil Eng* 2015; **5**(3): 23-9.
3. Kaveh A, and Khalegi HA. Prediction of strength for concrete specimens using artificial neural network, *Asian J Civ Eng* 2000; **2**(2): 1-13.
4. Sadowski L, Nikoo M. Corrosion current density prediction in reinforced concrete by imperialist competitive algorithm, *Neural Comput Appl* 2014, **25**(7-8): 1627-38.
5. Khademi F, Akbari M, Jamal SM. Prediction of compressive strength of concrete by data-driven models, *i-Manag J Civil Eng* 2015; **5**(2): 16-23.
6. Nikoo M, Torabian FM, Sadowski L. Prediction of concrete compressive strength by evolutionary artificial neural networks, *Adv Mater Sci Eng*, Volume 2015 (2015), Article ID 849126, 8 pages.
7. Nikoo M, Zarfam P, Sayahpour H. Determination of compressive strength of concrete using self organization feature map (SOFM), *Eng Comput* 2015; **31**(1): 113-21.
8. Sadowski Ł, Nikoo M, Nikoo M. Principal component analysis combined with a self organization feature map to determine the pull-off adhesion between concrete layers, *Constr Build Mater* 2015; **78**: 386-96.

9. Gregor T, Kavčič F, Turk G. Prediction of concrete strength using ultrasonic pulse velocity and artificial neural networks, *Ultrasonics* 2009; **49**(1): 53-60.
10. Chou Jui-Sheng, Tsai F. Concrete compressive strength analysis using a combined classification and regression technique, *Automat Constr* 2012; **24**: 52-60.
11. Deshpande Neela, Londhe S, Kulkarni S. Modeling compressive strength of recycled aggregate concrete by artificial neural network, model tree and non-linear regression, *Int J Sustainable Built Environ* 2014; **3**(2): 187-98.
12. Kaveh A, Servati H. Neural networks for the approximate analysis and design of double layer grids, *Int J Space Struct* 2002; **17**: 77-89.
13. Ince R. Prediction of fracture parameters of concrete by artificial neural networks, *Eng Fract Mech* 2004; **71**(15): 2143-59.
14. Chen Li. A multiple linear regression prediction of concrete compressive strength based on physical properties of electric arc furnace oxidizing slag, *Int J Appl Sci Eng* 2010; **7**(2): 153-8.
15. MATLAB and Statistics Toolbox Release 2014a the Math Works, Inc, Natick, Massachusetts, United States.
16. Nazari A, Khalaj Gh. Prediction compressive strength of lightweight geopolymers by ANFIS, *Ceram Int* 2012; **38**(6): 4501-10.