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PREDICTION OF COMPRESSIVE STRENGTH OF CONCRETE CONTAINING POZZOLANIC MATERIALS BY APPLYING NEURAL NETWORKS

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ABSTRACT

The most interesting aim of the study is to assess and compare the dependability of using the multiple linear regressions (MLR) model and the artificial neural networks (ANN) model to predict the concrete compressive strength using metakaolin (MK) and silica fume (SF) admixtures materials. A proposed prediction model of artificial neural network (ANN) for concrete compressive strength. That proposed model is trained, validated and tested using the available test data of 132 concretes with various mixture proportions that were collected from different technical literature. Next the prediction of concrete compressive strength is conducted on those models. The collected data organized in a form of eight input variables (parameters) which includes concrete specimen age, water, fine aggregate, metakaolin, cement, coarse aggregate, silica fume, and superplasticizer. Relating to these input parameters in the ANN model, the concrete compressive strength containing MK and SF, are predicted. The results from the training, validation, and testing stages from making use of the ANN model showed that neural networks (NN) have strong potential use for the prediction of concrete compressive strength that contain materials such as MK and SF. The correlation coefficient for the ANN model in the training, validation, and test stages that achieved are equal to 0.99661, 0.99093, and 0.98577, respectively. Whereas the correlation coefficient for the the MLR model was 0.794. The results suggest that the prediction using ANN model is more accurate than when using the MLR model.

Keywords: Metakaolin, Silica Fume, ANN, MLR, prediction, compressive strength

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1. INTRODUCTION

Around the world, pozzolanic materials are produced from clay and kaolin. Those pozzolanic materials are used to reduce the content of Portland cement in both mortar and concrete [1-4]. Many studies show the positive effect of using pozzolanic materials on the properties of Portland cement mortar. It has been recognized that the concrete has exceptional mechanical and durability properties is define as high performance concrete (HPC). HPC supplies advance either or both strength properties concrete and long term of concrete durability [5-6]. Fly ash (FA) and silica fume (SF) are the familiar types of pozzolanic materials and it is highly used in the producing of HPC.

In the last few years, there is interest that is growing in using of metakaolin (MK) to the same purpose of producing HPC [7-11]. Silica fume is used as a replacement material to develop the HPC, because it is increases the bond among the paste and the aggregate [12-14]. These pozzolanic materials are usually used, as mentioned before, as replacement material by the weight of Portland cement. The significant difference between SF, FA, and MK, that SF and FA materials are secondary products, while MK is a primary product in the producing of artificial pozzolans. At early ages of concrete containing MK, concrete showed a quicker strength, but the strength will be similar after 28 days [10]. Almost, compressive strength of concrete contains 10% of MK, be a higher than the control concrete (without MK) at all ages up to 180 days [9-10].

Recently, there are great interest in applying Artificial Neural Network (ANN) which is a type of data-driven models. This interest is due to the fact that those ANN models are simple and have high level of prediction accuracy. For the aim of prediction, estimation, simulation, and classification, ANN are usually effectively used due to that ANN models have the ability for finding complex forms and relationships between the inputs and the outputs data of the model. For a given set of data, ANN has the efficiency to learn non-linear static or dynamic behavior among the variables. Over the last two decades, ANN is useful tools used to estimate the chloride permeability and also the mechanical properties of concrete [15]. It was also used for the analysis of compressive strength of lightweight concrete after high temperatures [16], forecast of compressive strength for concrete with fly ash [17], modeling the compressive strength of the recycled aggregate concrete [18], predicting compressive strength of structural light weight concrete [19] , and in other application of concrete.

An artificial neural network is an easy system of the biological structures, which discovered in human's brain. There are three elements, which are especially essential in any model of ANN: first, the structure of nodes, second, the network topology, and third, the learning algorithm, which used to determine the network's weights [20]. In terms of ANN , the topology's structures of the neural networks (NN) may be divided in to two sorts: feed forward and recurrent networks. Whereas the learning algorithm used in NN has two kinds: supervised and unsupervised learning. The Back-propagation (BP) type of neural network is the most usable ANN models. The learning rule of BP networks uses the steepest descent method in which the output's errors of the BP network are to be propagate back to modify the weights of the interconnections so that the total error be minimized. A typical ANN has three layers: input layer, hidden layer, and output layer. The major variations among the different types of ANN are the network architecture (arrangement of neurons) and the method to find the weights and function of inputs and outputs.

In this work, one of the most widespread ANN algorithms , back-propagation neural network is utilized , which is a multilayered feed-forward network and follows typical supervised learning. The objective of this research is to construct a NN model used for the prediction of the compressive strength of HPC and that model reduces the number of sampling for HPC property that used MK and SF materials. The constructed NN model that has one hidden layer has been trained, tested, and validated using collected test data of 150 of various concrete mix design. The proposed NN model had eight input parameters (variables) and only one output parameter (target). The results obtained from this study were compared with the predicted results from the proposed model. To discover the best compressive strength prediction model; the ANN model is in contrast to the MLR model.

2. MATERIALS

Different materials were gathered from the technical literature [23-26]. The Ordinary Portland Cement (OPC) that used in producing concrete is conform to ASTM type I. While, the mineral admixture materials (MK and SF) was used as cement replacement on the basis of weight to weight. MK and SF materials were blended with OPC in the contents with various ratios according to the concrete mix design in the reference used. The aggregates (fine and coarse) used in the concrete mix were follows the BS requirements of 882:1992. To improve the workability of concrete mixture, super plasticizer was used.

2.1. Multiple Linear Regression:

The equation of the multiple linear regression (MLR) used as part of this paper is because the MLR depict the linear relationships including more than two variables. The MLR equation connotes a linear relationship concerning a response variable (Y) and more predictor variables (x_1, x_2, x_3, x_k). Equation (1) show the general formula of a MLR:

$$Y=b_0+b_1x_1+b_2x_2+ b_3x_3+b_kx_k \tag{1}$$

To find the best fit to the data in this study, the following multiple linear regression equation is used based on the work with minitab software version (18) and henece, it can be re-write as follows

$$Y=b_0+b_1x_1+b_2x_2+ b_3x_3+b_4x_4+b_5x_5+ b_6x_6+b_7x_7+b_8x_8 \tag{2}$$

Where,

Y: predicted value of concrete compressive strength

x_1 : Age of concrete specimen

x_2 : Cement

x_3 : Silica fume

x_4 : Metakaolin

x_5 : Water

x_6 : Fine aggregate

x_7 : Coarse aggregate

x_8 : Superplasticizer

b0 : The estimation value of Y-intercept (constant)

b_1 to b_8: The estimation value of the independent variable coefficient.

3. ARTIFICIAL NEURAL NETWORK:

Artificial Neural Network (ANN) is data processing model which is motivated by the brain and process information. Advantages of ANN contain adaptive learning , real time operation , and self-organization. BP neural network is a multi-layer feed-forward network utilizing back-propagation (BP) learning rule [22]

A three-layer network is used in this study as the ANN mode. The proposed ANN model including input layer, hidden layer and output layer. Input layer contains the eight parameters influencing the final concrete compressive strength ; in particular they are age of concrete specimen, metakaolin, cement, silica fume, fine aggregate, water, coarse aggregate, and superplasticizer. In the hidden layer, the number of neurons is calculated according to empirical equation and optimized by trial-and-error method. The empirical equation [21] that used is reported as

$$m = \sqrt{n + l} + c \tag{3}$$

Where, m, n, and l are the number of neurons in hidden layer , the number of input parameters and the number of output parameters , respectively ; c is a constant between 1 and 10. The final number of neurons in the hidden layer is optimized as 10. In the output layer , there is only one output layer that represents the concrete compressive strength The schematic drawing representation of the ANN model structure is shown in Fig.1.

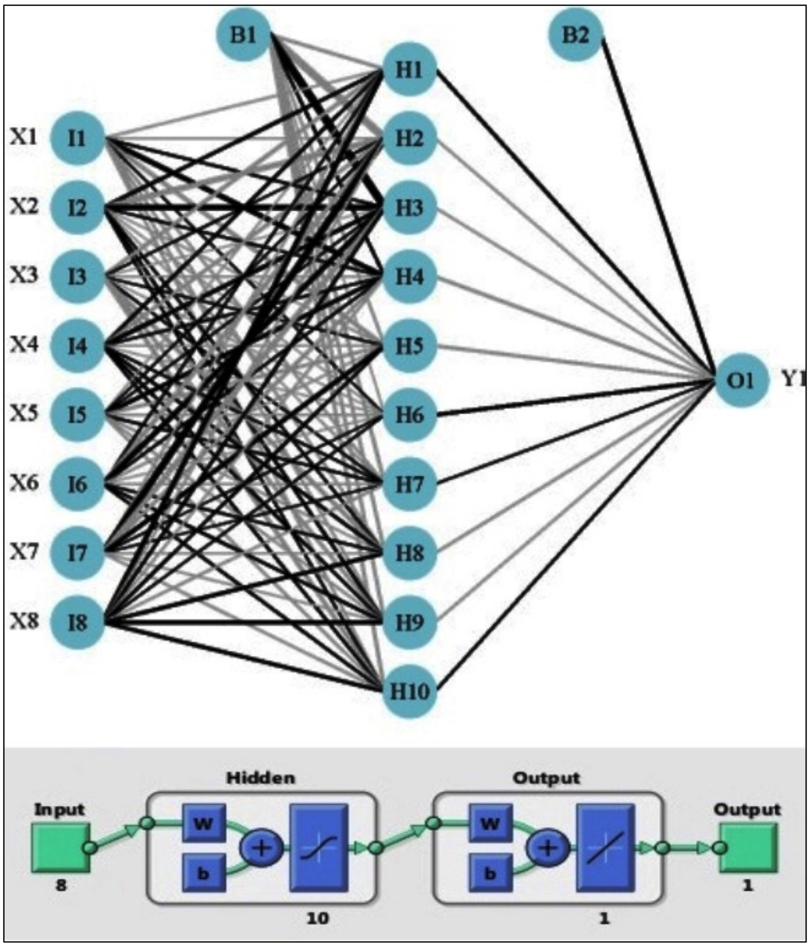

Figure.1 ANN model structure

4. CONSTRUCTION OF ANN MODEL:

Different architecture of ANN was selected in this work to solve the define problem of the non-linear input-output relationships between the inputs (influencing factors) and the output (compressive strength of concrete). The number of neurons in hidden layer was changes according to equation (3) and it was found that the value of 10 is the optimize value that designed in the ANN to get best structure of predicted model. The neurons (nodes) of the neighboring layers are fully connected as shown in Fig.1. All collected experimental data from the references were divided into three sets: training sets that used in network; training, testing sets that used in the testing of network, and the remaining sets called validation sets that used in the validation of network. Matlab 2011b, software was used for working with the ANN in this study. The range of used inputs and outputs parameters variables are shown in Table 1.

Table 1: The range of parameters.

Variables	Unit	Minimum	Maximum	Range
Age of concrete specimen	days	3	90	87
Cement	kg/m^3	328	500	172
Silica fume	kg/m^3	0	75	75
Metakaolin	kg/m^3	0	100	100
Water	kg/m^3	135	205	70
Fine aggregate	kg/m^3	648	725	77
Coarse aggregate	kg/m^3	1050	1087	37
Superplasticizer	l/m^3	0	43	43
Concretecompressive strength	MPa	25.8	120.3	94.5

5. EVALUATION OF PREDICTING PERFORMANCE:

To evaluate the prediction performance of the proposed ANN model, the correlation coefficient (R), absolute fraction of variance (R^2), the mean absolute percentage error (MAPE), mean square error (MSE), and root mean square error (RMSE) were utilized and expressed below:

$$R = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2 \sum_{i=1}^{n}(o_i - \bar{o})^2}} \tag{4}$$

$$R^2 = \frac{(n\sum t_i o_i - \sum t_i \sum o_i)^2}{[n\sum t_i^2 - (\sum t_i)^2]\ [n\sum o_i^2 - (\sum o_i)^2]} \tag{5}$$

$$MAPE = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}|t_i - o_i|}{\sum_{i=1}^{n} t_i} x\, 100\right] \tag{6}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2} \tag{8}$$

Where, t_i is the target value, o_i is the output value, n is the total number, $\bar{t}$ and $\bar{o}$ are the average value of target and output values, respectively.

6. RESULT AND DISCUSSION:

The approach of linear regression is used for modeling the relationship between the dependent variable (Y) and one or more other informative variables (denoted by x). In the case of one informative variable described as a simple linear regression (SLR). Where as in the case of more than one informative variable, it described as a multiple linear regression (MLR). From the experimental data used in this research, the estimation formula of concrete compressive strength (Eq.9) was determined by using MLR.

$$Y = 290+0.3295\ x_1-0.121\ x_2-0.031\ x_3-0.040\ x_4-0.886\ x_5+0.090\ x_6-0.074\ x_7-0.645\ x_8 \quad (9)$$

There are eight selected independent variables with 132 cases (collected from literature [23-26]). In Which the variables (x_1,x_2,x_3,x_4,x_5,x_6,x_7,and x_8) were expressed and descriped earlier in equation (2).

Table 2 displays the highest values of R-Square (0.794) and the adjusted R-Square (0.786). Consequently, since it noticed that the predicted equation of concrete compressive strength is appropriate to used. From the statistical analysis results (Tables 2 and 3), it could conclude that the estimation formula of concrete compressive strength using Multiple Linear Regression (MLR) is as shown in equation (3). The smaller P-value is the better.

Table 2: Analyzed data of Multiple Linear Regression for concrete compressive strength prediction

Predictor	Coef	SE Coef	T-Value	P-Value
Constant	290	724	0.40	0.690
Age	0.3295	0.0238	13.83	0.000
Cement	-0.121	0.433	-0.28	0.781
Silica fume	-0.031	0.375	-0.08	0.934
Metakaolin	-0.040	0.392	-0.10	0.920
Water	-0.886	0.479	-1.85	0.067
Sand	0.090	0.303	0.30	0.767
Aggregate	-0.074	0.592	-0.13	0.900
Superplasticizer	-0.645	0.697	-0.93	0.357
S = 9.52943 R-Sq = 79.40% R-Sq(adj) = 78.06% R-Sq(pred) = 76.27%				

Table 3 show some important factors must to be taken into consideration for suitable selecting of the best equation.

Table 3: Analysis of Variance of Multiple Linear Regression for concrete compressive strength prediction

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	8	43052.7	5381.6	59.26	0.000
Error	123	11169.6	90.8		
Total	131	54222.3			

In this research, about 70% of the input data were randomly used for training stage, and 15% of that data were randomly regarded for testing stage and the rest of data were considered for validation stage. In Fig. 2, the variations in value of mean square error (MSE) displayed with different iterations of train, test, and validation data. As it can be shown from the Fig. 2, that stop has occurred with 18 epochs (iterations) with an MSE value of approximately 9.4925.

Figures 3-6, shows the measured concrete compressive strength versus the predicted (output) concrete compressive strength by applying ANN model with R coefficients. From Fig.3, it could be observed that the ANN model predicted the concrete compressive strength, using MK and SF materials, with R coefficient equal to 0.99661, which is expectant, because the fact that the ANN model was developed using these collected data. Nevertheless, Figure 4 and 5, in which validation and testing concrete compressive strength data are plotted versus the predicted concrete compressive strength data, show that ANN model predict the concrete compressive strength using MK and SF materials with R coefficient equal to 0.99093 and 0.98577, respectively. Moreover, Figure 6, shows that the coefficient R is equal to 0.99423 for all used data in the ANN model, hence, ANN may be applied to predict the concrete compressive strength using same parameters of concrete constituents for the models. It can observed that the neural network were applied very successful in the modeling of concrete compressive strength data and it is prospering used for empirical data with a very high precision. Hence, this network model can be utilized with utilized reliability for the estimation of data that are not available, but it must be within the range of variables.

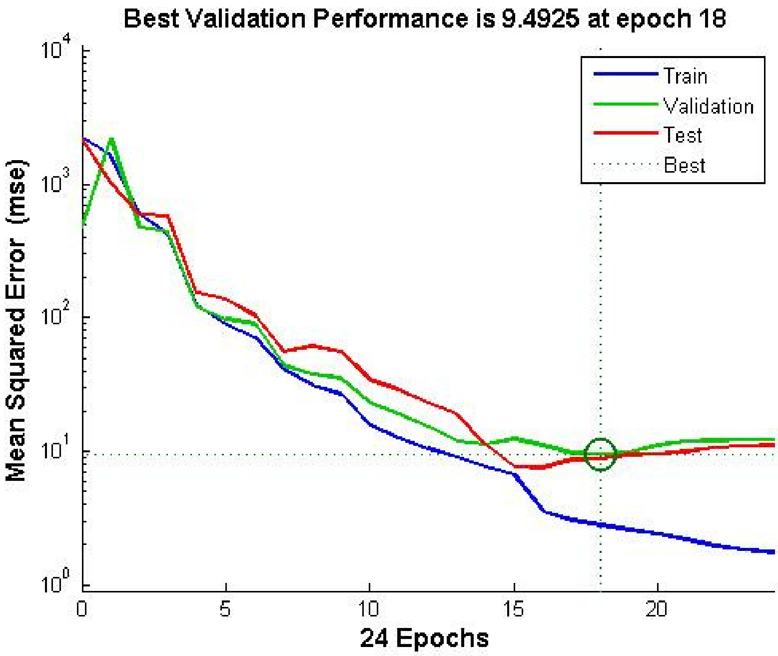

Figure.2 Performance of ANN model

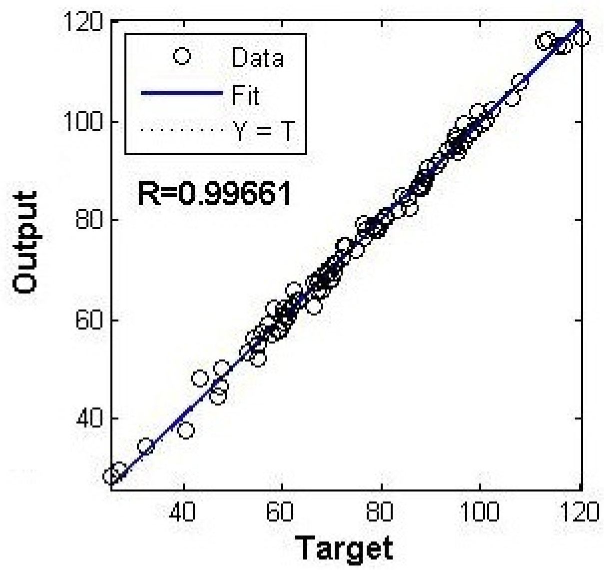

Figure.3. Correlation of the target and the output for ANN model of concrete compressive strength in the training stage.

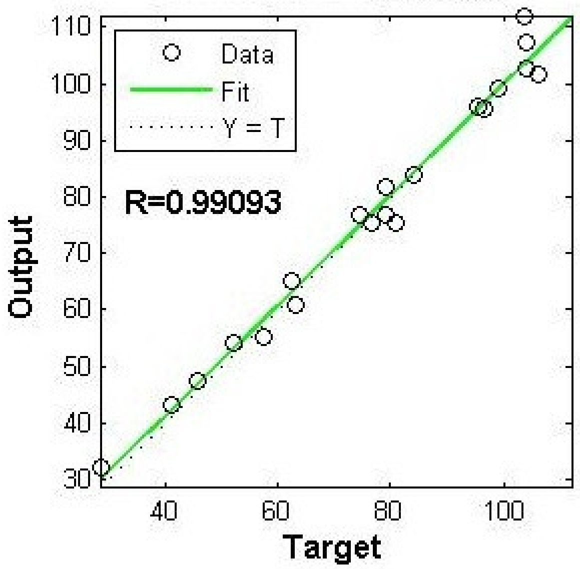

Figure.4. Correlation of the target and the output for ANN model of concrete compressive strength in the validation stage.

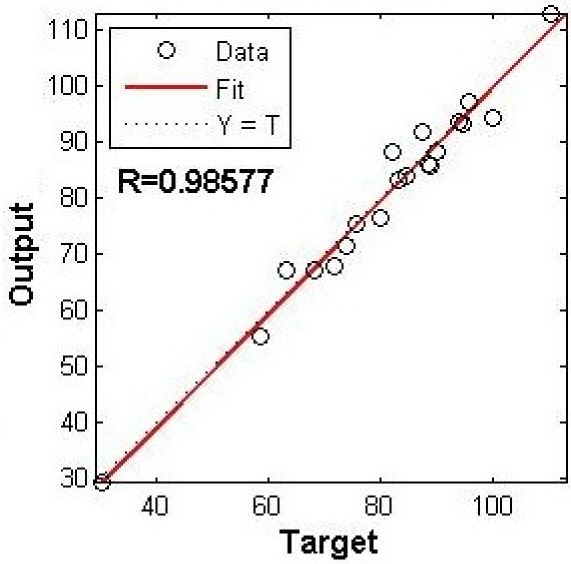

Figure.5. Correlation of the target and the output for ANN model of concrete compressive strength in the testing stage.

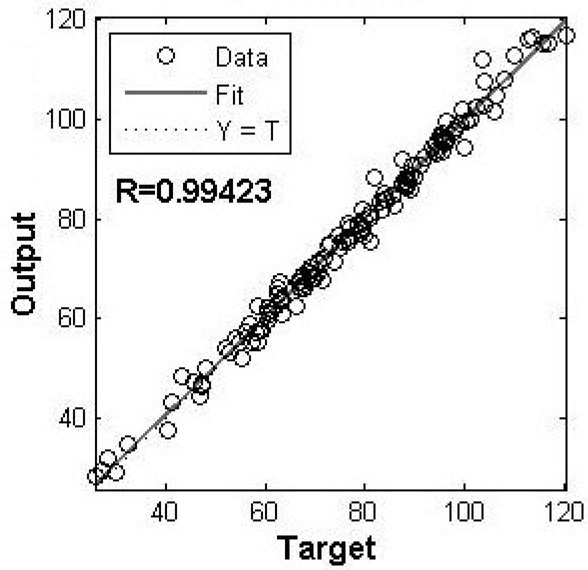

Figure.6. Correlation of the target and the output for the ANN model of concrete compressive strength for all data sets.

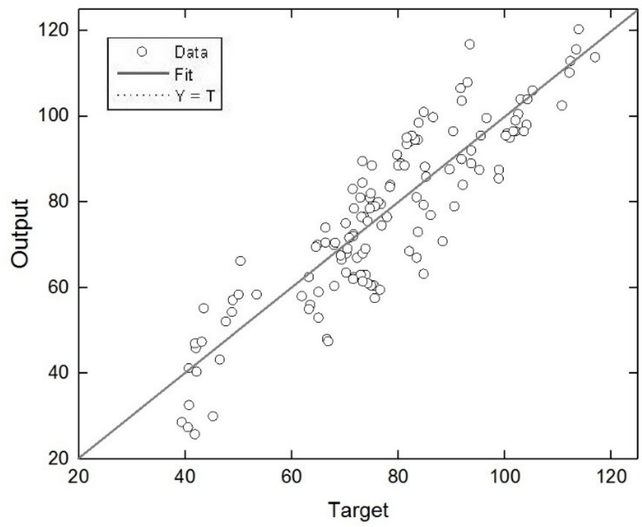

Figure. 7 Correlation of the target and the output for the MLR model of concrete compressive strength.

Fig. 3 shows the proposed regression model of ANN. Fig. 7 shows the computed regression model of MLR. It noticed that the results from ANN model is more practical in forecasting the compressive strength of concrete than the results of MLR model. Simply because of the large quantity of collected data that must be use for acquiring a good regression model, whereas the application of neural network could possibly identify the relationships between the variables with less data, as compared with the MLR model. Furthermore, the ANN model can possibly estimate the concrete compressive strength more effective than other model because of the greater essential capability and flexibility for modeling the nonlinear relationships.

7. CONCLUSIONS

In this research, two models were proposed using ANN and the MLR to evaluate the concrete compressive strength using MK and SF materials. Levenberg-Marquardt algorithm has been used in this work for the feed-forward back-propagation. MLR model has been formulated using Minitab software. The ANN model trained with about 70% of the total data sets. Furthermore, it noticed that the predicted values of concrete compressive strength are in good agreement with those values from the experiments. Neural networks have powerful potential as a workable tool for predicting concrete compressive strengths. The proposed ANN model in this study will save time, the reduce design cost, and decrease waste material. The obtained values of correlation coefficient for the compressive strength of concrete parameters in the training, validation, and test stages were achieved equal to 0.99661, 0.99093, and 0.98577, respectively. Whereas the correlation coefficient of the compressive strength for concrete parameters in the MLR model was 0.794. The results gained from both models recommend that the ANN model is a encouraging tool for precisely determining the concrete compressive strength contrast to MLR model. Therefore, the technique of neural network is better than statistical methods in estimation of concrete compressive strength. Hence, the work suggests that the ANN model is usable in practice for estimation of the concrete compressive strength.

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