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Research Article

Prediction of properties of self-compacting concrete containing various mineral admixtures using artificial neural network

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Abstract: The early prediction of SCC properties become essential for minimizing the time required to measure these properties experimentally, and also facilitating the modification of mixes proportions with non limited trials. This study illustrates the feasibility of applying artificial neural networks (ANNs) modeling in predicting the properties of self compacting concrete (SCC) containing different mineral admixtures as cement replacement. For constructing a model, a data set of experimental data was taken from an experimental research and used for training and testing the model. The data applied in ANNS models were arranged in a nine input parameters that include the contents of cement, water/binder ratio, coarse aggregate, fine aggregate, ground granulated blast furnace slag, fly ash, silica fume, metakaolin and superplasticizer. The output parameters were compressive strength at 28 days, slump flow and L-box ratio. A back propagation learning algorithm was used to train the network. The performance of network models was evaluated with statistical error criteria of root mean squared error and correlation coefficient. The study showed that the artificial neural network is a promised and feasible tool in the prediction of SCC properties, which containing different mineral admixtures.

Keywords: Self-compacting concrete, artificial neural network, rheological properties, mineral admixtures, hidden layer.

1. INTRODUCTION

Self-compacting concrete (SCC) is a new direction of high- performance concrete that can flow under its own weight without any external vibration, and self-compact without any blocking and segregation. The introduction of SCC shows a significant concrete technology, which presents a high quality and more economical of concrete production (Bouzoubaa, N., & Lachemi, M. 2001; De Schutter, G. 2001; & EFNARC, F. 2002). Every type of construction requires testing of the concrete to determine the fresh and hardened properties of SCC to ensure whether the concrete has the desired workability and strength or not. Thus, for the sake of saving time and decreasing the design cost, help of artificial intelligent techniques (AIT) is taken to develop models, so that the knowledge extracted from these models can be utilized to predict the SCC properties.

Artificial neural network (ANN) is one of the artificial intelligent techniques that have a good impression in data modeling for different branches of civil engineering applications. Several ANN models have been developed by some researchers for predicting mechanical and fresh properties of SCC, most of researches focused on forecasting SCC compressive strength (Abdollahzadeh, A. *et al.*, 2011; Atici, U. 2011; Deshpande, N. *et al.*, 2014; Kewalramani, M. A., & Gupta, R. 2006; Siddique, R. *et al.*, 2011; Wankhade, M. W., & Kambekar, A. R. 2013), while others predicted fresh properties of SCC (Agrawal, V., & Sharma, A. 2010; Li, F. X. *et al.*, 2011; & Mazloom, M. 2013). Also ANN was applied to many problems in structural engineering; such as modeling the design of post-tensioned concrete road bridges (García-Segura, T. *et al.*, 2017) and predicting the non linear response of plates under uniformly distributed load and different properties for ductile materials (Abdul-Razzak, A. A.,

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& Yousif, S. T). ANN was also used in the geotechnical engineering as a branch of civil engineering to predict the settlement of shallow foundation (Shahin, M. A. *et al.*, 2000). However, most of the previous studies were focused on the prediction of properties of SCC, which containing only one or two of mineral admixtures as cement replacement, and developed models to predict one property or more separately. The objective **FOR ANN MODEL**

Different models were developed using ANN technique to predict the properties of SCC. The first task was to determine the input parameters or independent of this study was to generate a high accuracy ANN model for predicting the hardened properties (compressive strength at 28 days) and fresh properties (slump flow and l-box ratio) combined in the same model for SCC containing different four mineral admixtures.

2. METHODOLOGY USED

Variables with relevant target output properties, after that sufficient data that cover all the domains of inputs and outputs variables were collected. The neural network was trained to gain the basic features between inputs and outputs data sets through the training, and then its capability in predicting similar data was evaluated using the unseen testing data and some of errors criteria. A total number of 65 experimental data sets were taken from the previous experimental research (Güneyisi, E. *et al.*, 2010). The data were arranged in a format of nine input parameters that include water/binder ratio and contents of cement, fly ash, ground granulated blast furnace slag, silica fume, metakaolin, fine aggregates, coarse aggregates and superplasticizer. Also, three output parameters were predicted using the ANN model, namely; compressive strength at 28 days, slump flow diameter and l-box ratio of SCC. A database was constructed to adjust the experimental results for the environment.

2.1 Development of ANN Model

A back propagation multi-layer perceptron (BPMLP) networks were developed to predict the SCC properties. BPMLP is one of the feed forward neural networks that consist of layers of neurons that are not connected in the same layer, but connected between one layer to the subsequent layer. The hidden layer nodes have no direct connection to the outside of the system. In this type of ANN, signals travel from the input layer to the output layer in one direction. The process of training is depending on the algorithm of back propagation. This algorithm searches for the minimum of the error function in weight space using gradient decent method. Fig.1 describes the topology of a BPNN with one hidden layer; additionally it can contain more than one hidden layer.

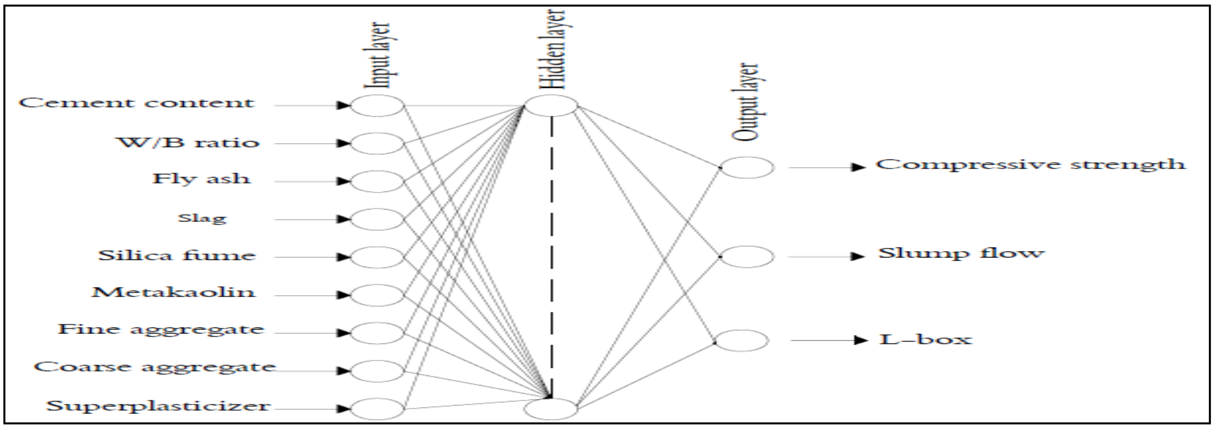

Fig. (1): Topology of back-propagation ANN.

A supervised learning approach was used in training the ANN. In the supervised learning, a pair of inputs-outputs data set was introduced to the network, as the network start to calculate the predicted outputs and comparing it with the target values, which were seen before by the network. After comparing, the error was calculated and then weights and biases were adjusted. For building the ANN model A NEUROSOLUTIONS software (2006 Neurosolutions software, version 5, http://www.neurosolutions.com) was used. Several models were constructed and various other parameters were used to perform the task. The collected data was divided into three groups. The first group contained the data that used in the training process, the second group contained the data that used in the validation process and the third group contained the data that used for testing the performance of ANN, as discussed earlier. The following procedure was followed:

a. The data set was arranged in columns and sorted randomly by the software, every column represented an input or output variable with all values for that variable. Then the whole data set was sorted in ascending manner.

b. The randomized data set was divided into three groups, the first was 70% of the total data set and it was used for training. This group was called the training data set. The second group (15% of the total data set) was used for validation and it was called the cross validation data set. The remaining data (15 % of the total data set) was used for testing, and it was called the testing data set. The parameters that may affect the results of ANN models are the number of hidden layers, number of nodes in each hidden layer, momentum rate, learning rate, type of transfer function, number of runs and max number of epochs. The number of hidden layers and number of nodes in each one are the most significant factors that control the performance of ANN, so in this study these two important factors were calculated by trialing different architectures up to reaching the optimum one. The network performance was reached through applying the mean square error criteria (MSE) that calculated using Eq. (1).

$$MSE = \left(\frac{1}{P}\right) * \sum_j \left(t_j - o_j\right)^2 \quad (1)$$

Also, the absolute fraction of variance (R^2) was calculated using Eq. (2).

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2}\right) \quad (2)$$

A tangent sigmoid transfer function was employed as an activation function for all neurons. Weights and biases were randomly initialized. A maximum number of epochs (learning cycles) reached during the training of the network model was 50000. The values of network training parameters were summarized in Table 1.

Table1: Parameters used in ANN model.

No	parameters	ANN
1	Number of input layer neurons	9
2	Number of output layer neurons	3
3	Momentum rate	0.70
4	Learning rate for the first hidden layer	1
5	Learning rate for the second hidden layer	0.10
6	Learning rate for the output layer	0.01
7	Number of runs	5
8	Number of epochs for each run	50000
9	Transfer function	TANSIG

2.2 Training of the ANN Model

NEUROSOLUTIONS software was developed and used in training the ANN. It consisted of the following steps:

a. Reading the training data and specifying the input and output variables to the ANN, The training data in this study was 45 mixes of total 65 data sets used for training the network.

b. Defining the topology of feed-forward ANN; this was fulfilled by assigning the number of hidden layers in addition to the input and output layers corresponding to the number of neurons in each layer. The numbers of inputs and outputs neurons were based on the nature of the problem. Thus the number of inputs neurons was 9 neurons equal to the number of input variables and the number of output neurons was 3 neurons according to number of output variables, while the number of hidden layers and corresponding number of neurons in each layer cannot be obtained through a fixed rule. They were determined through trial and error methods, which were 1 or 2 hidden layers that were used with different numbers of neurons in each layer; varying from (1-20) neuron.

c. A tangent sigmoid transfer function (tansig) was specified as an activation function for the hidden and output layers.

d. Specifying the different training parameters, which were required for building the model and for convergence. These parameters were specified as shown in Table 1.

e. Initial weights and biases were selected randomly at the beginning of the training process and then modified during the operation according to the level of convergence.

f. Training the ANN was done according to the above steps.

g. The ANN training efficiency was evaluated by plotting the output of ANN versus the original target values.

2.3 Determination and Selection of the Best Structure for the ANN

As shown in Table 2, the MSE was taken as arbitrary criteria for selecting the best model. The model was presented with a total of 10 unseen records employed for validating ANN and another 10 unseen records for testing the network. The optimum structure of the ANN consisted of nine input units, nine hidden nodes in the first hidden layer, nine hidden nodes in the second hidden layer and three output nodes (compressive strength, slump flow and L-box ratio). This optimum structure had the minimum MSE for both compressive strength and L-box ratio of 13.02 and 0.0026, respectively. And have a MSE of 314.72 for slump flow. The correlation coefficient resulted from testing the optimum model by the unseen testing data was 0.95, 0.71 and 0.88 for compressive strength, slump flow, L-box ratio, respectively (Table 3). Figures 2, 3, 4 illustrate the relationship between the actual (desired) and predicted (network output) values of the best obtained neural network structure for predicting SCC properties in the training, validation and testing phases.

Table 2: MSE for training, validation and test data sets for the optimum model

ANN structure	SCC property	Training set MSE	Validation set MSE	Test set MSE
9-9-9-3	Compressive strengrh(MPa)	30.75	26.71	13.01
	Slump flow (mm)	199.69	216.34	314.72
	L-box ratio	0.0028	0.0018	0.0027

Table 3: correlation coefficients for training, validation and test data sets for the optimum model

Best network structure	SCC properties	Training data set	Validation data set	Test data set
9-9-9-3	Compressive strength	0.94	0.94	0.95
	Slump flow diameter	0.77	0.68	0.71
	L-box ratio(H_2/H_1)	0.68	0.73	0.88

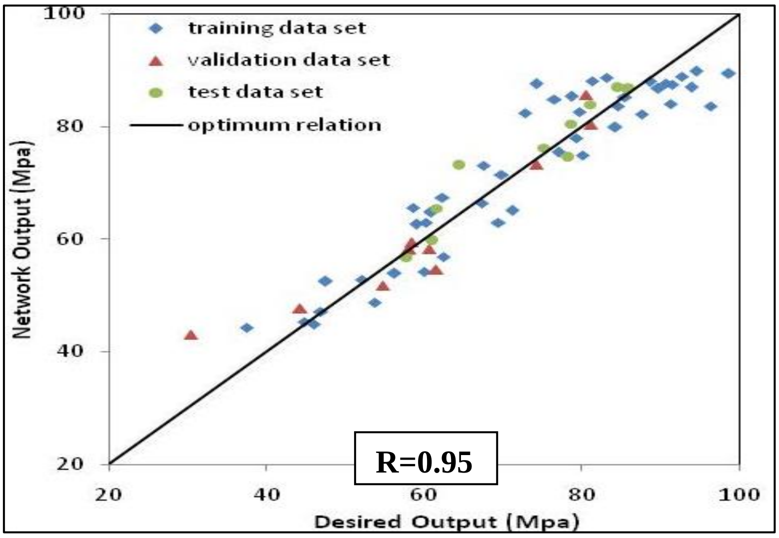

Fig. (2): Relationship between actual and predicted values of the best model for predicting the compressive strength (MPa).

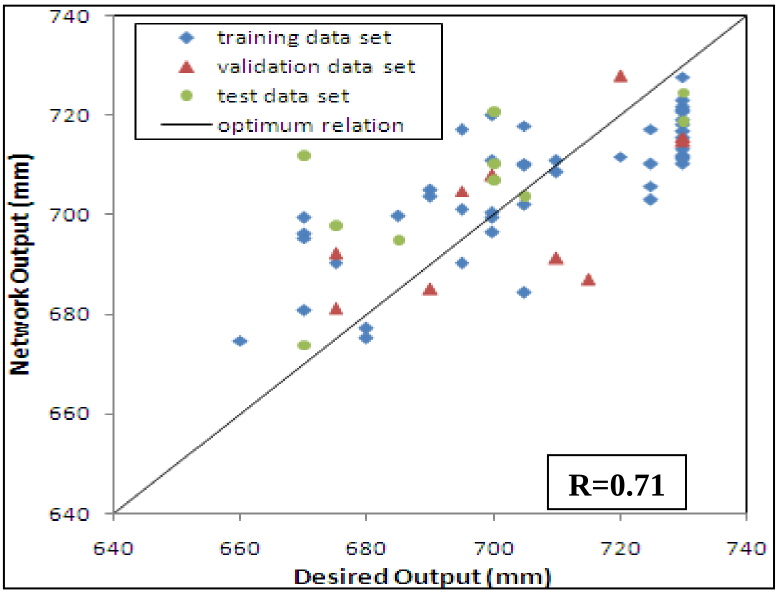

Fig. (3): Relationship between actual and predicted values of the best model for the slump flow diameter (mm).

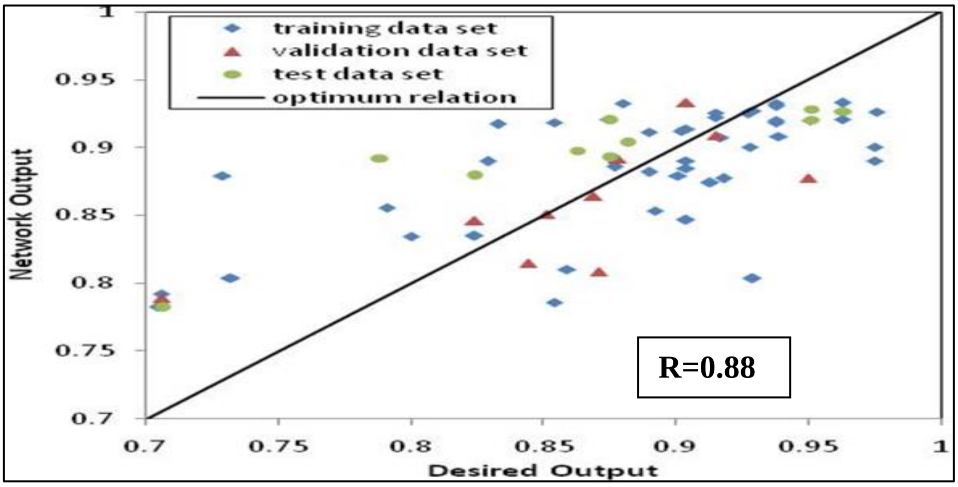

Fig. (4): Relationship between actual and predicted values of the best model for. The L-box ratio.

3. APPLICATION OF THE ANN OPTIMUM MODEL

In order to check the capability of the ANN model to capture the sensitivity of SCC mix properties to individual constituents, a parametric analysis was carried out.

3.1 Effect of Fly Ash Content

Figures (5, 6, 7) show the effect of fly ash % as a replacement of binder content on the different SCC properties, while the other mix parameters were kept constant to some extent. Studying the effect of fly ash on SCC properties was done at a total binder content of 550 and 450 kg/m^3, which corresponding water/binder ratio of 0.32 and 0.44, respectively. The compressive strength results predicted using the ANN model at the different contents of FA were identical to the experimental results, as shown in Fig. (5). However, the results predicted for the slump flow diameter and L-box ratio having the same trend of the experimental results but with slight difference in the values, see Figs. (6 and 7).

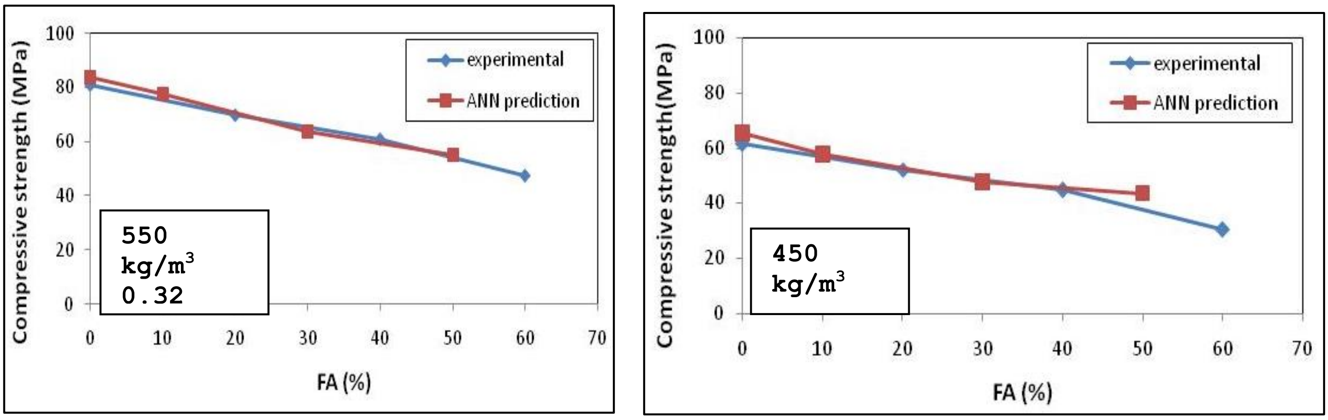

Fig. (5): Predicted and experimental results of compressive strength. At different contents of FA.

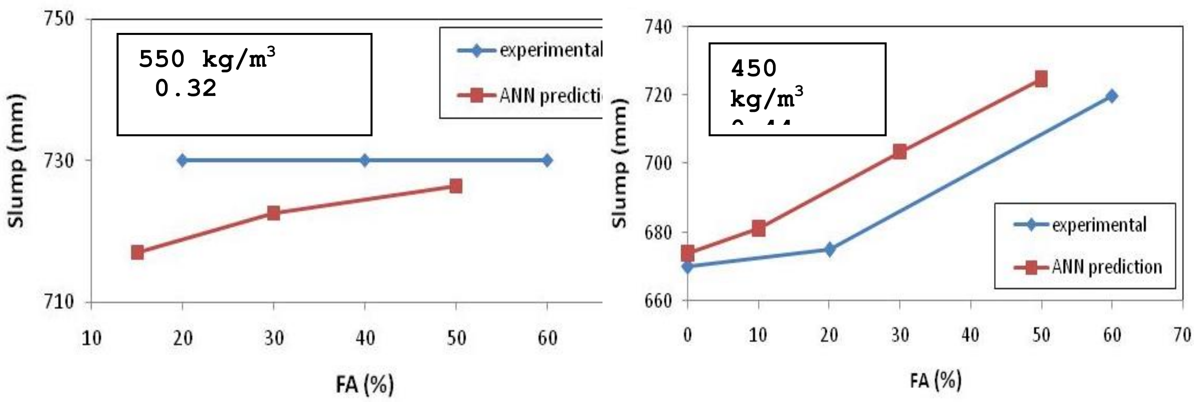

Fig. (6): Predicted and experimental results of slump flow diameter. At different contents of FA.

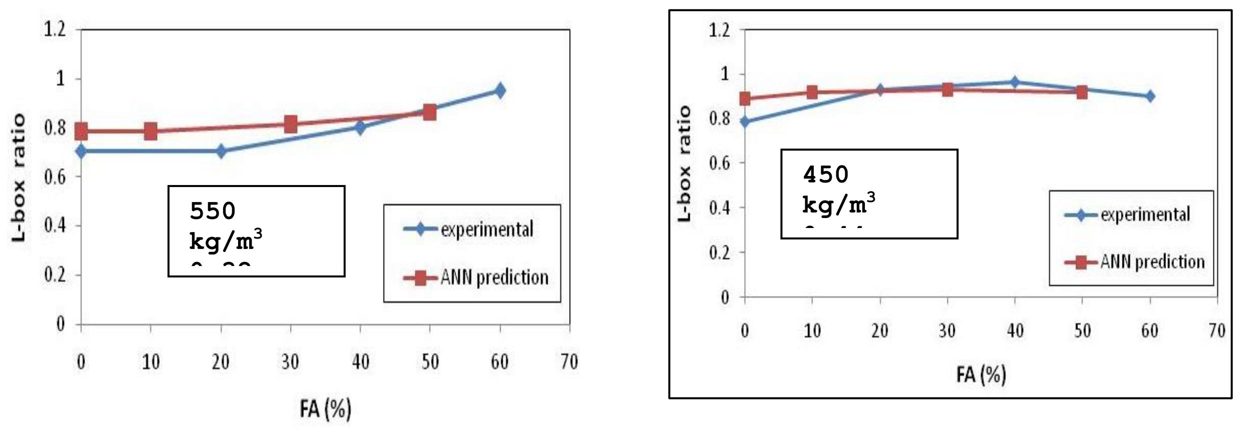

Fig. (7): Predicted and experimental results of L-box ratio at different contents of FA.

3.2 Sensitivity Analysis

The data was further analyzed for sensitivity to identify the impact of the varied input process parameters on the outputs properties. The results obtained were shown in Fig. (8).The fly ash had the highest influence on the compressive strength followed by the metakaolin. The super-plasticizer had the highest impact on the slump flow diameter followed by fly ash content, while the w/b ratio was the most important factor affecting the L-box ratio followed by the metakaolin content.

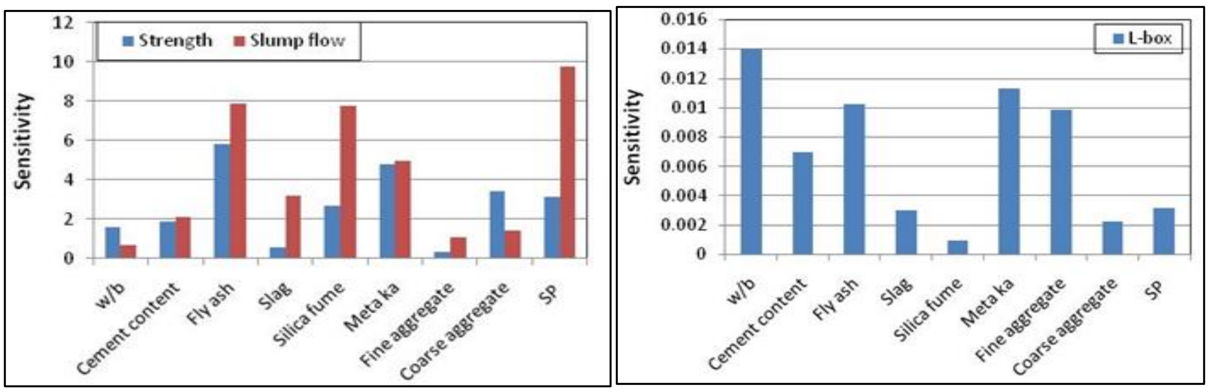

Fig. (8): Sensitivity analysis.

4. CONCLUSIONS

A feed-forward back propagation neural network technique was used to predict the different properties of SCC containing various mineral admixtures as a cement replacement. Several attempts were made to obtain the best structure of the network. The results obtained led to the following conclusions:

- The optimum ANN structure for predicting the compressive strength at 28 days, slump flow diameter and L-box ratio was found at 9-9-9-3; i.e, 9 nodes in the input layer, two hidden layers with 9 nodes in each one and 3 nodes in the output layer.
- The correlation coefficients for testing data sets for the optimum ANN were 0.95, 0.71 and 0.88 for compressive strength, slump flow and L-box ratio, respectively, which were acceptable and confirmed the feasibility of ANN to effectively model and predict the SCC properties.
- The optimum ANN was also used to study the effect of certain mix parameters on the different SCC properties; the relations developed showed trends similar to the experimental ones combined with very close values.
- The ANN model showed excellent capability to study the sensitivity of the different types of mineral admixtures and super-plasticizer content on the different properties of SCC.

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