Prediction of Compressive Strength and Workability Characteristics of Self-compacting Concrete Containing Fly Ash Using Artificial Neural Network

Nitesh Netam and T. Palanisamy

Abstract This study aims to propose an artificial neural network (ANN) model for predicting the properties of self-compacting concrete (SCC). SCC has enhanced properties such as very high workability and it can go through very tight spaces between reinforcements without any application of vibration. To get the desired strength and workability, it is necessary to understand the parameters determining the nature and properties of SCC and the relationships involved among those parameters. In this study binder content, water to binder ratio, fly ash percentage, coarse aggregate, fine aggregate, and superplasticizer content are chosen as input parameters, and output results from the model are slump flow value, L-box ratio, V-funnel time, and compressive strength. An ANN model is constructed and its architecture is selected by evaluating the performance of a network with a different number of neurons for the optimum results. Then this model is trained, tested, and validated through a database of experimental test results gathered from various literature. The accuracy of this model is evaluated by evaluation matrices such as R and MSE. To check the efficiency, the current model comparison was made with an existing data envelopment analysis model (DEA).

Keywords Self-Compacting Concrete · Fly ash · Artificial Neural Network · Compressive strength · Workability

1 Introduction

Self-Compacting Concrete (SCC) mixes can be defined as those mixes which, because of their enhanced flow characteristics, can effectively flow even around the congested reinforcement bars, without leaving any voids and get fully compacted by their own weight, without the need for any external compaction efforts.

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Presently RC structures are designed and constructed to resist earthquake load also, which further results in an increase in the density of reinforcing bar structural members and especially in locations such as beam-column joints. The current construction industry requires to use of such concrete which has sufficient strength and also be able to fill the most complex shapes and places. Thus SCC, which has high fluidity along with enough viscosity to carry aggregates and prevent segregation, has been developed and increasingly used. Construction methods have also been evolved in response to this with wide use of pump pouring of concrete, improvement in pumping capacity, and non-vibrational construction. These methods also reduce the noise generated due to the extensive use of vibrators for construction purposes.

Mineral additions such as fly ash are a very important element of SCC and its significance has increased in the current concrete scenario, as they enhance the concrete properties, especially with its immunity to aggressive environment and the use of such additives is economical too. Also, by increasing the use of mineral additives we making a move towards sustainable development, decreasing the waste of fly ash, reducing the amount of energy consumed in the production of cement, and ultimately helping the environment by reducing the emission of CO_2 [1].

Due to these merits, SCC has gained popularity in the construction industry, but the mix-proportioning and prediction of the workability properties and compressive strength are complex. Various researchers are trying to come up with new and more effective mix proportioning methods which can be used to produce concrete with desired properties [2]. Prediction of properties of SCC, before construction employing artificial intelligence (AI), could help to save cost and time. Thus, by using this method, an initial mix-proportion for desired properties can be obtained, and it will be more effective in optimizing the ingredient proportion from there onwards by various tests.

Various AI methods such as fuzzy logic (FL) system, artificial neural network (ANN) [3], expert systems (ES) along with some other statistical techniques such as least square support vector machine (LSSVM) [4, 5], relevance vector machine (RVM), data envelopment analysis (DEA) [6], etc. are used and popularised by many researchers in the field of civil engineering.

The aim of this study is to propose an ANN model for the prediction of flow properties and compressive strength of SCC.

2 Artificial Neural Network

ANN is a type of artificial intelligence that imitates the way how a human brain works by learning through experiences and utilizing that knowledge in solving future problems. ANN is a nonlinear information processing framework that is built from interconnected computing elements called neurons. Every neuron is linked with the neuron of the next layer by information transmitting channels called connections, and these connections are associated with weights. These weights indicate the influence of each input on the output response. The sum of weighted input signals is then

Table 1 Statistics of the database

Variables	Min	Max	Mean value	STD	Min	Max	Mean value	STD
	The database used for training				The database used for comparison			
Binder (kg/m^3)	400	589	517.7	50.2	431	539	486.875	27.818
Fly ash (kg/m^3)	0	381.88	148.29	82.64	0	60	27.187	19.491
W (kg/m^3)	150	242	194.72	27.88	0.31	0.41	0.36	0.028
FA (kg/m^3)	614.27	1038	852.23	78.26	743	971	875	81.507
CA (kg/m^3)	590	935	755.91	116.62	735	924	817.625	81.507
SP (%)	0.86	17.64	7.4	3.98	3.21	11.8	6.062	2.021
Slump flow (mm)	480	810	673.38	55.13	600	720	684.125	38.767
L-box ratio	0.6	1	0.88	0.09	0.89	0.96	0.93	0.029
V-funnel time (s)	2	34	8.91	4.79	6.1	8.1	7.15	1.1
Compressive strength (MPa)	17	86.8	47.13	15.29	37.2	73.3	58.731	9.2

applied with an activation (or transfer) function to obtain the output response This study consists of ANN modeling which consists of three layers (Input layer, Hidden layer, and output layer). First, the network is trained over several iterations with already available datasets, then it can be used for a dataset that the network has never encountered before.

3 Experimental Database

For the development of the ANN model, 138 datasets containing experimental results of various flow and strength tests are collected from published literature [8–22]. For the effective modeling of the network, only datasets conforming to EFNARC:2005 [7], are used for training. Furthermore, 16 more datasets are taken from the literature of the already existing model to test and compare the efficiency of the proposed ANN model [6]. Statistics of the datasets are presented in Table 1.

4 Parameters Considered for ANN Modeling

For the modeling of the current model contents of Binder (B), Fly ash (F), Water (W), Fine aggregate (FA), Coarse aggregate (CA), and Superplasticizer (SP) are taken as input parameters, and Slump flow diameter (D), L-box ratio (L), V-funnel flow time (V), and Compressive strength (f_c) are taken as output parameters. For better performance of the model, all the input parameters are taken in single units i.e.,

kg/m^3. The datasets which differ from this unit system in any literature are converted to kg/m^3 before it was included in datasets used for training. For compressive strength, cube strength is used. If in literature cylindrical compressive strength is measured, then it is converted into cube compressive strength based on assumption that the cube compressive strength is 25% greater than the cylindrical compressive strength.

5 ANN Modeling

MATLAB (R2021a-academic use) is used for developing the ANN model for this research. The architecture of the feed-forward neural network is modeled with one single hidden layer. A single hidden layer neural network is capable of approximating continuous function very effectively. Due to this reason, researchers have adapted the use of a single hidden layer in their studies [3]. The number of neurons in the input layer and output layer is 6 and 4 respectively and the number of neurons in the hidden layer is selected by evaluating the performance of the network with a varying number of hidden neurons, i.e., from 1 to 20 neurons. The performance of the network is evaluated using the correlation coefficient (R) for each network. A graph is plotted taking R-value along the Y-axis and the number of hidden neurons along the X-axis Re (Fig. 1).

The network with 15 neurons showed the best results in comparison to other networks, hence the hidden layer has 15 neurons Re (Fig. 2a). The Levenberg–Marquardt backpropagation algorithm is used for training the network. The activation function used in the hidden layer and output layer is 'tansig' and 'purelin' respectively. Dataset used is randomly divided into three parts. For training of the network 70%, for testing 15%, and for validation 15% of the data are used.
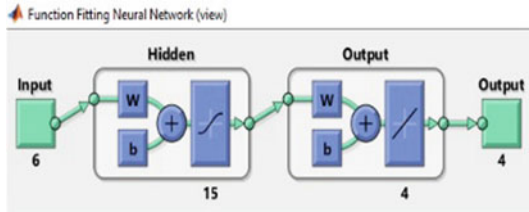
The architecture of ANN obtained from MATLAB is shown in Fig. 2b.
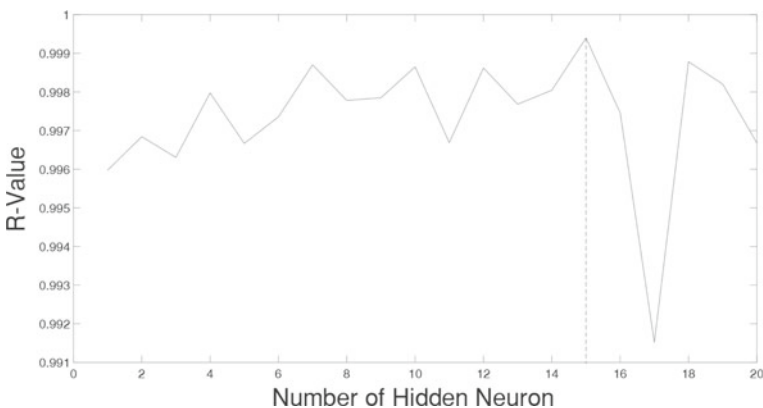
Fig. 1 Finding best architecture for the ANN model
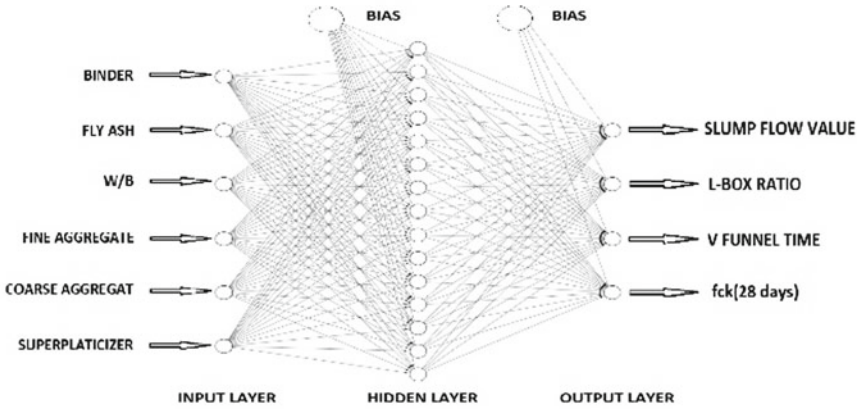
(a)

(b)

Fig. 2 The architecture of the ANN model

6 Result and Discussion

Once all the required parameters have been selected, the network is trained by running the MATLAB code. The training continues till the error arising during validation fails to decrease for six iterations or epochs and then validation stops. The maximum number of iterations that can be achieved during the training stage is set to 1000. For our current ANN model, it took 9 iterations or epochs to train the network, and the mean squared error (MSE) for each iteration is shown in Fig. 3. Mean squared error (MSE) is the average squared difference between the output and targets. Lower values are indicative of better results and zero indicates no error. The mean squared error is calculated as per Eq. (1).
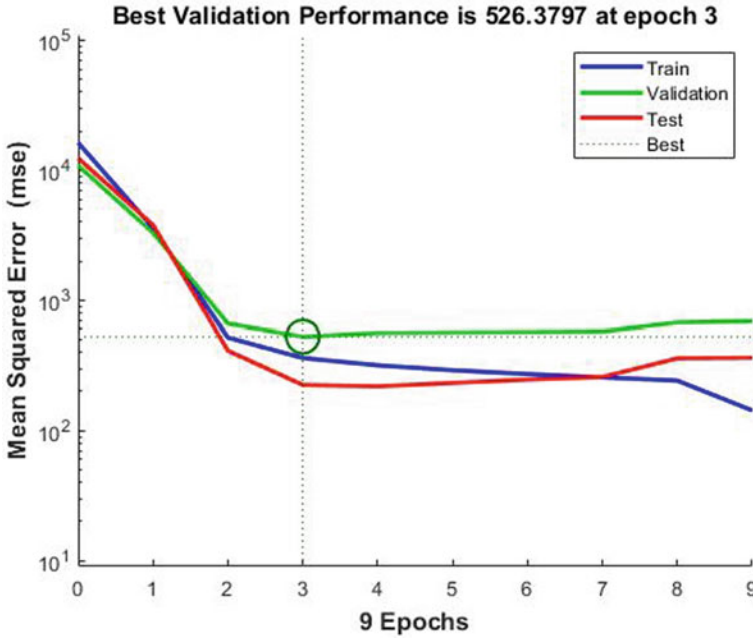
$$MSE = \frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2 \tag{1}$$

Fig. 3 Performance of network for each iteration

where O_i and P_i are observed and predicted output results respectively.

The performance of the current ANN model is checked by the coefficient of correlation (R) value, during training, testing, validation, and after that for whole datasets. The R-value determines the correlation between the output and targets. An R-value of 1 means a close relationship, and 0 means a random relationship. The R-value is defined as shown in Eq. (2).

$$R = \frac{\sum_{i=1}^{n}(O_i - \overline{O_i})(P_i - \overline{P_i})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O_i})^2(P_i - \overline{P_i})^2}} \tag{2}$$

where $\overline{O_i}$ and $\overline{P_i}$ are the mean observed and predicted output values. The R values and regression graphs are plotted with the help of MATLAB. Results obtained from the experiment show that the model achieved a very good predicting capacity for the given dataset. R values for the training, testing, and validation stage are 0.998, 0.99475, and 0.99807 respectively Re (Fig. 4). And the R-value obtained when the model was tested on the whole dataset is 0.99746 which shows the current model can predict output values very close to experimental results Re (Fig. 5).
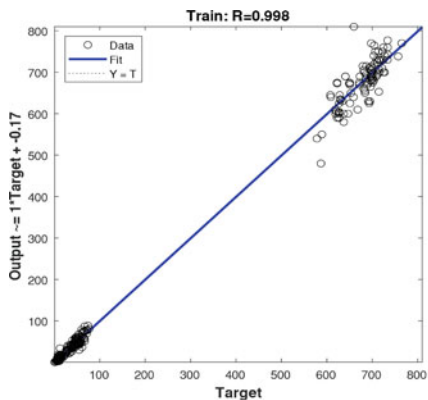
(a)
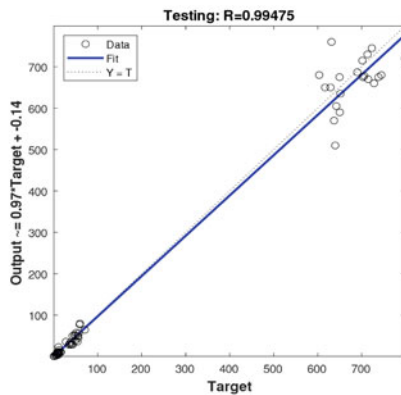
(b)
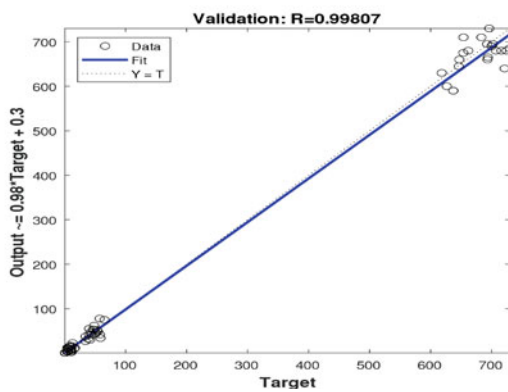
(c)

Fig. 4 a R plot for training data, b R plot for Testing data, c R plot for validation data
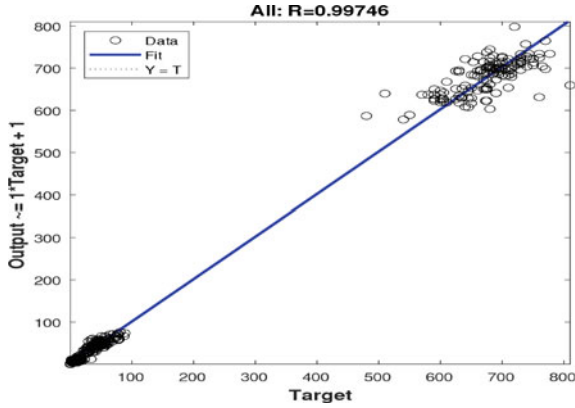
Fig. 5 R plot for actual values and predicted values for all data

7 Comparison with Data Envelopment Analysis (DEA) Model

To validate the actual performance of the proposed ANN model, the network is tested on a dataset that was not used for the training of the network. This dataset is obtained from the literature it is used to check the accuracy of the existing DEA model (Table 2).

Table 2 Comparison between DEA and ANN model with experimental results

N	D (mm)					L-box ratio (H2/H1)					V-funnel (s)					f$_{ck}$28 (MPa)				
	EXP	DEA	ANN	E$_{DEA}$ (%)	E$_{ANN}$ (%)	EXP	DEA	ANN	E$_{DEA}$ (%)	E$_{ANN}$ (%)	EXP	DEA	ANN	E$_{DEA}$ (%)	E$_{ANN}$ (%)	EXP	DEA	ANN	E$_{DEA}$ (%)	E$_{ANN}$ (%)
1	600	635.345	644.855	5.7	14.99											66.8	50.245	49.150	24.8	22.84
2	600	621.838	599.266	3.6	17.29											71.3	56.391	56.018	20.9	17.36
3	630	769.799	618.791	22.2	11.12											49.9	49.788	42.265	0.2	22.57
4	679	651.761	701.388	4	11.81											60	69.721	74.464	16.2	17.97
5	686	565.137	737.532	17.6	18.46											62	51.405	56.392	17.1	3.79
6	686	624.382	738.463	9	15.82											60	48.669	52.007	18.9	2.92
7	699	668.269	731.716	4.4	13.34											48	42.958	49.497	10.5	18.17
8	709	661.110	646.678	6.8	1.6	0.89	0.852	0.623	4.3	4.68						57.5	63.722	64.038	10.8	1.17
9	709	755.904	635.890	6.6	2.64	0.91	0.928	1.071	2.0	3.27						53.5	56.856	43.977	6.3	14.83
10	702	765.076	645.566	9	0.48	0.94	0.939	1.148	0.1	0.76						55	56.393	45.742	2.5	20.21
11	705	770.125	658.954	9.2	0.63	0.95	0.936	1.230	1.5	1.35						58	56.030	45.323	3.4	29.46
12	701	770.135	676.178	9.9	0.06	0.96	0.939	1.307	2.2	0.22						59	56.13	44.982	4.9	35.13
13	720	669.880	653.962	7	4.27						8.1	8.894	7.907	9.8	5.48	73.3	78.952	79.916	7.7	2.43
14	700	599.839	686.887	14.3	1.16						8.1	7.316	5.048	9.7	26.87	69.7	60.582	69.847	13.1	4.4
15	705	648.812	741.892	8	5.49						6.1	4.091	0.981	32.9	23.18	58.5	54.529	56.364	6.8	3.92
16	715	641.162	732.431	10.3	8.34						6.3	3.475	4.451	44.8	27.87	37.2	44.303	40.779	19.1	42.38
Mean absolute % error				9.26	7.97				2.0	2.1				24.3	20.85				11.45	16.23

8   Conclusion

1. ANN model is proposed for the prediction of the flow properties and compressive strength of SCCs.
2. The proposed ANN model shows relatively greater accuracy than the already existing DEA model. Hence, the proposed model can be utilized for the prediction of the properties of SCCs.
3. Through the application of ANN time and cost can be saved, which would have been spent on experimental works otherwise.

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