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Prediction of Compressive Strength for Self- Compacting Concrete (SCC) using Artificial Intelligence and Regression Analysis

S. Dhiviya Bharathi*, R. Manju and J. Premalatha

Department of Civil Engineering, Kumaraguru College of Technology, Coimbatore, India.

Abstract : In this study, Regression Analysis and Artificial Neural Network models are developed to predict the fresh and hardened properties of Self-Compacting Concrete containing Fly Ash as partial replacement of cement. The data collected from the literature were used for developing the models. The mix constituents such as Cement (C), Fly ash (F), Fine Aggregate (FA), Coarse Aggregate (CA), Superplasticizer dosage (SP) and Water-Binder ratio (W/B) were taken as input parameter. The fresh and hardened properties of SCC such as Slump Flow Diameter (SFD), L-Box ratio (LB), V Funnel Flow Time (VFT) and Compressive Strength (CS) at 28 days were taken as output parameter. Models were developed using Regression Analysis (RA) and Artificial Neural Network (ANN), trained and tested. Their results from both the models were compared. Artificial Neural Network models have predicted better results than Regression Analysis models.
Keywords : Self-Compacting Concrete, Regression analysis, Artificial Neural Network, Prediction, Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength.

1.0 Introduction

Self-Compacting Concrete is a flowable concrete that can fill formwork without any mechanical vibration, so that it can be easily placed, in complicated formwork, congested reinforced structural elements and hard to reach area[11]. For SCC, the use of super plasticizers is necessary in order to ensure adequate filling ability, passing ability and segregation resistance. However the use of chemical admixtures are expensive and results in increased material cost. But the use of mineral admixtures without increasing its cost could increase the slump of the concrete. These supplementary materials enhance the rheological properties and reduce the cracking of concrete due to the heat of hydration. Thus it improves the durability.

Fly ash is a building material, obtained from the combustion of coal in the thermal power plants. A number of studies[14-27] were carried out to study the presence of fly ash as a mineral admixture. It enhanced the strength and durability characteristics. It can be either used as an admixture or as a partial replacement of cement.

The experimental test results may fall short of required strength due to some error in designing the mix. Therefore, the concrete designing process has to be repeated, which may be expensive and time consuming. To ensure acceptable workability and mechanical properties it requires manipulation of several mixture variables[1].

Also, absence of theoretical relationship between mixture proportioning and measured engineering properties of SCC makes it more complex. In order to reduce the time and cost involved in it, a data driven solution is to be generated for predicting the mix proportion, flow properties and compressive strength of SCC.

Artificial intelligence is a field of study that seeks to explain and emulate intelligent behaviour in terms of computational processes. It discovers patterns buried in large repositories of data. It allows to construct rule-based models that quantify patterns and combine them. Artificial Neural Network (ANN) is a modelling method based on Artificial Intelligence techniques. An artificial neural network for concrete mixes can be developed their fresh and hardened properties can be predicted with ANN with minimum percentage of error [34].

Artificial neural network is a pattern classifier that behaves, in some ways, like the human mind. It consists of artificial neurons arrayed in a set of layers (Input layers, output layers and hidden layers). These neurons are connected by edges. Each edge connecting a neuron has a weight representing some previous learning process. By varying these weights the input-output relation can be predicted [1]. It is used due to its ability to learn input-output relation for any complex problem in an efficient way. It can also continuously restrain new data conveniently.

Regression analysis is a statistical processes that are used to estimate the relationship between a dependent variable and one or more independent variables which are known as predictors [3]. From the database of observations, the degrees of correlation between two variables are found and the regression techniques are used to find the equation that best fits the trend of the relationship.

The objective to be achieved in this study include:

1. To develop models between mix proportions of SCC and fresh and hardened properties of SCC using Artificial Neural Network and Regression analysis.
2. To train the data and predict the fresh and hardened properties of SCC containing fly ash.
3. To validate the models using various statistical parameters.
4. To compare both the models and find the best model that predicts the fresh and hardened properties of SCC.

2.0 Input and Output Parameters used

In training and testing of the models, twenty seven data obtained from various literature[14-32] were used. The parameters such as contents of Cement, Fly ash, Fine Aggregate, Coarse Aggregate, Water-Binder ratio and Super plasticizer dosage were used as input while parameters such as Slump flow diameter, V funnel flow time, L-Box ratio and compressive strength at 28 days were used as output. The input and output quantities used in the models for predicting the fresh and hardened properties are given the Table 1.

Table 1 Input and output quantities used in the models

Variables used in the model	Quantity	
	Min	Max
Input variables		
Cement (kg/m^3)	220	500
Fly ash (kg/m^3)	30	330

Fine aggregate (kg/m^3)	194	977
Coarse aggregate (kg/m^3)	561	924
Water-binder ratio	0.32	0.44
Superplasticizer dosage (%)	0.9	3.9
Output variables		
Slump Flow Diameter (mm)	650	750
L-Box Ratio	0.850	0.963
V funnel Flow Time (s)	7.560	15
Compressive strength at 28 days (MPa)	25.360	74.210

3.0 Artificial Neural Network

Layered feed forward back propagation networks are used in which the signals are sent forward and errors are propagated backwards[33]. The various topology of the Artificial Neural Network used in this study are as shown in the Fig.1 to Fig.4.

In Artificial Neural Network, the various algorithms that can be implemented are Levenberg-Marquardt backpropagation algorithm, BFGS quasi-Newton backpropagation algorithm, Powell-Beale conjugate gradient backpropagation algorithm, Fletcher-Powell conjugate gradient backpropagation algorithm, Polak-Ribiere conjugate gradient backpropagation algorithm and One Step Secant backpropagation algorithm[3]. In this study, Levenberg-Marquardt backpropagation algorithm is used due to its speed and efficiency[5-6].

The models were created in MATLAB software using Neural Network Toolbox. Four different models for predicting the slump flow diameter, L Box ratio, V funnel flow time and compressive strength at 28 days are developed. The models consist of one input layer, one output layer, one hidden layer and 10 neurons in the hidden layer. From the total experimental data, 70% of the data is considered for training, 15% for testing and 15% for validation.

The values of parameters used in the model for predicting Slump flow diameter, L-Box ratio, V funnel flow time and Compressive strength at 28 days are as shown in the Table 2.

Table 2 Values of Parameters used in ANN Model

Network parameters	**ANN**
Number of input layer	6
Number of hidden layers	1
Number of hidden neurons	10
Number of output layer	1
Number of training data	70%
Number of testing data	15%
Number of validation data	15%

4.0 Regression Analysis

The Regression Analysis is carried out using the Data Analysis Package in MS Excel. The regression equation for Slump flow diameter, V funnel flow time, L-Box ratio and compressive strength at 28 days are calculated by considering 95% confidence level [3]. Therefore, the error level that is allowed in predicting the output is limited to 5%.

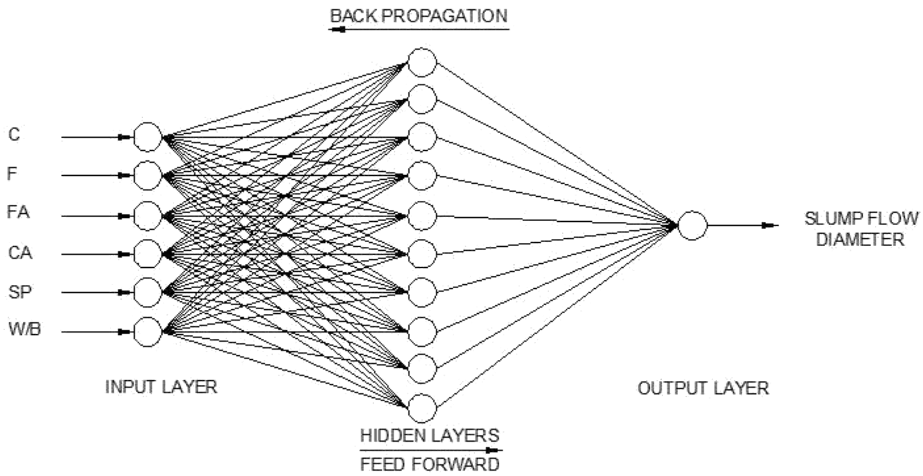

Fig. 1. ANN Topology for Predicting Slump Flow Diameter

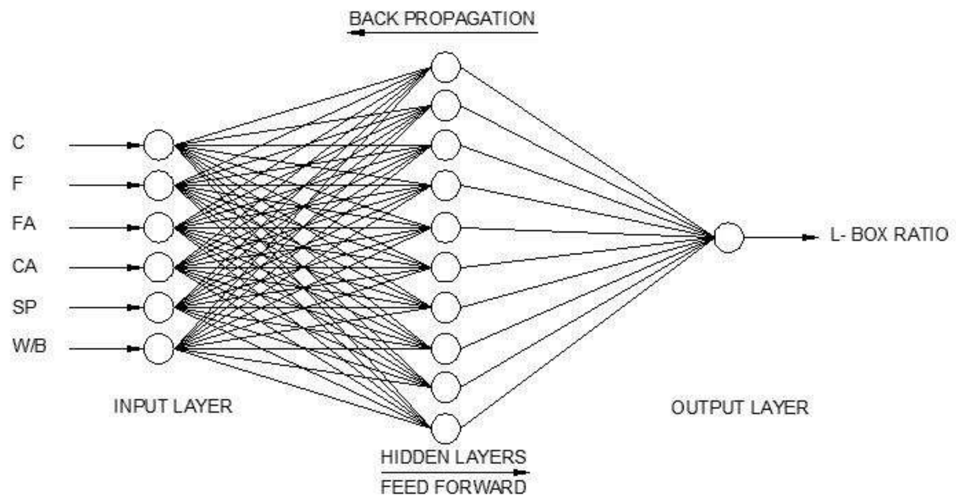

Fig. 2. ANN Topology for predicting L-Box Ratio

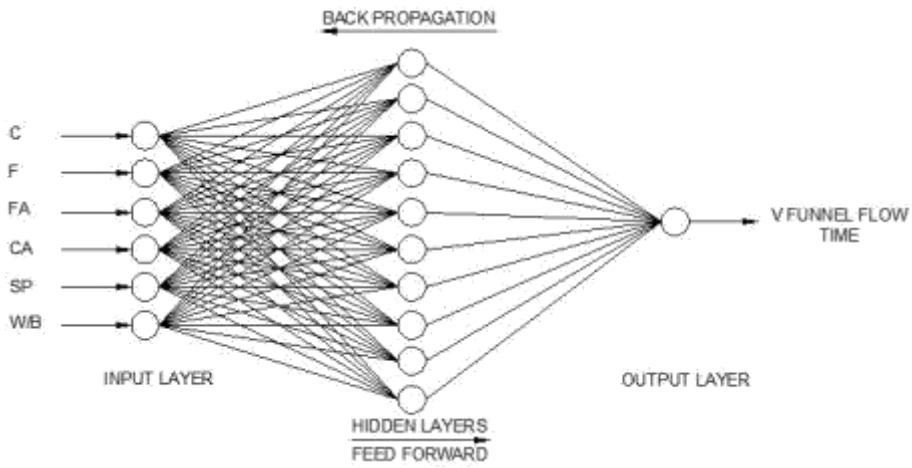

Fig. 3. ANN Topology for Predicting V Funnel Flow Time

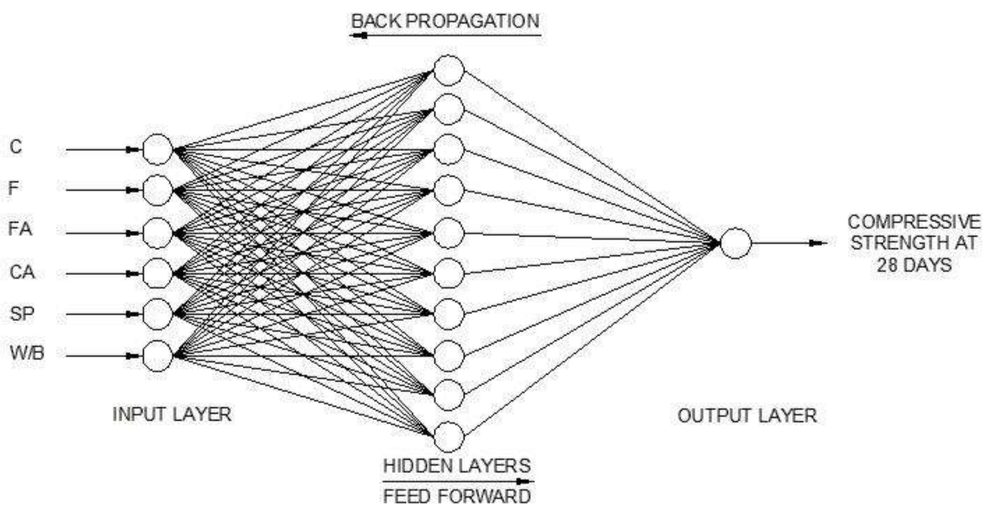

Fig. 4. ANN Topology for Predicting Compressive Strength at 28 days

5.0 Results and Analysis

5.1 Prediction of Fresh and Hardened Properties of SCC using ANN

The relationship between the Predicted and Literature Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days by Artificial Neural Network is depicted in Fig. 5 – 8.

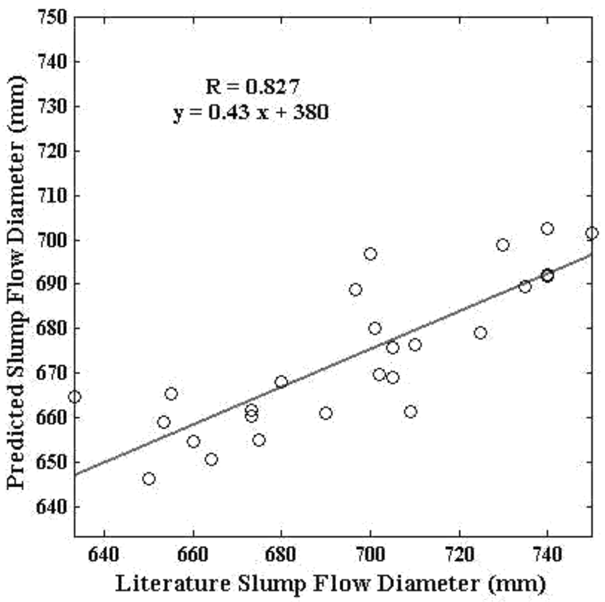

Figure 5 Predicted Vs Literature Slump Flow Diameter (ANN)

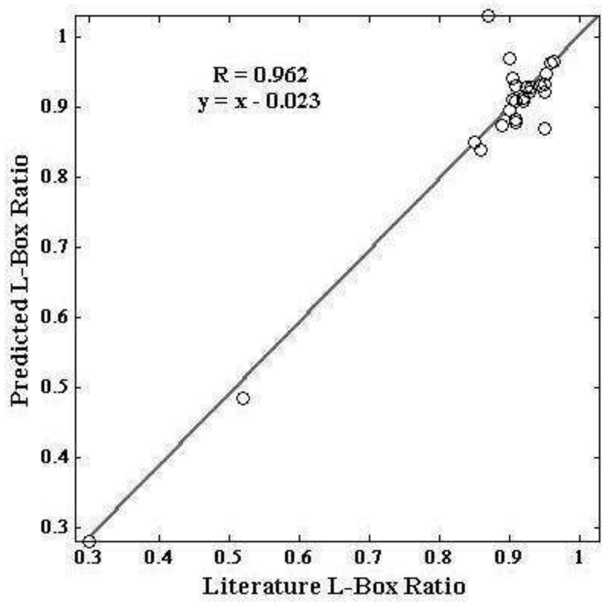

Figure 6 Predicted Vs Literature L-Box Ratio (ANN)

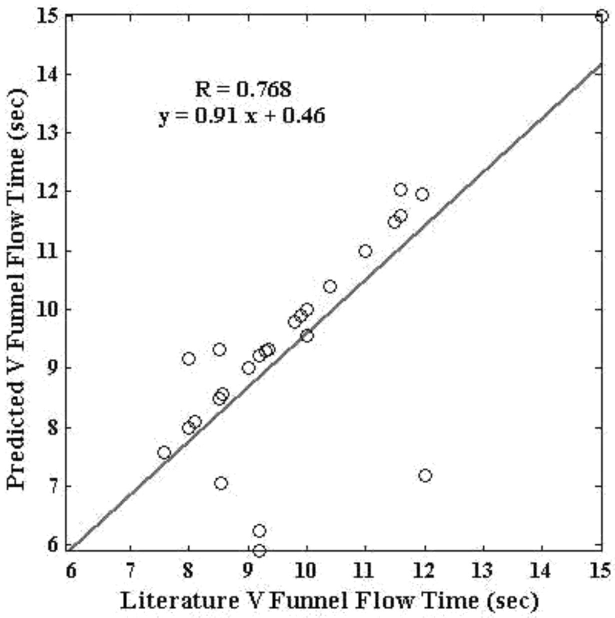

Figure 7 Predicted Vs Literature V Funnel Flow Time (ANN)

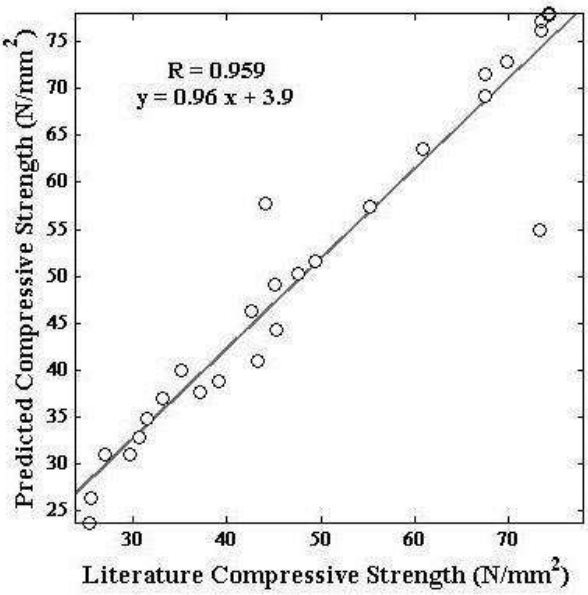

Figure 8 Predicted Vs Literature Compressive Strength at 28 Days (ANN)

The correlation coefficient (R) for Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days obtained from ANN model are 0.827, 0.962, 0.768 and 0.959 respectively. The linear equation between the Predicted and Literature values of Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days from ANN are as follows:

For Slump Flow Diameter,

$y = 0.43\ x + 380$

For L-Box ratio,

$y = x - 0.023$

For V Funnel Flow Time,

y = 0.91 x + 0.46

For Compressive Strength at 28 days,

y = 0.96 x + 3.9

where, y is the predicted value and x is the literature value.

5.2 Prediction of Fresh and Hardened Properties of SCC using RA

The relationship between the Predicted and Literature Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days by Regression Analysis is depicted in Fig. 9 – 12. The determination coefficient (R^2) for Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days obtained from RA model are 0.646, 0.792, 0.480 and 0.646 respectively.

The equations obtained by regression analysis are as follows:

Slump flow diameter = 210.812 + (C*0.585) + (F*0.818) + (FA*0.048) + (CA*0.206) - (S*51.652) - (W/B*15.310)

L-Box ratio = 1.91484– (C*0.00064) - (F*0.00018) - (FA*0.00010) - (CA*0.00044) - (S*0.73964) - (W/B*0.03484)

V funnel flow time = -11.409 + (C*0.020) + (F*0.030) + (FA*0.048) + (CA*0.008) + (S*4.658) + (W/B*0.010)

Compressive strength = -219.577 + (C*0.346) + (F*0.397) + (FA*0.035) + (CA*0.113) - (S*60.271) (W/B*5.175)

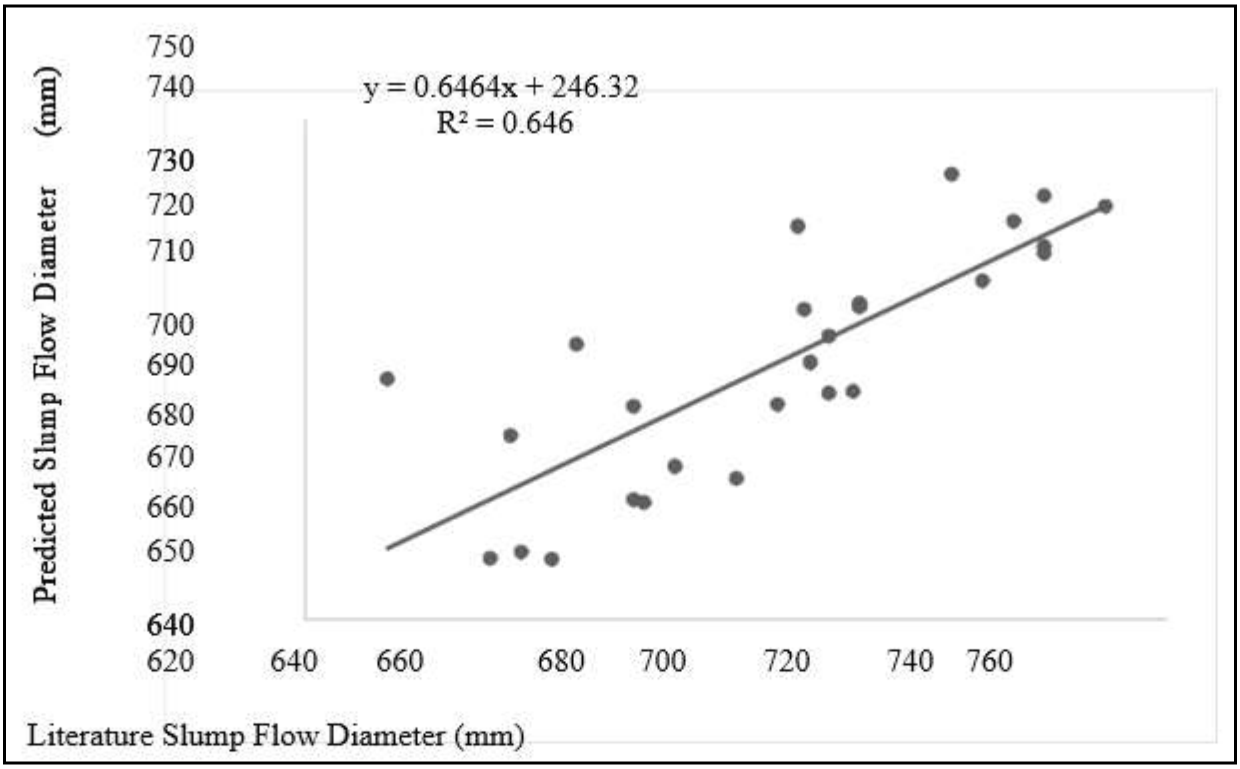

Figure 9 Predicted Vs Literature Slump Flow Diameter (RA)

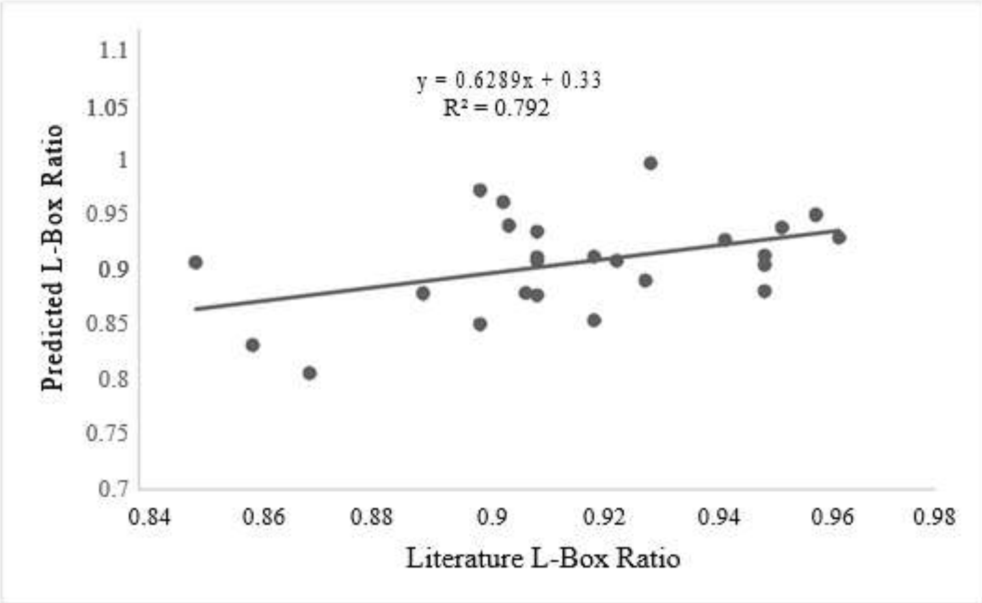

Figure 10 Predicted Vs Literature L-Box Ratio (RA)

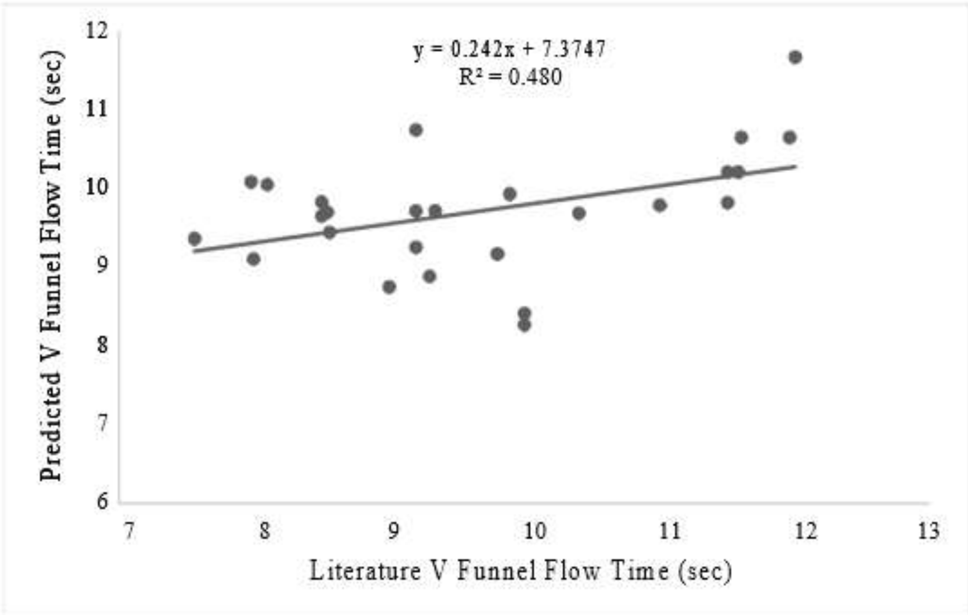

Figure 11 Predicted Vs Literature V Funnel Flow Time (RA)

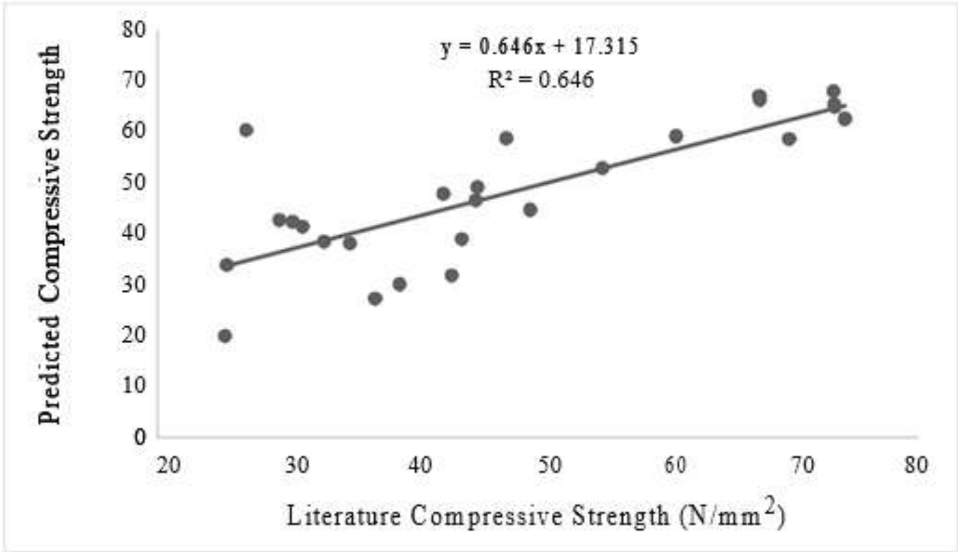

Figure 12 Predicted Vs Literature Compressive Strength at 28 Days (RA)

5.3 Validating the models using Statistical Parameters

5.3.1 Validating the ANN models

The performance of the model depends on the neurons in the hidden layer for an ANN model which are finalized by trial and error approach. The statistical values such as Correlation coefficient (R), Absolute fraction of variance (R^2), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used to validate the efficiency of the model[2].

In this study the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Absolute fraction of variance (R^2) are calculated using the following equations:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ER - PR)^2}$$

$$\text{MAPE} = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{ER - PR}{ER}\right|\right) \text{X } 100\%$$

$$R2 = 1 - \frac{\sum_i (LR - PR)2}{\sum_i (PR)^2}$$

Where, n is the number of observations, LR is the literature result and PR is the Predicted result from the model.

The RMSE value should be should be near 0 for better goodness of fit[4]

The statistical parameters of ANN models developed for predicting the Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days are presented in the Table 3.

Table 3 Statistical parameters of ANN model

Model	R	R^2	RMSE	MAPE
SFD	0.827	0.684	16.573	1.049
LB	0.962	0.925	0.015	1.248
VFT	0.768	0.590	0.306	1.905
CS	0.959	0.920	1.381	2.270

The MAPE values observed for models developed using ANN for predicting the Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days are 1.049, 1.248, 1.905 and 2.270 respectively which are less than 10% indicating that the models performance is excellent. The RMSE value near 1 for the models developed using ANN shows that the error between the Literature and the Predicted result from the model developed using ANN is very less.

5.3.2 Validating the RA models

The F-test generally denoted as Analysis of Variance or ANOVA Test is used to ascertain the elimination of null hypothesis. From ANOVA test two parameters, namely, F value and F-significant can be generated. The higher F value indicates the goodness of fit of the model[3]. The F-significant value should be less than 0.05 for 95% confidence level[3]. The statistical parameters of RA models developed for predicting the Slump Flow Diameter, L-Box ratio, V Funnel Flow Time and Compressive Strength at 28 days are presented in the Table 4.

The F-significant value for all the models developed using RA are within 5% indicating that the results fall within 95% confidence level. The F value was observed to be 6.092, 12.713, 30.072 and 6.082 respectively and it indicates a good for all the models developed using RA. The MAPE values of the regression models are observed to 0.033, 0.365, 0.679 and 2.317. The RMSE values are observed to be 12.538, 0.043, 0.799 and 6.771.

Table 4 Statistical parameters of RA model

Model	R^2	F value	F-sig	RMSE	MAPE (%)
SFD	0.646	6.092	0	12.538	0.033
LB	0.792	12.713	0	0.043	0.365
VFT	0.480	3.072	0.027	0.799	0.679
CS	0.646	6.082	0.001	6.771	2.317

6.0 Conclusion

The comparison of the models developed using ANN and RA showed that the goodness-of-fit of the ANN models is superior when compared to the RA models. The R – squared value obtained for model of Slump flow diameter and V funnel developed using artificial neural network are greater than 0.9 which is in contrast to the regression models with R – squared values of 0.792 and 0.646. This shows the lack of acceptability of the regression models. The neural network model exhibit very low RMSE and MAPE values. The regression models possesses low determination coefficient compared to neural network models and hence the usage of neural network model gives superior results. The regression equation can be applied for preliminary mix design calculation of SCC. However, in situations demanding higher accuracy, only neural network models are applicable. Models developed by implementing feed forward back propagation ANN generate better results in prediction of fresh and hardened properties of SCC.

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