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NEURAL NETWORKS FOR THE PREDICTION OF FRESH PROPERTIES AND COMPRESSIVE STRENGTH OF FLOWABLE CONCRETE

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Abstract: This paper presents the prediction of fresh concrete properties and compressive strength of flowable concrete through neural network approach. A comprehensive data set was generated from the experiments performed in the laboratory under standard conditions. The flowable concrete was made with two different types of micro particles and with single nano particles. The input parameter was chosen for the neural network model as cement, fine aggregate, coarse aggregate, superplasticizer, water-cement ratio, micro aluminium oxide particles, micro titanium oxide particles, and nano silica. The output parameter includes the slump Flow, L-Box flow, V Funnel flow and compressive strength of the flowable concrete. To develop a suitable neural network model, several training algorithms were used such as BFGS Quasi- Newton back propagation, Fletcher-Powell conjugate gradient back propagation, Polak - Ribiere conjugate gradient back propagation, Gradient descent with adaptive linear back propagation and Levenberg-Marquardt back propagation. It was found that BFGS Quasi- Newton back propagation and Levenberg-Marquardt back propagation algorithm provides more than 90% on the prediction accuracy. Hence, the model performance was agreeable for prediction purposes for the fresh properties and compressive strength of flowable concrete.

Keywords: compressive strength; flowable concrete; fresh properties; neural network; NN model; prediction.

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INTRODUCTION

Self compacting concrete is a flowable concrete which has the capability to compact under its own weight without the need of external vibrator. It has good filling ability, passing ability and adequate stability. By limiting the maximum size of coarse aggregate, using chemical admixtures such as superplasticizer, viscosity modifying admixtures and high range water reducers, incorporating mineral admixtures and using low water-to-binder ratios are the common practices to increase the filling ability, passing ability and stability of such concrete. Many researchers investigated with the various pozzolanic materials such as fly ash, silica fume, GGBS, metakaolin. (Dinakar *et al.* 2013; Mohammed, 2011; Badogiannis *et al.* 2015).

Currently, nano technology has attracted significant attention towards the potential use of small size particles (1 to 100 nanometer scale) in concrete (Sanchez & Sobolev, 2010), which alter its characteristics. Many investigators studied the utilization of nanoparticles in concrete or mortar including nano silica (nano SiO_2), nano iron (nano Fe_2O_3), nano titanium oxide (nano TiO_2), nano alumina (nano Al_2O_3), nano zinc oxide (nano ZnO) etc., (Heikal *et al.* 2013; Rashad, 2013; Mohseni et al. 2015). The information pertaining on the utilization of micro and nano particles nanoparticles in flowable concrete is not addressed so far.

An alternative to mathematical modeling emerged from the research into artificial intelligence system. Artificial neural network (ANN) provides a high level of accuracy in predicting the results. ANN has many effective features such as efficiency, generalization and simplicity which could be able to solve any models of complex system. ANN could be used to learn and reproduce rules or operations, analyse and generalize the data, make predictions, match or make associations from new data to old data in a variety of powerful ways. A considerable number of research works have been performed in the prediction of concrete materials and strength by using NN approach. The prediction of slump in concrete (Agarwal & Sharma, 2010, compressive strength of concrete (Chopra *et al.* 2015, Razavi *et al.* 2011), mixtures of self compacting concrete (Yaman et al. 2017; Nehdi et al. 2001, Heniegal, 2012), fresh properties of self compacting concrete (Sonebi *et al.* 2016), compressive strength of self compacting concrete (Venu & Prashanth (2014), Siddique *et al.* (2009). Hence, an attempt has been made to predict the fresh properties and compressive strength of flowable concrete through NN technique.

METHODOLOGY OF NN APPROACH

The intelligent computational body takes the input and corresponding results from observed data incorporate them and adjust their inner structure to suite the data and predictions. ANN is based on a collection of connected nodes called artificial neurons .The neuron that receives the signals can process it from one part to another part (input layer – output layer). Signals at interconnected neurons are a real number and the output of each neuron is calculated by a non-linear function of the sum of its inputs. Each neurons are assigned with weight. These weight increases or decreases represent the nature and strength of interconnected neurons. Models are generated based upon the training data and ANN functions. Models are generated with three layer such as input layer, hidden layer and output layer where the input variables are assigned in input layer and the actual output values are assigned in the output layer and hidden layer consist of neurons. New network model has to be created by using NN functions. Suitable network properties are selected for training dataset. Different architectural algorithms are present in ANN toolbar in the MATLAB. Different architectural algorithms may perform different kinds of training on their models.

One of the important works is to select the learning function. Learning function consist of two categories namely LEARNGDM & LEARNGD. Hence, the best and suitable learning function has to be selected for training the model. Performance function indicates the type of error function. Based on the error value the performance of the model is evaluated. The test error which determines the amount of weight changes during series of iterations to bring the predicted value within the acceptable range of the experimental values were adjusted within the hidden layers and neurons on trial basis. Selecting number of layer (one or two) and then assigning number of neurons will be processed by ANN. The main feature of the transfer function is to adjust the weight value of the input dataset to get the perfect trained ANN model. To evaluate the training network, statistical parameter error function must be defined to the system performance. An error function is important for effective design goals and choosing the algorithms. Error functions that are commonly used are shown in expression (1) and (2). The MAPE values represent the performance of the model that created with the NN function and also with the number of neurons in the hidden layers. The root mean square error value represents the error between the experimental and the predicted result, which should be nearer to 1.

- Root mean square error (RMSE)

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(ED-PD)^{2}} \qquad (1)$$

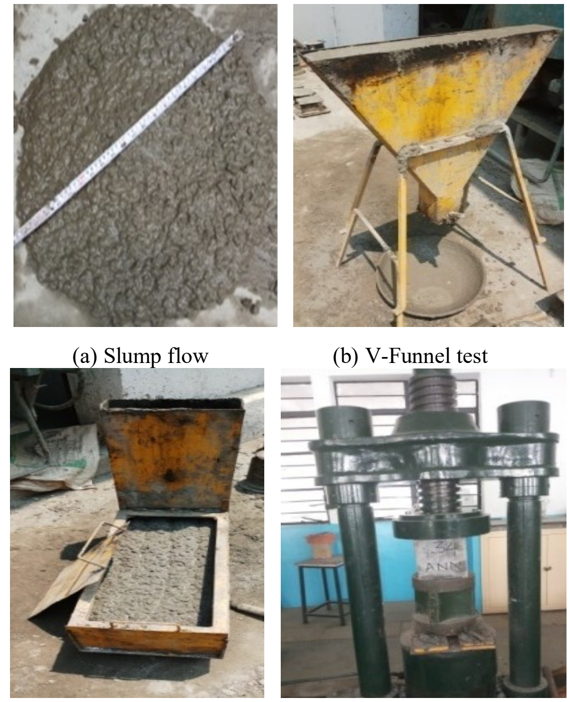
- Mean absolute percentage Error (MAPE)

$$\frac{1}{n}\sum_{i=1}^{n}\frac{(ER-PR)}{ER}X100\% \qquad (2)$$

where n - No. of data sets, ED - experimental data, PD - predicted data

DATA BASE FOR NN MODEL

For the prediction of fresh properties and compressive strength of flowable concrete, comprehensive data set was generated from the experiments performed in the laboratory under standard conditions. Ordinary Portland Cement of 53 grade was used in the experimental investigation. The specific gravity of the cement was found to be 3.15 with a standard consistency of 28%. River sand passing through 4.75mm IS sieve used as fine aggregate. Fine aggregate was categorized in zone II as per BIS 383 1970. The fineness modulus of 2.43 tested as per BIS 2720 1985 (part VI). Crushed granite rock of size less than 10 mm was used coarse aggregate in this study. Polycarboxylate ether based super-plasticizer was used in the concrete and adjusted to improve the flow property of modified flowable concrete. In this study, two different micro particles were used viz., Al_2O_3 particles and TiO_2 particles. The specific surface area of Al_2O_3 was 200 m^2/g, density of 0.14 g/cm^3 and purity was greater than 99.7%. The percentage addition of Al_2O_3 was in the range of 0.1 % to 1.0%. The particle size of TiO_2 was 100 µm with a specific surface area of 21 m^2/g and purity was greater than 99.5%. The percentage addition of TiO_2 was in the range of 0.2 % to 2%. In the present study, Nano SiO_2 of size 20 nm with a specific surface area of 202 m^2/g was used. The percentage addition of SiO2 was in the range of 0.5% to 5%. The percentage addition of micro and nano particles was considered to the weight of the cement. A total of 50 SCC mixes were prepared. For each mix, the fresh properties including slump flow, V-Funnel flow test, L-Box test and hardened property like compressive strength were carried out and are depicted in **Fig. 1**. **Table 1** presents the details of mixes and the results of flow properties of SCC on slump (SF), V-Funnel (VF), L-Box (LB) and compressive strength (CS).



(a) Slump flow (b) V-Funnel test

(c) L-Box test (d) Compressive strength test

Fig. 1 Fresh and hardened properties of flowable concrete

Table 1. Details of mixes and results of fresh properties & compressive strength of flowable concrete

MIX	C	FA	CA	MA	MT	NS	W/C	SP	SF sec	VF sec	LB	CS (MPa)
M1	508	860	772	0.51	0	0	0.4	0.8	4.1	3.8	0.6	26.74
M2	508	860	772	1.02	0	0	0.4	0.8	4.4	3.9	0.8	24.7
M3	508	860	772	1.53	0	0	0.4	0.8	4.9	4.8	0.7	28.64
M4	508	860	772	2.04	0	0	0.4	0.8	3.9	3.2	0.8	29.03
M5	508	860	772	2.55	0	0	0.4	1.0	2.9	4.9	0.8	31.34
M6	508	860	772	3.06	0	0	0.4	1.0	3.1	2.9	0.7	30.5
M7	508	860	772	3.57	0	0	0.4	1.0	3.1	3.5	0. 65	29.07
M8	508	860	772	4.08	0	0	0.4	1.2	4.9	4.6	0.6	24.13
M9	508	860	772	4.59	0	0	0.4	1.2	4.2	5.4	0.7	22.19
M10	508	860	772	5.1	0	0	0.4	1.2	3.7	4.0	0.5	27.37
M11	508	860	772	0	1.02	0	0.4	0.8	3.3	3.1	0.7	26.84
M12	508	860	772	0	2.04	0	0.4	0.8	4.1	4.3	0.5	31.11
M13	508	860	772	0	3.06	0	0.4	0.8	3.8	3.1	0.8	29.18
M14	508	860	772	0	4.08	0	0.4	1.0	3.8	3.3	0.6	30.11
M15	508	860	772	0	5.1	0	0.4	1.0	3.6	5.7	0.8	25.05
M16	508	860	772	0	6.12	0	0.4	1.2	5.1	3.6	0.8	25.13
M17	508	860	772	0	7.14	0	0.4	1.2	4.3	4.6	0.6	30.17
M18	508	860	772	0	8.16	0	0.4	1.2	3.8	4.2	1.0	31.10
M19	508	860	772	0	9.18	0	0.4	1.2	3.9	4.7	1.0	29.17
M20	508	860	772	0	10.2	0	0.4	1.2	3.0	3.2	0.7	27.13

MIX	C	FA	CA	MA	MT	NS	W/C	SP	SF sec	VF sec	LB	CS (MPa)
M21	508	860	772	0	0	2.54	0.4	0.8	4.5	4.8	1.0	32.5
M22	508	860	772	0	0	5.08	0.4	0.8	5.8	3.9	0.9	31.1
M23	508	860	772	0	0	7.62	0.4	1.2	3.8	5.8	0.8	29.7
M24	508	860	772	0	0	10.16	0.4	1.2	4.4	5.7	0.8	28.4
M25	508	860	772	0	0	12.7	0.4	1.2	3.8	3.4	0.9	26.6
M26	508	860	772	0	0	15.24	0.4	1.2	3.6	4.6	0.9	28.4
M27	508	860	772	0	0	17.78	0.4	1.2	3.6	3.7	0.7	24.23
M28	508	860	772	0	0	20.32	0.4	1.2	4.9	3.7	0.8	27.18
M29	508	860	772	0	0	22.86	0.4	1.2	4.8	3.5	0.8	28.16
M30	508	860	772	0	0	25.4	0.4	1.2	3.2	1.6	0.7	29.14
M31	508	860	772	0.51	1.02	0	0.4	0.8	6.2	2.4	0. 65	30.19
M32	508	860	772	1.02	2.04	0	0.4	0.8	5.2	2.0	0.6	29.36
M33	508	860	772	1.53	3.06	0	0.4	1.0	5.1	3.1	0.7	30.16
M34	508	860	772	2.04	4.08	0	0.4	1.2	4.3	2.3	0.5	31.2
M35	508	860	772	2.55	5.1	0	0.4	1.2	3.1	2.1	0.7	32.4
M36	508	860	772	3.06	6.12	0	0.4	1.2	4.5	3.3	0.5	30.57
M37	508	860	772	3.57	7.14	0	0.4	1.2	3.8	2.7	0.8	28.38
M38	508	860	772	4.08	8.16	0	0.4	1.2	4.2	1.6	0.6	30.18
M39	508	860	772	4.59	9.18	0	0.4	1.2	3.6	4.6	0.8	31.16
M40	508	860	772	5.1	10.2	0	0.4	1.2	3.1	2.2	0.8	28.26
M41	508	860	772	0.51	1.02	2.54	0.4	0.8	5.7	4.7	0.6	30.19
M42	508	860	772	1.02	2.04	5.08	0.4	1.0	4.4	3.2	1.0	32.3
M43	508	860	772	1.53	3.06	7.62	0.4	1.0	4.2	4.8	1.0	31.6
M44	508	860	772	2.04	4.08	10.16	0.4	1.2	4.4	3.9	0.7	28.65
M45	508	860	772	2.55	5.1	12.7	0.4	1.2	3.6	2.8	1.0	29.74
M46	508	860	772	3.06	6.12	15.24	0.4	1.2	3.5	5.7	0.9	32.15
M47	508	860	772	3.57	7.14	17.78	0.4	1.4	3.5	3.4	0.8	29.18
M48	508	860	772	4.08	8.16	20.32	0.4	1.4	3.6	2.6	0.8	32.16
M49	508	860	772	4.59	9.18	22.86	0.4	1.5	3.7	2.7	0.9	29.15
M50	508	860	772	5.1	10.2	25.4	0.4	1.6	4.5	3.7	0.9	30.5

Development of NN model

NN Models are generated for prediction of fresh properties and compressive strength of flowable concrete using the MATLAB. The various steps involved in processing of ANN are represented in **Fig. 2**. In this work, eight and four variables were considered as input and output layer respectively. The proposed architecture of the developed NN model is presented in **Fig. 3**. The variables represented as C – Cement, FA – Fine aggregate, CA – coarse aggregate, W/C – Water-cement ratio, SP – superplasticizer, MA – micro Al_2O_3, MT – microTiO_2, NS – nano SiO_2, SF – Slump flow, VF- V-Funnel, LB – L-Box, CS – compressive strength.

NN will randomly categories the whole data into three sets as 75% for training set, 15% for training set and 15% for testing set.

The NN models were generated with network properties such as network type, learning function, performance function, transfer function, number of hidden layer and neurons. These functions and hidden layers were important for predicting the output with least

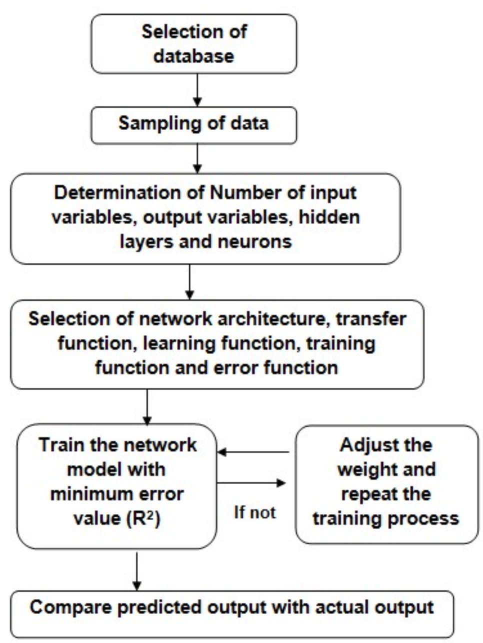


Fig. 2 Process of NN Modelling

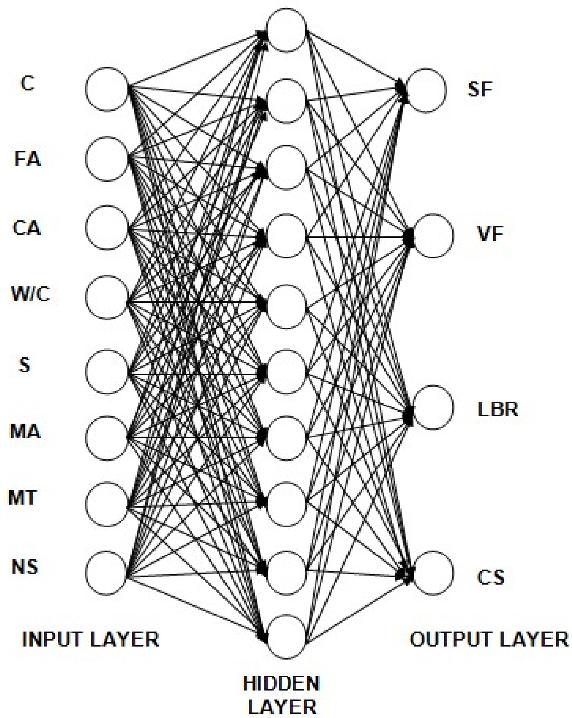


Fig. 3 Proposed Architecture of the developed NN model

Table 2. Types of network functions used in NN modelling

Function No.	Training Function	Algorithm
F1	trainbfg	BFGS Quasi- Newton back propagation
F2	traincgf	Fletcher-Powell conjugate gradient back propagation
F3	traincgp	Polak - Ribiere conjugate gradient back propagation
F4	traingda	Gradient descent with adaptive linear back propagation
F5	trainlm	Levenberg-Marquardt back propagation

Table 3. Selection of functions and hidden layers

Parameter	Values
Learning Function	learngdm
Performance Function	mse
Transfer Function	tansig
Number of Hidden Layer Neurons	10
No. of input layer	8
No. of output layer	4

minimum error. Based on Feed forward back propagation network type, models were created. These network types consist of various architectural algorithm functions. In total, fourteen architectural functions were involved in the NN toolbar. Among them five functions were selected upon the feasibility and accuracy. The five architectural functions used in this work are furnished in **Table 2**. **Table 3** presents the details of the selection of functions and hidden layers.

RESULTS AND DISCUSSION

Each model was trained with particular back propagation function for several times till the training level reached to its maximum epochs. Hence, R value would be nearer to zero to predict the output.

BFGS-Quasi Newton Back Propagation

Figure 4 presents the NN model output data of flowable concrete properties for function ‘F1’. For each experimental test value, separate ANN functions were applied and trained till R value nearer to zero. Here, models are trained under TRAINBFG - BFGS-Quasi Newton back propagation was applied to each test value and samplings of data were done. Hence, the trained result for the slump flow test value of R=0.91, V-Funnel test value of R=0.88, L-Box flow value of R=0.93 and compressive strength value of R=0.89.This shows that the experimental values were trained upto 90% and desired prediction vales were successfully done.

Fletcher-Powell conjugate gradient back propagation

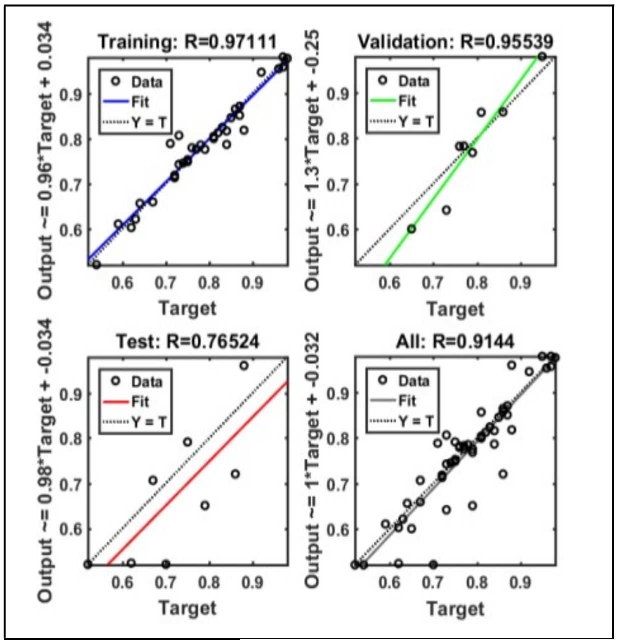
Figure 5 depicts the NN model output data of flowable concrete properties for function ‘F2’. The models were trained under TRAINCGF - Fletcher-Powell conjugate gradient back propagation for each test value and sampling of data. Hence, the trained results indicated that the slump flow test value of 0.84, V-Funnel flow of 0.77, L-Box flow of 0.77 and compressive strength value of 0.81.This shows that values of slump flow and L-Box test values were trained upto 77% and V-Funnel flow and compressive strength values were trained upto 80%.

Polak-Ribiere conjugate gradient back propagation

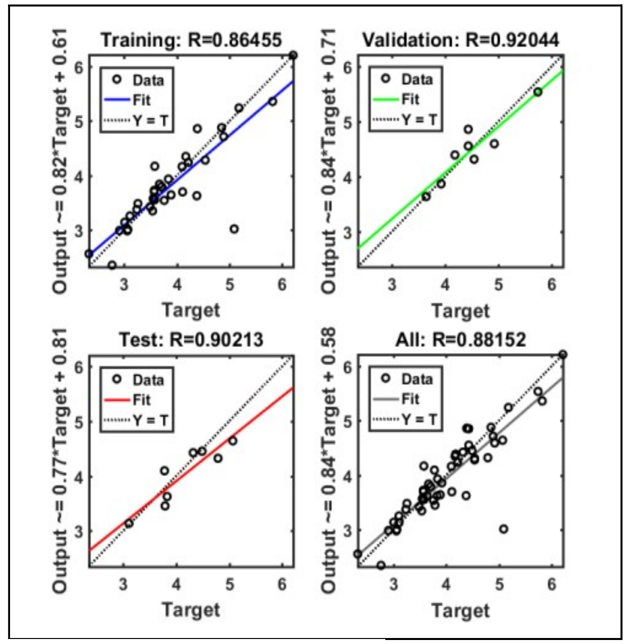
Figure 6 illustrates the model output data of flowable concrete properties for function ‘F3’ - TRAINCGP - Polak-Ribiere conjugate gradient back propagation. The trained result showed a maximum value of 0.88 for the flowable concrete.

Gradient descent with adaptive linear back propagation

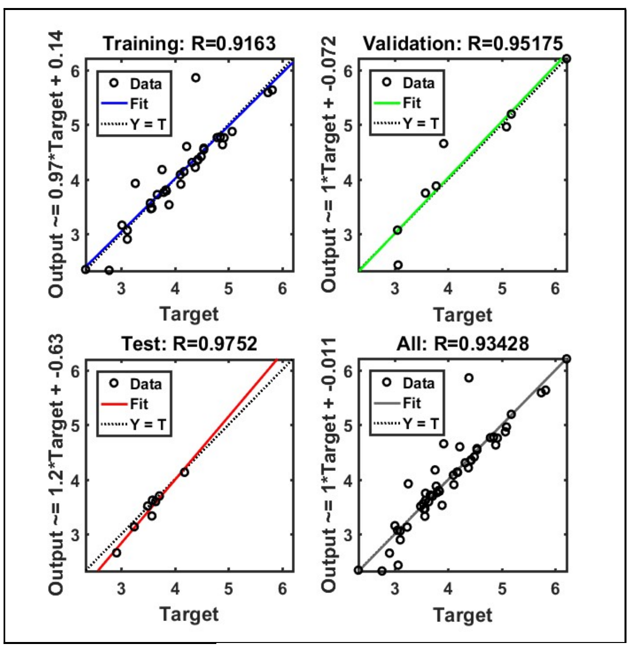
Similarly, **Fig. 7** represents then NN model output data of flowable concrete properties for function ‘F4’. For each test data, the model was trained under TRAINGD - gradient descent with adaptive linear back propagation. It shows that the values for the entire test data were trained upto 75% and desired prediction vales were successfully done.



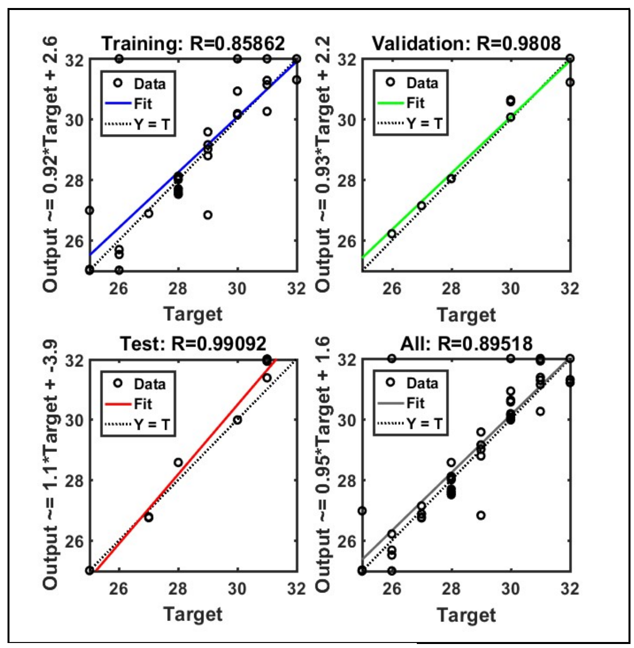
(a) Slump flow



(b) V- funnel flow

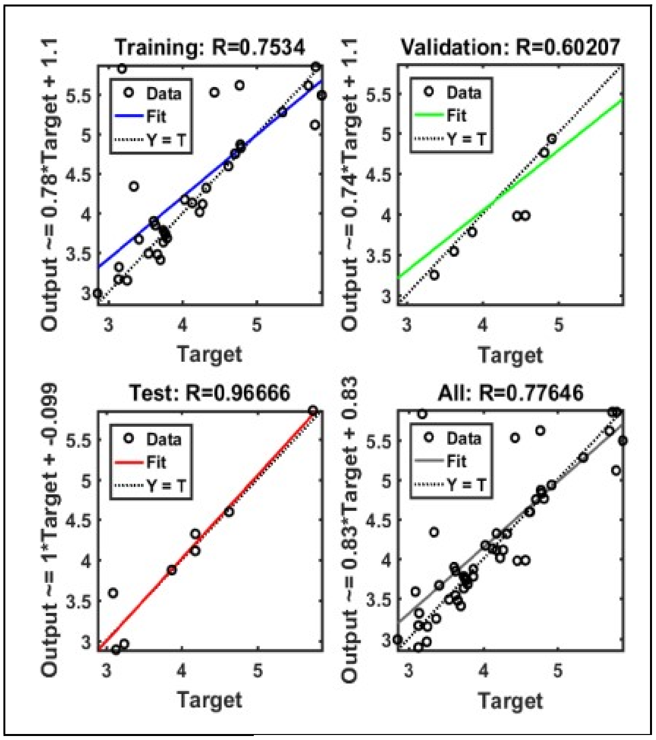


(c) L – Box flow

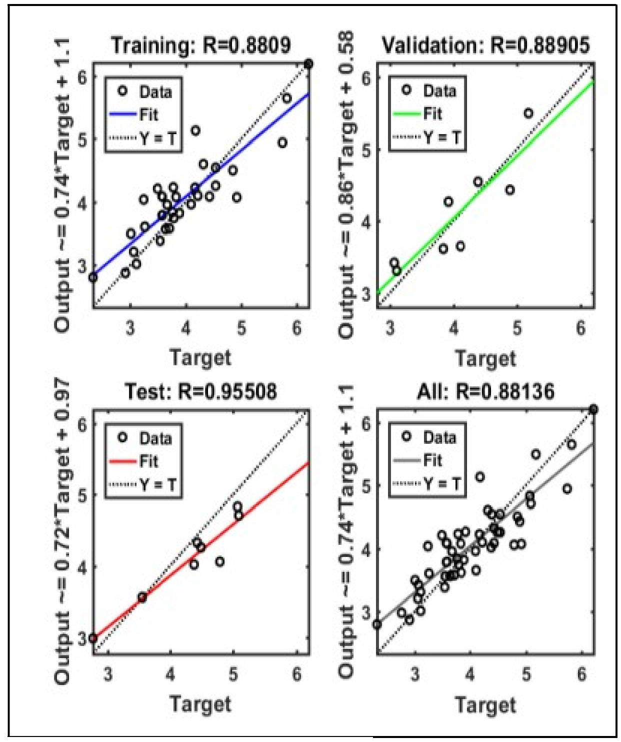


(d) Compressive strength

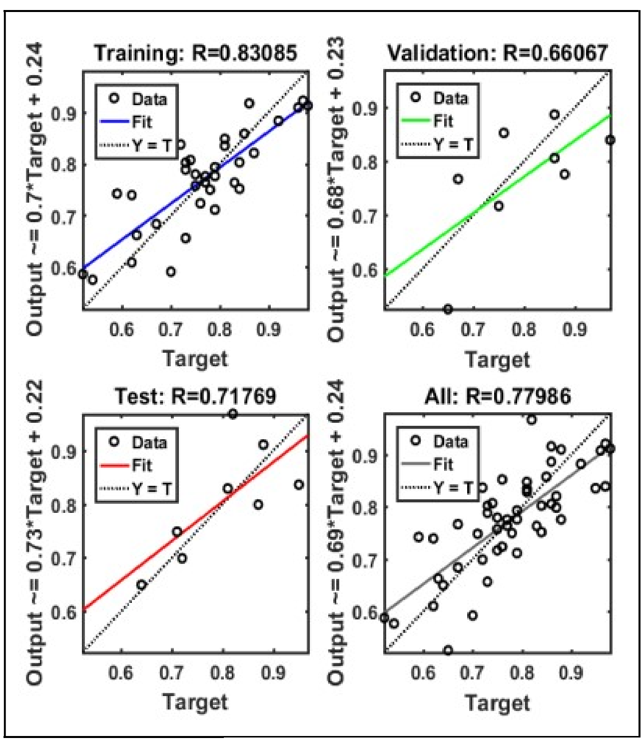
Fig. 4 NN model output data of flowable concrete properties for function 'F1'



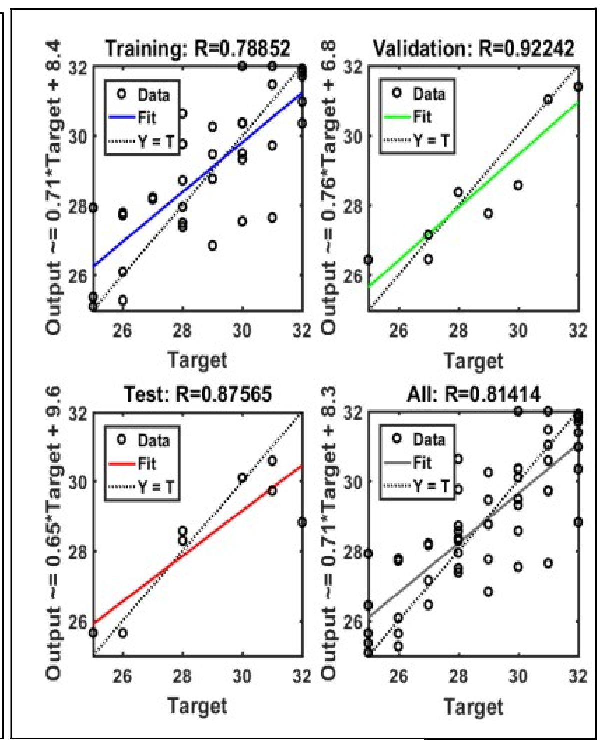
(a) Slump flow



(b) V- funnel flow

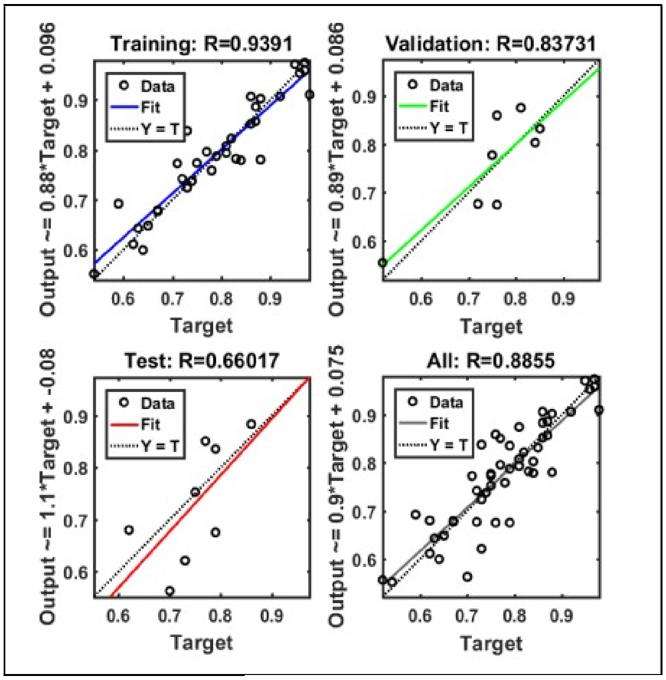


(c) L – Box flow

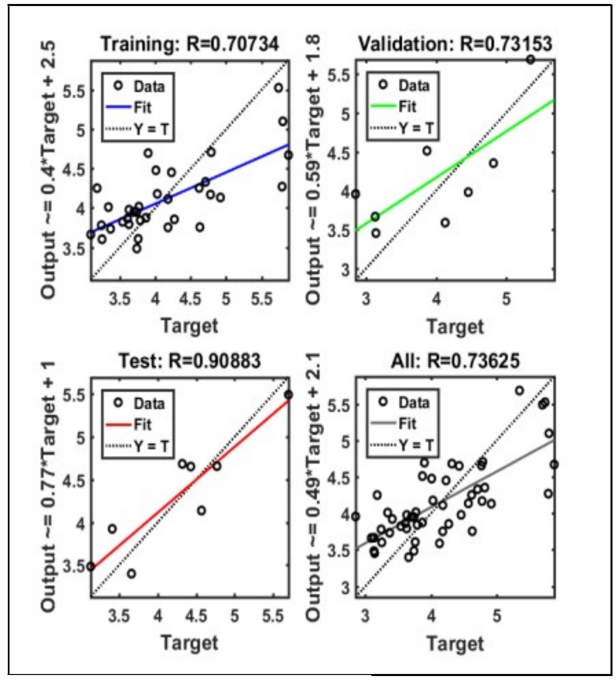


(d) Compressive strength

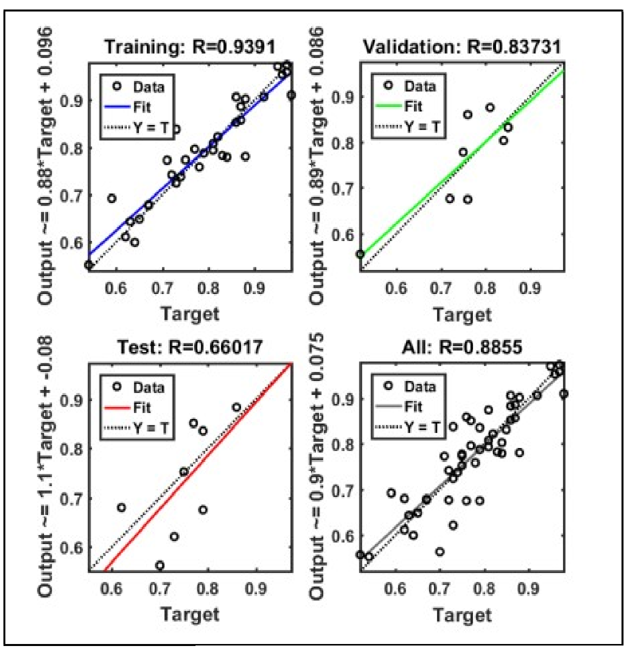
Fig. 5 NN model output data of flowable concrete properties for function 'F2'



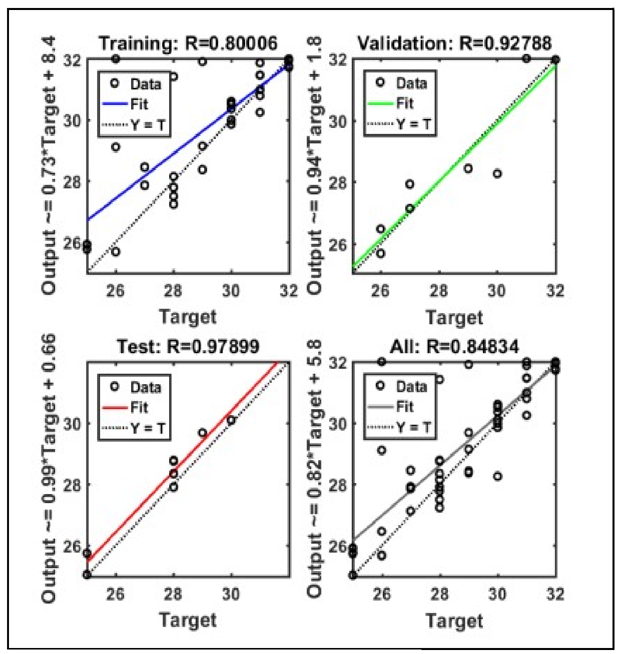
(a) Slump flow



(b) V- funnel flow

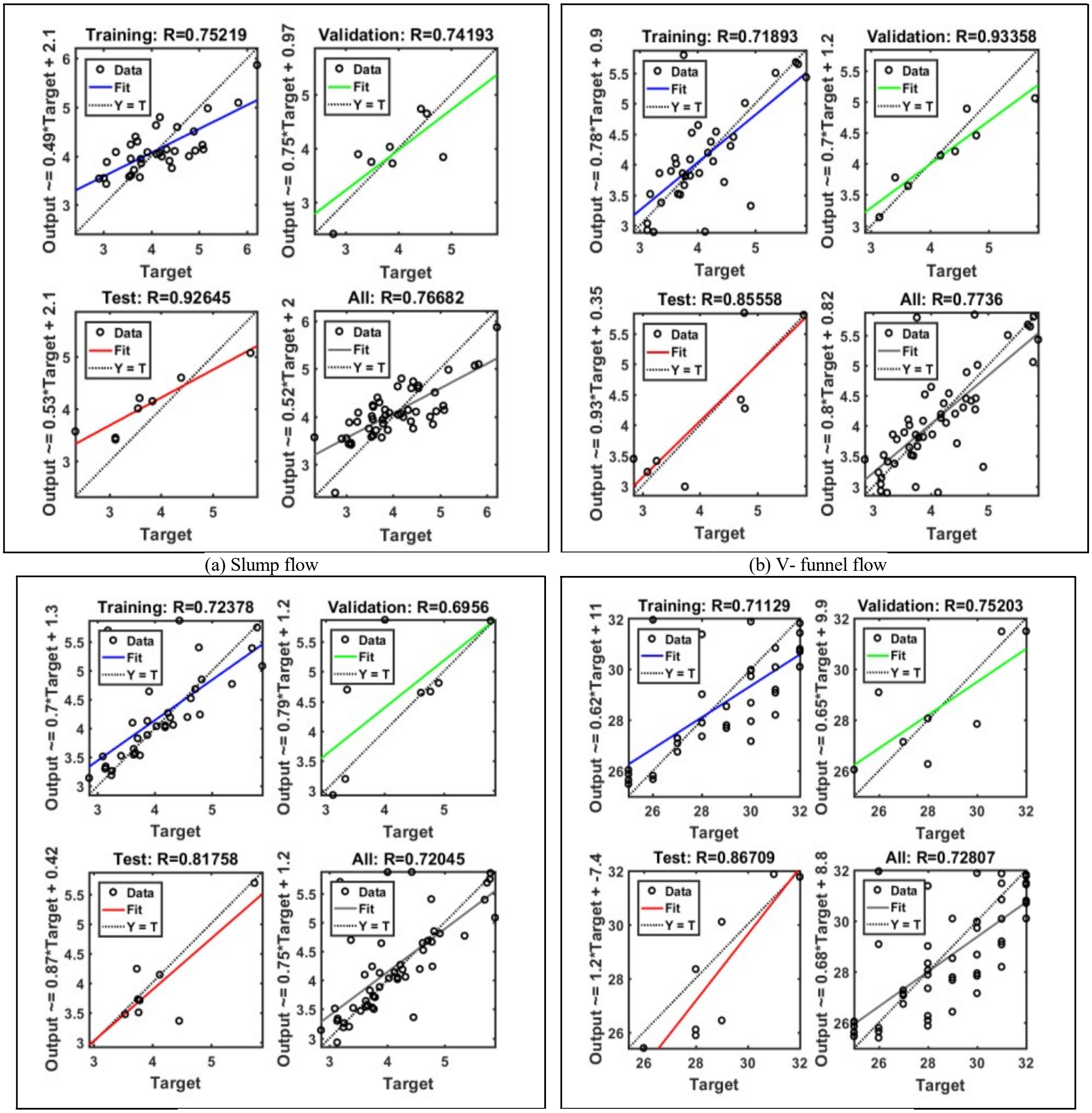


(c) L – Box flow



(d) Compressive strength

Fig. 6 NN model output data of flowable concrete properties for function 'F3'



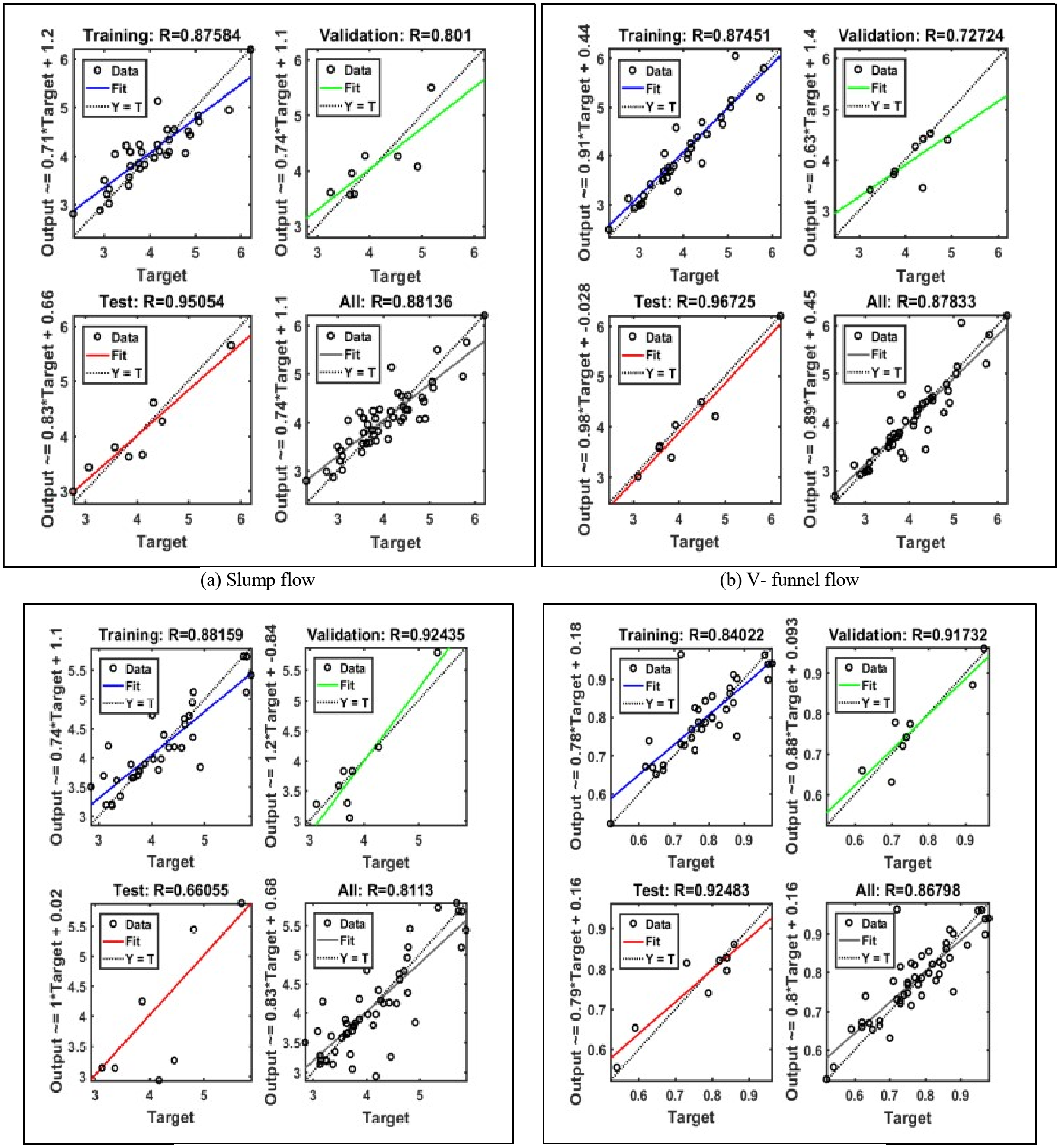
(a) Slump flow (b) V- funnel flow

(c) L – Box flow (d) Compressive strength

Fig.7 NN model output data of flowable concrete properties for function 'F4'

Levenberg-Marquardt back propagation

For each test data, the NN output data under function 'F5' is shown in **Fig. 8**. It was trained under TRAINLM - Levenberg-Marquardt back propagation. The trained result indicated that the slump flow test value of R=0.88, V-Funnel test flow of R=0.87, L-Box test flow of R=0.81 and compressive strength of R=0.86. Thus, it shows that the values for all test data were trained up to 88% and desired output values were successfully predicted. From all the function trained, this shows the best function for prediction of output values.



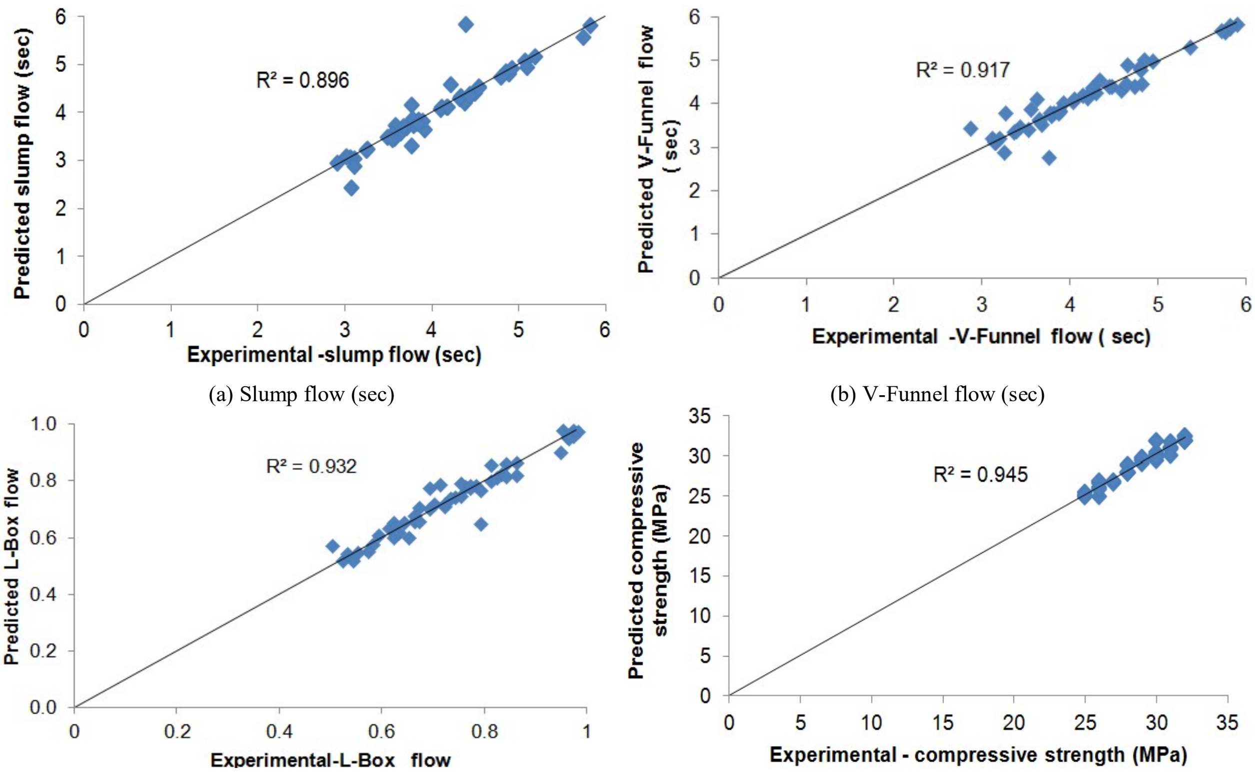
(a) Slump flow (b) V- funnel flow

(c) L – Box flow (d) Compressive strength

Fig. 8 NN model output data of flowable concrete properties for function 'F5'

Predicted Vs Experimental data of flowable concrete properties for function 'F1'

The responses of the experimental and predicted data of SCC properties are plotted in **Fig. 9**. The NN was performed to predict the flowable concrete properties by using 34 data sets for training, 8 for validation and 8 for testing. It has been clearly showed that the co-efficient of correlation was performed well



(a) Slump flow (sec)

(b) V-Funnel flow (sec)

(c) L-Box flow

(d) Compressive strength (MPa)

Fig. 9 Predicted Vs Experimental data of flowable concrete properties for function 'F1'

Table 4 furnishes the value of root mean square error and mean absolute percentage error. MAPE shows the percentage of performance of the model and RMSE shows the error between the actual and predicted output. The error between the predicted and experimental values are very nearer to zero that indicates less error and also MAPE vales of and slump flow ,V-funnel, L-Box ratio, compressive strength indicates the values are less than 10% and thus shows the good performance of the model.

Predicted Vs Experimental data of flowable concrete properties for function 'F2'

The predicted vs experimental data of flowable concrete properties for function 'F2' are plotted in **Fig. 10**. The predicted vs experimental data of flowable concrete properties for function 'F2' are plotted in **Fig. 10**. **Table 5** provides the statistical parameter of NN Function for 'F2'.RMSE values for slump flow, V-funnel flow, L-Box flow and compressive strength indicates that error between the predicted and experimental values are 75%. The MAPE vales of slump flow, V-funnel flow, L-Box flow and compressive strength indicates that the some values have exceeded 10%. This could be due to the higher variation in the experimental data which cause high value in MAPE.

Predicted Vs Experimental data of flowable concrete properties for function 'F3'

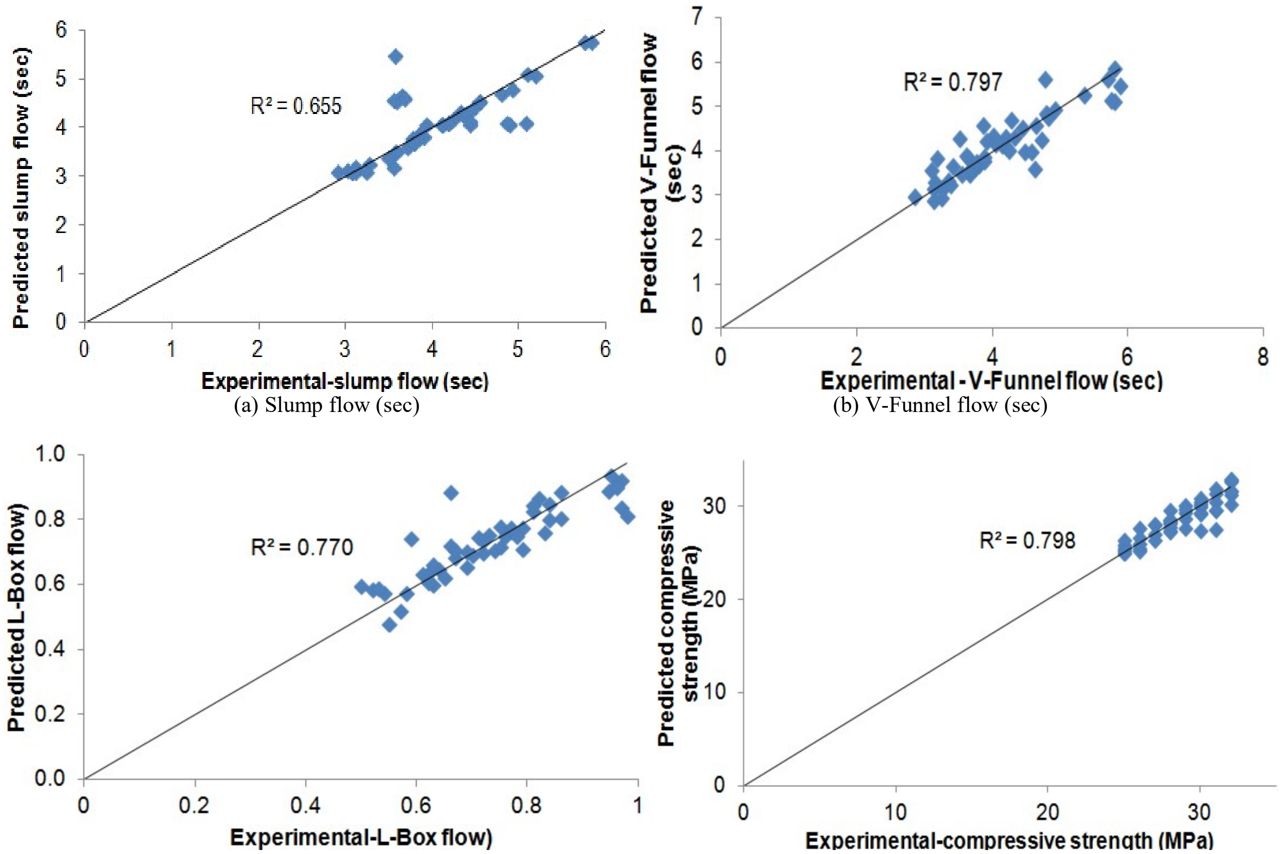
The predicted vs experimental data of flowable concrete properties for function 'F3' are presented in **Fig. 11**. **Table 6** presents the statistical parameter of NN Function for 'F3'. RMSE values for the study parameter of flowable concrete properties slump flow, V-funnel flow, L-Box flow and compressive strength indicates that error between the predicted and experimental values are more than 70%. The reason could be due to small errors in predictions lead to high errors in MAPE, also higher differences in the experimental data.

Table 4. Statistical parameter of NN Function 'F1'

Study Parameter	R^2	RMSE	MAPE
Slump flow (sec)	0.896	0.0169	1.696
V-Funnel flow (sec)	0.917	0.228	0.407
L-Box flow	0.932	0.033	0.61
Compressive strength (MPa)	0.945	0.609	0.872

Table 5. Statistical parameter of NN Function 'F2'

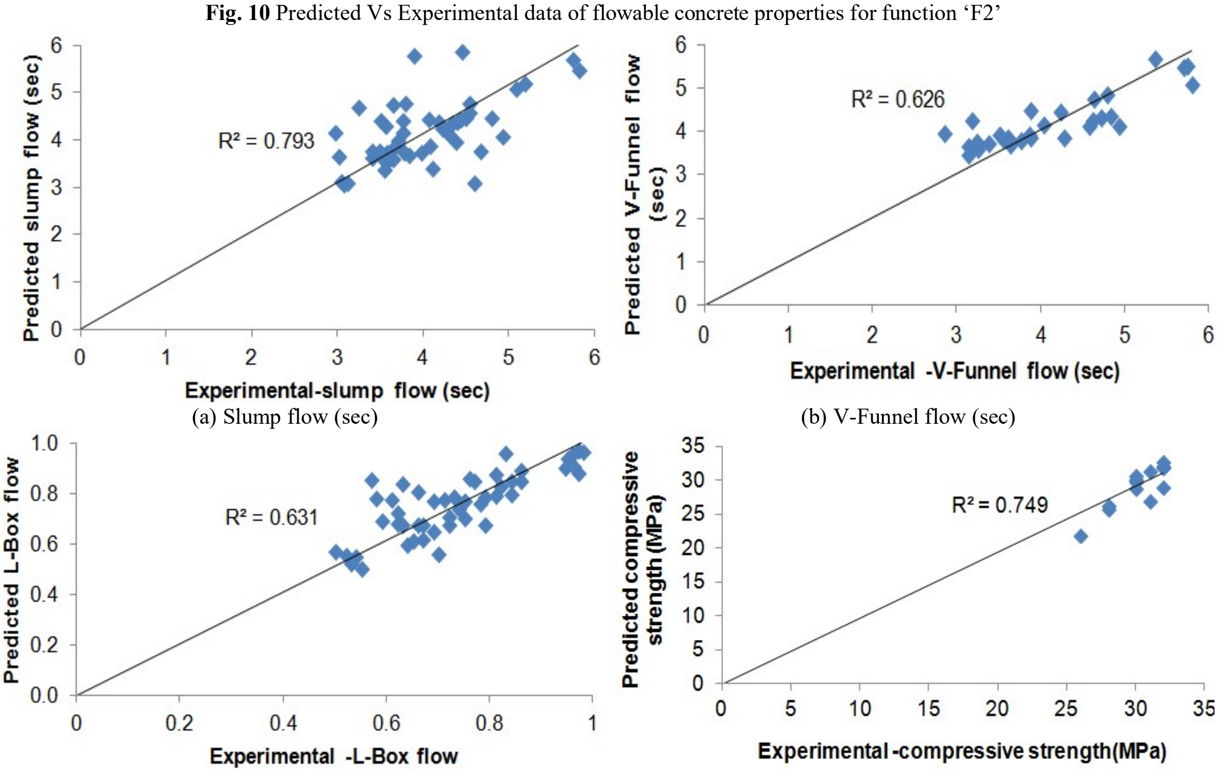
Study Parameter	R^2	RMSE	MAPE
Slump flow (sec)	0.655	0.457	1.697
V-Funnel flow (sec)	0.797	0.357	0.662
L-Box flow	0.770	0.062	0.728
Compressive strength (MPa)	0.798	1.063	11.76



(a) Slump flow (sec) (b) V-Funnel flow (sec)

(c) L-Box flow (d) Compressive strength (MPa)

Fig. 10 Predicted Vs Experimental data of flowable concrete properties for function 'F2'



(a) Slump flow (sec) (b) V-Funnel flow (sec)

(c) L-Box flow (d) Compressive strength (MPa)

Fig. 11 Predicted Vs Experimental data of flowable concrete properties for function 'F3'

Table 6. Statistical parameter of NN Function 'F3'

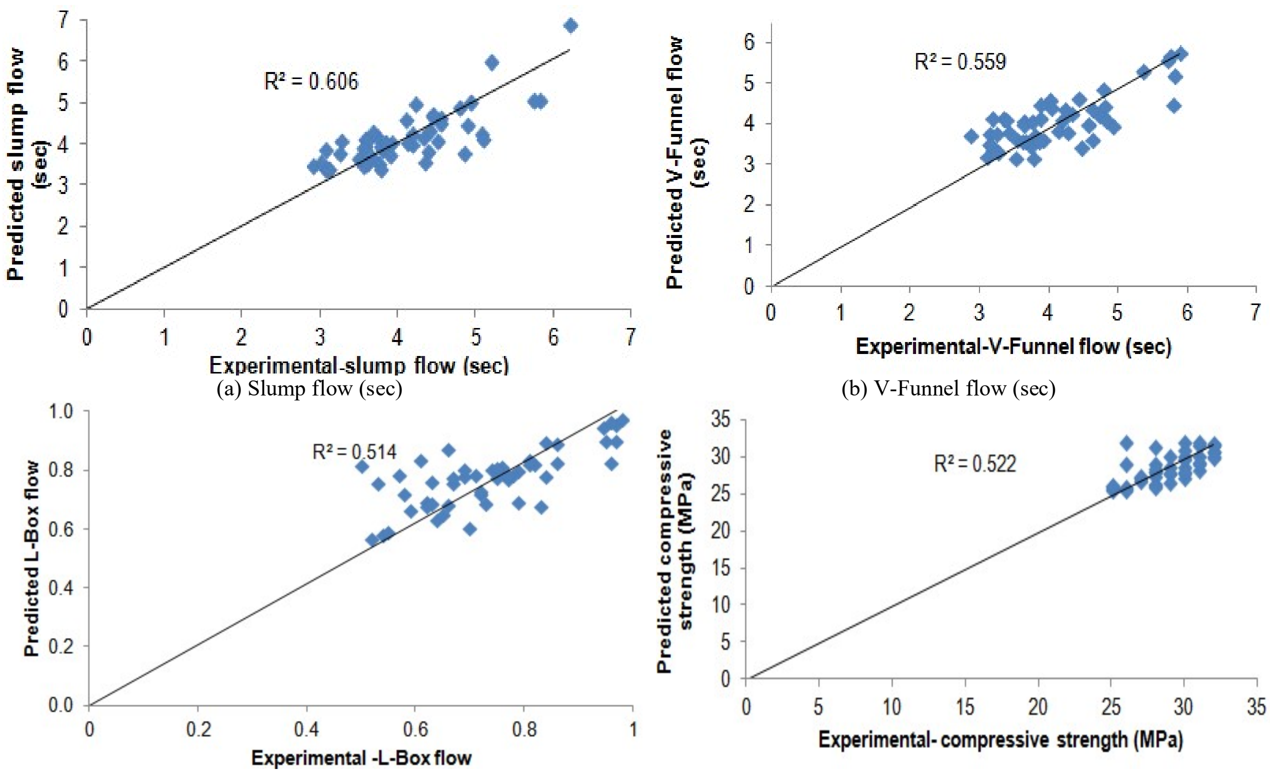
Study Parameter	R^2	RMSE	MAPE
Slump flow (sec)	0.793	0.624	5.317
V-Funnel flow (sec)	0.626	0.099	6.905
L-Box flow	0.631	0.085	4.197
Compressive strength (MPa)	0.749	1.11	0.149

Table 7. Statistical parameter of NN Function 'F4'

Study Parameter	R^2	RMSE	MAPE
Slump flow (sec)	0.606	0.481	2.921
V-Funnel flow (sec)	0.559	0.516	0.175
L-Box flow	0.514	0.098	6.904
Compressive strength (MPa)	0.522	1.646	0.753

Predicted Vs Experimental data of flowable concrete properties for function 'F4'

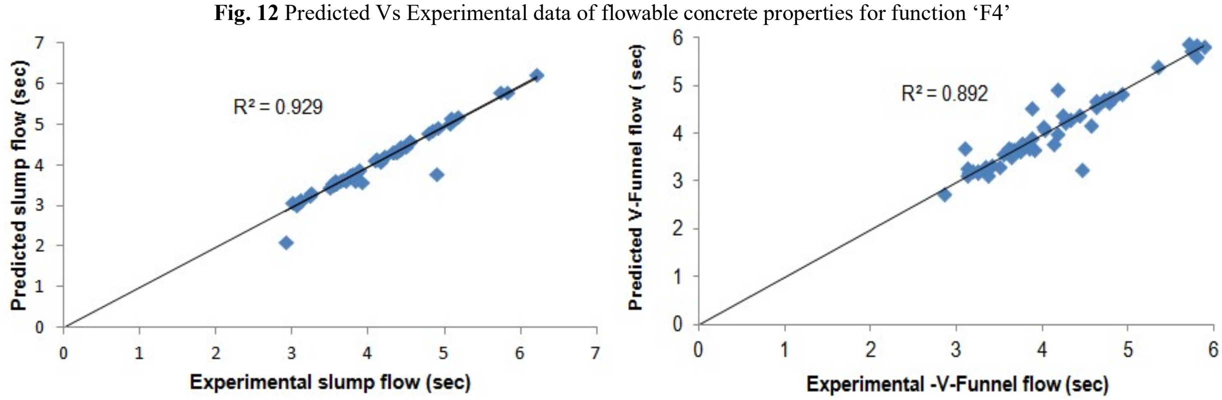
The predicted vs experimental data of flowable concrete properties for function 'F4' are shown in **Fig. 12**. **Table 7** gives the statistical parameter of NN function for 'F4'. RMSE values slump flow, V-funnel, L-Box ratio, compressive strength indicates that, error between the predicted and experimental values are 56% nearer to zero. This model has 50% error when compared to the previous network function. The MAPE vales of slump flow, V-funnel flow, L-Box flow and compressive strength indicates the values were below 10% and thus shows very less performance of the model.



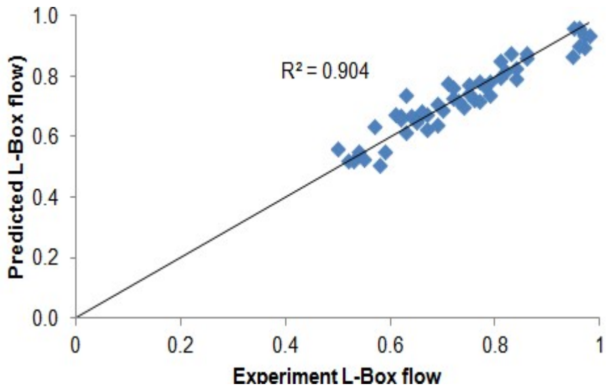
(a) Slump flow (sec) (b) V-Funnel flow (sec)

(c) L-Box flow (d) Compressive strength (MPa)

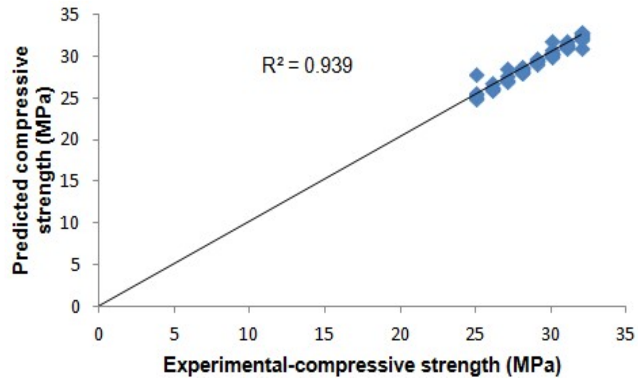
Fig. 12 Predicted Vs Experimental data of flowable concrete properties for function 'F4'



(a) Slump flow (sec) (b) V-Funnel flow (sec)



(c) L-Box flow



(d) Compressive strength (MPa)

Fig. 13 Predicted vs Experimental data of flowable concrete properties for function 'F5'

Predicted Vs Experimental data of flowable concrete properties for function 'F5'

The predicted vs experimental data of flowable concrete properties for function 'F5' are shown in **Fig. 13**. **Table 8** presents the statistical parameter of NN function for 'F5' of the various study parameters of SCC. RMSE values for slump flow, V-funnel flow, L-Box flow and compressive strength indicates that error between the predicted and experimental values are 92% which are almost nearer to zero. Hence, it indicates very less error when compared to the other network functions. The MAPE vales of slump flow, V-funnel flow, L-Box flow and compressive strength indicates that the values are less than 10% and thus shows the very good performance of the model.

CONCLUSIONS

This paper made an attempt to predict the fresh properties and compressive strength of flowable concrete using neural network technique. Based on the investigation, the following conclusions are drawn:

1. The NN technique performed well in predicting the fresh properties and compressive strength of flowable concrete.
2. Models were trained well with five architectural algorithms and comparison made between actual output and desired output were successfully done. The architectural function of TRAINBFG and TRAINLM has predicted the output result more than 90%.
3. The NN model exhibits a very less RMSE and MAPE values for the fresh properties and compressive strength of flowable concrete.
4. The use of ANN is an alternative modeling to mathematical modeling. ANN provides a high level of accuracy in predicting the results.

Table 8. Statistical parameter of NN Function 'F5'

Study Parameter	R^2	RMSE	MAPE
Slump flow (sec)	0.929	0.204	1.302
V-Funnel flow (sec)	0.892	0.267	0.542
L-Box flow	0.904	0.040	1.330
Compressive strength (MPa)	0.939	0.765	1.855

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