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Predicting strength of SCC using artificial neural network and multivariable regression analysis

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Abstract. In the present study an Artificial Neural Network (ANN) was used to predict the compressive strength of self-compacting concrete. The data developed experimentally for self-compacting concrete and the data sets of a total of 99 concrete samples were used in this work. ANN's are considered as nonlinear statistical data modeling tools where complex relationships between inputs and outputs are modeled or patterns are found. In the present ANN model, eight input parameters are used to predict the compressive strength of self-compacting of concrete. These include varying amounts of cement, coarse aggregate, fine aggregate, fly ash, fiber, water, super plasticizer (SP), viscosity modifying admixture (VMA) while the single output parameter is the compressive strength of concrete. The importance of different input parameters for predicting the strengths at various ages using neural network was discussed in the study. There is a perfect correlation between the experimental and prediction of the compressive strength of SCC based on ANN with very low root mean square errors. Also, the efficiency of ANN model is better compared to the multivariable regression analysis (MRA). Hence it can be concluded that the ANN model has more potential compared to MRA model in developing an optimum mix proportion for predicting the compressive strength of concrete without much loss of material and time.

Keywords: self-compacting concrete; compressive strength; artificial neural network; multivariable regression analysis; mean absolute error

1. Introduction

In recent years, Artificial Neural Network (ANN) technologies, Multivariable Regression Analysis (MRA), are being used to solve a wide variety of problems in civil engineering applications (Hasbi *et al.* 2013, Ehsan *et al.* 2015, Atici 2011). Artificial Neural Networks (ANN's) are biologically inspired and mimic the human brain. They consist of a large number of simple processing elements called neurons connected with a connection link. Each link has a weight that is multiplied by transmitted signal in network. Each neuron has activation function to determine the output (Cahit *et al.* 2009). While there are many kinds of activation functions, nonlinear activation functions such as sigmoid, and step are commonly used. ANN's are trained by training the neurons.

Self Compacting Concrete is a highly flowable homogenous concrete which can compact under its own weight without any need for external vibration and thus several common problem in an ordinary concretes as permeability, segregation and bleeding gets eliminated (Ouchi *et al.* 1996, Hossain *et al.* 2006). SCC has the excellent properties like filling ability, passing ability and resistance to segregation. SCC is best suited in highly congested reinforced areas which become in evitable in case of structural elements designed for seismic action. There is a considerable reduction in the cost of construction. Self-compacting concrete was first developed in 1980 (Okamura *et al.* 2003, Alqadi *et al.* 2012, Prasad *et al.* 2016). Since the introduction of SCC in modern concretes researchers are trying to establish an optimum mix proportion for a targeted compressive strength (Shuyang and Xuehui 2014). Also, the increased use of cement in the construction industry is polluting the environment with huge amounts of carbon dioxide (Cahit *et al.* 2009, Uysal and Yilmaz 2011). Waste materials like Fly Ash and GGBS can be used as supplementary cementitious materials (SCM) for replacing ordinary Portland cement which is creating a huge carbon foot print. These SCM's are widely used in construction industry to reduce the consumption of cement (Mehmet *et al.* 2017). Due to the use of SCM's the workability has to be adjusted and this can be done by using High Range Water Reducing Materials as superplasticizers. Poly carbolic Ether based superplasticizers are quite commonly used for SCC works (Khan *et al.* 2016, Prasad *et al.* 2016). This superplasticiser reduces the water content resulting in enhanced strength and durability.

In the last years, artificial neural networks (ANN) technology, a sub-field of artificial intelligence is being used to solve a wide variety of problems in civil engineering applications The artificial neural networks solve very complex problems with the help of interconnected computing elements (Dali Bondar 2014, Merye and Mustapha 2015). Basically, the processing elements of a neural network are similar to Neurons in the

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brain, which consist of many simple computational elements arranged in layers (Hasbi *et al.* 2013). Srdan and Dejan (2005), developed an ANN model to predict the compressive strength of concrete with water-cement ratio (w/c ratio), age and number of freeze/thaw cycles as input. For this purpose, a computer program was developed in MATLAB. Further, the results obtained from the ANN model were compared with the experimental results. A three layer feed forward back propagation technique was used. The six hidden nodes and nine hidden nodes have the good ability to predict the compressive strength of concrete. Merve *et al.* (2015), proposed a model with the main goal of developing the concrete mix proportion using parameters as amount of cement, water dosage, coarse aggregate, fine aggregate content, and superplasticiser. In this model, a feed forward model was used with six inputs. From the result, it was concluded that the ANN has a strong potential to evolve the concrete mix proportion without loss of time and raw material.

Hasbi *et al.* (2013) suggested an algorithm based concrete blended mix design using ANN. The input for the ANN is three types of cement, three different curing conditions and two water-cement (w/c) ratios. The authors have suggested that the ANN model provides an option to predict the compressive strength of concrete. Apart from the aforesaid model, in recent years ANN model has been used in predicting permeability properties of Nano silica-rice husk ash ternary blended concrete. Alireza *et al.* (2013) have been used a two layer feed forward neural network. This method has been used to determine the effect of mix proportion parameters on resistance of permeability properties.

Ehsan *et al.* (2015) built two analytical models based on Statistical Mixture Design (SMD) and artificial neural network to estimate the performance of ultra-high performance of concrete. It was concluded that the ANN model could predict the slump flow and compressive strength with better precision than the SMD. Duan *et al.* (2013) created an ANN model for predicting the elastic modulus of recycled aggregate concrete. In this model, a comparison between ANN and conventional regression analysis was carried out. It was proved that the prediction result found by ANN was far better than the regression analysis.

From the literature review it was revealed that only a limited amount of work has been done in the direction of developing self compacting concrete using ANN method. The present work focuses on using ANN to produce SCC that will reduce the cost of construction, conserve energy and maximize the usage of waste material which will eventually lead to the reduction of CO_2 production from cement industries.

2. Scope of the investigation

Artificial neural networks (ANN's) are data-processing paradigms that are inspired by biological nervous systems. The neural network modeling method is simpler and more direct in comparison with traditional statistical methods, particularly when modeling nonlinear multivariate interrelationships (Cahit *et al.* 2009, Alqadi *et al.* 2012).

For statistical analysis, multivariable linear regression analysis was employed (Li *et al.* 2012, Atici *et al.* 2011). The purpose of is to simultaneously identify two or more independent variables that explain variations in the dependent variable (Murali and Kandasamy 2009). The validity of the models was assessed by considering the criteria viz: behaviour of the correlation coefficient R^2, the t-test, the F-test. The main contribution of the work is predicting the compressive strength of Self Compacting Concrete by using artificial neural networks and multivariable linear regression analysis. Prediction efficacy of the developed ANN model was compared with that of MRA model.

3. Artificial neural networks

The fundamental concept of neural networks is the structure of the information processing system (Cahit *et al.* 2009, Ehsan *et al.* 2015). Generally, an ANN is made of an input layer of neurons, sometimes referred to as nodes or processing units, one or several hidden layer/s of neurons and output layer/s of neurons. The neighboring layers are fully interconnected by weight. The input layer neurons receive information from outside environment and transmit them to the neurons of the hidden layer without performing any calculation (Rafat *et al.* 2011, Alireza *et al.* 2013). Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units (Shanker and Sachan 2014). All problems, which can be solved by a perception can be solved with only one hidden layer, but it is sometimes more efficient to use two or three hidden layers. Finally, the output layer neurons produce the network predictions to the outside world (Duan *et al.* 2013, Dali Bondar 2014). Each neuron of a layer other than the input layer computes first a linear combination of the output of neurons of the previous layer plus a bias. The coefficients of the linear combinations plus the biases are called weights. Neurons in the hidden layer then compute a nonlinear function of their input. Generally, the nonlinear function is the sigmoid function (Srdan and Dejan 2015).

4. Experimental programme

4.1 Materials used

Ordinary Portland cement of 53 grade is used in the investigation. The Cement used has been tested for various proportions and found to be confirming to various specifications as per IS: 12269-2013. The specific gravity was 3.10 and fineness was 3200 cm^2/gm. Fine aggregate was standard river sand procured locally and was confirming to zone-II as per IS: 2386-2002. Crushed angular granite metal of 16 mm size from a local source was used as coarse aggregate (IS: 2386 2002). A Viscosity modified admixture for Rheodynamic Concrete which is a colorless free flowing liquid and having Specific gravity of 1.01 at 25°C and pH value as 8 and with zero Chloride

Content was used as Viscosity Modifying Agent. The Modified Polycarboxylated Ether based Super Plasticizer which is Brown Color and free flowing liquid and having Relative density 1.08 and pH value as 7 and with zero Chloride Content was used as Super Plasticizer. Fly ash confirming to IS: 3812 Part 1-2003 is used as a mineral admixture and the source is from a coal fired thermal power station. Optimum dosages of glass fiber (GSF) and polypropylene fiber (PPF) was used in the preparation of fibrous SCC.

4.2 Methodology

An experimental program was designed to evaluate the compressive strength of self- compacting concrete without and with fiber addition. The key properties of SCC at fresh state are filling ability, passing ability and resistance to segregation at required levels. To satisfy these conditions Europe Guidelines (EFNARC 2015) for Self Compacting Concrete has formulated certain test procedures. The powder content of self-compacting concrete is relatively high. The ratio of fine to coarse aggregate is increased, with fine aggregate often making more than 50% of the total aggregate fraction. Fine fillers can be used in addition to cement. It is used to facilitate and ensure proper filling, easy mouldability to the desired architectural shape and good structural performance in case of restricted areas and heavily reinforced structural members. Cubes of standard dimensions were cast and tested to determine the compressive strength of Self- Compacting Concrete without and with fiber additions. The mixes were designed as per Nan Su method of mix design (Su *et al.* 2011). In the present investigation 99 mix samples were taken with various combinations of ingredients to get the compressive strength values of SCC without and with glass and polypropylene fiber additions and the experimental results indicated the potential role of the influence of these variables on the strength of SCC but not in a same manner, both in magnitude and their resulting effect (direct or inverse).All the specimens were cured for 28 day water curing and 2000 KN Servo Controlled Universal Testing Machine (UTM) was used for testing the specimens under load control. While testing, precautions were taken to ensure axial loading. For ccompressive strength, standard loading was adopted as per Indian Standard Code IS: 516-1956 (Reaffirmed 2004). Average test results of three specimens were reported as the compressive strength of the specimens.

5. Network development for ANN

Artificial Neural Network (ANN) is an artificial intelligence technique that can be applied to tasks where there is a large database of a problem and the model learns by example. It is a powerful tool that gives viable solutions to problems which are difficult to solve by conventional techniques. They are capable of pattern recognition and machine learning method. ANN solves problems like a brain, which involve thinking, learning, remembering, reasoning, and solving ability. It was first developed by McCulloch and Pitts in 1943. After that, it has been applied

Table 1 Details of experimental variables and test results

Sl No	Cement (Kg)	Sand (Kg)	Coarse Aggregate (Kg)	Fine Aggregate (Kg)	Fiber (Kg)			Water (lit)	SP (lit)	VMA (lit)	Compressive Strength MPa
					WF	GSF	PPF				
1	276	961	808	150	0.0			204	8.50	0.42	31.64
2	276	961	808	155		0.25		204	9.20	0.42	31.87
3	276	961	808	160		0.50		204	9.90	0.43	32.14
4	276	961	808	165		0.75		204	10.50	0.44	32.28
5	276	961	808	170		1.00		204	11.20	0.45	32.87
6	276	961	808	175		1.20		204	11.90	0.45	32.20
7	412	913	781	138	0.0			193	13.75	0.48	52.90
8	412	913	781	145		0.25		193	14.50	0.48	53.44
9	412	913	781	152		0.50		193	14.70	0.48	53.76
10	412	913	781	159		0.75		193	15.25	0.48	54.05
11	412	913	781	166		1.00		193	16.00	0.48	54.26
12	412	913	781	173		1.20		193	17.20	0.48	53.52
13	276	961	808	150	0.0			204	8.50	0.42	31.64
14	276	961	808	155			0.35	204	9.20	0.42	31.70
15	276	961	808	160			0.70	204	9.90	0.43	31.77
16	276	961	808	165			1.05	204	10.50	0.44	31.82
17	276	961	808	170			1.40	204	11.20	0.45	32.26
18	276	961	808	175			1.75	204	11.90	0.45	31.71
19	412	913	781	138	0.0			193	13.75	0.46	52.90
20	412	913	781	145			0.35	193	14.50	0.48	52.28
21	412	913	781	152			0.70	193	14.70	0.48	52.54
22	412	913	781	159			1.05	193	15.25	0.48	52.98
23	412	913	781	166			1.40	193	16.00	0.48	53.87
24	412	913	781	173			1.75	193	17.20	0.48	52.94
25	276	969	774	150	0.0			204	8.50	0.42	29.87
26	276	969	774	170			1.40	204	11.20	0.45	30.58
27	276	969	774	170		1.00		204	11.20	0.45	31.69
28	276	978	735	150	0.0			204	8.50	0.42	28.24
29	276	978	735	170			1.40	204	11.20	0.45	29.16
30	276	978	735	170		1.00		204	11.20	0.45	30.12
31	412	934	744	138	0.0			193	13.75	0.46	49.68
32	412	934	744	166			1.40	193	16.00	0.48	50.64
33	412	934	744	166		1.00		193	16.00	0.48	51.82
34	412	944	707	138	0.0			193	13.75	0.46	47.06
35	412	944	707	166			1.40	193	16.00	0.48	48.52
36	412	944	707	166		1.00		193	16.00	0.48	49.26
37	430	1050	715	100	0.0			185	5.00	0.60	67.58
38	430	1050	700	100	0.0			185	5.00	0.60	65.19
39	430	1100	690	100	0.0			185	5.00	0.60	64.18
40	430	1050	715	110		1.00		185	6.00	0.70	68.53
41	430	1050	700	110		1.00		185	6.70	0.70	66.25
42	430	1100	690	115		1.00		185	7.00	0.75	65.38
43	430	1050	715	110			1.40	185	6.50	0.70	68.12
44	430	1050	700	110			1.40	185	7.00	0.70	65.61
45	430	1100	690	120			1.40	185	7.50	0.75	64.75
46	340	920	815	75	0.0			190	7.00	0.50	37.00
47	340	920	800	75	0.0			190	7.00	0.50	34.90
48	340	950	795	75	0.0			190	7.00	0.50	32.50
49	340	920	815	85		1.00		190	8.00	0.50	37.25

Table 1 Continued

50	340	950	800	85		1.00		190	8.00	0.50	35.31
51	340	950	795	90		1.00		190	8.00	0.50	32.78
52	340	920	815	85		1.20		190	8.00	0.50	36.85
53	340	920	800	90			1.40	190	8.50	0.50	35.19
54	340	950	795	90			1.40	190	8.50	0.50	32.46
55	360	920	815	100	0.0			180	8.00	0.50	42.00
56	360	935	790	100	0.0			180	8.00	0.50	40.70
57	360	945	790	100	0.0			180	8.00	0.50	38.50
58	360	920	815	100		1.00		180	8.50	0.60	42.46
59	360	935	790	110		1.00		180	8.50	0.60	41.25
60	360	945	790	110		1.00		180	8.50	0.60	38.95
61	360	920	815	120			1.40	180	9.00	0.60	42.12
62	360	935	790	120			1.40	180	9.00	0.60	40.98
63	360	945	790	120			1.40	180	9.00	0.60	38.54
64	440	920	815	180	0.0			210	7.00	0.70	55.00
65	440	940	780	180	0.0			210	7.00	0.70	53.60
66	440	955	780	180	0.0			210	7.00	0.70	51.40
67	440	920	815	180		1.00		210	7.50	0.70	55.45
68	440	940	780	185		1.00		210	7.50	0.70	54.03
69	440	955	780	190		1.00		210	8.00	0.70	51.89
70	440	920	815	190			1.40	210	8.00	0.70	55.26
71	440	940	780	190			1.40	210	8.50	0.70	53.72
72	440	955	780	190			1.40	210	8.50	0.70	51.69
73	500	840	870	70	0.0			198	8.30	0.75	68.00
74	500	855	830	70	0.0			198	8.30	0.75	67.00
75	500	870	830	70	0.0			198	8.30	0.75	65.30
76	500	840	870	80		1.00		198	9.00	0.75	68.50
77	500	855	830	80		1.00		198	9.00	0.75	67.67
78	500	870	830	85		1.00		198	9.00	0.75	65.10
79	500	840	870	85			1.40	198	9.00	0.75	67.29
80	500	855	830	85			1.40	198	9.00	0.75	65.00
81	500	870	830	85			1.40	198	9.00	0.75	64.86
82	440	840	870	85	0.0			187	9.00	0.80	59.00
83	440	860	840	85	0.0			187	9.00	0.80	57.70
84	440	875	840	85	0.0			187	9.00	0.80	55.40
85	440	840	870	90		1.00		187	10.00	0.80	59.70
86	440	860	840	90		1.00		187	10.00	0.80	58.51
87	440	875	840	95		1.00		187	10.00	0.80	55.96
88	440	840	870	95			1.40	187	10.00	0.80	59.41
89	440	860	840	95			1.40	187	10.00	0.80	58.26
90	440	875	840	95			1.40	187	10.00	0.80	55.67
91	460	840	870	70	0.0			183	9.20	0.90	63.00
92	460	865	850	70	0.0			183	9.20	0.90	60.90
93	460	880	850	70	0.0			183	9.20	0.90	58.90
94	460	840	870	80		1.00		183	9.70	0.90	63.60
95	460	865	850	80		1.00		183	9.70	0.90	61.45
96	460	880	850	80		1.00		183	9.70	0.90	64.48
97	460	840	870	80			1.40	183	9.70	0.90	63.27
98	460	865	850	80			1.40	183	9.70	0.90	61.29
99	460	880	850	80			1.40	183	9.70	0.90	64.13

WF=Without Fiber; GSF=Glass Fiber; PPF=Polypropylene Fiber

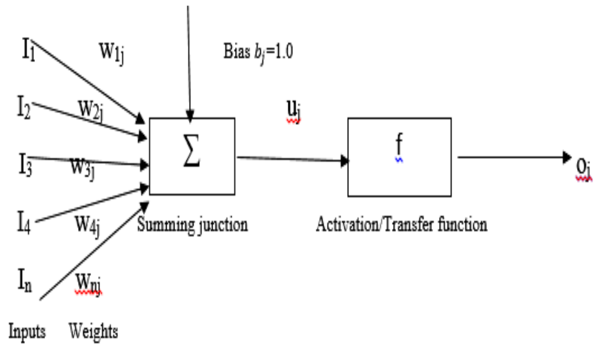

Fig. 1 Schematic diagram showing an artificial neuron

to many research areas. It can be applied to civil engineering problems for those are hard to solve using mathematical methods.

Fig. 1 shows a schematic diagram of an artificial neuron in which a biological neuron has been modeled artificially. Supposing that there are n inputs (such as I_1, $I_2 \ldots I_n$) to a neuron j. The weights connecting n numbers of inputs to j^{th} neuron are represented by $(W)=(W_{1j}, W_{2j}, \ldots, W_{nj})$. The function of summing junction of an artificial neuron is to collect the weighted inputs and sum them up. Thus, it is similar to the function of combined dendrites and cell body. The activation function (also known as the transfer function) performs the task of axon and synapse. The output of summing junction may sometimes become equal to zero and to prevent such a situation, a bias of fixed value b_j is added to it. Thus, the input to transfer function f is determined as $u_j = \sum_{k=1}^{n} I_k W_{kj} + b_j$. The output of j^{th} neuron, that is O_j can be obtained as follows

$$O_j = f(u_j) = f(\sum_{k=1}^{n} I_k W_{kj} + b_j) \quad (1)$$

In an ANN, the output of a neuron largely depends on its transfer function. Different types of transfer function are in use such as hard limit, linear, log-sigmoid tan-sigmoid and others.

5.1 Feed forward algorithm

Among the different types of available algorithms, the Feed forward ANN algorithm was used in this work. In the Feed Forward, the neuron in each layer is connected to a neuron in the next layer. The neurons in the same layer are not connected. Each layer neuron is connected to another layer by using weights. To determine the best configuration ANN is based on a number of trials and requires training of neurons to make it.

5.2 Back propagation algorithm

The back propagation technique is an iterative process to modify the weights from the output layer to input layer till no further betterment is required. The back propagation technique determines the error, and then distributes this error in a backward direction from the output node to input node till the error is minimized. This method is mainly based on steepest gradient descent principle. The main aim

Table 2 statistical parameters of ANNS model

Model variable	Cement	Sand	Coarse aggregate	Fly ash	Fibre	Water	SP	VMA	Compressive strength (MPa)
Mean	395	929.12	795.48	124.50	0.74	193.36	9.91	0.61	49.87
Standard deviation	70.21	59.79	47.41	39.53	0.54	9.25	2.90	0.16	12.89
Maximum	500	1100	870	190.00	1.75	210	17.2	0.90	68.53
Minimum	276	840	690	70.00	0	180	5.00	0.42	28.24

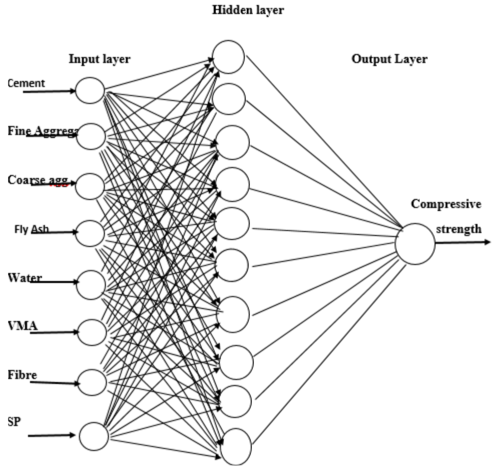

Fig. 2 Applied ANNS model in this study

is to minimize the error of actual test data and output of the model.

6. Predictive model development

6.1 ANN model development for SCC

An ANN based predicted model for SCC is identified as ANNS for self-compacting concrete in the present context. ANNS model has cement, coarse aggregate, fine aggregate, fly ash, fiber, water, superplastisizer (SP) and viscosity modifying agent (VMA) as input parameters and 28 days compressive strength as an output parameter. For working out the ANNS model, in the present work, 70% data was used as training parameters and 30% data as testing parameters. The statistical parameters of maximum, minimum, mean and the standard deviation of input and output variables are shown in Table 2. In this study, data sample was scaled within the range of 0 to 1. The performance of ANNS model was reported in terms of statistical parameters namely linear correlation coefficient (R), mean absolute percentage error (MAPE) and mean square error (MSE).The optimum architecture of ANNS model was ten number of neurons in a hidden layer with a tan-sigmoid transfer function and linear function as the output layer. Levenberg-Marquardt algorithm is used for its better generalization to the training data.

6.2 Steps to be followed to design a suitable neural network

The following steps are followed to design a suitable neural network.

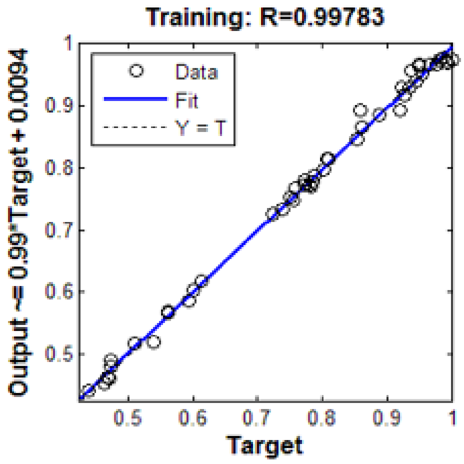

Fig. 3 Training data results of ANN

(a) Identification of the input and output variables of the process to be modeled. Input variable shall be independent in nature;

(b) Normalize the variable in the range of 0.0 to 1.0;

(c) Initialize the number of hidden layers and that of neurons in each layer and select appropriate transfer functions for the neurons in each layer;

(d) Generate the connection weights in normalized scale, bias values and coefficient of transfer functions at random;

(e) Update the above parameters iteratively using a Back propagation algorithm implemented through either an incremental or batch mode training;

(f) Continue the iterations until the termination criterion is reached;

(g) Testing of the optimized neural network.

6.3 Multivariable regression analysis model development for SCC

In the present study, multivariable regression analysis was also conducted to predict the compressive strength of concrete. Similar to ANN's model, 70% data was used to develop the MRA model, and the rest 30% data was used to predict the efficiency of the model. The relationship between dependable variable and undependable is in the form of

$$Y = a_0 + a_1 x_1 + a_2 x_2 \ldots\ldots\ldots a_p x_p \pm e \quad (2)$$

Where, Y is the dependent variable, a_0 is the Y intercept. a_1, a_2 and a_p are the slopes associated with x_1, x_2, and x_p. x_1, x_2 and x_p are the values of independent variables, e is the error. "a" values are obtained via least square optimization of error. MRA model was developed with compressive strength as the dependent variable and cement, coarse aggregate, fine aggregate, fly ash, fiber, water, admixture, superplasticiser as independent variables.

7. Results and discussion of ANNS and MRA models

The ANN model was performed under Matlab software using neural network toolbox. A total of 99 data samples

Table 3 Performance of ANNS and MRA model for self-compacting concrete

Model	Dataset	Statistical parameters		
		R	MSE	MAPE
ANNS	Training Data	0.9935	0.992072	1.672876
	Testing Data	0.9916	1.56613	2.480244
MRA	Training Data	0.9434	8.567942	4.769289
	Testing Data	0.9502	8.269568	5.542265

MSE*mean square error; MAPE=mean absolute percentage error; Statistical performance of the developed ANNS and MRA models for SCC is summarized in Table 3. The values of R, MSE and MAPE for SCC through ANNS model for training and testing data were 0.9935, 0.992072 and 1.672876 & 0.9916, 1.56613 and 2.480244 respectively. While for MRA model, these values for SCC were found to be 0.9434, 8.567942 and 4.769289 & 0.9502, 8.269568 and 5.542265 respectively.

Table 4 Analysis of variance (ANOVA) of MRA model

Source	DF	SS	MS	F	P
Regression	8	9997.712	1249.714	127.106	4.4E-35
Residual	61	599.756	9.832065	-	-
Total	69	10597.47	-	-	-

DF=Degree of Freedom; SS=Sum of Square; MS=Mean Square

obtained from experimental studies were used for ANN. Out of the 99 data samples, 70 data sets were used for training the network and remaining 29 were used for testing the data set. The applied ANNS model is depicted in Fig. 2. The ANN trained with 70 percent of data until the RMS error value is well within the acceptable level, and the correlation of the training data was above 99.78% (Fig. 3).

Twenty nine validation data sets were also predicted correctly (Fig. 4). Further, for testing data (Fig. 5), the ANN produced extremely close results to experimental values. The correlation of the testing data was 99.35%. Based on these high correlation values (Fig. 6 for fall data), it was observed that the accuracy of the network is acceptable, which indicates that the ANN was successful in learning this problem and predicting a concrete mix composition of SCC from this data.

The statistical values in Table 3 suggest that compared to MRA model, ANNS model for SCC predicted the experimental data very well. The regression plot of the predicted compressive strength (Y) of SCC against the experimental compressive strength (T) of testing data of ANNS model is presented in Fig. 7. The best fitting line with R=0.9916, showed good agreement with a line of equality (defined as the locus of all the points where Y is equal to T). From Fig. 7 it may be observed that almost all the data points lie well within the 99% confidence interval band. Tables 4 and 5 show the details of the analysis of variance (ANOVA) and statistical information of predictor variables of MRA model.

The regression analysis data shown in Tables 4 and 5 was interpreted with the aid of F-test and t-test at 95%

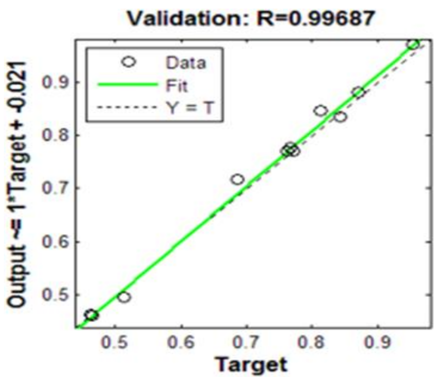

Fig. 4 Validation data results of ANN

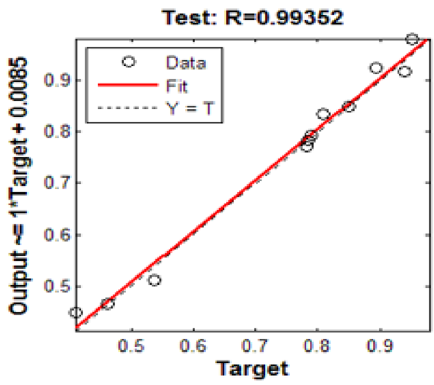

Fig. 5 Test data results of ANN

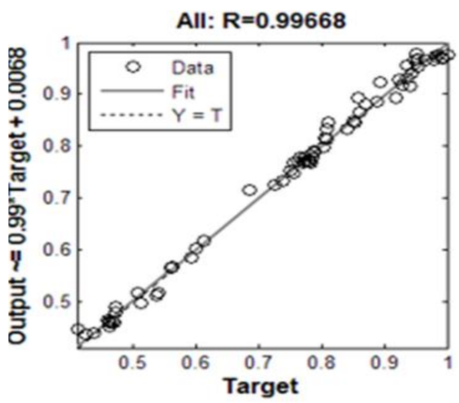

Fig. 6 All data results of ANN

confidence level. From Table 4, it may be observed that the P value (4.4E-35) is very low, which suggests that with confidence level (1-P) is almost 100%, if at least one of the coefficients of MRA model is significant. However, this F-test is not sufficient to point out which coefficients are significant in the MRA model. Further, t-tests were conducted to identify significance of individual coefficients.

Table 5 gives the t-stat and corresponding P value of individual coefficients. It is observed that P values of coefficients of fly ash, fiber and water corresponds to pretty low confidence levels (1-P<0.95) and is not significant for MRA model. On the other hand, P values of cement, fine aggregate, coarse aggregate, SP and VMA are fairly low with high confidence level (1-P>0.95) and suggest that these coefficients are significant for MRA model. Table 5 also shows the lower and upper limit of 95% confidence

Table 5 statistical information of predictor variable of MRA model

Predictor variable	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-222.766	47.21304	-4.71831	1.43E-05	-317.174	-128.358
Cement	0.180126	0.012214	14.74776	8.81E-22	0.155703	0.204549
Sand	0.129153	0.022425	5.759305	2.95E-07	0.084311	0.173995
Aggregate	0.076519	0.026396	2.898915	0.005197	0.023737	0.129301
Fly Ash	-0.03986	0.022843	-1.74505	0.086012	-0.08554	0.005815
Fibre	-0.39638	0.792705	-0.50004	0.618846	-1.9815	1.188727
Water	0.031982	0.081649	0.3917	0.696645	-0.13129	0.195249
SP(lit)	1.109338	0.279159	3.973853	0.00019	0.551124	1.667551
VMA(lit)	14.2316	5.919721	2.4041	0.019265	2.394386	26.06881

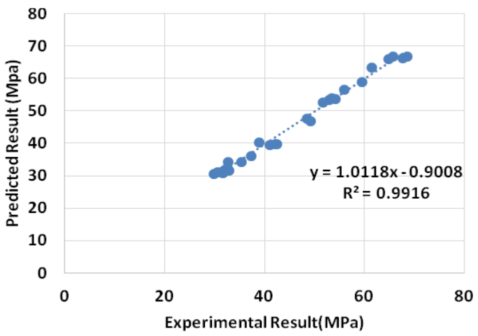

Fig. 7 Regression plot of predicted vs experimental compressive strength of ANNS model

interval. The fact that with 95% probability zero falls in this interval of fly ash, fibre, water with the insignificance obtained from t-tests of these parameters. Confidence intervals of cement, fine aggregate, coarse aggregate, chemical admixtures do not include zero and hence agrees with the significance of t-tests.

8. Conclusions

The present study aims at using the applications of neural network to predict the compressive strength of SCC based on several variables. SCC is different from traditional concrete as it can accommodate more fines.

Also, the concrete mix can be identified as SCC only if it satisfies various fresh properties like J-Ring, Slump flow, L-box, U-box etc. The amount of water required for SCC mix is also more related to traditional concrete, thus, the prediction of SCC strength differ from normal concrete. Also, it signifies the practicability of using neural networks for capturing nonlinear interactions between various parameters in civil engineering problem.

The following conclusions can be drawn from the present study:

• A simple Feed forward back-propagation technique was used to model problems involving non-linear variables.

• The actual experimental test data was used from a SCC mix data set. After training from a set of selected data, the neural network model was able to produce sensible precise projection of compressive strength.

• The modeling using artificial neural network carried for the test data for compressive strength at 28 days based on ANN method could predict with a correlation coefficient of 0.9919.

• MRA model showed that the parameters cement, fine aggregate, coarse aggregate, superplastisizer and viscosity modifying agent are the significant parameters for compressive strength prediction.

• The models developed may be extended to predict the compressive strength of fibrous self-compacting concretes with different percentage of fiber and the results can be checked in the form of mean absolute error, and Mean absolute percentage, correlation coefficient error.

• The superiority of ANNS model over MRA model in predicting the compressive strength of SCC can be attributed to its flexibility and adaptability in generalizing the data.

• By using an ANN model the process time and the number of trial mixes can be reduced for the design of fiber reinforced self-compacting concrete, thus, an economic design process can be employed without the loss of material.

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