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Prediction of Compressive Strength of SCC Containing Bottom Ash using Artificial Neural Networks

Yogesh Aggarwal[1], Paratibha Aggarwal

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***Abstract*—**The paper presents a comparative performance of the models developed to predict 28 days compressive strengths using neural network techniques for data taken from literature (ANN-I) and data developed experimentally for SCC containing bottom ash as partial replacement of fine aggregates (ANN-II). The data used in the models are arranged in the format of six and eight input parameters that cover the contents of cement, sand, coarse aggregate, fly ash as partial replacement of cement, bottom ash as partial replacement of sand, water and water/powder ratio, superplasticizer dosage and an output parameter that is 28-days compressive strength and compressive strengths at 7 days, 28 days, 90 days and 365 days, respectively for ANN-I and ANN-II. The importance of different input parameters is also given for predicting the strengths at various ages using neural network. The model developed from literature data could be easily extended to the experimental data, with bottom ash as partial replacement of sand with some modifications.

***Keywords*—**Self compacting concrete, bottom ash, strength, prediction, neural network, importance factor.

I. Introduction

CONCRETE is essentially a mixture of paste and aggregate. The paste, comprised of cement and water, binds the aggregate into a hard mass; the paste hardens because of the chemical reaction of the cement and water called hydration. In concrete mix design and quality control, the uniaxial compressive strength of concrete is considered as the most valuable property, which in turn is influenced by a number of factors. Various factors affect the concrete mix design like to designate a concrete as HPC, it should possesses, in addition to good strength, several other favorable qualities. The water/cement (w/c) ratio in the concrete is lower than normal concrete which requires special additives in the concrete, along with a superplasticizer to obtain good workability. Usually special cements are also required. The type of aggregate is important to obtain high strength. The grading of the aggregate influences the workability. The order in which the materials are mixed is also important for the workability of the concrete. Strength performance remains the most important property of structural concrete, from an engineering viewpoint. The strength of the concrete is determined by the characteristics of the mortar, coarse aggregate, and the interface. For the same quality mortar, different types of coarse aggregate with different shape, texture, mineralogy, and strength may result in different concrete strengths. The tests for compressive strength are generally carried out at about 7 or 28 days from the date of placing the concrete. The testing at 28-days is standard and therefore essential and at other ages can be carried out if necessary. If due to some experimental error in designing the mix, the test results fall short of required strength, the entire process of concrete design has to be repeated which may be a costly and time consuming. The same applies to all types of concrete i.e. normal concrete, self-compacting concrete, ready mixed concrete etc. It is well recognized that prediction of concrete strength is important in modern concrete constructions and in engineering judgments.

The successful development of self-compacting concrete (SCC), which is defined as the type of high performance concrete, filling all corners of formwork without vibration, and having good deformability, high segregation resistance and no blocking around reinforcement, must ensure a good balance between deformability and stability. It requires manipulation of several mixture variables to ensure acceptable flowable behaviour and proper mechanical properties. Also, absence of theoretical relationships between mixture proportioning and measured engineering properties of SCC makes it more complex.

Within last decade, researchers have explored the potential of artificial neural networks (ANNs), a nonlinear modeling approach, in predicting the compressive strength of the concrete, due to its ability to learn input-output relation for any complex problem in an efficient way. Artificial neural network (ANN) does not need specific equation form. Instead, it only needs sufficient input-output data. It can also continuously retrain new data to adapt new data conveniently. ANNs have been investigated to deal with the problems involving incomplete or imprecise information. The capability of artificial neural network to act as universal function approximators has been traditionally used to model problems in which the relation between dependent and independent variables is not clearly understood. When the number of components increases, the relationship between variables becomes usually complex and the use of a nonlinear modelling approach is required. In recent years, ANNs have been applied to many civil engineering applications with some degree of success. ANNs have been applied to geotechnical problem like prediction of settlement of shallow foundations [1]. Researchers have also used ANN in structural engineering [2]. Some researchers have recently proposed a new method of mix design and prediction of concrete strength using neural network [3, 4]. Also, several works were reported on the use of neural network based modelling approach in predicting the

Yogesh Aggarwal and Paratibha Aggarwal are with the National Institute of Technology, Kurukshetra,, 136119, INDIA (phone: 0091-1744-225741; fax: 0091-1744-238050; e-mail: yogesh.24@rediffmail.com).

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concrete strength [5-14]. Some attempts have been made to describe the compressive strength properties using traditional regression analysis tools and statistical models [15-17]. However, the development of neural network models for predicting the strength of SCC has not been fully investigated. Thus, it was required to develop some suitable methodology to estimate the compressive strength of self-compacting concrete based on its constituents at the time of design.

Therefore, the objective of the present study was to examine the potential of ANN for predicting the 28-day compressive strength of SCC mixtures, with data obtained from literature. These models were further applied to prediction of strength at 7, 28, 90 and 365 days to the data obtained experimentally. The complex relationship between mixture proportions and engineering properties of SCC was generated based on data obtained experimentally. It was observed that the neural network could effectively predict compressive strength in spite of intricate data and could be used as a tool to support decision making, by improving the efficiency of the process.

II. ARTIFICIAL NEURAL NETWORK

Artificial neural network exhibit analogies to the way arrays of neuron function in biological learning and memory. The fundamental building blocks are units ('nodes') comparable to neurons, weighted connections that can be likened to synapses in biological systems. Nodes are simple information processing elements. The number of nodes in ANNs and the connection patterns of the nodes can vary. The total number of nodes in the input and output layers coincide with the number of input and output variables in the data set. The ideal number of nodes in the hidden layer has to be found through trial and error. It is known that more neurons give the ability to memorize and reduce the reasoning capability of the ANN. As a general rule, an ANN should contain the minimum number of neurons that are capable of simulating the training data. Each connection between nodes carries a weight representing some previous learning process. By varying these weights, the input-output relation can be simulated. The network has to be trained to reproduce this input-output relation, which is to find the optimal weights.

Training consists of i) calculating outputs from input data, ii) comparing the measured and calculated outputs, and iii) adjusting the weights for each node to decrease the difference between the measured and calculated values. The accuracy of the predictions of a network was quantified by the root of the mean squared error difference (RMSE), between the measured and the predicted values, mean absolute error (MAE) and the multiple coefficient of determination, R^2.

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(actual - predicted)^2}$$

$$R^2 = 1 - \frac{SSE}{SS_y}$$

Where $SSE = \sum (y-\hat{y})^2$ and, $SS_y = \sum (y-\bar{y})^2$, y is the actual value, $\hat{y}$ is the predicted value of y, and $\bar{y}$ is the mean of the y values.

Mean absolute error is the same as root mean square except using absolute differences instead of squared difference and is calculated in a similar way as root mean square error.

The multiple coefficient of determination compares the accuracy of the model with the accuracy of a trivial benchmark model wherein the prediction is the mean of all samples. A perfect fit would result in an R^2 of 1, and poor fit near 0.

The design of an artificial neural network requires the determination of suitable architecture. A back propagation neural network based modelling algorithm requires setting up of different learning parameters (like learning rate, momentum etc), the optimal number of nodes in the hidden layer and the number of hidden layers so as to have a less complex network with a relatively better generalization capability. In most of the reported applications, selection of a number of hidden layers and the number of nodes in hidden layer is done by using a rule of thumb or trying several arbitrary architectures and selecting one that gives the best performance. Further, a suitable value of parameters like learning rate and momentum is also required for selected hidden layers and nodes.

III. DATABASE

The model's success in predicting the behaviour of SCC mixtures depends on comprehensiveness of the training data. Availability of large variety of experimental data was required to develop the relationship between the mixture variables of SCC and its measured properties. The basic parameters considered in this study were cement content, sand content, coarse aggregate content, fly ash content, water-to-powder ratio and superplasticizer dosage. A database of 80 mixes from the literature was retrieved having mixture composition with comparable physical and chemical properties. The exclusion of one or more of SCC properties in some studies and the ambiguity of mixture proportions and testing methods in others was responsible for setting the criteria for identification of data. The ANNs were designed using 80 pairs of input and output vectors for strength prediction, collected from various studies [16-21].The predicted results obtained from neural network were compared with the experimental values obtained experimentally. The training of ANNs was carried out using pair of input vector and output vector. Input vector consisted of mixture variables and an output vector of one element i.e. 28-day compressive strength in the ANN-I model. The complete list of data is given in Table I, where the name and the source of each specimen are referenced.

In general, a good training data set should include comprehensive information about the characteristics of the materials behavior, since that the trained neural network will contain sufficient information to qualify as material model.

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ANN-II model included 31 SCC compressive strength results, generated experimentally by the authors. The response

TABLE I
DETAILS OF THE DATA RANGE FROM LITERATURE

No. of data	Cement (kg/m^3)	Fly ash (kg/m^3)	Water/ Powder	SP Dosage (%)	Sand (kg/m^3)	Coarse Agg (kg/m^3)	Strength MPa	Researcher
18	183-317	100-220	0.38-0.72	0.20-1.00	470-919	837	11-42.7	Sonebi (2004)
21	160-280	133-232	0.39-0.43	0.10-0.60	808-1024	900	31-52	Patel et al. (2004)
09	161-247	155-250	0.35-0.45	0.0-0.40	842-866	843-864	26.2-48.3	Bouzoubaa & Lachemi (2001)
14	275-430	90-250	0.48-0.77	0.09-0.43	768-988	620-900	51.5-73.5	Bui et al. (2002)
18	249-400	0-96	0.55-0.87	0.12-0.75	718-1080	850	13.3-41.2	Ghezal and Khayat (2002)

models were valid for mixes made with water/powder ratios of 0.41 to 0.62 that contain from 90 to 200 kg/m^3 of fly ash in total powder content of 550 kg/m^3. Coarse aggregate content was fixed at 588.59 kg/m^3. Further, the cement content in these mixes was partially replaced by fly ash in varying percentages of 15 to 35% and fine aggregate content was partially replaced by bottom ash in varying percentages of 0 to 30% in the total content of 912.60 kg/m^3 of fine aggregates. Bottom ash was used with fineness modulus of 1.60 and bulk densities (loose and compacted) were 776 and 948 kg/m^3 and specific gravity as 1.93 conforming to IS: 3812-2003 [22]. The sand was observed to conform to grading zone III as per IS: 383-1970 [23] with fineness modulus as 2.20 and bulk densities (loose and compacted) as 1590 and 1780 kg/m^3 and specific gravity as 2.67. The objective was to replace fine aggregates partially with bottom ash, a locally available material. No comparison regarding the grading of fine aggregate and bottom ash was carried out. In the research work emphasis was on the replacement of fine aggregate with bottom ash, a locally available waste material. The particle size distribution of bottom ash was measured, of the particles 100% were smaller than 56μm and 38% were smaller than 31.3μm with average diameter of the particle size distribution was 33.4μm with standard mean deviation of 8.1μm.

The data ranges for data given in Table III along with the ranges of the data from literature are listed in Table II.

TABLE II
RANGE OF PARAMETERS IN DATA BASE FOR ANN-I AND ANN-II

Parameters	Data base Range (ANN-I)	Data base Range (ANN-II)
Cement (kg/m^3)	160-430	350-460
Sand (kg/m^3)	470-1080	635-915
Coarse aggregate (kg/m^3)	620-900	590
Fly ash (kg/m^3)	0-250	90-200
Water-powder ratio	0.33-0.87	0.41-0.62
Superplasticizer dosage	0-1.0 (%)	7.4- 11.15(kg/m^3)
Bottom ash (kg/m^3)	-	0-275
Water (kg/m^3)	-	225-345

TABLE III
DETAILS OF THE EXPERIMENTAL DATA

Mix no.	Cement (kg/m^3)	Fly ash (kg/m^3)	Coarse aggregate (kg/m^3)	Fine aggregate (kg/m^3)	Bottom ash (kg/m^3)	Water (kg/m^3)	S.P. (kg/m^3)	w/p
1	350	200	588.59	912.60	0.0	241.6	9.91	0.4
2	350	200	588.59	821.34	91.26	276.2	9.36	0.5
3	350	200	588.59	730.08	182.52	321.7	8.81	0.5
4	350	200	588.59	638.82	273.78	341.6	7.16	0.6
5	380	170	588.59	912.60	0.0	234.4	9.91	0.4
6	380	170	588.59	866.97	45.63	252.6	9.20	0.4
7	380	170	588.59	821.34	91.26	268.9	8.81	0.4
8	380	170	588.59	730.08	182.52	306.1	7.71	0.5
9	380	170	588.59	638.82	273.78	333.1	7.16	0.6
10	410	140	588.59	912.60	0.0	233.3	9.91	0.4
11	410	140	588.59	866.97	45.63	247.5	9.10	0.4
12	410	140	588.59	821.34	91.60	265.9	8.23	0.4
13	410	140	588.59	775.71	136.89	280.4	7.97	0.5
14	410	140	588.59	730.08	182.52	298.3	7.70	0.5
15	410	140	588.59	684.45	228.15	301.5	7.42	0.5
16	410	140	588.59	638.82	273.78	312.6	7.16	0.5
17	425	125	588.59	912.60	0.0	229.1	11.14	0.4
18	425	125	588.59	866.97	45.63	247.4	9.57	0.4
19	425	125	588.59	821.34	91.26	264.5	7.99	0.4
20	425	125	588.59	775.71	136.89	274.5	8.50	0.5
21	425	125	588.59	730.08	182.52	289.4	9.36	0.5
22	425	125	588.59	684.45	228.15	297.0	10.19	0.5
23	425	125	588.59	638.82	273.78	311.7	11.01	0.5
24	440	110	588.59	912.60	0.0	228.6	11.01	0.4
25	440	110	588.59	821.34	91.26	263.1	9.91	0.4
26	440	110	588.59	730.08	182.52	283.8	8.26	0.5
27	440	110	588.59	638.82	273.78	303.9	7.43	0.5
28	460	90	588.59	912.60	0.0	227.7	10.73	0.4
29	460	90	588.59	821.34	91.26	260.9	10.19	0.4
39	460	90	588.59	730.08	182.52	281.4	10.46	0.5
31	460	90	588.59	638.82	273.78	300.5	10.34	0.5

A. The Six Major Variables Used for ANN-I

Cement content
Fly ash content
Fine aggregate (sand) content
Coarse aggregate content
Water-powder ratio
Superplasticizer dosage

B. The Eight Major Variables Used for ANN-II

Cement content
Fly ash content
Fine aggregate (sand) content

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Bottom ash (as partial replacement of fine aggregate) content

Coarse aggregate content
Water-powder ratio
Water content
Superplasticizer dosage

In other words, the input layer of the neural network ANN-I consisted of six processing units representing these six variables, and the output layer included one neuron representing 28-day strength and eight processing units representing these eight variables, and the output layer included one neuron representing strength either at 7 days, 28 days, 90 days or 365 days, for ANN-II.

IV. Training and Testing of Neural Networks

Training means to present the network with the experimental data and have it learn, or modify its weights, such that it correctly reproduces the strength behaviour of mix. However, training the network successfully requires many choices and training experiences. After a number of trials, the values of the network parameters considered by this study are as given in Table IV.

TABLE IV
SUMMARY OF NETWORK PARAMETERS

Network parameters	ANN-I	ANN-II			
	28 days	7 days	28 days	90 days	365 days
No. of hidden layers	1	1	1	1	1
Number of hidden neurons	8	8	8	8	8
Learning rate	0.04	.6	0.04	0.5	0.2
Momentum	0.1	.3	0.1	0.2	0.1
Iterations	500	500	500	1000	1300

V. RESULTS AND ANALYSIS

The acceptance / rejection of the model developed is determined by its ability to predict the strength of SCC. Also, a successfully trained model is characterized by its ability to predict strength values for the data it was trained on. A 10-fold cross validation is used to predict the strength for the data set used in this study. The cross validation is the method of accuracy of a classification or regression model. The input data set is divided into several parts (a number defined by the user), with each part intern used to test a model fitted to the remaining part. The correlation coefficient, root mean square error (RMSE), and mean absolute error is used to judge the performance of the neural network approach in predicting the strength.

Neural networks can be effective for analyzing a system containing a number of variables, to establish patterns and characteristics not previously known. In addition, it can generalize correct responses that only broadly resemble the data in the training set. Illustration of quantitative information is given in Table V related to the prediction models ANN-I and ANN-II is incorporated into the model. During training, irrelevant input variables are assigned low connection weights. These variables can then be omitted from the model. The values when compared from Table VI and VII show slight variations, on omission of variables with low connection weights. Since the neural networks are trained on actual test data, they are trained to deal with inherent noisy or imprecise data. As new data become available, the neural network model can be readily updated by retraining with patterns which include these new data.

TABLE V
IMPORTANCE FACTORS OF VARIOUS INPUTS IN ANN-I AND ANN-II

	Age days	Cement	Fly ash	Coarse Agg	Fine aggregate	W/P	SP
ANN-I	28	26.11	21.61	9.45	20.62	13.53	8.69

	Age days	Cement	Fly ash	Coarse Agg	Fine Agg.	Bottom ash	Water	W/P	SP
ANN-II	7	18.78	18.48	0.85	13.68	15.02	15.05	9.09	9.05
	28	15.48	17.35	4.85	21.07	18.62	9.46	6.96	6.21
	90	10.61	7.94	0.91	16.73	14.81	11.81	11.13	26.07
	365	20.89	19.67	1.34	14.44	13.77	9.47	8.31	12.11

TABLE VI
SUMMARY OF COEFFICIENTS FOR NEURAL NETWORK MODELS

Neural network model	Strength	Correlation Coefficient	Mean Absolute Error	Root Mean Square Error
ANN-I	28 days	0.9188	4.4381	5.557
ANN-II	7 days	0.9677	0.6337	0.7575
	28 days	0.9584	0.8984	1.1711
	90 days	0.9348	1.8837	2.6308
	365days	0.9691	0.9801	1.3644

TABLE VII
SUMMARY OF COEFFICIENTS FOR NEURAL NETWORK MODELS
(LEAST IMPORTANCE FACTOR INPUT PARAMETER REMOVED)

Neural Network Model	Strengh	Correlation Coefficient	Mean Absolute Error	Root Mean Square Error
ANN-I	28 days	0.9187	4.4395	5.570
ANN-II	7 days	0.9692	0.6137	0.739
	28 days	0.9587	0.8939	1.167
	90 days	0.9482	1.7409	2.448
	365days	0.9689	0.9605	1.367

The procedure for partitioning the connection weights to determine the relative importance of the various inputs is adopted using the method proposed by Garson [24]. The method essentially involves partitioning the hidden output connection weights of each hidden neuron into components associated with each input neuron. The minimum importance factor of 0.85 to 4.85 in ANN-II was observed for coarse aggregate content as it was kept constant throughout the study. The maximum importance factor was observed for cementitious materials (cement + fly ash) in both ANN-I and ANN-II models. Keeping in view the importance of various parameters, the input parameter can be varied to achieve the output parameter with desired results. The importance of various input parameters for output prediction of strengths as determined by using neural network technique is given in Table V.

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Table VI provides the correlation coefficient (R^2) and RMSE obtained with this data to predict various strengths. To compare the performance of models, graphs between actual and predicted strength are plotted. The performance of ANN-I model in predicting the compressive strength is shown in Fig.1. Results suggest that most of the points are lying within ± 20% of the line of perfect agreement, which suggest that neural network, can effectively be used to predict the strength for self-compacting concrete data. A correlation coefficient of 0.919 (RMSE = 5.570) was achieved.

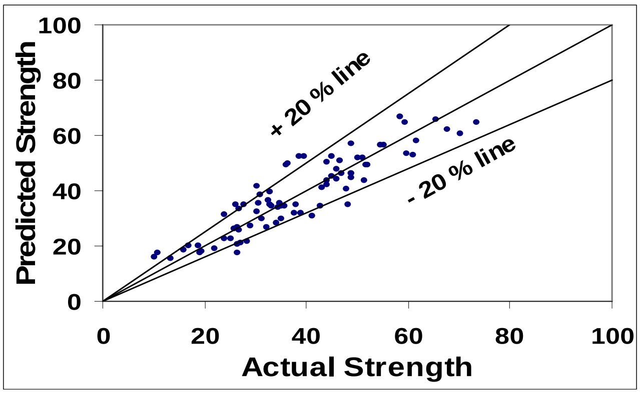

Fig.1 Actual v/s predicted value for 28day strength (MPa) for ANN-I

Figs.2-5 shows the plot between the actual and predicted values of strengths for 7-d, 28-d, 90-d and 365-d (ANN-II). Results suggested a better performance for this data set also, in strength prediction for all ages. Most of the points are again lying within ± 10% of the line of perfect agreement (Fig.2, 3, 4 and 5). ANN-II is observed to be better than ANN-I as the data for ANN-II is less it is giving good results. Also, number of input parameters is more in ANN-II and it could be used to predict the strengths at various ages whereas ANN-I is limited to 28-days strength.

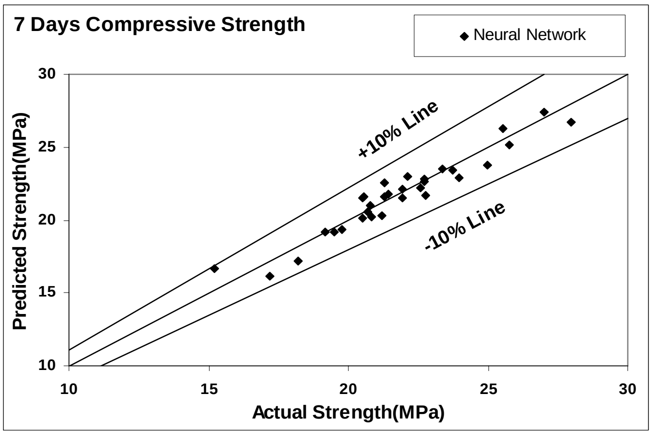

Fig.2 Actual v/s predicted value for 7day strength (MPa) for ANN-II

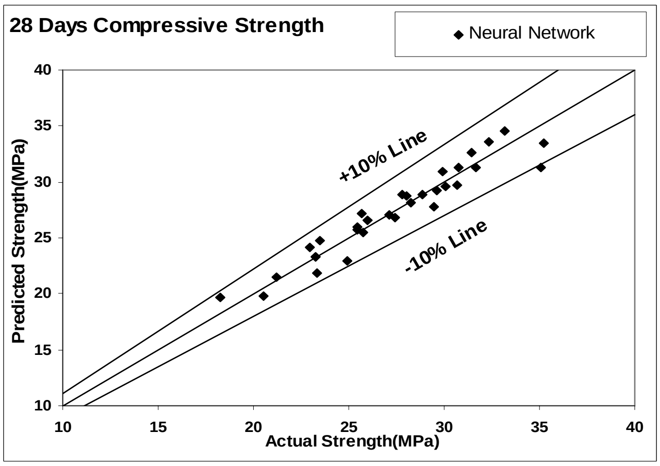

Fig.3 Actual v/s predicted value for 28day strength(MPa) for ANN-II

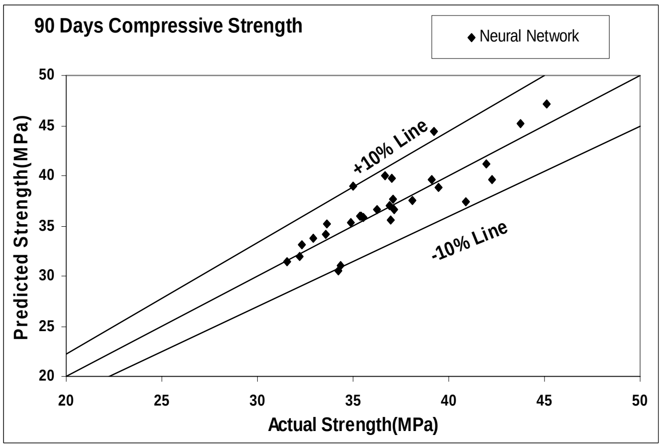

Fig.4 Actual v/s predicted value for 90day strength(MPa) for ANN-II

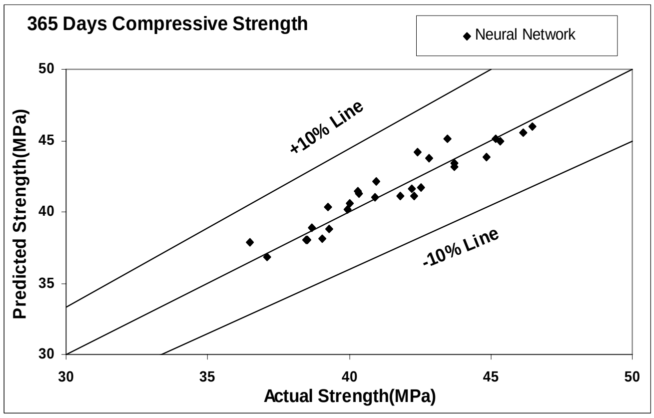

Fig.5Actual v/s predicted value for 365day strength(MPa)for ANN-II

Correlation coefficient, mean absolute error and RMSE achieved using neural network modelling approach for strength in ANN-II model are given in Table VI. Further, Table VII shows the variation in the results of the network if the input parameters with minimum importance factor are not taken into consideration. Also, the results on comparison show

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slight variation in prediction values of RMSE, Correlation coefficient and MAE on removal of the input parameter with minimum importance factor, thus the models can also be developed without these parameters.

The general trend observed was the maximum importance factor for cement + fly-ash), however samples aged at 90 day showed exception in all importance factors with SP and fine aggregates having higher importance factors. If strength models are taken in isolation i.e only 7-days strength ANN-II or 28-days strength ANN-II, then importance factors of various parameters have more relevance as compared to when taken together for all ages in ANN-II.

VI. CONCLUSIONS

Artificial neural networks are viable computational models for a wide variety of problems including prediction problems. The neural network can be used for a particular problem when deviation in the available data is expected and accepted and also when a defined methodology is not available as in the case of present study.

1) This study presents the application of neural network to predict the compressive strength of SCC based on several parameters. SCC is different from conventional concrete such that it contains more fines. Also, mix can be designated as SCC only if satisfies various fresh properties like Slump flow, U-box, L-box, JRing etc. The amount of water required for SCC mix is also more as compared to conventional concrete, thus the prediction of SCC strength differ from conventional concrete. Also, it demonstrates the feasibility of using neural networks for capturing nonlinear interactions between various parameters in complex civil engineering systems.

2) A simple back-propagation neural network was used to model two problems involving nonlinear variables. Actual field data were used. After learning from a set of selected patterns, the neural network models were able to produce reasonably accurate predictions.

3) The modeling using artificial neural network was carried out for the data from literature for compressive strength at 28 days, in ANN-I with a correlation coefficient above 0.9.

4) The models developed were extended to the prediction of compressive strength at various ages (ANN-II) and the results in the form of correlation coefficient, mean absolute error and RMSE values were found to be better at all ages for the data obtained experimentally.

5) In ANN-I, the maximum effect was observed for Powder content (cement + fly ash) and in ANN-II the same was observed with exception of ANN-II for 90-day strength. The importance factor in ANN-I was observed to be 20 for fine aggregates as fine aggregate is not replaced with any other type of aggregates. For ANN-II, it is between 30-40 for fine aggregates (sand + bottom ash), taking into consideration effect of bottom ash. Coarse aggregates showed minimum importance factor in all models of ANN-II.

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