International Journal of Engineering, Mathematical and Physical Sciences
ISSN: 2517-9934
Vol:5, No:5, 2011

Prediction of Compressive Strength of Self-Compacting Concrete with Fuzzy Logic

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***Abstract*—**The paper presents the potential of fuzzy logic (FL-I) and neural network techniques (ANN-I) for predicting the compressive strength, for SCC mixtures. Six input parameters that is contents of cement, sand, coarse aggregate, fly ash, superplasticizer percentage and water-to-binder ratio and an output parameter i.e. 28-day compressive strength for ANN-I and FL-I are used for modeling. The fuzzy logic model showed better performance than neural network model.

***Keywords*—**Self compacting concrete, compressive strength, prediction, neural network, Fuzzy logic.

I. Introduction

IN todays fast paced world of increasing and innovative new technology, fuzzy logic is a practical mathematical addition to classic Boolean logic. Fuzzy logic is considered as a superset of standard logic which is extended to deal with partial truth. Fuzzy set theory is basicaly used to mathematically represent uncertainity and vagueness and provide tools to deal with the imprecision in many problems. For the last two decades, the different modeling methods based on artificial neural networks (ANN) and fuzzy logic (FL) systems have become popular and has been used by many researchers for a variety of engineering applications. The basic strategy for developing ANN and FL systems based models for material behavior is to train ANN and FL systems on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained ANN and FL systems will contain sufficient information about material's behavior to qualify as a material model. Such a trained ANN and FL systems not only would be able to reproduce the experimental results, but also they would be able to approximate the results in other experiments through their generalization capability [1]. Also, 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. ANNs have been investigated to deal with the problems involving incomplete or imprecise information. 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 [2]. Researchers have also used ANN in structural engineering [3]. Some researchers have recently proposed a new method of mix design and prediction of concrete strength using neural network [4, 5]. Also, several works were reported on the use of neural network based modelling approach in predicting the concrete strength [6-15]. Some attempts have been made to describe the compressive strength properties using traditional regression analysis tools and statistical models [16-18].

The objective of the present study was to examine the potential of Fuzzy Logic and ANN for predicting the 28-day compressive strength of SCC mixtures, with data obtained from literature. 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, requires manipulation of several mixture variables to ensure acceptable flowable behaviour and proper mechanical properties The complex relationship between mixture proportions and engineering properties of SCC was generated based on data obtained experimentally by various researchers. It was observed that the neural network along with fuzzy logic 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. Thus, study was carried out to develop and compare the performance of the models developed using artificial neural network and fuzzy logic techniques.

II. Artificial Neural Network

Neural networks are networks of many simple processes, which are called units, nodes, or neurons, with dense parallel interconnections. The connections between the neurons are called synapses. Each neuron receives weighted inputs from other neurons and communicates its outputs to other neurons by using an activation function. Thus, information is represented by massive cross-weighted interconnections. Neural networks might be single or multi layered. The basic methodology of neural networks consists of three processes: network training, testing, and implementation. The connection weights of the neural network are adjusted through the training process, while the training effect is referred to as learning. Then, other testing data are used to check the generalization. The initial weights and biases joining nodes of an input layer, hidden layers, and an output layer are commonly assigned randomly. The final sets of weights and biases comprise the long-term memory, or synapses, of respective events. Consequently, learning corresponds to determining the weights and biases associated with the

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connections in the networks. The back-propagation networks was used in this study. Figure.1 presents a simple architectural layout of the back propagation networks that consist of an input layer, a hidden layer, an output layer, and connections between them. The learning mechanism of the back-propagation networks is a generalized delta rule that performs a gradient descent on the error space to minimize the total error between the actual calculated values and the desired ones of an output layer during modification of connection weights. In other words, a least mean square procedure is carried out to find the values of the connection weights that minimize the error function by using a gradient descent method.

Artificial neural networks (ANNs) have been successfully used to predict various concrete properties. Their prediction ability, however, depends, to a large extent, on the completeness and accuracy of the experimental database used in the training process. The main objective in building an ANN-based model is to train a specific network architecture using a comprehensive database to search for an optimum set of weights (connection strengths between its processing units) for which the trained ANN can predict accurate values of outputs for a given set of inputs from within the range of the training data. A neural network model requires no functional relationship among the variables, as is the case with most of other regression analysis techniques. A neural network based modelling algorithm requires setting up of different learning parameters (like learning rate, momentum), 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.

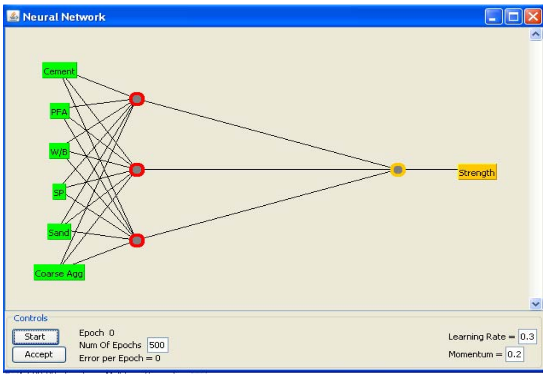

Fig. 1 Architecture of Artificial Neural Network

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 and mean absolute error (MAE).

III. FUZZY LOGIC

The concept of ‘‘fuzzy set’’ was preliminarily introduced by Zadeh [19], who pioneered the development of fuzzy logic (FL) replacing Aristotelian logic which has two possibilities only. FL concept provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables [20, 21]. Herein, uncertainties do not mean random, probabilistic and stochastic variations, all of which are based on the numerical data. Fuzzy set theory provides a systematic calculus to deal with such information linguistically. Fuzzy approach performs numerical computation by using linguistic labels stimulated by membership functions. Therefore, Zadeh introduced linguistic variables as variables whose values are sentences in a natural or artificial language. Although FL was brought forward by Zadeh in 1965, fuzzy concepts and systems attracted attention after a real control application in 1975 conducted by Mamdani and Assilian [22]. The key idea in FL is the allowance of partial belongings of any object to different subsets of the universal set instead of belonging to a single set totally. Partial belonging to set can be described numerically by a membership function which assumes values between 0 and 1 contain. For instance, Fig.2 shows a typical membership function for small, medium and large class sizes in a universe, U. Hence, these verbal assignments are fuzzy subsets of the universal set. In this figure, set values less than 2 are definitely ‘‘small’’; those between 4 and 6 are certainly ‘‘medium’’; while values larger than 8 are definitely ‘‘large’’. However, intermediate values such as 2.2 partially belong to the subsets ‘‘small’’ and ‘‘medium’’. In fuzzy terminology 2.2 has a membership value of 0.9 in ‘‘small’’ and 0.1 in ‘‘medium’’, but 0.0 in ‘‘large’’ subsets [20, 21, 25].

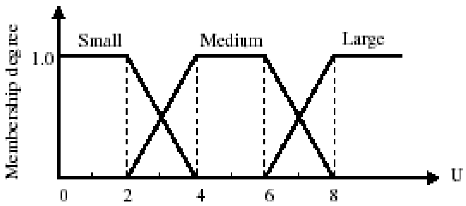

Fig. 2 typical membership function

A. Fuzzy Logic Inference System

A general fuzzy inference system (FIS) has basically four components: fuzzification, fuzzy rule base, fuzzy output engine and defuzzification [26]. Moreover, input and output data can be added. Fuzzification converts each piece of input data to degrees of membership by a lookup in one or more several membership functions. Fuzzy rule base contains rules that include all possible fuzzy relation between inputs and outputs. These rules are expressed in the IF–THEN format. In this study, the Sugeno-type fuzzy rules were constituted. Fuzzy inference engine takes into consideration all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. There are basically two kinds of inference operators: minimization (min) and product (prod). In this study, the prod method was employed because of its better performance. Defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are many defuzzification methods such as weighted average (wtaver) or weighted sum (wtsum). In this study, the weighted average method was employed. Fuzzy inference systems are powerful tools for the simulation of non-linear behaviors with the help of FL and linguistic fuzzy rules [27]. A FIS employing fuzzy ‘‘IF–THEN rules’’ can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses [23–30].

There are various FIS methodologies, such as Mamdani and Sugeno [22–29]. The fuzzy modeling or fuzzy identification, first explored systematically by Sugeno and Kang [28] and Takagi and Sugeno [29], has found numerous practical applications in control, prediction and FIS [28–30]. In the Sugeno FIS,(Fig.3) outcomes of fuzzy rules are characterized by function crisp outputs. From mathematical viewpoint, if F denotes a real continuous mapping within a closed interval, then the parameterized non-linear mapping of a Sugeno-type FIS may be given in the following equation:

$$F = \frac{\sum_{i=1}^{m} w_i \prod_{j=1}^{n} \mu_{A_j^i}(x_j)}{\sum_{i=1}^{m} \prod_{j=1}^{n} \mu_{A_j^i}(x_j)}$$

Where m denotes number of rules, n defines number of data points, and Ai is the membership function of fuzzy set A. Considering a first-order Sugeno-type FIS, a fuzzy model contains two rules [26, 29]:

Rule1 : IF x is A_1 and y is B_1; THEN $z1 = p_1x + q_1y + r_1$
Rule2 : IF x is A_2 and y is B_2; THEN $z2 = p_2x + q_2y + r_2$

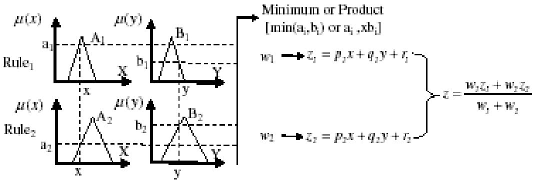

Fig. 3 Interference methodology of first order Sugeno type model with two fuzzy rules

All of the proposed membership functions in this study consist of six inputs and one output. The membership function plots of input variables and output variable used in the training are shown in Fig. 4-Fig. 5 respectively. In Fig. 6, based on the results of prediction runs of the model; shows the effects of two factors at a time on each surface plot of the strength.

IV. 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, pulverised fly ash (PFA) content, water-to-powder ratio and superplasticizer dosage. A database of 60 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 60 pairs of input and output vectors for strength prediction, collected from studies [17,31-33].The predicted results obtained from neural network were compared with the results obtained from FL-I. The training of models 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. The complete list of data is given in Table I, where the name and the source of each specimen are referenced.

Fuzzy modeling is a system identification task, which involves two phases: structure identification and parameter prediction. Structure identification contains the issues like selecting relevant input variables, choosing a specific type of FIS, determining the number of fuzzy rules, their antecedents and consequents, and determining the type and number of membership functions. Parameter prediction is determination of aimed values response to evident input values of constituted model. For this aim, in the study 60 data results from literature were used in the processes of Sugeno-type fuzzy inference model in FL system. The limit values of input and output variables used in Sugeno-type fuzzy inference model are listed in Table II.

The data is given in Table I with ranges listed in Table II.
The six major variables used for ANN-I and FL-I
Cement content
Sand content
PFA content
Coarse aggregate content
Water-binder ratio
SP (%)

In other words, the input layer of the neural network ANN-I and FL-I consisted of six processing units representing these six variables, and the output layer included one neuron representing 28-day strength.

TABLE I
DETAILS OF THE DATA FROM LITERATURE

Sr. No.	Cement	PFA	W/B	SP	Sand	Coarse Agg	Strength	Researcher
1	250	261	0.55	0.5	478	837	17	
2	210	100	0.65	0.8	910	837	19.1	
3	210	220	0.45	0.8	768	837	26.7	
4	290	220	0.45	0.2	625	837	32.9	
5	250	160	0.38	0.5	919	837	36.3	
6	250	160	0.55	1	746	837	26.7	Sonebi 2004)
7	220	180	0.39	0.35	916	900	49	
8	160	240	0.39	0.35	886	900	44	
9	193	158	0.39	0.35	1024	900	44	
10	220	180	0.45	0.35	850	900	38	

11	198	232	0.34	0.2	874	900	46	
12	248	203	0.39	0.35	808	900	50	
13	237	133	0.36	0.2	1034	900	49	
14	220	180	0.39	0.35	916	900	49	
15	237	133	0.43	0.5	960	900	46	
16	275	155	0.43	0.5	827	900	48	
17	280	120	0.39	0.35	946	900	45	
18	170	200	0.43	0.2	930	900	31	
19	220	180	0.39	0.6	916	900	43	
20	220	180	0.39	0.35	916	900	47	
21	220	180	0.39	0.1	916	900	44	
22	198	232	0.36	0.5	872	900	52	
23	220	180	0.39	0.35	916	900	45	
24	220	180	0.33	0.35	982	900	51	
25	170	200	0.43	0.5	928	900	33	
26	275	155	0.43	0.2	830	900	36	
27	247	165	0.45	0.12	845	846	34.6	
28	238	159	0.4	0.29	844	844	37.8	
29	232	155	0.35	0.38	846	847	48.3	Patel et al. (2004)
30	207	207	0.45	0.4	845	843	33.2	
31	200	200	0.4	0.17	842	843	34.9	
32	197	197	0.35	0.28	856	856	38.9	
33	169	254	0.45	0	853	853	30.2	
34	163	245	0.4	0.2	851	851	26.2	
35	161	241	0.35	0.3	866	864	35.8	
36	350	162	0.59	0.09	768	840	51.7	
37	350	133	0.52	0.16	815	883	55.3	
38	250	257	0.77	0.11	787	853	51.5	
39	427	115	0.45	0.12	779	844	59.4	
40	350	90	0.48	0.14	852	923	46.5	
41	427	173	0.53	0.2	902	803	61.6	
42	380	145	0.48	0.13	988	621	65.5	
43	380	192	0.53	0.1	931	621	67.8	
44	275	250	0.67	0.09	775	840	54.5	Bouzoubaa and Lachemi (2001)
45	325	60	0.65	0.43	899	850	30.8	
46	325	60	0.65	0.43	899	850	32.6	
47	325	120	0.75	0.43	755	850	32.2	
48	249	60	0.68	0.43	1079	850	24	
49	370	96	0.57	0.25	833	850	39.5	
50	400	60	0.63	0.43	718	850	30.4	
51	325	60	0.65	0.43	899	850	35.3	
52	370	24	0.87	0.62	770	850	18.7	Bui et al. (2002)
53	325	0	0.55	0.43	1042	850	41.2	
54	280	96	0.87	0.25	820	850	19.6	
55	325	60	0.65	0.75	896	850	27.7	
56	325	60	0.65	0.43	898	850	35	
57	370	96	0.57	0.62	830	850	38.8	
58	325	60	0.65	0.43	898	850	34.3	
59	280	96	0.87	0.62	817	850	15.9	
60	370	24	0.69	0.25	772	850	26.4	

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

Parameters	Data base Range (ANN-I)	Data base Range (FL-I)
cement (kg/m^3)	160-427	160-427
sand (kg/m^3)	478-1079	478-1079
coarse aggregate (kg/m^3)	621-923	621-923
PFA (kg/m^3)	0-261	0-261
water-binder ratio	0.35-0.87	0.35-0.87
superplasticizer	0-1.0(%)	0-1.0(%)

V. TRAINING AND TESTING OF MODELS

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 III.

TABLE III
SUMMARY OF ARTIFICIAL NEURAL NETWORK PARAMETERS

Network parameters	No. of hidden layers	Number of hidden neurons	Learning rate	Momentum	Iterations
ANN-I	1	6	0.3	0.2	500

VI. 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

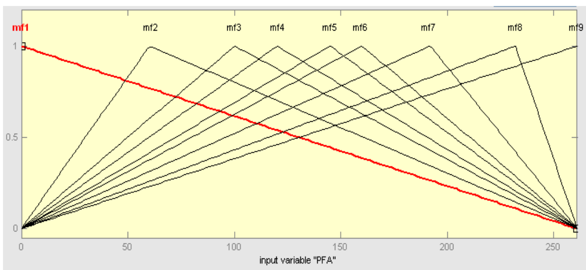

Fig. 4a Membership Functions

International Journal of Engineering, Mathematical and Physical Sciences
ISSN: 2517-9934
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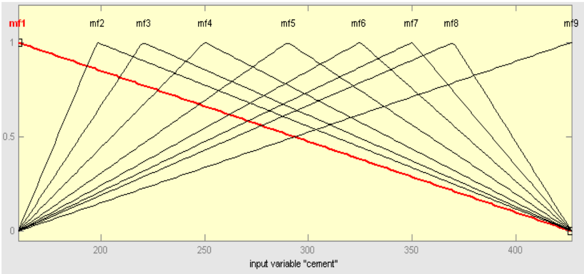

Fig. 4b Membership functions of input parameters

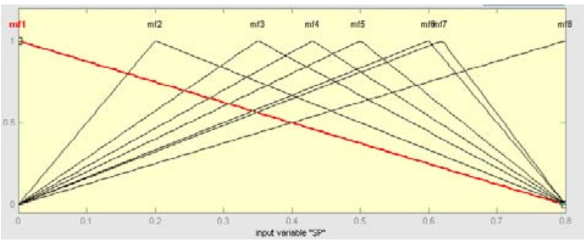

Fig. 4c Membership functions of input parameters

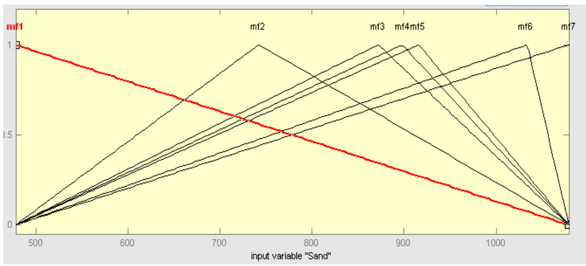

Fig. 4d Membership functions of input parameters

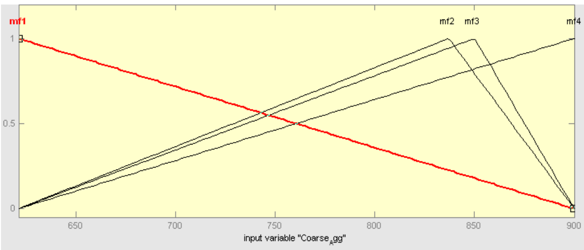

Fig. 4e Membership functions of input parameters

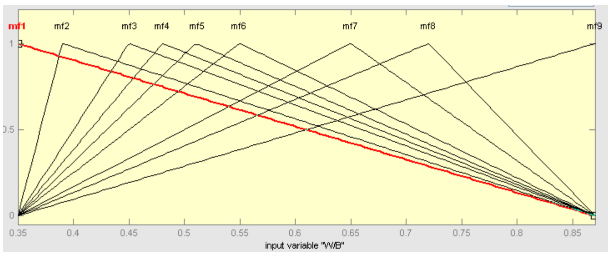

Fig. 4f Membership functions of input parameters

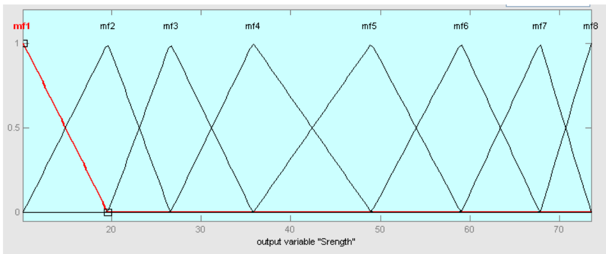

Fig. 5 Membership functions of output parameters (strength)

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 MAE are used to judge the performance of the neural network and fuzzy logic approach in predicting the strength (Table IV).

Statistical methods are commonly used in the development of empirical relationships between various interacting factors. This is often complex and circuitous, particularly for nonlinear relationships. Also, to formulate the statistical model, the important parameters must be known. By comparison, the modeling process in back-propagation neural networks is more direct, as there is no necessity to specify a mathematical relationship between the input and output variables.

TABLE IV
SUMMARY OF ACTUAL STRENGTH AND PREDICTED STRENGTHS

Sr. no.	Actual Strength (MPa)	Predicted strength (MPa)	
		Fuzzy logic model	ANN model
1	17	18.8	16.765
2	19.1	22.4	14.851
3	26.7	28.8	27.09
4	32.9	41.2	35.092
5	36.3	42.3	42.43
6	26.7	23.4	23.299
7	49	41.2	45.697
8	44	41.9	39.914
9	44	40.5	44.742
10	38	39.8	38.375
11	46	47.9	44.982
12	50	41	45.993
13	49	44.4	47.8
14	49	41.2	45.697
15	46	41.3	46.316
16	48	41.5	45.283
17	45	41.1	49.381
18	31	38.6	31.688
19	43	42.3	45.977
20	47	41.2	45.697
21	44	42.2	39.41
22	52	44.4	46.107
23	45	41.2	45.697
24	51	47.8	49.982
25	33	38.6	40.54
26	36	40.9	42.759
27	34.6	42.4	30.636
28	37.8	42.2	35.529
29	48.3	43	39.037
30	33.2	39.7	33.283
31	34.9	40.6	29.305
32	38.9	42.7	37.145
33	30.2	33.3	25.02

International Journal of Engineering, Mathematical and Physical Sciences
ISSN: 2517-9934
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34	26.2	32	29.421
35	35.8	37.7	37.03
36	51.7	44.4	44.881
37	55.3	45.3	46.246
38	51.5	45.2	47.501
39	59.4	58.5	51.655
40	46.5	46.6	47.011
41	61.6	58.5	62.436
42	65.5	67.9	61.508
43	67.8	68	66.739
44	54.5	44.6	49.004
45	30.8	40.1	31.101
46	32.6	40.1	31.101
47	32.2	38.3	25.54
48	24	31.9	24.327
49	39.5	43.8	43.291
50	30.4	42.4	34.686
51	35.3	40.1	31.101
52	18.7	16.8	16.413
53	41.2	34.6	40.621
54	19.6	17.1	23.34
55	27.7	23.9	32.983
56	35	40.1	31.206
57	38.8	38.8	38.948
58	34.3	40.1	31.026
59	15.9	17.8	15.339
60	26.4	36.1	21.86

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. 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 provides the correlation coefficient (R^2) and RMSE obtained with this data using 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.7 and the performance of FL-I model in predicting the compressive strength is shown in Fig.8 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 = 5.557) was achieved for ANN-I and a correlation coefficient of 0.987 (RMSE = 5.626) was achieved for FL-I.

TABLE V
SUMMARY OF COEFFICIENTS FOR NEURAL NETWORK AND FUZZY LOGIC MODELS

Models	Strength	Correlation Coefficient	Mean Absolute Error	Root Mean Square Error
ANN-I	28 days	0.919	4.438	5.557
FL-I	28 days	0.987	4.885	5.626

VII. CONCLUSIONS

Compressive strength estimations have so far been obtained in the literature experimentally. The herein developed fuzzy algorithm can adjust itself to any type of linear or non linear form through fuzzy subsets of linguistic compressive strength variables. It is also possible to augment the conditional statements in the fuzzy implications used in this paper to include additional relevant characteristics of aggregate variables that might increase the precision of compressive strength estimation. The necessary fuzzy rule bases of the compressive strength estimation from available experimental results are given and applied to some test data. The application of the proposed fuzzy subsets and rule bases is straight forward for compressive strength of SCC.

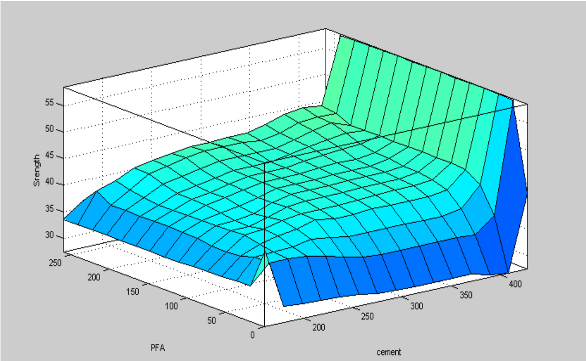

Fig. 6a Surface diagrams for various inputs with output

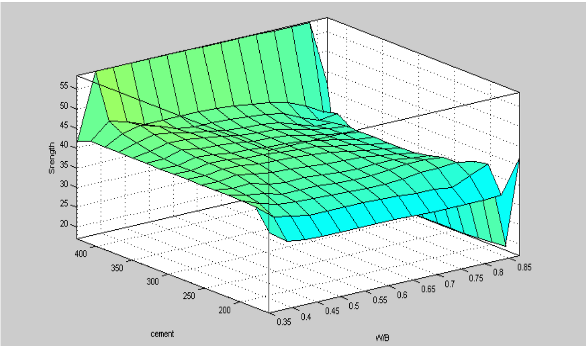

Fig. 6b Surface diagrams for various inputs with output

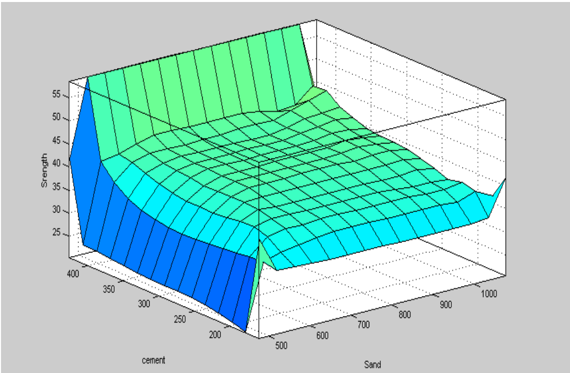

Fig. 6c Surface diagrams for various inputs with output

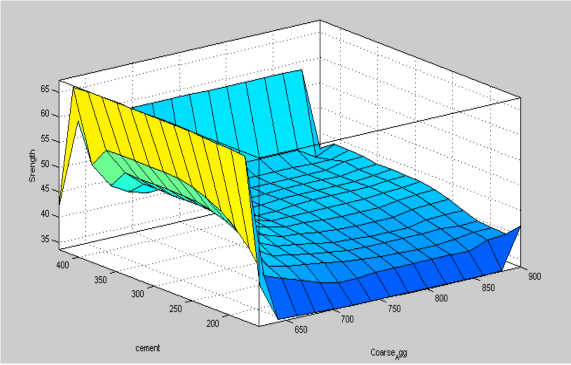

Fig. 6d Surface diagrams for various inputs with output

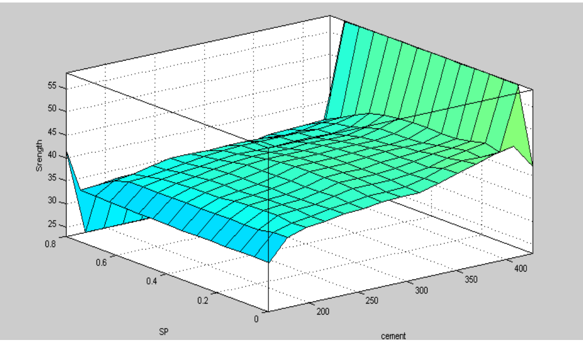

Fig. 6e Surface diagrams for various inputs with output

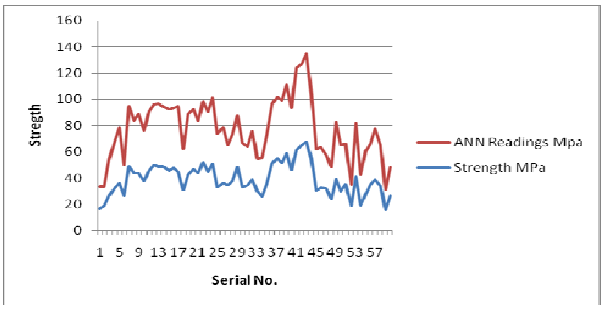

Fig.7 Actual v/s predicted value for 28-day strength (MPa) for ANN-I

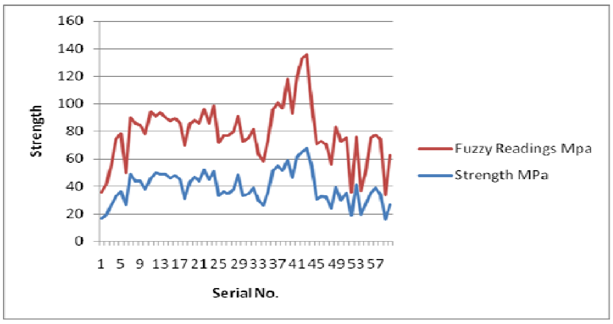

Fig.8 Actual v/s predicted value for 28-day strength (MPa) for FL-I

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