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RESEARCH ARTICLE

Prediction of Concrete Properties Using Fuzzy Logic

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ABSTRACT

In the recent years, artificial intelligence based techniques are widely applied in simulation of the non-linear and complex behavior of concrete in combination with the traditional methods. Concrete properties in fresh and hardened state are important for evaluating its performance in civil engineering. However, testing of slump and compressive strength of concrete is complex and time-consuming process. Therefore, prediction of these properties before the placement of concrete is highly in demand. In this work, prediction of slump as well as 7 and 28 days compressive strength of Ready Mix Concrete (RMC) is determined using fuzzy modeling. Slump and compressive strength is modeled as a function of various input variables that include cement, fine aggregate, a coarse aggregate of size 10mm, 20mm and water. Simulation results obtained with fuzzy logic are compared with the observed results. It has been found that fuzzy logic has strong potential for predicting slump and compressive strength effectively.
Keywords: Artificial intelligence, Ready-mix concrete, Slump, Compressive strength, Fuzzy logic.

1. INTRODUCTION

Nowadays, use of RMC has been increased considerably due to demand of high rise structure and faster construction. RMC industry in India is still in its formative years and concrete is one of the most popular building materials in the construction industry which gives better quality control compared to site mixed concrete [1, 2]. RMC is suitable for all kinds of constructions and is more advantageous than the concretes prepared by the conventional methods [3, 4]. The types of concrete strength include compressive, tensile, flexural, shear and bond strength. Among them, compressive strength is the vital property for structural designers and construction engineers. 28 days compressive strength is usually considered as a standard index for evaluating concrete quality [5]. Generally, tests on concrete in fresh as well as the hardened state are complex and time-consuming, and experimental errors are unavoidable. Therefore, it is important to predict slump and compressive strength before its use on construction sites. For better learning ability and adaptive capability, an artificial intelligence has been widely used in system modeling and identification [6, 7]. A quick and accurate prediction of concrete properties without wasting material, time and money is important in research. Several studies are found in the literature that employ fuzzy based prediction; each trying to enhance the accuracy of prediction. Some of the significant studies are discussed below.

Fuzzy based compressive strength prediction for developing models with partial replacement of cement by nano silica has been carried out using triangular membership function [8]. Results are expressed in terms of statistical parameters like correlation coefficient and root mean square error. 28 days compressive strength of self-compacting concrete is studied using Mamdani based model and multilayer feed forward network [9]. [10] has employed both Gaussian and triangular membership function and found that Gaussian membership function has yielded better results for prediction. [11] has presented a data-driven approach based on Fuzzy C-Means clustering (FCM). They employed both Mamdani and Sugeno FIS models for predicting compressive strength. The best prediction model by Mamdani system is obtained at high cluster value i.e. 27. Another work consists of fuzzy modeling using ultrasonic pulse velocity, curing conditions, curing time and fly ash for prediction of 3, 7, 14 and 28 days compressive strength. Predicted value by fuzzy model is nearly close to the experimental values. For predicting fresh properties of self-compacting concrete, percentage of fly ash [12] and granulated blast furnace

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slag, as replacement of cement, and percentage of micronized calcite, as replacement of total aggregate are used as inputs [13].

The slump flow diameter, time and V-funnel time are used as outputs. It predicts the fresh properties of self-compacting concrete well. It has been found that prediction of grade wise 7 and 28 days concrete strength and slump is not studied and has scope to focus. In the construction industry, use of concrete is generally based on the type of work and accordingly the grade of concrete is chosen [14]. In this paper, fuzzy logic is employed to predict slump as well as 7 and 28 days compressive strength for M20 to M70 grades of concrete. The combination of two concrete grades like M20-M25, M30-M35, M40-M45, M50-M55, and M60-M70 are considered for the prediction to solve various complex problems related to time consumption and wastage of material and economy. Fuzzy logic

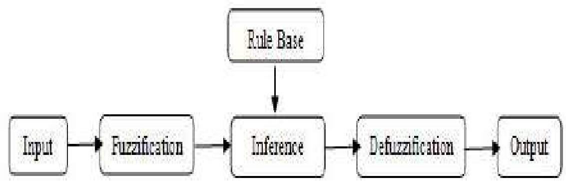

Figure 1.Fuzzy interference system

improves its performance through learning from its environment [15, 16]. Figure 1 shows the general form of fuzzy system which has four components: Fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification. In fuzzification, each piece of input data is converted to the degree of membership by a lookup in one or more membership functions. The fuzzy rule base uses IF-THEN format. Sugeno and Mamdani are the types of fuzzy systems. In fuzzy inference engine, all the fuzzy rules in the rule base are considered, where conversion of input set to corresponding outputs takes place. In defuzzification, the resulting fuzzy outputs from the fuzzy inference engine are converted to a number [17-19].

2. DATA COLLECTION AND METHODOLOGY

2.1. Data set

The work proposed in this paper is based on powerful resource i.e. concrete mix design database obtained from various RMC plants from Mumbai, Navi Mumbai and Panvel region of Maharashtra State. Ultra Tech RMC plant is located in Kongoan, Raigad. Data from 210 trials is collected from this RMC plant with various grades of concrete ranging from M20 to M70. Lafarge India Pvt. Ltd is located in Jogeshwari, Mumbai. The data of 100 trials is collected from range of grades M20 to M50. Another set of database is collected from Amit Infra logic India Pvt. Ltd. located in Chembur. 120 trials data of M25 to M50 grade mix is collected from this plant. Swastik Infra logic Pvt. Ltd. located in CBD Belapur, Navi Mumbai area has provided 90 trials data of range of M20 to M45 grade of concrete. A database of 100 trials is collected from a well-known company Indiabulls from on-going construction located at Kongoan in Raigad district. The mix include contains of cement, blast furnace slag, fly ash, a coarse aggregate of size 10mm and 20mm, fine aggregate, water and dosage of super plasticizer. The testing is carried out in the laboratories where slump as well as 7 and 28 days compressive strength for respective trials are recorded.

2.2. Methodology

In this study, models are built for various concrete grades in groups of M20-M25, M30-M35, M40-M45, M50-M55 and M60-M70 for the purpose of comparison. The number of inputs is determined primarily from the standard essential ingredients required and also with the addition of supporting ingredients from the trial mix that has an excessive effect on concrete slump and compressive strength. The input parameters considered for fuzzy modelling are cement, fine aggregate, a coarse aggregate of 10mm and 20mm size and water. Predicted parameters are slump and 7 days and 28 days compressive strength. Each input and output variable is categorized into linguistic variables Low (L), Medium (M), and High (H) as shown in figure 2(a-f). Mamdani fuzzy system is developed for these input and output.

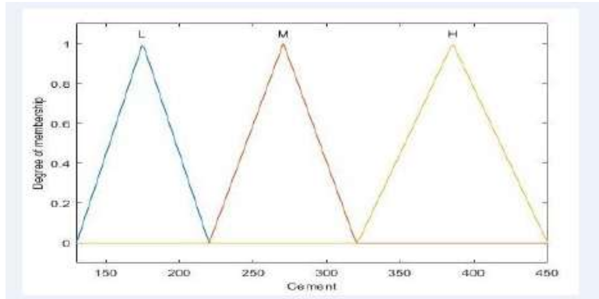

Figure (a).Input variable: cement

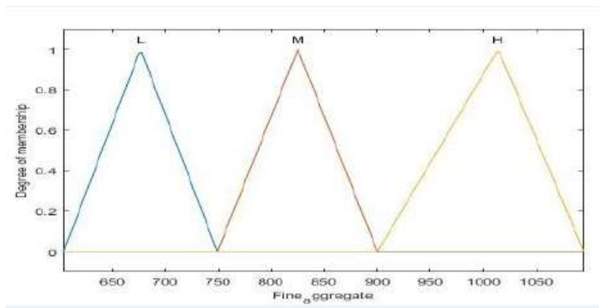

Figure (b).Input variable: fine aggregate

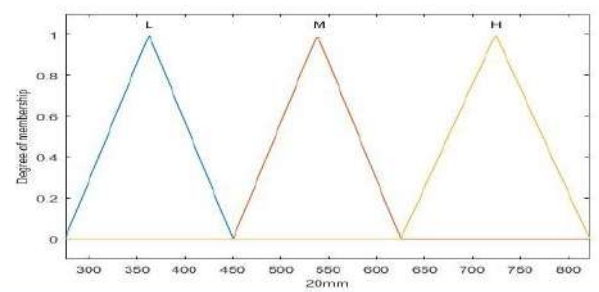

Figure (c).Input variable: 20mm aggregate

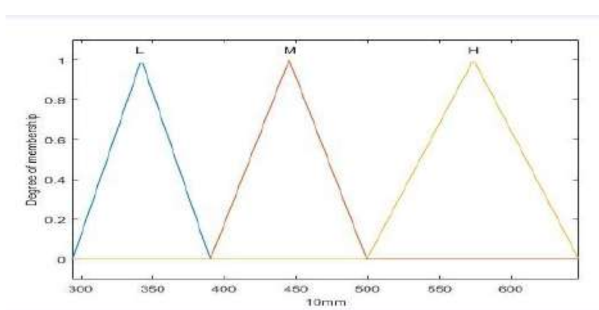

Figure (d).Input variable: 10mm aggregate

Table 1 indicates min and max values available in the database for an M20-M25 grade of concrete. Similarly min and max values for remaining grades are studied and analysed.

In fuzzy approach, there are no mathematical equations and model parameters, and all the uncertainties, nonlinear relationships, and model complications are available as description in fuzzy rule system. There are different forms of membership functions such as triangular, trapezoidal, piecewise linear, Gaussian and singleton. In practical applications, simple linear functions such as triangular functions are preferable [20, 21].

Structures that need significant dynamic variation in a short period of time and a triangular or trapezoidal

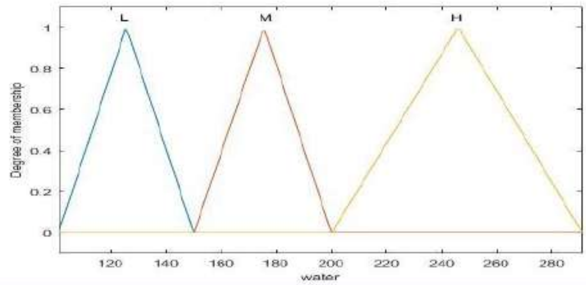

Figure (e).Input variable: water

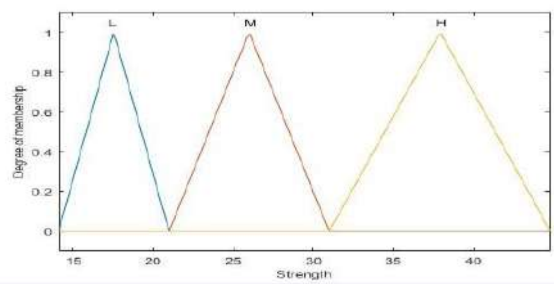

Figure (f).Output variable: 28 days compressive strength
Figure 2(a-f).Membership functions for input & output variable

Table 1.Range of input and output variables (M20-M25)

	Database range (kg/m^3)		
Variables	Parameters	Min	Max
Inputs	Cement I	130	450
	Fine aggregate (FA)	604	1095
	Coarse aggregate		
	10mm (CA10)	294	647
	20mm (CA20)	275	822
	Water	101	291
Outputs	Slump (S)	100	450
	7 CS (7 days compressive strength)	14.1	44.84
	28 CS	20	55.56

function should be utilized. In this work, triangular membership function is employed for slump and compressive strength prediction modelling. Figures 3 and 4 exhibit fuzzy interference system for prediction of slump and 28 days compressive strength of M20-M25 grade respectively. Fuzzy rule base contains all possible fuzzy relations between input and output variables and is expressed in the form of if-then rules. E.g. If (cement is L) and (fine aggregate is L) and (10mm is L) and (20mm is L) and (water is L) then (strength is L)

There are two kinds of inference operators i.e. minimization (min) and product (prod) respectively. Minimization method is employed in this work because it is more accurate [22]. Total 243 fuzzy rules are developed and employed for prediction. Defuzzification is the process of converting a fuzzified output into a single crisp value. The following are the well-known methods of defuzzification: 1) Centre of Sums method (COS), 2) Centre of Gravity (COG) / Centroid of Area (COA), 3) Centre of area / Bisector of Area (BOA), 4) Weighted average and 5) maxima methods [4, 6]. In this study, centroid method is employed for defuzzification.

3. PERFORMANCE METRICS

Performance metrics like coefficient of correlation , Mean Absolute Error (MAE) and Normalized Mean Square Error (NMSE) are considered to validate the accuracy of predicted results. These are given in equations (1)

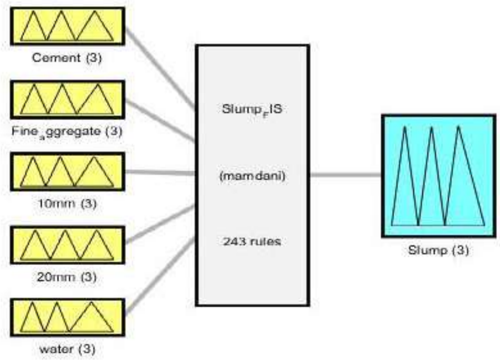

Figure 3.Mamdani FIS models with membership functions for slump (M20-M25)

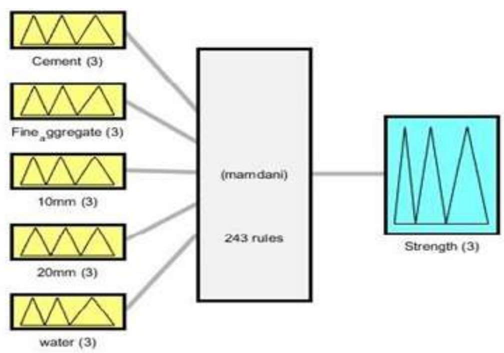

Figure 4.Mamdani FIS models with membership functions for compressive strength (M20-M25)

to (3).
• Correlation coefficient

$$R = \frac{\sum_{i=1}^{n}((X_i - \bar{X})(Y_i - \bar{Y}))}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{1}$$

where, X_i is the observed compressive strength of ith specimen, $\bar{X}$ is the mean of observed compressive strength of i^{th} specimen, Y_I is the predicted compressive strength of i^{th} specimen, $\bar{Y}$ is mean of compressive strength of i^{th} specimen.
• Mean absolute error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Predictedvalue - Observedvalue| \tag{2}$$

• Normalized mean square error

$$NMSE = \frac{1}{n}\sum_{i=1}^{n}\frac{(Predictedvalue - Observedvalue)^2}{ObservedvalueXPredictedvalue} \tag{3}$$

4. RESULTS AND DISCUSSION

In this study, simulation results are obtained with MATLAB R2011a. Table 2 gives comparison between sample values of observed and the predicted slump as well as 7 days and 28 days compressive strength of concrete for different grades. Table 3 shows qualitative performances of fuzzy logic model in terms of R, NMSE and MAE for the slump of various ranges of concrete grades. It can be seen that correlation coefficient ranges from 0.89-0.96 for group of concrete grades from M20-25 to M60-70. The errors are low in all the cases. However table 3 shows that the accuracy of the fuzzy logic model predicted values for grades M50-M55 is the highest. The low error values indicate that the variables observed and predicted for slump have a positive correlation. Minimizing the NMSE and MAE is the key criterion to validate fuzzy logic model and getting it close to zero suggests ideal condition.

Table 2.Comparison of observed and predicted values

Sl.No	Observed values			Predicted values		
1	Slump	7days Compressive Strength	28days Compressive Strength	Slump	7days Compressive Strength	28days Compressive Strength
2	215	20.36	35.20	228	22.22	37.78
3	200	21.30	36.20	215	22.45	37.00
4	240	26.78	38.74	250	27.89	41.72
5	180	30.25	42.80	190	31.51	43.18
6	161	31.70	43.70	170	31.51	43.75
7	170	29.99	43.24	175	31.51	43.95
8	150	27.11	46.14	150	29.99	49.49
9	200	41.36	61.75	230	46.23	62.34
10	246	46.21	55.25	255	47.14	55.99
11	300	44.70	50.19	300	47.60	51.84
12	350	44.30	55.21	370	49.70	59.97
13	250	53.39	55.20	269	55.64	55.70
14	135	45.69	65.26	155	48.49	70.50
15	120	43.02	69.32	135	48.23	71.25

Table 3.Performance metrics for slump testing

	M20-25	M30-35	M40-45	M50-55	M60-70
R	0.90	0.91	0.89	0.92	0.96
MAE	93.0	50.6	98.6	14.9	90.4
NMSE	6.76	0.18	5.51	0.25	6.22

Tables 4 and 5 represent the performance metrics for 7 and 28 days compressive strength. The correlation of coefficient of all models for 7 and 28 days compressive strength ranges from 0.90-0.96, which indicates that the observed and predicted values are in close agreement. The low values of errors produced by fuzzy model in the testing measured in terms of MAE and NMSE amplifies that, the model performed well, especially in the range of M30-M35. The values of MAE and NMSE are found to be in the range of 1.5-7.99 and 0.40-1 respectively. The advantage of MAE or NMSE is that it provides a quadratic loss function and also measures the uncertainty in forecasting. Lower values of NMSE indicate better fit. To verify the developed fuzzy models for the slump, figure 5(a-b) compares the slump values predicted by fuzzy with the real empirical data used in this study.

Table 4.Performance metrics for 7 days compressive strength

	M20-25	M30-35	M40-45	M50-55	M60-70
R	0.91	0.90	0.93	0.90	0.91
MAE	4.14	1.61	3.76	3.47	4.99
NMSE	1.14	0.40	0.61	0.19	0.72

Table 5.Performance metrics for 28 days compressive strength

	M20-25	M30-35	M40-45	M50-55	M60-70
R	0.91	0.96	0.91	0.91	0.90
MAE	4.14	3.17	2.81	4.01	4.13
NMSE	0.30	0.33	0.18	0.08	0.18

Figure 5(a-b) shows a good agreement between the observed and the model predicted values. In M40 - M45 model, the over prediction is also observed. This may be due to limited dataset available in training the model. In the group of M30 to M35 model, predicted values are found close to the observed values and the accuracy is also reflected in low error measures.

Figures 6(a-b) and 7(a-b) show the qualitative analysis in terms of the scatter plots of observed and the predicted values of compressive strength for 7 days and 28 days respectively. Here the results are presented for

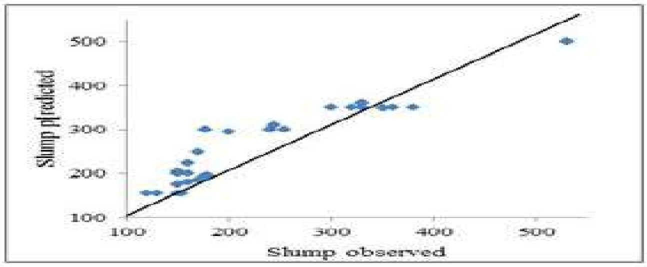

Figure (a).M30-M35

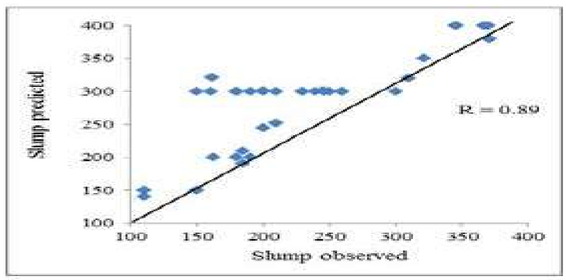

Figure (b).M40-M45

Figure 5(a-b).Scatter plot of observed and predicted slump for M30 - M35 and M40 - M45 concrete grades

groups M30 - M35 and M60 -M70. From the scatter plots for both the type of concrete, the values are mostly falling on the best fit lines.

The errors evaluated in the model also reported low showing a good performance in all the cases. 28 days strength is much important to test the quality and strength of the construction hence accurate measure of the compressive strength of 28 days plays a vital role. The fuzzy logic model has given excellent prediction in these cases.

Figure 8(a-b) represents comparison between observed and predicted slump by fuzzy model for M30-M35

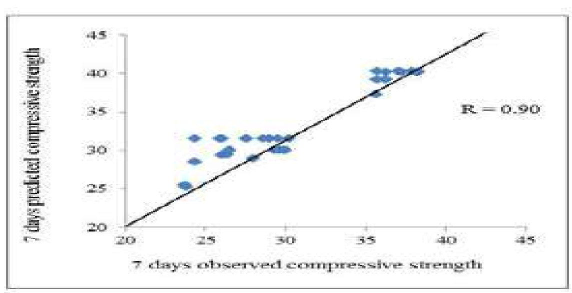

Figure (a).M30-M35

and M40-M45 grade concrete. Figure 9(a-b) represents comparison between 28 days observed and predicted compressive strength by fuzzy model for M20-M25 and M60-M70 grade concrete.

The surface viewer in the form of surface diagrams is used to display the dependency of one output on any two inputs and relationship between them. Figure 10(a-c) gives the surface diagrams for various parameters for the M20-M25 grade of concrete and the similar process is followed for all grades i.e. M30-M35, M40-M45, M50-M55, and M60-M70.

Based on the result of prediction, the effect of cement, fine aggregate, coarse aggregate of 10mm and 20mm and water on 28 days compressive strength are shown in surface plots. In figure 10(a and c), the effect of increasing fine aggregate is found to produce higher 28 days compressive strength with the increase in cement and 20mm

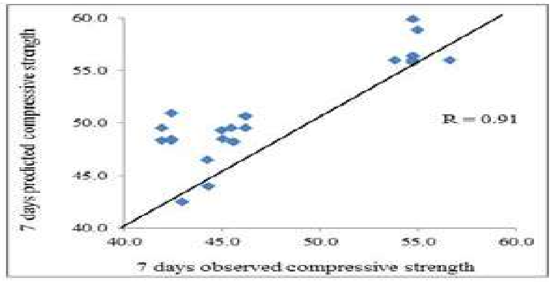

Figure (b).M60-M70
Figure 6(a-b).Scatter plot of 7 days observed and predicted compressive strength for M30 - M35 and M60 - M70 concrete grades

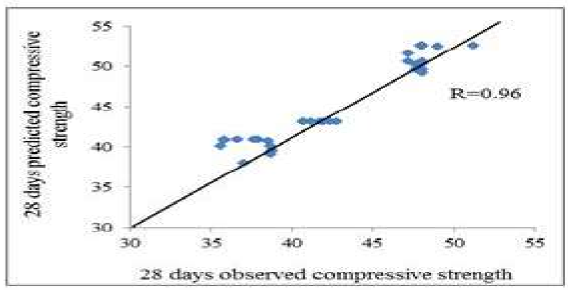

Figure (a).M30-M35

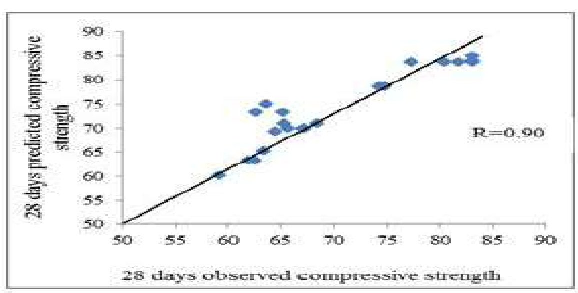

Figure (b).M60-M70
Figure 7(a-b).Scatter plot of 28 days observed and predicted compressive strength for M30-M35 and M60-M70 concrete grades

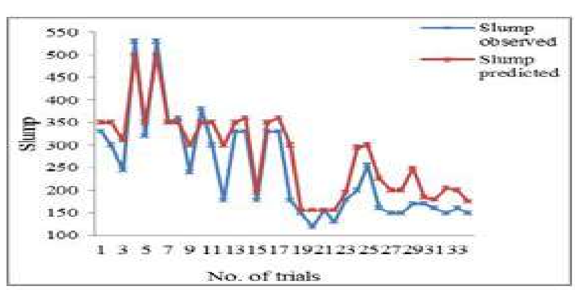

Figure (a).M30-M35

aggregate.

Figure 10(b) shows that the effect of increasing cement with the increasing 10mm aggregate leads to increase in 28 days compressive strength. Figure 11 indicates that the decrease in 10mm aggregate with increase in cement

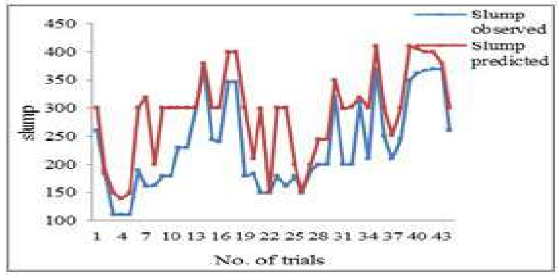

Figure (b).M40-M45
Figure 8(a-b).Comparison between observed and predicted slump

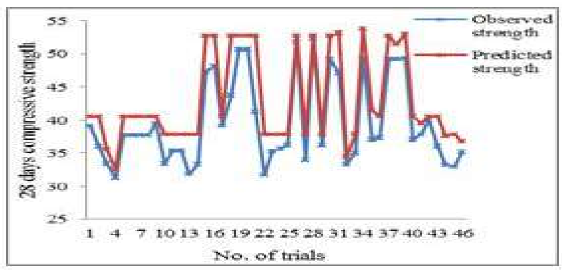

Figure (a).M20-M25

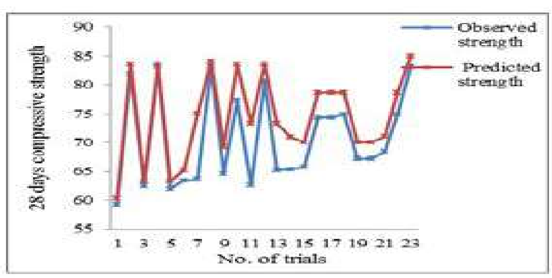

Figure (b).M60-M70
Figure 9(a-b).Comparison between 28 days observed and predicted compressive strength

helps to increase compressive strength of M60-M70 grade of concrete.

Figures 12 and 13 represent the effect of water on slump for M20-M25 and M60-M70 grade. Slump increases as

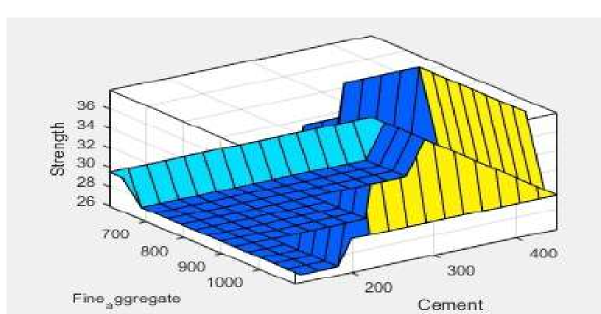

Figure (a).Between cement, fine aggregate and 28 day compressive strength

the cement quantity increases with decrease in water quantity, due to addition of super-plasticizer. From literature review, it is observed that the prediction is carried out for specific grade of concrete. In this study, an attempt is

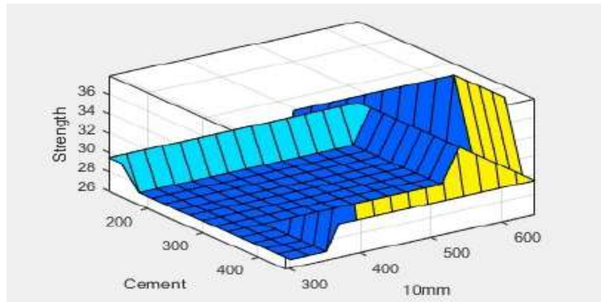

Figure (b).Between 10mm aggregate, cement and 28 days compressive strength

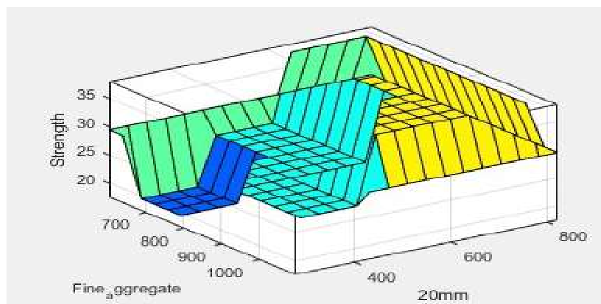

Figure (c).Between 20mm aggregate, fine aggregate and 28 days compressive strength
Figure 10(a-c).Surface diagrams for M20-M25 concrete grade

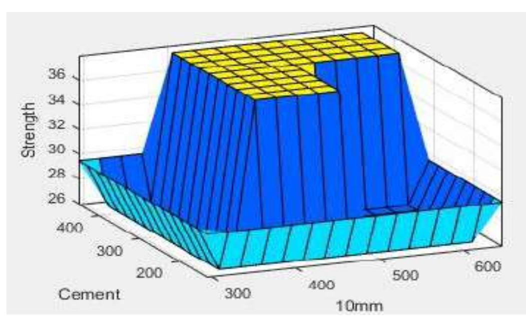

Figure 11.Surface diagram between 10mm aggregate, cement and 28 days compressive strength for M60-M70 concrete grade

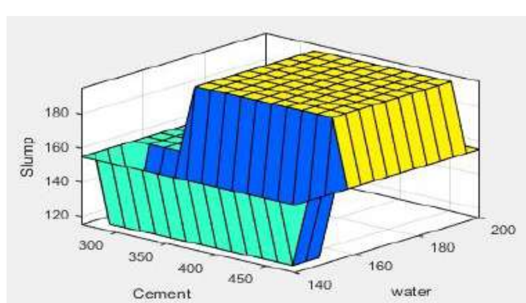

Figure 12.Surface diagram between water, cement and slump for M20-M25 grade

made to predict slump and compressive strength M20 to M70 grades of concrete forming groups of two grades. The specific grade is used for variety of constructions. The fuzzy logic model predicted values are well matching and falling near to the observed values.

The model predicted error for 28 days concrete strength is low compared to the results reported in [11] and [15]. The correlation coefficient obtained by fuzzy model for M20 to M70 grade of concrete for 28 days

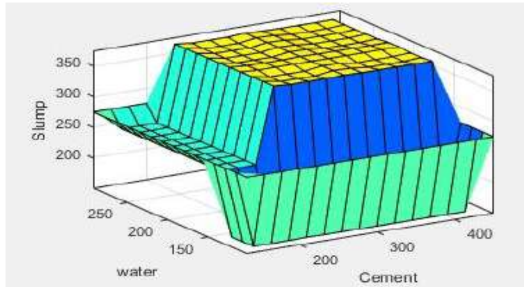

Figure 13.Surface diagram between cement, water and slump for M60-M70 grade

compressive strength is 0.90-0.96 which is better than the results obtained by the other researchers [13, 19].

5. CONCLUSION

In this paper, fuzzy logic models are developed to predict the slump as well as 7 and 28 days compressive strength. The fuzzy logic model predicted values in all the cases are close to the observed one especially in the medium grade mix. Fuzzy logic gives the scope to address such issues and provides more flexible option. The prediction of the slump, as well as 7 and 28 days compressive strength data by the fuzzy model, indicates that the employed min activator and centroid defuzzification methods with triangular membership function are appropriate.

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