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Fuzzy Logic Approach in Determination of Strength in Concrete

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Abstract : The aim of this thesis is to address capabilities in prediction of compressive strength of concrete to affect quality control in construction. To comprehend this, a compressive strength predicting model using the principles of fuzzy logic set theory had been employed. The model put into use 'fuzzy logic' as a tool to predict the compressive strength of concrete at a given day. Data collected from previous researches and laboratory work had been put into use in the model construction and testing. The input variables of water/binder ratio, cement content, water content, and fly ash percentage and the output variable of 28-day cement compressive strength were fuzzified by the use of triangular membership functions and Gaussian membership functions which were deployed for the fuzzy subsets. The prediction of the 28-day cement strength data by the developed fuzzy model proved to be quite satisfactory. The training and testing of 4 different models was done. The Minimum average percentage error levels in the fuzzy model were seen to be as low as (3%) in case of Model 3. Comparative study of the different models (all 3 Triangular and 1 Gaussian) had been done. The results indicated that the application of fuzzy logic algorithm was quite satisfactory when triangular membership function with decreased subset range was used. The outputs of Triangular and Gaussian model were almost similar.

Keywords: Compressive strength, Fly ash concrete, Fuzzy Logic, Membership function

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I. INTRODUCTION

Concrete is one of the most basic and widely utilised construction materials on the earth. There are various reasons for dominance of concrete, but among the most important are: widespread availability of its constituent materials; the economy as it is affordable; its nature to be moulded in any desired shape, its feasibility and adaptability; its high compressive strength, rigidity and durability; and how a flowing material transform into a solid building block. The area in concrete advancement continues to attract numerous researchers today. As per new environmental ordinance regarding disposal of industrial waste such as fly ash or slag has developed interest in using the waste product as partial replacement of cement in concrete. Fly ash has been used to partially replace cement in concrete, and replacement percentage ranges from 20 to 50% of total cementitious materials. Among most of its characteristics, compressive strength of concrete is one of the most important mechanical properties to determine the quality of concrete and used as necessary criteria in specifications and standards. Also, other important properties of concrete such as, split tensile strength, direct tensile strength, flexural strength, and modulus of elasticity, are related to compressive strength. Hence, proper prediction of concrete compressive strength is important to schedule and handle concrete works such as removal of formwork and pre- or post-tensioning tasks. The conventional method is to take chosen samples from the mix and perform testing in laboratory. The 28th day testing is carried out to know the compressive strength of concrete. Concrete obtain maximum of its strength after 28 days so the samples will have to take that long to be tested. The 28th day testing is also used as standard to calculate the compressive strength at any desired time. However, these design codes fails to understand the actual framework when constituents of concrete are more or less than the conventional cement, water and aggregate. Thus, the compressive strength of concrete is complex, becoming more and more complicated as the constituents varies.

In projects where 28 days test results are not to be waited, a sound and dependable model fit for deciding the compressive strength of a concrete sample at any age is vital. In this way we can avoid time spent on waiting test results, which further helps in speedy construction. In past two decades, Artificial Intelligence based modelling methods have been widely used in civil engineering including determination of concrete mix design, modelling of constituent's behaviour and prediction of strength of concrete. Fuzzy logic enables the use of planned mathematical model for investigating and identifying different type of unknown problems. It provides a simple way of dealing with difficult problems. It has played a vital role in solving problems related to civil engineering. Many researchers used FIS in predicting the compressive strength of concrete. Besides this, it is used as a controller in drip irrigation and used in Design of truss structures, and evaluating performance of reinforced concrete structures.

II. LITERATURE REVIEW

Sedat Akkurta, Gokmen Tayfurb, Sever Can[1] created a fuzzy logic prediction model for the 28-day compressive strength of cement mortar under standard curing conditions. Data collected from a cement plant were used in the model construction and testing. The input variables of alkali, Blaine, SO3, and C3S and the output variable of 28-day cement strength were fuzzified by the use of artificial neural networks (ANNs), and triangular membership functions were employed for the fuzzy subsets. Successful predictions of the observed cement strength by the model indicate that fuzzy logic could be a useful modelling tool for engineers and research scientists in the area of cement and concrete. Gökmen Tayfur1; Tahir Kemal Erdem2; and Önder Kırca[2] created a High-strength concretes (HSC) were prepared with five different binder contents, each of which had several silica fume (SF) ratios (0–15%). The compressive strength was determined at 3, 7, and 28 days, resulting in a total of 60 sets of data. In a fuzzy logic (FL) algorithm, three input variables (SF content, binder content, and age) and the output variable (compressive strength) were fuzzified using triangular membership functions. A total of 24 fuzzy rules were inferred from 60% of the data. Moreover, the FL model was tested against an artificial neural networks (ANNs) model. The results show that FL can successfully be applied to predict the compressive strength of HSC. Three input variables were sufficient to obtain accurate results. Bahador Abolpour , Benafsheh Abolpour , Roozbeh Abolpour , Hossein Bakhshi[3]: Concrete mix design was a process of proportioning the ingredients in right proportions. The aim of this study was to design a fuzzy logic model for determination of the compressive strength of a concrete. It was shown how the model can be used to compute the compressive strength versus the concrete mixture. Furthermore, it was shown that, for higher strength concrete, lower water–cement ratios were used, along with a plasticizer to increase flowability. Syed Afzal Basha, P.Pavithra, B.Sudharshan Reddy[4]:In this research an attempt was made for assessment of compressive strength of Fly ash based cement concrete. Concrete mixes M25, M30, was designed as per the Indian standard code (WAS-10262-82) by adding, 0%, 10%, 20%, 30% and 40% of fly ash. Concrete cubes of size 150mm X 150mm X 150 mm were casted and tested for compressive strength at 7 days, 14 days, 21 days and 28 days curing for all mixes and the results was compared with that of conventional concrete. Concrete mixes M25, M30, were designed as per the Indian standard code (WAS-10262-82) by adding, 0%, 10%, 20%, 30% and 40% of fly ash. The compressive strength of fly ash cement concrete was assessed for concrete mixes M25 and M30 grade concrete with 0%, 10%, 20%, 30% and 40% of fly ash. It was found that there was a decrease in compressive strength for M25 and M30 grade concrete with increase in the percentage of fly ash. Jino John, M. Ashok The objective of their research was to study the mechanical strength behaviour of High Volume Fly ash concrete pavement slab. The mechanical properties were studied with various replacements with cement like 50%, 60%, and 70% of Fly ash. % saves the higher compressive strength. When compared with control mix the strength of HVFA concrete reduced % for 50%, 60% and 70% at 7 day and 28 day respectively. In this investigation, the mechanical properties of HVFA concrete, and control concrete were studied and compared.

Paratibha Aggarwal, Yogesh Aggarwal [8]: 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 was contents of cement, sand, coarse aggregate, fly ash, super plasticizer percentage and water-to-binder ratio and an output parameter i.e. 28- day compressive strength for ANN-I and FL-I were used for modelling. The fuzzy logic model showed better performance than neural network model. Nasir B. Siraj, Aminah Robinson Fayek, and Abraham A. Tsehayae[9]: The main contributions of this paper are: (1) providing accurate concrete compressive strength prediction models that represent the complex, nonlinear relationship between the constituent materials and concrete compressive strength; (2) presenting a data-driven methodology for the development of FIS concrete compressive strength models; and (3) subjecting artificial intelligence-based concrete compressive strength models to structure and parameter optimization to improve prediction accuracy. Papadakis et al.[12] studied physicochemical processes and mathematical modelling of concrete chlorination, and also experimental investigation and mathematical modelling of the concrete carbonation problem. Nataraja et al.[11] designed a fuzzy-neuro model for normal concrete mix design. The results in terms of quantities of cement, fine aggregate, coarse aggregate, and water obtained through the present method for various grades of standard concrete mixes are in good agreement with those obtained by the prevalent conventional methods. Methods involving the use of the derivatograph in the determination of the expected decrease in strength of high alumina cement have been described. Abdullahi et al. have reviewed expert systems for concrete mix design. For their developed expert systems, mix design codes were derived from data obtained from experience with concrete materials. Tesfamariam and Najjaran[13] designed adaptive network– fuzzy inferencing to estimate concrete strength using mix design. In this paper, the use of the adaptive network–fuzzy inferencing system (ANFIS) is proposed to train 708 B. Bilgehan [14] worked on a comparative study for the concrete compressive strength (CCS) estimation using neural network and neuro-fuzzy modeling approaches. The final results show that the ANFIS modeling with Gaussian membership function may constitute an efficient tool for prediction of the concrete compressive strength. Nehdi and Bassuoni [15] found a fuzzy logic approach for estimating the durability of concrete. It was shown that the proposed fuzzy Inference model is rational, clear, reliable, versatile, and flexible, since it can be easily updated with new data or modified to accommodate future findings.

Tanyildizi and Qoskun [16] used the fuzzy logic model for prediction of compressive strength of lightweight concrete made with scoria aggregate and fly ash. Uyunoglu and Unal [17] studied a new approach to determination of compressive strength of fly ash concrete using fuzzy logic. Yang et al [18]. have studied concrete strength evaluation based on fuzzy neural networks (FNN). They built a FNN to evaluate the concrete strength. It takes full advantage of the merits of the common concrete testing methods, i.e. rebounding and drilling core, and the abilities of FNN, including self-learning, generation and fuzzy logic inference. Furthermore, some recent articles have described effects of various parameters on the properties and strength of the concrete M.C.Nataraja, M.A.Jayaram and C.N.Ravikumar [19] designed A Fuzzy-Neuro Model for Normal Concrete Mix Design. This paper presents the development of a novel technique for approximate proportioning of standard concrete mixes. Distinct fuzzy inference modules in five layers have been framed to capture the vagueness and approximations in various steps of design as suggested in IS: 10262-2003 and IS456-2000. A trained three layer back propagation neural network is integrated in the model to remember experimental data pertaining to w/c ratio v/s 28 days compressive strength relationship of three popular brands of cement. The results in terms of quantities of cement, fine aggregate, course aggregate and water obtained through the present method for various grades of standard concrete mixes are in good agreement with those obtained by the prevalent conventional method.

III. OBJECTIVE OF STUDY

Various objectives of this thesis have been:

1. To study concrete mix design procedure as per IS codes of practice. (Old as well as new)
2. To study the effect of various parameters on compressive strength of concrete
3. Literature review on application of Fuzzy interface system.
4. To design worksheet in excel for fuzzy logic model of compressive strength.
5. To design concrete mixes for M40 and M45 grade in the laboratory.
6. To examine the potential of Fuzzy Interface System for predicting the 28-day compressive strength of mixtures by comparing experimental results with results of fuzzy logic model.
7. To analyse and discuss the results and write conclusion.

IV. TECHNICAL PROGRAM

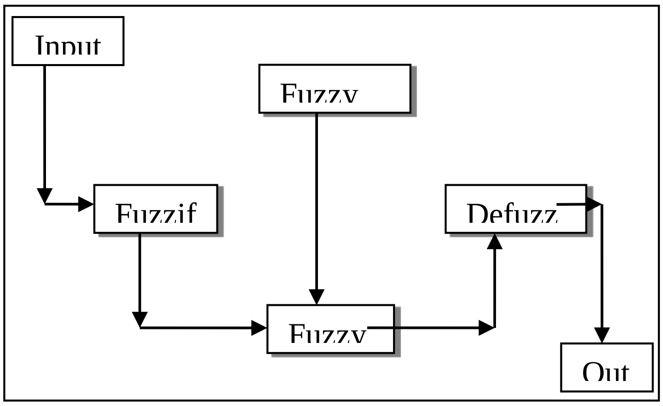
The technical program was divided into two parts:

1. Model Creation 2. Experimental Work

1. Model Creation

A common fuzzy Interface system has 4 steps—

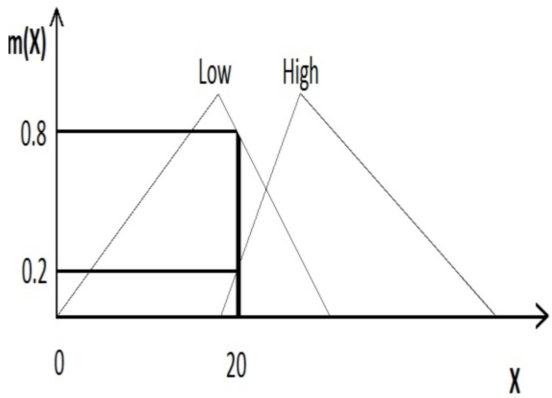
1. Fuzzification 2. Fuzzy rule bases
3. Fuzzy inference engine 4. Defuzzification



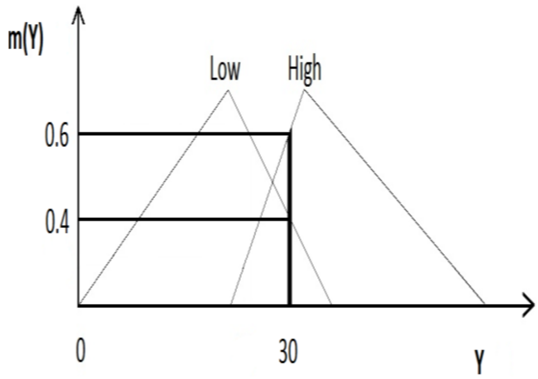
1. Fuzzification: In this part of the system various fuzzy set for input-output variables are formed by making use of membership functions. Fuzzy membership functions (MF's) may be used in any form, but in actual practice there are mainly 3 types of membership functions used in

fuzzy: Triangular, Bell Shaped, Trapezoidal. It converts each segment of input to degrees of membership by a query in at least one or several membership functions. The basic idea in fuzzy logic is the consideration of partial belonging of any object to various subsets of a universal set rather than belonging to single set entirely. Partial belonging to any set can be represented numerically by a membership function that takes values between 0 and 1 including 0 and 1. In our case there are four inputs that is; water/binder ratio, cement content, water content, fly ash as replacement of cement. So, we will have membership functions for various inputs. In this FIS triangular shaped membership function is employed.

2. Fuzzy Rule Base: The Fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs. These rules are expressed in the IF-THEN format. There are basically two types of rule system, Sugenov and Mamdani. Depending upon the problem under consideration, a user can choose the appropriate rule system. The following rule is an example for Sugeno-type fuzzy rule: IF Binder (B) is high, THEN strength (S) $S = aB^b$. The first part of a fuzzy rule (from IF to THEN part) is called as the antecedent part of the rule and the rest is called the consequent part. In the Sugeno-type rule just described, the antecedent part of the rule contains a verbal statement but the consequent part involves a mathematical expression. In the Mamdani Rule system, both antecedent and the consequent parts of a rule contain verbal statements. The following example for a Mamdani rule: IF binder content (B) is high THEN strength (S) is high. The Sugeno rule system is more appropriate for neuro-fuzzy systems. Mamdani rules can be intuitively produced. They can also be constructed from available data. In order to explain the rule construction methodology let us take an example.



(a)



(b)

Fig 1(a) Membership function for input variable X (b) Membership function for input variable Y

X and Y are two input variables Fig.1 (a) and Fig.1 (b) respectively and one output variable of Z Fig.1(c). Assume that the values of X= 20, Y = 30, Z = 40. According to Fig. 1 (a) X=20 is a segment of high subset with membership 0.2 and low subset with membership 0.8; Fig.1 (b) Y = 30 is a segment of high subset with membership 0.6 and low subset with 0.4 membership; and Fig.1 (c) Z = 40 is a segment of high subset with 0.9 membership and low with 0.4 membership. As per derivation of rule described, following rule can be formed using above information A common fuzzy Interface system has 4 parts

IF X is Low AND Y is high THEN Z is high I

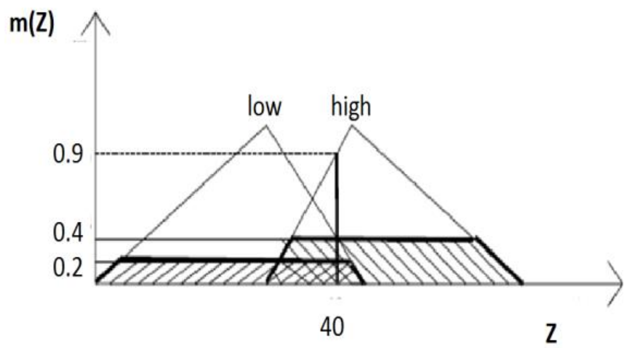


Fig.1 (c) Membership function for output variable Z

As it is clearly figure out from this rule construction, the subsets corresponding to high-3 degree membership as a result of X, Y and Z values are considered.

3. Fuzzy Interference Engine: The fuzzy interference engine considers all fuzzy rules into account in fuzzy rules base and grasp how to convert a set of given input data to corresponding output data. In order to do that, it uses product or minimum activation, operators. In pro activation membership curves are scaled, thus sustaining the primary shape, but in min activation membership curves are clipped. In order to demonstrate the inferencing methodology, let us consider a case given in Fig and for

the system, following assumptions are made regarding fuzzy rules: is clearly shown that there are different sets
IF Y is low and X is high THEN Z is low.
IF Y is high and X is low THEN Z is high.
Now, see how the inference engine would produce fuzzy outputs for a given input vector of X = 20 and Y = 30. As we can see in Fig.1 (a) X = 20 is a part on high and low subsets with 0.2 and 0.8 membership degree respectively. Likewise, In Fig.1 (b) Y = 30 is a part of high and low subsets with 0.6 and 0.4 membership degree respectively. When this input is fed into fuzzy models, the inference engine would activate the rules previously mentioned. From the activated first and second rule, the engine would find, by min operation, fuzzy output subsets of high and low respectively, with different strengths. The acquired subsets are schematically presented as shaded areas in Fig.3.8 (c), which shows that

- The 1st ruled results in high subset with 0.4 firing strength by min activation i.e minimum of (0.8 and 0.4) = 0.4 Fig.1 (c) shaded trapezoid in the right side. If product activation is applied than the value will be 0.32 that is product (0.8 and 0.4) = 0.32.

- The 2nd rule results in low subset with 0.2 firing strength by minimum activation i.e minimum of (0.2, 0.6) = 0.2 see Fig.1(c) the shaded trapezoid in left side. If product activation is applied than the value will be 0.12 i.e product (0.2, 0.6) = 0.12.

The next process in then inferencing engine is the formation where all of the fuzzy output subsets acquired as a result of the activation operators from the triggered rules, are merged to obtain a unique fuzzy subset for the output variable. For this, there are generally two methods: Summation (sum) and Maximization (max). In maximization composition, the integrated output fuzzy subset is formed by taking point wise maximum comprehensive of fuzzy output subsets. In Summation composition, the integrated output fuzzy subset is formed by taking the point-wise sum over all of the fuzzy output subsets.
4. Defuzzification: In this output will come as a number. Defuzzification transforms the fuzzy output from fuzzy inference engine to a number. There are numerous defuzzification methods:
Center of gravity (COG), Bisector of area (BOA), Mean of maxima (MOM), Leftmost maximum (LM), and Rightmostmaximum (RM).

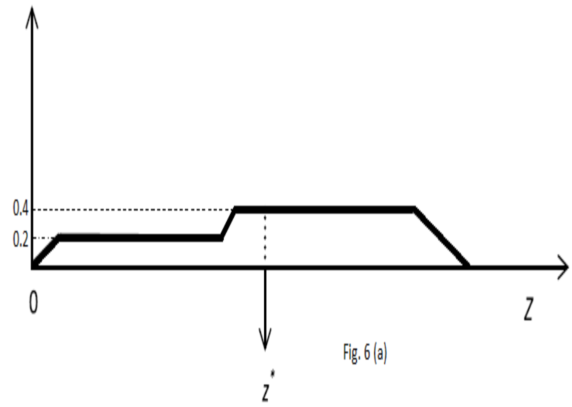


Fig.2 (a) Defuzzication method 1

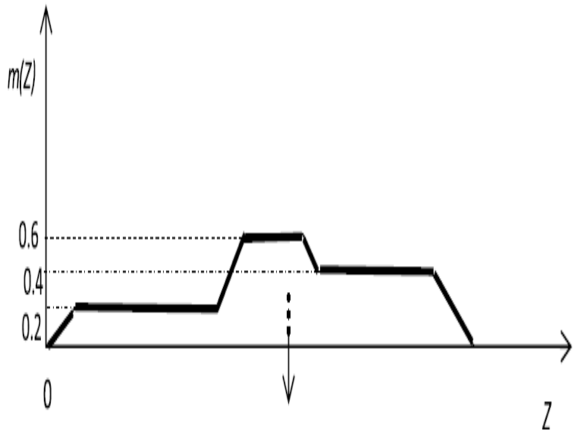


Fig.2 (b) Defuzzification method 2

The MOM, LM, and RM methods ignore the shape of the fuzzy set and that's why, they are used in particular problems. The BOA method picks the abscissa of the vertical line that divides the area of the combined fuzzy output subset in two equal halves. In Fig. 2 (a), z^* is assumed to halve the area and thus be the crisp value. In the centroid, or COG method, the crisp output value is the abscissa under the center of gravity of the combined fuzzy output subset.
In Fig. 2 (b), z^* is assumed to be the centroid of the area and to be the crisp value. The centroid method is the most commonly used defuzzification method and for a discrete case it can be expressed as

$$z^* = \frac{\sum_i \mu(z_i) z_i}{\sum_i \mu(z_i)}$$

Where z* is defuzzified output value; z_i is output value in the i^{th} subset; and $\mu(z_i)$ is membership value of the output value in the i^{th} subset

2. Experimental Work
For compressive strength cubes of 15cm X 15cm X 15cm are used. The concrete is poured in the mould and tempered properly so as not to have any voids. Various

samples with different percentage of fly ash i.e 0,20,30 are made. After 24 hours these moulds are removed and test specimens are put in water for curing. The top surface of these specimens should be made even and smooth. These specimens are tested by compression testing machine after 7 days curing or 28 days curing. Load should be applied gradually at the rate of 140 kg/cm2 per minute till the Specimens fails. Load at the failure divided by area of specimen gives the compressive strength of concrete

V. RESULTS AND DISCUSSION

In this study the compressive strength of concrete is predicted using fuzzy logic interface system and effect of flyash on strength of concrete is studied. Total 6 design mix samples are prepared and tested in laboratory. Total of 149 research data is used to construct fuzzy interference model. Experimental results and estimated values are compared and evaluated. Four Models are trained and tested.

MODEL 1: Fuzzy logic Model with Triangular membership Function.

MODEL 2: Fuzzy logic Model with Triangular membership Function with increased subset range.

MODEL 3: Fuzzy logic Model with Triangular membership Function with decreased subset range.

MODEL 4: Fuzzy logic Model with Gaussian membership Function.

Experimental 28th day compressive strength of concrete cubes with different mix proportions are

Table 1 Experimental Compressive strength of different mixes

Mix	Experimental Strength (MPa)
Mix 1	43.7
Mix 2	37.7
Mix 3	34
Mix 4	46.5
Mix 5	41.2
Mix 6	37.9

Table 2: Different Mix proportions with different fly ash percentage

S.No	w/b	Cement (Kg/m^3)	Fly ash %	Water (Kg/m^3)	Coarse Aggregate (Kg/mm^3)	Fine Aggregate (Kg/mm^3)	Admixture (Kg/m^3)
Mix 1	0.45	350	0	158	1168	660	2.4
Mix 2	0.45	280	20	158	1168	660	2.4
Mix 3	0.45	245	30	158	1168	660	2.4
Mix 4	0.4	400	0	160	1180	668	2.4
Mix 5	0.4	320	20	160	1180	668	2.4
Mix 6	0.4	280	30	160	1180	668	2.4

Fuzzy logic Model outputs

Table 3 Comparison of experimental and predicted strength

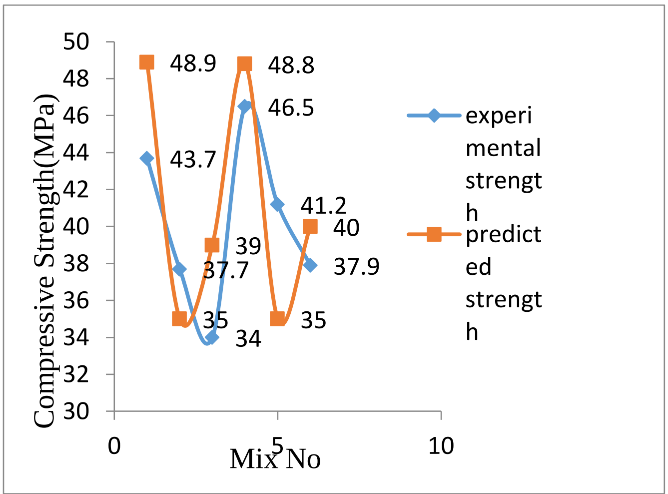
Mix No.	Experimental Strength (MPa)	Predicted Strength(MPa) Model 1	Predicted strength(MPa) Model 2	Predicted strength (MPa) Model 3	Predicted Strength (MPa) Model 4
Mix 1	43.7	48.9	53.5	42.5	45.5
Mix 2	37.7	35	36.6	37.5	41.1
Mix 3	34	39	43.8	35	38.8
Mix 4	46.5	48.8	53.4	47.5	45
Mix 5	41.2	35	56.5	40	44.2
Mix 6	37.9	40		40.5	41

Table 4 Percentage variation of experimental and predicted strength

Mix No	% variation MODEL 1	% variation MODEL 2	% variation MODEL 3	% variation MODEL 4
Mix 1	11.89	-22.43	2.75	-4.11
Mix 2	-7.16	2.92	0.53	-9.02
Mix 3	14.70	-28.82	-2.94	-14.12
Mix 4	4.94	-14.84	-2.15	3.22
Mix 5	-15.04	-37.14	2.91	-7.28
Mix 6	5.54	-21.90	-6.86	-8.18

Graphical Variations of various MODELS

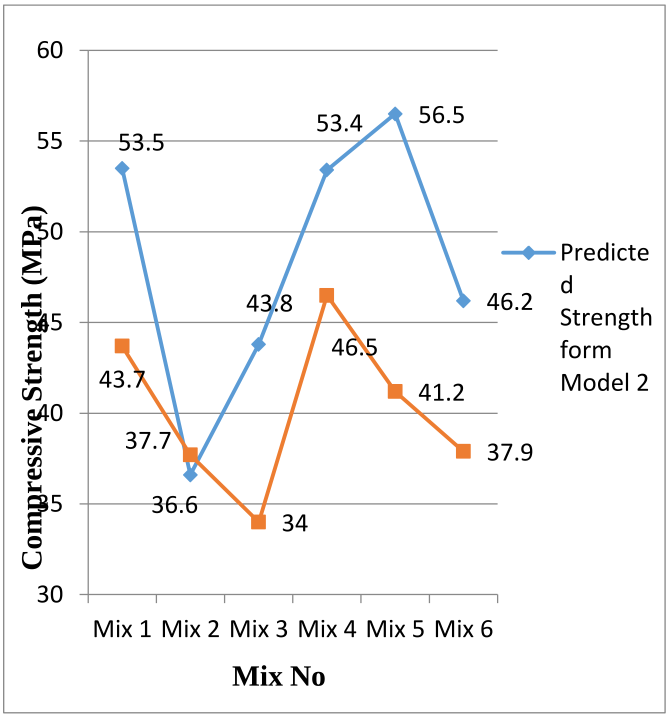
1. MODEL 1 v/s Experimental Strength



Comparison of output of Model 2 and Experimental Strength

In above graph experimental compressive strength is compared with fuzzy logic Model 1 predicted strength. Maximum variation in experimental compressive strength and fuzzy logic predicted strength is around 12% and minimum around 5%. Average variation in strength is about 10%. As concrete is a homogenous mixture and its compressive strength depends on many factors such as temperature during mixing, type and duration of curing, type of water used etc. So in this case 10% variation is acceptable

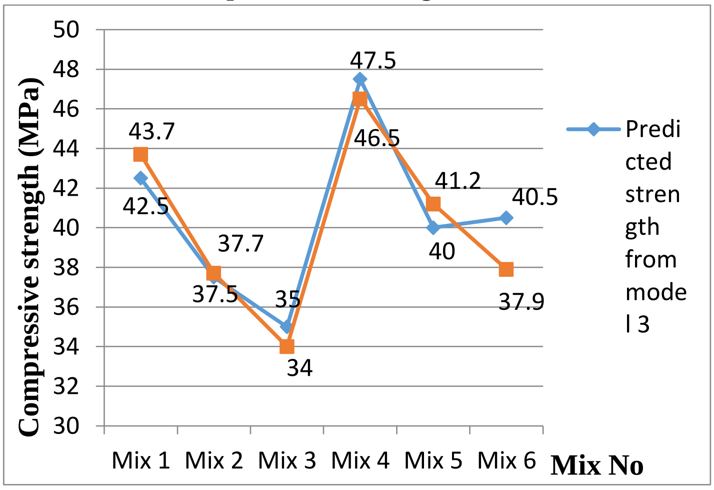
2. MODEL 2 v/s Experimental Strength



Comparison of output of Model 2 and Experimental Strength

From above table we can see that variation in output of Model 2 is more than Model 1 when we compare it with experimental value. In this case average variation is about 21% which is much higher value than previous value (10%) So, we can conclude that with increase in range of subset accuracy of model decreases.

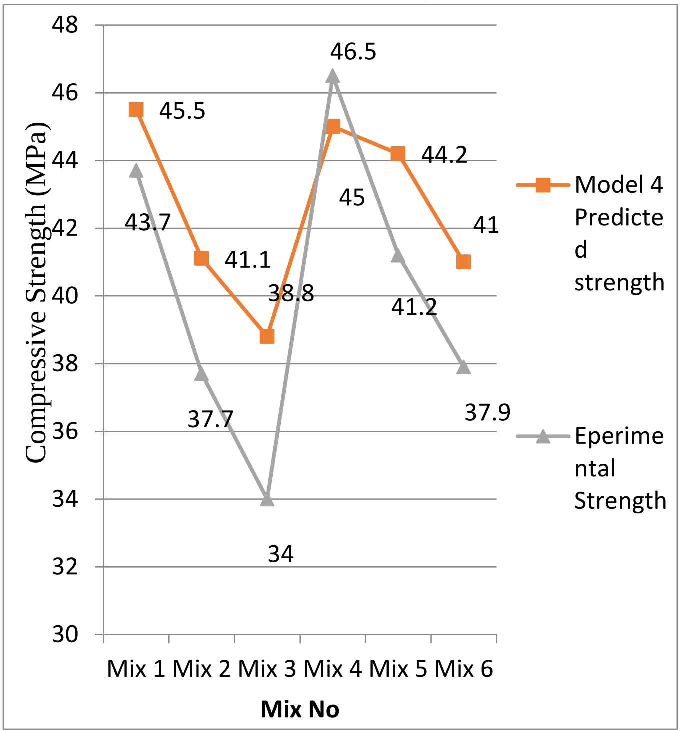
3. MODEL 4 v/s Experimental Strength



Comparison of output of Model 3 and experimental strength

From Table we can see that variation in output of Model 3 is less than Model 1 when we compare it with experimental value. In this case average variation is about 3% which is much less than model 1 (10%) and model 2 (21%) So, we can conclude that with decrease in range of subset accuracy of model increases.

4. MODEL 4 v/s Experimental Strength



Comparison of output of Model 4 and Experimental strength

In this case variation is around 7.5% which is more or less similar to variation in case of Model 1 (10%). Both produce almost similar results (2.5% variation). So, it can be concluded that we can choose any of MF either Gaussian or triangular. It is recommended to use triangular MF model as it is easy to train.

VI. CONCLUSION

1. The study of fuzzy logic as an alternative approach can provide an efficient and rapid means of obtaining optimal solutions to predict the compressive strength concrete containing fly ash.

2. The fuzzy system model with triangular membership functions is obtained from clustering of the training data set. Input parameters used in model creation process included (water/binder ratio, cement content, water content, and fly ash).

3. It was observed that the fuzzy logic could effectively predict compressive strength in spite of complex data and could be used as a tool to support decision making, by improving the efficiency of the process.

4. It was observed that with increase in percentage of flyash as replacement of cement, compressive strength of concrete decreases.

5. Results obtained were nearly similar to experimental results. It was demonstrated that the developed FL model was successfully trained and tested. The model could may or may not be further perfected as the data source used for the model was a combination of different sets with possibly different testing conditions.

6. It is found that if the subset range is decreased then it shows much better results than the subsets with increased range. As in our case variation is about 3% when subset range is decreased and is about 21% when it is increased. So it is recommended to use small subset range MF as they show better results.

7. It was observed that Gaussian Membership Function Fuzzy model shows almost similar results as of triangular fuzzy model. In Gaussian model variation is around 7.5% and in triangular model is 10% which is almost similar. As Triangular model is easy to train so it is recommended to use it instead of Gaussian which is complex and difficult to train.

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