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Using Fuzzy Logic Approach for Prediction of Compressive Strength of Ready Mix Concrete

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ABSTRACT: *This research paper work focuses on development of models in prediction of compressive strength of concrete after 7and 28 days.The data set for fuzzy logic are analyzed by using two different membership functions viz. Triangular and Gaussian. Further these membership functions are fuzzified with fuzzy rule inference with min, max rule principles, these are defuzzified with centroid method.Various models have been developed for different input scenarios, non-dimensional ratios were used for modeling and the ratios such that their changes resulted in corresponding changes in the output. The Mamdani fuzzy rules relating the input variables to the output variable were created by the FL model and were laid out in the If–Then format.A comparative evaluation of the outcomes is subsequently conducted, leveraging statistical benchmarks like the Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Relative Error (MRE),Correlation Coefficient(CC), and with the aim of identifying the most proficient model. The results underscore the remarkable effectiveness of the FL model.*

KEYWORDS*: Artificial Intelligence (AI), Fuzzy Logic (FL),Ready Mix Concrete(RMC).Membership Function*

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I. INTRODUCTION

The term **fuzzy** refers to things that are not clear ,noisy or are vague . Fuzzy logic /systems can be used when systems with uncertainties due to imprecision,vagueness,ambiguity,randomness,partial truth and approximation.Fuzzy logic is a language ,precisely is a mathematical language like any language also used to express something which is meaningful to others,means that, it has grammar, it has it own syntax, semantics like a language for communication. Fuzzy logic is an essential component for the soft computing where as fuzzy systems is one of the key agents of computational intelligence., computational intelligence is an equivalent name of artificial intelligence. Fuzzy systems theory which is based on fuzzy logic, professor Lotfi Aliasker Zade.(LAZ) which is who is also known as the father of fuzzy systems theory. proposed the idea of fuzzy logic in 1965[1]. Fuzzy Sets introduced by prof.L.A.Zadeh university of California USA in 1965.Potential tool for handling imprecision and uncertainties. Sets with imprecise /vague boundaries.There is no well-defined boundary for this particular set and that is why this is known as the fuzzy set, that is set with imprecise or the vague boundaries.There are many uncertainties,which cannot be tackled using only the probability theory,which which works based on the classical set or the crisp set.Tackled with the help of the fuzzy sets Fuzzy set theory is a generalization of classical set theory

which tries to capture the way humans represent and reason with real-world knowledge in the face of uncertainty [2].FL has the ability to learn from its environment and to improve its performance through learning [3]To represent/express the fuzzy set with membership and this membership is nothing, but the degree of belongingness and that is defined by μ[3] A membership function is the relationship between the values of an element and its degree of membership in a set.Membership functions give the weight of each object in a set. This degree of gravity can be from 0 to 1.A graph that defines how each point in the input space is mapped to membership value between 0 and 1.Input space is often referred to as the universe of discourse or universal set(U),which contains all the possible elements of concern in each particular application.Fuzzy membership function is responsible for giving the membership values to the corresponding value of the generic variable.MF is denoted by $\mu(x)$ and provides the membership values.This membership function assigns the corresponding

membership values which are more than 0 up to 1.Any value in between is the membership value up to 1. The part of the subset where the items with membership degrees equal to 1 are is called the core of that subset.Here μ(x)=1. In contrast the range containing all the elements of a set is called the support of that set. Each underlying item has more or less degrees of membership (between 0 and 1.The mathematical expression for this is 0<μ(x)<1.The parts formed by the elements whose
membership degrees are not equal to 1 or 0 are called the boundary regions of the membership function. There are some commonly employed membership functions (fuzzifiers) listed are .Triangular MF,Trapezoidal MF.Gaussian MF,Genralized bell shaped MF,Sigmoidal MF,Left Right MF(L-R MF),∏ pie MF,Open Left MF,Open Right MF,.S-shaped MF,)NKV. Triangular and gaussian membership functions are most commonly used but selection depends on the level of detail intend to capture [4] [5].

II. RELATED WORK

Fuzzy rule base encloses rules that include all feasible fuzzy relation between the inputs and the outputs.These rules are expressed in the IF–THEN format. These rules are used to map inputs to outputs based on linguistic terms and fuzzy sets. if and $then$ rule has a typical form of

(i)Single rule with single antecedent: **IF x is A Then y is B**

(ii)Single rule with multiple antecedent: **IF x is A and y is B Then z is C**

(iii)Multiple rule with multiple antecedent.

IF y is B AND z is C THEN W is D

Input x& y are fuzzy sets (antecedent) and A,,B,C,D are fuzzy values ,w is new output. This is multiple antecedent mamdani fuzzy rule because two conditions are connected using AND.

IF binder content (B) is high, THEN strength=?

In the Mamdani rule system both antecedent and consequent parts of a rule contains verbal statements. The following is an example for a Mamdani rule [1] [6].

IF binder content (B) is high THEN strength (S) is high

III. METHODOLOGY

Experimental data collected from five different batching plants of a RMC company at city for a period of six months for a specified strength concrete produced with the same type of materials are used to train ,test and validate the strength prediction models with normalization. Statistical analysis of the data set develop reliable and accurate models based on ANN techniques comprehensive data set of 272 required for training ,testing and validation phases. In this research a great attempt was made to collect reliable data with appropriate scattering range about the compressive strength of ready mix concrete

i) Normalization Method:
The normalization method in this research is minmax function formulated and given in following equation

$$Normalization\ Value = \frac{(Input\ Value - (Minimum\ Value)}{(Maximum\ Value - Minimumm\ Value)}$$

The descriptive statics of dataset is given in table 3.1

Table3.1:Descriptive Statics of Input and Output Parameters (M10-M40)

Parameter	C	GGBS	CA	FA	SC	W	SP	W/C	CS
Min	140	80	717	475	977	150	2.42	0.68	150
Max	310	90	674	447	824	170	2.80	0.43	480
Mean	225	85	695.5	461	905	160	2.61	0.555	315
S.D	85	5	21.5	14	76.5	10	0.19	0.125	165
C.V %	37.78	5.88	3.09	3.04	8.49	6.25	7.28	22.52	315

ii) Data Pre Processing:

In this research paper to provide an FL model with good generalization capability the databases were randomly divided into five datasets 70 % of input values are considered as training, 15 % as validating 15%, remaining 15 % as testing

iii) Training Testing and Validation System Models:

In this study the following input variables obtained through different stages of the ready mix concrete production are considered to ultimately affect the 7,28 day compressive strength of the concrete for Training Testing and Validation system models Considering the input variables five different system models (M1 to M5) consisting of different sets of these input variables are considered for the prediction of 7,28 day compressive strength of concrete.Data sets of selected feature factors are given below [7].

System Model 1, M1 :CS 7,28 = CS Model1: (C, GGBS,FA,CA,SC,W, SP, W//C,Age, CS)
System Model 2, M2 : CS 7, 28 = CS Model2: (C, GGBS,FA,CA,SC,W,W/C)
System Model 3, M3 : CS 7,28 = CS Model3 : (C, FA,CA,SC,W, SP)
System Model 4, M4 : CS 7, 28 = CS Model4 : (C,GGBS, FA,CA,SC,W, W/C,SP)
System Model 5, M5 : CS 7,28 = CS Model5 : (C, FA,CA,SC,W, SP,CS)

iv) Hyper(Network) Parameters of Fuzzy Logic Model:

In the present study, a Mamdani-type fuzzy logic model is developed to predict the compressive strength of ready mix concrete based on influential mix design and material parameters. In a Mamdani fuzzy inference system hyperparameters are design choices that govern the structure and behavior of the model rather than being learned automatically from data. Proper selection of these hyperparameters significantly influences prediction accuracy and generalization capability.The fuzzy logic hyperparameters and there range are given in following table 3.2

Table 3.2: Hyper(Network) Parameters of FL Model

FIS Model	Mamdani fuzzy rule type
Fuzzy operator (AND)	Min
Implication	Min
Aggregation	Max
Defuzzification	Centroid
Number of membership functions	10
Type of input membership function	Variable
operator	prod method
Operator rule	"max-min"
Inference operator's	minimization (min) and product (prod)
Membership functions	Triangular, Gaussian
input and output categorization	*Low (L), Medium (M), and High (H),* Linguistic variables
MFdegree	*0-1*

IV. RESULT

4.1 Histogram:

Histogram {graphical) representation of all input data that shows the frequency distribution of a set of continuous data for understanding the distribution of data and identifying patterns and trends while identifying outliers which can indicate underlying issues or opportunities and important as they can aid in indicating the range of the values for a particular parameter that is required or insufficient. A nested plot composed of the frequency distributions for each material constituent investigated in this study is presented in

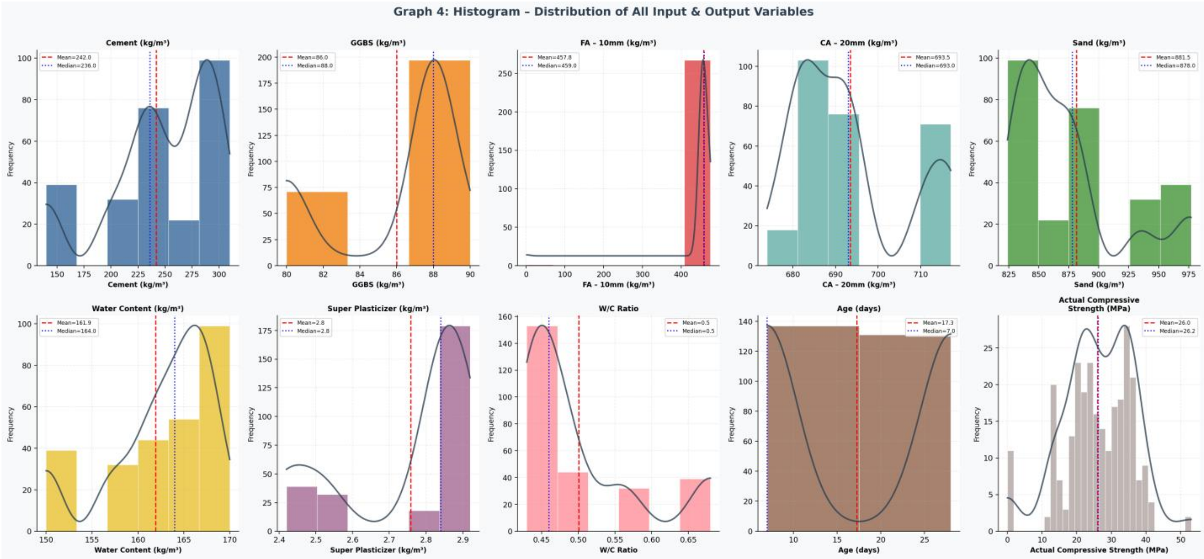

Fig. 4.1 Combined histogram of input and frequency are as (i)Cement(ii)Ground Granulated Blast Slag (iii)Fine Aggregate(iv)Coarse Aggregate (v)Crushed sand (vi)Water content (vii)Super Plasticizer (viii) Water Cement ratio (ix)Age (x) Actual Compressive Strength.

4.2 Scatter plots:

Scatter plots are used to show the values for two different numeric variables using dots.These plots are used to analyze the relationship between the different variable inputs and make use of Cartesian coordinates to represent the values of the variables in a data set .The scatter plots of the current study are shown in Fig.4. 2.

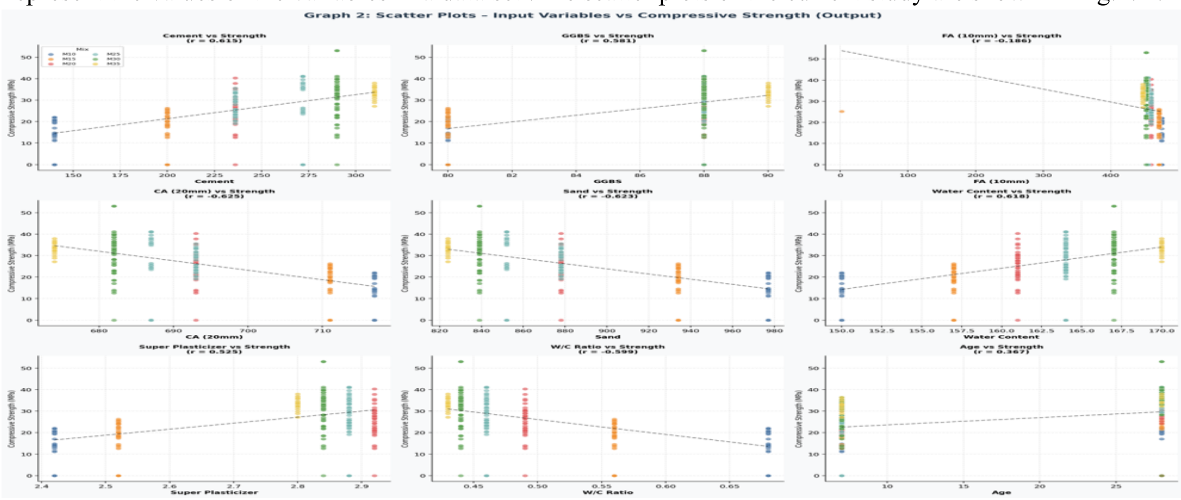

Fig. 4.2 Scatter plots of Input parameters vs Compressive strength

The scatter plots input parameters vs Compressive strength are plotted as under
(i)Cement vs Compressive strength(ii)Ground Granulated Blast Slag vs Compressive strength(iii)Fine Aggregate vs Compressive strength (iv) Coarse Aggregate vs Compressive strength(v) Crushed Sand vs Compressive strength(vi) Water Content vs Compressive strength(vii) Super Plasticizer vs Compressive strength(viii) Water Cement Ratio vs Compressive strength)(xi) Age vs Compressive strength

Based on Fig.4.2 it can be inferred that the input parameters are directly associated with the output parameter compressive strength.Each model works in different ways, causing a difference in the output.The linear fit line of data points shows the strong relationship between one input parameter corresponding to the compressive strength.Where as in some of the plots a moderate linear relationship has been observed.The involvement of a new variable significantly correlated with a variable in the prior step equation will not produce a better prediction equation because the new attribute is coded data of a parameter already in the analysis.

4.3 Correlation matrix

A correlation matrix is a table showing the correlation coefficients between multiple variables.It is a useful tool for understanding the relationships between different variables in a dataset identifying multi-linearity and outliers and can aid in identifying dependent and independent variables that can support further analysis and modeling correlation coefficient of 1 indicates a perfect positive correlation,a coefficient of -1 indicates a perfect negative correlation and a coefficient of 0 indicates no correlation. In the context of the current study the concrete variables are dependent on each other.Therefore the coefficient of correlation of all variables has been extracted and shown in Table 4.3.Since none of the input variables are entirely uncorrelated with the output all selected parameters are retained for model development. This ensures that the predictive model captures the combined influence of all relevant factors affecting the compressive strength of concrete [8].

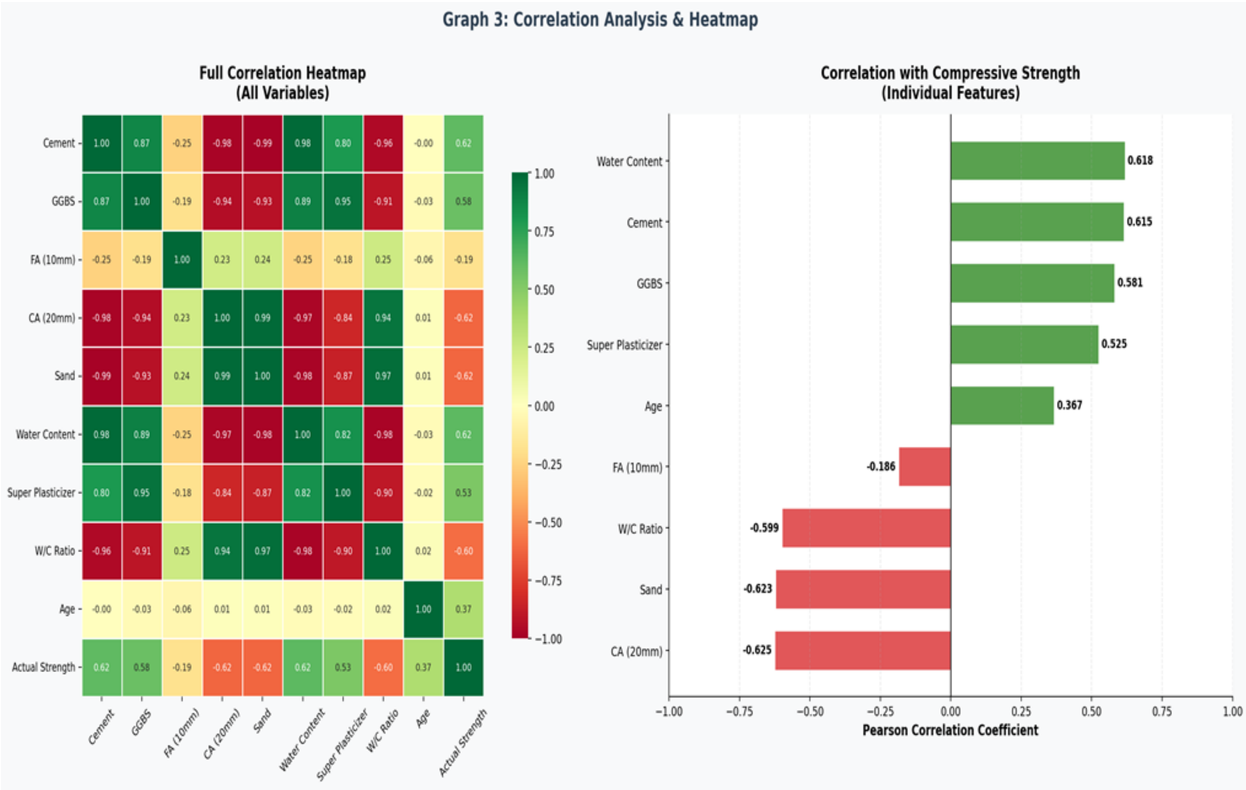

Fig. 4.3. Correlation matrix in the form of Heat map for the variables considered in the current study

4.4 Predicted v/s Actual Strength

As shown in Figure 4.4, scatter plots prove helpful in- formation on the performance of each adopted model by explaining the diversion of every predicted point to the actual value. According to the figure, it can be shown that the FL model is considered the best model in the prediction of CS of concrete [9]

Table 4.1 Comparison of designed, predicted and actual strengths.

Concrete Grade	Designated strength	Predicted Strength	Actual Strength
M10	10	20.15	21.80
M15	15	22.26	24.21
M20	20	25.68	27.63
M25	25	28.57	30.22
M30	30	34.27	36.22
M35	35	37.47	39.42

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Table 4.1 indicates the comparison of designed, predicted and actual strengths of ready mix concrete for fuzzy logic .

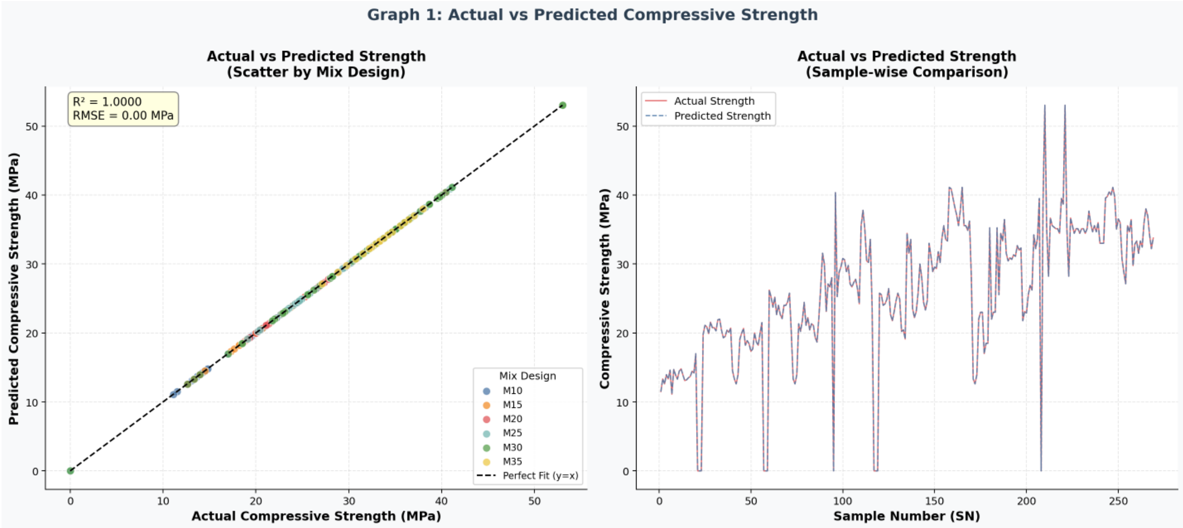

Fig.4.4:Plot between predicted and actual strength by fuzzy logic model

The comparison between predicted and actual strengths values for the fuzzy logic model is shown in figure 4.4(a) while (b)presents the error distribution .The FL model exhibit the higher prediction accuracy.The model achieved an adjusted value of 1.65 along MAE, and MSE value of 2.86 and 15.99 respectively .These results indicate a low error distribution and strong predictive capability.The superior performance of the fuzzy model can be attributed to it's effectively capturing complex nonlinear relationships and reduces over fitting. It is seen from Figure 4.4 (a-b) It shows a good agreement between the observed and the model predicted values.

4.5 Visualization Membership Functions:

It can be helpful to visualize the membership functions to understand how the crisp input values are mapped to the fuzzy sets (e.g., 'low', 'medium', 'high'). This helps in verifying if the defined fuzzy sets align with your domain knowledge.

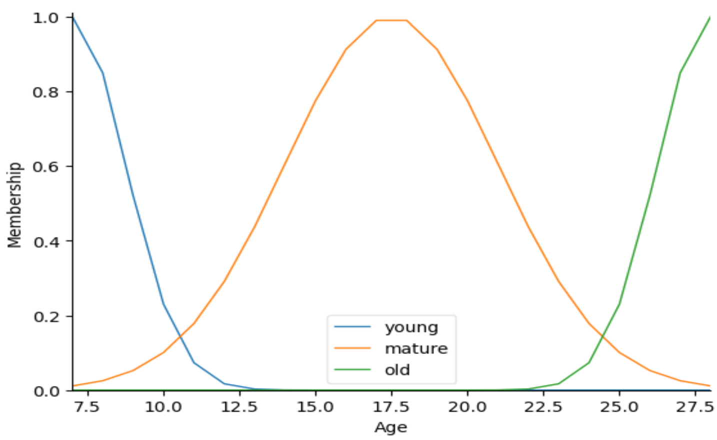

Fig 4.5:Visualization of membership functions for 'Age'

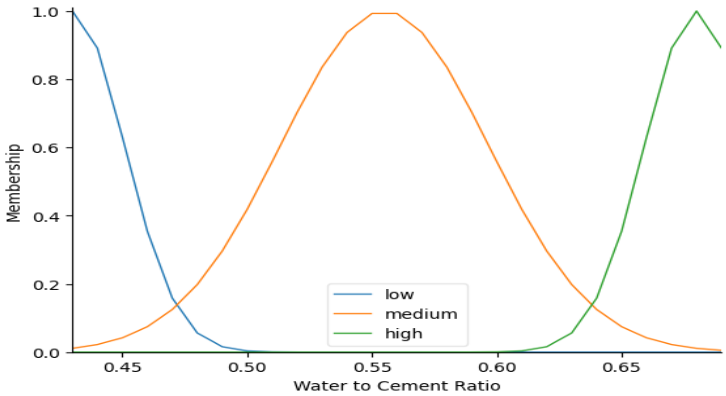

Fig 4.6:Visualization of membership functions for 'Water to Cement Ratio'

i) Visualizing Output Membership Functions for a Prediction

To better understand how the fuzzy system arrives at a specific prediction visualizing the membership functions of the output variable (`Compressive Strength`) after a simulation has been performed. This allows you to see which output fuzzy sets were activated and to what degree, and how they contributed to the defuzzified crisp output.

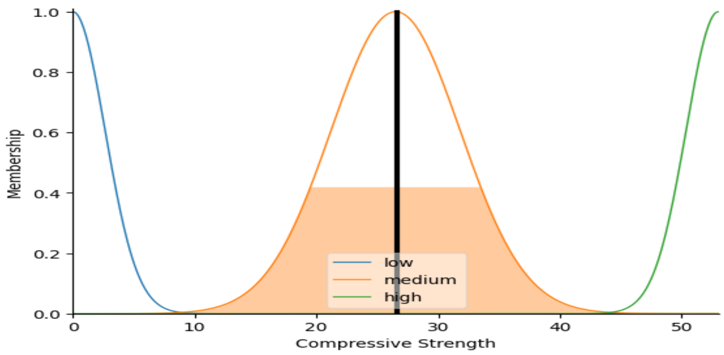

Fig4.7: Visualizing Output Membership Functions for 'Compressive Strength'

ii) Visualizing Output Membership Functions for 'Compressive Strength':
Now, let's use our fuzzy logic system to predict `Compressive Strength` for each entry in `df_cleaned` based on 'Age' and 'Water to Cement Ratio'. We will then compare these predictions with the actual.`Compressive Strength` values in a scatter plot

V. CONCLUSION

(i)It is observed that fuzzy logic model of AI reduces experimental and analytical efforts and thus gives optimum concrete mix design for good quality construction. It is considered to be the finest algorithm of AI in selecting optimum mix design of concrete as it establishes good correlation with experimental and algorithm processed data.

(ii) Soft computing is an efficient approach ,can estimate the magnitude of the compressive strength of ready mix concrete.One of the significant soft computing advantages is providing solutions for linear and non linear problems where the mathematical models cannot easily derive the relation among the involved parameters in a particular
situation.

(iii) Fuzzy logic network with their remarkable ability to derive meaning from complicated or imprecise data can be used to extract patterns and detect trends that are too complex to be noticed by other computer techniques due to adaptive learning.

(iv)The computational intelligence models used are reliable to solve different complex problems such as prediction problems.These models can be used to solve a specific problem when a deviation in available data is expected and accepted and when a defined methodology is not available.

(v) The predictions made using fuzzy logic far superior ,which begs the question of reliability.As the alternative approach of utilizing data to instantly predict the compressive strength (among other properties) has been shown to be possible; experiments carried out should be properly handled and recorded for future use.A data-banking system is a good way forward that facilitates contributions of data fromdifferent laboratories to one common entity.

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