FUZZY LOGIC APPROACH IN DETERMINATION OF STRENGTH IN CONCRETE

Thesis submitted in partial fulfilment of the requirements for award of the degree of

MASTER OF TECHNOLOGY

in

STRUCTURAL ENGINEERING

SUBMITTED BY

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(2k15/STE/02)

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JULY 2017

CANDIDATE'S DECLARATION

I hereby declare that the project work entitled **"FUZZY LOGIC APPROACH IN DETERMINATION OF STRENGTH IN CONCRETE"** submitted to Department of Civil Engineering, DTU is a record of an original work done by **AMAN GUPTA** under the guidance of **Dr. ALOK VERMA**, Associate Professor, Department of Civil Engineering, DTU, and this project work has not performed the basis for the award of any Degree or diploma/fellowship and similar project, if any.

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CERTIFICATE

This is to certify that the project entitled **"FUZZY LOGIC APPROACH IN DETERMINATION OF STRENGTH IN CONCRETE"** submitted by **AMAN GUPTA,** in partial fulfilment of the requirements for award of the degree of Master of Technology (STRUCTURAL ENGINEERING) to Delhi Technological University is the record of student's own work and was carried out under my supervision.

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(**AMAN GUPTA)**

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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. MATLAB software had been used to create an intuitive Graphical User Interface. The model put into use 'fuzzy logic' as a tool to predict the compressive strength of concrete at a given day**.** A fuzzy logic prediction model for the 28-day compressive strength of cement mortar under standard curing conditions was created. 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 Mamdani fuzzy rules relating the input variables to the output variables were created by the fuzzy model and were laid out in the If–Then format. Product (prod) inference operator and the centre of gravity (COG; centroid) defuzzification methods had been put to use. 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.

CHAPTER- 1

INTRODUCTION

1.1 Background

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.

Concrete is classified according to motive, type and range of compositions, characteristics of performance. Now a day's most widely used concrete types are: High Strength, Heavyweight, Lightweight, Self-compacting (SCC), High Performance (HPC) and Fibre reinforced concrete. 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.

Earlier, certain techniques either based on empirical methods or computational modelling has been tested, and empirical methods based on Multiple Linear Regression have been recommended to predict compressive strength. But, these empirical methods are not able to predict compressive strength precisely, as there are number of factors influencing the compressive strength and relationships among these factors are not accurately known because it is very complex and non linear. Artificial modelling employing Artificial Intelligence techniques such as Fuzzy Interface System, Artificial Neural Network provide a better environment to deal with this complex and non linear relationship.

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. Many Fuzzy Interference System models developed for compressive strength prediction typically depends on ones knowledge to create fuzzy interface rules, rather than applying a Data driven approach.

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.

1.2 OBJECTIVE

Various objectives of this thesis have been:

- To study concrete mix design procedure as per IS codes of practice. (Old as well as new)
- To study the effect of various parameters on compressive strength of concrete.
- Literature review on application of Fuzzy interface system.
- To design worksheet in excel for fuzzy logic model of compressive strength.
- To design concrete mixes for M40 and M45 grade in the laboratory.
- 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.
- To analyse and discuss the results and write conclusion.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

In this chapter we have given brief history and basic principle of fuzzy logic modelling. We have also discussed about the researches made by various researchers.

2.2 IS code recommendation for mix design: IS-10262-2009

The following points should be remembered before proportioning a concrete mix a per IS-10262-2009.

- This method of concrete mix proportioning is applicable only for ordinary and standard concrete grades.
- The air content in concrete is considered as nil.
- The proportioning is carried out to achieve specified characteristic compressive strength at specified age, workability of fresh concrete and durability requirements.

Concrete Mix Design

This method of concrete mix design consist of following 11 steps

1. Design specification
2. Testing of materials
3. Calculating target strength for mix proportioning
4. Selecting water/cement ratio
5. Calculating water content
6. Calculating cement content
7. Finding out volume proportions for Coarse aggregate & fine aggregate
8. Mix calculations
9. Trial mixing and
10. Workability measurement (using slump cone method)
11. Repeating step 9 & 10 until all requirements is fulfilled.

Let us discuss all of the above steps in detail

STEP-1 Design Specifications

This is the step where we gather all the required information for designing a concrete mix from the client. The data required for mix proportioning is as follows.

- Grade designation (whether M10, M15, M20 etc)
- Type of cement to be used
- Maximum nominal size of aggregates
- Minimum & maximum cement content
- Maximum water-cement ratio
- Workability
- Exposure conditions (As per IS-456-Table-4)
- Maximum temperature of concrete at the time of placing
- Method of transporting & placing
- Early age strength requirement (if any)
- Type of aggregate (angular, sub angular, rounded etc)
- Type of admixture to be used (if any)

STEP-2 Testing of materials

The table given below shows the list of most necessary tests to be done on cement, coarse aggregate, fine aggregate and admixture. After doing the test, store the test data for further calculation.

Concrete Ingredients	Tests to be done			
Cement	Specific gravity	—	—	—
Coarse aggregate	Specific gravity	Water absorption	Free surface moisture	Sieve analysis
Fine aggregate	Specific gravity	Water absorption	Free surface moisture	Sieve analysis

Admixture (if any)	Specific gravity	—	—	—

Table 2.1 List of tests to be done for mix design

STEP-3 Target strength calculation

Calculate the target compressive strength of concrete using the formula given below.

$$f'_{ck} = f_{ck} + 1.65s$$

where,

f'_{ck} = Target compressive strength at 28 days in N/mm2.

f_{ck} = Characteristic compressive strength at 28 days in N/mm2. (same as grade of concrete, see table below)

s = Standard deviation

The value of standard deviation, given in the table below, can be taken for initial calculation.

Sl.No	Grade of Concrete	Assumed standard deviation (N/mm2)
1.	M10	3.5
2.	M15	
3.	M20	4.0
4.	M25	
5.	M30	5.0
6.	M35	
7.	M40	
8.	M45	
9.	M50	
10.	M55	

Table 2.2 Value of standard deviation

STEP-4 Selection of water-cement ratio

For preliminary calculation, water cement ratio as given is IS-456-Table 5 (also given below) for different environmental exposure condition, may be used.

Note: Use Table-2.3 for finding out water-cement ratio of Plain Concrete and use Table-2.4 for finding out water-cement ratio of Reinforced Concrete.

Table -2.3				
Sl.No.	Environmental Exposure Condition	Plain Concrete		
		Minimum Cement Content (kg/m3)	Maximum Free Water-Cement Ratio	Minimum Grade of Concrete
1	Mild	220	0.60	—
2	Moderate	240	0.60	M15
3	Severe	250	0.50	M20
4	Very Severe	260	0.45	M20
5	Extreme	280	0.40	M25

Table 2.3 For finding out water-cement ratio of Plain Concrete

Table -2.4				
Sl.No.	Environmental Exposure Condition	Reinforced Concrete		
		Minimum Cement Content (kg/m3)	Maximum Free Water-Cement Ratio	Minimum Grade of Concrete
1	Mild	300	0.55	M20
2	Moderate	300	0.50	M25
3	Severe	320	0.45	M30
4	Very Severe	340	0.45	M35
5	Extreme	360		

Table 2.4 for finding out water-cement ratio of Reinforced Concrete

Refer the table given below (As per IS-456) to choose right type of environment depending upon different exposure conditions to concrete.

Sl.No	Environment	Exposure condition
1	Mild	Concrete surfaces protected against weather or aggressive conditions, except those situated in coastal areas.
2	Moderate	Concrete surfaces sheltered from severe rain or freezing whilst wetConcrete exposed to condensation and rain Concrete continuously under water Concrete in contact or buried under non aggressive soil/ground water
3	Severe	Concrete surfaces exposed to severe rain, alternate wetting and drying or occasional freezing whilst wet or severe condensation Concrete completely immersed in sea water Concrete exposed to coastal environment
4	Very severe	Concrete surfaces exposed to sea water spray, corrosive fumes or severe freezing condition whilst wet Concrete in contact with or buried under aggressive sub-soil/ground water
5	Extreme	Surface members in tidal zone Members in direct contact with liquid/solid aggressive chemicals

Table 2.5 Different exposure conditions

STEP-5 Selection of water content

Selection of water content depends upon a number of factors such as

- Aggregate size, shape & texture
- Workability
- Water cement ratio
- Type of cement and its amount
- Type of admixture and environmental conditions.

Factors that can reduce water demand are as follows

- Using increased aggregate size
- Reducing water cement ratio
- Reducing the slump requirement
- Using rounded aggregate
- Using water reducing admixture

Factors that can increase water demand are as follows

- Increased temp. at site
- Increased cement content
- Increased slump
- Increased water cement ratio
- Increased aggregate angularity
- Decrease in proportion of the coarse aggregate to fine aggregate

The quantity of maximum mixing water per unit volume of concrete may be selected from the table given below.

Maximum water content per cubic meter of concrete for nominal maximum size of aggregate		
Sl.No.	Nominal maximum size of aggregate	Maximum water content
1	10	208
2	20	186
3	40	165

Table 2.6 Quantity of maximum mixing water per unit volume of concrete

The values given in the table shown above is applicable only for angular coarse aggregate and for a slump value in between 25 to 50mm.

Do the following adjustments if the material used differs from the specified condition.

Type of material/condition	Adjustment required
For sub angular aggregate	Reduce the selected value by 10kg
For gravel with crushed stone	Reduce the selected value by 20kg
For rounded gravel	Reduce the selected value by 25kg
For every addition of 25mm slump	Increase the selected value by 3%
If using plasticizer	Decrease the selected value by 5-10%
If using super plasticizer	Decrease the selected value by 20-30%

Table 2.7 Adjustments to be done if the material used differs from the specified condition

Note: Aggregates should be used in saturated surface dry condition. While computing the requirement of mixing water, allowance shall be made for the free surface moisture contributed by the fine and coarse aggregates. On the other hand, if the aggregate are completely dry, the amount of mixing water should be increased by an amount equal to moisture likely to be absorbed by the aggregate

STEP-6 Calculating cementious material content

From the water cement ratio and the quantity of water per unit volume of cement, calculate the amount of cementious material. After calculating the quantity of cementious material, compare it with the values given in the table shown in Step-4. The greater of the two values is then adopted.

If any mineral admixture (such as fly ash) is to be used, then decide the percentage of mineral admixture to be used based on project requirement and quality of material.

STEP-7 Finding out volume proportions for coarse aggregate and fine aggregate

Volume of coarse aggregate corresponding to unit volume of total aggregate for different zones of fine aggregate is given in the following table.

Sl.No.	Nominal Maximum Size of Aggregate (mm)	Volume of coarse aggregate per unit volume of total aggregate for different zones of fine aggregate			
		Zone IV	Zone III	Zone II	Zone I
1	10	0.50	0.48	0.46	0.44
2	20	0.66	0.64	0.62	0.60
3	40	0.75	0.73	0.71	0.69

Table 2.8 Volume of coarse aggregate corresponding to unit volume of total aggregate for different zones of fine aggregate

The values given in the table shown above is applicable only for a water-cement ratio of 0.5 and based on aggregates in saturated surface dry condition.

If water-cement ratio other than 0.5 is to be used then apply correction using the rule given below.

Rule: For every increase or decrease by 0.05 in water-cement ratio, the above values will be decreased or increased by 0.01, respectively.

If the placement of concrete is done by a pump or where is required to be worked around congested reinforcing steel, it may be desirable to reduce the estimated coarse aggregate content determined as above, upto 10 percent.

After calculating volume of coarse aggregate, subtract it from 1, to find out the volume of fine aggregate.

STEP-8 Mix calculations

The mix calculations per unit volume of concrete shall be done as follows.

A	Volume of concrete=	1m3
B	Volume of cement=	(Mass of cement/specific gravity of cement)*(1/1000)
C	Volume of water=	(Mass of water/specific gravity of water)*(1/1000)
D	Volume of admixture=	(Mass of admixture/specific gravity of admixture)*(1/1000)
E	Volume of total aggregate (C.A+F.A)=	[a-(b+c+d)]
F	Mass of coarse aggregate=	e*Volume of coarse aggregate*specific gravity of coarse aggregate*1000
G	Mass of fine aggregate=	e*Volume of fine aggregate*specific gravity of fine aggregate*1000

Table 2.9 Mix calculations per unit volume of concrete

STEP-9 Trial Mix

Conduct a trial mix as per the amount of material calculated above.

STEP-10 Measurement of workability (By slump cone method)

The workability of the trial mix no.1 shall be measured. The mix shall be carefully observed for freedom from segregation and bleeding and its finishing properties.

STEP-11 Repeating trial steps

If the measured workability of trial mix no.1 is different from stipulated value, the water and/or admixture content shall be adjusted suitably. With this adjustment, the mix proportion shall be recalculated keeping the free water-cement ratio at pre-selected value.

Trial-2 – increase water or admixture, keeping water-cement ratio constant

Trial-3 – Keep water content same as trial-2, but increase water-cement ratio by 10%.

Trial-4 – Keep water content same as trial-2, but decrease water-cement ratio by 10%

Trial mix no 2 to 4 normally provides sufficient information, including the relationship between compressive strength and water-cement ratio.

2.3 Previous research paper work on mix design and fuzzy logic

In this chapter we have given brief history and basic principle of fuzzy logic modelling. We have also discussed about the researches made by various researchers.

Sedat Akkurta, Gokmen Tayfurb, Sever Can[1] : A fuzzy logic prediction model for the 28-day compressive strength of cement mortar under standard curing conditions was created. 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. The Mamdani fuzzy rules relating the input variables to the output variable were created by the ANN model and were laid out in the If–Then format. Product (prod) inference operator and the centre of gravity (COG; centroid) defuzzification methods were employed. The prediction of 50 sets of the 28-day cement strength data by the developed **fuzzy** model was quite satwasfactory. The average percentage error levels in the fuzzy model were successfully low (2.69%). The model was compwered with the ANN model for its error levels and ease of application. The results indicated that through the application of fuzzy logic algorithm, a more user friendly and more explicit model than the ANNs could be produced within successfully low error margins. A fuzzy logic model was created to predict the 28-day cement strength. Input parameters used in model creation process included C3S, SO3, total alkali, and surface werea (Blaine). The model was created from a local cement plant process control data. A four-parameter ANN model was used to produce the fuzzy rule sets in the fuzzy model building stage. 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] : 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. The operators used in constructing the FL model were found to be appropriate for compressive strength prediction. The performance of FL was comparable to that of ANN. The extrapolation capability of FL and ANNs were found to be satisfactory. The following conclusions can be drawn from this study: FL can accurately predict the compressive strengths of HSCs with silica fume. The performance of FL was comparable to that of ANN; Employing three input variables (binder content, age, and SF content) with 24 optimal fuzzy rules was sufficient for the FL model to make satisfactory compressive strength predictions;

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. The datasets which has been loaded into a fuzzy logic model contain 1,030 concrete mixtures. Input fields of the fuzzy expert system were weight percent of cement, water, blast furnace slag, fly ash, super plasticizer, fine aggregate, coarse aggregate, and age of the concrete. Output field was concrete compressive strength. Finally, 897 rules used for this fuzzy logic modelling. A fuzzy logic controller was proposed for determination of the compressive strength of 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. In addition, slow early strength gain resulting from the use of fly ash and blast furnace slag was an advantage as it allows more time to place and finish the concrete. Finally, it was shown that increasing the coarse aggregate decreases the 3-day-old concrete compressive strength, but increases the older concrete compressive strength.

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.

Sumathy Raju, Brindha Dharmar [5]: This paper presents a laboratory study about the influence of combination of Fly Ash (FA) on the mechanical properties of concrete. Concrete mixtures were made with 10%, 20% and 30% replacement of cement with low lime (class F) fly ash by mass and fine aggregate was replaced by CS from 0 - 100% with an increment of 20% by volume. On the hardened concrete, Destructive Test (DT) methods such as compressive strength (7, 28, 56 and 90 days), split tensile strength (28 days) and flexural strength (28 days) were determined. Moreover, Non-Destructive Test (NDT) methods such as Ultrasonic Pulse Velocity (UPV) and Digital Schmidt Rebound Hammer (RH) tests were also determined. Based on the experimental results, both NDT and DT techniques, the results were favourable for concrete with industrial wastes such as Fly Ash and Copper Slag and also superior to control concrete. Concrete with FA alone, the initial rate of gain of compressive strength has been decreased due to slow pozzolanic action, but the strength was developed at later ages (56 - 90 days) higher than the control mix. Compressive strength concrete incorporating with industrial waste such as FA and CS was increased from the early ages to lateral ages due the positive effects of CS compensate the strength loss due to the presence of FA. This indicates that, FA and CS react with surplus lime resulting from hydration of cement and give additional binding property continuously to the concrete. Hence, industrial wastes haven't affected the compressive strength. Based on 90 days compressive strength, concrete mixtures with 30% of FA and 100% of CS has contributed higher strength than the control mix for all the time. Optimum strength was reached, when concrete with cement was replaced by 30% of FA and 80% of CS for fine aggregate. It was 36.83% better than the strength of control mix and also thwas mix proportion was suitable for concrete structures.

Hong-zhu Quan and Hideo Kasami[6]: In order to improve the durability of fly ash concrete, a series of experimental studies were carried out, where durability improving admixture was used to reduce drying shrinkage and improve freezing-thawing resistance. The effects of durability improving admixture, air content, water-binder ratio, and fly ash replacement ratio on the performance of fly ash concrete were discussed. The results show that by using durability improving admixture in non air-entraining fly ash concrete, the compressive strength of fly ash concrete can be improved by 10%–20%, and the drying shrinkage was reduced by 60%. Carbonation resistance of concrete was roughly proportional to water-cement ratio regardless of water-binder ratio and fly ash replacement ratio. For the specimens cured in air for 2 weeks, the freezing-thawing resistance was improved. In addition, by making use of durability improving admixture, it was easier to control the air content and make fly ash concrete into non air-entraining one. The quality of fly ash concrete was thereby optimized. By using durability improving admixture in non air entraining fly ash concrete, the compressive strength of fly ash concrete can be improved by 10%–20%, and its initial compressive strength improved also. Irrespective of the presence of air, durability improving admixture, or fly ash replacement ratio, both tensile strength and modulus of elasticity were dependent on compressive strength. By using durability improving admixture in fly ash concrete, the drying shrinkage was reduced by 60%. By using durability improving admixture for 2 weeks of curing in air, the freezing-thawing reswastance can be improved even in non air-entraining concrete.

Jino John, M. Ashok [7]: The objective of the 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. The weight replacements of cement used were 50%, 60% and 70% and following conclusion were arrived. HVFA concrete attained lesser compressive and tensile strength when compared with OPC concrete. The maximum values 28 days strength of HVFA concrete with 0.34 w/b ratio was obtained with 50% replacement followed by 60% and 70% with 0.34 w/b ratio. The mechanical properties show that the HVFA concrete given lower strength than the control mix concrete.

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. 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

C. Bas¸yigit, Waskender Akkurt ,S. Kilincarslan,A. Beycioglu [10]: The compressive strength of heavyweight concrete which was produced using baryte aggregates has been predicted by artificial neural network (ANN) and fuzzy logic (FL) models. For these models 45 experimental results were used and trained. Cement rate, water rate, periods (7–28–90 days) and baryte (BaSO4) rate (%) were used as inputs and compressive strength (MPa) was used as output while developing both ANN and FL models. In the models, training and testing results have shown that ANN and FL systems have strong potential for predicting compressive strength of concretes containing baryte (BaSO4). It was seen that the physical and mechanical properties of concrete such as compressive strength can be estimated using developed models of ANN and FL without performing any more experiments.

Nasir B. Siraj, Aminah Robinson Fayek, and Abraham A. Tsehayae[9]: In this study, the application of three artificial intelligence techniques, namely, the Artificial Neural Network (ANN), Fuzzy Inference System (FIS), and Adaptive Neuro-Fuzzy Inference System (ANFIS) techniques, are explored. A data-driven approach based on fuzzy c-means clustering (FCM) is employed to generate both the Mamdani and Sugeno FIS models. Different model structures and parameters—such as number of neurons and choice of transfer function for the ANN technique, and number of clusters and choice of fuzzification coefficient and inference methods for the FIS and ANFIS techniques—are optimized to improve the accuracy of each technique. Results of this study indicate that ANFIS and ANN perform better than the FIS models in predicting the compressive strength of HPC. 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.

M. L. Nehdi and M. T. Bassuoni [20] found a Fuzzy logic approach for estimating durability of concrete. A fuzzy inference system was built for the specific case of various self-consolidating concrete mixtures subjected to ammonium sulfate attack. The performance of this model was compared with that of other models that enable decision making: the remaining service life model and compromise programming. Results of the fuzzy inference system had a better correlation with compromise programming ($R^2 = 0{\cdot}7$) than that with the remaining service life model ($R^2 = 0{\cdot}5$), and better represented the actual degradation observed in test specimens. It is 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

Song-Sen Yang and Jing Xu and Guang-Zhu Yao [21] have studied on Concrete strength evaluation based on fuzzy neural networks. They were built a fuzzy neural network (FNN) to evaluate 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. Verification test shows that the max relative error of the predicted results is 1.12%, which meets the need of practical engineering.

2.4 Principle of fuzzy logic:

Today control systems are usually described by mathematical models that follow the laws of physics, stochastic models or models which have emerged from mathematical logic. A general difficulty of such constructed model is how to move from a given problem to a proper mathematical model. Undoubtedly, today's advanced computer technology makes it possible; however managing such systems is still too complex.

These complex systems can be simplified by employing a tolerance margin for a reasonable amount of imprecision, vagueness and uncertainty during the modelling phase. As an outcome, not completely perfect system comes to existence; nevertheless in most of the cases it is capable of solving the problem in appropriate way. Even missing input information has already turned out to be satisfactory in knowledge-based systems.

Fuzzy logic allows to lower complexity by allowing the use of imperfect information in sensible way. It can be implemented in hardware, software, or a combination of both. In other words, fuzzy logic approach to problems' control mimics how a person would make decisions, only much faster.

The fuzzy logic analysis and control methods shown in Figure 2.1 can be described as:

1. Receiving one or large number of measurements or other assessment of conditions existing in some system that will be analysed or controlled.
2. Processing all received inputs according to human based, fuzzy "if-then" rules, which can be expressed in simple language words, and combined with traditional non-fuzzy processing.

3. Averaging and weighting the results from all the individual rules into one single output decision or signal which decides what to do or tells a controlled system what to do. The result output signal is a precise defuzzified value.

The following is Fuzzy Logic Control/Analysis Method diagram.

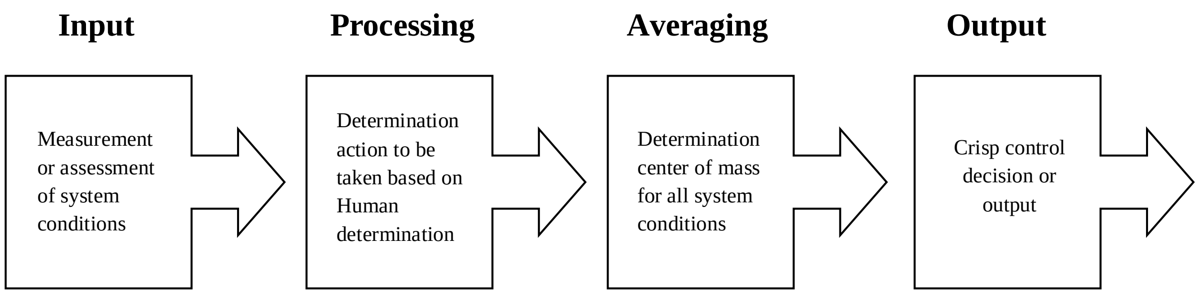


Fig. 2.1 The fuzzy logic Control-Analysis method

In order to operate fuzzy logic needs to be represented by numbers or descriptions. For example, speed can be represented by value 5 m/s or by description “slow”. Term “slow” can have different meaning if used by different persons and must be interpreted with respect to the observed environment. Some values are easy to classify, while others can be difficult to determine because of human understanding of different situations. One can say “slow”, while other can say “not fast” when describing the same speed. These differences can be distinguished with help of so-called fuzzy sets.

2.5 Effect of various parameters on compressive strength of concrete

Concrete strength is affected by many factors, such as quality of raw materials, water/cement ratio, coarse/fine aggregate ratio, age of concrete, compaction of concrete, temperature, and curing of concrete.

1. Quality of Raw Materials:

Cement: Provided the cement conforms with the appropriate standard and it has been stored correctly (i.e. in dry conditions), it should be suitable for use in concrete.

Aggregates: Quality of aggregates, its size, shape, texture, strength etc determines the strength of concrete. The presence of salts (chlorides and sulphates), silt and clay also reduces the strength of concrete.

Water: frequently the quality of the water is covered by a clause stating "..the water should be fit for drinking..". This criterion though is not absolute and reference should be made to respective codes for testing of water construction purpose.

2. Water / Cement Ratio:

The relation between water cement ratio and strength of concrete is shown in the plot as shown below.

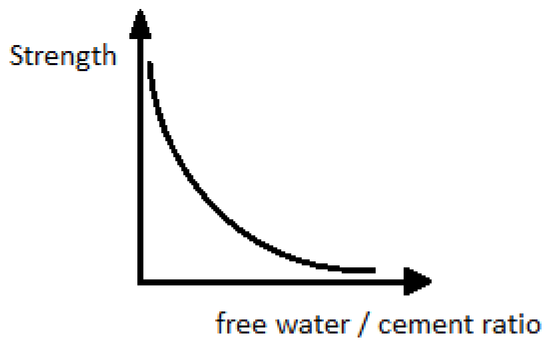


Fig 2.2 Relation between water cement ratio and strength of concrete

The higher the water/cement ratio, the greater the initial spacing between the cement grain sand the greater the volume of residual voids not filled by hydration products.

There is one thing missing on the graph. For a given cement content, the workability of the concrete is reduced if the water/cement ratio is reduced. A lower water cement ratio means less water, or more cement and lower workability.

However if the workability becomes too low the concrete becomes difficult to compact and the strength reduces. For a given set of materials and environment conditions, the strength at any age depends only on the water-cement ratio, providing full compaction can be achieved.

3. Coarse / fine aggregate ratio:

Following points should be noted for coarse/fine aggregate ratio:

- If the proportion of fines is increased in relation to the coarse aggregate, the overall aggregate surface area will increase.

- If the surface area of the aggregate has increased, the water demand will also increase.
- Assuming the water demand has increased, the water cement ratio will increase.
- Since the water cement ratio has increased, the compressive strength will decrease.

4. Aggregate / Cement Ratio:

Following points must be noted for aggregate cement ratio:

- If the volume remains the same and the proportion of cement in relation to that of sand is increased the surface area of the solid will increase.

- If the surface area of the solids has increased, the water demand will stay the same for the constant workability.

- Assuming an increase in cement content for no increase in water demand, the water cement ratio will decrease.

- If the water cement ratio reduces, the strength of the concrete will increase.

The influence of cement content on workability and strength is an important one to remember and can be summarized as follows:

1. 2. 3.

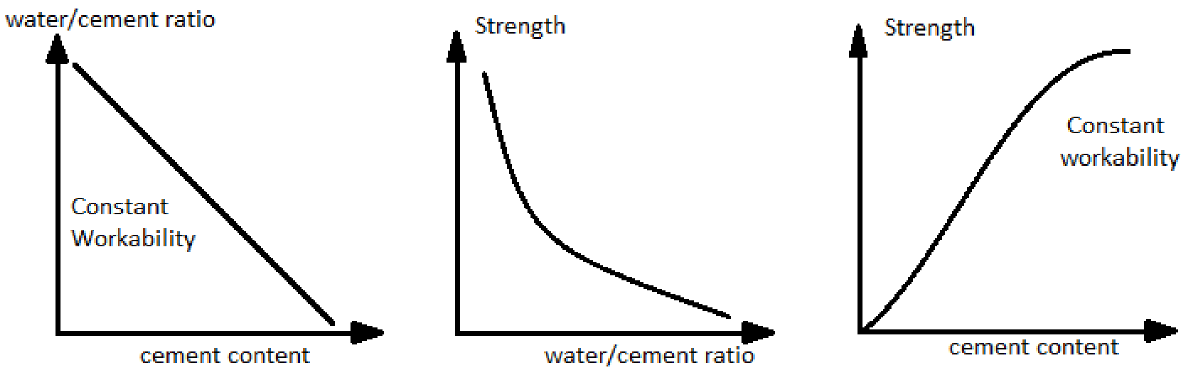


Fig 2.3 influence of cement content on workability and strength

1. For a given workability an increase in the proportion of cement in a mix has little effect on the water demand and results in a reduction in the water/cement ratio.

2. The reduction in water/cement ratio leads to an increase in strength of concrete.

3. Therefore, for a given workability an increase in the cement content results in an increase in strength of concrete.

5. Age of concrete:

The degree of hydration is synonymous with the age of concrete provided the concrete has not been allowed to dry out or the temperature is too low.

In theory, provided the concrete is not allowed to dry out, then it wil always be increasing albeit at an ever reducing rate. For convenience and for most practical applications, it is generally accepted that the majority of the strength has been achieved by 28 days.

6. Compaction of concrete:

Any entrapped air resulting from inadequate compaction of the plastic concrete will lead to a reduction in strength. If there was 10% trapped air in the concrete, the strength will fall down in the range of 30 to 40%.

7. Temperature:

The rate of hydration reaction is temperature dependent. If the temperature increases the reaction also increases. This means that the concrete kept at higher temperature will gain strength more quickly than a similar concrete kept at a lower temperature.

However, the final strength of the concrete kept at the higher temperature will be lower. This is because the physical form of the hardened cement paste is less well structured and more porous when hydration proceeds at faster rate.

This is an important point to remember because temperature has a similar but more pronounced detrimental effect on permeability of the concrete.

8. Curing:

It should be clear from what has been said above that the detrimental effects of storage of concrete in a dry environment can be reduced if the concrete is adequately cured to prevent excessive moisture loss.

2.6 Application of fuzzy logic in civil engineering

During the last decade there has been a growing interest in the application of these concepts to engineering problems. Fuzzy concepts provide an easy way of dealing with complex problems, because it can be built with fuzzy models containing vagueness and impreciseness in knowledge representation. Hence, it is suited for applications where the ability to model real world design problem in precise mathematical form is difficult.

Also by integrating Fuzzy concepts with Genetic Algorithms (GA) or Genetic Programming (GP) and Neural Networks (NN), the complex problems can be more efficiently and effectively solved in order to arrive at optimal soln.

This concept is effectively used in;

1. Structural analysis and Design

- For structural optimization and optimum Design of structures
- Computation Morphogenesis of Discrete structures.

2. Construction field

- For management problems like construction scheduling of the project
- For planning of life cycle of project problems like selection of best construction equipment.

3. The field of Hydrology & Water Resource engineering

- For forecasting rainfall, rainfall runoff, river stage,etc
- Hydrologic flow routing

4. Traffic engineering

- For automatic control of traffic signals based on fuzzy stochastic model

5. Reliability of structures

- For damage assessment in structures

6. Metal structures

- For predicting fatigue & Creep characteristics [J. Harris (2001)]

Fuzzy concepts thrown its wide variety of application for the field of civil engineering. Hence, we the engineers should explore it for its potential application for the problems we face in this engineering world.

2.7 Advantage of Fuzzy logic

I think the main advantages of Fuzzy logic are:

- The ease to model your reasoning, and the ability to deal with uncertainty and nonlinearity.
- The ease of implementation, and the use of linguistic variables.
- Can accommodate small changes in system or controller parameters. This is the aging effect and nonlinear effects such as flexibility of beams.
- Experience has been that these techniques seem to handle nonlinearity well.
- Tools have been developed to assist in studying and building fuzzy controllers in short times.

2.8 Some Issues of Fuzzy control system

Some issues related to fuzzy logic interference system are:

- Definition of membership functions is arbitrary and controller designer dependent.
- Procedures for selecting membership functions and defuzzifier options are not firmly established in the control community.
- There are limited sources for fuzzy control system

CHAPTER 3

MATERIALS AND METHODOLOGY

3.1 Introduction

FIS should be modelled in such a way that it produce output with minimum error and work efficiently.

The initial work is to collect data samples to be used in modelling. Data samples should cover the entire range of inputs of the problem. Also, redundant or useless data should be removed from data sets. Training intends to give the network the information as an example so that it can learn, or change its weights, to such an extent that it accurately replicates the compressive quality when new data is presented to them.

As mentioned, data were collected for 149 concrete samples for developing model. They cover a wide range of different mix proportions. There range is shown below:

Water/binder	0.4-0.66
Cement	55-600gm
Fly ash%	0-20%
Water	103-204gm
Coarse aggregate	775-1277gm
Fine aggregate	491-937 gm

Table: 3.1 Range of constituents of different mix proportion

3.2 Overview of Fuzzy Logic Algorithm

Fuzzy logic is a way to computing established on degrees of truth rather than the usual true or false (1 or 0) Boolean logic on which the modern computer is based. This is a knowledge based approach which consists of following parts:

- Data: It include knowledge used to specify fuzzy control rules and fuzzy data alteration in a fuzzy logic controller

- Rules: is characterized by the construction of a set of linguistic rules based on an expert's knowledge. The expert's knowledge is usually in the form of cause and effect, i.e. IF–THEN. Fuzzy statements can thus easily implement this

A common fuzzy Interface system has 4 steps—

- Fuzzification
- Fuzzy rule bases
- Fuzzy inference engine and
- Defuzzification

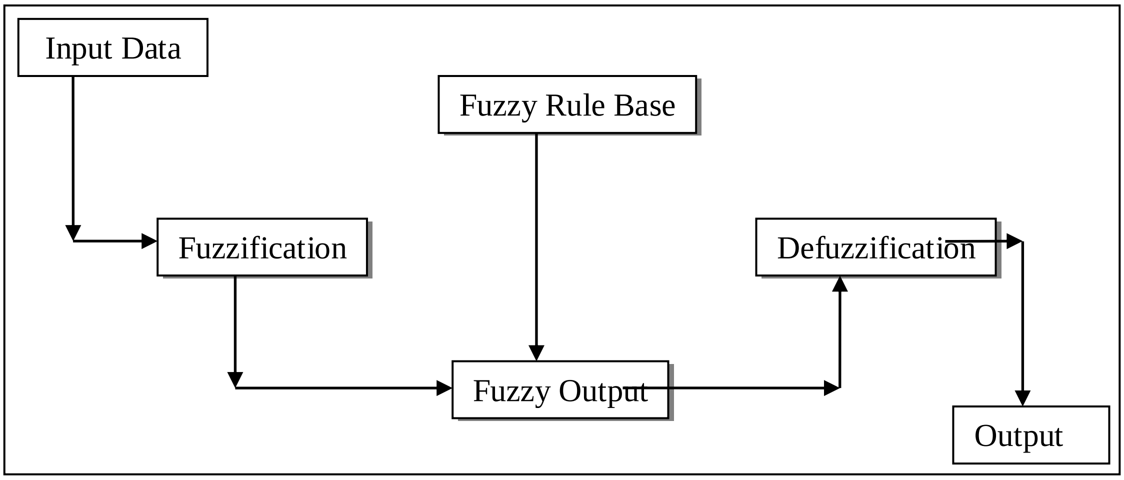


Fig.3.1 Flow chart showing Fuzzy Interface System

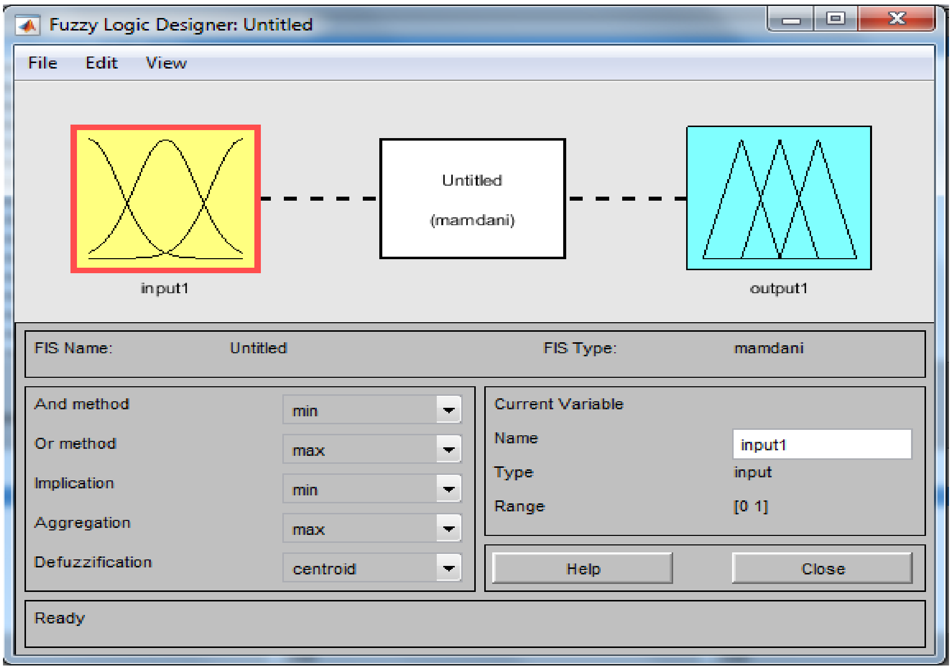


Fig.3.2 Fuzzy logic interface

3.2.1 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.

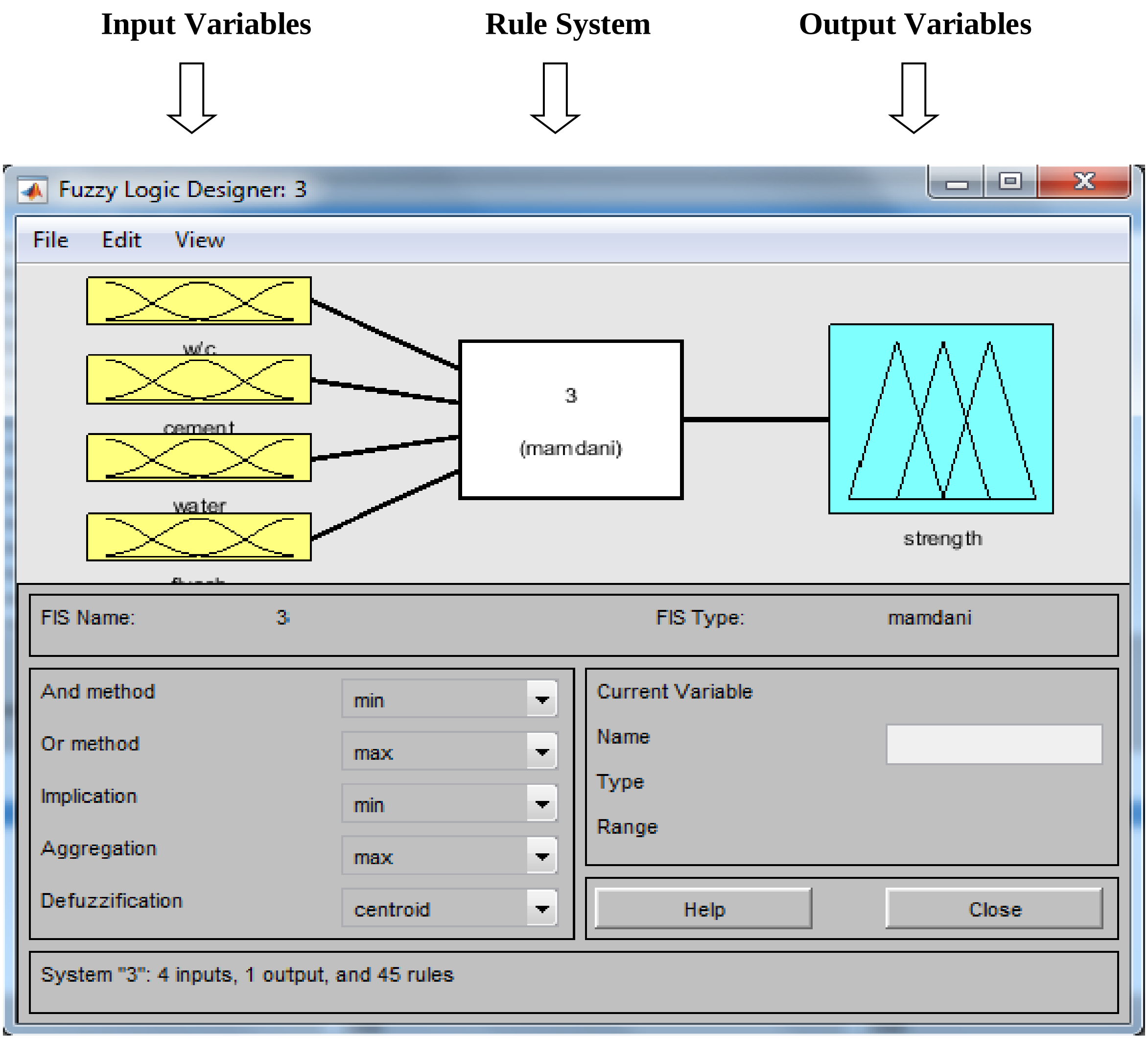


Fig 3.3 Figure showing input and output variables

Fig 1, 2 and 3 shows the membership functions for water/binder ratio, water and cement respectively. It is clearly shown that there are different sets which belong to a universal set. In Fig.1 for water to binder ratio there are five subsets: wc1, wc2, wc3, wc4, wc5. The membership degree varies in between 0 and 1. In this universal set 0.3 can be a member of both subset wc1 and wc2 with membership degree x_1 and x_2 respectively where x_1 and x_2 are in between 0 and 1

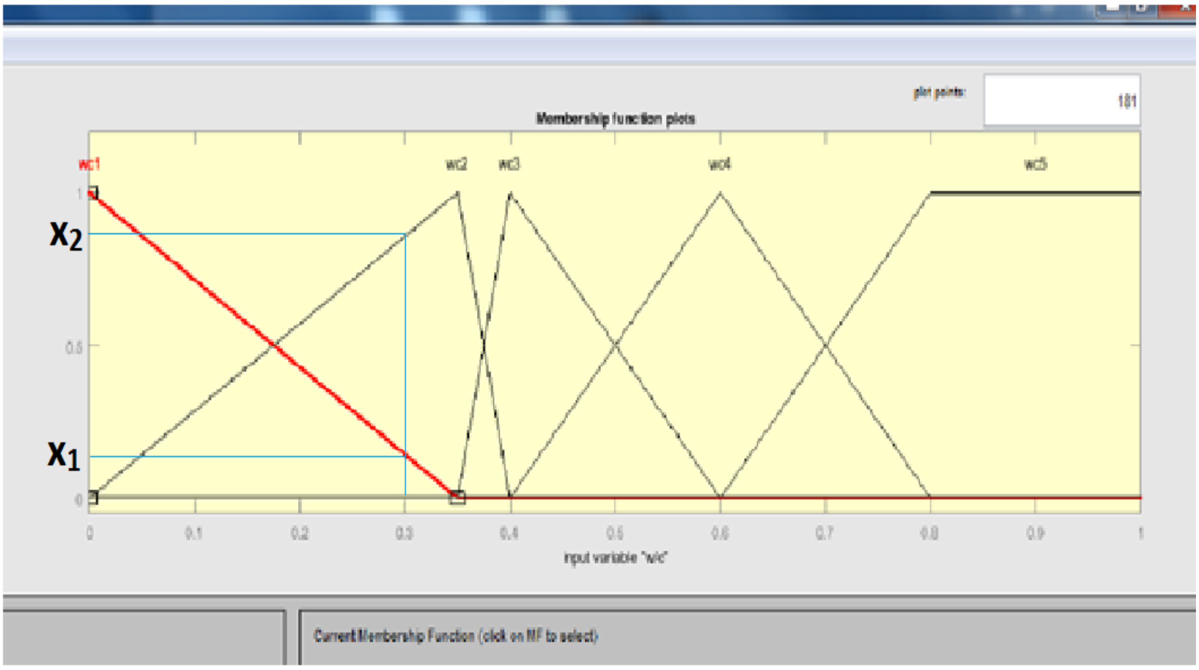


Fig. 3.4 Triangular membership functions for water/binder ratio.

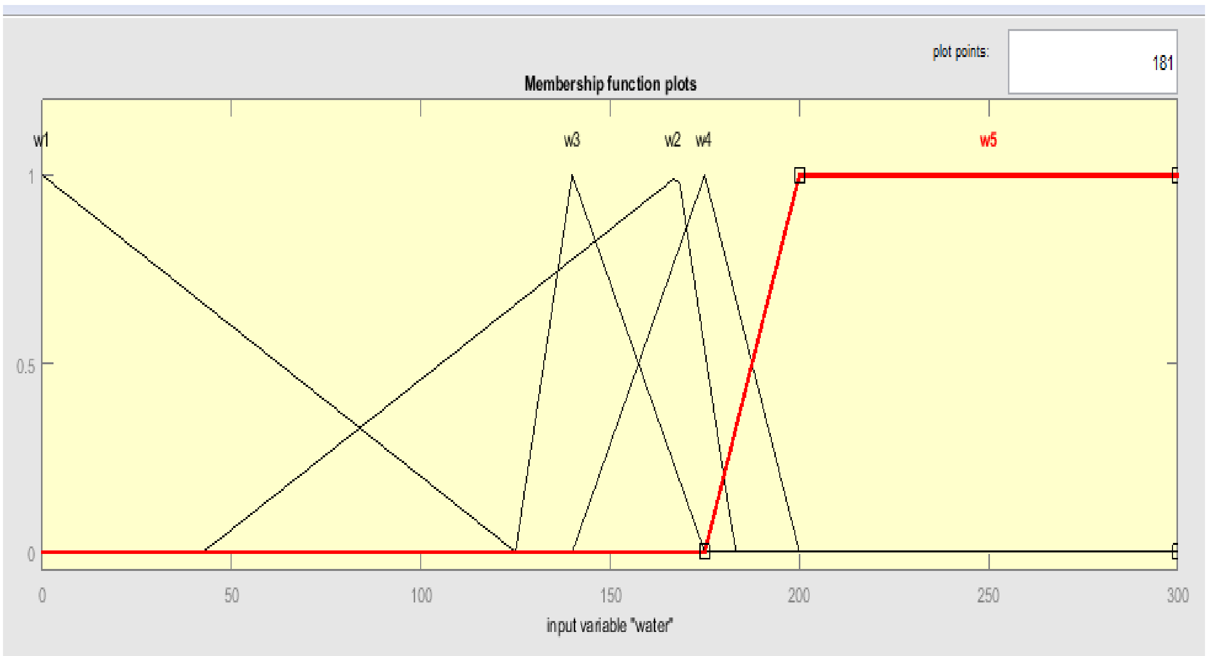


Fig. 3.5 Triangular membership functions for water content

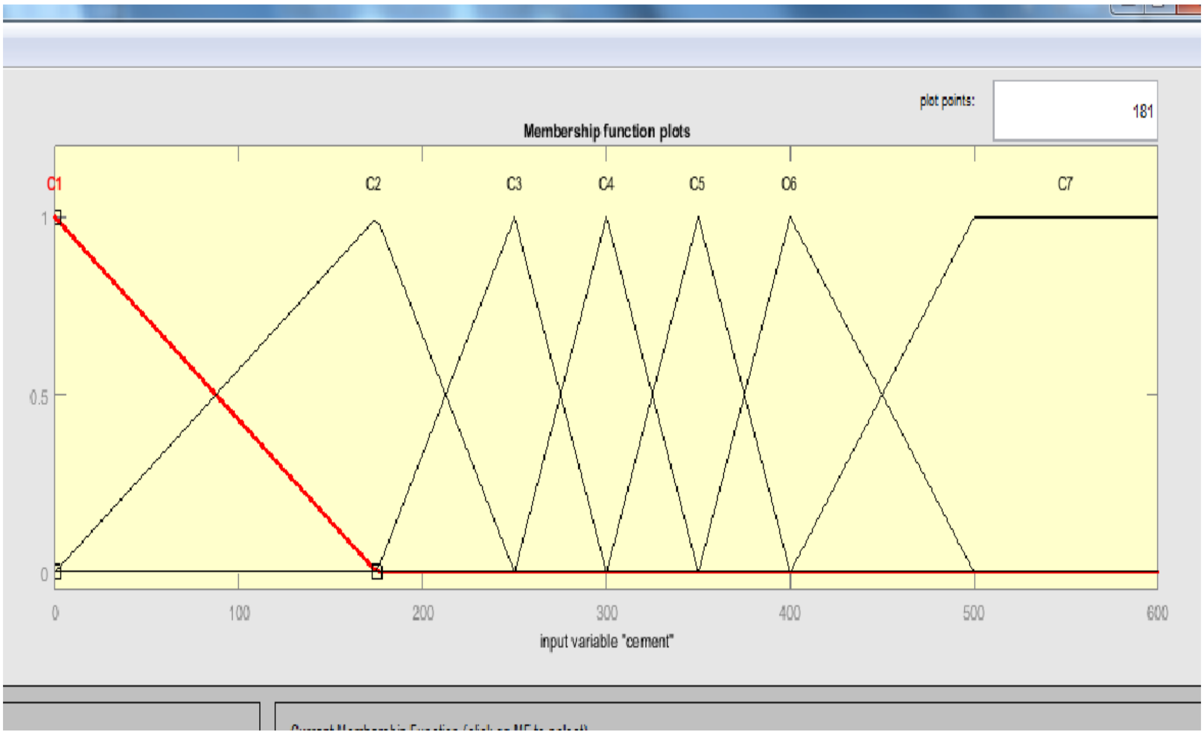


Fig. 3.6 Triangular membership functions for cement content.

3.2.2 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.

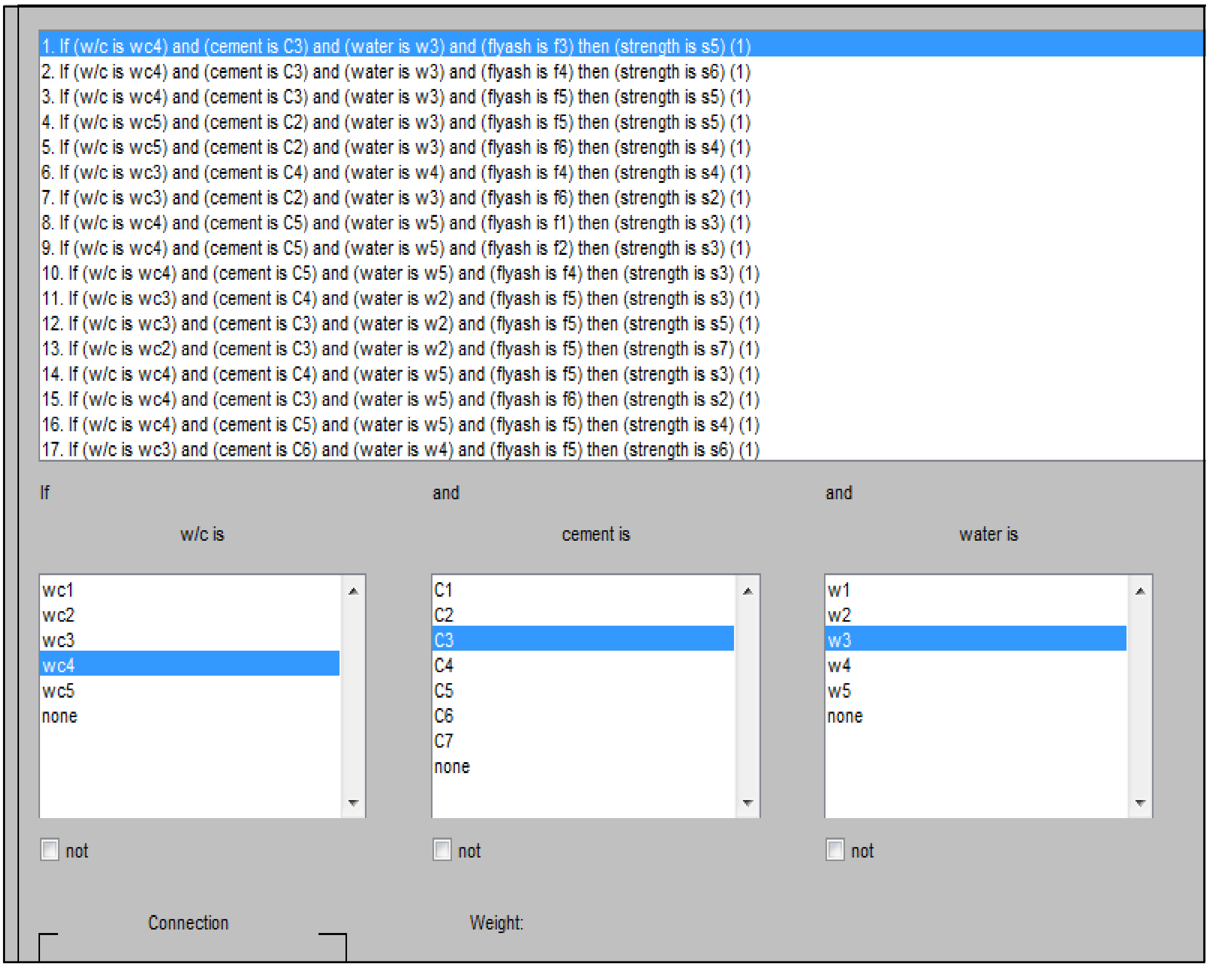


Fig 3.7 Rules expressed as IF-THEN format

In order to explain the rule construction methodology let us take an example.

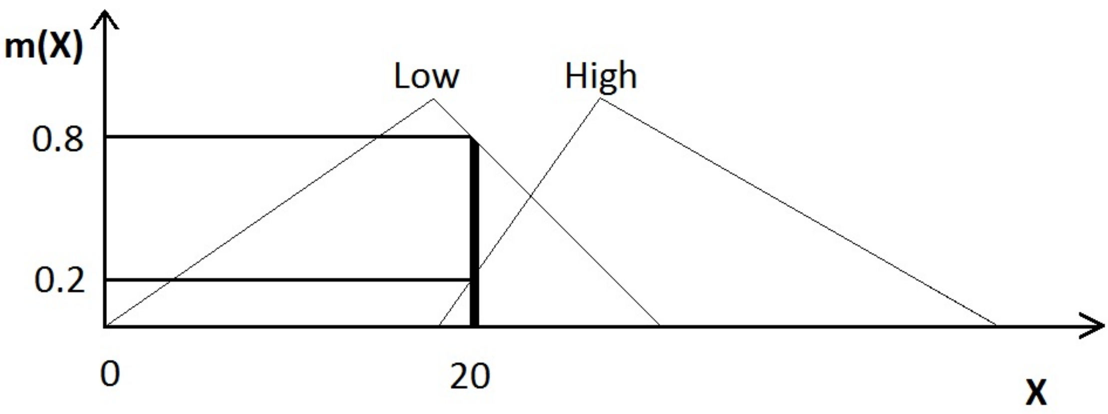


Fig 3.8 (a) Membership function for input variable X

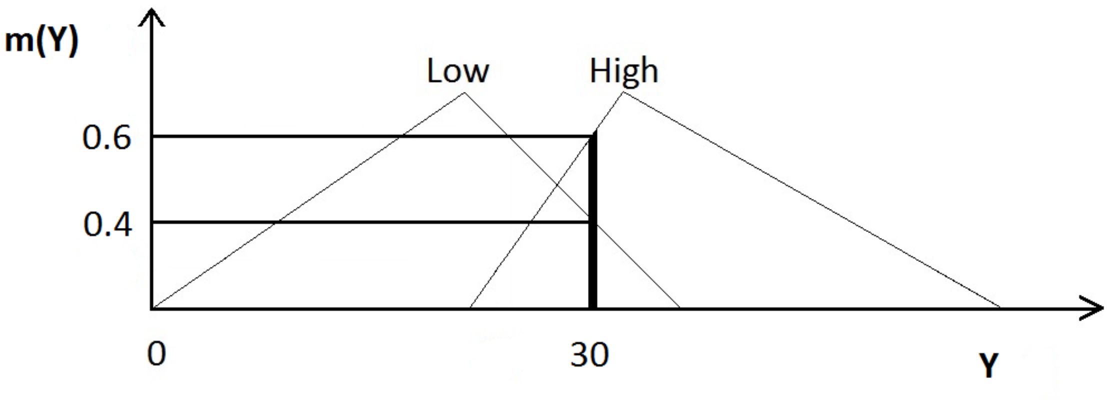


Fig.3.8 (b) Membership function for input variable Y

In Fig.5 X and Y are two input variables Fig.3.8 (a) and Fig.3.8 (b) respectively and one output variable of Z Fig.3.8(c). Assume that the values of X= 20, Y = 30, Z = 40. According to Fig.3.8 (a) X=20 is a segment of high subset with membership 0.2 and low subset with membership 0.8; Fig.3.8 (b) Y = 30 is a segment of high subset with membership 0.6 and low subset with 0.4 membership; and Fig.3.8 (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

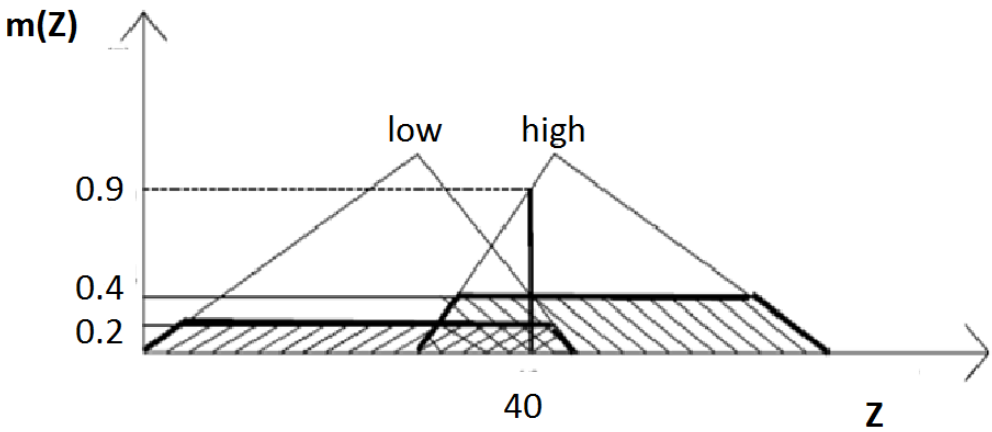


Fig.3.8 (c) Membership function for output variable Z

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.

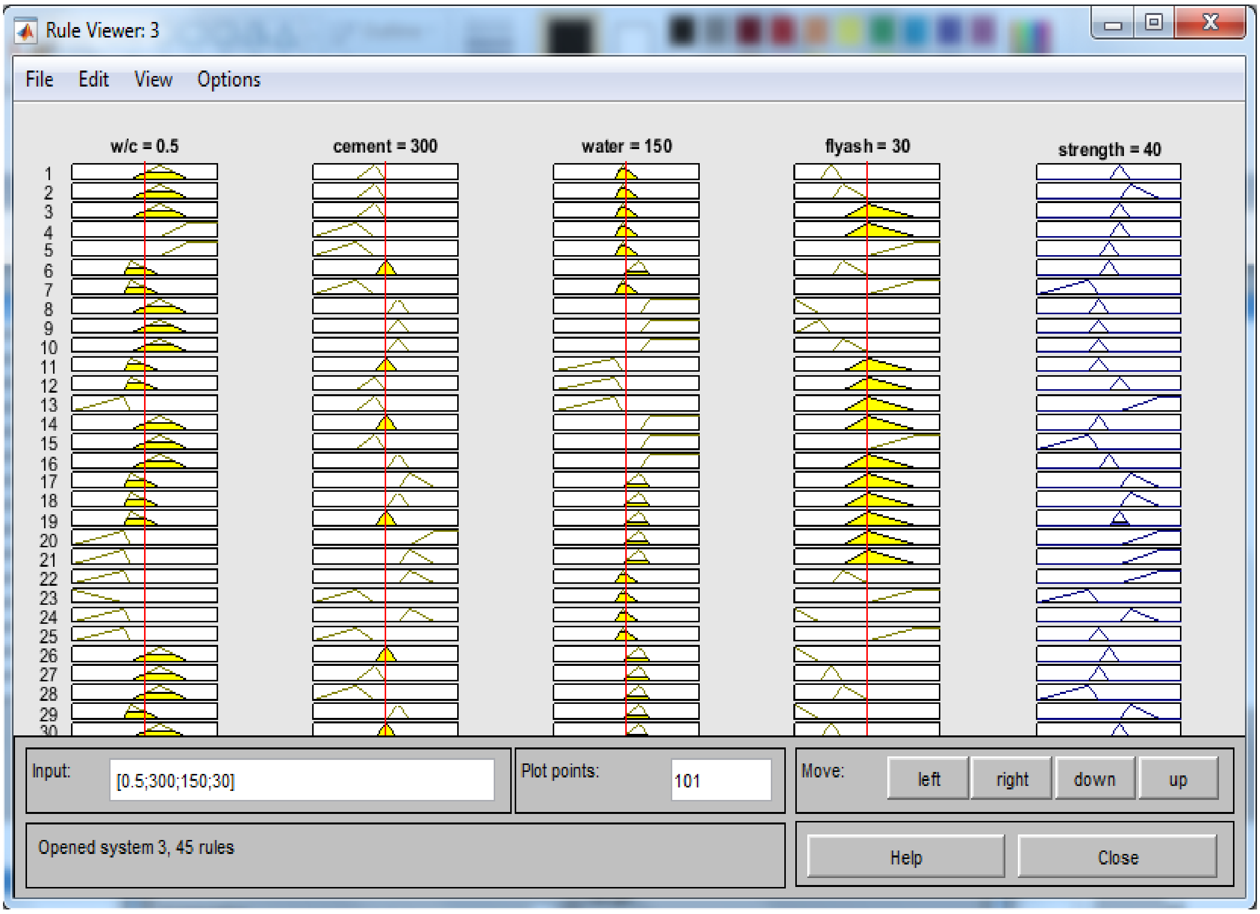


Fig.3.9 Rule Viewer Mode

3.2.3 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.3.8 (a) X = 20 is a part on high and low subsets with 0.2 and 0.8 membership degree respectively. Likewise, In Fig.3.8 (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.3.8 (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.3.8(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.

3.2.4 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 Rightmost maximum (RM).

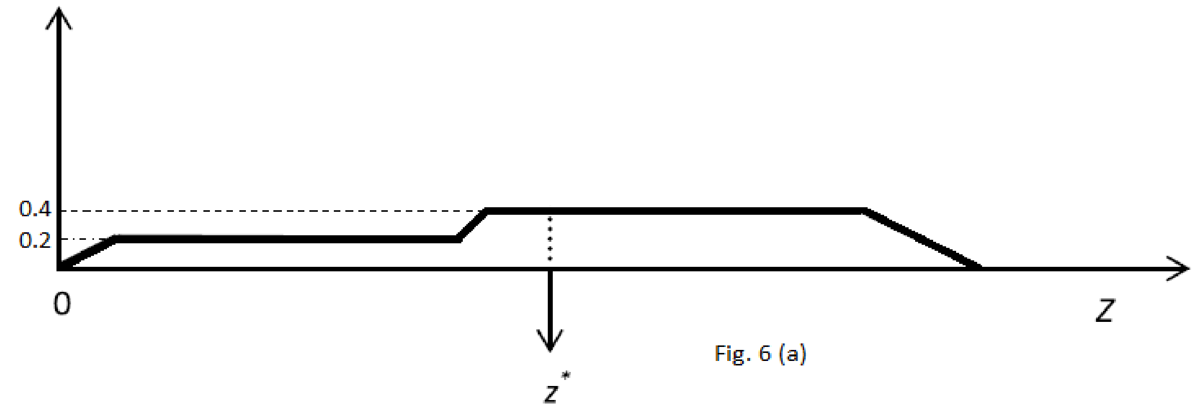


Fig.3.10 (a) Defuzzication method 1

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. 3.10 (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.

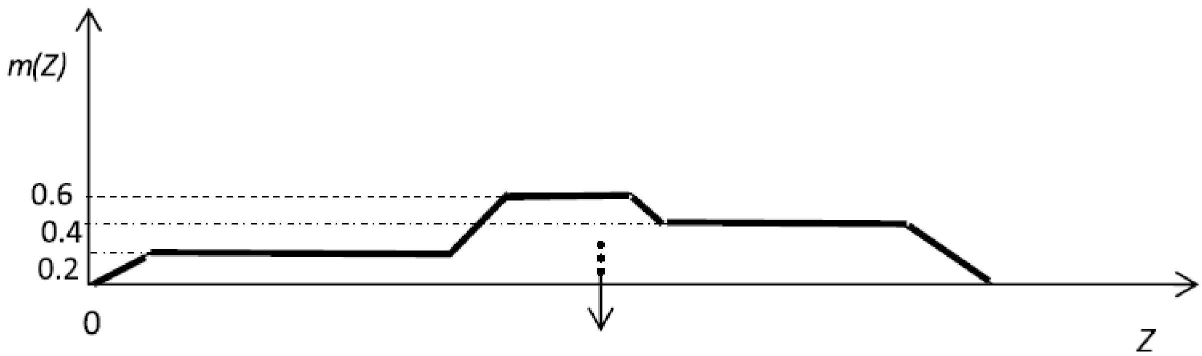


Fig.3.10 (b) Defuzzification method 2

In Fig. 3.10 (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.

3.3 Materials Used:

Following materials are used in preparation of concrete mixes:

- Cement (OPC of 43 grade)
- Water
- Flyash
- Fine aggregate
- Coarse aggregate

Fig 3.11 (a) Cement used in study

Fig 3.11 (b) Fine Aggregate

In the present study, total 6 mixes are prepared with varying percentage of flyash. Cement is partially replaced with 0%, 10% and 20% flyash by weight. Mix design is done to prepare concrete cubes of M40 and M45 characteristic strength.

3.4 Experimental Program:

- For compressive strength cubes of 15cm X 15cm X 15cm
- This 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.

3.5 Mix design Calculation:

3.5.1. For M40 grade concrete

- Grade= f_{ck}= M40
- Target Mean Strength = f_{target} = f_{ck} + 1.65 x S
  = 40 + 1.65 x 5
  = 48.25 MPa
- Assume w/c ratio = 0.45 (From Table 5 of IS456)
- Assume Cement Content = 350 kg/m^3
- Water Content = 0.45×350
  =158 kg

  (which is less than maximum water content for 20mm aggregate = 180 Kg)

Now,

$$V = \frac{[w + \frac{C}{S_C} + \frac{1}{p}(\frac{fa}{S_{fa}})]}{1000}$$

$$c_a = (\frac{1-p}{p}) * f_a * (\frac{S_{ca}}{S_{fa}})$$

Where,

- V = absolute volume of fresh concrete, which is equal to gross volume (m^3) minus the volume of entrapped air,
- w = mass of water (kg) per m^3 of concrete,
- c = mass of cement (kg) per m^3 of concrete,
- S_c = specific gravity of cement (assumed 3.15),
- p = ratio of fine aggregate to total aggregate by absolute volume,

- f_a, c_a = total mass of fine aggregate and coarse aggregate (kg) per m^3 of concrete respectively,
- S_{fa}, S_{ca} = specific gravities of saturated surface dry fine aggregate and coarse aggregate respectively.

For 20mm maximum size entrapped air is 2%.

Assume f.a. by % of volume of total aggregate = 36.5%

Putting these values in above formula

$$0.98 = \frac{[158 + (\frac{350}{3.15}) + (\frac{1}{0.365})(\frac{fa}{2.61})]}{1000}$$

f_a = 660 kg

c_a = 1168 kg

Considering 20 mm: 10mm = 0.6: 0.4

Using,

20mm aggregate = 701 kg

10mm aggregate = 467 kg

Admixture = 0.6% of cement weight = 2.4 Kg

3.5.2. For M45 grade concrete

- Grade = f_{ck} = M45
- Target Mean Strength = f_{target} = f_{ck}+ 1.65 x S
  =45 + (5×1.65) = 53.25 MPa
- Assume w/c ratio = 0.4 (From Table 5 of IS456)
- Assume cement content= 400 kg/m^3
- Water content = 0.4×400= 160 kg (which is less than maximum water content for 20mm aggregate = 180 Kg)

Now,

For 20mm maximum size entrapped air is 2%.

Assume f.a. by % of volume of total aggregate = 36.5%

$$0.98 = \frac{[160 + (\frac{400}{3.15}) + (\frac{1}{0.365})(\frac{fa}{2.61})]}{1000}$$

f_a = 668 kg

c_a = 1180 kg

Considering 20 mm: 10mm = 0.6: 0.4

Using,

20mm aggregate = 708 kg

10mm aggregate = 472 kg.

Admixture = 0.6% of cement weight = 2.4 Kg

Concrete cube specimens of size 150mm×150mm×150mm were prepared. The concrete was left in the mould and allowed to set for 24 hours before the specimens were remoulded and placed in curing tank. All samples were cured in curing tank for 28 days. Then 28^{th} day compressive strength was measured from failure load obtained in compression testing machine.

3.6 Laboratory Work

Fig. 3.12 (a) Concrete cube after curing

Fig. 3.12 (b) Placing of concrete in mould of size 150mm X 150mm X 150mm

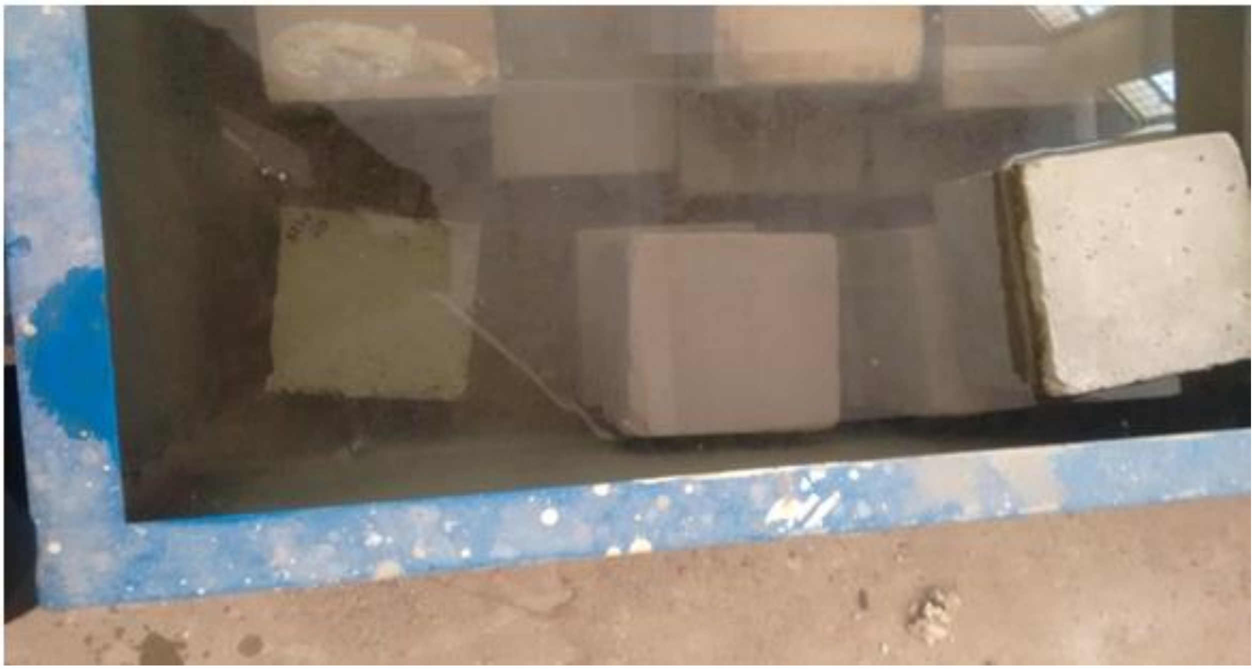


Fig. 3.12 (c) Concrete cube placed inside curing tank for 28 days

Fig. 3.12 (d) Concrete cube after 28 days curing

Fig. 3.12 (e) Concrete Cube in CTM for testing

Fig. 3.12 (f) Concrete cubes after testing

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

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.

4.2 Experimental Results:

S.No	w/b	Cement (Kg/mm^3)	Flyash %	Water (Kg/mm^3)	Coarse Aggregate (Kg/mm^3)	Fine Aggregate (Kg/mm^3)	Admixture (Kg/mm^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

Table 4.1 Different Mix proportions with different fly ash percentage

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

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

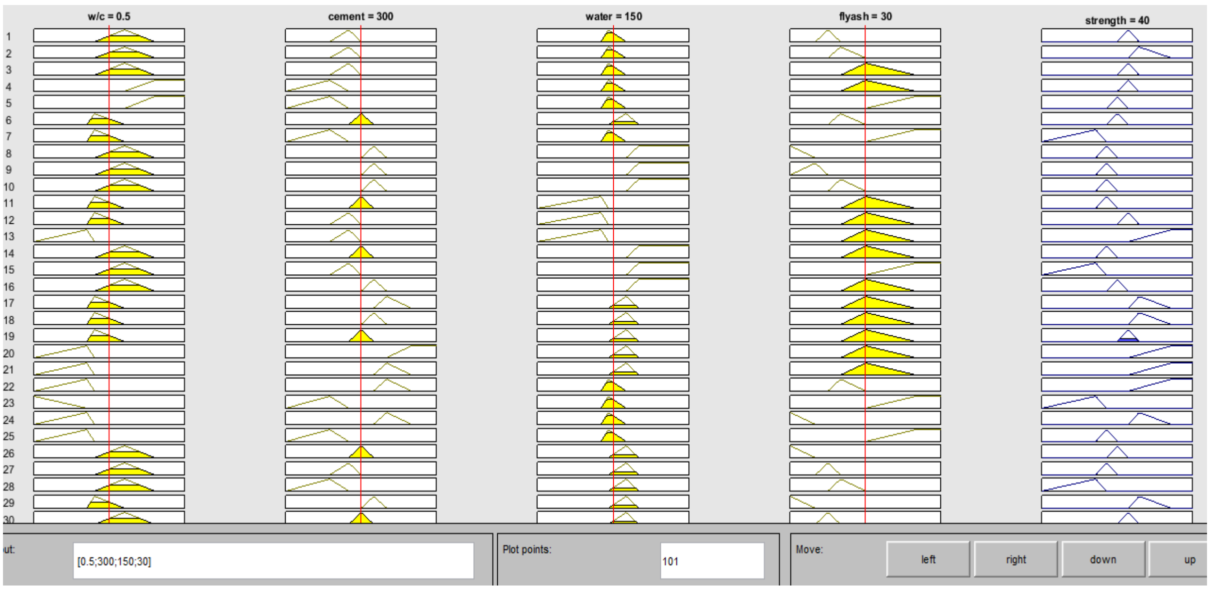
Table 4.2 Experimental Compressive strength of different mixes

4.3 Fuzzy logic Model outputs

MODEL 1

Predicted strength is directly observed when we enter input data ie w/b, cement, flyash, water

Water/binder **Cement Content** **Water** **Flyash** **Strength**



Here we enter our input values like [w/b, cement, water, flyash]

Output obtained after training fuzzy logic models of different mixes are as follows:

Mix No	Predicted Strength (MPa) From Model 1
Mix 1	48.9
Mix 2	35
Mix 3	39
Mix 4	48.8
Mix 5	35
Mix 6	40

Table 4.3 Output of model for different mixes

For Mix 1 Output will be

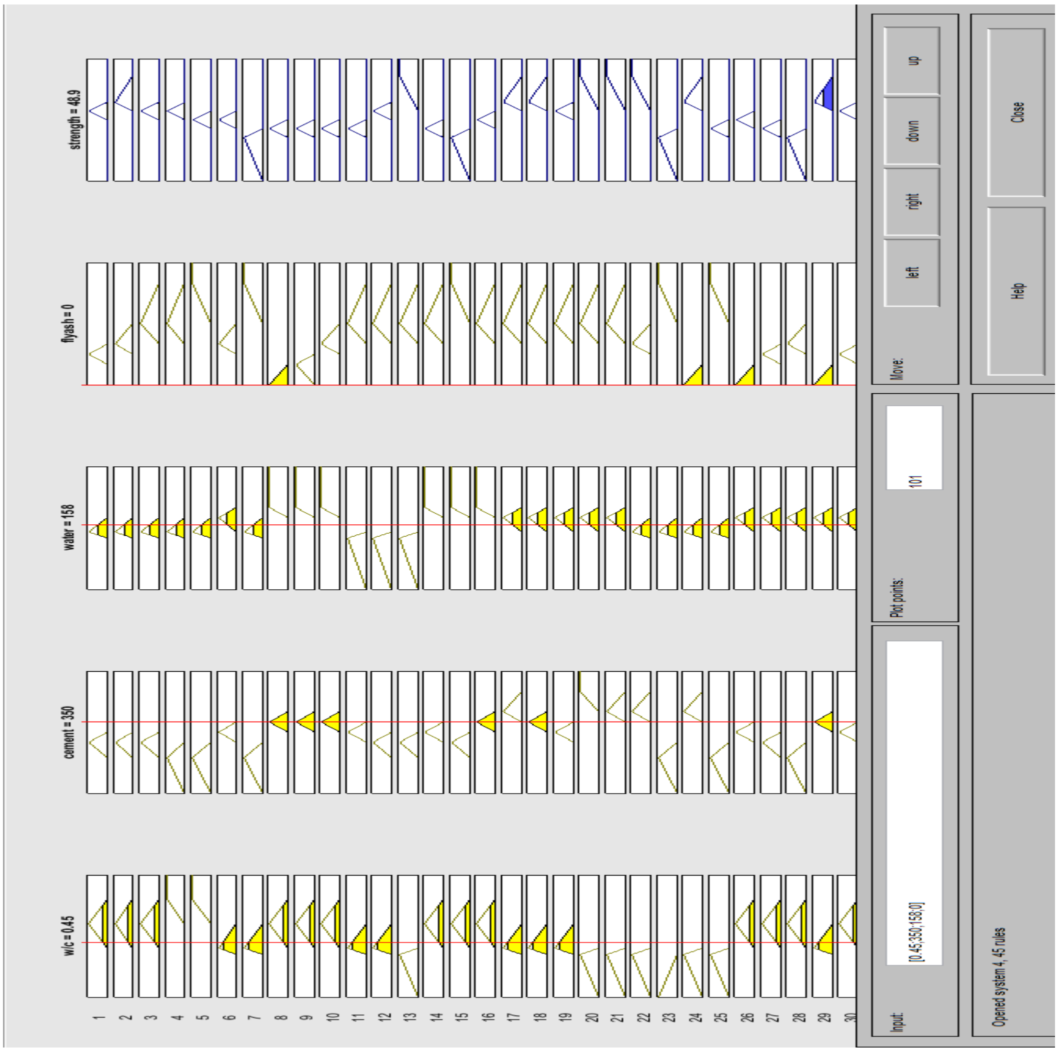


Fig. 4.1 Output of Mix 1 using Triangular Fuzzy Model

For Mix 6 Output will be

Fig. 4.2 Output of Mix 6 using Triangular Fuzzy Model

Comparing the results of experimental strength and fuzzy predicted strength, the percentage variation on an average is 10%.

Mix No.	Experimental Strength (MPa)	Predicted Strength(MPa) Model 1	Percentage Variation (%)
Mix 1	43.7	48.9	11.89
Mix 2	37.7	35	-7.16
Mix 3	34	39	14.70
Mix 4	46.5	48.8	4.94
Mix 5	41.2	35	-15.04
Mix 6	37.9	40	5.54

Table 4.4 Comparison of experimental and predicted strength

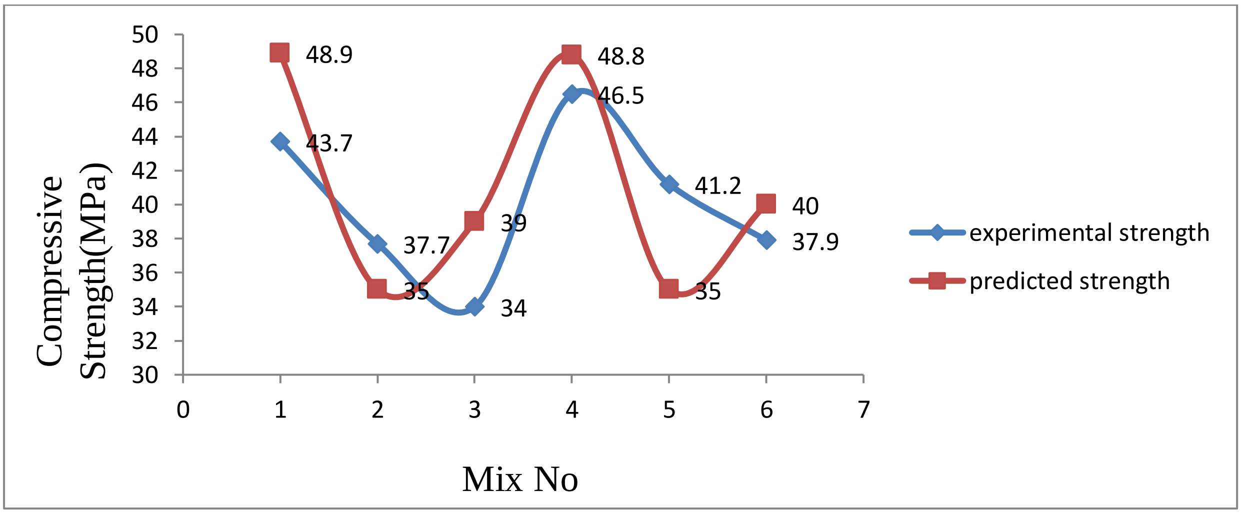


Fig 4.3 Experimental & Predicted Strength from Model 1

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

4.4 Effect of Variation of subset range on Output

In this part we discuss the change in output of fuzzy with respect to change in subset range of membership function of any input and output variables. To illustrate this we need to build two different models with different range of subsets and different set of rules. Models are trained and tested and comparison of both is done later on.

MODEL 2

In this model subset range of different variables is increased. So, number of memberships function decreases.

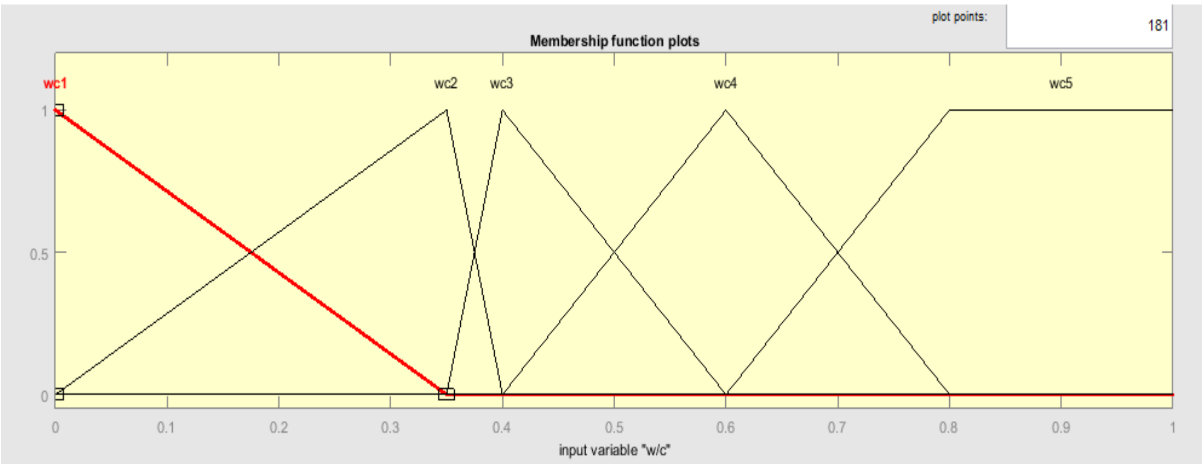


Fig.4.4 (a) Model 1 membership function (previous)

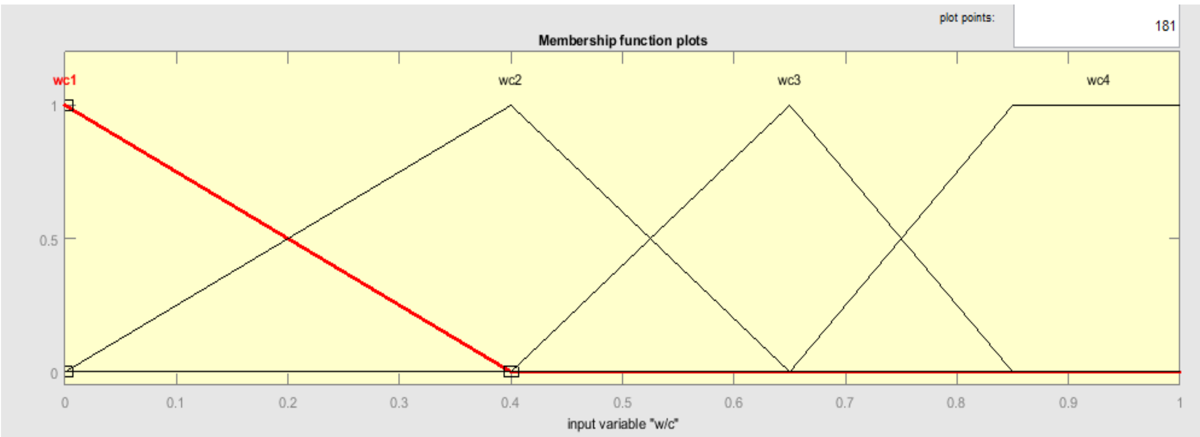


Fig.4.4 (b) Model 2 membership function

We can clearly see that membership functions are decreased from 5 to 4. Similarly, other variables are also analysed in this way. In this case number of rules are also decreased as some of them coincide with each other.

Results of Model 2 are discussed below:

Mix No	Predicted Strength (MPa) from Model 2
Mix 1	53.5
Mix 2	36.6
Mix 3	43.8
Mix 4	53.4
Mix 5	56.5
Mix 6	46.2

Table 4.5 Predicted strength from model 2

Comparison of Model 1 and Model 2(with increased subset range)

Mix No	Predicted Strength (MPa) from **Model 1**	Predicted strength (MPa) From **Model 2**	Experimental Strength (MPa)
Mix 1	48.9	53.5	43.7
Mix 2	35	36.6	37.7
Mix 3	39	43.8	34
Mix 4	48.8	53.4	46.5
Mix 5	35	56.5	41.2
Mix 6	40	46.2	37.9

Table 4.6 Comparison of Model 1, Model 2 and Experimental Strength

Predicted strength(MPa) From **Model 2**	Experimental Strength (MPa)	**Percentage Variation (%)**
53.5	43.7	-22.43
36.6	37.7	2.92
43.8	34	-28.82
53.4	46.5	-14.84
56.5	41.2	-37.14
46.2	37.9	-21.90

Table 4.7 Percentage variation in strength values for Model 2 and experiment

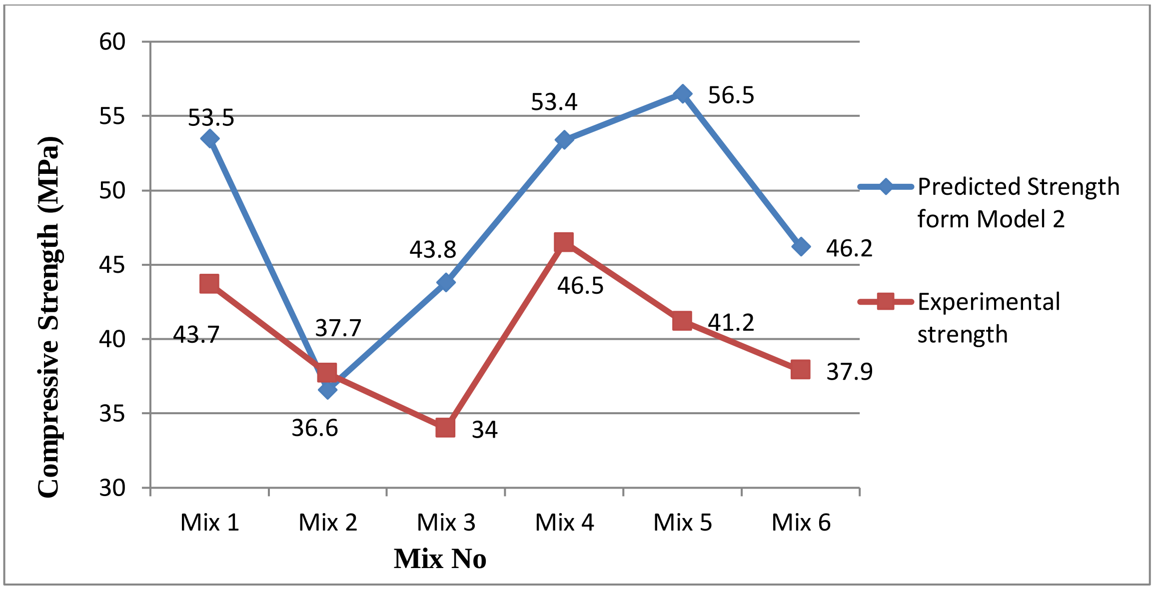


Fig 4.5 Comparison of output of Model 2 and Experimental Strength

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.

MODEL 3

In this model subset range of different variables is decreased. So, number of memberships function increases.

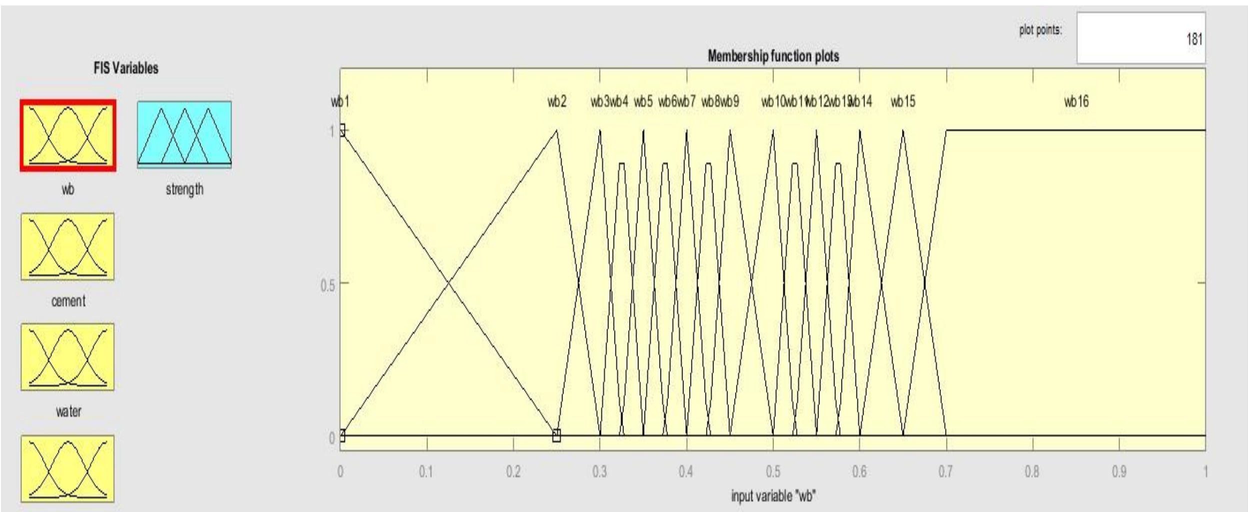


Fig 4.6 Model 3 membership function (with decreased range)

We can clearly see that membership functions are increased 16. In this case number of rules has also increased because of increase in uncertainly to some extent.

Results of Model 3 are discussed below:

Mix No	Predicted Strength (MPa) from Model 3
Mix 1	42.5
Mix 2	37.5
Mix 3	35
Mix 4	47.5
Mix 5	40
Mix 6	40.5

Table 4.8 Predicted strength from model 3

Comparison of Model 1 and Model 3(with increased subset range)

Mix No	Predicted Strength (MPa) from **Model 1**	Predicted strength (MPa) From **Model 3**	Experimental Strength (MPa)
Mix 1	48.9	42.5	43.7
Mix 2	35	37.5	37.7
Mix 3	39	35	34
Mix 4	48.8	47.5	46.5
Mix 5	35	40	41.2
Mix 6	40	40.5	37.9

Table 4.9 Comparison of output of Model 1, Model 3 and Experimental Strength

Predicted strength(MPa) From Model 3	Experimental Strength (MPa)	**Percentage Variation (%)**
42.5	43.7	2.75
37.5	37.7	0.53
35	34	-2.94
47.5	46.5	-2.15
40	41.2	2.91
40.5	37.9	-6.86

Table 4.10 Percentage variation in strength values

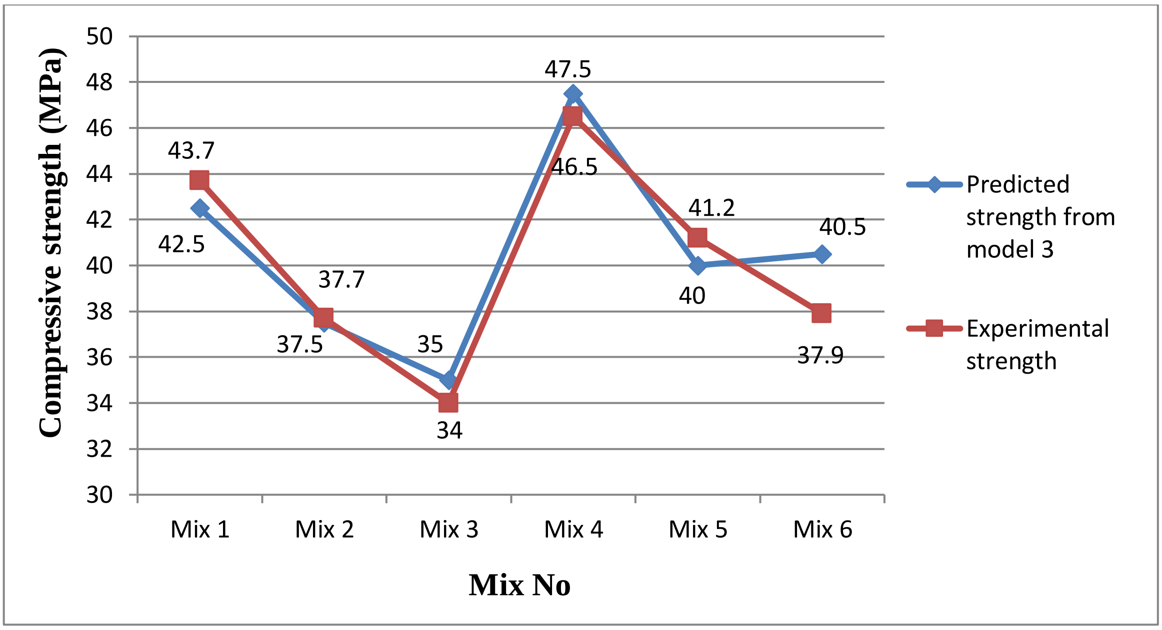


Fig. 4.7 Comparison of output of Model 3 and experimental strength

From Table 4.9 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.

4.5 Fuzzy logic Model Using Gaussian Membership Function:

MODEL 4

Now, we have used Gaussian membership function instead of triangular membership function to see whether there will be any change in the output values or not. Output of this model shows better result than the previous one.

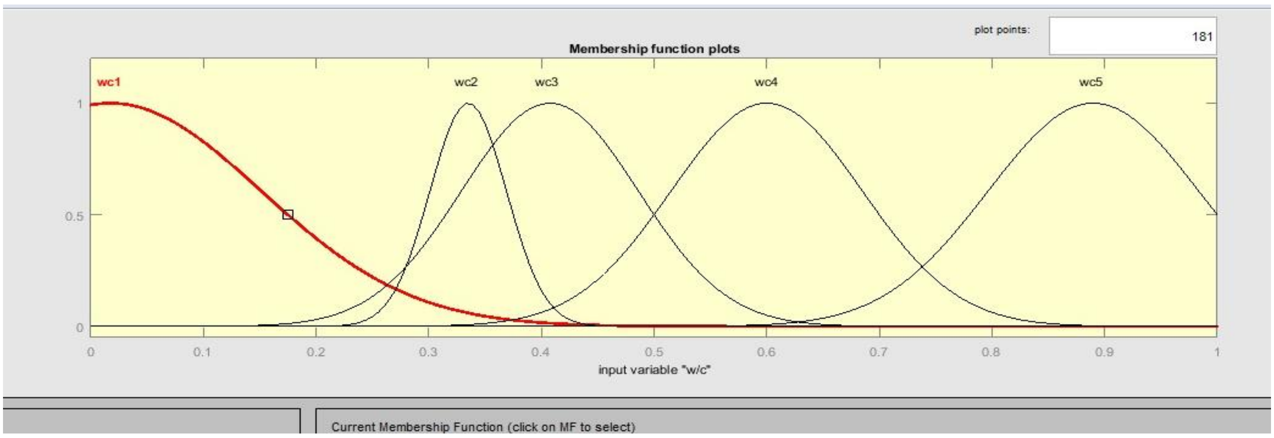


Fig 4.8 Gaussian membership function for water/binder ratio

Output of this model:

Mix	Predicted Strength (MPa)
Mix 1	45.5
Mix 2	41.1
Mix 3	38.8
Mix 4	45
Mix 5	44.2
Mix 6	41

Table 4.11 Output of Gaussian Fuzzy Model

Comparison of models Model 1 and Model 4

Mix No	Predicted strength (MPa) From **Model 1**	Predicted Strength (MPa) From **Model 4**	Experimental Strength (MPa)
Mix 1	48.9	45.5	43.7
Mix 2	35	41.1	37.7
Mix 3	39	38.8	34
Mix 4	48.8	45	46.5
Mix 5	35	44.2	41.2
Mix 6	40	41	37.9

Table 4.12 Comparison of Gaussian and Triangulated Fuzzy model predicted strengths

Above Table Shows that Gaussian MF model predicted values are better than values of triangular MF model. So we can say that Gaussian Fuzzy model can be used in place of triangular fuzzy model for better output.

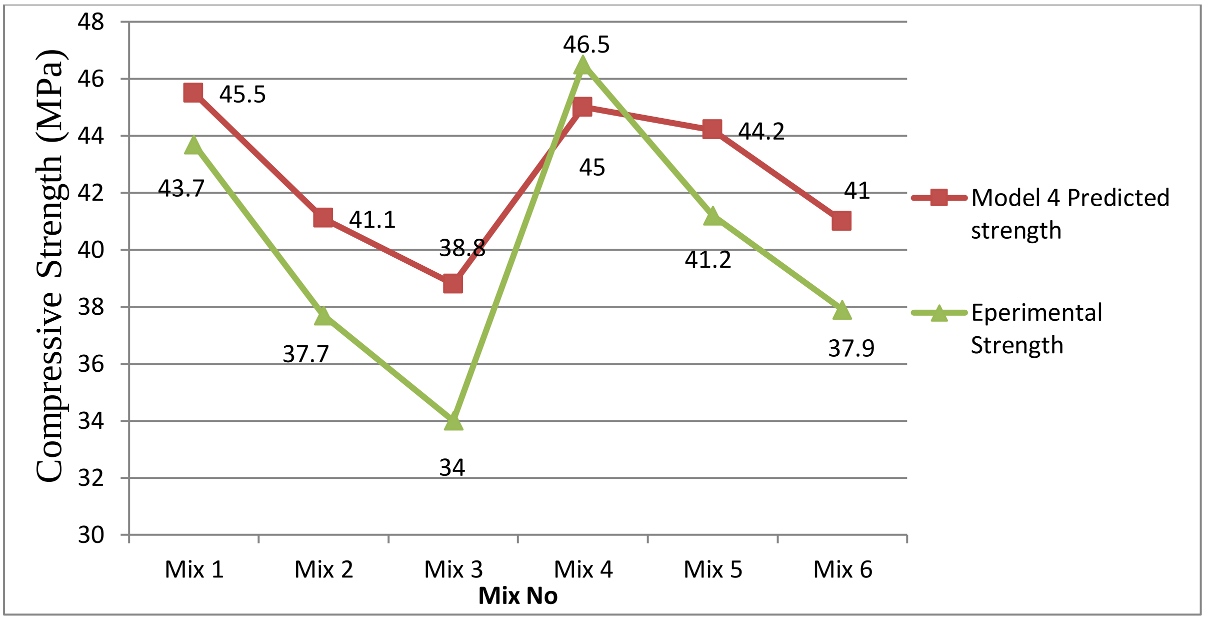


Fig. 4.9 Comparison of output of Model 4 and Experimental strength

Predicted Strength (MPa) From **Model 4**	Experimental Strength (MPa)	Percentage Variation (%)
45.5	43.7	-4.11
41.1	37.7	-9.02
38.8	34	-14.12
45	46.5	3.22
44.2	41.2	-7.28
41	37.9	-8.18

Table 4.13 Variation of experimental strengths and Output of Model 4

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.

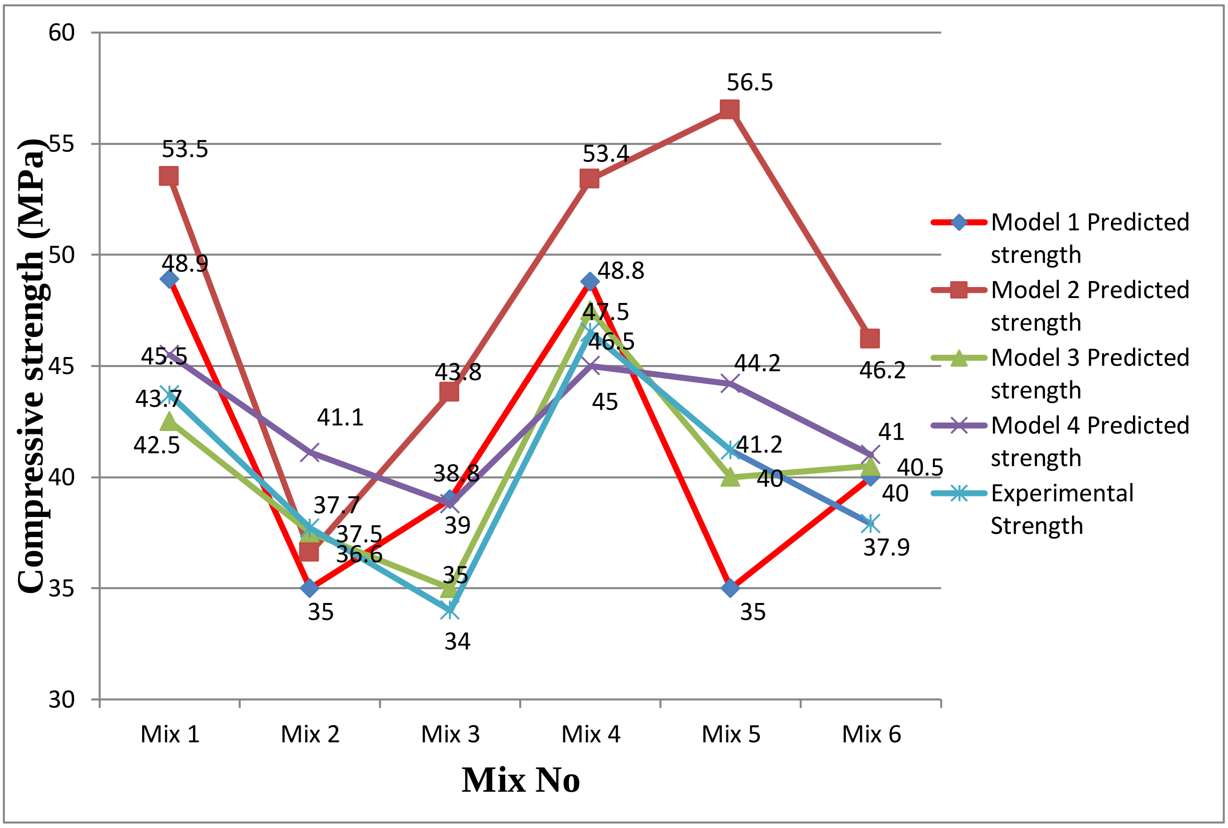


Fig. 4.10 Comparison of output of Model 1, 2, 3 and 4 and Experimental strength

In case of Model 2 variation is maximum and in Model 3 it is minimum. Among Model 1 and model 4 results are almost similar. But, Model 1 is easy to train as model 4 is complex and difficult to train. So if we compare all the models, model 3 gives better results.

CHAPTER5

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.

REFERENCES

[1] Sedat Akkurta, Gokmen Tayfurb, Sever Can, fuzzy logic model for the prediction of cement compressive strength, Cement and Concrete Research 34 (2004) 1429–1433.

[2] Gökmen Tayfur, Tahir Kemal Erdem, and Önder Kırca, Strength Prediction of High-Strength Concrete by Fuzzy Logic and Artificial Neural Networks, 2014 American Society of Civil Engineers, DOI: 10.1061/(ASCE) MT.1943-5533.0000985.

[3] Bahador Abolpour , Benafsheh Abolpour , Roozbeh Abolpour , Hossein Bakhshi, Estimation of concrete compressive strength by a fuzzy logic model, Res Chem Intermed (2013) 39:707–719 DOI 10.1007/s11164-012-0591-0

[4] Syed Afzal Basha, P.Pavithra, B.Sudharshan Reddy, Compressive Strength of Fly Ash Based Cement Concrete, International Journal of Innovations in Engineering and Technology Volume 4 Issue 4 December 2014 , ISSN: 2319 – 1058.

[5] Sumathy Raju, Brindha Dharmar, Mechanical Properties of Concrete with Copper Slag and Fly Ash by DT and NDT, 60(3), pp. 313–322, 2016 DOI: 10.3311/PPci.7904 Creative Commons Attribution.

[6] Hong-zhu Quan and Hideo Kasami, Experimental Study on Durability Improvement of Fly Ash Concrete with Durability Improving Admixture, The Scientific World Journal, Volume 2014 (2014), Article ID 818103,

[7] Jino John, M. Ashok , Strength study on high volume fly ash concrete , International Journal of Advanced Structures and Geotechnical Engineering ISSN 2319-5347, Vol. 03, No. 02, April 2014.

[8] Paratibha Aggarwal, Yogesh Aggarwal, Prediction of Compressive Strength of Self-Compacting Concrete with Fuzzy Logic, International Scholarly and Scientific Research & Innovation 5(5) 2011, scholar.waset.org/1999.7/3539, Vol:5, No:5, 2011.

[9] Nasir B. Siraj, Aminah Robinson Fayek, and Abraham A. Tsehayae, Development and Optimization of Artificial Intelligence-Based Concrete Compressive Strength Predictive Models , International Journal of Structural and Civil Engineering Research Vol. 5, No. 3, August 2016.

[10] C. Bas¸yigit, Waskender Akkurt ,S. Kilincarslan,A. Beycioglu, Prediction of compressive strength of heavyweight concrete by ANN and FL models, Neural Comput & Applic,DOI 10.1007/s00521-009-0292-9.

[11] Nataraja, A Fuzzy-Neuro Model for Normal Concrete Mix Design, Engineering Letters, 13:2, EL_13_2_8 (Advance online publication: 4 August 2006)

[12] Papadakis ,Physicochemical processes and mathematical modelling of concrete chlorination, DOI: 10.1016/0009-2509(95)00318-5.

[13] Tesfamariam and Najjaran, Adaptive Network–Fuzzy Inferencing to Estimate Concrete Using Mix Design, https://doi.org/10.1061/(ASCE)0899-1561(2007)19:7(550),Journal of Materials in Civil Engineering, Vol. 19, Issue 7 (July 2007)

[14] Bilgehan, A comparative study for the concrete compressive strength estimation using neural network and neuro-fuzzy modelling approaches, Pages 35-55 | Accepted 01 Mar 2010, Published online: 27 Apr 2010, http://dx.doi.org/10.1080/10589751003770100

[15] Nehdi and Bassuoni, Fuzzy logic approach for estimating durability of concrete, https://doi.org/10.1680/coma.2009.162.2.81,

[16] Tanyildizi and Qoskun, FUZZY LOGIC MODEL FOR PREDICTION OF COMPRESSIVE STRENGTH OF LIGHTWEIGHT CONCRETE MADE WITH SCORIA AGGREGATE AND FLY ASH, International Earthquake symposium kocaeli 2007, 22-26 October 2007

[17] Uyunoglu and Unal | A new approach to determination of compressive strength of fly ash concrete using fuzzy logic| Journal of scientific & Industrial Research | Vol.65, November 2006, pp 848-899

[18] Yang et al| Concrete strength evaluation based on fuzzy neural networks| DOI: 10.1109/ICMLC.2004.1380356| Machine Learning and Cybernetics, 2004. Proceedings of 2004 International Conference on, Volume:6

[19] M.C.Nataraja, M.A.Jayaram and C.N.Ravikumar | A Fuzzy-Neuro Model for Normal Concrete Mix Design| Engineering Letters, 13:2, EL_13_2_8 (Advance online publication: 4 August 2006)

[20] M. L. Nehdi and M. T. Bassuoni |A Fuzzy logic approach for estimating durability of concrete| Volume 162 Issue 2, May 2009, pp. 81-92.

[21] Song-Sen Yang and Jing Xu and Guang-Zhu Yao | A Comparative Study on ANFIS and Fuzzy Expert System Models for Concrete Mix Design| IJCSI International Journal of Computer Science Issues| Vol. 8, Issue 3, No. 2, May 2011 | ISSN (Online): 1694-0814

[21] IS CODE 10262: 2009

[22]Sarıdemir, M. (2009), predicting the compressive strength of mortars containing metakaolin by artificial neural networks and fuzzy logic.” Adv. Eng. Software, 40(9), 920–927.

[23]Şen, Z. (1998), Fuzzy algorithm for estimation of solar irradiation from sunshine duration, Sol. Energy, 63(1), 39–49.

[24]Şen, Z. (2016). Fuzzy logic and system models in water sciences, Turkish Water Foundation, İstanbul, Turkey,

[25]Sugeno, M. (2009). Industrial applications of fuzzy control, Elsevier Science, Amsterdam, The Netherland,.

[26]Tayfur, G. (2006). Fuzzy, ANN, and regression models to predict longitudinal dispersion coefficient in natural streams, Nordic Hydrology, 37(2), 143–164.

[27]Topçu, İ. B., and Sarıdemir,M. (2016). Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic, Comput. Mater. Sci., 41(3), 305–311.

APPENDIX

IT contains the tables having the data that were used to train the Fuzzy logic Model

Table A.1: Data collected from previous research works

		Quantities in kg/m³					
Researchers	w/b ratio	cement	flyash %	water	coarse aggregate	fine aggregate	compressive strength(in Mpa)
Nagabhushana	0.40	465.00	0.00	186.0	1069.00	707.00	26.00
	0.40	163.00	55.10	132.0	1277.00	653.00	18.00
	0.40	127.00	65.01	132.0	1270.00	649.00	17.00
	0.40	91.00	74.93	132.0	1259.00	644.00	16.00
	0.40	55.00	84.85	132.0	1252.00	640.00	13.00
Namagga & Atadero	0.50	249.48	14.99	147.0	774.28	573.79	39.30
	0.50	234.96	20.06	147.0	774.28	571.98	44.82
	0.50	220.45	25.00	147.0	774.28	569.71	42.06
	0.50	205.48	29.98	146.5	774.28	567.90	46.88
	0.50	190.96	35.03	146.5	774.28	566.08	44.13
	0.50	176.45	39.97	146.5	774.28	563.81	42.06
	0.50	161.48	44.98	146.5	774.28	562.00	40.68
	0.50	146.96	50.00	146.5	774.28	559.73	35.16
Myadaraboina et.al.	0.30	450.00	0.00	137.0	994.00	912.00	79.00
	0.30	225.00	50.00	141.0	994.00	835.00	71.00
	0.30	225.00	50.00	141.0	994.00	835.00	78.50
	0.30	225.00	50.00	139.0	994.00	811.00	66.50
Kalra & Kumar	0.46	398.00	0.00	183.0	1266.00	599.00	36.00
	0.46	298.50	25.00	183.0	1266.00	599.00	35.50
	0.46	238.80	40.00	183.0	1266.00	599.00	33.00
	0.46	199.00	50.00	183.0	1266.00	599.00	26.00
	0.46	159.20	59.97	183.0	1266.00	599.00	23.00
Bajad et.al.	0.50	371.33	0.00	185.7	1142.15	761.43	28.20
	0.50	367.38	9.93	203.9	1131.29	723.41	30.92
	0.50	326.40	19.97	203.9	1122.99	716.99	31.88
	0.50	261.22	31.92	191.8	1113.50	711.56	31.48
	0.50	371.33	0.00	185.7	1141.65	761.43	26.40
	0.50	371.33	0.00	185.7	1142.64	761.43	27.30
	0.50	371.33	0.00	185.7	799.46	761.43	24.90
	0.50	371.33	0.00	185.7	1141.66	761.43	22.10
	0.50	367.37	9.93	203.9	1131.29	723.41	30.10
	0.50	367.37	9.93	203.9	1130.83	723.41	28.80
	0.50	367.37	9.93	203.9	1130.84	723.41	26.70
	`0.50	367.37	9.93	203.9	1130.83	723.41	22.60
	0.50	328.39	19.88	204.9	1122.44	717.03	29.61
	0.50	328.39	19.88	204.9	1122.89	717.03	28.88

	0.50	328.39	19.88	204.9	1122.40	717.03	27.21
	0.50	328.39	19.88	204.9	1122.40	717.03	23.10
	0.50	285.91	29.99	204.2	1130.03	711.56	29.34
	0.50	285.91	29.99	204.2	1113.51	711.56	30.21
	0.50	285.91	29.99	204.2	1113.01	711.56	27.85
	0.50	285.91	29.99	204.2	1113.51	711.56	24.61
Naik & Ramme	0.45	284.86	0.00	128.4	819.64	579.69	32.92
	0.41	259.45	11.86	119.3	830.07	586.95	37.20
	0.38	251.29	17.68	114.8	851.39	602.37	47.09
	0.36	239.50	23.26	112.5	861.37	609.17	55.71
	0.34	222.71	28.74	107.5	854.57	604.18	58.16
	0.33	208.20	34.15	103.0	855.93	621.42	57.67
Raju & Dharmar	0.40	380.00	0.00	152.0	1293.00	596.00	43.20
	0.40	380.00	0.00	152.0	1293.00	520.00	44.23
	0.40	380.00	0.00	152.0	1293.00	390.00	46.34
	0.40	380.00	0.00	152.0	1293.00	260.00	44.81
	0.40	380.00	0.00	152.0	1293.00	131.00	45.42
	0.40	380.00	0.00	152.0	1293.00	0.00	45.71
	0.40	342.00	10.00	152.0	1293.00	596.00	41.34
	0.40	342.00	10.00	152.0	1293.00	520.00	44.74
	0.40	342.00	10.00	152.0	1293.00	390.00	48.90
	0.40	342.00	10.00	152.0	1293.00	260.00	44.45
	0.40	342.00	10.00	152.0	1293.00	131.00	41.90
	0.40	342.00	10.00	152.0	1293.00	0.00	48.90
	0.40	304.00	20.00	152.0	1293.00	596.00	38.51
	0.40	304.00	20.00	152.0	1293.00	520.00	37.93
	0.40	304.00	20.00	152.0	1293.00	390.00	39.11
	0.40	304.00	20.00	152.0	1293.00	260.00	42.96
	0.40	304.00	20.00	152.0	1293.00	131.00	52.01
	0.40	304.00	20.00	152.0	1293.00	0.00	45.48
	0.40	266.00	30.00	152.0	1293.00	596.00	36.53
	0.40	266.00	30.00	152.0	1293.00	520.00	38.22
	0.40	266.00	30.00	152.0	1293.00	390.00	43.26
	0.40	266.00	30.00	152.0	1293.00	260.00	33.78
	0.40	266.00	30.00	152.0	1293.00	131.00	46.50
	0.40	266.00	30.00	152.0	1293.00	0.00	47.70
Solikin	0.30	225.00	50.00	141.0	994.00	835.00	70.90
	0.30	225.00	50.00	141.0	994.00	809.00	73.78
	0.30	225.00	50.00	139.0	994.00	785.00	52.97
	0.30	225.00	50.00	139.0	994.00	811.00	66.69
Han et.al.	0.60	330.00	0.00	198.0	963.00	788.00	32.90
	0.60	297.00	10.00	198.0	955.00	781.00	33.80
	0.60	264.00	20.00	198.0	947.00	775.00	28.00
	0.60	231.00	30.00	198.0	938.00	768.00	25.00
	0.55	350.00	0.00	193.0	962.00	787.00	36.10

	0.55	315.00	10.00	193.0	953.00	780.00	38.30
	0.55	280.00	20.00	193.0	945.00	773.00	33.80
	0.55	254.00	28.25	193.0	936.00	766.00	30.90
	0.40	420.00	0.00	168.0	1054.00	703.00	49.70
	0.40	378.00	10.00	168.0	1044.00	696.00	50.30
	0.40	336.00	20.00	168.0	1032.00	688.00	48.00
	0.40	294.00	30.00	168.0	1020.00	680.00	42.80
	0.35	480.00	0.00	168.0	1025.00	683.00	56.30
	0.35	432.00	10.00	168.0	1012.00	675.00	55.70
	0.35	384.00	20.00	168.0	999.00	666.00	56.00
	0.35	336.00	30.00	168.0	986.00	657.00	51.80
	0.32	520.00	0.00	166.0	1042.00	638.00	62.10
	0.32	468.00	10.00	166.0	1027.00	629.00	61.70
	0.32	416.00	20.00	166.0	1013.00	621.00	58.60
	0.32	364.00	30.00	166.0	998.00	612.00	44.20
	0.27	600.00	0.00	162.0	1056.00	569.00	71.80
	0.27	540.00	10.00	162.0	1039.00	560.00	67.70
	0.27	480.00	20.00	162.0	1022.00	550.00	65.00
	0.27	420.00	30.00	162.0	1005.00	541.00	51.90
Awanti & Harwalkar	0.35	440.00	0.00	154.0	1059.00	871.00	56.10
	0.35	220.00	50.00	154.0	1059.00	807.00	42.44
	0.35	198.00	55.00	154.0	1059.00	800.00	40.62
	0.35	176.00	60.00	154.0	1059.00	794.00	35.17
	0.35	155.00	64.77	154.0	1059.00	787.00	24.42
	0.30	440.00	0.00	132.0	1059.00	937.60	62.28
	0.30	220.00	50.00	132.0	1059.00	871.00	52.10
	0.30	198.00	55.00	132.0	1059.00	864.80	47.31
	0.30	176.00	60.00	132.0	1059.00	858.20	40.84
	0.30	155.00	64.77	132.0	1059.00	851.80	27.69
Mukherjee et.al.	0.35	400.00	0.00	140.0	1158.00	637.00	50.35
	0.35	240.00	40.00	140.0	1158.00	637.00	43.65
	0.35	200.00	50.00	140.0	1158.00	637.00	35.31
	0.35	160.00	60.00	140.0	1158.00	637.00	31.40
	0.35	120.00	70.00	140.0	1158.00	637.00	23.67
	0.35	240.00	40.00	140.0	1158.00	637.00	31.72
	0.35	200.00	50.00	140.0	1158.00	637.00	29.42
	0.35	160.00	60.00	140.0	1158.00	637.00	27.99
	0.35	120.00	70.00	140.0	1158.00	637.00	24.72
Quan and Kasami	0.60	303.00	0.00	182.0	1014.00	856.00	35.50
	0.60	283.00	0.00	170.0	1014.00	813.00	36.10
	0.60	235.00	15.16	166.0	1014.00	880.00	29.20
	0.60	235.00	15.16	166.0	1014.00	815.00	27.70
	0.60	205.00	24.91	164.0	1014.00	879.00	20.40
	0.60	209.00	25.09	167.0	1014.00	801.00	22.60
	0.50	364.00	0.00	182.0	1014.00	806.00	47.50

	0.50	368.00	0.00	174.0	1014.00	814.00	46.40
	0.50	340.00	0.00	170.0	1014.00	766.00	45.50
	0.50	296.00	14.94	174.0	1014.00	823.00	43.20
	0.50	282.00	15.06	166.0	1014.00	831.00	38.30
	0.50	282.00	15.06	166.0	1014.00	766.00	36.50
	0.50	258.00	25.00	172.0	1014.00	820.00	34.50
	0.50	246.00	25.00	164.0	1014.00	829.00	33.80
	0.50	251.00	25.07	167.0	1014.00	751.00	31.30
	0.43	440.00	0.00	189.0	1014.00	726.00	57.80
	0.43	414.00	0.00	178.0	1014.00	684.00	50.70
	0.43	342.00	14.93	173.0	1014.00	752.00	47.90
	0.43	348.00	14.91	176.0	1014.00	673.00	43.90
	0.43	298.00	24.94	171.0	1014.00	748.00	42.60
	0.43	309.00	25.00	177.0	1014.00	655.00	37.60
Singh	0.47	360.00	0.00	170.0	1140.00	700.00	33.30
	0.31	220.00	50.00	138.0	1112.00	681.00	30.00
	0.36	190.00	50.00	136.0	1150.00	705.00	32.70
Sarika et.al.	0.55	213.00	33.44	178.0	1134.00	718.00	35.15
	0.53	223.00	33.43	178.0	1138.00	706.00	37.38
	0.50	237.00	33.43	178.0	1140.00	693.00	39.39
	0.48	246.00	33.51	178.0	1154.00	672.00	42.55
	0.46	258.00	33.33	178.0	1165.00	651.00	44.13
	0.44	270.00	33.17	178.0	1178.00	630.00	46.91
	0.42	283.00	33.41	178.0	1190.00	609.00	48.87
	0.40	296.00	33.48	178.0	1200.00	588.00	55.80
	0.38	313.00	33.40	178.0	1209.00	566.00	61.17
	0.36	330.00	33.33	178.0	1207.00	553.00	62.66
	0.34	350.00	33.21	178.0	1205.00	539.00	64.18
	0.32	370.00	33.45	178.0	1202.00	525.00	66.40
	0.30	396.00	33.33	178.0	1196.00	511.00	68.19
	0.27	440.00	33.33	178.0	1178.00	491.00	70.66
John & Ashok	0.38	416.00	0.00	158.0	1242.00	668.00	36.13
	0.34	229.00	50.00	158.0	1184.00	610.00	30.71
	0.34	183.00	60.04	158.0	1170.00	602.00	31.00
	0.34	137.00	70.09	158.0	1158.00	596.00	29.30
Basha et.al.	0.46	219.08	99.79	771.1	605.09	605.09	44.82
	0.49	75.30	83.91	831.9	665.42	665.41	23.10
	0.35	113.40	89.81	831.9	566.99	566.99	37.92
	0.28	136.08	83.91	839.1	574.25	574.24	57.23
Naik & Ramme	0.66	192.78	0.00	127.5	821.00	730.28	27.96
	0.62	154.67	22.68	123.8	821.00	730.28	30.61
	0.60	136.08	33.33	123.4	821.00	730.28	33.02
	0.57	115.67	44.92	118.8	821.00	730.28	34.50
	0.55	95.25	55.32	117.0	821.00	730.28	31.41
	0.52	77.56	64.45	112.9	821.00	730.28	23.41

0.57	234.51	0.00	134.7	821.00	694.00	31.80
0.53	187.79	23.19	128.8	821.00	694.00	35.18
0.49	165.11	34.30	123.8	821.00	694.00	37.72
0.49	140.61	44.74	124.3	821.00	694.00	40.27
0.48	117.48	54.48	123.4	821.00	694.00	39.64
0.41	94.80	64.21	109.8	821.00	694.00	33.49