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Prediction of Early Strength of Concrete: A Fuzzy Inference System Model

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The strength development in concrete with its age is essentially a constant volume solidification process, which is controlled by multivarious parameters. However, the concrete mixes are designed for 28 day's target compressive strength. In a more general characterization, it can be said that increase in strength of concrete is achieved by decrease in water cement ratio and decrease in aggregate cement ratio. However, it is impossible to develop a precise mathematical model that can predict crisp numerical values of strength that correspond to crisp values of w/c ratio and a/c ratio. This is due to uncertainties involved in these parameters, the uncertain behavior of constituent materials, and tolerances. The potential of fuzzy logic in developing a model for characterization by approximate reasoning really lies here. This paper presents a modest attempt made to characterize 28 day's strength of concrete using Fuzzy Inference System (FIS). The methodology consists of two steps; (1) developing the basic model using generalized Abram's law and (2) validating the basic model, using the experimental data. The water-cement ratio and aggregate-cement ratio are treated as antecedents and 28 day's strength is the consequent. The results have shown that, the fuzzy inference system provides a prudent way to capture uncertainty (non-statistical) in relationships among parameters that control the early strength of concrete.

Key words: Early strength of concrete, water-cement ratio, aggregate-cement ratio, fuzzy inference system, antecedents, consequents, approximate reasoning.

INTRODUCTION

In the last decade, fuzzy set theory has been successfully applied in many different areas of engineering including automatic control, system identification, pattern recognition, design of structures, structural modeling and many more (Adam E. Gaweda, 2003) . The property that makes fuzzy set theory particularly interesting is its ability to handle the imprecision inherently present in a system. Fuzzy reasoning becomes a powerful tool for solving problems when human expert knowledge is available. Even more attractive is the idea of utilizing fuzzy set theory in data driven extraction of easy to understand rule-based models (Adam E. Gaweda, 2003). In a more general context, this concept is based on the fact that certain fuzzy systems possess the universal approximation property (Wang, 1992). For the most complex systems where a few numerical data exist and where only ambiguous and imprecise information may be available, fuzzy reasoning provides a way to understand system behavior by allowing us to interpolate approximately between observed input and output situations. The imprecision in fuzzy models is generally quite high (Ross, 1997). Numerous examples of fuzzy and neuro-fuzzy systems, capable of data-driven function approximation can be found in literature (Jang et all, 1997).

This paper presents a FIS based model to predict early strength of concrete by making use of available experimental results. The prediction is done at two stages. In the first stage fuzzy inference system is developed in two layers. In The first layer, one antecedent and one consequent are considered. The

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water-cement ratio is treated as the lone independent variable that can significantly govern the strength of concrete. In the second layer, water-cement ratio as well as aggregate-cement ratio has been considered as two fuzzy antecedents. In both the layers, the compressive strength of concrete is the consequent. In the second stage, the model is validated using the published experimental works of the first author. There have been quite a good number of applications of fuzzy logic in allied fields of civil engineering. Fuat Demir (2005) developed a fuzzy logic algorithm for estimating elastic modulus of concrete from its compressive strength using experimental data. The algorithm does not provide an equation but can adjust itself to any type of linear or non-linear form through fuzzy subsets of linguistic elastic modulus and compressive strength variables. The application of proposed fuzzy subsets and rule bases is straight forward for any elastic modulus and compressive strength.

Sedat Akkurt et al. (2004) have developed a fuzzy-neuro model for 28-day compressive strength of cement mortar under standard curing conditions. Data collected from a cement plant were used in the model construction and testing. The input variables of alkali, Blaine, SO3, and C3S and the output variable of 28-day cement strength were fuzzified by the use of artificial neural networks, 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 inference operator and the centre of gravity defuzzification methods were employed. The average percentage error levels in the fuzzy model were found to be low (2.69%). The results reported indicate that through the application of fuzzy logic algorithm, a more user friendly and more explicit model than the neural networks could be produced within successfully low error margins. G Fa-Liang (1997) has analyzed the fuzzy logic method of predicting cement strength. In order to compare, regression method has been used. Root mean square error has been considered for the comparison. It is shown that fuzzy logic method compares well with conventional regression method of prediction.

Fuzzy logic techniques were applied to simulate uncertainties involved in construction operations (Hong Zhang et al, 2003). A possible approach to the problem of predicting the durability of Ferro cement structures using fuzzy relations has been attempted (Adidam SR. Sai and Anuj Jain, 1993). An Indian standard (IS) design code anomaly pertaining to design criterion has been resolved using fuzzy logic criterion (Srinivas and Devdas Menon, 2000). A variety of applications of fuzzy models in civil engineering particularly in geotechnical engineering and construction management has presented (Thomas Fetz, 1999). In an interactive procedure to solve multicriteria optimization problems, fuzzy sets have been effectively used to qualitatively model the engineer's judgment on each objective function (Fulvio Tonon et al, 1999). The authors have developed a layered fuzzy inference system for design of normal concrete mixes (Nataraja et al, 2006). However, there seems to be paucity for predictive models involving fuzzy inferencing. This paper is an attempt in that direction. This paper presents the development of a model for the prediction of early compressive strength of concrete through an FIS.

Concrete is most widely used construction material in the world. Strength development in concrete during its early age, customarily during 28 day's of its placement depends on several parameters. However, it is a common opinion among researchers that, the compressive strength of concrete depends mainly on water cement ratio when all other factors are kept constant (Neville AM, 1981). Abrams' law proposed in 1918 was the beginning of a rational approach towards mix proportioning where water-cement ratio is taken as the governing parameter that controls the strength of concrete. As per Indian code (SP-23, 1982) some assumptions made in proportioning concrete mixes of medium strength are: a) the compressive strength of concrete is governed by its water-cement ratio; and b) for the given aggregate characteristics, the workability of concrete is governed by its water content. But, when all other constituents are kept the same and the cement is changed, the compressive strength also changes because the final concrete strength depends on the chemical composition and fineness of cement. A detailed examination of the implications of Abram's law and on the basis of experimental findings, Gilkey(1961) revised the law which stated that, the strength of concrete is influenced by, the ratio of cement to mixing water, the ratio of cement to aggregate, the grading, surface texture and stiffness of the aggregate and the maximum size of the aggregate.

FUZZY SET THEORY

Fuzzy theory is a method that facilitates uncertainty analysis of systems where uncertainty arises due to vagueness or fuzziness rather than due to randomness alone (Dubois and Prade, 1980). This is based on superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth–false values between completely true and completely false. It was introduced by Zadeh in 1965 as a means to model the uncertainty of natural language. Fuzzy theory uses the process of Fuzzification as a methodology to generalize any specific theory from a crisp (discrete) to a continuous (fuzzy) form.

Classical set theory has a crisp definition as to whether an element is a member of a set or not. However, certain attributes of systems cannot be ascribed to one set or another. For example, an attribute of a system can be

specified as either *low* or *high*. In such a case, uncertainty arises out of vagueness involved in the definition of that attribute. Classical set theory allows for either one or the other value. On the other hand, fuzzy set theory provides for a gradual degree of membership. This can be illustrated as follows:
In the classical set theory, the truth-value of a statement can be given by the membership function $\mu_A(x)$ (Eq. 1), as:

$$\mu_A(x) = \begin{cases} 1 \text{ iff } x \in A \\ 0 \text{ iff } x \notin A \end{cases} \quad (1)$$

On the other hand, fuzzy theory allows for a continuous value of μ_A(Eq. 2), between 0 and 1 as:

$$\mu_A(x) = \begin{cases} 1 \text{ iff } x \in A \\ 0 \text{ iff } x \notin A \\ p\ ;\ 0<p<1 \text{ if } x \text{ partially belongs to A} \end{cases} \quad (2)$$

In fuzzy theory, statements are described in terms of membership functions, that are continuous and have a range [0,1] (Dubois and Prade, 1980). For example, given the measured value of a parameter, the membership function gives the "degree of truth" that the member is *high* or *low*. Further, fuzzy logic is defined by the following set relationships as (Eq. 3):

$$\begin{aligned} \mu_{A'}(x) &= 1 - \mu_A(x) \\ \mu_{A \cup B}(x) &= \min(\mu_A(x), \mu_B(x)) \\ \mu_{A \cap B}(x) &= \max(\mu_A(x), \mu_B(x)) \end{aligned} \quad (3)$$

Using fuzzy arithmetic, based on grade of membership of a parameter of interest in a set, the grade of membership of a model output in another set can be calculated (Hellendoorn and Driankov, 1997). Fuzzy theory can be considered to be a generalization of the classical set theory.

FUZZY INFERENCE SYSTEMS

Fuzzy inference systems (FIS) are one of the most famous applications of fuzzy logic and fuzzy sets theory (Zadeh, 1967). The strength of FIS relies on their two-fold identity. On the one hand, they are able to handle linguistic concepts. On the other hand, they are universal approximators able to perform non-linear mappings between inputs and outputs (Serge Guillaume, 2001). Fuzzy rule based system incorporates the flexibility of human decision making by means of the use of fuzzy set theory. Fuzzy rules of the system make use of fuzzy linguistic terms described by membership functions (Ross, 1997; Bezdek, 1993). These functions are intended to represent a human expert's conception of the linguistic terms Fuzzy rules take the form IF (conditions) THEN (actions), where conditions and actions are linguistic labels applied to input and output variables respectively. In general, most of these specifications in codes and the functional requirements set by the users must be given in natural language to describe the expert's empirical knowledge of design modifications (Michio Sugeno and Takahiro Yasukawa, 1993). In a nutshell, the process can be divided into three stages (Ross, 1997). They are:

Fuzzification: Is a process of evaluation of input variables with respect to the corresponding linguistic terms in the condition side.
Fuzzy Inference: Is the process of calculating fuzzy output or the process of evaluating the activation strength of every rule and to combine their action sides.

Defuzzification: Is the process of calculating the actual output, i.e., to convert fuzzy output into a precise numerical value.
The important feature of a fuzzy model is input space partitioning. Three methods of partitioning are popular.

Grid partition: The number of fuzzy sets per input is fixed in advance by the designer, as are their locations. This type of partitioning was used in (Wang and Mende, 1992). Although very simple, it becomes useless for tasks of high dimensional inputs. It also covers regions where no input data occur.

Tree partition: The distribution of fuzzy sets can be determined by the corresponding decision tree algorithm (Jang et all, 1997). This approach eliminates the problem of rule explosion, but the rules may still cover irrelevant input regions and the membership functions may not bear a clear linguistic meaning.

Scatter partition: Covers only the subset of the input space where data exist. This allows the limiting the number of rules, as well as covering the appropriate regions of the input space (Jang et all, 1997).

THE FIS MODEL

The model is built on two steps each step is conveniently termed as fuzzy system layer. The first layer has single antecedent and the second layer has two antecedents. In the method introduced by Wang and Mendel (1992), the number of rules is limited by the number of training pairs.
The following procedure proposed by above researchers

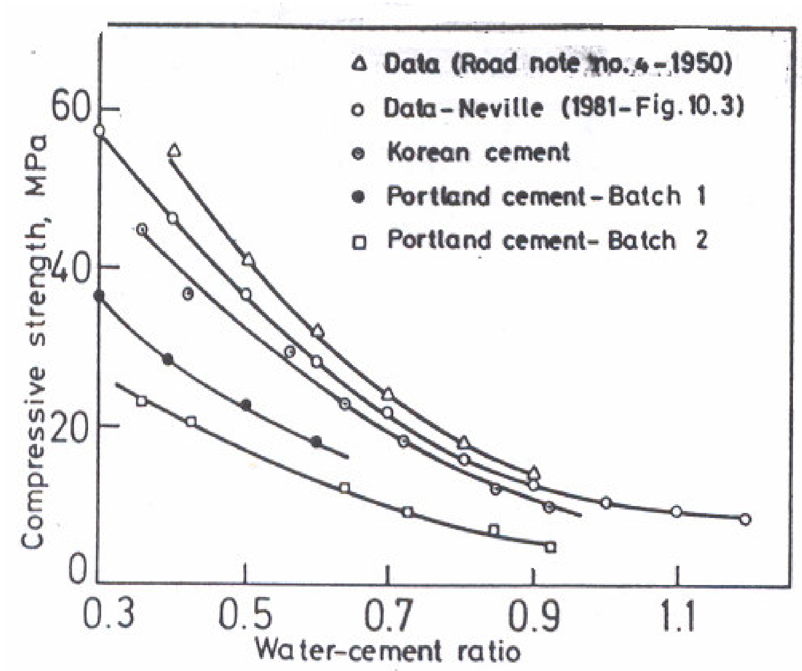

Figure 1. Relationship between water-cement ratio and Strength for different Cements (Nagaraj TS et all, 1993).

is used in both steps of the model.

Each variable of the input space is divided into number of π -shaped membership functions.

One rule is generated for each data pair, the ith pair one is written

If X_1 is A_1^i and x_2 is A_2^i …….and x_p^i is A_p^i the y is C^i

The fuzzy sets A_j^i are those for which the degree of match of x_j^i is maximum for each input variable j from pair i. The fuzzy set C_i is the one for which the degree of match of the observed output, y_i is maximum.

The output is computed through various methods of defuzzification.

The development of these two layers is elaborated in the following sections.

FIS layer-1

This layer is built on one-to-one fuzzy relation. Water-cement ratio is considered as the sole parameter that controls the strength of concrete. Figure 1 shows the water-cement-ratio-versus-compressive strength plots for different cements. Although, the figure follows a property that the strength reduces as the water –cement ratio increases; there are different curves for different cements, indicating the influence of cement type. In a bid to normalize these sets of curves attempts were made (T.S.Nagaraja, 1996) to define a normalization parameter. Compressive strength of concrete for a water cement ratio of 0.5 ($S_{0.5}$) was taken as the normalization parameter. It is a reference mark to reflect the synergy between different constituents of concrete. This theory is denoted as generalized Abram's law (T.S.Nagaraj et al, 1990). Though this theory is widely accepted in concrete technology, it is obvious that it is approximate and more general. Therefore when dealing with characterization of concrete with regard to its 28 day's strength, it would be more appropriate to model with fuzzy implications such as " Low water cement ratio then, high strength"," moderate water cement ratio then, moderate strength" than crisp statements like " If water cement ratio is 0.35 then, the strength is 50 MPa". The potentials of fuzzy logic concepts really lie here in making qualitative assertions based on approximate reasoning.

The fuzzy sets in the antecedent space are derived from universe of possible water cement ratios given by;

$$WC = \{ x \mid 0.3 \le x \le 1.2\} \qquad (4)$$

The term set used to denote fuzzy sets in the antecedent space is;

{low_w/c(Lwc),low_to_medium_w/c(LMwc),moderate_w/c (Mwc),Moderate_to_high_w/c(MHwc) ,high_w/c (Hwc) }

To account for the non-linearity, π-shaped membership functions as shown in Figure 2 are considered. The 28 day's compressive strength is the linguistic variable in the

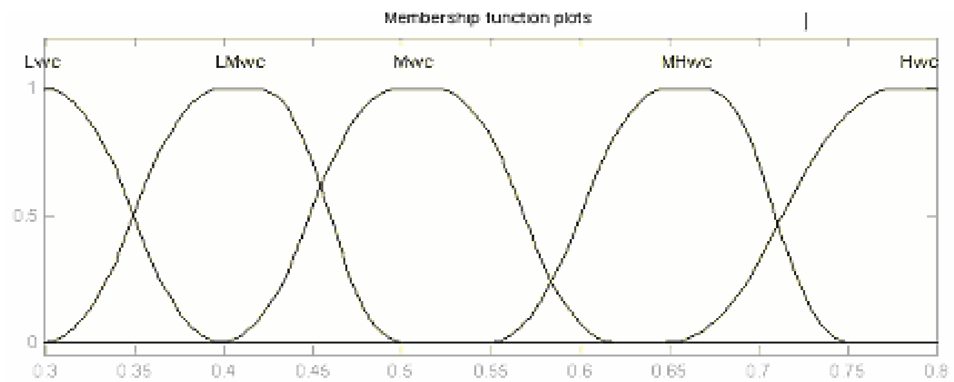

Figure 3. Fuzzy sets depicting approximate water-cement ratios used as antecedents in layer-1 of the model.

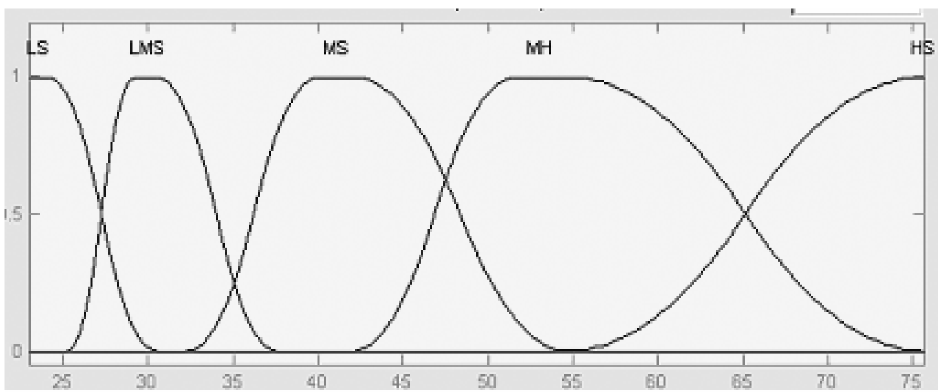

Figure 4. The consequent fuzzy sets depicting approximate strengths (Layer-1).

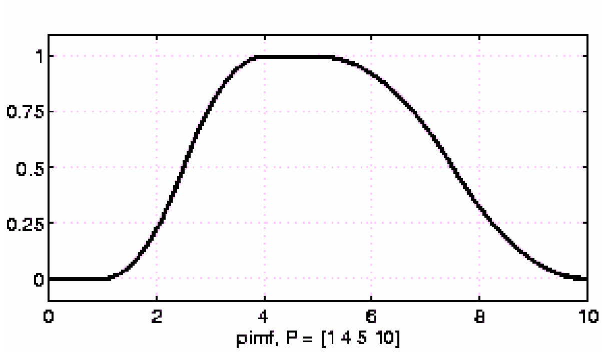

Figure 2. π shaped membership function, y = pimf(x, [a b c d]).

consequent space. The term set of this linguistic variable is;

{high_strength(hs),low_to_medium(lm),moderate_strength(ms),moderate_to_highstrength(mh), high_strength(hs)}

The approximate strength values associated with the w/c values the antecedent space are computed from the equations developed by T.S.Nagaraj (1996). They are given as;

$$S/S_{0.5} = -0.2 + 0.6\left(\frac{1}{w/c}\right) \text{ for } s_{0.5}>30 \quad (5)$$

The above equation has been recently used for reproportioning of steel fiber reinforced concrete mixes (Nataraja, 2005).

The universe of strengths considered is given by;

$$S = \{ s \mid s = (-0.2-0.6\left(\frac{1}{w/c}\right)) \times s_{0.5} \} \quad (6)$$

The average strength corresponding to water-cement ratio of 0.5 was found to be 42 MPa (Nataraja, 1993). The antecedent and consequent fuzzy sets are shown in Figure 3 and Figure 4 respectively. Fuzzy rules are constructed using scatter method. The rules are of the form;

IF *low water-cement ratio* THEN High compressive strength

A sample output of this layer is shown in Figure 5.

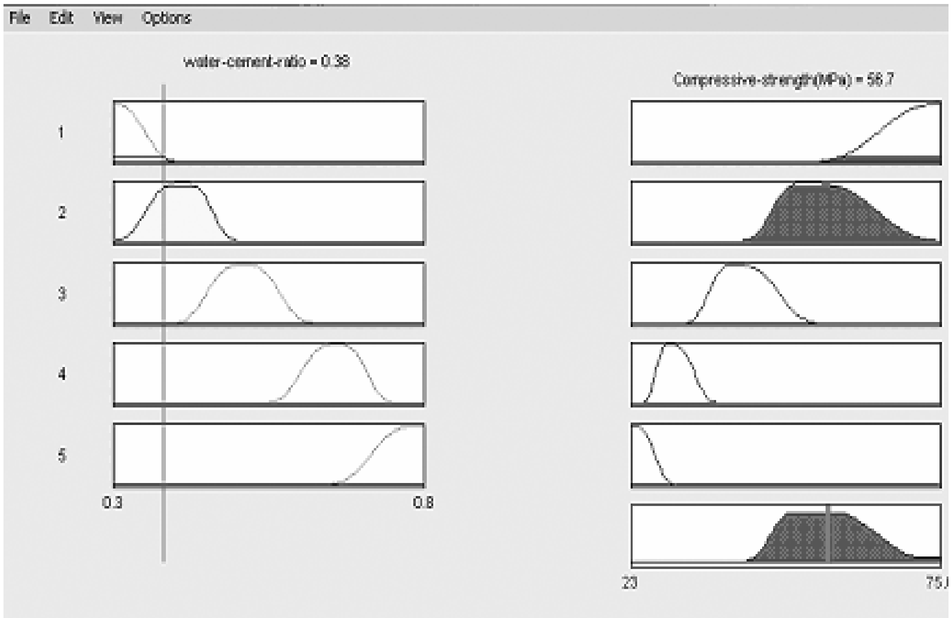

Figure 5. A sample depicting the prediction of strength by the layer-1 of the model for a given input (experimental value).

FIS Layer-2

The workability of concrete depends on water-cement and aggregate-cement ratio(a/c). Because changing the water-cement ratio changes the strength, it is the aggregate-cement ratio that must be addressed to obtain the required workability without affecting the strength. In other words, aggregate-cement ratio that reflects the quantity of cement paste adequate for the aggregate particles to float (Nagaraj, 1993). Thus it is necessary to account for aggregate–cement ratio also as a contributing factor for early strength of concrete.

In this layer, two antecedents are mapped to a consequent mapping done. The antecedents are water-cement ratio and aggregate-cement ratio. The relationship between water-cement ratio and aggregate-cement ratio is given by (Nagaraj, 1993);

$$A/A_{0.5} = 2.495\, w/c - 0.262 \qquad (7)$$

where $A_{0.5}$ is aggregate-cement ratio corresponding to a water-cement ratio of 0.5. From the experimental results the average aggregate-cement ratio corresponding to water-cement ratio of 0.5 was found to be 4.875.

The development of fuzzy sets to represent various levels of aggregate-cement ratios corresponding to water-cement ratios are based on fuzzy extension principle. Vertex method has been used for this purpose. The vertex method (Dong and Shaw, 1987) is based on α-cut concept and interval analysis. An α-cut is the real interval of the fuzzy set which corresponds to constant membership value domains of variables instead on variable domains themselves. When $y=f(x_1,x_2,\ldots\ldots\ldots x_m)$ is continuous in the m-dimensional rectangular region, the value of the interval function can be obtained by;

$$Y = f(x_1,x_2,\ldots\ldots\ldots x_m) = [\ \min_i(f(V_i)),\ \max(f(V_i)] \qquad (8)$$

Equation 7 has been used for the construction of second category of antecedent sets pertaining to aggregate cement ratio. Since all the fuzzy sets representing water-cement ratio are of identical membership functions (π-shaped), only two α-cuts at α=0 and α=1 have been considered.

The so developed fuzzy sets in the antecedent space are;

$$AC = \{Lac\ ,\ LMac\ ,\ Mac,\ MHac,\ Hac\} \qquad (9)$$

Where Lac- Low a/c, LMac- Low to Moderate a/c, Mac-Moderate a/c, MHac-Moderate to high a/c and Hac – High a/c. Figure 6 shows the fuzzy sets considered in the antecedent space of aggregate-cement ratio. This module consists of fuzzy linguistic rules such as;

IF w/c is low AND a/c is low THEN Strength is high

A sample output of this layer for a given input, is shown in Figure 7. The fuzzy surface representing approximate

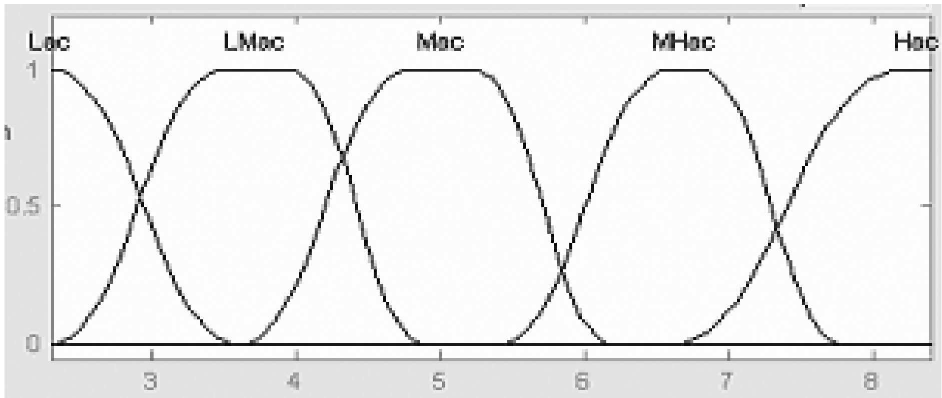

Figure 6. Fuzzy sets representing approximate aggregate-cement ratios (antecedent-2, layer-II).

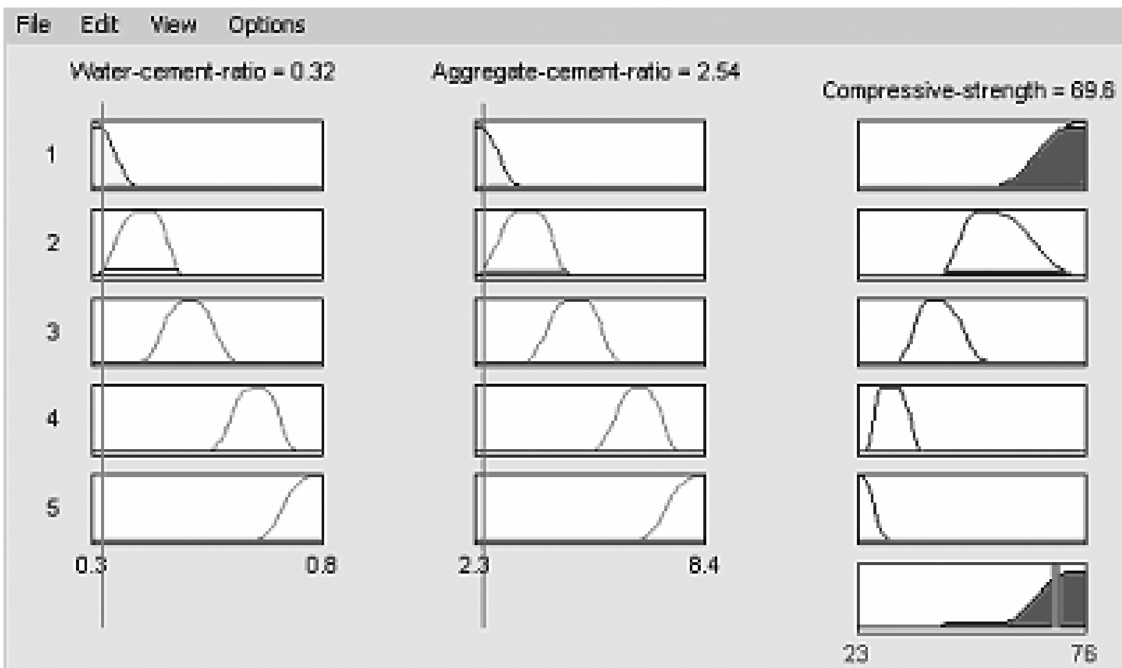

Figure 7. A sample depicting the prediction of strength by the layer-2 of the model for a given inputs (experimental values).

relationship between input parameters and the output is shown in Figure 8.

RESULTS AND DISCUSSION

The FIS model is tested for its validity using the published experimental results (Nataraja, 1993; Patil Gopal Reddy, 1993). The detail of materials used in the experiment is presented in Table 1. Table 2 presents the average values of 28 day's strength of concrete. For each set of water-cement ratio and aggregate-cement ratio, seven cubes were cast and tested for compressive strength involving a total number of cubes to be around 150. The prediction of early strength of concrete considering water-cement ratio as a sole parameter in governing the strength was made using the model with different defuzzification techniques such as centroid, mean of maximum (MOM), bisection, sum of moments (SOM) and is presented in the form of graph shown in Figure 9. The results of prediction of strength considering water-cement ratio as well as aggregate-cement ratio as parameters governing the strength are given in Figure 10. The actual values observed in the experimentation are superposed in these graphs. The prediction in both the cases is found to be excellent. The centroid and bisection method of defzzification resulted in almost close values of strength as compared to experimental values. The percentage

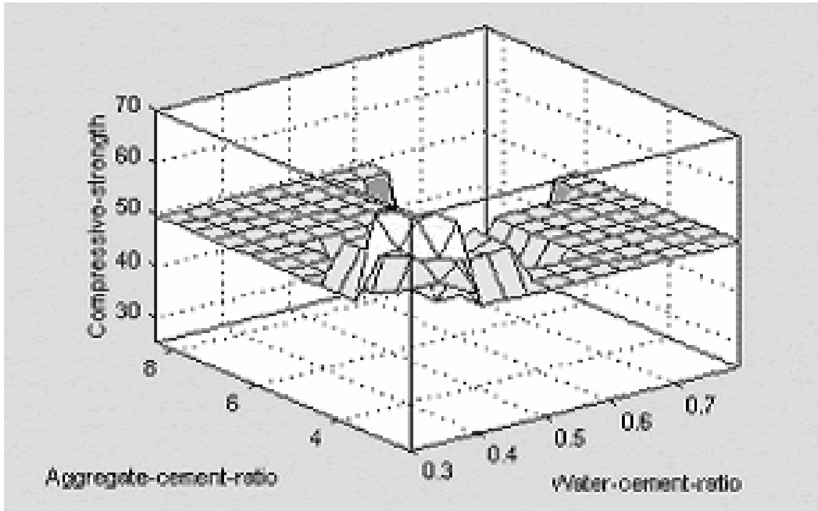

Figure 8. Fuzzy surface as depicted by the model representing approximate relationship among w/c, a/c and compressive strength of concrete

Table 1. Details of the materials used (MC Nataraja, 1993).

Material Used	Description of the properties
Cement	Ordinary Portland cement confirming to IS: 12269-1987. Grade-53.
Fine Aggregate	Locally available river sand confirming to zone III of Indian standards.
Coarse Aggregate	Hand broken granite of 20 mm and 10 mm down sizes. Angular and 60-40 gradation was used as per the code.
Water	Potable water free from injurious salts was used for mixing and curing.

Table 2. Experimental data used for validation of the model.

a/c ratio	w/c ratio	a/c ratio	w/c ratio	a/c ratio	w/c ratio	Average strength
6.85	0.68	6.65	0.65	5.79	0.67	27.63
5.46	0.56	5.22	0.54	4.58	0.55	37.38
4.29	0.46	4.04	0.44	3.58	0.45	47.29
3.33	0.38	3.07	0.36	2.76	0.37	56.57
2.54	0.32	2.29	0.29	2.08	0.31	65.47
1.89	0.26	1.64	0.24	1.52	0.25	71.35
1.34	0.22	1.10	0.19	1.06	0.21	72.79

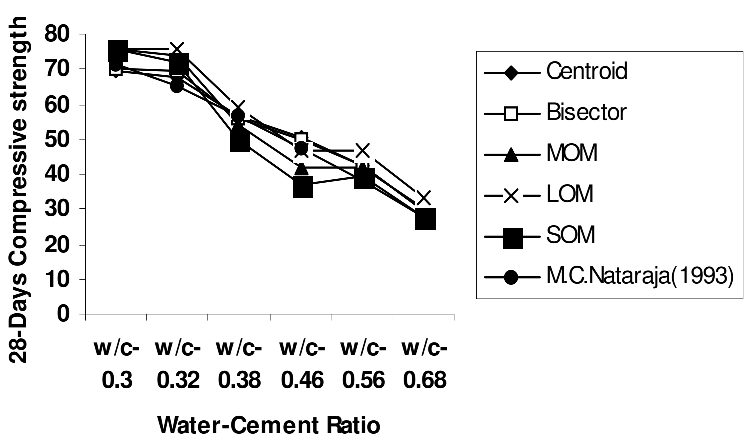

Figure 9. A comparative graph showing the predicted value by the model (considering different defuzzification techniques) and experimental value of strength.

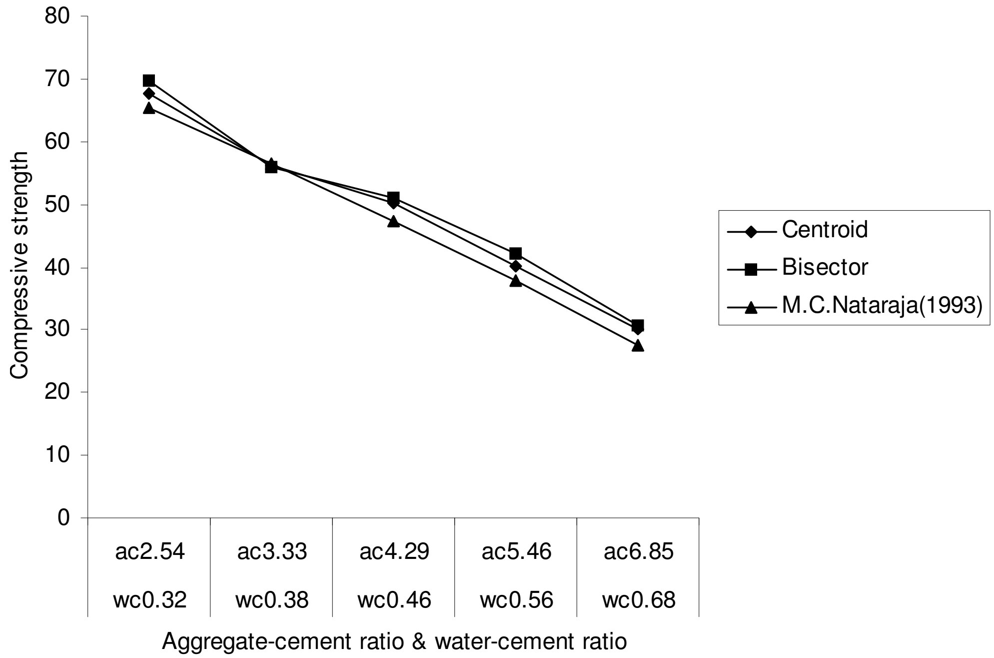

Figure 10. Strength as predicted by layer-II of the model and the experimental values of strength.

error is in the range of 2-10%. Higher percentage of error was noticed in case of other defuzzification techniques. For the second layer, only centroid and bisection methods of defuzzification were considered because, the other defuzzification methods showed very high error rates.

CONCLUSIONS

This work presented a Fuzzy Inferences System for the prediction of early strength of concrete in a two-stage model. In the first stage, water-cement ratio alone was treated as the controlling parameter. In the second stage two parameters viz., water-cement ratio and aggregate–cement ratio were considered. The basic model was developed using generalized Abram's law. To make the model data driven, experimental data was used and the basic model was validated. Scatter method of partitioning is used. The model was developed using Mat Lab. The results of prediction were excellent particularly with centroid and bisector methods of defuzzyfication techniques. Finally, it has been felt that, fuzzy logic concepts would auger well for modeling on uncertain material like concrete and that for relatively a small set of data. However, the sensitivity of the model is to be explored for different types of cements and aggregates.

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