Engineering Letters, 13:2, EL_13_2_8 (Advance online publication: 4 August 2006)

A Fuzzy-Neuro Model for Normal Concrete Mix Design

M.C.Nataraja, M.A.Jayaram, C.N.Ravikumar

Abstract: **Concrete mix design is a process of proportioning the ingredients in right proportions. Though it is based on sound technical principles and heuristics, the entire process is not in the realm of science and precise mathematical calculations. This is because of impreciseness, vagueness, approximations and tolerances involved. 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. Details of the system model are described and comparative graphs are presented.**

Index Terms— **Layered fuzzy systems, standard concrete mix, antecedents, consequent, vertex method.**

I. INTRODUCTION

Human experts perform the design of concrete mix and the design process is not amenable to precise mathematical formulations. It is practically impossible to achieve the design strength of the mix in the field and what is realized in field is somewhere *around* the design strength. This is due to uncertain behavior of constituent materials, impreciseness and vagueness in various parameters involved in the design (like degree of control, types of exposure, shape of aggregates etc…) and approximations in codal guidelines. Due to this, the process of mix design turns out to be approximate. It is thus essential to formulate approximate procedure of mix design in a way that is more natural, humanistic and more scientific. The potential of fuzzy logic really lies here. Neural networks are other class of powerful tools that are bestowed with the capability of realizing non-linear functions from examples presented to them. The power of a trained network is its ability to recognize not only the examples it has learned but also those outside the training set. This paper explores the power of artificial neural networks and fuzzy logic when they are integrated.

Though different in technique, neural networks and fuzzy logic can be conjointly used to accomplish the specification of relationships among numerous variables in a complex dynamic process, perform mappings with some degree of imprecision and to control non linear systems to an extent not possible with linear systems [1][2][3]. Fuzzy-neuro systems have demonstrated the potential to extend the capabilities of systems beyond either of these technologies when applied individually [3][4]. Many such attempts in civil engineering have been reported [5][6][7][8].

II. THE MODEL

The present work is an attempt towards development of *standard concrete mix* design procedure, which consists of five layers of fuzzy inference modules coupled with a trained neural network. The Neural network is trained to learn experimental data that pertains to 28-day compressive strength of concrete cubes v/s water cement ratio of three commercial brands of cements that are popularly used in India. The data for training and testing of the net is generated through the manual interpolation of graph availed from reference [9]. The five layers of fuzzy inference schemes are for finding target mean strength, maximum w/c ratio, water content, sand content and the minimum cement content. To account for non-linearity involved in various inputs and consequent outputs, Gaussian and sigmoid membership functions are considered in all the five layers.

The fuzzy logic modules in MATLAB files and a C++ program for BPN network are interfaced with VB-6.0 as a front-end tool. The model is highly interactive and a novice user can also participate in the design process. The schematic representation of the model is depicted in fig 1.

Manuscript received January 10,2006. This work is part of the ongoing research work on applications of soft computing techniques in concrete technology.

M.C.Nataraja is with Department of Civil Engineering,Sri Jayachamarajendra College of Engineering, Mysore, Karnataka, India.(e-mail: nataraja96@ yahoo.com).

M.A.Jayaram, is with Department of Master of Computer Applications, Sri Siddaganga Institute of Technology, Tumkur,572103, India(Corresponding author: phone.+91-0816-2291148 , fax : +91-0816-2282994 e-mail: ma_jayaram@rediffmail.com)

C.N.Ravikumar is the head of the Department of Computer Science and Engineering, Sri Jayachamarajendra College of Engineering, Mysore, Karnataka, India (e-mail:kumarcnr@yahoo.com)

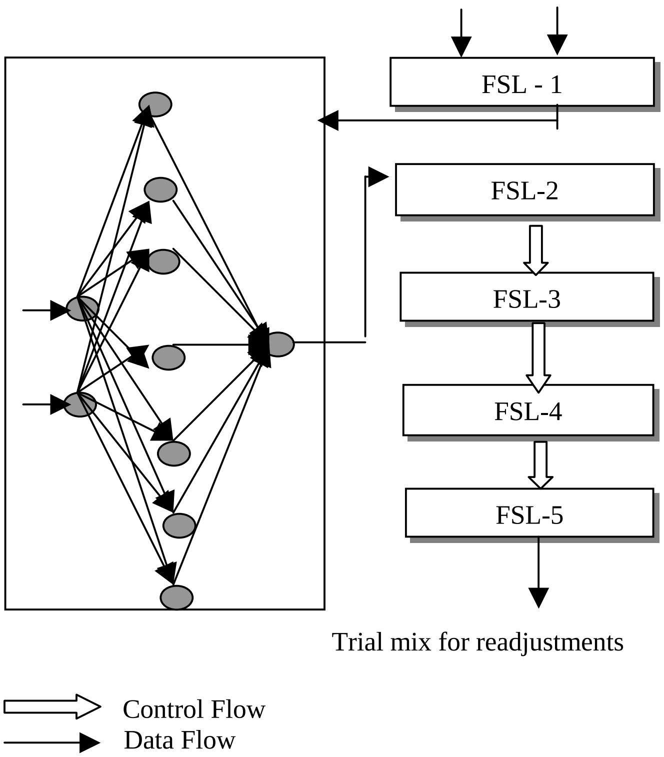

Fig 1. Schematic representation of the Model

III. SIGNIFICANCE OF THE RESEARCH

Traditionally concrete is designed in a way following previous experiences. The available examples are, however often of a limited value, because many combinations of the components, proportions, and mixing techniques have never been investigated or published [10]. The number of properties to be adjusted has also increased, so that empirical methods are no longer sufficient in concrete mix design. In this regard, soft-computing techniques are of immense help. Several researchers in the area of concrete technology have used artificial neural networks as tools in predicting properties of fresh concrete mixtures as well as hardened concrete [10]-[15]. A hybrid model for optimizing high-performance concrete mix proportioning for a given workability and compressive strength using artificial neural networks and nonlinear programming is reported by I.Cheng Yeh[16]. The authors have developed a hybrid system for design of lightweight concrete mixes [17]. The present work is an effort towards development of *normal weight concrete* mix design procedure, which comprises five layers of fuzzy inference modules coupled with a trained back propagation neural network model. Fuzzy inference modules are intended to capture uncertainties, vagueness associated with five predominant steps of design as outlined in codes [18][19] and also to extend flexibility in design and tolerance to human errors. The neural network model is intended to learn experimental data.

IV.FUZZY INFERENCE MODULES

A fuzzy inference module is a rule-based system. Fuzzy rule based systems are mainly based on the use of production rules. These rules control the direction and magnitude of the modification of the design variables in the design domain toward the next best design candidate. They have the following format:

IF A (Antecident1) and B (Antecedent2), THEN C (Consequence)

Where A, B and C are the specific knowledge related to the design variables. Such rule will facilitate functional setting of the requirements in natural language [20]. Transforming them into production rules leads to a loss of information if the system cannot handle terms like " IF required strength is around 30MPa and degree of control is moderate then target mean strength is moderate". Traditional rule systems allow only exact definitions like "IF required strength is 30 MPa and degree of control is 0.5 then target mean strength is 60MPa", which is not an adequate description of the system. Therefore, a way of describing production rules in fuzzy logic environment is adopted here. In the following sections we elaborate on different fuzzy system layers constituting the model.

A. Fuzzy System layer -I

This layer consists of two inputs, the *characteristic* compressive strength (f_{ck}) at 28 days and degree of quality control. The output is *target mean* strength (f'_{ck}). In order that not more than the specified proportion of test results is likely to fall below the characteristic strength, the concrete mix has to be proportioned for somewhat higher target average compressive strength. The mix proportioning is performed for target mean strength, which is the magnified value. The target mean strength [18] is obtained by,

$$f'_{ck} = f_{ck} + tS \tag{1}$$

Here, S is standard deviation representing the quality control that predicates the margin over the characteristic strength. The quality control is itself a fuzzy term and cannot be quantified by a lone crisp value as suggested in code [19]. The value of t, a statistical parameter depends on expected proportion of results and it is called risk factor. It is taken as 1.65 for a tolerance level of 1 in 15. According to IS: 456-2000 [19] and IS: 1343-1980 [21], the characteristic strength is defined as that value below which not more than 5 percent results are expected to fall. Thus the input space consists of fuzzy sets for various categories of strength representing *standard concrete mix*. The partitioning of the input space has the basis of general classification of standard concrete mix as mentioned in code guidelines [19]. The required strength (minimum cube strength) as one of the inputs is denoted as:

$$A = \{A25, A30, A35, A40, A45, A50, A55) \tag{2}$$

Where A25 : Around 25MPa, A30:Around 30MPa, A35 : Around 35MPa etc………

The second input in this layer is the degree of quality control. However, it is rather difficult to quantize the degree of control, as it is vague. It can be captured by fuzzy sets fairly well. To have granularity and to account for the transitory degrees of control (the control that is neither very good nor fair), four fuzzy sets are formed in the antecedent space. The *degree of control* as a linguistic variable is represented as:

$$B = \{\text{very high, high, moderate, low}\} \quad (3)$$

These fuzzy sets are shown in fig 2 and fig 3 respectively.

The target mean strength is linguistic variable in the output space. The development of fuzzy sets in the consequent space is based on fuzzy extension principle. Vertex method has been used for this purpose. The vertex method [22] 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;

$$Y = f(x1, x2, \ldots\ldots\ldots x_m) = [\ \min_i(f(V_i)), \max_i(f(V_i))\ ] \quad (4)$$

Equation (1) has been used for the transformation of input space to output space. Since all the fuzzy inputs are of identical membership functions (gausian), only two α-cuts at α=0 and α=1 have been considered. The output fuzzy sets are defined as;

$$C = \{T31, T32, T33, T34, T36, T37, T38, \ldots\ldots, T64\} \quad (5)$$

Where: T31: Around 31Mpa, T36: Around 36 Mpa , T38 : Around 38 Mpa etc…. The portion of fuzzy sets considered in the output space is shown in fig 4. The rule base consists of 28 rules, which are of the form:

IF *Around M25* and Very High Degree of control
THEN Target Strength is *around 31Mpa*

The output of this layer forms one of the inputs to the trained BPN network.

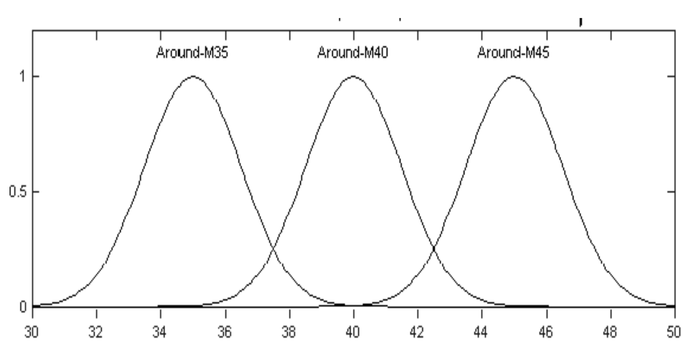

Fig.2: Characteristic Strength of Concrete
(Antecedent 1, fuzzy layer 1)

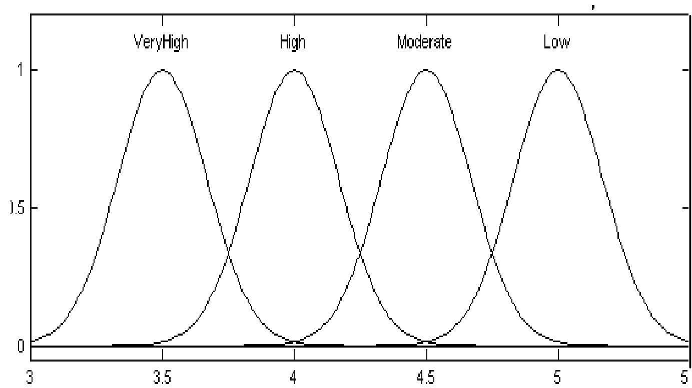

Fig 3: The Degree of Control
(Antecedent 2, fuzzy layer 1).

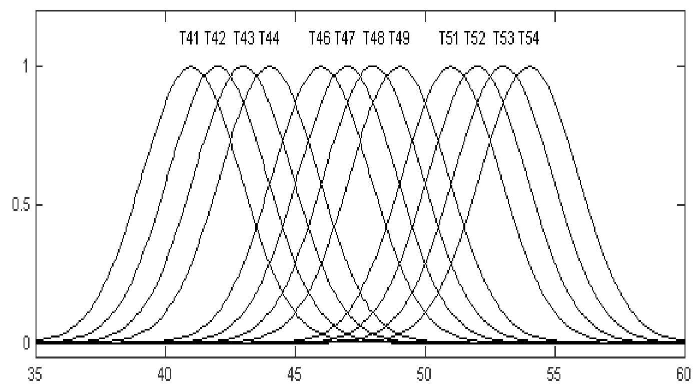

Fig 4: The Target Mean Strength of Concrete
(Consequent, fuzzy layer 1).

B. Fuzzy System layer-II

In this layer, *maximum water cement ratio* is determined. As per the code guidelines [12], the maximum w/c ratio depends on the exposure condition. Code affixes crisp values of maximum w/c ratio for five-exposure conditions viz., mild, moderate, severe, very severe and extreme. This is vague as the exposure conditions are ambiguous and overlapping. As such, they cannot be quantified by lone crisp values. Therefore, exposure conditions are made as fuzzy sets in antecedent space, while the maximum w/c ratio is treated as consequent fuzzy sets.

The term set for antecedent space (type of exposure E) and consequent space (maximum w/c ratio W/C) are;

E = { mild , Moderate, Severe , Very Severe, Extreme } (6)

W/C = { A0.55, A0.50 , A0.45, A 0.4} (7)

In set W/C, A0.55 is *around 0.55*, A0.50 is *around 0.50* . This layer has single antecedent. The fuzzy sets are shown in fig 5 and fig 6. This layer has five rules. The output of this layer is used to compare and limit the w/c ratio that is predicted by trained neural net.

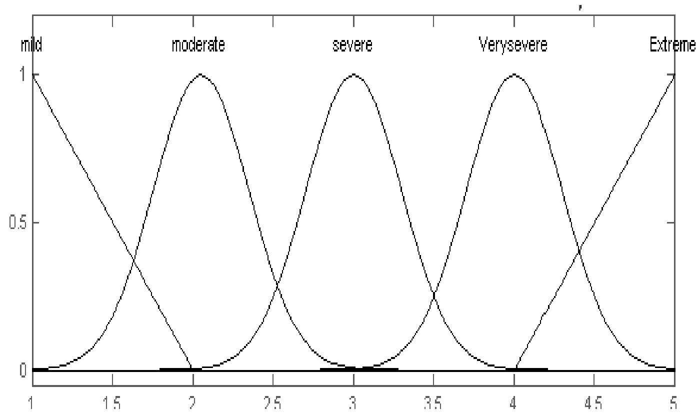

Fig 5: Types of Exposure
(Antecedent, fuzzy layer 2).

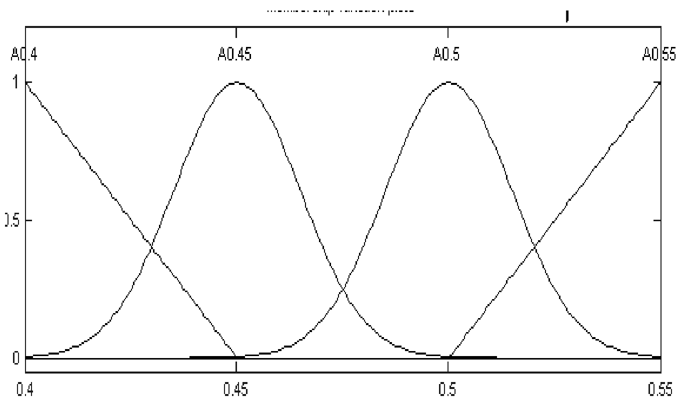

Fig 6: Maximum Water Cement Ratio
(Consequent, fuzzy layer 2).

C. Fuzzy System Layer-III

In this layer, the *approximate maximum* water (QW) content of the mix is determined. The code stipulates the maximum water content based on the nominal maximum size of *angular* aggregates. Further, it advocates an approximate reduction of 10 kg for sub angular aggregates, 25 kg for rounded aggregates. Thus laying emphasis on shape of the aggregates. Therefore, the *nominal size* of the aggregate and *shape* of the aggregate are treated as fuzzy variables in input space. The shape is accounted by the range of angularity index values for different shapes of aggregates [23]. The maximum water content is the fuzzy variable in the output space. The term sets are;

Size = {pred-10mm, pred-20 mm, pred-40mm} (8)

Shape ={round, slightly rounded, sub-angular, angular} (9)

QW = {Around-208 Kg/m^3, around 186 Kg/m^3, around 165Kg/m^3.} (10)

The rules in this layer are of the form;

IF Size is *predominantly* 10 mm and shape is *angular*
THEN Water content is *around* 208 Kg/m^3

Twelve such rules have been framed. The fuzzy sets considered in this layer are depicted in fig 7 , fig 8 and fig 9.

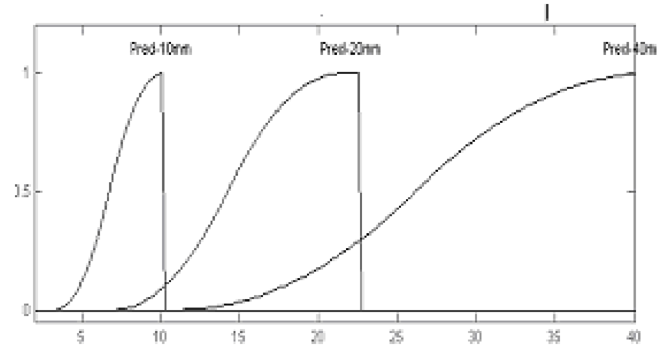

Fig 7: Size of Aggregates
(Antecedent 1 , fuzzy layer 3).

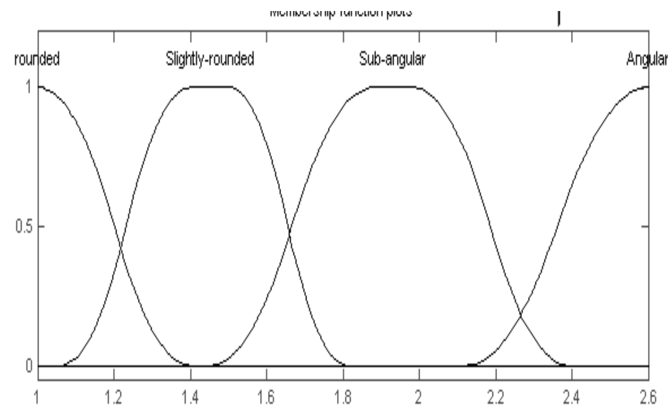

Fig 8: Shape of Aggregates (antecedent 2, fuzzy layer

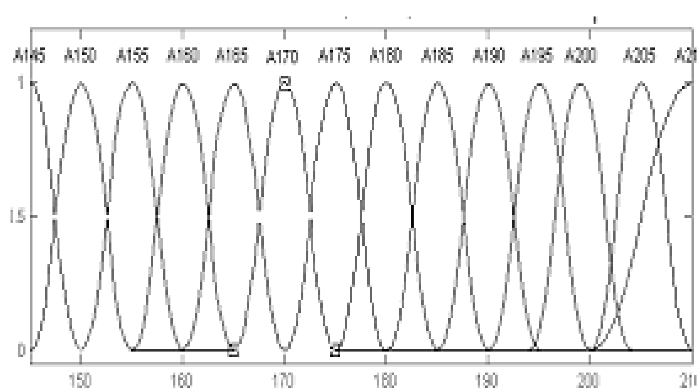

Fig .9: Approximate Water Content
(Consequent, fuzzy layer 3).

D.Fuzzy system layer -IV

In this layer, the *minimum cement content* required from the point of durability is found out. The code recommends minimum cement content as approximate crisp values for five exposure conditions. This layer has a rule base that works on a single antecedent and a consequent. The antecedent fuzzy sets are same as the ones used in layer 2.

The consequent fuzzy sets capture approximate quantities of minimum cement content (CC) corresponding to various exposure conditions.

CC ={around 300 Kg, around 320 Kg, around 340Kg, around 360 Kg} (11)

The output of this layer is used to check the quantity of cement content estimated in the previous step using the known value of w/c. This module has five rules. The rules are of the form;

IF exposure is *mild* THEN
Minimum Cement content is *around 300kg*.

E.Fuzzy System Layer-V

In this layer, the *approximate volume* of course aggregate per unit volume of concrete is determined. It is based on the **premise** that for equal workability, the volume of course aggregate in a unit volume of concrete is dependent only on its *nominal maximum* size and *grading zone* of fine aggregate [23]. This layer has two inputs. The nominal maximum size of aggregate and the four grading zones of fine aggregate and the output is the volume of course aggregate. The grading zones of fine aggregate are zone 1, zone 2, zone 3 and zone 4. Where concrete of high strength and good durability is required, fine aggregate conforming to any one of the four grading zones may be used. As the fine aggregate grading becomes progressively finer, that is from grading zones I to IV; the ratio of the fine aggregate to course aggregate should be progressively reduced. In practice, it is difficult to get the fine aggregate to conform to any one particular standard curve exactly. The grading zones thus overlap. Therefore, they are captured in four overlapping fuzzy sets. The term sets of input and output space in this layer are;

Size = { pred-10mm, pred-20 mm, pred-40mm} (12)

GZ = { Zone-1, Zone-2 , Zone-3 , Zone-4} (13)

The fuzzy sets in output space are;

UV = {around 0.44, around 0.46, around 0.48,..} (14)

Fuzzy sets representing zones of gradation of fine aggregate is shown in fig 10. Fig 11 depicts the consequent fuzzy sets representing approximate volume of course aggregate. This layer is built on 12 rules. The rules are of the form;

IF size of the aggregate is predominantly 10 mm AND
the fine aggregate gradation zone is around zone-1
THEN the volume of course aggregate is approximately
0.44.

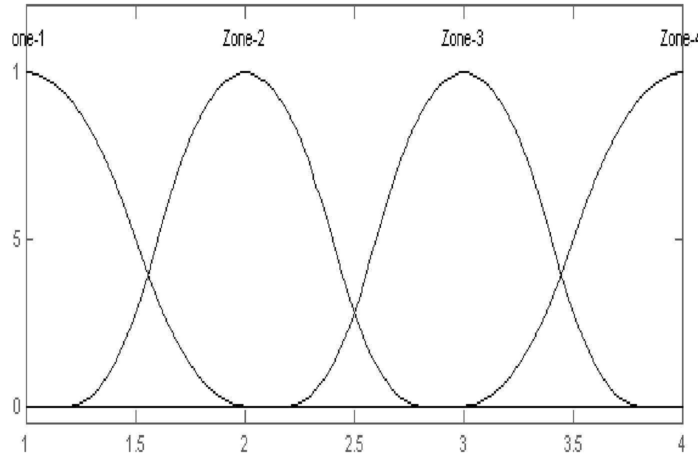

Fig.10: Zone of Gradation of fine aggregate
(Antecedent 2, fuzzy layer 5).

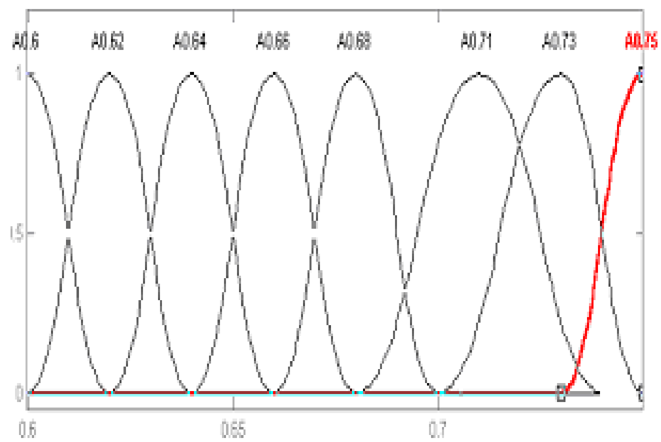

Fig. 11: Approximate volume of Course aggregate
(Consequent, fuzzy layer 5).

V. BACK PROPAGATION NEURAL NETWORK

Back propagation network is briefly discussed for the sake of completeness. In the back propagation model each node is connected to all nodes in the adjoining layer and each connection has an unbounded positive or negative weight associated with it [24][25]. Considering a single node j with n input, the output o_j of node j is a function of the total input fed to that node.

$$o_i = f(net_j) \quad (15)$$

$$net_j = \sum_i w_{ji} o_i + \theta_j \quad (16)$$

Where w_{ji} is the weight of the connection from the ith node to the jth node, o_i is the output of the ith node, θ_j is a variable bias with similar function to a threshold, and a summation is over all units feeding into node j. The activation function that is used is given by

$$o_j = \frac{1}{1+e^{-net_j}} \quad (17)$$

The term back propagation refers to an iterative training process in which an output error E is defined by

$$E = \sum_p E_p = \frac{1}{2}\sum_p \sum_j (t_{pj} - o_{pj})^2 \quad (18)$$

Where summation is performed over all output nodes j and t_j is the desired or target value of output o_j for a given input vector. The direction of steepest descent in parameter space is determined by the partial derivatives of E with respect to the weights and bias in the network,

$$\frac{\partial E}{\partial w_{ji}} = -\sum_p \partial_{pj} o_{pj} \quad (19)$$

$$\frac{\partial E}{\partial \theta_j} = -\frac{\partial E_p}{\partial net_{pj}} \quad (20)$$

and it can be shown that,

$$\partial_{pj} = (t_{pj} - o_{pj})(1 - o_{pj})o_{pj} \quad (21)$$

for output nodes j and

$$\partial_{pj} = (1 - o_{pj})o_{pj} \sum_k \partial_{pk} w_{kj} \quad (22)$$

For all nodes in the intermediate layer where j refers to a node in one of the intermediate layers, and the summation is over all units k, which receive a signal from node j.
Further it can be shown that the learning rule is given by

$$\Delta w_{ij}(t) = \eta \sum_p \partial_{pj} o_{pj} \quad (23)$$

$$\Delta \theta_j(t) = \eta \sum_p \partial_{pj} \quad (24)$$

Where t denotes a given instant of time and η is the learning parameter.

V. THE ANN MODEL

To find the best topology of the net, three different configurations were explored. Normally, the training of an ANN is terminated on reaching a predefined error or on completion of a predefined number of training iterations. In this study, a combination of these was adopted. However, the training was terminated when the number of iterations reached its predetermined value. In any simulation exercise, the most suitable model is chosen on the basis of the least error produced during both training (calibration) and testing (validation) stages. At the model development stage, however, it has to be chosen on the basis of the least error during the training stage alone. About 60 input-output pairs were manually interpolated from the empirical graph cited in the reference [9]. The graph used for this purpose is shown in fig 12. All the 60 patterns were used during training.

For testing the network models, 25 input patterns were randomly chosen from the sixty sets. The details of the networks are furnished in table 1. Model 1(2-8-1) showed an excellent performance in terms of perfect matching between actual output and predicted output. It also showed a high correlation coefficient (Pearson) and took less time for training. Therefore the topology 1(2-8-1) is integrated in the model.

VI. DESIGN STEPS

The design steps to be followed to arrive at the proportions of ingredients for one cubic meter of standard concrete mix are summarized in this section.

Step 1: Invoke fuzzy layer 1, with required minimum cube strength and degree of control as inputs (fuzzy singletons). The output obtained is crisp value of target mean strength.

Step 2: The trained ANN module is invoked. The inputs are the cement brand number and the target mean strength availed in the first step. Output is the w/c ratio.

Step 3: Using fuzzy layer2, obtain the maximum water-cement ratio for type of exposure considered.

Step 4: Compare the w/c obtained in step 2 and 3 and select the minimum value among them.

Step 5: With known size and angularity index, obtain the quantity of water using fuzzy layer 3.

Step 6: Using the known values of water-cement ratio and quantity of water, determine the approximate quantity of cement.

Step 7: Invoke fuzzy layer 4, obtain the minimum quantity of cement required. Compare this valve with the value obtained in the previous step.

Step 8: Using fuzzy layer 5, find out the volume of course aggregate.

Step 8: Find the volume of fine aggregate by weight method.

VII. CONCLUSIONS

A sample input-output of the model for standard concrete mixes of grades M25, M35 and M50 have been presented in table 2. The outputs in terms of quantity of cement, quantity of water, quantity of course aggregate and quantity of fine aggregate for the trial mixes have been compared with those obtained by conventional method as suggested in codal guidelines. Figures 13-15 serve as comparative graphs. The common parameters considered for comparison are moderate exposure, 20 mm angular shaped aggregates and brand-3 cement. The graphs show a marginal difference between the methods. In all the cases, centroid method of defuzzification is employed. The difference in quantities estimated using the model and using conventional method is found to be well with in 1-5% for all combinations of inputs. This difference is acceptable as both the methods are approximate**.** This clearly shows that, the conventional method, which is approximate, is tenable to be treated under the integrated soft computing concepts of fuzzy logic and neural nets. Thus providing a mathematical (fuzzy) standpoint for the mix proportioning. From the end user (engineers) point of view, outcome of the model is significant on following counts; Firstly, it provides a way to capture inherent vagueness in the design steps proposed by codes. Secondly, it offers flexibility for the mix design expert to decide appropriate value for ambiguous parameters like degree of control, type of exposure and shape of aggregates. Finally, the ANN module helps to capture experimental data and to use it expeditiously during the design of fresh batches of trial mixes.

Table 1: Details of BPN models tried.

BPN topology	Learning parameter	Error tolerance & no of iterations	Mean error per cycle	Co-efficient of correlation
2-8-1	0.25	0.001, 20000	0.07	0.95
2-8-8-1	0.25	0.001, 22000	0.08	0.86
2-8-8-8-1	0.25	0.001, 18000	0.08	0.92

Table 2: Typical Inputs for the model

Category of Mix	Around-M25	Around M35	Around M50
Characteristic Strength	25 MPa	35 MPa	50Mpa
Degree of Control	Moderate	Low	Low
Aggregate Size	Pred- 20mm	Pred- 20mm	Pred- 20mm
Shape of aggregate	Angular	Sub-angular	Angular
Gradation zone of fine aggregate	Zone-I	Zone-II	Between I&II
Brand of cement	Type-1	Type-2	Type-3
Quantity of Cement	348 kg	364 kg	550kg
Quantity of Water	186 kg	175 kg	187 kg
Course aggregate	1180 kg	1268 kg	1107kg
Fine aggregate	472 kg	690 kg	410kg

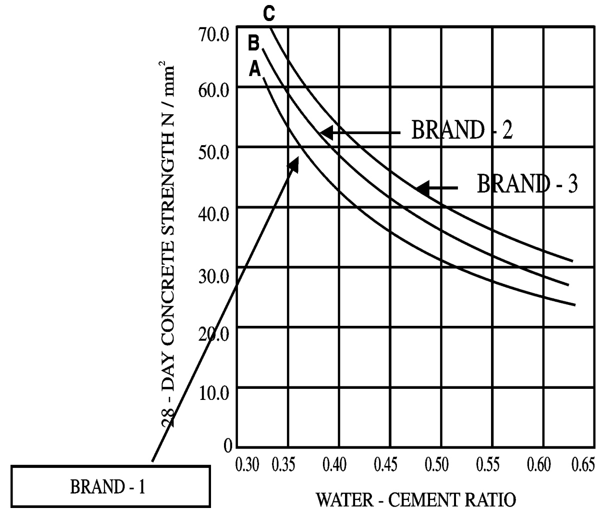

Fig 12: Experimental data in the form of graph showing characteristic compressive strength of cubes after 28 days v/s water cement ratio

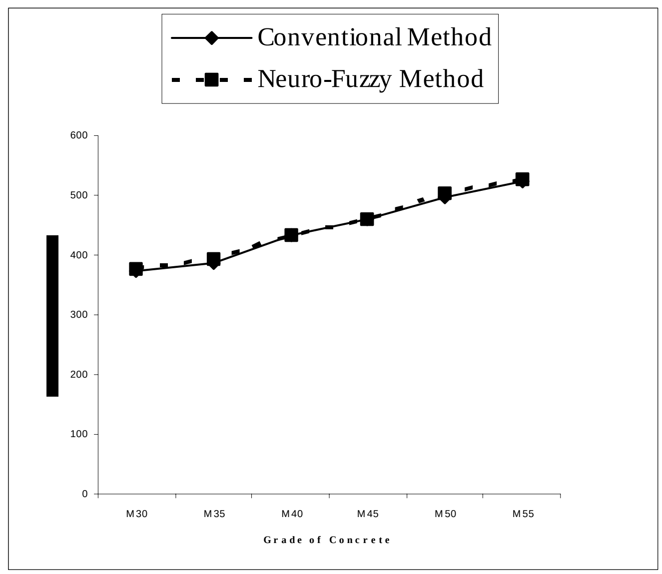

Fig. 13: Comparative graph showing the quantity of cement (kg, y-axis) per cum of concrete for various mix grades (x-axis) by prevalent conventional method and the fuzzy-neuro method.

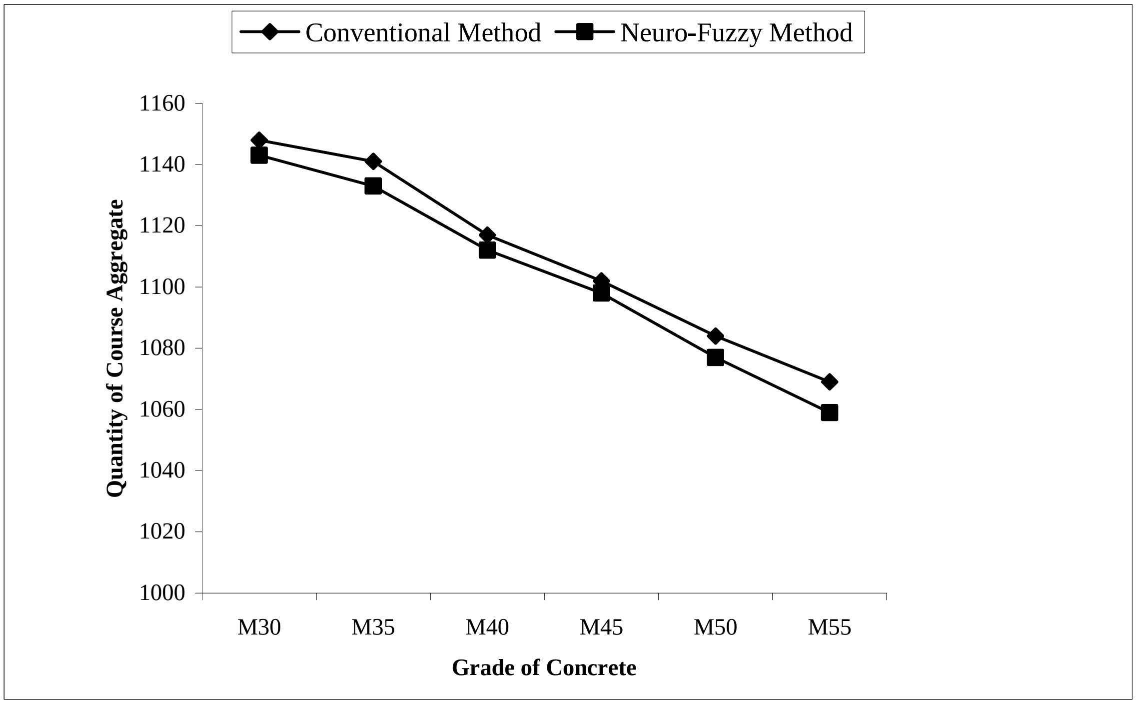

Fig 14. Comparative graph showing the quantity of course aggregate per cum of concrete obtained by conventional method and the fuzzy-neuro method for various grades of concrete.

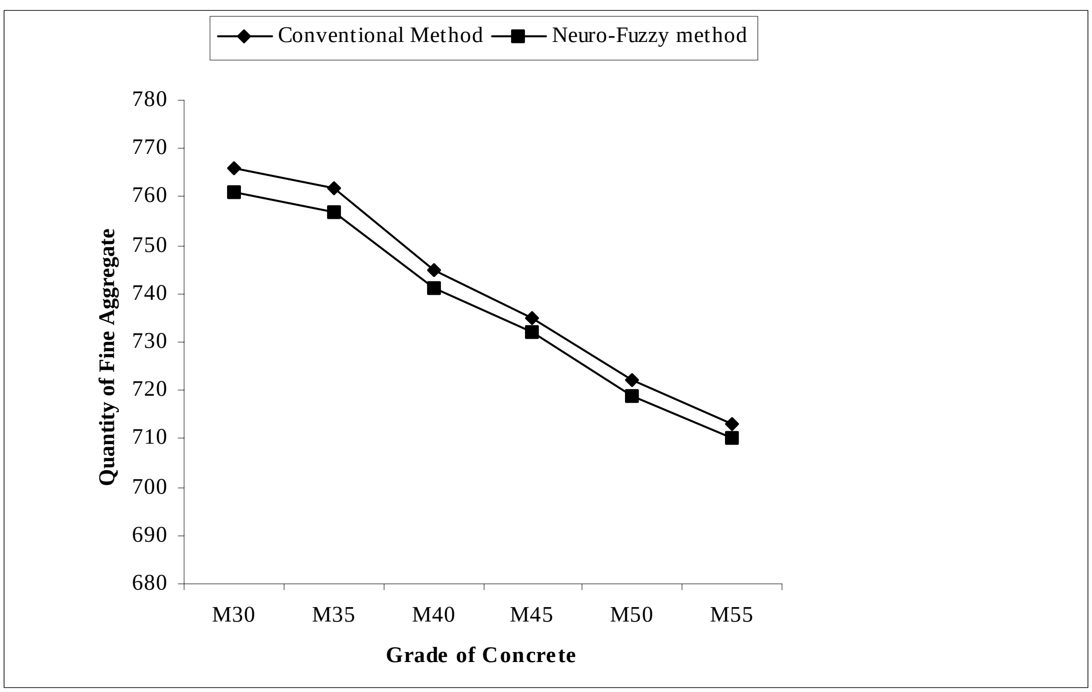

Fig. 15: Comparative graph showing the quantity of fine aggregate per cum of concrete obtained by conventional method and the fuzzy-neuro method for various grades of concrete.

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M.C.Nataraja received the B.E (Civil Engineering) degree from Sri Jayachamarajendra College of Engineering, Mysore in 1983 securing VIII rank. He obtained the M.Tech in Industrial Structures from National Institute of technology, Mangalore University. Later, he obtained his PhD from Indian Institute of Technology (IIT), Kharagpur.

He is at present, working as assistant professor, in the department of civil engineering, Sri Jayachamarajendra College of Engineering, Mysore, India. He has 19 years of postgraduate teaching and research experience. He has published over 70 technical papers in leading International and National Journals and Conferences. His areas of interest include concrete materials and mix design, High Performance Concrete and marginal materials in concrete. He has attended and presented papers in 18 international conferences and chaired few sessions. He has guided several postgraduate dissertations and currently, he is guiding two research scholars.

Dr.M.C.Nataraja is the recipient of best technical paper award from Indian Concrete Institute and International Council for Fibre Reinforced Concrete, India. He is a life member of Indian Society of Technical Education, Indian Concrete Institute, Indian Institute of engineers and American Society of Civil Engineers (Indian Chapter)

M.A.Jayaram received his B.E.(Civil Engg.,) from University Visveswaraya College of Engineering, Bangalore in 1983 with distinction. Later in 1987, he obtained his M.Tech in Marine Structures with distinction from National Institute of Technology, Surathkal.

In addition, he received degree in Master of Computer Applications from Indira Gandhi National Open University, New Delhi in 2002.

He is at present, working as assistant professor, in the department of Master of Computer Applications, Siddaganga Institute of Technology, Tumkur, India. He has 18 years of teaching experience in the areas of civil engineering and a decade long teaching experience in computer science and engineering. He has published over 25 technical papers in leading International and National Conferences and Journals. His areas of major interest include soft-computing techniques, evolutionary computing techniques, analysis and design of algorithms and artificial intelligence. He is the co-author of books "Design of Bridge Structures" published by Prentice-hall of India and " A Computer Lab referral for Diploma and Engineering Students" published by orient_longman. Currently, he is pursuing his PhD in the area of applications of soft–computing techniques in Concrete technology.

M.A.Jayaram is a life member of Indian Society for technical Education, Indian Institute of Engineers, Indian Concrete Institute and Continuing Education Center, IIT, Roorkee.

C.N. Ravikumar received *his Bachelor degree in Electronics and* Communication in the year 1979 from Sri Jayachamarajendra College of Engineering, Mysore. Later, he obtained his MSc(by research)in the year 1985 from Mysore University. He received his PhD in computer science and engineering in the year 2000 from Mysore University.

He is at present professor and head of the department of computer science and engineering, Sri Jayachamarajendra College of Engineering, Mysore,India. He has published more than 35 papers in International conferences and Journals. His research interests are in image processing, pattern recognition, biometrics and data mining. He is the principal investigator and co-investigator for several research projects under All India Council for Technical Education and University Grants Commission. Currently, he is guiding five research scholars.

Dr.C.N.Ravikumar is life member of Indian Society of Technical Education, Computer Society of India.