A Comparative Study on ANFIS and Fuzzy Expert System Models for Concrete Mix Design

Mehdi Neshat[1], Ali Adeli[2] , Azra masoumi[3] , Mehdi sargolzae[4]

[1] Department of Computer, Shirvan Branch, Islamic Azad University, Shirvan, Iran

[2] Department of Computer, Shirvan Branch, Islamic Azad University, Shirvan, Iran

[3] Department of Computer, Shirvan Branch, Islamic Azad University, Shirvan, Iran

[4]Department of Computer, Shirvan Branch, Islamic Azad University, Shirvan, Iran

Abstract

The aim of this study is to design ANFIS model and Fuzzy Expert System for determination of concrete mix design and finally compare their results. The datasets which has been loaded into ANFIS contains 552 mix designs and has been based on ACI mix designs. Moreover, in this study, a Fuzzy Expert System has been designed. Input fields of fuzzy expert system are Slump, Maximum Size of Aggregate (D_{max}), Concrete Compressive Strength (CCS) and Fineness Modulus (FM). Output fields are quantities of water, Cement, Fine Aggregate (F.A) and Course Aggregate (C.A).In the ANFIS model, there are 4 layers (4 ANFIS models) that first layer takes values of D_{max} and Slump and then determines the quantity of Water, second layer takes values of Water (that computed in previous layer) and CCS to measure the value of Cement, third layer takes values of D_{max} and F.M to computes the measure of C.A and 4^{th} layer takes values of Water, Cement, C.A (which determined in previous layers) and the measure of concrete density to compute the value of F.A. Comparison of two systems (FIS and ANFIS) results showed that results of ANFIS model are better than Fuzzy Expert System when these systems designed and tested. In ANFIS model, for Water output field, training and average testing errors are 0.86 and 0.8, respectively. In cement field, training error and average testing error are 0.21 and 0.22, respectively. Training and average testing error of C.A are 0.0001 and 0.0004, respectively and finally, F.A's training and average testing errors are 0.0049 and 0.0063, respectively.

Keywords: *concrete mix design, ANFIS, fuzzy expert system, Water, Cement, slump.*

1. Introduction

The Artificial intelligence (AI) is receiving greater attention from the building industry to aid in the decision making process in areas such as diagnostics, design, and repair and rehabilitation .

In the civil engineering field, acquiring the concrete mix design is so difficult and sensitive. Classical way to determination of concrete mix design is based on uncertainty and depends on expert idea.

Concrete is a material consisting of a binder within which aggregate particles are imbedded [8].

Under normal conditions, concrete grows stronger as it grows older .The chemical reactions between cement and water that cause the paste to harden and bind the aggregates together require time .The reactions take place very rapidly at first and then more slowly over a long period of time [16].

Concrete production is a complex process that involves the effect of several processing parameters on the quality control parameter of 28-day compressive strength. These parameters are all effective in producing a single strength quantity of 28-day compressive strength. So, an inconvenient mix design doesn't have very good result. These factors are: Water, Cement, Slump, Maximum Size of Aggregate, Fine aggregate, Coarse aggregate, Age(day), Exposure condition, Absorption of fine aggregate and coarse aggregate, Specific gravity of water and cement and fine aggregate and coarse aggregate and etc.

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. 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 [10].

Motivated by the need of such an important tool, in this comparative study, first, a fuzzy expert system and an ANFIS model have been developed to design best concrete mix designs. These models which deal with mix design have been implemented and experimental results showed that ANFIS model did quite better than the FIS system and the other non-fuzzy systems.

Remaining of the paper organized as follows. Previous research concerning concrete mix design will be shown in the next part .In section 3, the dataset has been introduced . In section 4, method of designing will be shown that includes fuzzy expert systems designing. In section 4-1-1, FIS designing will be introduced. Rule base of FIS has been described in section 4-1-2, and in section 4-1-3, we show fuzzification and defuzzification of FIS. Section 4-1-4 contains FIS testing. Designing of ANFIS models starts from section 4-2 that has been divided to four parts: In section 4-2-1, we introduce method of designing that includes The ANFIS model 1 designing. Section 4-2-2 includes the designing of The ANFIS model 2, section 4-2-3 includes The ANFIS model 3 designing and final part is about The ANFIS model 4 designing. Final section (section 5) shows conclusion.

2. Previous Research

Despite the fact that these fields, in which the computers are used, have very high complexity and uncertainty and the use of intelligent systems such as fuzzy logic[3], artificial neural network[4] and genetic algorithm have been developed. These papers will be reviewed as following section:

M.C.Nataraja, M.A.Jayaram and C.N.Ravikumar 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 [10].

M. Abdullahi, H. M. A. Al-Mattarneh, A. H. Hassan, M. H. Abu Hassan and B. S. Mohammed have studied on A Review on Expert Systems for Concrete Mix Design. For their developed expert systems, mix design codes derived from data obtained from experience with concrete materials. The expert systems were developed using expert system shells such as EXSYS Professional, level 5, level 5 object and kappa-PC [16].

Lawrence J. Kaetzel and James R. Clifton have worked on Expert/Knowledge-Based Systems for Cement and Concrete. This survey is the initial step in the development of expert systems for the SHRP C-206 project. The report addresses three topics: 1)the potential for the application of expert systems for concrete mixture design and diagnostics, repair and rehabilitation, 2)a description of inference procedures that are best suited for representing the concrete pavement and structure knowledge domain, and 3)recent expert/knowledge based systems activities [15].

S. Tesfamariam and H. Najjaran designed Adaptive Network-Fuzzy Inferencing to Estimate Concrete Strength Using Mix Design. In this paper, the use of adaptive neuro-fuzzy inferencing system (ANFIS) is proposed to train a fuzzy model and estimate concrete strength. The efficiency of the proposed method is verified using actual concrete mix proportioning datasets reported in the literature, and the corresponding coefficient of determination r2 range from 0.970-0.999. Further, sensitivity analysis is carried out to highlight the impact of different mix constituents on the estimate concrete strength [17].

Mahmut Bilgehan worked a comparative study for the concrete compressive strength estimation using neural network and neuro-fuzzy modeling approaches. In this paper, adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) model have been successfully used for the evaluation of relationships between concrete compressive strength and ultrasonic pulse velocity (UPV) values using the experimental data obtained from many cores taken from different reinforced concrete structures having different ages and unknown ratios of concrete mixtures. A comparative study is made using the neural nets and neuro-fuzzy (NF) techniques. Comparing of the results, it is found that the proposed ANFIS architecture with Gaussian membership function is found to perform better than the multilayer feed-forward ANN learning by backpropagation algorithm. The final results show that especially the ANFIS modelling may constitute an efficient tool for prediction of the concrete compressive strength [5].

M. L. Nehdi and M. T. Bassuoni 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 = 0·7) than that with the remaining service life model (R 2 = 0·5), 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 [2]. Harun Tanyildizi and Ahmet Qoskun, fuzzy logic model for prediction of compressive strength of lightweight concrete made with scoria aggregate and fly ash[6]. Tayfun Uyunoglu, Osman Unal, A new approach to determination of compressive strength of fly ash concrete using fuzzy logic[11].

Song-Sen Yang and Jing Xu and Guang-Zhu Yao 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 [7].

3. Dataset

The idea of these systems has been based on two powerful resources: first, rules and principles of American Concrete Institute (ACI) for determination of mix designs and second, concrete mix designs database at the University of California (UCI) that has been collected via Prof. I-Cheng Yeh[14]. In the UCI's database, input fields are quantities of water, cement, blast furnace slag, fly ash, Super plasticizer, coarse aggregate, fine aggregate and age (day) and output field is the quantity of concrete compressive strength.
The ACI rules has been based on ACI-211-89 that in FIS system, have been used for determination of range of variables, membership functions and rules but in ANFIS model, have been used for FIS training.

Table 1: Relation between water/cement ratio and average compressive strength of concrete (Fm)

Average compressive strength at 28 days (Kg/m^3)	Effective water/cement ratio	
	Non-air entrained concrete	Entrained concrete
40	0.42	-
35	0.47	0.39
30	0.54	0.45
25	0.61	0.52
20	0.69	0.6
15	0.79	0.7

Note that in designing FIS and ANFIS models, structures have been based on non-air entrained concrete. To measure of coarse aggregate in kg/m^3 unit, values of Table 2 must be multiplied to seeming specified gravity of coarse aggregate in range of [1600, 1800]. For these models, all values of Table 2 have been multiplied to 1700 (average value of above range).

With analyzing of these two datasets, two systems have been purposed for acquiring mix design that has been based on Fuzzy Logic. First designed system is fuzzy expert system and second is Adaptive Neural-Fuzzy Inference System (ANFIS) model.

Table 2: Dry bulk volume of coarse aggregate per unit volume of concrete

Maximum size of aggregate (mm)	***Dry bulk volume of coarse aggregate per unit volume of concrete for fineness modulus of sand***			
	2.4	2.6	2.8	3
9.5	0.5	0.48	0.46	0.44
12.5	0.59	0.57	0.55	0.53
19	0.66	0.64	0.62	0.6
25	0.71	0.69	0.67	0.65
37.5	0.75	0.73	0.71	0.69
50	0.78	0.76	0.74	0.72
75	0.82	0.8	0.78	0.76
150	0.87	0.85	0.83	0.81

Table 3: Approximate requirement for mixing water and air content for different work abilities and maximum sizes of aggregate (Non-air entrained)

Workability or Air content	***Water content (kg/m^3) of concrete for indicated maximum aggregate size (mm)***						
	9.5	12.5	25	37.5	50	75	150
Slump (mm)	***Non-air entrained concrete***						
25-50	207	199	179	166	154	130	113
75-100	228	216	193	181	169	145	124
150-175	243	228	202	190	178	160	-
Approximate entrapped air content (%)	3	2.5	1.5	1	0.5	0.3	0.2

Table 4: First estimate of density (unit weight) of concrete

Maximum size of aggregate (mm)	***First estimate of density of concrete (kg/m^3)***	
	Non-air entrained concrete	***Entrained concrete***
9.5	2280	2200
12.5	2310	2230
19	2345	2275

25	2380	2290
37.5	2410	2350
50	2445	2345
75	2490	2405
150	2530	2435

4. Methods

Inspired by human's remarkable capability to perform a wide variety of physical and mental task without any measurement and computations and dissatisfied with classical logic as a tool for modeling human reasoning in an imprecise environment, Lotfi A.Zadeh developed the theory and foundation of fuzzy logic with his 1965 paper "Fuzzy Sets" [5].

The most important application of fuzzy system (fuzzy logic) is in uncertain issues .When a problem has dynamic behavior, fuzzy logic is a suitable tool that deals with this problem [2].

The term "uncertainty" refers to a set of questions that human experts ask themselves almost daily. Since these (and related questions) represent issues which every human decision maker must constantly face, they are also issues that an automated expert system should be able to handle.

In the first part of this section, we will show fuzzy expert system designing, membership functions, fuzzy rule base, fuzzification and defuzzification and in second part, the ANFIS model will be introduced completely.

4.1 Fuzzy expert system design

First step of FIS designing is determination of input and output variables .There are four inputs and four outputs. After that, membership functions designing of all variables will be started.

At first, input variables of FIS with their membership functions will be described .In second step, output variables of FIS with its membership functions will be shown.

Input variables of FIS are:

Slump: A measure of consistency of freshly-mixed concrete obtained by placing the concrete in a truncated cone of standard dimensions, removing the cone, and measuring the subsidence of the concrete to the nearest 6 mm (1/4 in.) [14] following the ASTM C 143-90 or EN 12350-2 test standards. With increasing of slump value, measures of water and cement increase and value of fine aggregate decreases and vice versa.

This field accepts values in [20, 200] millimeter. The interval conations three fuzzy sets such as: "Low", "Medium" and "High". Membership functions of "Low" and "High" sets are trapezoidal and membership function of "Medium" set is triangular. Eq.(1) shows mathematical equations of membership expressions. These fuzzy sets will be shown in Table 5 .Membership functions of this field will be shown in Fig.1.

Table 5: Classification OF Slump

INPUT FIELD	*RANGE*	*FUZZY SETS*
Slump	< 80 60 - 140 120>	Low=L Medium=M High =H

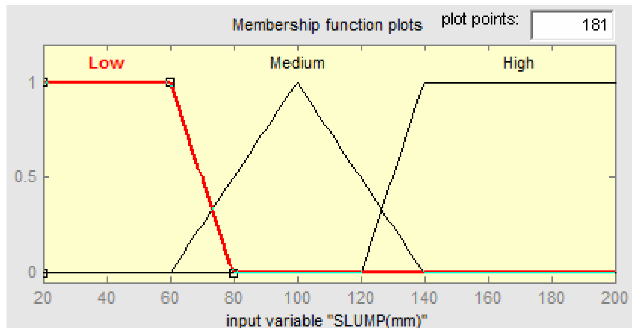

Fig. 1 Membership functions of Slump

$$\mu_L(x) = \begin{cases} 1 & x < 60 \\ (80-x)/20 & 60 \le x < 80 \end{cases}$$

$$\mu_M(x) = \begin{cases} (x-60)/40 & 60 \le x < 100 \\ 1 & x = 100 \\ (140-x)/40 & 100 \le x < 140 \end{cases} \qquad (1)$$

$$\mu_H(x) = \begin{cases} (x-120)/20 & 120 \le x < 140 \\ 1 & x \ge 140 \end{cases}$$

Maximum Size of Aggregate (D_{max}): According to ASTM definition, in specifications for aggregates, the smallest sieve opening through which the entire amount of aggregate is required to pass is called the maximum size [14]. There is a direct relationship between D_{max} and C.A and a reverse relationship between D_{max} and water, cement and F.A. In the other word, with increasing of D_{max}, the values of water, cement and fine aggregation decrease, but value of coarse aggregate increases and vice versa.

This input field accepts values in [9, 160] millimeter unit. The interval has been divided to five fuzzy sets.

These sets are "Very Low", "Low", "Medium", "High" and "Very High". Membership functions of "Very Low" and "Very High" sets are trapezoidal and membership functions of "Low", "Medium" and "High" sets are triangular. Mathematical equations of Membership functions of D_{max} field have been shown in Eq.(2). Fuzzy sets will be shown in Table 6 .Membership functions of this field will be shown in Fig.2.

Table 6: classification of Dmax

INPUT FIELD	*RANGE*	*FUZZY SETS*
Maximum Size of Aggregate	< 27	Very Low=VL
	16 - 51	Low=L
	35-75	Medium=M
	60-105	High =H
	90>	Very High=VH

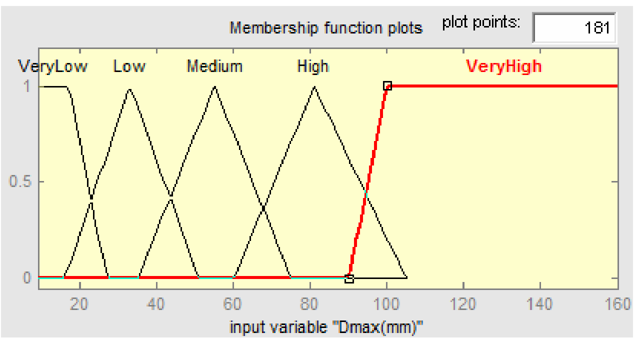

Fig. 2 Membership functions of Maximum Size of Aggregate

$$\mu_{VL}(x)=\begin{cases}1 & x<17\\ (27-x)/10 & 17\le x<27\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-16)/17 & 16\le x<33\\ 1 & x=33\\ (51-x)/18 & 33\le x<51\end{cases}\qquad \mu_{H}(x)=\begin{cases}(x-60)/21 & 60\le x<81\\ 1 & x=81\\ (105-x)/24 & 81\le x<105\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-33)/22 & 33\le x<55\\ 1 & x=55\\ (75-x)/20 & 55\le x<75\end{cases}\qquad \mu_{VH}(x)=\begin{cases}(x-90)/10 & 90\le x<100\\ 1 & x\ge 100\end{cases} \tag{2}$$

Concrete Compressive Strength (CCS): The field refers to the measure of concrete compressive strength in Mpa unit. Compressive strength is a measure of the ability of the concrete to withstand crushing loads [12]. The CCS field effects on the cement and the F.A fields. In the other word, with increasing of CCS value, the measure of cement increases and the measure of F.A decreases [9][10]. So there is a direct relationship between CCS and cement and a reverse relationship between CCS and F.A. This input field takes values in [10, 50] boundary. CCS input field has six fuzzy sets such as: "Very Low", "Low", "Medium", "High", "Very High" and "Best". Membership functions of "Very Low" and "Best" sets are trapezoidal and membership functions of "Low", "Medium", "high" and "Very High" sets are triangular. These membership functions will be shown in Fig.3. Table 7 shows these fuzzy sets with their ranges. Eq.(3) shows mathematical equations of membership functions.

Table 7: classification of CCS

OUTPUT FIELD	*RANGE*	*FUZZY SETS*
CCS	< 20	Very Low=VL
	15-25	Low=L
	20-30	Medium=M
	25-35	High =H
	30-40	Very High=VH
	35>	Best= B

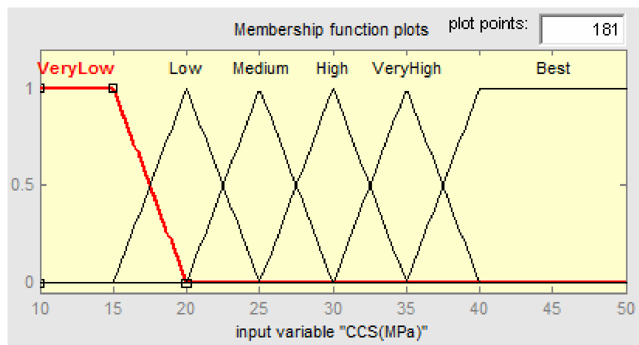

Fig. 3 Membership functions of CCS

$$\mu_{VL}(x)=\begin{cases}1 & x<15\\ (20-x)/5 & 15\le x<20\end{cases}\qquad \mu_{H}(x)=\begin{cases}(x-25)/5 & 25\le x<30\\ 1 & x=30\\ (35-x)/5 & 30\le x<35\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-15)/5 & 15\le x<20\\ 1 & x=20\\ (25-x)/5 & 20\le x<25\end{cases}\qquad \mu_{VH}(x)=\begin{cases}(x-30)/5 & 30\le x<35\\ 1 & x=35\\ (40-x)/5 & 35\le x<40\end{cases} \tag{3}$$

$$\mu_{M}(x)=\begin{cases}(x-20)/5 & 20\le x<25\\ 1 & x=25\\ (30-x)/4 & 25\le x<30\end{cases}\qquad \mu_{B}(x)=\begin{cases}(x-35)/5 & 35\le x<40\\ 1 & x\ge 40\end{cases}$$

Fineness Modulus (FM): Using the sieve analysis results, a numerical index called the fineness modulus (FM) is often computed .The FM is the sum of the total percentages coarser than each of a specified series of sieves, divided by 100 [14]. With increasing in quantity of FM, the value of F.A increases, but the value of C.A decreases.

The field accepts values from [2.3, 3.2] range. The FM field has four fuzzy sets such as: "Very Low", "Low", "Medium" and "High". Membership functions of "Very Low" and "High" fuzzy sets are trapezoidal and membership functions of "Low" and "Medium" sets are triangular that have been shown in Fig .4. These fuzzy sets have been shown in Table 8 with their ranges. Mathematical equations of membership functions will be analyzed in Eq.(4).

Table 8: classification of FM

INPUT FIELD	*RANGE*	*FUZZY SETS*
FM	<2.5	Very Low=VL
	2.4-2.8	Low=L
	2.6-3	Medium=M
	2.85>	High =H

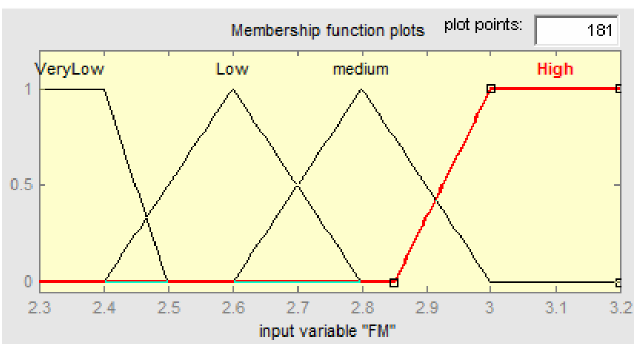

Fig. 4 Membership functions of FM

$$\mu_{VL}(x)=\begin{cases}1 & x<2.4\\ (2.5-x)/1 & 2.4\le x<2.5\end{cases}\qquad \mu_{M}(x)=\begin{cases}(x-2.6)/2 & 2.6\le x<2.8\\ 1 & x=2.8\\ (3-x)/2 & 2.8\le x<3\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-2.4)/2 & 2.4\le x<2.6\\ 1 & x=2.6\\ (2.8-x)/2 & 2.6\le x<2.8\end{cases}\qquad \mu_{H}(x)=\begin{cases}(x-2.85)/0.15 & 2.85\le x<3\\ 1 & x\ge 3\end{cases}\tag{4}$$

Output fields of FIS are:

Water: Water field is a very important factor in concrete mix design. This output field takes quantities from [100, 250] kg/m^3. This field has been divided to five fuzzy sets such as: "Very Low", "Low", "Medium", "High" and "Very High". Membership functions of "Very Low" and "Very High" sets are trapezoidal and membership functions of "Low", "Medium" and "High" sets are triangular. Eq.(5) introduces mathematical equations of membership functions. These fuzzy sets will be shown in Table 9. Membership functions of water field will be shown in Fig.5.

Table 9: classification of water

INPUT FIELD	*RANGE*	*FUZZY SETS*
Water	<143	Very Low=VL
	130-173	Low=L
	157-200	Medium=M
	183 -226	High =H
	207>	Very High=VH

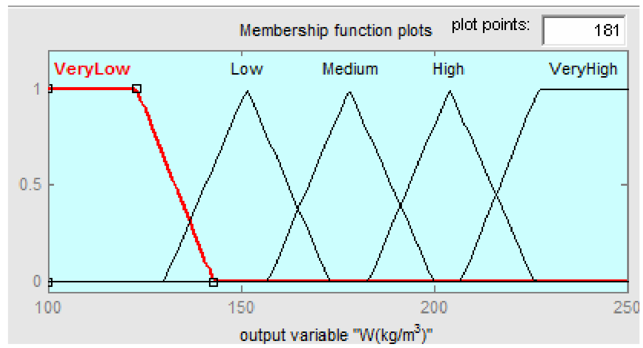

Fig. 5 Membership functions of water

$$\mu_{VL}(x)=\begin{cases}1 & x<123\\ (143-x)/20 & 123\le x<143\end{cases}\qquad \mu_{H}(x)=\begin{cases}(x-183)/21 & 183\le x<204\\ 1 & x=204\\ (226-x)/22 & 204\le x<226\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-130)/21.5 & 130\le x<151.5\\ 1 & x=151.5\\ (173-x)/21.5 & 151.5\le x<173\end{cases}\qquad \mu_{VH}(x)=\begin{cases}(x-207)/20 & 207\le x<227\\ 1 & x\ge 227\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-178)/21 & 157\le x<178\\ 1 & x=178\\ (200-x)/22 & 178\le x<200\end{cases}\tag{5}$$

Cement: The role of cement in concrete mix design is to pasting aggregates. In the other word, after mixing with water, changes to cement paste and causes to pasting aggregates. If there is not enough fine aggregate to fill the voids between coarse aggregate particles, the space must be filled with cement paste.

This output field accepts values just from [100, 650] interval in kg/m^3 unit. This field has been divided to five fuzzy sets such as: "Very Low", "Low", "Medium", "High" and "Very High". Membership functions of "Very

Low" and "Very High" sets are trapezoidal and membership functions of "Low", "Medium" and "High" sets are triangular. Mathematical equations of membership functions of water field have been shown in Eq.(6). These fuzzy sets will be shown in Table 10 .Membership functions of water field will be shown in Fig.6.

Table 10: classification of cement

INPUT FIELD	*RANGE*	*FUZZY SETS*
Cement	<250 200-350 300-450 400 -550 500>	Very Low=VL Low=L Medium=M High =H Very High=VH

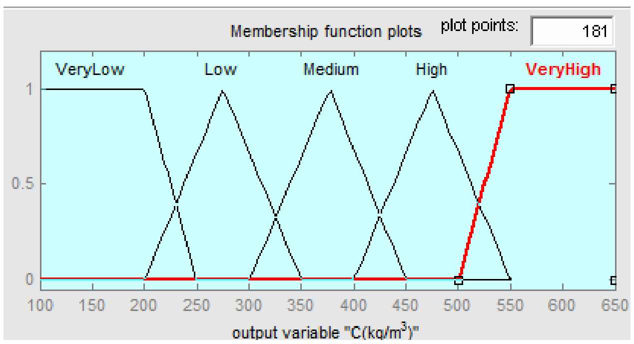

Fig. 6 Membership functions of cement

$$\mu_{VL}(x)=\begin{cases}1 & x<200\\ (250-x)/50 & 200\le x<250\end{cases}\qquad \mu_{H}(x)=\begin{cases}(x-400)/75 & 400\le x<475\\ 1 & x=475\\ (550-x)/75 & 475\le x<550\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-200)/75 & 200\le x<275\\ 1 & x=275\\ (350-x)/75 & 275\le x<350\end{cases}\qquad \mu_{VH}(x)=\begin{cases}(x-500)/50 & 500\le x<550\\ 1 & x\ge 550\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-300)/77 & 300\le x<377\\ 1 & x=377\\ (450-x)/73 & 377\le x<450\end{cases}\qquad (6)$$

Coarse Aggregate (C.A): This type of Aggregate predominantly retained on the 4.75 mm sieve [14]. Coarse aggregate may be available in several different size groups, such as 19 to 4.75 mm or 37.5 to 19 mm [14]. "ASTM C 33" contains standard specification for concrete aggregates [14].This field takes input values from [600, 1600] in form of kg/m^3. The interval has five fuzzy sets such as: "Very Low", "Low", "Medium", "High" and "Very High". Membership functions of "Very Low" and "Very High" sets are trapezoidal and membership functions of "Low", "Medium" and "High" sets are triangular. Mathematical equations of membership function of coarse aggregate field will be illustrated in Eq.(7) . Table 11 will show fuzzy sets with their values. Fig .7 shows the membership function of coarse aggregate.

Table 11classification of C.A

INPUT FIELD	*RANGE*	*FUZZY SETS*
Coarse Aggregate	< 877.8 766.7-1044 944.4-1222 1137-1411 1322>	Very Low=VL Low=L Medium=M High =H Very High=VH

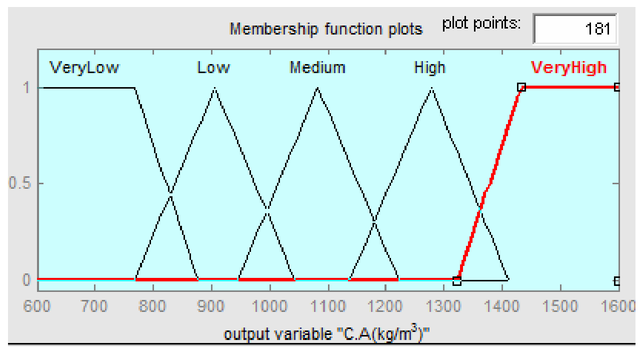

Fig. 7 Membership functions of C.A

$$\mu_{VL}(x)=\begin{cases}1 & x<766.7\\ (877.8-x)/111.1 & 766.7\le x<877.8\end{cases}\qquad \mu_{H}(x)=\begin{cases}(x-1137)/141 & 1137\le x<1278\\ 1 & x=1278\\ (1411-x)/133 & 1278\le x<1411\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-766.7)/138.9 & 766.7\le x<905.6\\ 1 & x=905.6\\ (1044-x)/138.4 & 905.6\le x<1044\end{cases}\qquad \mu_{VH}(x)=\begin{cases}(x-1322)/111 & 1322\le x<1433\\ 1 & x\ge 1433\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-944.4)/138.6 & 944.4\le x<1083\\ 1 & x=1083\\ (1222-x)/139 & 1083\le x<1222\end{cases}\qquad (7)$$

Fine Aggregate (F.A): Aggregate passing the 9.5 mm (3/8 in.) sieve and almost entirely passing the 4.75 mm sieve and predominantly retained on the 75 μm sieve [14]. One of the most important characteristics of the fine aggregate grading is the amount of material passing the 300 and 150 μm sieves**.** Inadequate amounts of materials in these size ranges can cause excessive bleeding,

difficulties in pumping concrete, and difficulties in obtaining smooth troweled surfaces [14].
For input values of fine aggregate, we have defined [500, 1300] interval that takes values in kg/m^3 unit. This interval has been divided to five fuzzy sets such as: "Very Low", "Low", "Medium", "High" and "Very High". Membership functions of "Very Low" and "Very High" sets are trapezoidal and membership functions of "Low", "Medium" and "High" sets are triangular that will be shown in Fig .8. Eq.(8) shows mathematical equations of membership functions. In Table 12, these fuzzy sets have been defined.

Table 12 classification of F.A

INPUT FIELD	*RANGE*	*FUZZY SETS*
Fine Aggregate	< 730	Very Low=VL
	615-845	Low=L
	730-1000	Medium=M
	900-1150	High =H
	1070>	Very High=VH

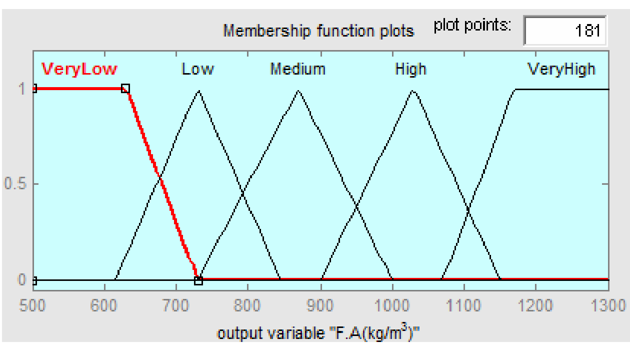

Fig. 8 Membership functions of F.A

$$\mu_{VL}(x)=\begin{cases}1 & x<630\\ {(730-x)}/{100} & 630\le x<730\end{cases}$$

$$\mu_{L}(x)=\begin{cases}{(x-615)}/{115} & 615\le x<730\\ 1 & x=730\\ {(845-x)}/{115} & 730\le x<845\end{cases}$$

$$\mu_{M}(x)=\begin{cases}{(x-730)}/{140} & 730\le x<870\\ 1 & x=870\\ {(1000-x)}/{130} & 870\le x<1000\end{cases}\qquad(9)$$

$$\mu_{H}(x)=\begin{cases}{(x-900)}/{130} & 900\le x<1030\\ 1 & x=1030\\ {(1150-x)}/{120} & 1030\le x<1150\end{cases}$$

$$\mu_{VH}(x)=\begin{cases}{(x-1070)}/{100} & 1070\le x<1170\\ 1 & x\ge 1170\end{cases}$$

4.2 Fuzzy rule base

Rule base is the main part of FIS and quality of results in fuzzy system depends on the fuzzy rules [5] . A reasoning procedure known as the compositional rule of inference, enables conclusions to be drawn by generalization from the qualitative information stored in the knowledge base [13]. The fuzzy rules can express him with the natural language in the following way :if x is small and y is middle, then z is great.The variables x, y and z are type linguistic [5].This system includes 131 rules .Results with 131 rules tend to the expert’s idea and laboratory results .

4.3 Fuzzification and Defuzzification

Designed system uses inference mechanism Mamdoni approach . The FIS system uses AND logical combination of inputs in the rules. The FIS system has following properties:

And method: Min
Or method: Max
Implication: Min
Aggregation: Probor
Defuzzification: Centroid

The surface viewer of all output fields with some input fields have been shown as follow.

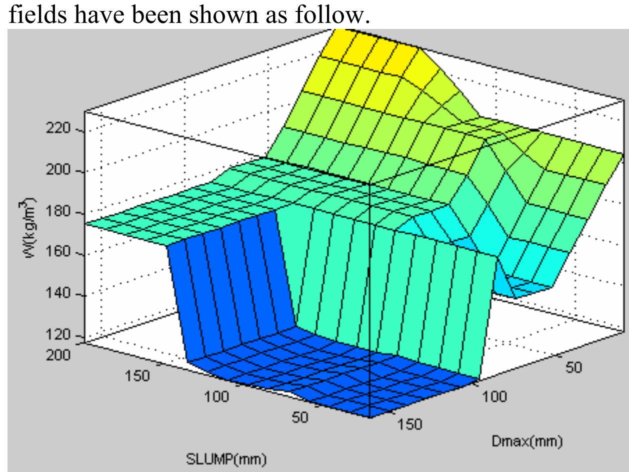

Fig. 9 Surface Viewer Water, Slump and D_{max}

4.4 System Testing

The designed system had been tested that will be shown in Table 14. The obtained results had been compared with the experimental methods and had been found that the average error for Water, Cement, Coarse Aggregate and Fine Aggregate are 9.5%, 27.6%, 96.5 and 49%, respectively.

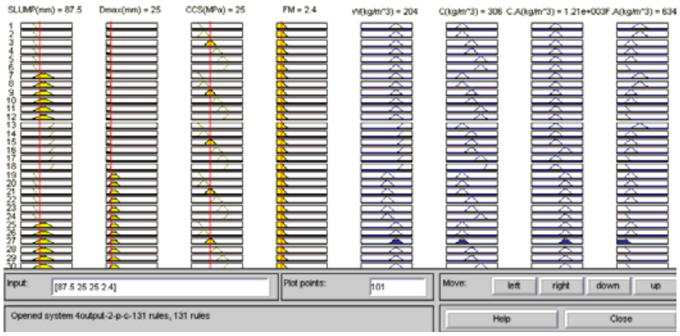

Fig. 10 Rule Viewer of FIS model Testing for Second Sample

Table 13 Results of FIS Testing

INPUTS				OUTPUTS							
Slump (mm)	D_{max} (mm)	CCS (Mpa)	FM	Laboratory (ACI) results				FIS results			
				Water (kg/m^3)	Cement (kg/m^3)	C.A (kg/m^3)	F.A (kg/m^3)	Water (kg/m^3)	Cement (kg/m^3)	C.A (kg/m^3)	F.A (kg/m^3)
37.5	19	30	2.4	190	351	1122	682	198	375	1130	730
87.5	25	25	2.4	193	316	1207	664	204	306	1210	634
87.5	50	20	2.4	169	244	1326	706	181	275	1270	730
162.5	50	25	2.4	178	291	1326	650	181	285	1280	597
37.5	9.5	20	2.4	207	300	850	923	204	275	1080	867
87.5	9.5	15	2.4	228	288	850	914	204	275	1080	866
37.5	12.5	35	2.4	199	423	1003	685	204	475	1080	730
162.5	25	40	2.4	202	480	1207	491	213	510	1210	603
37.5	9.5	30	2.6	207	383	816	874	204	376	905	867
37.5	12.5	30	2.6	199	368	969	774	204	376	905	730
162.5	19	35	2.6	216	459	1088	582	204	449	951	697
37.5	37.5	40	2.6	166	395	1241	608	173	455	1080	706
37.5	50	15	2.6	154	194	1292	805	154	172	1080	745
37.5	9.5	20	2.6	207	300	816	957	204	275	905	1030
162	19	20	2.6	216	313	1088	728	204	275	951	730
87.5	50	20	2.8	169	244	1258	774	178	275	1080	866
162.5	50	40	2.8	178	423	1258	586	178	475	1080	595
37.5	150	25	2.8	113	185	1411	821	117	162	1490	867
87.5	150	35	2.8	124	263	1411	732	118	275	1480	730
37.5	150	30	2.8	113	209	1411	797	117	162	1490	867
162.5	50	15	2.8	178	225	1258	784	178	275	1080	730

4.5 Adaptive Neural - Fuzzy Inference System (ANFIS) DESIGNING

ANFIS is a multi-layer adaptive network-based fuzzy inference system proposed by Jang. An ANFIS consists of totally five layers to implement different node functions to learn and tune parameters in a FIS using a hybrid learning mode .

In ANFIS model, system computes the measures of water, cement, F.A and C.A, separately. There is important problem that ANFIS model has just one output. Because of that, we should design four different ANFIS models. First ANFIS takes input values of Slump and Maximum size of Aggregate (D_{max}) and then measures the value of Water. Second ANFIS takes input values of Concrete Compressive Strength (CCS) and Water (it has been computed in past ANFIS model) and then measures the value of Cement. For computing the value of Coarse Aggregate (C.A), third ANFIS model takes input values of D_{max} and Fineness Modulus (FM). For measuring the value of Fine Aggregate (F.A), final ANFIS model needs the values of Water, Cement, C.A (they have been computed in past ANFIS models and the value of first estimate of concrete density. For training of each ANFIS model, we used a dataset which contains 552 concrete mix designs. These 552 mix designs have been collected from Tables 1, 2, 3 and 4 that have been based on ACI rules.

4.5.1 ANFIS model 1 Designing

This ANFIS model (model 1) has been used for water value estimation that needs input values of Slump and D_{max}.For ANFIS designing, model should be passed 4 steps: 1) Load date, 2) Generate FIS, 3) Train FIS, and 4) Test FIS.

There are three different data types for loading to model. These dataset includes Training data, checking data and testing data. At first, usage dataset contains three columns (D_{max}, Slump and water) and 552 rows. After that, this set was further broken down into three sets: training set, checking set and testing set. The Checking and testing sets known as validation set .The validation set monitors the fuzzy system's ability to generalize during training (the same principle as cross validation training in neural networks terminology). Fig.11 shows the loaded dataset into ANFIS.

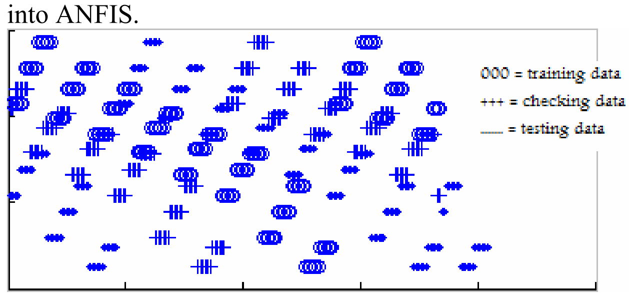

Fig. 11 Loaded dataset into The ANFIS model 1

4.5.1.1 Generate FIS

For FIS generation, model has three selections, which are designed FIS, Grid Partition and Subtractive Clustering.

Grid partition divides the data space into rectangular sub-spaces using axis-paralleled partition based on pre-defined number of membership functions and their types in each dimension [18].

The wider application of grid partition in FL and FIS is blocked by the curse of dimensions, which means that the number of fuzzy rules increases exponentially when the number of input variables increases .For example, if there are averagely m MF for every input variable and a total of n input variables for the problem, the total number of fuzzy rules is m^n .It is obvious that the wide application of grid partition is threatened by the large number of rules . According to [18], grid partition is only suitable for cases with small number of input variables (e.g .less than 6).

The subtractive clustering method clusters data points in an unsupervised way by measuring the potential of data points in the feature space .When there is not a clear idea how many clusters there should be used for a given data set, it can be used for estimating the number of clusters and the cluster centers [18] .Subtractive clustering assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points .Then data point with highest potential is selected as the first cluster center, and the potential of data points near the first cluster center)within the influential radius (is destroyed .Then data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster [18].

This ANFIS model (model 1) uses Grid Partition method for FIS generation. Generated FIS includes two inputs and one output. Input variables are: Maximum Size of Aggregate (D_{max}) and Slump. The number and type of membership functions for each input variable is four and triangular. Output field is the water measure estimation. Membership function type of output variable is linear. Input ranges of D_{max} and Slump are [9.5, 150] and [37.5, 162.5], respectively. FIG.12 and FIG.13 show tuned membership functions of each input in the ANFIS model 1.

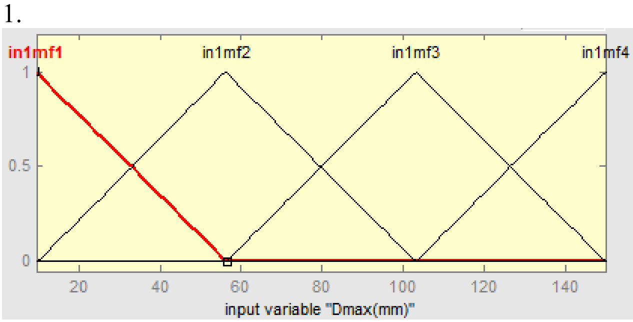

Fig. 12 Tuned membership functions of D_{max} in the ANFIS model 1

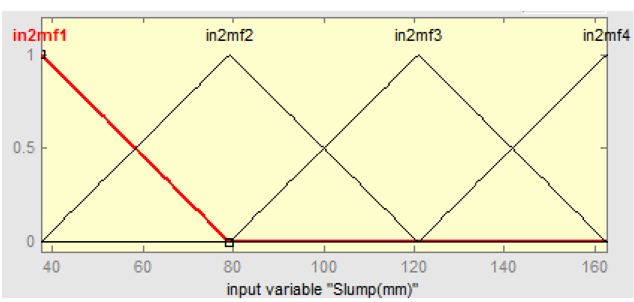

Fig. 13 Tuned membership functions of Slump in the ANFIS model 1

The structure (rules) of tuned FIS has been shown in FIG.14 and contains 16 rules with AND logical connector for all rules.

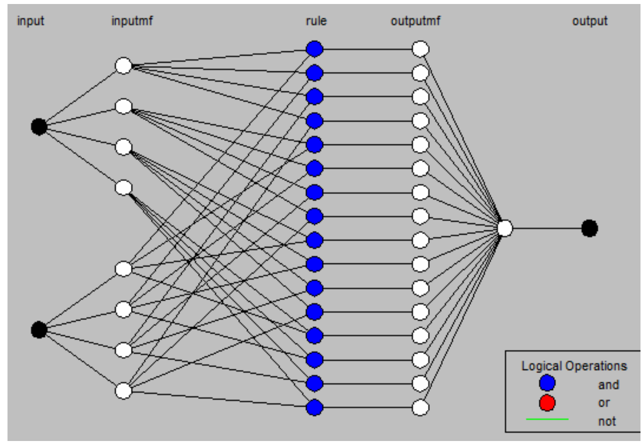

Fig. 14 Structure of the ANFIS model 1 and 2

4.5.1.2 Train FIS

The optimization methods train membership function parameters to emulate the training data.In this step, there are two optimization methods: Hybrid method and Back propagation. The hybrid optimization method is a combination of least-squares and back propagation gradient descent method. In hybrid method, model tunes with to pass: forward pass and backward pass. In the forward pass, with fixed premise parameters, the least squared error estimate approach is employed to update the consequent parameters and to pass the errors to the backward pass .In the backward pass, the consequent parameters are fixed and the gradient descent method is applied to update the premise parameters .Premise and consequent parameters will be identified for MF and FIS by repeating the forward and backward passes. The ANFIS model 1 uses hybrid optimization method. For this ANFIS model, the number of training epochs is 50 and training error tolerance sets to zero. The training process stops whenever the maximum epoch number is reached or the training error goal is achieved.

4.5.1.3 Test FIS

After FIS training, validate the model using a testing or checking data that differs from the one you used to train the FIS. Average testing error of training and testing data in the ANFIS model 1 are 0.86 and 0.8, respectively that have been shown in FIG.15 and FIG.16, respectively.

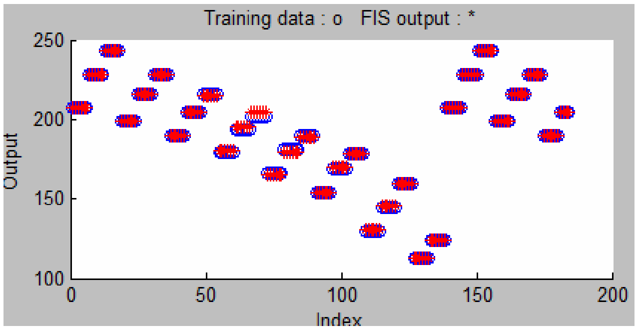

Fig. 15 Result of the ANFIS model 1 testing with Training Data

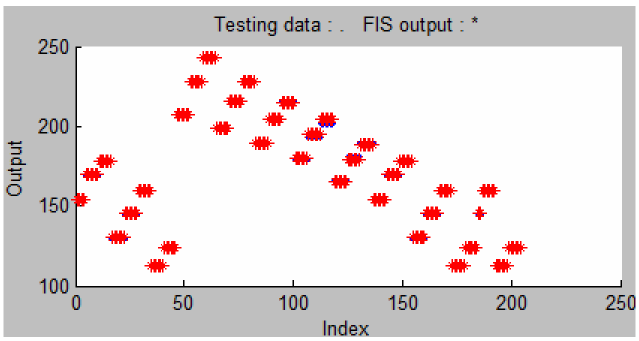

Fig. 16 Result of the ANFIS model 1testing with Testing Data

4.5.2 ANFIS model 2 Designing

This ANFIS model (model 2) has been used for cement value estimation and needs input values of Concrete Compressive Strength (CCS) and water (it is computed in the past ANFIS model (model 1)). For ANFIS designing, model will pass four steps: 1) Load date, 2) Generate FIS, 3) Train FIS, and 4) Test FIS. The usage dataset for this model includes 3 columns (Water, CCS and Cement) and 552 rows. This set was further broken down into three sets: training set, checking set and testing set. FIG.17 shows loaded dataset into the ANFIS model 2.

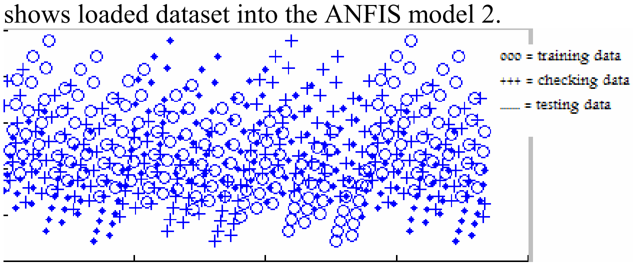

Fig. 17 Loaded dataset into the ANFIS model 2

4.5.2.1 Generate FIS

This ANFIS model (model 2) uses Grid Partition method for FIS generation. Generated FIS has two inputs and one output. Input variables are: Water and CCS. The number and type of membership function for each input variable are four and triangular. Output is the cement value estimation. Membership function type of output variable is linear. Input range of water is [113, 243] and CCS is [15, 40].

4.5.2.2 Train and Test FIS

For this step, the ANFIS model 2 uses hybrid optimization method. In this ANFIS model, the number of training epochs is 50 and training error tolerance sets to zero (same as previous model).
In the ANFIS model 2, the average testing error of training and testing data are 0.21 and 0.22, respectively, although they have been shown in FIG.20 and FIG.21, respectively.

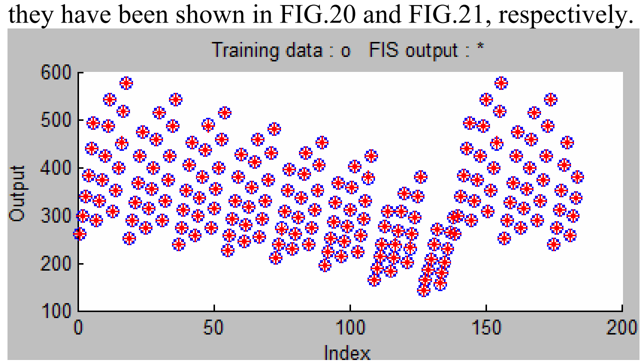

Fig. 18 Result of the ANFIS model 2 testing with Training Data

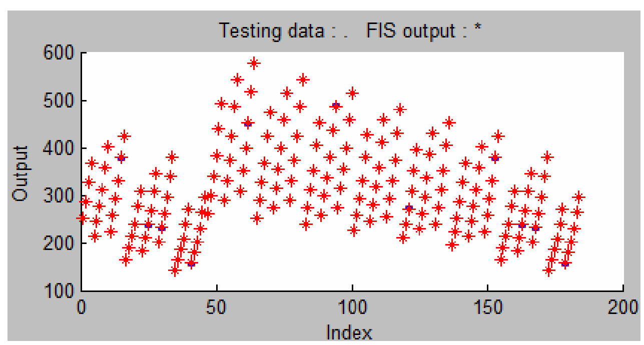

Fig. 19 Result of the ANFIS model 2 testing with Testing Data

4.5.3 ANFIS model 3 Designing

This ANFIS model (model 3) has been used for determining of Coarse Aggregate (C.A) measure although it needs input values of maximum size of aggregate (D_{max}) and Fineness Modulus (FM).in ANFIS designing step, model will pass four steps: 1) Load date, 2) Generate FIS, 3) Train FIS, and 4) Test FIS.

In this model, the usage dataset contains three columns (D_{max}, FM and C.A) and 552 rows. This set was further broken down into three sets :a training set, a checking set and testing sets. FIG.22 shows loaded dataset into the ANFIS model 3.

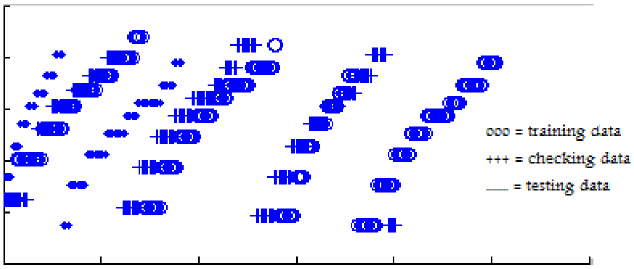

Fig. 20 Loaded dataset into the ANFIS model 3

4.5.3.1 *Generate FIS*

For first time, this ANFIS model (model 3) used Grid Partition method for FIS generation. Generated FIS had two inputs and one output. Input variables were: D_{max} and FM. The number and type of membership functions for each input variable were four and triangular. Output field was the measure of C.A. Membership function type of output variable was linear. This model had two problems: high average testing and training errors on testing data which are 9.88 and 278.07. Because of that, in second time, the ANFIS model 3 has been developed to Subtractive Clustering method with following options: Range of Influence, 0.1, Squash Factor, 1.25, Accept Ratio, 0.5 and Reject Ratio, 0.15. The model contains 31 membership functions for each input. The type of membership functions of input fields is Gaussian. The second designed version of the ANFIS model 3 shows better result than first model 3. The result will be introduced in Test FIS section. Input ranges of D_{max} and FM are [9.5, 150] and is [2.4, 3], respectively. The FIG.23 and FIG.24 show tuned membership functions of each input in the ANFIS model 3. The figures are non-clear because some membership functions put over the other membership functions.

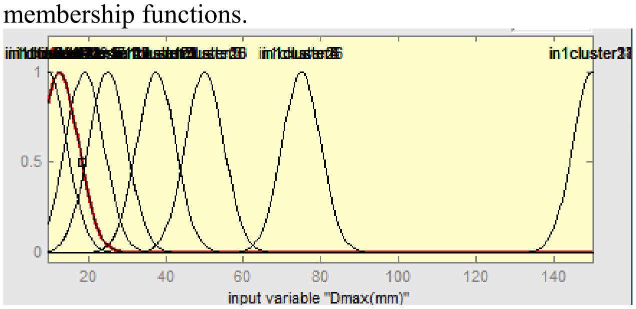

Fig. 21 Tuned membership functions of D_{max} in the ANFIS model 3

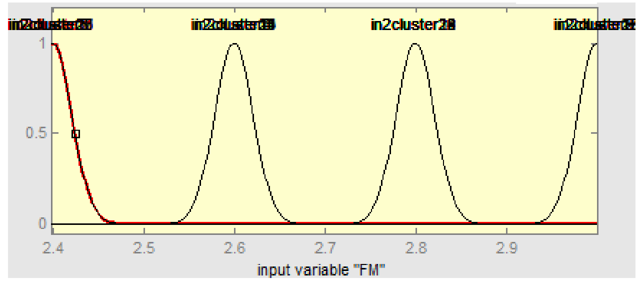

Fig. 22 Tuned membership functions of FM in the ANFIS model 3

The structure (rules) of tuned FIS of the ANFIS model 3 has been shown in FIG.25 although it has 31 rules with AND logical connector for all rules.

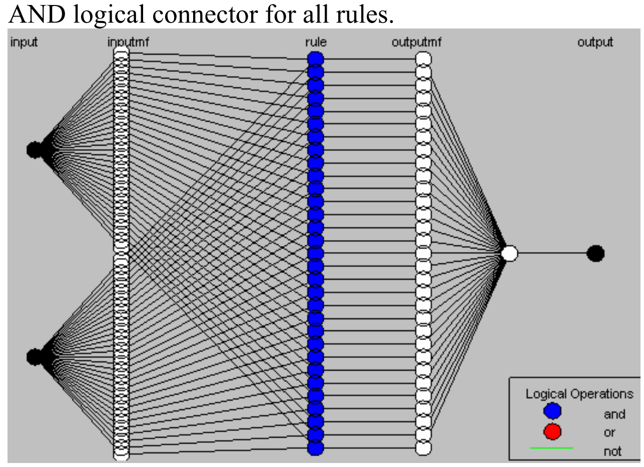

Fig. 22 Structure of the ANFIS model 3

4.5.3.2 *Train and Test FIS*

The ANFIS model 3 uses the hybrid optimization method. In this ANFIS model, the number of training epochs is 50 and training error tolerance sets to zero (same as previous models). With FIS testing, average testing error of training and checking data in the ANFIS model 3 are 0.0001 and 0.0004, respectively. They have been shown in FIG.26 and FIG.27.

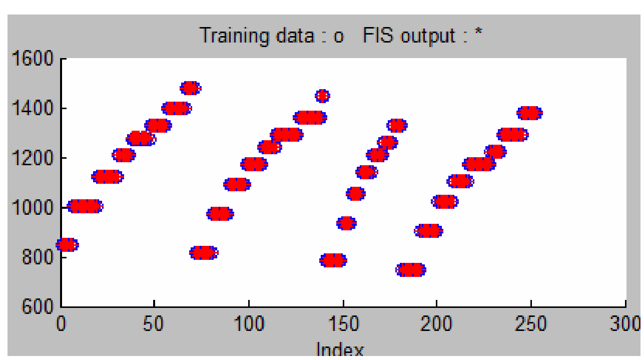

Fig. 23 Result of the ANFIS model 3 testing with Training Data

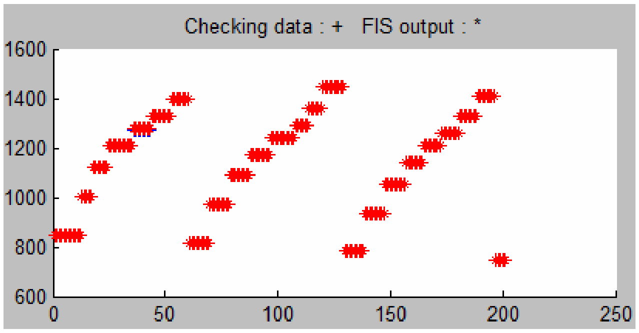

Fig. 23 Result of the ANFIS model 2 testing with Checking Data

4.5.4 ANFIS model 4 Designing

This ANFIS model (model 4) takes input values of water, cement, C.A (they have been computed in previous models) and also the value of first estimate of concrete density. After that, it measures the value of Fine Aggregate. In ANFIS designing section, model will pass four steps: 1) Load date, 2) Generate FIS, 3) Train FIS, and 4) Test FIS.In this model, the usage dataset contains four columns (Concrete density, Water, Cement and C.A) and 552 rows. This set has been divided into three sets: training set, checking set and testing set. The FIG.28 shows loaded dataset into the ANFIS model 4.

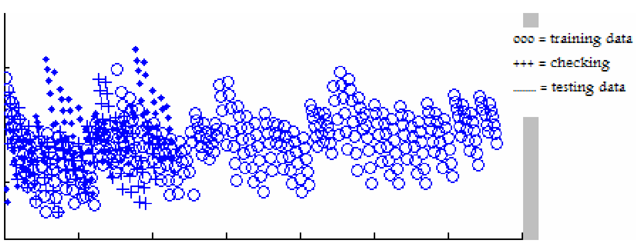

Fig. 24 Loaded dataset into the ANFIS model 4

4.5.4.1 Generate FIS

In this ANFIS model (model 4), FIS had been generated with Grid Partition method and result of system showed high average testing error for testing and checking datasets. In second time, the ANFIS model (model 4) had been developed to Subtractive Clustering with following options: Range of Influence, 0.5, Squash Factor, 1.25, Accept Ratio, 0.5 and Reject Ratio, 0.1. The Generated FIS includes four inputs and one output. Input variables are: Concrete Density, Water, Cement and C.A. The number and type of membership functions for each input variable are Seven and Gaussian. Output field produces the measure of Fine Aggregate (F.A). Membership function type of output is linear. Input range of concrete density, water, cement and C.A are [2280, 2530], [113, 243], [143, 578] and [748, 1479], respectively. The tuned Membership functions of each input will be shown in FIG.29, FIG.30, FIG.31 and FIG.32. The figures are non-clear because some membership functions put over the other membership functions.

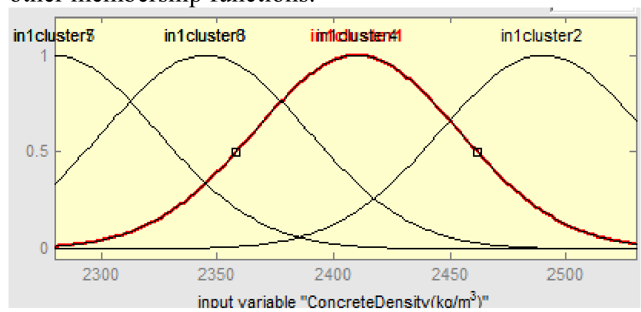

Fig. 25 Tuned Membership functions of Concrete Density in the ANFIS model 4

The structure (rules) of tuned FIS of the ANFIS model 4 has been shown in FIG.33 and contains seven rules with AND logical connector for all rules (same as the ANFIS model 1).

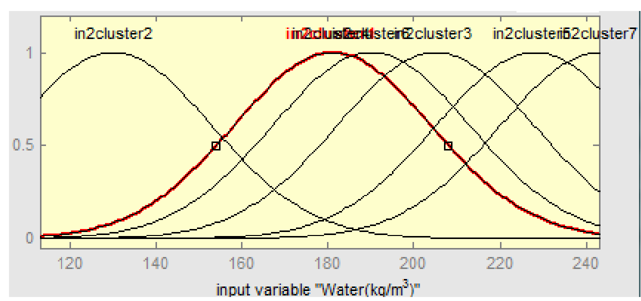

Fig. 26 Tuned Membership functions of Water in the ANFIS model 4

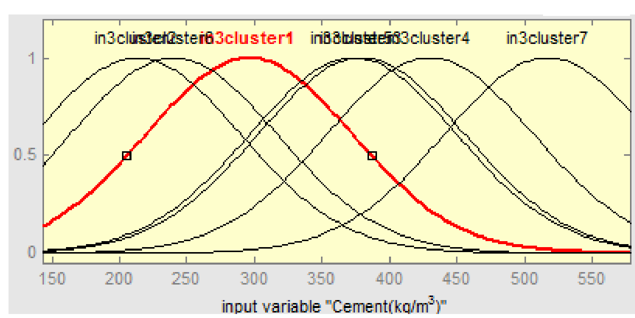

Fig. 27 Tuned Membership functions of Cement in the ANFIS model 4

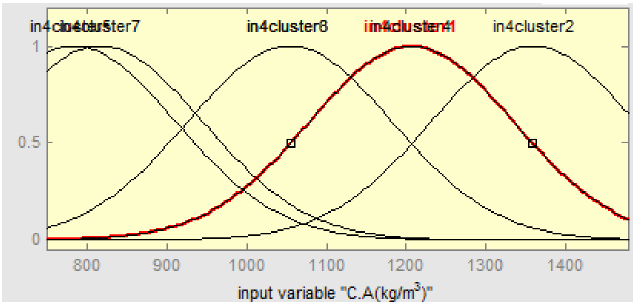

Fig. 28 Tuned Membership functions of C.A in the ANFIS model 4

4.5.4.2 *Train and Test FIS*

In this step, the hybrid optimization method has been used for the ANFIS model 4. In this ANFIS model, the number of training epochs is 50 and training error tolerance sets to zero (same as previous models).
The average testing error of training and testing datasets in the ANFIS model 4 are 0.0049 and 0.0063, respectively that have been shown in FIG.34 and FIG.35.

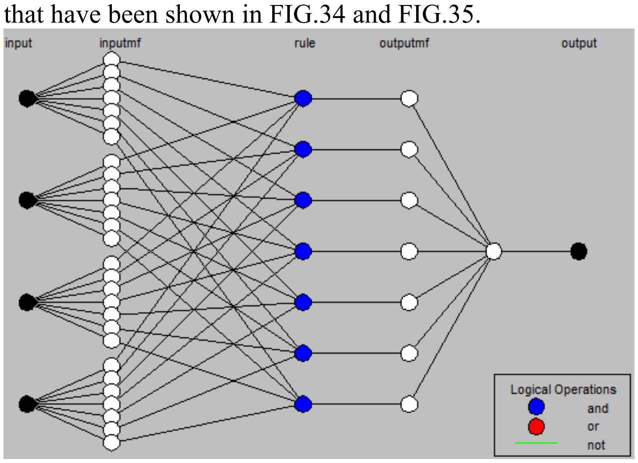

Fig. 29 Membership functions of C.A in the ANFIS model 4

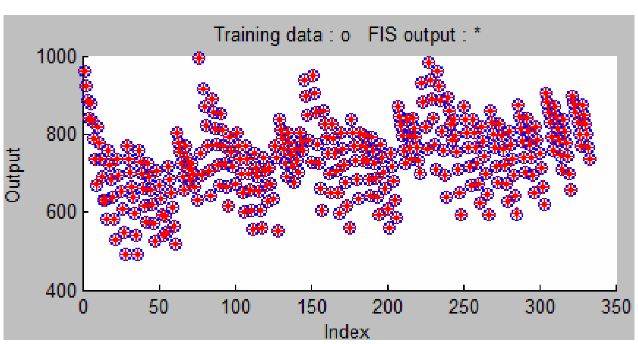

Fig. 30 Result of the ANFIS model 2 testing with Training Data

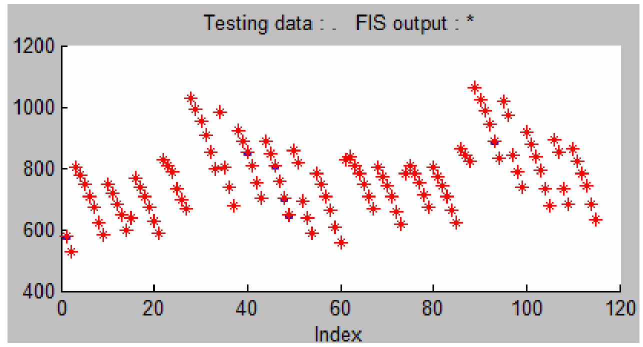

Fig. 31 Result of the ANFIS model 2 testing with Testing Data

4. Conclusions

In civil engineering, offering a good mix design is nonlinear completely and based on experiments. So fuzzy logic based model is suitable for estimation of concrete mix design.
In this comparative study, two fuzzy logic based models has been developed to offering good and reasonable mix design for 28-day concrete: Fuzzy Expert System and Adaptive Neural-Fuzzy Inference System (ANFIS). Rules, input/output variables, membership functions and ranges of them based on the ACI standards. The ANFIS model contains four models that each model has been used for a task: the ANFIS model 1 for estimating of water measure, the ANFIS model 2 for measuring of cement value, the ANFIS model 3 for computation of C.A value and the ANFIS model 4 for computation of F.A measure. The usage dataset for training the FIS systems has been collected from ACI concrete mix design.
After systems designing and testing, comparison between two systems (FIS and ANFIS) results showed that results of ANFIS model are better than Fuzzy Expert System results. In ANFIS model, for Water output field, training and average testing errors are 0.86 and 0.8, respectively, for cement field, training error and average testing error are 0.21 and 0.22, respectively, training and average testing error of C.A are 0.0001 and 0.0004, respectively and training and average testing errors of F.A are 0.0049 and 0.0063, respectively. Results of Fuzzy Expert System in comparison to ACI results have following average testing errors: average error of Water, Cement, C.A and F.A are 9.5%, 27.6%, 96.5% and 49% respectively.

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Mehdi Neshat was born in 1980.He received the B.Sc. degree in computer engineering from Azad University, Maybod, Iran, in 2006, the M.Sc. degree in Artificial Intelligence from the University of mashhad, in 2008 and is a member of the IEEE and the IEEE Computer Society
He is with Islamic Azad University, Shirvan Branch, Faculty of Engineering, and computer Engineering Dept., Shirvan /Iran since 2007. His research interests are fuzzy logic, fuzzy systems, and fuzzy neural networks, particle swarm optimization, genetic algorithms, ant colony optimization, and other evolutionary computation techniques. He has publications and submissions in international conferences like applied soft computing, Applied Mathematical Modeling, Expert Systems with Applications, Fuzzy Sets & Systems, Computers in Industry Information Sciences, Mathematical & Computer Modeling.

Ali Adeli was born in 1986.He received the B.Sc. degree in computer engineering from Azad University, Shirvan, Iran, in 2009, the M.Sc. student in computer engineering from the University of shiraz, in 2009.

Azra Masoumi was born in 1981.He received the B.Sc. degree in computer engineering from Azad University, shirvan, Iran, in 2008.

Mehdi sargolzae was born in 1978.He received the B.Sc. degree in computer engineering from Ferdowsi University, mashhad, Iran, in 2005, the M.Sc. degree in computer engineering from the Amirkabir University of Tehran, in 2007 and Dr student in computer engineering from the Amsterdam University.