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Full Length Research Paper

Comparative study on fuzzy inference systems for prediction of concrete compressive strength

Mehdi Neshat*, Ali Adeli, Ghodrat Sepidnam and Mehdi Sargolzaei

Department of Computer Engineering, Shirvan branch, Islamic Azad University, Shirvan, Iran.

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The aim of this comparative study is to evaluate the effects of different methods, used for "aggregation" and "defuzzification", on the output. To reach this goal, six fuzzy inference systems (FIS-1, FIS-2, FIS-3, FIS-4, FIS-5 and FIS-6) have been designed (with the same rule bases) with different methods used for aggregation, defuzzification, and overlapping between the fuzzy sets. The idea of this system is based on the UCI dataset. To design the systems, some of the input fields of UCI dataset have been replaced with other important fields that made system more applicable and suitable. All of these designed systems have the same input fields such as: Water/cement ratio, slump, maximum size of aggregate, coarse aggregate, fine aggregate and age (day). The output field of all systems measures the compressive strength of concrete. These three differences in 401 laboratory samples have caused the average error of predicted compressive strength, that is, 6.43% FIS-1, 6.64% FIS-2, 6.48% FIS-3, 5.56% FIS-4, 4.73% FIS-5 and 5.07% FIS-6. The experimental results reveal that the methods of "sum" and "Centroid" (used in the FIS-5) show the best results (among other methods) for the "aggregation" and the "defuzzification", respectively.

Key words: Aggregation step, defuzzification step, concrete compressive strength (CCS), fuzzy inference system (FIS), W/C ratio, slump, maximum size of aggregate, coarse aggregate, fine aggregate, age.

INTRODUCTION

In fuzzy inference system, there are 5 steps such as fuzzy inputs, combination of inputs with AND (OR) method, implication, aggregation of all outputs and defuzzification (Tinkir, 2011). In the mentioned steps, steps "2 to 5" have different methods. In other word, step 2 uses four methods for AND (min and product) and OR (max and probability OR) logical operations, step 3 has two methods (min and product), step 4 contains three methods (max, sum and probability OR) and steps 5 includes five methods (centroid, bisector, mom, lom and som). The steps 4 and 5 are important in deduction. Furthermore, we should know about the properties and influence of the methods used to reach robust and accurate results. Therefore, in this paper, some methods used for aggregation and defuzzification are studied based on the designed fuzzy inference systems to predict the compressive strength of concrete.

Nowadays, because of the computer technology in the fields of concrete and cement (Alwathaf et al., 2011; Marar and Eren, 2011), the treatment of concrete in several situations has highly changed (Karim et al., 2011). Despite this fact that these fields, in which the computers are used, have high complexity and uncertainty, the intelligent systems such as fuzzy logic, artificial neural network and genetic algorithm have been developed.

Concrete is a material consisting of a binder within which aggregate particles are imbedded (Suchorski, 2007). Concrete production is a complex process which 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 quantity of 28-day compressive strength. These factors are water to cement ratio, slump, maximum size of aggregate (D_{max}), fine aggregation, coarse aggregation, age(day), exposure condition, absorption of fine and coarse aggregation, specific gravity of water, cement, fine aggregate, coarse aggregate, etc. All of these factors result in different CCS from one situation to another with the same input values. So, the determination

*Corresponding author. E-mail: Neshat_mehdi@ieee.org.

of CCS is very hard and imprecise. Having so many factors to analyze CCS level makes the expert's job difficult. So, experts require an accurate tool which can consider these risk factors and show certain result in uncertain term.

Motivated by the need of such an important tool in this comparative study, we, first designed the fuzzy system to predict the compressive strength of concrete, and then, improved it. The paper deals with the six fuzzy inference systems (FIS-1, FIS-2, FIS-3, FIS-4, FIS-5 and FIS-6). These fuzzy inference systems have been implemented, so that the experimental results showed that the "FIS-5" system is quite better than the other FIS systems (FIS-1, FIS-2, FIS-3, FIS-4 and FIS-6), because of using the "sum" and "Centroid" methods for aggregation and defuzzification, respectively.

PREVIOUS RESEARCH

Despite the fact that these fields, in which the computers are used, have high complexity and uncertainty and the use of intelligent systems such as fuzzy logic, artificial neural network and genetic algorithm have been developed. These papers have been shown as follows.

Nehdi found a fuzzy logic approach to estimate the durability of the 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 those of others 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 the one with the remaining service life model (R^2 = 0.5), and it represented, the actual degradation is better observed in test specimens (Nehdi and Bassuoni, 2009).

Tanyildizi studied on fuzzy logic model to predict the bond strength of high-strength lightweight concrete. A controlled concrete mixture containing only Portland cement, another mixture having fly ash replaced with 15% mass of cement, and a third mixture having silica fume replaced with 10% mass of cement are produced, and all the specimens from these three mixtures are cured in three different conditions, which are: (1) in water tank of 20±2^^{o}C, (2) sealed in plastic bags in the laboratory, and (3) in the air in the laboratory. At the end of each curing period, three specimens out of each concrete combination and curing condition were tested for compressive and bond strengths, and then, the average of the three values were taken. The obtained results from the fuzzy logic prediction model were compared with the average results of the experiments, and they were found to be remarkably close to each other. The results show that the fuzzy logic can be used to predict the bond strength of lightweight concrete (Tanyildizi, 2009a,b).

Sarıdemir designed an artificial neural network to predict the compressive strength of concretes containing metakaolin and silica fume. The ANN model has been developed at the age of 1, 3, 7, 28, 56, 90 and 180 days. The data used in the multilayer feed-forward neural networks models are arranged in an eight input parameters format which covers the age of specimen, cement, metakaolin (MK), silica fume (SF), water, sand, aggregate, and super plasticizer. These input parameters, in the multilayer feed forward neural networks models, predicted the compressive strength values of concretes containing metakaolin and silica fume. The training and testing results in the neural network models have shown that neural networks have strong potential to predict 1, 3, 7, 28, 56, 90 and 180 days compressive strength values of concretes containing metakaolin and silica fume (Sarıdemir, 2009).

Bilgehan proposed 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 the 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. In Comparison of the results, it is found that the proposed ANFIS architecture with Gaussian membership function performs better than the multilayer feed-forward ANN learning by back propagation algorithm (Razavi et al., 2011). The final results show that especially the ANFIS modeling may constitute an efficient tool to predict the concrete compressive strength (Bilgehan, 2011; Yang et al., 2005).

Özcan had a paper on the comparison of artificial neural network and fuzzy logic models to predict long-term compressive strength of silica fume concrete. In this investigation, an artificial neural network (ANN) and fuzzy logic (FL) study were developed to predict the compressive strength of silica fume concrete. A data set of a laboratory work, in which a total of 48 concretes were produced, was utilized in the ANNs and FL study. The concrete mixture parameters were four different water-cement ratios, three different cement dosages and three partial silica fume replacement ratios. Compressive strength of moist cured specimens was measured at five different ages. The results showed that ANN and FL can be considered as alternative approaches to predict compressive strength of silica fume concrete (Özcan et al., 2009; Hakim et al., 2011).

Tanyildizi introduced a fuzzy logic model to predict the compressive strength of lightweight concrete made up of scoria aggregate and fly ash. The fuzzy logic was utilized to predict the compressive strength of lightweight concrete

Table 1. Differences between FISs in methods used for aggregation and defuzzification methods.

System	Overlapping between sets	Aggregation method	Defuzzification method	Average error (%)
FIS-1	Same as FIS-3	Max	Bisector	6.43
FIS-2	More than FIS-1	Max	Bisector	6.64
FIS-3	Same as FIS-1	Sum	Bisector	6.48
FIS-4	Same as FIS-2	Sum	Bisector	5.56
FIS-5	Same as FIS-1	Sum	Centroid	**4.73**
FIS-6	Same as FIS-2	Sum	Bisector	5.07

Table 2. The properties of all systems.

System	And method	OR method	Implication method	Aggregation method	Defuzzification method
FIS-1	Min	Max	Min	Max	Bisector
FIS-2	Min	Max	Min	Max	Bisector
FIS-3	Min	Max	Min	Sum	Bisector
FIS-4	Min	Max	Min	Sum	Bisector
FIS-5	Min	Max	Min	Sum	Centroid
FIS-6	Min	Max	Min	Sum	Bisector

based on curing condition, ultrasonic pulse velocity, curing time (day), and fly ash. They found that the average error for predicted compressive strength is 7.15% (Tanyildizi and Qoskun, 2007).

MATERIALS AND METHODS

Data set

The idea of system is based on the database at the University of California (UCI) that had been collected by Yeh (2006). In this 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 level of concrete compressive strength (Yeh, 2003).

In the first FIS, "water" field was combined with "cement" field, and changed into a field called water/cement ratio. The field takes quantities in the form of percent. Slump has been used rather than the blast furnace slag. This input field takes values in centimeter unit. Also, the fly ash field has been replaced with maximum size of aggregate (D_{max}) in millimeter unit. The super plasticizer input field has been omitted from the system because in the past recent years, it was not useable anymore. The other input fields such as fine aggregate (F.A), coarse aggregate (C.A), and age (day) have been transformed into dataset. The units of F.A and C.A are kg/m^3.

The values which define the membership functions determining the linguistic labels used in FIS variables were selected from UCI dataset, and by experts in the concrete field.

After that, the first FIS was developed to six FIS systems. All of these six systems have the same input fields and rule bases. There are two differences in the methods used for aggregation and defuzzification, and overlapping among the fuzzy sets for some fields. The differences between FISs and the average errors are shown in Table 1.

METHODS

Inspired by human's remarkable capability to perform a wide variety of physical and mental tasks without any measurement and computations, and dissatisfied with classical logic as a tool for modeling human reasoning in an imprecise environment, (Nikravesh and Zadeh, 2007) developed the theory and foundation of fuzzy logic with his 1965 paper "Fuzzy Sets".

The most important application of fuzzy system (fuzzy logic) is in uncertain issue . When a problem has dynamic behavior, fuzzy logic is a suitable tool that deals with this problem (Passino and Yurkovich, 1998; Rajasekaran and vijayalakshmi, 2003). The term "uncertainty" refers to a set of questions that almost human experts ask them-selves each day. Since these (and related questions) represent issues which every human decision maker must constantly face, they are also issues that an automated inference system should be able to handle (Keung and Abramson, 1990).

Here, the designing process of all FISs has been introduced.

Designing process of fuzzy inference systems (all FISs)

The first step of FIS designing process is to determine the input and output variables .There are six inputs and one output. After that, the designing process of membership functions (MF) of all variables will be reviewed. The properties of all FISs are demonstrated in Table 2.

First of all, input variables with their membership functions for all those FISs are introduced . Second step is to describe the output variable with its membership functions for all those systems.

Input variables

Input variables of all systems are:

Water/cement ratio: W/C ratio is a very important factor that

Table 3.Classification of water/cement ratio for all systems.

System	Range	Fuzzy sets
FIS-1, FIS-2, FIS-3; FIS-4, FIS-5, FIS-6	<52	Very Low=VL
	48-62	Low=L
	55-72	Medium=M
	65>	High =H

$$\mu_{VL}(x)=\begin{cases}1 & x<48\\ (52-x)/4 & 48\le x<52\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-48)/7 & 48\le x<55\\ 1 & x=55\\ (62-x)/7 & 55\le x<62\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-55)/8 & 55\le x<63\\ 1 & x=63\\ (72-x)/9 & 63\le x<72\end{cases}$$

$$\mu_{H}(x)=\begin{cases}(x-65)/5 & 65\le x<70\\ 1 & x\ge 70\end{cases}$$

Equation 1. The mathematical equations of the membership functions of W/C ratio.

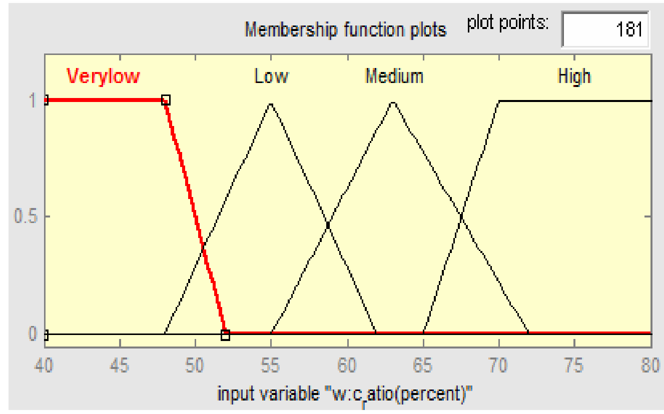


Figure 1. Membership functions of water/cement ratio for all FISs.

influences on concrete compressive strength, directly (Suchorski, 2007). The quantity of CCS will increase when W/C ratio decreases and vice versa [15, 16]. This is the same for all systems. This input takes quantities from [40, 80] interval in percent. Input interval of W/C ratio for all systems is shown in Table 3. Table 3 shows the same range and fuzzy sets for all FIS systems.

The mathematical equations of the membership functions of W/C ratio for all systems are shown in Equation (1). The membership functions of W/C ratio field for all systems are shown in Figure 1.

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. (Suchorski, 2007) following the ASTM C 143-90 or EN 12350-2 test standards. Therefore CCS will be increased when the measure of slump decreases and vice versa.

Note that the FIS-1, FIS-3 and FIS-5 have the same membership functions and fuzzy sets and other systems have the same membership functions and fuzzy sets too.

Mathematical equations of membership functions of slump for all systems are introduced in Equation (2). These fuzzy sets for all systems are shown in Table 4 . The membership functions of slump in all systems are shown in Figure 2.

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 (Suchorski, 2007). With increasing the amount of D_{max}, the quantity of CCS will increase. So, there is a direct relationship between the maximum size of aggregate and CCS. Note that the FIS-1, FIS-3 and FIS-5 have the same membership functions and fuzzy sets and the other systems have the same membership functions and fuzzy sets, too.

Equation (3) introduces the mathematical equations of the membership functions of D_{max} for all systems. Table 5 shows these fuzzy sets. The membership functions of the maximum size of aggregate are shown in Figure 3.

Course aggregate (C.A): This type of aggregate is predominantly retained on the 4.75 mm sieve (Suchorski, 2007). Coarse aggregate may be available in several different size groups, such as 19 to 4.75 mm or 37.5 to 19 mm. "ASTM C 33" contains standard specification for concrete aggregates.

The systems (FIS-1, FIS-3 and FIS-5) have no changes in the boundary of these sets, but the mathematical equations of $\mu_{VL}(x)$ =1 and $\mu_H(x)$ =1 of C.A's membership function have changed. In FIS-1, FIS-3, and FIS-5, $\mu_{VL}(x)$ =1 has been defined for $x<770$ but, in the other ones, it has been defined for $x<820$. It shows that in FIS-2, FIS-4 and FIS-6, the number of acceptable inputs (x) with $\mu_{VL}(x)$ =1 is more than the other systems. In FIS-1, FIS-3 and FIS-5, $\mu_H(x)$ =1 has been defined for $x\ge 1110$, and in the other FISs, it has been defined for $x\ge 1080$. It shows that in FIS-2, FIS-4 and FIS-6, the number of acceptable inputs (x) with $\mu_{VL}(x)$ =1 is more than the others.

The mathematical equations of the membership functions of coarse aggregate are reviewed in Equation (4). Table 6 shows that the fuzzy sets with their ranges are the same for all systems. Figure 4 shows the membership function of coarse aggregate for all systems.

Fine aggregate (F.A): The aggregate passes the 9.5 mm (3/8 in.)

$$\mu_{VL}(x) = \begin{cases} 1 & x < 1.034 \\ (2.069 - x)/1.035 & 1.034 \le x < 2.069 \end{cases}$$

$$\mu_{L}(x) = \begin{cases} (x - 1.034)/2.069 & 1.034 \le x < 3.103 \\ 1 & x = 3.103 \\ (5.172 - x)/2.069 & 3.103 \le x < 5.172 \end{cases}$$

$$\mu_{M}(x) = \begin{cases} (x - 3)/3 & 3 \le x < 6 \\ 1 & x = 6 \\ (9 - x)/3 & 6 \le x < 9 \end{cases}$$

$$\mu_{H}(x) = \begin{cases} (x - 8)/3 & 8 \le x < 11 \\ 1 & x \ge 11 \end{cases}$$

(a)

$$\mu_{VL}(x) = \begin{cases} 1 & x < 2 \\ (6 - x)/4 & 2 \le x < 6 \end{cases}$$

$$\mu_{L}(x) = \begin{cases} (x - 2)/4 & 2 \le x < 6 \\ 1 & x = 6 \\ (10 - x)/4 & 6 \le x < 10 \end{cases}$$

$$\mu_{M}(x) = \begin{cases} (x - 6)/4 & 6 \le x < 10 \\ 1 & x = 10 \\ (15 - x)/5 & 10 \le x < 15 \end{cases}$$

$$\mu_{H}(x) = \begin{cases} (x - 10)/5 & 10 \le x < 15 \\ 1 & x \ge 15 \end{cases}$$

(b)

Equation 2. Mathematical equation of slump (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.

Table 4. Classification of slump for all systems.

System	Range	Fuzzy sets
FIS-1,FIS-3,FIS-5	< 2.69	Very low=VL
	1.034 - 5.172	Low=L
	3-9	Medium=M
	8>	High =H
FIS-2,FIS-4,FIS-6	< 6	Very Low=VL
	2 -10	Low=L
	6-15	Medium=M
	10>	High =H

sieve and almost entirely passes the 4.75 mm sieve and predominantly retained on the 75 µm sieve (Suchorski, 2007). 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.

Notice that the amount of coarse aggregate will increase, but the amount of fine aggregate will decrease when the amount of CCS increases, and vice versa. So, there is a direct relationship between coarse aggregate and CCS, but an inverse relationship between fine aggregate and CCS.

The membership functions of all systems, shown in Figure 5, are the same. Equation (5) shows the same mathematical equations of the membership functions for all systems. In Table 7, these fuzzy sets have been defined.

Age (day): Age is a very important and effective factor. The amount of CCS will increase when the amount of age increases (Uyunoglu and Unal, 2006). Figure 6 shows the membership functions of all systems. These fuzzy sets are shown in Table 8 with their ranges. Equation (6) defines the mathematical equations of the age membership functions for all systems.

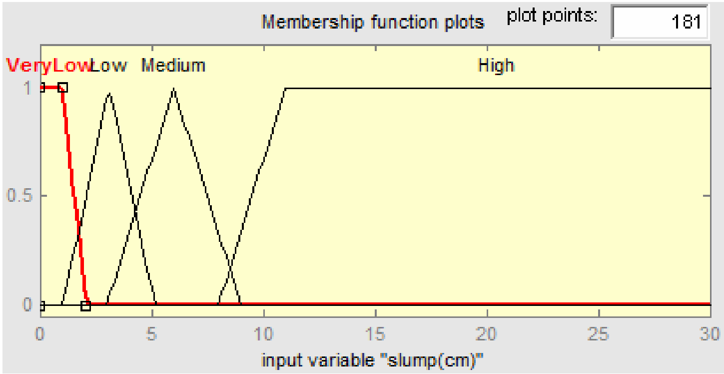
Input variables

The output of all systems is:

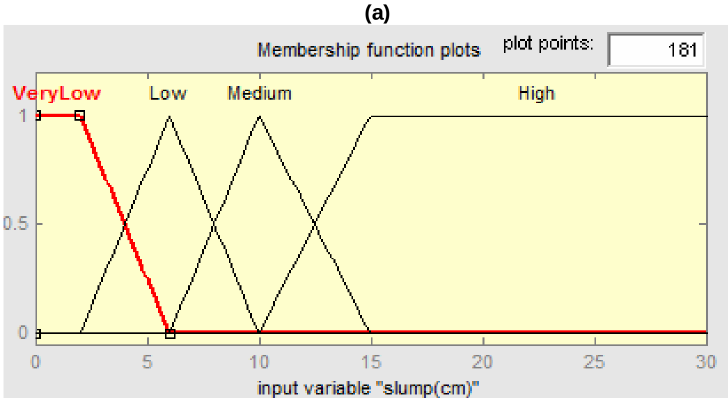
Concrete compressive strength (CCS): The goal of this field refers to the measure of concrete compressive strength in Mpa unit. Compressive strength is a measure of the ability of concrete to withstand crushing loads (Charles and Suchorski, 2006). All of aforementioned input factors are important, and have direct effects on the compressive strength. The CCS membership functions of all systems are shown in Figure 7. Table 9 shows these fuzzy sets with their ranges in all systems. Equation (7) shows the mathematical equations of the CCS membership functions for all systems.

Fuzzy rulebase

Rule base is the main part of FIS, and the quality of results in fuzzy system depends on the fuzzy rules (Nikravesh and Zadeh, 2007). 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(Nikravesh and Zadeh, 2007; Andina and Pham, 2007). 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. The knowledge included in the FIS rules originated from



(a)



(b)

Figure 2. Membership functions of slump (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.

$$\mu_{VL}(x) = \begin{cases} 1 & x < 12 \\ (15-x)/3 & 12 \le x < 15 \end{cases}$$

$$\mu_{L}(x) = \begin{cases} (x-13)/6 & 13 \le x < 19 \\ 1 & x = 19 \\ (25-x)/6 & 19 \le x < 25 \end{cases}$$

$$\mu_{M}(x) = \begin{cases} (x-20)/13 & 20 \le x < 33 \\ 1 & x = 33 \\ (50-x)/17 & 33 \le x < 50 \end{cases}$$

$$\mu_{H}(x) = \begin{cases} (x-40)/20 & 40 \le x < 60 \\ 1 & x \ge 60 \end{cases}$$

(a)

$$\mu_{VL}(x) = \begin{cases} 1 & x < 14 \\ (20-x)/6 & 14 \le x < 20 \end{cases}$$

$$\mu_{L}(x) = \begin{cases} (x-13)/9 & 13 \le x < 22 \\ 1 & x = 22 \\ (30-x)/8 & 22 \le x < 30 \end{cases}$$

$$\mu_{M}(x) = \begin{cases} (x-20)/13 & 20 \le x < 33 \\ 1 & x = 33 \\ (50-x)/17 & 33 \le x < 50 \end{cases}$$

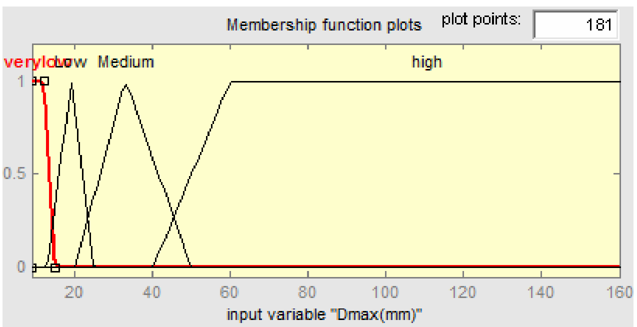
$$\mu_{H}(x) = \begin{cases} (x-33)/16 & 33 \le x < 49 \\ 1 & x \ge 49 \end{cases}$$

(b)

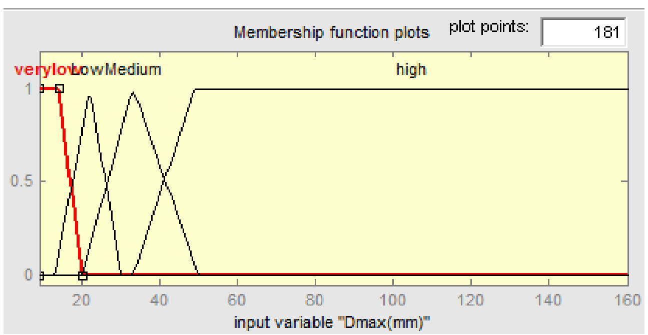
Equation 3. Mathematical equation of D_{max} (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.

Table 5. Classification of d_{max} for all systems.

System	Range	Fuzzy sets
FIS-1, FIS-3, FIS-5	< 15	Very low=VL
	13 - 25	Low=L
	20-50	Medium=M
	40>	High =H
FIS-2, FIS-4, FIS-6	< 20	Very low=VL
	13 - 30	Low=L
	20-50	Medium=M
	33>	High =H



(a)



(b)

Figure 3. Membership functions of D_{max} (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.

(Suchorski, 2007; Nmai, 2001; Nataraja et al., 2006a; and Nataraja et al., 2006b).

All FIS systems include 24 rules. The antecedent part of all rules has a section. The results with 24 rules are in line with the expert's idea and laboratory results .The rules are shown in Figure 8.

Fuzzification and defuzzification

All designed systems use the inference mechanism of Mamdoni approach .In these systems, we did not use any logical combination (AND/OR) of inputs because the antecedent part of all rules has a section. A validity degree (k) has been defined for each rule which is shown as follows.

k1 = W: C ratio(x)

K6 = Slump(x)

K12 = D_{max}(x)

K24 = Day(x)

For aggregation of rules and defuzzification process, each system uses different methods demonstrated in Table 1.

The surface viewer of some fields of all FIS systems is shown in Figure 9.

EXPERIMENTAL RESULTS AND DISCUSSION

All of the 401 mix designs tested in laboratory have the following situation:

Specimen = standard cylinder (150-300 mm)
Type of Concrete = Reinforced cast with non-air entrained
Exposure Condition = Fresh water

Because of the noise in the laboratory data, we used the software of "Concrete Mix Designer" (Sobhy, 2011). After testing the 401 mix designs in the laboratory, we used these 401 samples to test the designed systems. The result of system testing for some mix designs are shown in Table 10. All samples were tested for 28 days.

All in all, when we use the method of "Sum" rather than the method of "Max" for the aggregation step, we can observe accurate and robust results. On the other hand, we observe any types of the concrete strength (with method "Sum") such as very low, low, medium and high strengths, but when we use the method of "Max", we observe just the medium and high strengths. So, the attributes of the method of "Sum" for the aggregation step provide wide variations range for quantities of CCS. Another issue is about the method of "Centroid" that is replaced with the method of "Bisector" for the defuzzification step. The method of "Centroid" affects variations range of CCS quantities. So, it provides better result than the method of "Bisector". Notice that if an FIS system (like FIS-5) uses the methods of "Centroid" and "Sum", then it shows better results.

It is important that the FIS-2 results in the lowest accuracy (high error) because it uses the methods of "Max" and "Bisector" for the aggregation and defuzzification, respectively. So, the use of these two methods at the same time is not efficient.

W.C is one of the most important parameters in producing high-strength concrete. The laboratory data and the results obtained from the systems indicate that the optimum concrete compressive strength is obtained when water/cement ratio is 48%. When the system's inputs include (W.C = 62, slump = 7, MSA = 40, CA = 976, FA = 919) values, it will have the lowest average error. This ratio has also an optimum concrete compressive strength. Table 11 shows the average error of FIS1-FIS6 calculated for the inputs of each row in which the max average error is 8.73 and the min one is 1.55.

$$\mu_{VL}(x)=\begin{cases}1 & x<770\\ {(880-x)}/{110} & 770\le x<880\end{cases}$$

$$\mu_{L}(x)=\begin{cases}{(x-780)}/{110} & 780\le x<890\\ 1 & x=890\\ {(1000-x)}/{110} & 890\le x<1000\end{cases}$$

$$\mu_{M}(x)=\begin{cases}{(x-890)}/{110} & 890\le x<1000\\ 1 & x=1000\\ {(1100-x)}/{100} & 1000\le x<1100\end{cases}$$

$$\mu_{H}(x)=\begin{cases}{(x-1000)}/{110} & 1000\le x<1110\\ 1 & x\ge 1110\end{cases}$$

(a)

$$\mu_{VL}(x)=\begin{cases}1 & x<820\\ {(880-x)}/{60} & 820\le x<880\end{cases}$$

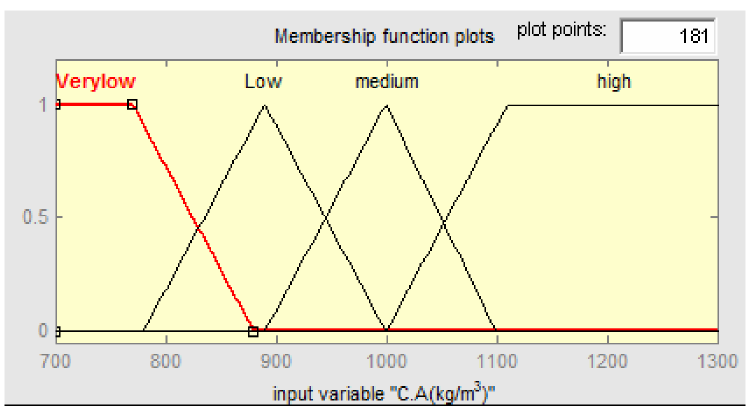
$$\mu_{L}(x)=\begin{cases}{(x-780)}/{110} & 780\le x<890\\ 1 & x=890\\ {(1000-x)}/{110} & 890\le x<1000\end{cases}$$

$$\mu_{M}(x)=\begin{cases}{(x-890)}/{110} & 890\le x<1000\\ 1 & x=1000\\ {(1100-x)}/{100} & 1000\le x<1100\end{cases}$$

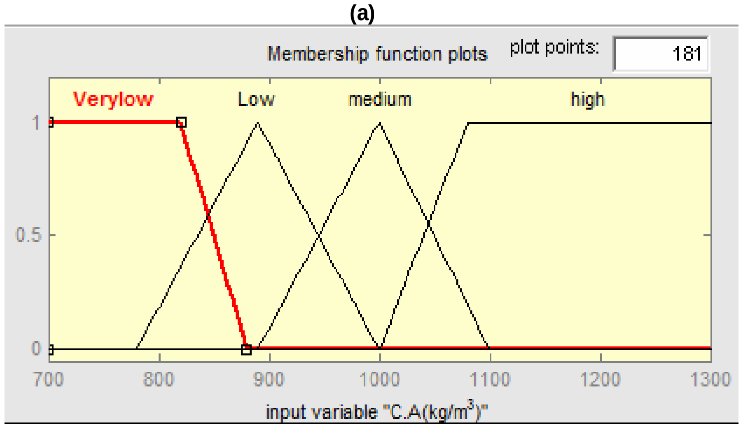
$$\mu_{H}(x)=\begin{cases}{(x-1000)}/{80} & 1000\le x<1080\\ 1 & x\ge 1080\end{cases}$$

(b)

Equation 4. Mathematical equation of coarse aggregate (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.



(a)



(b)

Figure 4. Membership functions of coarse aggregate (a) for FIS-1, FIS-3 and FIS-5; (b) FIS-2, FIS-4 and FIS-6.

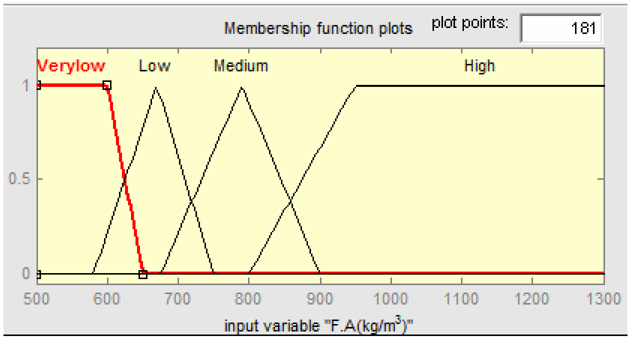


Figure 5. Membership functions of fine aggregate for all systems.

$$
\mu_{VL}(x) = \begin{cases} 1 & x < 600 \\ (650 - x)/50 & 600 \le x < 650 \end{cases}
$$

$$
\mu_{L}(x) = \begin{cases} (x - 580)/90 & 580 \le x < 670 \\ 1 & x = 670 \\ (750 - x)/80 & 670 \le x < 750 \end{cases}
$$

$$
\mu_{M}(x) = \begin{cases} (x - 675)/115 & 675 \le x < 790 \\ 1 & x = 790 \\ (900 - x)/110 & 790 \le x < 900 \end{cases}
$$

$$
\mu_{H}(x) = \begin{cases} (x - 800)/150 & 800 \le x < 950 \\ 1 & x \ge 950 \end{cases}
$$

Equation 5. Mathematical equation of fine aggregate for all systems.

Table 6. Classification of coarse aggregate for all systems.

System	Range	Fuzzy sets
FIS-1, FIS-2, FIS-3, FIS-4, FIS-5, FIS-6	< 880	Very Low=VL
	780-1000	Low=L
	890-1100	Medium=M
	1000>	High =H

Table 7. Classification of fine aggregate for all system.

System	Range	Fuzzy sets
FIS-1, FIS-2, FIS-3	< 650	Very low=VL
	580-750	Low=L
FIS-4, FIS-5, FIS-6	675-900	Medium=M
	800>	High =H

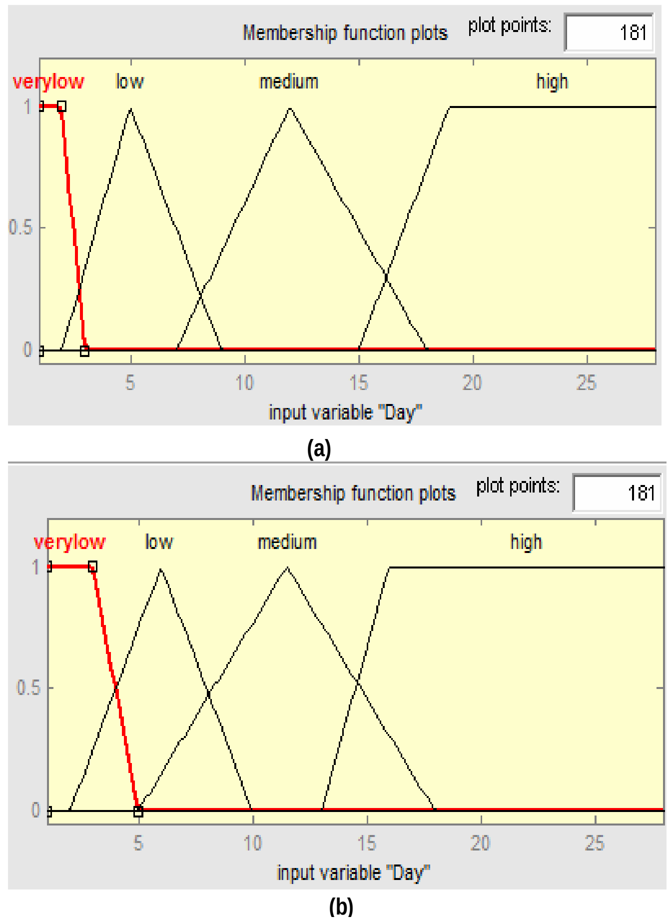


Figure 6. Membership functions of age (day) (a) for FIS-1, FIS-3 and FIS-5 (b) for FIS-2, FIS-4 and FIS-6.

Table 8. Classification of age for all systems.

System	Range	Fuzzy sets
FIS-1, FIS-3, FIS-5	< 3	Very Low=VL
	2-9	Low=L
	7-18	Medium=M
	15>	High =H
FIS-2, FIS-4, FIS-6	< 5	Very Low=VL
	2-10	Low=L
	5-18	Medium=M
	13>	High =H

$$\mu_{VL}(x)=\begin{cases}1 & x<2\\ (3-x)/1 & 2\le x<3\end{cases}$$

$$\mu_{L}(x)=\begin{cases}(x-2)/3 & 2\le x<5\\ 1 & x=5\\ (9-x)/4 & 5\le x<9\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-7)/5 & 7\le x<12\\ 1 & x=12\\ (18-x)/6 & 12\le x<18\end{cases}$$

$$\mu_{H}(x)=\begin{cases}(x-15)/4 & 15\le x<19\\ 1 & x\ge 19\end{cases}$$

(*a*)

$$\mu_{VL}(x)=\begin{cases}1 & x<3\\ (5-x)/2 & 3\le x<5\end{cases}$$

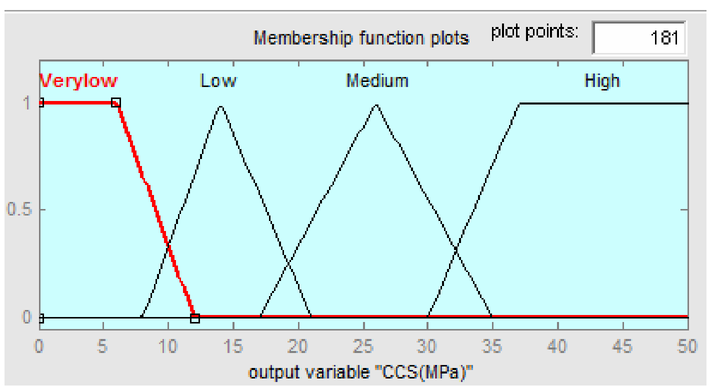
$$\mu_{L}(x)=\begin{cases}(x-2)/4 & 2\le x<6\\ 1 & x=6\\ (10-x)/4 & 6\le x<10\end{cases}$$

$$\mu_{M}(x)=\begin{cases}(x-5)/6.5 & 5\le x<11.5\\ 1 & x=11.5\\ (18-x)/6.5 & 11.5\le x<18\end{cases}$$

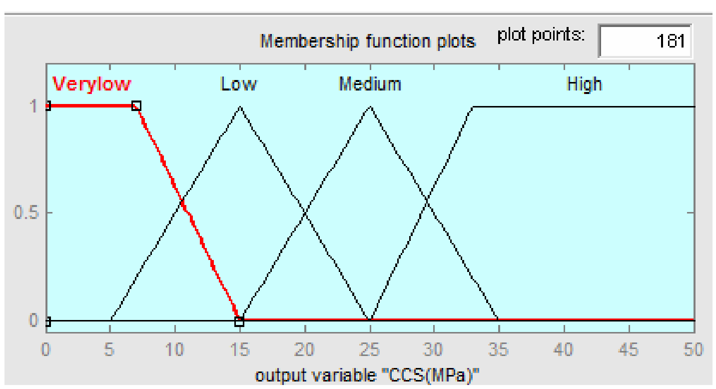
$$\mu_{H}(x)=\begin{cases}(x-13)/3 & 13\le x<16\\ 1 & x\ge 16\end{cases}$$

(*b*)

Equation 6. Mathematical equation of age membership functions (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.



(a)



(b)

Figure 7. Membership functions of CCS (a) for FIS-1, FIS-3 and FIS-5; (b) for FIS-2, FIS-4 and FIS-6.

$$\mu_{VL}(x) = \begin{cases} 1 & x < 7 \\ (15 - x)/8 & 7 \le x < 15 \end{cases}$$

$$\mu_{L}(x) = \begin{cases} (x - 5)/10 & 5 \le x < 15 \\ 1 & x = 15 \\ (25 - x)/10 & 15 \le x < 25 \end{cases}$$

$$\mu_{M}(x) = \begin{cases} (x - 15)/10 & 15 \le x < 25 \\ 1 & x = 25 \\ (35 - x)/10 & 25 \le x < 35 \end{cases}$$

$$\mu_{H}(x) = \begin{cases} (x - 25)/8 & 25 \le x < 33 \\ 1 & x \ge 33 \end{cases}$$

$$\mu_{VL}(x) = \begin{cases} 1 & x < 6 \\ (12 - x)/6 & 6 \le x < 12 \end{cases}$$

$$\mu_{L}(x) = \begin{cases} (x - 8)/6 & 8 \le x < 14 \\ 1 & x = 14 \\ (21 - x)/7 & 14 \le x < 21 \end{cases}$$

$$\mu_{M}(x) = \begin{cases} (x - 17)/9 & 17 \le x < 26 \\ 1 & x = 26 \\ (35 - x)/9 & 26 \le x < 35 \end{cases}$$

$$\mu_{H}(x) = \begin{cases} (x - 30)/7 & 30 \le x < 37 \\ 1 & x \ge 37 \end{cases}$$

Equation 7. Mathematical equation of CCS (a) for FIS-1, FIS-3 and FIS-5 (b) for FIS-2, FIS-4 and FIS-6.

1. If (w:c_ratio(percent) is Verylow) then (CCS(MPa) is High) (1)
2. If (w:c_ratio(percent) is Low) then (CCS(MPa) is Medium) (1)
3. If (w:c_ratio(percent) is Medium) then (CCS(MPa) is Low) (1)
4. If (w:c_ratio(percent) is High) then (CCS(MPa) is Verylow) (1)
5. If (slump(cm) is VeryLow) then (CCS(MPa) is High) (1)
6. If (slump(cm) is Low) then (CCS(MPa) is Medium) (1)
7. If (slump(cm) is Medium) then (CCS(MPa) is Low) (1)
8. If (slump(cm) is High) then (CCS(MPa) is Verylow) (1)
9. If (Dmax(mm) is verylow) then (CCS(MPa) is Verylow) (1)
10. If (Dmax(mm) is Low) then (CCS(MPa) is Low) (1)
11. If (Dmax(mm) is Medium) then (CCS(MPa) is Medium) (1)
12. If (Dmax(mm) is high) then (CCS(MPa) is High) (1)
13. If (Coarse_aggregation is Verylow) then (CCS(MPa) is Verylow) (1)
14. If (Coarse_aggregation is Low) then (CCS(MPa) is Low) (1)
15. If (Coarse_aggregation is medium) then (CCS(MPa) is Medium) (1)
16. If (Coarse_aggregation is high) then (CCS(MPa) is High) (1)
17. If (fine_aggregation(kg) is Verylow) then (CCS(MPa) is High) (1)
18. If (fine_aggregation(kg) is Low) then (CCS(MPa) is Medium) (1)
19. If (fine_aggregation(kg) is Medium) then (CCS(MPa) is Low) (1)
20. If (fine_aggregation(kg) is High) then (CCS(MPa) is Verylow) (1)
21. If (Day is verylow) then (CCS(MPa) is Verylow) (1)
22. If (Day is low) then (CCS(MPa) is Low) (1)
23. If (Day is medium) then (CCS(MPa) is Medium) (1)
24. If (Day is high) then (CCS(MPa) is High) (1)

Figure 8. Rule base of FIS-1, FIS-2, FIS-3, FIS-4, FIS-5 and FIS-6.

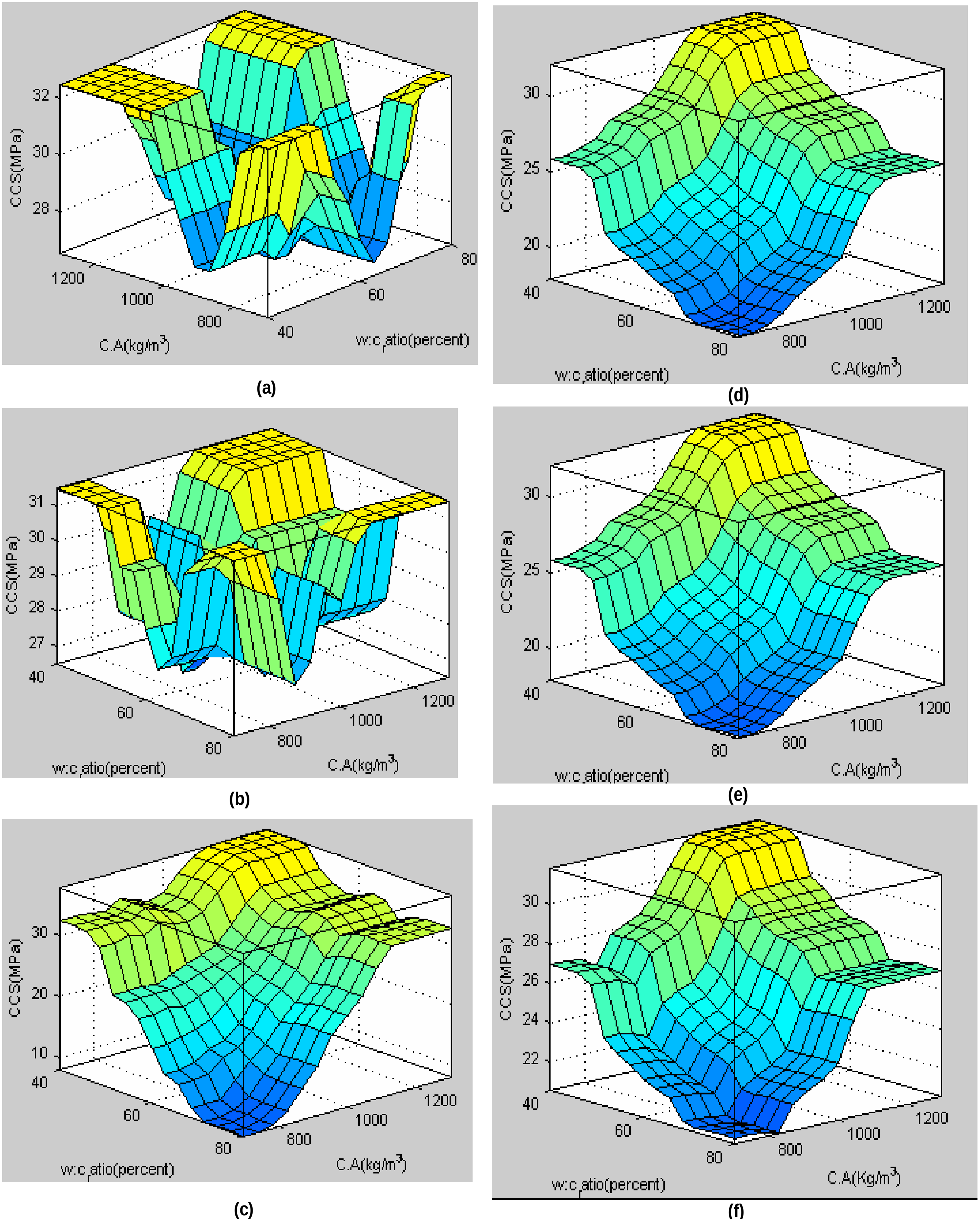


Figure 9. Surface viewer of W/C ratio, C.A and CCS (a) in FIS-1 (b) in FIS-2 (c) in FIS-3 (d) in FIS-4 (e) in FIS-5 and (f) in FIS-6.

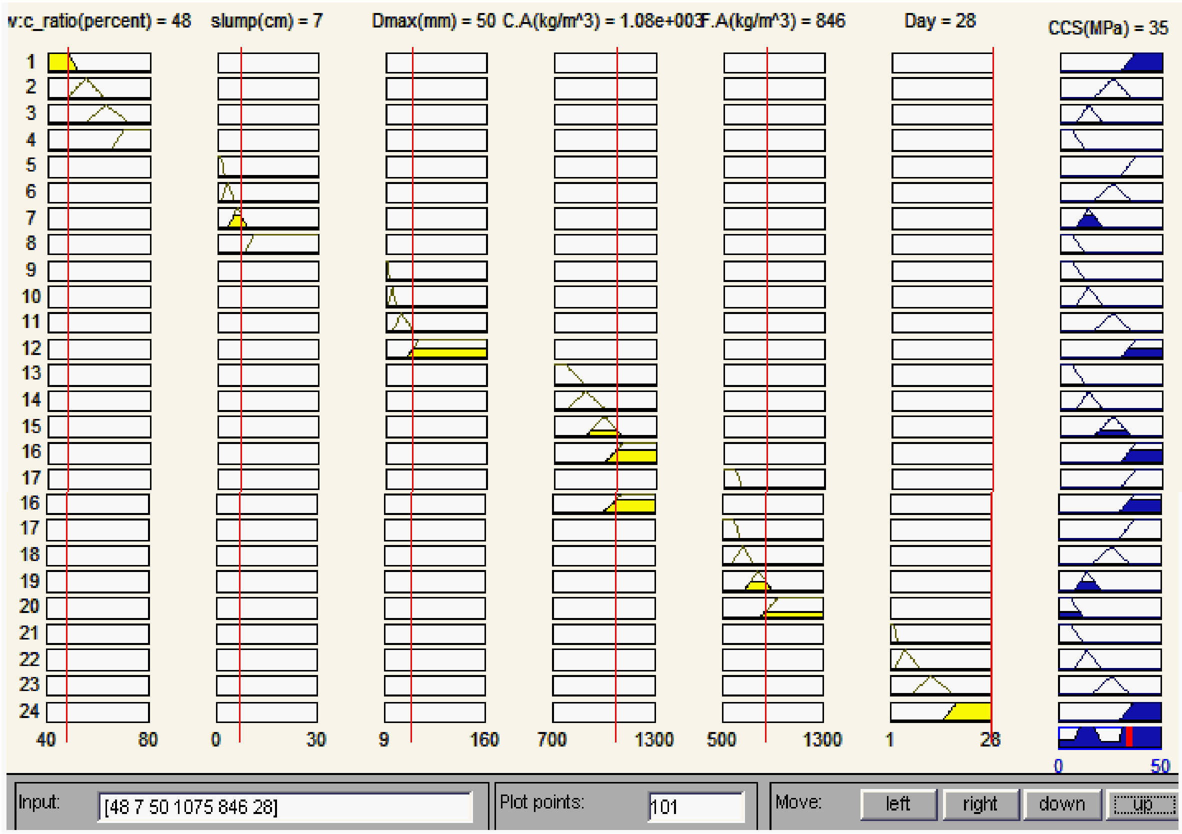


Figure 10. Rule viewer of FIS-5 for 24th sample.

Table 9. Classification of CCS for all systems.

System	Range	Fuzzy sets
FIS-1, FIS-3, FIS-5	< 12	Very Low=VL
	8-21	Low=L
	17-35	Medium=M
	30>	High=H
FIS-2, FIS-4, FIS-6	< 15	Very Low=VL
	5-25	Low=L
	15-35	Medium=M
	25>	High =H

Concrete experts believe that the error less than 10 is acceptable while the average error of the whole systems is equal to 6.025.

Table 12 explains the average error of each system for all the inputs. The best system is FIS5 with the average error of 4.73, which is optimum between the works performed. With respect to the different inputs, the system is able to predict the concrete compressive strength with the accuracy of 95.2±1.38%, which is both timesaving and cost-effective. Systems FIS6 and FIS7 take the second and the third positions, respectively. These two systems also operated well and they could predict the concrete compressive strength with the accuracy of 94.4±1.65. Systems FIS3, FIS1, and FIS2 take the fourth, the fifth, and the sixth positions, respectively.

Human errors are inevitable in manufacturing and testing laboratory samples, whereas the proposed systems do not make such errors. Laboratory ambient conditions (temperature, humidity, wind) can have negative effects on the samples and create a hidden error. These systems may save time. This way, there is no need to put the concrete in water for 28 days. Reducing costs and using no laboratory samples are among the advantages of these systems.

Conclusion

Concrete is a highly complex material, and prediction of the best compressive strength of concrete is quite a difficult task to model. The proposed fuzzy logic models will save time, reduce the waste of material and the design cost.

In this paper, the effect of different methods of aggregation and defuzzification on the result of the fuzzy system has been studied. Because of that, six fuzzy inference systems have been developed to estimate the compressive strength of concrete. Those noted designed

Table 10. Results obtained from fuzzy inference systems.

Inputs						Outputs: CCS (Mpa)					
W:C ratio (percent)	**Slump (cm)**	**Maximum size of aggregate (mm)**	**Coarse aggregate (kg/m^3)**	**Fine aggregate (kg/m^3)**	**Day**	**Laboratory result**	**FIS-1**	**FIS-2**	**FIS-3**	**FIS-4**	**FIS-6**
80	7	12.5	778	892	28	15	34	30	8.5	11	17.9
80	4	12.5	834	881	28	15	28.5	30	12.5	16	20.7
80	7	10	700	988	28	15	34	30	7.5	10	17.4
80	4	10	707	970	28	15	30	31.5	8	12	20.2
80	3	10	700	997	28	15	30.5	33	8	12.5	21.2
70	3	25	947	888	28	20	27.5	29	24	24	24.6
70	4	20	904	895	28	20	27.5	27.5	17	21	23.3
70	3	12.5	806	909	28	20	29	32.5	10.5	14.5	21.1
70	3	20	848	928	28	20	27	29.5	16	19	22.6
70	3	12.5	834	881	28	20	27.5	31	13.5	17	21.4
62	2	40	976	964	28	25	27	26.5	26	31	29.2
62	2	20	904	895	28	25	30.5	32	19.5	28.5	27
62	4	25	947	888	28	25	30	31	24	24	25.5
62	7	40	976	919	28	25	28	28	24	26	26
62	7	50	1046	889	28	25	30	29.5	34	32	30.1
55	2	25	1004	831	28	30	33.5	32.5	28	29.5	29.5
55	2	40	1032	908	28	30	33	31.5	29	33	32.2
55	3	25	1004	831	28	30	33.5	32.5	27.5	28.5	28.7
55	4	25	1004	831	28	30	33.5	32.5	27	27.5	27.9
55	3	40	1032	908	28	30	33	31.5	28.5	32	31.5
48	2	70	1075	943	28	35	34	33	39	38	35.9
48	7	50	1075	846	28	35	36	33	39	36	34
48	7	70	1075	897	28	35	34	32	39.5	36	34.1
48	7	50	1046	874	28	35	32	33	38	35	33.2
48	2	50	1046	921	28	35	34	32	38	37.5	35.6

systems are differing in the methods used for aggregation and defuzzification, and in overlapping the fuzzy sets for some fields, too. The results of FIS-5 (Figure 10) are the best (in comparison to the other systems), and have the lowest average error about 4.73%. It implies that the methods of "Sum" and "Centroid" are the best choices for aggregation and defuzzification. Different methods for aggregation and defuzzification show different results. Therefore, choosing the best method for noted steps is a crucial issue. This paper solves the problems of the future research on the fuzzy for choosing the best method for the important stages such as aggregation and defuzzification. Because of some problems in logical operation (AND/OR) between input/output fields in FIS system that caused error in the result, in future work, we want to propose a new method for logical operation to solve the aforementioned problems of combination of inputs and outputs.

Table 11. The average error of the systems (FIS1-FIS6).

W:C ratio (percent)	Slump (cm)	Maximum size of aggregate (mm)	Coarse aggregate(kg/m^3)	Fine aggregate(kg/m^3)	Day	The average error of the systems(FIS1-FIS6)
80	7	12.5	778	892	28	8.21
80	4	12.5	834	881	28	6.94
80	7	10	700	988	28	8.48
80	4	10	707	970	28	8.15
80	3	10	700	997	28	8.73
70	3	25	947	888	28	5.41
70	4	20	904	895	28	3.9
70	3	12.5	806	909	28	6.52
70	3	20	848	928	28	4.06
70	3	12.5	834	881	28	5.05
62	2	40	976	964	28	2.57
62	2	20	904	895	28	4.02
62	4	25	947	888	28	2.43
62	7	40	976	919	28	1.55
62	7	50	1046	889	28	5.9
55	2	25	1004	831	28	1.63
55	2	40	1032	908	28	1.86
55	3	25	1004	831	28	2.08
55	4	25	1004	831	28	2.6
55	3	40	1032	908	28	1.75
48	2	70	1075	943	28	1.94
48	7	50	1075	846	28	1.5
48	7	70	1075	897	28	1.68
48	7	50	1046	874	28	1.8
48	2	50	1046	921	28	1.75

Table 12. The average error of each system for all the inputs.

System	FIS1	FIS2	FIS3	FIS4	FIS5	FIS6
Average error	9.58	9.9	7.18	5.66	**4.73**	5.44

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