

## Prediction with Fuzzy Logic Approach of Compressive Strength of Concrete Containing of Normal and Crushed Stone Aggregates

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### Abstract

This study assays the detection of concrete compressive strength values using Fuzzy Logic (FL) in comparison with the compressive strength values obtained from TUBITAK-supported research which measured compressive strength values of concrete at specific curing periods and produced with various mixes. The detection of the compressive strength of formed concrete is a time-consuming process. Especially when mixture values are considered, a large number of alternatives must be considered. Therefore, the determination of the proportions and quantities of materials in a mixture and the effects of these on concrete strength are significant concerns in the fields of civil engineering and architecture. In practice, compressive strength has generally been measured by breaking concrete formed using alternative mixtures produced via aggregates taken from different places at the end of 3, 7, 14, 28, 56 and 90 days. It is now possible, however, to undertake these time-consuming and difficult tasks by means of computer science. To this end, a model is suggested to obtain compressive strength values via a fuzzy logic approach, and the compressive strength value results of that approach are compared to the laboratory results from the TUBITAK study, with the result that the data obtained via FL are shown to overlap the existing data.

**Keywords:** Fuzzy logic, aggregate, crushed stone, concrete, compressive strength

### INTRODUCTION

Aggrawal (2011) showed the potential of fuzzy logic (FL-I) and neural network techniques (ANN-I) in predicting the compressive strength of SCC mixtures. The fuzzy logic model showed better performance than a neural network model in that study [1]. Özel (2011) applied a soft computing technique called adaptive neuro-fuzzy inference system (ANFIS) to predict the compressive strength of concretes based on mix design and flow properties. The results showed that the implemented models did well in predicting compressive strength [2]. Özcan et al. (2009) developed an artificial neural network (ANN) and fuzzy logic (FL) to predict the compressive strength of silica fume concrete. A data set of laboratory work, for which a total of 48 concretes were produced, was utilized in the ANNs and FL in that study. The comparison of the results obtained using the experimental methods and those obtained using ANN and FL showed that ANN and FL are viable alternative approaches for predicting the compressive strength of silica fume concrete [3].

Beycioğlu et al. (2008) constructed a prediction model via an artificial neural network (ANN) as an alternative approach to determining the compressive strength of concretes. The results showed the ANN model data and the experimentally obtained data to be in harmony. It was suggested that this ANN approach could be used as an appropriate prediction method, in cases where experimental studies were excessively difficult and the necessary laboratory environment was unavailable [4]. Topçu et al. (2008) developed and applied artificial neural networks and fuzzy logic models to predict the 7-, 28- and 90-day compressive strength of concretes containing high-lime and low-lime fly ashes. For the purpose of constructing these models, data for 52 distinct mixes and 180 specimens were gathered from the literature. The training and testing results showed that the artificial neural networks and fuzzy logic system had a strong potential to accurately predict the 7- 28- and 90-day compressive strength of concretes containing fly ash [5]. Topçu et al. (2008) also demonstrated that the properties of

fresh concrete could be determined without attempting any experiments using ANN and FL models based on the given rubberized concrete data from another study. Similar results were observed between the experimental results and those of ANN and FL models. Moreover, the possibility that lighter concrete could be produced using recycled waste tires as a light material was raised [6]. Using multiple regression analysis and artificial neural networks, Kewalramani et al. (2006) predicted the compressive strength of concrete based on weight and UPV for two concrete mixtures (M20 and M30) involving specimens of two different sizes and shapes as a result of the need for a rapid test method to predict the long-term compressive strength of concrete. A comparison between the two methods showed that artificial neural networks can be effectively used to predict the compressive strength of concrete. The experimentally evaluated compressive strength versus the predicted strength through both methods of analysis were favorably compared [7]. Nataraja and colleagues (2006) characterized the 28-day strength of concrete using a Fuzzy Inference System (FIS) under a methodology consisting of two steps: (1) developing the basic model using the generalized Abram's law and (2) validating the basic model using experimental data. The water-cement ratio and aggregate-cement ratio were treated as antecedents and the 28-day strength as the consequent. Results showed that the fuzzy inference system provides a prudent way to capture uncertainty (non-statistical) in relationships among parameters that control the early strength of concrete [8]. Demir (2005) argued that the main advantage of fuzzy models was their ability to describe knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables only. Demir also showed that many parameters are affected and elastic modulus can easily be taken into account using the fuzzy model he proposed [9]. In their study of the compressive strength of concrete, Poon et al. (2004) prepared concrete specimens using a recycled normal-strength concrete (NC) aggregate, a recycled high performance concrete (HPC) aggregate and a natural aggregate (NA) as control. The

results showed that the compressive strength of the concrete prepared with natural aggregates was higher than that of the recycled aggregate concrete. Also, the strength development of the HPC recycled aggregate concrete was faster than that of the NC recycled aggregate concrete. The recycled HPC aggregate achieved similar strength values to the natural aggregate concrete in 90 days. The results are explained by the differences in the porosity and pore structures of the two types of aggregates, and by possible interactions between the aggregates and the cement paste [10].

Akkurt et al. (2004) used a fuzzy logic prediction model to assess the 28-day compressive strength of cement mortar under standard curing conditions. Data collected from a cement plant were used in the model construction and testing. The prediction of 50 sets of the 28-day cement strength data via the fuzzy model was quite satisfactory, with low average percentage error levels (2.69%). The model was compared with the ANN model in terms of error levels and ease of application. The results indicated that through the application of fuzzy logic algorithm, a more user-friendly and explicit model could be produced with successfully low error margins, as compared to the ANN process [11]. Previously, Akkurt et al. (2003) had modeled the compressive strength of cement mortar under standard curing conditions. Plant data were collected for 6 months concerning the chemical and physical properties of the cement used in model construction and testing. The training and testing data were separated from the complete original data set by the use of genetic algorithms (GAs). A GA-ANN model based on the training data of the cement strength was constructed and the model proved to fall within low average error levels (2.24%). The model was subjected to a sensitivity analysis to predict the response of the system to different values of factors affecting strength. The model showed good potential ability to control processing parameters so as to yield desired strength levels and to provide information regarding the most favorable experimental conditions for obtaining maximum compressive strength [12].

Kim et al. (2003) applied the neural network technique to predict the compressive strength of concrete based on concrete mix proportions. For training and testing, the data sets for the mix proportions of two ready-mixed concrete brands were used, and the required compressive strength was predicted by trial and error. The predicted compressive strengths were verified by comparing the predicted results with those obtained in the laboratory. The results demonstrated that the neural networks were very efficient in predicting the compressive strength of concrete with good accuracy [13]. Nehdi et al. (2001) demonstrated that artificial neural networks (ANN) can be effectively used

to predict the performance of SCC mixtures. Initial tests showed that the ANN method could accurately predict the slump flow, filling capacity, segregation, and compressive strength test results of SCC mixtures. A model for the acceptance/rejection of SCC mixtures based on knowledge of their mixture proportions was proposed, to be used after sufficient development of a more comprehensive database on an industrial scale for the proportioning of SCC with tailor-made properties [14]. Yeh (1998) demonstrated the possibility of adapting ANN to predict the compressive strength of high-performance concrete. A set of trial batches of HPC was produced in the laboratory and demonstrated satisfactory experimental results. That study showed that 1) A strength model based on ANN is more accurate than one based on regression analysis; and 2) ANN models are a convenient and easy method of numerical experimentation to review the effects of the proportions of each variable on a concrete mix [15].

The present study consists of 5 sections. After the Introduction, effective factors and the production of concrete are reviewed in Section 2, and Section 3 provides general information concerning FL. The implemented FL concrete experiments and resulting detection of values are explained in Section 4, and Section 5 discusses the results.

#### **Production of concrete and effective factors**

As has been widely mentioned in the literature, concrete is a mixture of cement, sand, crushed stone or gravel (aggregate) and water. Sometimes, liquid or mineral additives can be added as necessary for the environment or to attain desired specifications. Structural concrete used with steel in carcass structures, insulation concrete for building insulation, fibre concrete, bituminous concrete, gypsum concrete and the concrete produced for mortar and plaster are each produced according to their functions in various types and sizes of aggregates and using various types of cement and additives.

Strength, function, aesthetics and cost factors are considered in the design of concrete structures. In addition to the location and size of structural elements, the quality of concrete greatly determines the strength of a structure [16, 17]. Production of concrete in the desired quality is associated with the proportion and properties of the mixture materials that form the concrete.

Certain main elements, such as cement properties, dose, quantity of water, aggregate type, size, proportions, state of concrete production and protection and so on comprise the parameters which affect the compressive strength of concrete [18]. Details are provided in Table 1.

**Table 1.** Parameters affecting the compressive strength of concrete

Parameters	Properties
Aggregate	<ol style="list-style-type: none"> <li>1. Grain distribution (granulometry)</li> <li>2. Surface roughness</li> <li>3. Grain shape (cubic)</li> <li>4. Grain structure (mineralogical and petrographic structure)               <ol style="list-style-type: none"> <li>a. Grain resistance</li> <li>b. Capability of transformation to clay</li> <li>c. Feature of the chemical reaction with cement and environmental effects</li> <li>d. Adherence with cement paste</li> </ol> </li> <li>5. Content of foreign and fine material (cleaning)</li> </ol>
Cement	<ol style="list-style-type: none"> <li>1. Thickness (90–6.5 microns)</li> <li>2. Storage conditions (must not be damp)</li> <li>3. Type of cement (PÇ, KPÇ, TÇ, SDC, ...)</li> <li>4. Norm resistance (PÇ32.5, PÇ42.5)</li> <li>5. Dose (amount)</li> <li>6. Mineral additives (silica fume, other additives such as fly ash)</li> </ol>
Water	<ol style="list-style-type: none"> <li>1. Water / cement ratio</li> <li>2. Quality and appropriateness of water</li> </ol>
Environmental Conditions	<ol style="list-style-type: none"> <li>1. Carbonization</li> <li>2. Sea salt (sea water and sea sand)</li> <li>3. Effect of sulfate               <ol style="list-style-type: none"> <li>a. Contact of main with the ground</li> <li>b. Contact with underground water (contact water)</li> <li>c. Water of mixture and care (cure)</li> <li>d. Alkali-aggregate and activity</li> <li>e. Effect of chlorine and formation of acidic environment</li> </ol> </li> </ol>
Compactness	<ol style="list-style-type: none"> <li>1. Good placement (vibration)</li> <li>2. Ratio of clay, amount of water and aggregate shape</li> <li>3. Plasticizer or addition of tightness additives</li> </ol>
Requirements of production, casting and maintenance	<ol style="list-style-type: none"> <li>1. Measurement of mixture materials</li> <li>2. Mixing in mixer</li> <li>3. Transport</li> <li>4. Placement into pattern and tightening (vibration)</li> <li>5. Maintenance and protection (water and steam cure)</li> </ol>

A geological map of the sand, gravel and crushed stones called “aggregate” is firstly examined in detail in the quarry, where these materials are first investigated, and physico-mechanical tests of the collected samples are performed in the laboratory. Coarse sand and pebbles are examined using binocular and polarizing microscopes. Which physico-mechanical tests are to be used is decided according to the results of petrographic and petrochemical analysis. XRD, DTA and chemical analysis methods are used in the study of clay-sized aggregates. Thus, based on the obtained data, it is understood that a high-quality concrete production is possible based on all the inputs entering into the mix and given compliance with technical requirements. As may be seen, concrete production and processing are laborious matters taking a great deal of time and requiring difficult investigations [19]. However, it is possible to reduce the difficulty of this process using the latest techniques of and developments in computer science. For example, such methods as artificial neural networks, genetic algorithms, fuzzy set theory and fuzzy logic systems, are currently being researched to determine their utility in the fields of architecture and civil engineering.

## FUZZY LOGIC

### Fuzzy logic principles

Fuzzy logic, unlike Boolean or crisp logic, deals with problems that have vagueness, uncertainty, or imprecision, and uses membership functions (MF) with values varying between 0 and 1. Fuzzy logic tends to mimic human thinking, which is often usefully fuzzy in nature. In conventional set theory based on Boolean logic, a particular object or variable is either a member (logic 1) of a given set or it is not (logic 0). On the other hand, in fuzzy set theory based on fuzzy logic, a particular object has a degree of membership in a given set that may be anywhere in the range of 0 (completely not in the set) to 1 (completely in the set). This property allows fuzzy logic to deal with uncertain situations in a fairly natural way.

The change in Boolean logic is abrupt between 0 and 1. In fuzzy set terminology, all the possible values that a variable (speed) can assume are called the universe of discourse, and the fuzzy sets (characterized by membership functions) cover the entire universe of discourse.

Fuzzy control, similar to the expert system-based control, is described by a set of IF . . . THEN . . . rules (called implications), where the rule has the following general structure:

IF  $x$  is  $A$  AND  $y$  is  $B$  THEN  $z$  is  $C$

where  $x$ ,  $y$ , and  $z$  are the fuzzy variables and  $A$ ,  $B$ , and  $C$  are the fuzzy subsets in the universe of discourses  $x$ ,  $y$ , and  $z$ , respectively. Fuzzy logic is often defined as a “fuzzy expert system,” in which the knowledge base is fuzzy or imprecise in nature [20].

### Why is the fuzzy logic approach preferred?

Fuzzy logic, unlike traditional control technology, is able to work with the gray areas of complex processes. In some ways, fuzzy logic is not “fuzzy.” It is capable of dealing with the sometimes imprecise or vague inputs of any process. The fuzzy logic algorithm is firmly rooted in the mathematics of the traditional control function. It uses these algorithms to describe system relationships and also uses these high-level mathematics to describe subjective concepts in terms that microprocessors can understand.

While microprocessors can deal only with 0/1 and TRUE/FALSE situations, a fuzzy logic algorithm uses all numbers between 0 and 1. Fuzzy logic does not require a “crisp” set, but instead can understand the gray areas that occur in any almost any process. However, it must not be forgotten that fuzzy logic is not a panacea. Although in certain applications fuzzy logic can provide additional functionality and better performance, traditional control methods will often provide more than satisfactory control results (Wilkinson, 1995).

## IMPLEMENTATION

Various alternatives have been assayed in the production of high-quality concrete using aggregates from Denizli and surrounding areas in the scope of a two-year study funded by TUBITAK. Mixtures of 1m<sup>3</sup> were founded following the recommended routes in TS802 using various diameters of natural river aggregates, limestone-based crushed stones, and various amounts of cement and water. The attempted aggregates were undertaken in accordance with the normal aggregates in TS706 and the literature, with a specific weight of 2.5–2.8 g/cm<sup>3</sup> [21, 22]. Aggregate groups were tested at sizes of 0–8 mm, 8–16 mm, 16–32 mm to achieve the desired strength. The Buldan stream aggregates were

coded as A and Y, while crushed stones were coded B and  . Normal Portland cement 32.5 and tap water were used in the experiments. Mixture quantities are given in kilograms in Table 2. The cure periods tested were 3, 7, 14, 28, 56 and 90

days in performed production. Three 15 X 30 cm cylinder-shaped concrete samples were prepared, and their averages estimated for each curing period [23].

**Table 2.** Mixture amounts

Sample Series	Aggregate Groups (kg/m <sup>3</sup> )			Cement (kg/m <sup>3</sup> )	Water (kg/m <sup>3</sup> )
	0-8 mm	8-16 mm	16-32 mm		
�23	1112	334	386	350	175
�24	1141	343	390	350	158
�25	1344	439	314	350	175
�26	1379	450	307	350	158
�27	1056	317	367	350	210
�28	1275	417	327	350	210
B1	1020	477	397	316	167
B2	1080	360	382	373	176
B3	1072	378	378	400	172
B4	1106	391	391	400	146
A1	868	639	320	300	159
A2	1400	470	301	313	167
A3	1106	377	377	325	180
A4	1117	379	379	325	180
A5	1052	629	315	338	159
A6	1324	441	317	388	186
A7	1059	361	361	375	194
A8	1034	365	365	375	194
A9	1031	352	352	400	172
A10	1064	363	363	400	146
A11	Tuvenan (1820)			313	190
Y1	887	553	369	327	173
Y2	1106	388	383	325	180
Y3	1108	385	385	325	180
Y4	870	543	362	369	173
Y5	1059	367	367	375	194
Y6	1114	371	371	375	194
Y7	1038	360	360	400	167
Y8 (1% alloyed)	1074	372	372	400	139
Y9Y%60	1059	782	782	375	194
Y9�%40	1056	390	390	375	194
Y10Y%50	530	184	184	375	194
Y10�%50	550	195	195	375	194
Y50Yenice%50	552	166	192	350	157
Y50�amlık%50	574	176	203	350	157

**Table 3.** Compressive Strength

Sample Series	Compressive Strength (Mpa) EXPERIMENTAL					
	3 days	7 days	14 days	28 days	56 days	90 days
Ç23	15,5	20,6	22,1	27,0	28,9	35,3
Ç24	19,1	20,5	24,0	27,9	34,8	36,6
Ç25	17,9	19,8	22,4	25,7	29,0	35,4
Ç26	22,8	25,4	27,9	26,6	41,3	45,3
Ç27	13,4	15,3	17,4	21,4	25,2	32,8
Ç28	10,2	14,7	17,9	23,4	25,2	32,0
B1	10,6	17,1	18,2	22,8	23,3	29,1
B2	15,7	19,6	24,6	25,4	27,9	34,4
B3	16,1	20,4	22,3	23,5	27,6	33,3
B4	17,9	23,6	25,0	28,7	32,0	33,0
A1	8,6	10,6	12,3	16,8	18,0	20,9
A2	8,1	13,2	15,2	17,1	18,6	23,7
A3	6,3	8,4	13,6	15,2	26,7	27,2
A4	17,8	19,4	21,1	23,5	26,7	35,1
A5	10,5	19	22,5	23,6	23,6	25,2
A6	12,9	18	19,3	19,1	23,5	28,5
A7	7,8	12,7	18,9	19,8	21,0	25,2
A8	18,2	20,1	25,6	26,3	38,0	41,8
A9	15,2	15,8	25,5	28,8	30,0	34,3
A10	24,0	24,4	31,5	33,2	37,9	40,5
A11	7,0	8,8	9,6	10,6	13,5	15,4
Y1	10,8	13,3	19,0	20,5	22,5	26,7
Y2	7,9	10,4	16,9	17,6	28,6	30,4
Y3	9,5	14,8	20,0	22,9	32,5	38,8
Y4	11,7	14,9	20,4	25,0	29,7	32,7
Y5	10,9	15,7	17,6	21,6	25,8	32,1
Y6	17,9	24,4	29,5	31,0	39,4	40,7
Y7	11,5	15,5	18,7	25,4	29,4	33,6
Y8 (1% alloyed)	18,9	21,5	23,3	29,8	32,9	37,4
Y9Y%60	9,8	16	19,4	21,1	24,7	29,1
Y9Ç%40	9,8	16	19,4	21,1	24,7	29,1
Y10Y%50	14,8	16,7	21,0	22,2	29,5	31,1
Y10Ç%50	14,8	16,7	21,0	22,2	29,5	31,1
Y50Yenice%50	13,1	17,2	20,0	24,6	31,2	35,0
Y50Çamlık%50	13,1	17,2	20,0	24,6	31,2	35,0

According to the graphics, on the order of a 20–30% compressive strength reduction occurs as the amount of water increases 10%. The results obtained were in harmony with the results of previous studies [24]. A compressive

strength prediction model is here formed using the fuzzy logic approach based on the data obtained from these experiments.

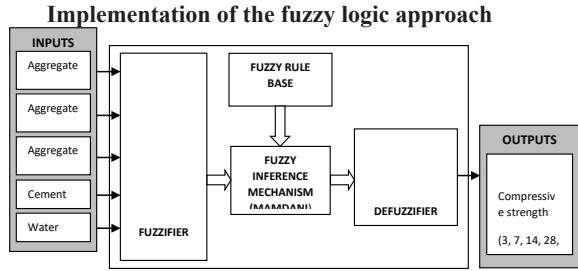


Figure 1. Structure of fuzzy logic approach for the pressure strength

As may be seen in Figure 1, the FLC consists of two main parts: the Fuzzifier Unit and the Defuzzifier Unit. Before moving on to fuzzification and defuzzification operations, it is necessary to identify output and membership values, form the rules base and select the appropriate method.

In the FLC, which was designed for the control of pressure strength, a rules base was formed comprised of 3 linguistic expressions for the thickness input value, 5 linguistic expressions for the age input value and 5 linguistic expressions for the session input value. For period and power output values, three linguistic values were used. Since the necessary parameters to form the rules base were only the number of input values, a rules base of (3 x 3 x 3 x 3 x 3) 243 rules was formed. Mamdani has been used as the inference mechanism and the Weighted Average Method has been used for defuzzification. The input variables are fuzzified and after proper defuzzification using rule base and aggregation methods, the output is evaluated for use in the control action.

The membership function for the input variable “Aggregate (0–8 mm)” is shown in Figure 2. Three linguistic variables have been used: small, medium and large. Ranges of membership function are shown in Table 4.

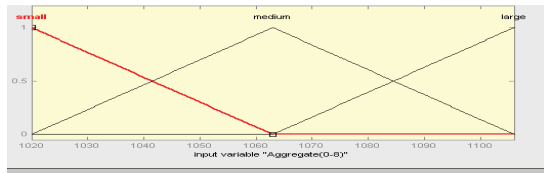


Figure 2. Membership function plot for the input variable “Aggregate 0–8 mm”

Table 4. Aggregate (0–8 mm)

Crisp Input Range	Fuzzy Linguistic Variable
977 – 1063	SMALL
1020 – 1106	MEDIUM
1063 – 1149	LARGE

The membership function for the input variable “Aggregate (8–16 mm)” is shown in Figure 3. Three linguistic variables have been used: small, medium and large. Ranges of membership function are shown in Table 5.

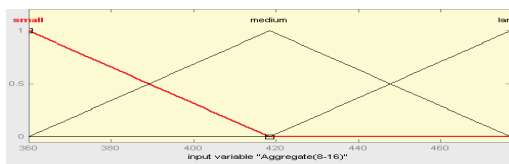


Figure 3. Membership function plot for the input variable “Aggregate 8–16 mm”

Table 5. Aggregate (8–16 mm)

Crisp Input Range	Fuzzy Linguistic Variable
301.5 - 418.5	SMALL
360 - 477	MEDIUM
418.5 - 535.5	LARGE

The membership function for the input variable “Aggregate (16–32 mm)” is shown in Figure 4. Three linguistic variables have been used: small, medium and large. Ranges of membership function are shown in Table 6.

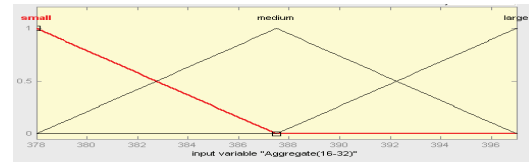


Figure 4. Membership function plot for the input variable “Aggregate 16–32 mm”

Table 6. Aggregate (16–32 mm)

Crisp Input Range	Fuzzy Linguistic Variable
368.5 - 387.5	SMALL
378 - 397	MEDIUM
387.5 - 406.5	LARGE

The membership function for the input variable “Cement” is shown in Figure 5. Three linguistic variables have been used: small, medium and large. Ranges of membership function are shown in Table 7.

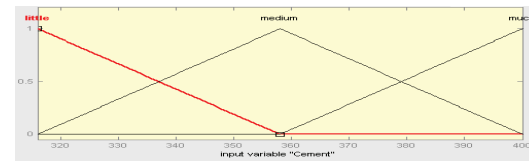


Figure 5. Membership function plot for the input variable “Cement”

Table 7. Cement (kg/m3)

Crisp Input Range	Fuzzy Linguistic Variable
274 - 358	LITTLE
316 - 400	MEDIUM
358 - 442	MUCH

The membership function for the input variable “Water” is shown in Figure 6. Three linguistic variables have been used: small, medium and large. Ranges of membership function are shown in Table 8.

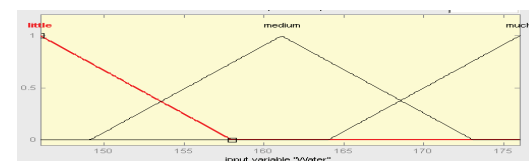
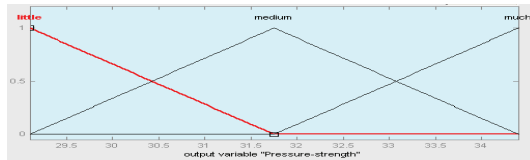


Figure 6. Membership function plot for the input variable “Water”

**Table 8.** Water (kg/m<sup>3</sup>)

Crisp Input Range	Fuzzy Linguistic Variable
134 - 158	LITTLE
149.1 - 173.1	MEDIUM
164 - 188	MUCH

The membership function for the output variable “Pressure Strength” is shown in Figure 7. Three linguistic variables have been used: small, medium and large. Ranges of membership function are shown in Table 9.



**Figure 7.** Membership function plot for the output variable “Pressure Strength”

**Table 10.** Some Rules in the Rule Base

Rule No	Inputs					Outputs
	Aggregate (0–8 mm)	Aggregate (8–16 mm)	Aggregate (16–32 mm)	Cement	Water	Compressive Strength
1	Small	Large	Large	Little	Medium	Little
5	Medium	Small	Medium	Medium	Much	Medium
48	Medium	Medium	Small	Much	Much	Much
108	Large	Medium	Large	Much	Little	Much
133	Large	Medium	Small	Little	Medium	Little
210	Small	Small	Medium	Much	Medium	Medium

We can explain these rules as follows:

1. If (Aggregate (0–8 mm) is Small) and (Aggregate (8–16 mm) is Large) and (Aggregate (16–32 mm) is Large) and (Cement is little) and (Water is Medium) then (Pressure is little).

5. If (Aggregate (0-8 mm) is Medium) and (Aggregate (8-16 mm) is Small) and (Aggregate (16-32 mm) is Medium) and (Cement is Medium) and (Water is Much) then (Pressure is Medium).

48. If (Aggregate (0-8 mm) is Medium) and (Aggregate (8-16 mm) is Medium) and (Aggregate (16-32 mm) is Small) and (Cement is Much) and (Water is Much) then (Pressure is Much).

108. If (Aggregate (0-8 mm) is Large) and (Aggregate (8-16 mm) is Medium) and (Aggregate (16-32 mm) is Large) and (Cement is Much) and (Water is little) then (Pressure is Much).

133. If (Aggregate (0-8 mm) is Large) and (Aggregate (8-16 mm) is Medium) and (Aggregate (16-32 mm) is Small) and (Cement is little) and (Water is Medium) then (Pressure is Little).

210. If (Aggregate (0–8 mm) is Small) and (Aggregate (8–16 mm) is Small) and (Aggregate (16–32 mm) is Medium) and (Cement is Much) and (Water is Medium) then (Pressure is Medium).

**Table 9.** Pressure strength (Mpa)

Crisp Output Range	Fuzzy Linguistic Variable
26.45 - 31.75	LITTLE
29.1 - 34.4	MEDIUM
31.75 - 37.05	MUCH

Some of the rules in the rules base are shown in Table 10.

## CONCLUSIONS

Concrete manufacturers must carry out long-term, intensive experimental operations to produce the concrete appropriate for the standards and needs of the construction sector. Many alternatives to normal aggregates and crushed stones are tried and new samples prepared with changing amounts of water, cement and aggregates. Time and materials are casualties of such efforts, and such methods also require intensive labor and significant economic liability. FL has been implemented in order to make the results of such experiments accessible via a computer program and to give the inquiry a more scientific basis.

A comparison of the FLC data and the specialist data for Ç26 are shown in Table 11.

**Table 11.** FLC vs. specialist data for Ç26

Days (day)	3	7	14	28	56	90
Pressure Strength (Results of Experimental) (Mpa)	22,8	25,4	27,9	26,6	41,3	45,3
Pressure Strength (Fuzzy Logic Control) (Mpa)	20,7	237	26,2	26,8	38,7	43,1

Figure 8 graphically represents the data gathered from FL designed with Ç26 and Ç26 values taken from a specialist.

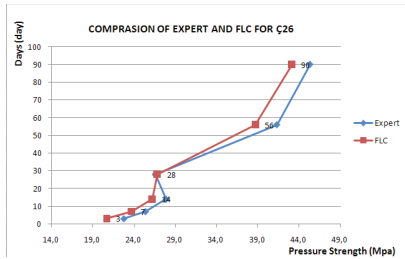


Figure 8. Response of Expert and FLC for Ç26.

A comparison of the FLC data and the specialist data for B2 are shown in Table 12.

Table 12. FLC vs. specialist data for B2

Days (day)	3	7	14	28	56	90
Pressure Strength (Results of Experimental) (Mpa)	15,7	19,6	24,6	25,4	27,9	34,4
Pressure Strength (Fuzzy Logic Control) (Mpa)	14,2	20,3	21,9	25,7	27,6	33,3

Figure 9 graphically represents the data gathered from FL designed with B2 and B2 values taken from a specialist.

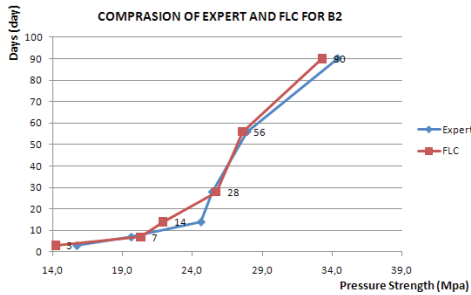


Figure 9. Response of Expert and FLC for B2.

A comparison of the FLC data and the specialist data for A6 are shown in Table 13.

Table 13. FLC vs. specialist data for A6

Days (day)	3	7	14	28	56	90
Pressure Strength (Results of Experimental) (Mpa)	12,9	18	19,3	19,1	23,5	28,5
Pressure Strength (Fuzzy Logic Control) (Mpa)	15,1	16,4	21,9	18,9	22,1	31,3

Figure 10 graphically represents the data gathered from FL designed with A6 and A6 values taken from a specialist.

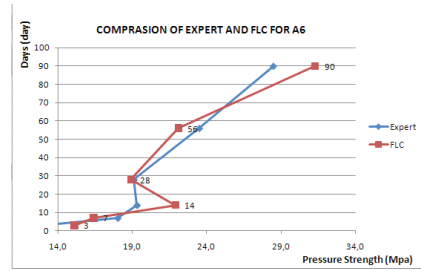


Figure 10. Response of Expert and FLC for A6.

A comparison of the FLC data and the specialist data for Y4 are shown in Table 14.

Table 14. FLC vs. specialist data for Y4

Days (day)	3	7	14	28	56	90
Pressure Strength (Results of Experimental) (Mpa)	12,9	18	19,3	19,1	23,5	28,5
Pressure Strength (Fuzzy Logic Control) (Mpa)	15,1	16,4	21,9	18,9	22,1	31,3

Figure 11 graphically represents the data gathered from FL designed with Y4 and Y4 values taken from a specialist.

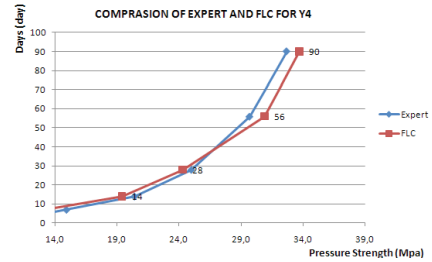


Figure 11. Response of Expert and FLC for Y4.

It may be seen that the results obtained by applying FL and the values from the TUBITAK-supported study entitled “Physical and Mechanical Properties of Denizli Aggregates and Their Use in the Production of High-Quality Concrete” are quite close. This result demonstrates that the developed model could be used to predict the compressive strength of concrete based on various mixtures. Moreover, it has been demonstrated that concrete compressive strength can be detected via the model implemented on these mixture values.

Using the FL program, the compressive strengths of concretes to be produced using mixture values which have never been tested except for in produced mixtures, can be predicted with high accuracy. Accordingly, the human or technical errors associated with experimental studies can be minimized.

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In this study, we relied upon data from the TUBITAK-supported study “Physical and Mechanical Properties of Denizli Aggregates and Their Use in the Production of High-Quality Concrete”.

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