PREDICȚIA REZISTENȚEI LA COMPRESIUNE A BETONULUI PE BAZA UNUI MODEL FUZZY ȘI A REZULTATELOR UNOR TESTE NON-DESTRUCTIVE
A FUZZY LOGIC MODEL FOR PREDICTION OF COMPRESSIVE STRENGTH OF CONCRETE BY USE OF NON-DESTRUCTIVE TEST RESULTS

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In this study, a fuzzy logic prediction model for compressive strength of concrete was developed based on various non-destructive tests, such as Windsor Probe Penetration Test, Ultrasonic Pulse Velocity and Schmidt Hammer. Experimental results of non-destructive tests were used to construct the fuzzy logic model. The obtained results with fuzzy logic were compared with the multiple linear regression model and experimental values. It was observed that, non-destructive tests' determination abilities were increased by using fuzzy logic. Results have shown that, fuzzy logic systems have strong potential for predicting 28 days compressive strength using Windsor Probe Penetration value, Ultrasonic Pulse Velocity and Schmidt Hammer rebound as inputs variables.

Keywords: *Non-destructive testing, Concrete, Fuzzy logic, Compressive strength, Statistical Modelling*

1. Introduction

Due to several disadvantages of destructive tests, various non-destructive test (NDT) methods were developed for determination of concrete compressive strength (CSC), which provides convenience in practise [1-3].

Schmidt Rebound Hammer (RH) test is used to provide a convenient and rapid indication of the CSC. In this method, a rebound value is measured and CSC is determined indirectly. It is the most widely used method, because it is both easy and it does not damage the structural element. On the other hand, if this method is used unconsciously test results may give misleading information. Because RH test gives information about the surface of the concrete. However, the concrete internal structure cannot be reflected. Therefore, the results obtained, do not provide the actual concrete compressive strength, it is only able to present additional complementary and useful information [4-6].

Another commonly used NDT method is the Ultrasonic Pulse Velocity (UPV) test. In this method, by measuring the speed pressure waves through the hardened concrete, an indirect information about the CSC is obtained. However, it is difficult to establish a good relationship between CSC and pressure wave speed for each concrete type. It is necessary to detect the pressure wave speed with very high sensitivity and stability. Therefore, large dispersions may occur during measurements [7,8].

Besides all of the methods listed above, another test method is also available. It is called the Windsor Probe (WP) and is widely used in the US, Canada and European countries. The WP test device manufacturers claim, that the CSC can be estimated within 5 % of error. In the WP method, CSC is determined by measuring the depth of a steel probe loaded with explosives, driven into concrete. The smaller the probe penetrates the surface, the higher is the CSC [9,10]. Manufacturers of WP associated probe penetration only with aggregate hardness. However, it is considered that in addition to the aggregate hardness, type, shape and grain diameter of aggregate are also effective and these factors can affect the depth of the probe entering into concrete. In addition to aggregate properties, concrete mixture ratio, moisture content, curing method and surface conditions have also a profound effect on WP. The age of concrete and carbonation depth are also important parameters, which can affect the CSC. As it is known, carbonation can change the physical and chemical properties of concrete up to a certain depth and this change can affect the penetration depth. Advantages and limitations of WP method are given in Table 1.

A lot of empirical equations based on the regression technique have been developed for the prediction of CSC, by using NDT test results. However, the biggest problem for users is, selecting the best equation for CSC prediction [1,12-16].

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Table 1

WP test method advantages and limitations [11]

The advantages	The limitations
• The test is relatively quick and the result is achieved immediately provided an appropriate correlation curve is available. • The probe is simple to operate, requires little maintenance except cleaning the barrel and is not sensitive to operator technique. • Access is only needed to one surface. The correlation with concrete strength is affected by a relatively small number of variables. • The test result is likely to represent the concrete at a depth of from 2.5 cm to 7.5 cm from the surface rather than just the property of the surface layer as in the Schmidt rebound test.	• The minimum acceptable distance from a test location to any edges of the concrete member or between two test locations is of the order of 15 cm to 20 cm. • The minimum thickness of the member, which can be tested, is about three times the expected depth of probe penetration. • The distance from reinforcement can also have an effect on the depth of probe penetration especially when the distance is less than about 10 cm. • The test is limited to <40 MPa and if two different powder levels are used in an investigation to accommodate a larger range of concrete strengths, the correlation procedure becomes complicated. • The test leaves an 8 mm hole in the concrete where the probe penetrated and, in older concrete, the area around the point of penetration is heavily fractured. • On an exposed face the probes have to be removed and the damaged area repaired.

During preliminary design stage, undertaking experiments for the determining of physical and mechanical properties of concrete may not be possible. Due to this reason, researchers have developed many estimation models using artificial intelligence methods for various engineering applications. The FL approach is the most popular one of these artificial intelligence techniques. FL approach is used very successfully in civil engineering applications, such as construction management, building materials, hydraulic, geotechnical and transportation engineering [17-19].

There are many studies available in the literature [20-23], focused on estimating CSC by using FL approach. In the significant part of these studies, FL models were established by using different concrete properties and mixtures as input variables. On the other hand, some of these studies focused on developing an FL prediction model by using NDT results. Subasi at al. [24] developed an FL model for predicting CSCs containing silica fume, by using NDT results, such as PV and RH. Abolpour at al. [25] designed an FL model for determination of the CSC. In this model, input variables of the fuzzy expert system are weight percent of cement, water, blast furnace slag, fly ash, super plasticizer, fine aggregate, coarse aggregate, and age of the concrete. Gencel at al. [26] developed an FL prediction model for fresh and hardened properties of self-compacting concrete containing fly ash and polypropylene fibres. In their models, properties of fresh and hardened concrete containing fibres, fly ash and cement content are predicted for fresh as well as a function of time for hardened concrete. Guler at al. [27] presented a fuzzy approach for modelling of high strength concrete under uniaxial loading. Tanyildizi [28], devised an FL prediction model for compressive and splitting tensile strength of lightweight concrete made with scoria aggregate and fly ash after exposed to high temperature. In another study, Tanyildizi [29], developed an FL prediction model for the bond strength of lightweight concrete containing mineral admixtures under different curing conditions. Beycioglu and Basyigit [30], introduced a rule-based Mamdani-type fuzzy logic model for prediction of compressive strength of lightweight concretes containing silica fume and fly ash.

CSC prediction has an ambiguous structure, because of some reasons, such as, it is not suitable for precise mathematical formulations and destructive and non-destructive test methods used to measure CSC in the field have some disadvantages. By examining the literature on this subject, it is seen that, FL approach has an important potential to solve problems, such as CSC prediction [25].

This study focused on the development of an FL based model to predict CSC. In this model, experimental variables of WP, UPV and RH were used as inputs and 28 day compressive strength was used as output. The obtained results from compressive strength tests were compared with fuzzy results.

2. Theory of Fuzzy Logic

FL concept was preliminarily introduced by Zadeh [31] and is based on fuzzy sets and subsets. Fuzzy logic is the extension of the classical set display. In the fuzzy elements set, each element has a degree of membership and this degree can take any value in the range between 0 and 1. Mathematical modelling of the system is not necessary and each logical system can be expressed as fuzzy. FL is providing good solutions, for the controlling of the ambiguous, time-varying, complex and ill-defined systems encountered in the daily life. Although, FL approach was first introduced by Zadeh in 1965, it has attracted attention after a fuzzy control of a steam machine which was developed by Mamdani and Assilian [32,33].

A fuzzy inference system basically consists of three stages: fuzzification, inference mechanism and defuzzification. Fuzzification is a process, which converts each input data into symbolic linguistic values. By using the membership functions, an input data belonging to any fuzzy set and membership degree is determined. Next, the connection between the input and output data is created and a fuzzy output is produced. This is done by using the guidelines mentioned in the rule base with the information of rule processing, such as, "if… and…then…else". This output is converted from fuzzy value to the real value, because it will be used in the real world. Mamdani type fuzzy inference system is the most commonly used inference mechanism in the literature [34]. In this study, a max–min Mamdani inference was used based on the rules and the centroid method was used for defuzzification [34].

3. Experimental Studies and Data Collection

Experimental studies consist of sample preparation, curing, application of NDTs, coring, compressive strength determination by destructive tests. In this study, crushed limestone aggregate, whose grain size distribution is given in Table 2, CEM I 42.5 Portland cement and ordinary tap water, are used for sample preparation. Table 2 presents the grain size distributions of aggregate, cement and water amount for 1 m³ fresh concrete.

Table 2

Amount of materials used for fresh concrete production

Mix proportion	Amount/m^3
Crushed coarse aggregate (16-25 mm)	334 kg
Crushed medium aggregate (4-16 mm)	632 kg
Crushed fine aggregate (0-4 mm)	761 kg
Cement (CEM I 42.5)	426 kg
Water	190 lt

Concrete mix was prepared according to C 20 type concrete, and slump of fresh concrete was about 20 cm. After the placement of fresh concrete to formworks, compaction was achieved using a vibrating screed. After 28 day period, a total of 100 core samples having 75 mm diameter were extracted from concrete slabs according to ASTM C 42/C 42M (1999) [35]. Length to diameter ratio of core samples was about 2.

After the determination of physical properties, UPV tests of core samples were performed according to ASTM C 597 [36]. Compressive strength values of core samples were determined using a stress/or strain controlled compression machine according to ASTM C 39 [37]. WP (ASTM C 803/C803M, 1999) [38] and RH tests (ASTM C 805, 1997 [39]) were performed directly on concrete slabs prior to coring. In WP test, exposed length of the probe was measured in cm, and in RH tests, rebound number was determined.

Table 3 demonstrates the relationships between CSC, UPV, RH and WP tests results. According to this study, WP is the best NDT method for prediction of CSC with a regression coefficient (R^2) of 0.883.

However, the WP method can be affected from carbonation of concrete, type or size of aggregate, voids in concrete etc. The manufacturer of the WP system has published tables relating the exposed length of the probe with the CSC. For each exposed length value, different values for compressive strength are given, depending on the hardness of the aggregate, as measured by the Mohs' scale of hardness. The tables provided by the manufacturer are based on empirical relationships developed according to their experimental studies. Investigations indicate that the manufacturer's tables do not always give satisfactory results [11]. Sometimes they considerably overestimate the actual strength and in other instances, they underestimate the strength. Swamy and Al-Hamed [40] reported that the Windsor probe estimated the wet cube strength better than compressive strength tests using small diameter cores for ages up to 28 days. As the concrete gets older, estimation performance of WP decreases.

4. Developed Fuzzy Model

The fuzzy model developed in this study is intended to provide a better prediction performance than NDT tests. The main focus or aim of this fuzzy model is to overcome the inefficiencies of the used NDT methods.

The limit values of input and output variables used in Mamdani-type fuzzy inference model are listed in Table 4. Developed FL model was applied to predict the CSC by using data obtained from 100 tests. These test results were used to train the FL model.

The FL model has three input parameters; WP, UPV and RH and one output parameter; CSC. Membership functions for input and output parameters used for fuzzy modelling are given in Figure 1. Limited number of membership functions were used because the model becomes exponentially more complex, as this number of variables or membership functions increases. The choice of the membership functions is based on the experiences gained. In the model, number of

Table 3

The relationships between test results

Eq. No	LR Equation	Explanations	R^2
1	$CSC = 0.047 \times WP + 3.106$	CSC [MPa], WP[cm]	0.883
2	$CSC = -0.174 \times UPV + 40.807$	CSC [MPa], UPV[µs]	0.731
3	$CSC = 1.132 \times RH - 1.299$	CSC [MPa]	0.635

Table 4

The input and output variables used in the model.

Variables	Data used for training and testing models	
	Minimum	Maximum
Windsor Probe (cm)	4.23	4.62
Ultrasonic Pulse Velocity (μs)	348	370
Rebound Hardness (R)	24	38
Compressive Strength of Concrete (MPa)	24.10	33.03

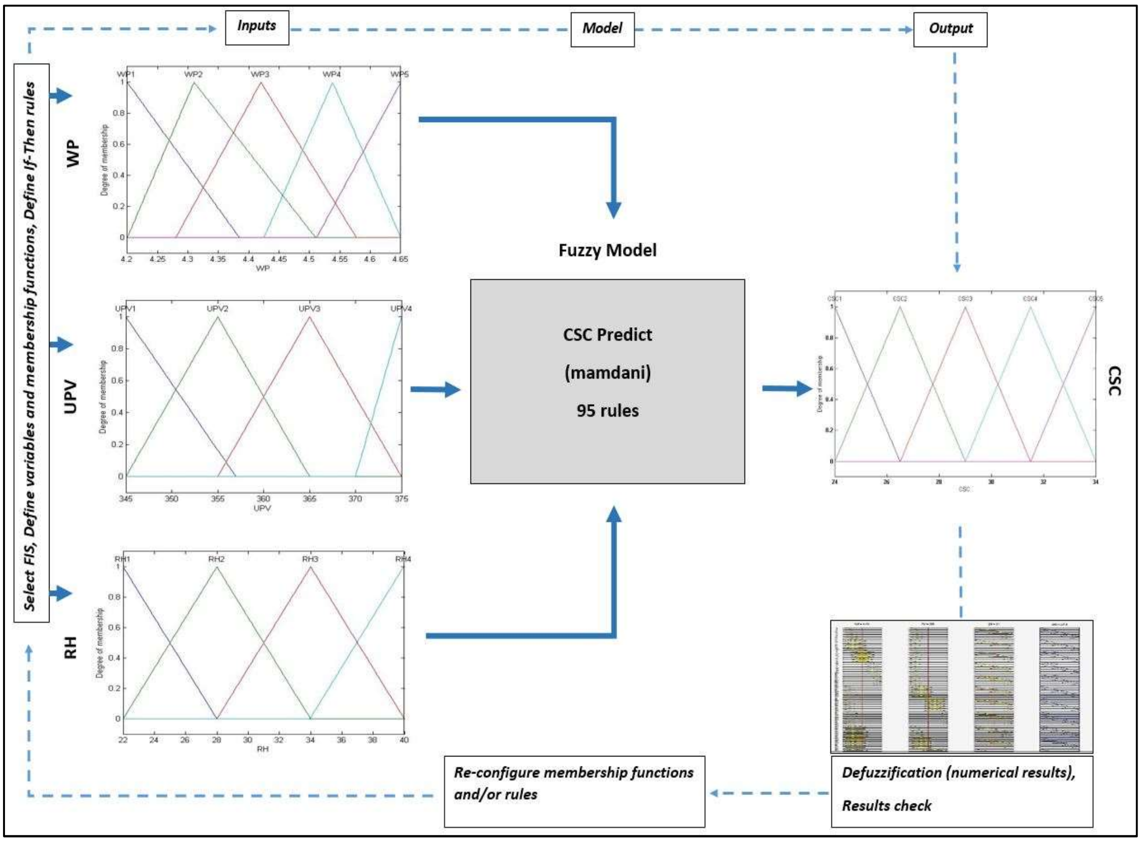

Fig. 1 - General structure and steps of the fuzzy model.

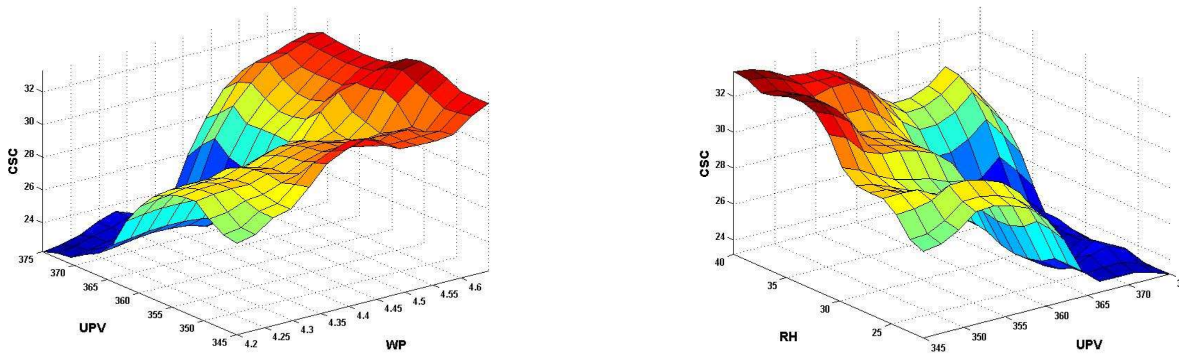

Fig. 2 - Compressive strength as a function of inputs.

membership functions for WP, UPV and RH were 5, 4 and 4 respectively. For prediction of CSC, 5 membership functions were defined to ensure sufficient accuracy of the output.

After determining membership functions, 95 fuzzy rules were formed in modelling. These rules are obtained as in the following:

$Rule_i$: (WP is WP_j) and (UPV is UPV_k) and (RH is RH_m) then (CSC is CSC_n)
where $i = 1,..,95$; $j = 1,..,5$, $k = 1,..,4$; $m = 1,..,4$; $n = 1,...,5$.

To obtain numeric output values, defuzzification is performed by the centroid of area method. This is the most commonly used technique

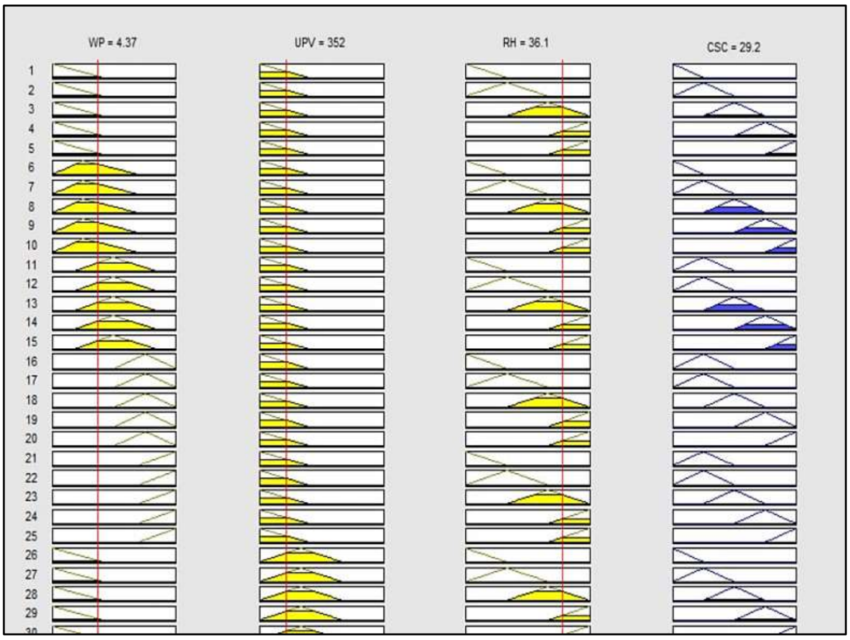

Fig. 3 - Defuzzification of the model.

and is very accurate. The compressive strength values obtained from developed FL model as a function of WP, UPV and RH are displayed in Figure 2. These figures illustrate the relationship between the inputs and the output.

After creating the model, the model results were obtained from the defuzzification monitor (Figure 3).

5. Results and Discussion

In this study, a multilinear regression (MLR) analysis was performed by using IBM SPSS Statistics™, to compare with FL model. Obtained regression coefficients are given in Table 5.

Table 5

Multilinear regression model coefficients

	Unstandardized Coefficients	
	B	Std. Error
Constant	16.890	13.178
WP	12.900	1.300
UPV	-0.133	0.025
RH	0.068	0.036

The performance of MLR and FL models can be evaluated using root mean squared error (RMSE) which is calculated by using Eq. (1). In Eq. (1), subscripts m and p indicates measured and predicted data respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|m_i - p_i|^2} \qquad (1)$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are calculated by using Eq. (2) and (3) respectively.

$$R^2 = \frac{(N\sum m_i p_i - \sum m_i \sum p_i)^2}{[N\sum m_i^2 - (\sum m_i)^2][N\sum p_i^2 - (\sum p_i)^2]} \qquad (2)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|m_i - p_i|}{m_i}\Big) * 100 \qquad (3)$$

where m is the measured value, p is the model predicted value, N is the pattern. Calculated values of R^2, RMSE and MAPE for each model are presented in Table 6.

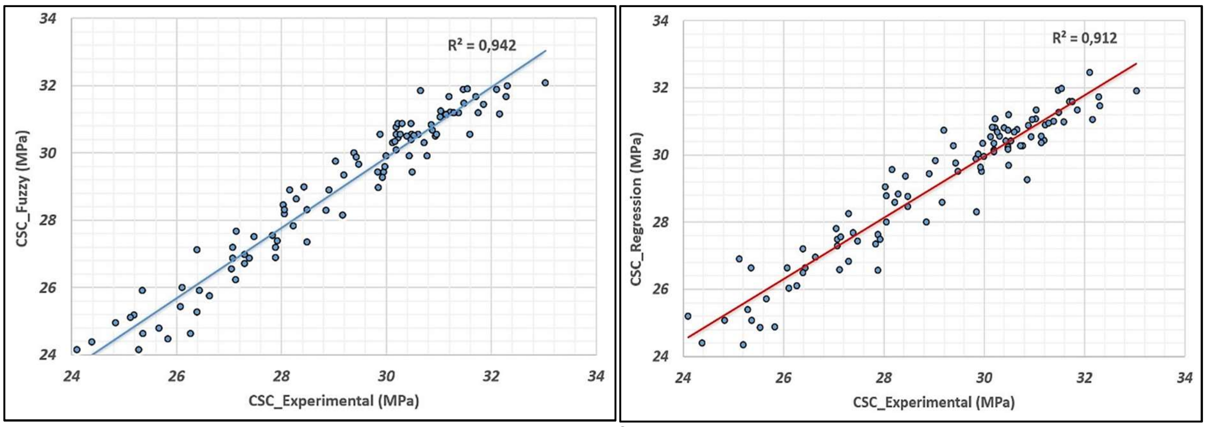

Fig. 4 - Explanation ability of the FL model.

Table 6

Statistical values of training models

Statistics	Model	
	Fuzzy Logic	MLR
R^2	0.942	0.912
RMSE	0.590	0.637
MAPE (%)	1.592	1.726

Performance of the MLR model and the FL model for the prediction of CSC is compared using R^2 values shown in Figure 4.

As shown in Figure 4, the results obtained from both model are very close to the experimental results. However, as shown in Table 6 and Figure 4, calculated statistical values of FL model, such as RMSE=0.590 and MAPE=1.592%, are better than the MLR model. The proposed FL model is suitable and can predict the CSC values very close to the measured values using the NDT values.

6. Conclusions

In this paper, an FL prediction model was developed for prediction of CSC. Developed model has three input variables and one output. The input variables are WP results (cm), UPV (µs), and RH (R), and the output is 28 days CSC (MPa). After the modelling process, the results obtained from the developed model and MLR model compared with the experimental results using performance indices, RMSE and MAPE (%). The statistical values show that values obtained from FL model were very close to the experimental results.

Among single variable prediction equations, the one using WP as predictor variable has a good prediction performance. However, WP penetration affected from carbonation of concrete, type or size of aggregate, voids in concrete etc. Developed FL model can predict CSC values with a high degree of accuracy. Its prediction performance is better than that of MLR, because it uses expert experience and the compressive strength of concrete depends NDT parameters nonlinearly. Thus, the present study suggests an alternative approach to evaluate CSC using NDT values.

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