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Prediction Compressive Strength of Self-Compacting Concrete Containing Fly Ash Using Fuzzy Logic Inference System

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***Abstract*—**Self-compacting concrete (SCC) developed in Japan in the late 80s has enabled the construction industry to reduce demand on the resources, improve the work condition and also reduce the impact of environment by elimination of the need for compaction. Fuzzy logic (FL) approaches has recently been used to model some of the human activities in many areas of civil engineering applications. Especially from these systems in the model experimental studies, very good results have been obtained. In the present study, a model for predicting compressive strength of SCC containing various proportions of fly ash, as partial replacement of cement has been developed by using Fuzzy Inference System (FIS). For the purpose of building this model, a database of experimental data were gathered from the literature and used for training and testing the model. The used data as the inputs of fuzzy logic models are arranged in a format of five parameters that cover the total binder content, fly ash replacement percentage, water content, superplasticizer and age of specimens. The training and testing results in the fuzzy logic model have shown a strong potential for predicting the compressive strength of SCC containing fly ash in the considered range.

***Keywords*—**Self-compacting concrete, fly ash, strength prediction, fuzzy logic.

I. Introduction

SELF-compacting concrete (SCC) has emerged in Japan in the late 1980s as a material that can flow under its own weight, so that it can be easily placed, without need for additional mechanical compaction, in complicated formwork, congested reinforced structural elements and hard to reach areas [1]–[3]. This saves time, reduces overall cost, improves working environment and opens the way for the automation of the concrete construction. It is an innovative concrete that in hardened state is dense, homogeneous and has the same engineering properties and durability as traditional vibrated concrete [4]. Because of these significant benefits, SCC is expected to gradually replace most of the ordinary concrete currently produced [5], [6].

For SCC, it is generally necessary to use superplasticizers in order to obtain high mobility, and a large volume of viscosity modifying admixture to eliminate segregation. Adding chemical admixtures are, however, expensive, and their use may increase the materials cost. Savings in labor cost might offset the increased cost, but the use of mineral admixtures could increase the slump of the concrete mixture without increasing its cost. These new building materials known as supplementary cementing materials (SCM) are pre-consumer materials that are defined as material from the waste stream of a manufacturing process. These include fly ash, blast furnace slag, and silica fume or limestone filler. Their use as a partial replacement for Portland cement reduces the amount of cement needed for concrete. This reduces the energy and CO_2 impacts and helps improve the workability and long-term properties of concrete.

Fly ash (FA) is an industrial by-product, generated from the combustion of coal in the thermal power plants and is considered one of the most widely used in different concrete application. Several researches indicate that the presence of fly ash as a mineral admixture in concrete, improves its strength and durability characteristics. FA can be used either as an admixture or as a partial replacement of cement. It can also be used as a partial replacement of fine aggregates, as a total replacement of fine aggregates and as supplementary addition to achieve different properties of concrete [7], [8]. Previous investigations show that the use of FA in SCC reduces the dosage of superplasticizer needed to obtain similar slump flow compared to concrete made with Portland cement only [9]. Also, the use of FA improves significantly the rheological properties and reduces cracking of concrete due to the heat of hydration of the cement [10].

A few studies have been carried out on the optimisation of the mix proportion for the addition of FA to SCC. Meanwhile, there is insufficient research on modeling the rheological and mechanical properties of SCC with FA where the most of the research are based on conventional and traditional methods.

For the last three decades, the different modeling methods based on Artificial Intelligence (AI) techniques like artificial neural networks (ANN), fuzzy logic (FL) systems and genetic algorithms (GA) have become popular and have been used by many researchers for a variety of engineering applications.

The FL approach combined with ANN is being widely used to solve a wide variety of problems in civil engineering applications [11]–[14]. For SCC, these techniques are also used by some researchers proposing many predictive models. A fuzzy logic prediction model for fresh and hardened properties of SCC containing fly ash and polypropylene fibers has been developed by Gencel et al. [15]. A compressive strength prediction models for SCC was designed based on an independent methodology that combines fuzzy logic and

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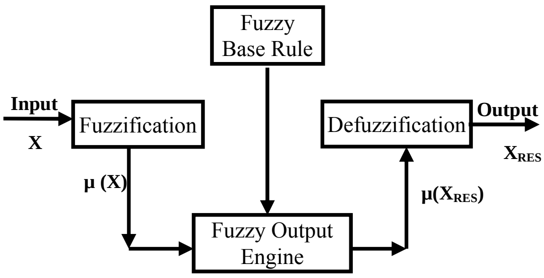
genetic algorithm was developed [16]. A fuzzy inference system was built for the specific case of various SCC mixtures subjected to ammonium sulfate attack [17].

In many applications, the Fuzzy Inference System (FIS) modeling was found better than Artificial Neural Network (ANN) modeling [18]. In this context, the main purpose of this study is to develop a model for predicting compressive strength of SCC containing fly ash based on an FIS model.

II. Fuzzy Logic Inference System

FL concept which was first introduced by Zadeh (1996) provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables [19]. It performs numerical computation by using linguistic labels stimulated by membership functions and linguistic fuzzy rules. Fuzzy inference systems (FIS) are powerful tools for the simulation of nonlinear behaviors with the help of FL concept and linguistic fuzzy rules [20].

Fuzzy inference systems, which are also called fuzzy rule-based systems or fuzzy models, comprise four basic components: fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification (Fig. 1).



X: the input vector, X_{RES}: the input commands, μ(x) and μ(X_{RES}): the correspond memberships functions

Fig. 1 The fuzzy logic modeling process

The first module (Fuzzification) is attributed to the actual value of each entry, at time t and its membership function μ that represent fuzzy sets of input variables. Fuzzification converts each piece of input data to degrees of membership by a lookup in one or more several membership functions. The key idea in fuzzy logic, in fact, is the allowance of partial belongings of any object to different subsets of a universal set instead of belonging to a single set completely. Partial belonging to a set can be described numerically by a membership function, which assumes values between 0 and 1 inclusive. Intuition, inference, rank ordering, angular fuzzy sets, neural networks, genetic algorithms, and inductive reasoning can be, among many, ways to assign membership values or functions to fuzzy variables. Fuzzy membership functions may take many forms, but in practical applications, simple linear functions, such as triangular ones, are preferable.

The second module (Fuzzy Rule Base) is the application of rules such as (IF...THEN...). Fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs. In the fuzzy approach, there are no mathematical equations and model parameters, and all the uncertainties, nonlinear relationships, and model complications are included in the descriptive fuzzy inference procedure in the form of If–Then statements.

The third module (Fuzzy output engine) takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. There are basically two kinds of inference operators: minimization (min) and product (prod).

The four and the final module (defuzzification) is the reverse transformation of the first module converts the resulting fuzzy outputs from the fuzzy inference engine to a number. It means converting the fuzzy results to actual results by defuzzification methods. There are many defuzzification methods such as centre of gravity (COG; centroid), bisector of area (BOA), mean of maxima (MOM), left most maximum (LM), right most maximum (RM) [21].

Fuzzy inference systems are powerful tools for the simulation of nonlinear behaviors with the help of fuzzy logic and linguistic fuzzy rules [22], [23]. There are various fuzzy inference systems methodologies, such as Mamdani and Assilian [24] and Sugeno [25]. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

III. Developing of the FL Based Model

Structure identification and parameter prediction are the most important in system identification task on fuzzy modeling. Structure identification contains issues like selecting pertinent input variables, choosing a specific type of fuzzy inference system, determining the number of fuzzy rules, their antecedents and consequents, and determining the type and number of membership functions [26].

A. Experimental Database

The binder content, fly ash replacement percentage, water content, superplasticizer and age of specimens are the determination of values response to evident input values of the developed model. The compressive strength of SCC is used in the output layer. In this study, a database of 145 of experimental data gathered from the literature [27]–[33] was used to develop this FL model. A set of 124 data were used for training the model and the other 21 data were used for testing the trained model. The limit values of input and output variables used in Sugeno-type fuzzy inference model are listed in Table I.

TABLE I
INPUT AND OUTPUT VALUES OF FL MODEL

Components	Minimum	Maximum	Average
Input variables			
Binder (kg/m3)	375	600	483.8
Water	131.4	238.5	173.8
Fly ash (%)	0	70	32.7
Age of specimen (days)	3	365	58.7
Superplastisizer (kg/m3)	0	23.8	6.0
Output variables			
Compressive strength (MPa)	20.4	94.5	49.7

B. Design of Fuzzy Inference System Model

In this part of study, the developed fuzzy logic-based model was applied to predict the compressive strength of SCC containing fly ash. The fuzzy rules were written for this purpose. The fuzzy logic-based algorithm model by using the FL toolbox in MATLAB was adopted.

The data sets are loaded using Grid partition method for the FIS. The performance of particular membership functions is good for certain data patterns. Hence triangular membership function along with three parameters was used for the present study.

In the rule base, fuzzy variables were connected with "prod'' operators and the implication of each rule was calculated using "wtaver'' (weighted average) defuzzification method. The output membership function can either be a constant membership function or a linear membership function. The optimization methods train membership function parameters to emulate the training data. The hybrid optimization method is a combination of least-squares and back propagation gradient descent method. In hybrid method, model tunes with forward pass and backward pass [22].

For the present data, constant output membership function produced minimum error. Fuzzy inference system is trained by hybrid network for 50 numbers of epochs and process terminated by the observation of the stability in error reduction. The model having 243 fuzzy rules is created and details of various parameters obtained after training are as showed in Table II.

TABLE II
THE VALUES OF PARAMETERS USED IN THE FL MODEL

Parameters	FL
Number of input variables	5
Number of output	1
Number of training data	124
Number of testing data	21
Number of fuzzy rules	243
Error	1.3

IV. RESULTS AND DISCUSSION

In this study, the error that arose during the training and testing in the Sugeno-type inference system can be expressed as a mean-squared error (MSE) which is calculated as shown in (1):

$$MSE = \left(\frac{1}{p}\right) * \sum_j \left(t_j - o_j\right)^2 \tag{1}$$

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

$$R^2 = 1 - \left(\frac{\sum_j \left(t_j - o_j\right)^2}{\sum_j \left(o_j\right)^2}\right) \tag{2}$$

$$MAPE = \frac{1}{p}\sum_j \left(\left|\frac{o_j - t_j}{o_j}\right| * 100\right) \tag{3}$$

where "t" is the target value, "o" is the output value, and "p" is the pattern.

The performance of the Sugeno-type inference system is determined according to these statistical parameters given above ((1)-(3)) and showed in Table III.

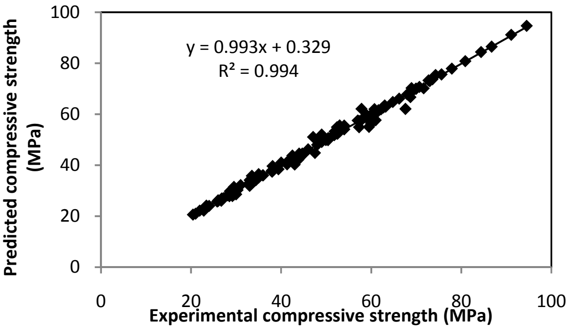
TABLE III
THE STATISTICAL VALUES OF PROPOSED FL MODEL

Statistical parameters	FL
MSE	1.70
R^2	0.96
MAPE	1.65

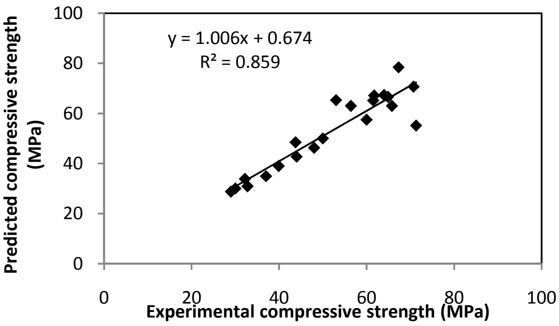
All of the results obtained from experimental studies and predicted by using the training and testing results of FL model are given in Figs. 2 (a) and (b), respectively. The linear least square fit line, its equation and the R^2 values were shown in these figures for the training and testing data. Also, inputs values and experimental results with testing results obtained from FL model were given in Table IV. As it is visible in Fig. 2, the values obtained from the training and testing in FL model are very close to the experimental results. The result of testing phase in Fig. 2 (b) shows that the FL model is capable of generalizing between input and output variables with reasonably good predictions.

TABLE IV
TESTING DATA

Data sets used for testing the FL model (kg/m3)							
Age of specimens	Fly ash (%)	Water	Binder	SP	Compressive strength (MPa) Experimental	FL	Error (%)
7	35	180.00	450	4.80	44.00	42.74	2.87
7	20	180.00	450	3.40	43.78	48.45	10.68
7	0	161.50	425	12.88	30.00	30.03	0.09
28	16	176.00	550	0.00	70.73	70.70	0.04
28	10	238.50	530	4.55	32.19	33.87	5.22
28	0	138.75	375	3.50	61.50	65.15	5.94
28	70	175.00	500	2.10	29.00	28.81	0.65
28	0	180.00	500	5.00	64.00	67.29	5.14
28	0	172.97	494	9.26	61.71	67.11	8.75
28	55	180.00	450	3.30	48.00	46.27	3.61
28	35	180.00	450	2.90	60.00	57.52	4.13
28	60	157.50	450	6.75	39.90	38.99	2.28
28	50	175.00	500	2.53	37.00	34.95	5.55
56	40	168.00	600	19.98	50.00	49.99	0.02
90	30	155.05	443	6.75	64.90	66.58	2.60
168	70	150.00	500	1.69	32.80	30.90	5.80
365	60	161.50	425	6.75	65.80	62.98	4.28
365	40	146.54	431	6.75	67.30	78.44	16.56
365	60	161.50	425	6.75	56.40	62.98	11.68



(a)



(b)

Fig. 2 Comparison of the experimental compressive strength results with (a) the training and (b) testing results of FL model

Also, the mean-squared error (MSE), absolute fraction of variance and the mean absolute percentage error (MAPE) are shown above for the training and testing data. The value of R^2 is 99.4% for training set and 85.9% for testing set in the FL model.

All the statistical parameter values demonstrate that the proposed FL model are suitable and predict the compressive strength of SCC. The compressive strength of SCC values predicted by FL model is very close to the experimental values.

V. Conclusion

The study of fuzzy logic as an alternative approach can provide an efficient and rapid means of obtaining optimal solutions to predict the compressive strength of SCC containing fly ash. The model developed based in this approach was used a Sugeno-type fuzzy inference system. This model was trained and tested with input and output data gathered from the literature. The training and testing results obtained from FL model are very close to the experimental results. It was demonstrated that the developed FL model was successfully trained and tested. The statistical parameter values of RMS, R^2 and MAPE have shown obviously this situation. As a result, the fuzzy logic model was able to predict the compressive strength values of SCC containing fly ash.

References

[1] Ozawa K, Maekawa K, Kunishima H, Okamura H, “Performance of concrete based on the durability design of concrete structures” in Proc Sec East Asia Pacific CSEC, 1989, pp. 445–456.

[2] Rols S, Ambroise JP, Pera J, “Effects of different viscosity agents on the properties of self-levelling concrete”, Cem Concr Res, vol 29, pp. 261-266, 1999.

[3] Okamura H, M., Ozawa,K. and Ouchi, M, “Self-compacting high performance concrete”, In: proceedings of the fifth EA SEC1995, pp. 2381-2388.

[4] European Guidelines for Self-Compacting Concrete: Specification, Production and Use, European Project Group, 2005.

[5] Bartos, P.J.M. y Grauers, M, “Self-Compacting Concrete”, Concrete, Vol. 33, nº 4, pp. 9-13, 1999.

[6] Skarendahl A, Ozawa K, Ouchi M, “Market acceptance of self-compacting concrete”, The Swedish experience. In. Proc. 2nd inter symp on SCC, Coms Engineering Corporation Tokyo, pp. 1–13, 2001.

[7] Dhiyaneshwaran S, Ramanathan P, Baskar I and Venkatasubramani R, “Study on Durability Characteristics of Self-Compacting Concrete with Fly Ash”, Jordan Journal of Civil Engineering, Vol. 7, nº. 3, pp. 342-352, 2013.

[8] Jino, John, Maya TM and Meenambal T, “Mathematical modeling for durability characteristics of fly ash concrete”. International Journal of Engineering Science and Technology, Vol. 4, n°. 1, pp. 353-361, 2012.

[9] Yahia A, Tanimura M, Shimabukuro A, Shimovama Y, “Effect of rheological parameters on self-compactability of concrete containing various mineral admixtures”, In International RILEM symposium on self-compacting concrete, pp. 523-535, 1999.

[10] Kurita M, Nomura T, “Highly-flowable steel fiber-reinforced concrete containing fly ash”. ACI Special Publication, Vol. 178, 1998.

[11] Gao, F. L, “A new way of predicting cement strength-fuzzy logic”, Cement and Concrete Research, Vol. 27, n° 6, pp. 883-888, 1997.

[12] Muthukumaran P, Demirli K, Stiharu I, Bhat RB “Boundary conditioning for structural tuning using fuzzy logic approach”, Comput Struct, Vol 74, n° 5, pp. 547-557, 2000.

[13] Akkurt, S., Tayfur, G., & Can, S, “Fuzzy logic model for the prediction of cement compressive strength”, Cement and Concrete Research, Vol. 34, n° 8, pp. 1429-1433, 2004.

[14] Nehdi ML, Bassuoni MT, “Fuzzy logic approach for estimating durability of concrete”, Proceedings of the ICE-Construction Materials, Vol. 62, n° 2, pp. 81-92, 2009.

[15] Gencel O, Ozel C, Koksal F, Martinez-Barrera G, Brostow W, Polat H, “Fuzzy Logic Model for Prediction of Properties of Fiber Reinforced Self-compacting Concrete ”, Materials Science, Vol. 19, n° 2, pp. 203-215, 2013.

[16] Da Silva WRL, Štemberk P, “Predicting self-compacting concrete shrinkage based on a modified fuzzy logic model”, Engineering Mechanics, Vol. 229, pp. 1173-1183, 2012.

[17] G, Goktepe A. B, Ramyar K, Sezer A, “Prediction of sulfate expansion of PC mortar using adaptive neuro-fuzzy methodology”. Build Environ, Vol. 42, n° 7, pp. 1264-1269, 2007.

[18] Deka P. C and Diwate S. N, “Modeling Compressive Strength of Ready Mix Concrete Using Soft Computing Techniques”, International Journal of Earth Sciences and Engineering, Vol. 4, n° 6, pp. 793-796, 2011.

[19] Zadeh L. A, Klir G. J and Yuan B, “Advances in Fuzzy Systems - Applications and Theory”, Vol. 6, River Edge, NJ: World Scientific, 1996.

[20] Yurkovich S, Passino, K. M, “A Laboratory Course of Fuzzy Control”, *IEEE Transactions on Education*, Vol. 42, n° 1, pp.15-21, 1999.

[21] Sen Z, “Fuzzy Modeling in Engineering”, Class Notes, Civil Engineering Faculty, Istanbul Technical University, Istanbul, Turkey, 1999.

[22] Demuth H, Beale M, Hagan M, “Neural Network Toolbox 5, User’s Guide”, The MathWorks, Inc, 849 pp, 2007.

[23] Topçu İ B, Sarıdemir M, “Prediction of mechanical properties of recycled aggregate concretes containing silica fume using artificial neural networks and fuzzy logic”. *Computational Materials Science*, Vol. 42, n° 1, pp. 74-82, 2008.

[24] Mamdani E H, Assilian S, “An experiment in linguistic synthesis with a fuzzy logic controller”, Int J Man-Mach Stud, Vol. 7, pp. 1-13, 1975.

[25] Takagi T, Sugeno M, “Fuzzy identification of systems and its applications to modeling and control”, IEEE Trans Syst Man Cyber, Vol. 15, pp. 116-132, 1985.

[26] Sugeno M, Kang GT. "Structure identification of fuzzy model", Fuzzy Sets SystMan Cyber,Vol. 23, pp. 665-685, 1993.
[27] Bingöl, Ferhat A., Tohumcu I, "Effects of different curing regimes on the compressive strength properties of self compacting concrete incorporating fly ash and silica fume". Materials & Design, Vol. 51, pp. 12-18, 2013.
[28] Mahmoud, E, Ibrahim A, El-Chabib H, Patibandla V. C, "Self-Consolidating Concrete Incorporating High Volume of Fly Ash, Slag, and Recycled Asphalt Pavement", *International Journal of Concrete Structures and Materials*, Vol. 7, n° 2, pp. 155-163, 2013.
[29] Güneyisi E, Gesoğlu M, Özbay E, "Strength and drying shrinkage properties of self-compacting concretes incorporating multi-system blended mineral admixtures", Construction and Building Materials, Vol. 24, n° 10, pp. 1878-1887, 2010.
[30] Khatib J. M, "Performance of self-compacting concrete containing fly ash", Construction and Building Materials, Vol. 22, n° 9, pp. 1963-1971, 2008.
[31] Naik, T. R, Kumar R, Ramme B. W, Canpolat F, "Development of high-strength, economical self-consolidating concrete", *Construction and Building Materials, Vol.* 30, pp. 463-469, 2012.
[32] Şahmaran M, Yaman İ. Ö, Tokyay M, "Transport and mechanical properties of self consolidating concrete with high volume fly ash", *Cement and concrete composites, Vol.* 31, n° 2, pp. 99-106, 2009.
[33] Yazıcı H, "The effect of silica fume and high-volume Class C fly ash on mechanical properties, chloride penetration and freeze–thaw resistance of self-compacting concrete", Construction and building Materials, Vol. 22, n° 4, pp. 456-462, 2008.

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