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Fuzzy inference systems based prediction of engineering properties of two-stage concrete

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Abstract. Two-stage concrete (TSC), also known as pre-placed aggregate concrete, is characterized by its unique placement technique, whereby the coarse aggregate is first placed in the formwork, then injected with a special grout. Despite its superior sustainability and technical features, TSC has remained a basic concrete technology without much use of modern chemical admixtures, new binders, fiber reinforcement or other emerging additions. In the present study, an experimental database for TSC was built. Different types of cementitious binders (single, binary, and ternary) comprising ordinary portland cement, fly ash, silica fume, and metakaolin were used to produce the various TSC mixtures. Different dosages of steel fibres having different lengths were also incorporated to enhance the mechanical properties of TSC. The database thus created was used to develop fuzzy logic models as predictive tools for the grout flowability and mechanical properties of TSC mixtures. The performance of the developed models was evaluated using statistical parameters and error analyses. The results indicate that the fuzzy logic models thus developed can be powerful tools for predicting the TSC grout flowability and mechanical properties and a useful aid for the design of TSC mixtures.

Keywords: two-stage concrete; fuzzy logic; efflux time; spread flow; compressive strength; tensile strength

1. Introduction

Two-stage concrete (TSC), also known as preplaced aggregate concrete, has been successfully used for many years in numerous applications such as underwater construction and the rehabilitation of concrete structures (ACI 304.1 2005, Najjar *et al*. 2014). It is cast differently from conventional concrete. Coarse aggregates are first preplaced and then injected with a mixture of cement, water, fine sand, and possibly chemical admixtures, commonly termed “grout” in TSC practice (Abdul Awal 1984). The properties of the grout used and its ability to flow around the preplaced aggregate particles and effectively fill voids have a governing effect on the mechanical properties and durability of the final product (Abdelgader 1996, ACI 304.1 2005).

Grout flowability is primarily dependent on the chemical and physical properties of the ingredients used in the mixture (i.e., sand, cement, supplementary cementitious materials (SCMs), and admixtures) along with their respective proportions (Abdelgader and Elgalhud 2008, O’Malley and Abdelgader 2010, Najjar *et al*. 2014, Coo and Pheeraphan 2015). It has been argued that using SCMs could enhance the mechanical properties and durability of TSC (ACI 304.1 2005). However, limited research has been devoted to the investigation of the effects of SCMs on the grout flowability and the mechanical properties of TSC. A recent study has involved the examination of the mechanical properties of TSC incorporating a variety of SCMs. It was found that the type of SCM and the binder composition have a significant influence on the mechanical properties of TSC (Najjar *et al*. 2016).

Over the last few decades, considerable research has been directed to generating models for predicting the properties of various types of concrete (Kute and Kale 2013). However, only very few researchers have attempted to proposed equations that are essentially based on nonlinear regression analysis for predicting the flowability and mechanical properties of TSC. For example, nonlinear regression analysis was used as a means of establishing the relationship between the compressive strength of TSC and the mixture proportions of the grout (i.e., water-to-cement ratio (w/c) and sand-to-cement ratio (s/c)) (Abdelgader 1999, Abdelgader and Elgalhud 2008). Some of the proposed formulas are dependent on the shape of the coarse aggregate (Abdelgader 1999), while others are based on the admixtures used (Abdelgader and Elgalhud 2008). Empirical correlations between the grout properties and mechanical properties of the corresponding TSC have also been suggested (Najjar *et al*. 2016).

A number of modeling methods based on fuzzy logic systems (FLS) have recently been employed for a variety of civil engineering applications (Kute and Kale 2013). The primary advantage of fuzzy logic (FL) models is their ability to describe knowledge in a descriptive human-like manner in the form of simple rules based on the use of linguistic variables (Demir 2005). For instance, an FL

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Table 1 Chemical analysis and physical properties of OPC, FA, SF, and MK

	OPC	FA	SF	MK
SiO_2 (%)	19.60	43.39	95.30	53.50
Al_2O_3 (%)	4.80	22.08	00.17	42.50
CaO (%)	61.50	15.63	00.49	0.20
Fe_2O_3 (%)	3.30	7.74	00.08	1.90
SO_3 (%)	3.50	1.72	00.24	0.05
Na_2O (%)	0.70	1.01	00.19	0.05
Loss on ignition (%)	1.90	1.17	4.7	0.50
Specific gravity	3.15	2.50	2.20	2.60
Surface area (m^2/kg)*	371	280	19500	15000

*1 m^2/kg=4.882 ft^2/lb

model can be effectively used for estimating the properties of concrete without the necessity for performing costly experimental investigations (Feng *et al*. 2009). However, there has been so far no attempt to develop FL models for estimating the flowability and mechanical properties of TSC in the open literature. The goal of this study is therefore to create FL models that can estimate the flowability and mechanical properties of TSC and serve as accurate predictive tools for designing TSC mixtures in which a variety of types and dosages of SCMs can be incorporated.

2. Overvıew of fuzzy logıc models

Fuzzy set theory was introduced for the first time in 1965 by Zadeh, who developed fuzzy logic as an alternative to Aristotelian logic, in which only two possibilities are defined: true and false (Zadeh 1965). FL corresponds to a natural way of thinking, in which verbally expressed rules are applied to address vagueness. This type of logic also encompasses the concept of any object belonging partially to different subsets of the universal set, rather than belonging entirely to only a single set. Partial belonging to a set can be described numerically by a membership function, which assumes values between 0 (completely false) and 1 (completely true) (Topçu and Sarıdemir 2008, Da Silva and Stemberk 2013). The ability to deal with imprecise and vague information makes FL reasoning a robust and flexible tool for use in a number of engineering applications (Nehdi and Bassuoni 2009).

Fuzzy inference systems (FIS) are modeling tools that can address ambiguity in complex systems. In general, a FIS has four basic components: fuzzification, a fuzzy rule base, a fuzzy output engine, and de-fuzzification (Ross 2010). The purpose of fuzzification is to map the crisp input to values from 0 to 1 using a set of input membership functions (Subaşı *et al*. 2013). Fuzzy membership functions have different forms; however, the linear forms (i.e., triangular shapes) are suitable for most practical applications (Nehdi and Bassuoni 2009).

In a fuzzy rule base, all possible fuzzy relations between the input and output data are expressed as IF-HEN statements, which convey human knowledge and expertise (Ross 2010). Fuzzy rules can be written in the following form (Sivanandam *et al*. 2007):

If ($input_1$ is membership $function_1$) and/or ($input_2$ is membership $function_2$) and/or……THEN ($output_n$ is membership $function_n$)

Language connectives such as “logical and” or “logical or”, which are similar to the operations of “intersection” and “union”, respectively, are commonly used in compounded rules (Nehdi and Bassuoni 2009). For example, the fuzzy intersection of two fuzzy sets A and B in a universe of discourse X can be expressed in terms of membership functions $\mu(x)$, as follows

$$\mu(x) = min[\mu_A(x), \mu_B(x)] = \mu_A(x) \cap \mu_B(x) \quad (1)$$

Where x is an input element of the universe X; $\mu_A(x)$ and $\mu_B(x)$ are the degrees of membership in fuzzy sets (A) and (B), respectively; and “min” stands for a minimization operator.

In a fuzzy inference engine, all fuzzy rules in the fuzzy rule base are collected in order to generate an overall conclusion arising from the individual consequences of each rule. The Mamdani inference method is the methodology most commonly applied in the research reported in the literature. It was proposed by Mamdani (1975) as an attempt to control a steam engine by synthesizing a set of linguistic control rules obtained from experienced human operators (Nehdi and Bassuoni 2009, Subaşı *et al*. 2013). In this method, the consequences of individual rules are truncated by minimization (min) or scaled by product operators. In both cases, all consequences are then aggregated by a maximization (max) operator in order to obtain the final conclusion (Ross 2010, Sivanandam *et al*. 2007).

In de-fuzzification, the fuzzy output from the fuzzy interference engine is converted to a number (Bassuoni and Nehdi 2008, Subaşı *et al*. 2013). The centroid method is the approach most widely employed for the de-fuzzification of fuzzy output sets. The centroid de-fuzzification technique can be expressed as follows

$$z^* = \int \frac{\mu(z)zdz}{\mu(z)dz} \quad (2)$$

Where z^* is the defuzzified output value, z is the output value in a fuzzy subset (s), and $\mu(z)$ is the corresponding degree of membership of the output in the same fuzzy subsets. Extensive details about FL methods, the associated mathematical background, and the application of these methods are beyond the scope of the study presented in this chapter and have been published previously by Ross (2010). Examples of fuzzy logic models use in the realm of concrete research can be found in (Bedirhanoglu 2014, Tsai *et al*. 2015, Zhang 2015).

3. Experımental program

3.1 Materials and grout mixture proportions

Ordinary portland cement (OPC) was used as the main

Table 2 Grout mixture proportions

Grout Mixture No.	Grout Mixture Notation	Binder (kg/m^3)*				Sand (kg/m^3)*	Water (kg/m^3)*
		OPC	FA	SF	MK		
C-0.35	100OPC	957	--	--	--	957	335
F1-0.35	90OPC-10FA	855	95	--	--	950	332
F3-0.35	70OPC-30FA	654	280	--	--	935	327
F5-0.35	50OPC-50FA	460	460	--	--	921	322
S1-0.35	90OPC-10SF	850	--	94	--	945	331
SF4-0.35	50OPC-10SF-40FA	458	366	92	--	916	321
M1-0.35	90OPC-10MK	856	--	--	95	951	333
MF4-0.35	50OPC-10MK-40FA	461	369	--	92	922	323
C-0.45	100OPC	874	--	--	--	874	393
F1-0.45	90OPC-10FA	781	87	--	--	867	390
F3-0.45	70OPC-30FA	599	257	--	--	855	385
F5-0.45	50OPC-50FA	422	422	--	--	843	379
S1-0.45	90OPC-10SF	777	--	86	--	863	388
SF4-0.45	50OPC-10SF-40FA	420	336	84	--	839	378
M1-0.45	90OPC-10MK	782	--	--	87	868	391
MF4-0.45	50OPC-10MK-40FA	422	338	--	84	844	380
C-0.55	100OPC	803	--	--	--	803	442
F1-0.55	90OPC-10FA	718	80	--	--	798	439
F3-0.55	70OPC-30FA	551	236	--	--	788	433
F5-0.55	50OPC-50FA	389	389	--	--	778	428
S1-0.55	90OPC-10SF	715	--	79	--	795	437
SF4-0.55	50OPC-10SF-40FA	387	310	77	--	774	426
M1-0.55	90OPC-10MK	719	--	--	80	799	439
MF4-0.55	50OPC-10MK-40FA	389	311	--	78	778	428

*1 kg/m^3=0.06247 lb/ft^3

Table 3 Properties of hooked-end steel fibres

Steel Fibre Type	Length (mm)*	Diameter (mm)*	Aspect ratio	Specific gravity	Tensile strength (MPa)*
Short (S)	33	0.75	80	7.85	1100
Long (L)	60	0.75	44	7.85	1100

*1 in.=25.4 mm, 1 ksi=6.894 MPa

binder for all tested grout mixtures. Three types of SCMs including fly ash (FA), silica fume (SF), and metakaolin (MK) were used as partial replacement for OPC. Table 1 summarizes physical and chemical properties of the used materials. Silica sand with a fineness modulus of 1.47 and a saturated surface specific gravity of 2.65 was used as the fine aggregate. The silica sand gradation was selected according to ACI 304.1 grading limits for TSC fine aggregate. All grout mixtures had the same sand-to-binder ratio (s/b=1.0), which the commonly accepted practice. Three water-to-binder ratios (w/b) of 0.35, 0.45 and 0.55 were tested. A poly-carboxylate high-range water-reducing admixture (HRWRA) with a specific gravity of 1.064, a

Table 4 Adjustment of grout flowability (Flow Cone Method)

Grout Mixture Number	Optimum HRWRA dosage (%)
C-0.45	0.40
F1-0.45	0.40
F3-0.45	0.20
F5-0.45	0.00
S1-0.45	0.80
SF4-0.45	0.20
M1-0.45	0.80
MF4-0.45	0.40

solid content of 34% and pH of 5 was added at different dosages. Several TSC grout mixtures were prepared using single, binary, and ternary binders corresponding with different HRWRA dosages. The mixture proportions of the tested grouts are provided in Table 2. Crushed limestone coarse aggregate with a maximum nominal size of 40 mm, a saturated surface dry specific gravity of 2.65, and a water absorption of 1.63% was used for the production of the various TSC mixtures. The gradation of the limestone aggregate was selected to comply with the ACI 304.1 grading limits for TSC coarse aggregate. Two types of cold-drawn hooked-end steel fibres were employed; their properties are listed in Table 3. The steel fibre dosages (i.e., volumetric percentage of concrete) used in the TSC were 1%, 2%, 4%, and 6% by concrete volume, which covers the practical dosage range.

3.2 Experimental procedures

All grout mixtures were prepared as per the guidelines of ASTM C938 (Standard Practice for Proportioning Grout Mixtures for Preplaced-Aggregate Concrete). Mixing and flowability measurements were conducted at room temperature (T=23°C±2°C) (73.4°F±3.6°F). Immediately following the mixing, grout flowability was evaluated using a flow cone test according to ASTM C939 (Standard Test Method for Flow of Grout for Preplaced-Aggregate Concrete-Flow Cone Method). The flow cone test entails measuring the time required for the efflux of 1725 ml (0.06 ft^3) of the grout through a specific cone that has a 12.7 mm (0.5-in.) discharge tube. A spread flow test was also conducted in order to study the effects of SCMs on the point at which the grout mixture begins to flow freely, which identifies the optimum water content (Hunger and Brouwers 2009). The grout is placed into a special conical mold, which is lifted straight upwards in order to allow free flow.

Based on the efflux time and spread flow results for the various grout mixtures, it was found that all grout mixtures made with a w/b ratio=0.45 could achieve the efflux time of 35 to 40±2 s recommended by ACI 304.1 (2005) for successful TSC production. The optimum HRWRA dosage that meets the efflux time recommendations was considered for each grout mixture made with the selected w/b ratio. Table 4 illustrates the optimum HRWRA dosage for the selected grout mixtures. The compressive strength of the

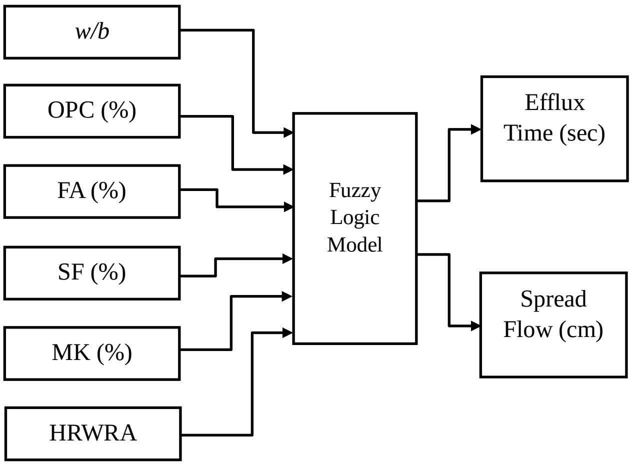

Fig. 1 General structure of the developed FL model I

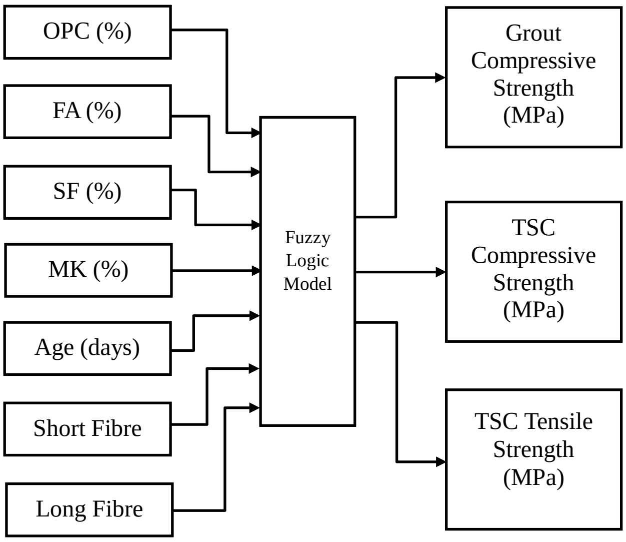

Fig. 2 General structure of the developed FL model II

selected grouts was tested on 50 mm (2 in.) cubic specimens at ages of 7, 28, and 56 days according to ASTM C 942 (Standard Test Method for Compressive Strength of Grouts for Preplaced-Aggregate Concrete in the Laboratory).

Thereafter, the effects of incorporating various rates and types of SCMs on the mechanical properties of the TSC mixtures made with the selected grouts were investigated. The mechanical performance of two-stage steel fibre-reinforced concrete (TSSFRC) incorporating different steel fibre dosages and lengths was also explored. Cylindrical TSC and TSSFRC specimens (150 mm×300 mm (6-in.×12-in.)) were prepared. For the TSC specimens, all molds were filled with the coarse limestone aggregate, and the specific grout was then injected in a manner similar to the procedure adopted in previous TSC studies (e.g., Abdelgader *et al*. 2010, O'Malley and Abdelgader 2010). For the TSSFRC specimens, the coarse aggregates and steel fibres were premixed and preplaced in the molds. A grout made with 100% OPC (i.e., grout mixture (C-0.45)) was subsequently injected to fill in the space around the coarse aggregates and fibres. Specimens were covered with wet burlap immediately after casting in order to prevent surface drying.

Table 5 Range of input variables for models I and II

FL Model/input parameter	Min.	Max.	Avg.
I/*w/b* ratio	0.35	0.55	0.45
I/OPC (%)	50.0	100.0	77.5
I/FA (%)	0.0	50.0	26.0
I/SF (%)	0.0	10.0	5.0
I/MK (%)	0.0	10.0	5.0
I/HRWRA (%)	0.0	2.0	0.8
II/OPC (%)	50.0	100.0	75.0
II/FA (%)	0.0	50.0	25.0
II/SF (%)	0.0	10.0	5.0
II/MK (%)	0.0	10.0	5.0
II/Age (days)	7.0	56.0	30.3
II/ Short steel fibre (%)	0.0	6.0	2.6
II/ Long steel fibre (%)	0.0	6.0	2.6

Table 6 Range of training and testing output variables for models I and II

FL Model/Property	Training Data			Testing Data		
	Min.	Max.	Avg.	Min.	Max.	Avg.
I/Grout efflux time (sec)	11.0	194.0	59.7	14.0	196.0	70.6
I/Grout spread flow (cm)	25.9	41.0	11.3	11.3	39.7	26.1
II/Grout compressive strength (MPa)	20.7	64.4	43.4	21.5	52.7	43.5
II/TSC compressive strength (MPa)	11.6	48.8	28.6	12.7	47.1	28.8
II/TSC tensile strength (MPa)	2.3	8.4	3.8	2.4	7.5	3.9

After 24 h, specimens were demolded and cured in a moist curing room (temperature (*T*)=25°C (77°F) and relative humidity (*RH*)=98%) until the desired testing ages. At each testing age (i.e., 7, 28 and 56 days), the compressive and splitting tensile strengths of the TSC specimens were evaluated according to ASTM 943 (Standard Practice for Making Test Cylinders and Prisms for Determining Strength and Density of Preplaced-Aggregate Concrete in the Laboratory) and ASTM C496/C496M (Standard Test Method for Splitting Tensile Strength of Cylindrical Concrete Specimens), respectively.

The results obtained from this experimental program were used to build a database for the development of FL models for predicting the grout efflux time, grout spread flow, grout compressive strength, TSC compressive strength, and TSC tensile strength.

4. Fuzzy logıc models

4.1 Database

In this study, two FL models were created with the goal of predicting the grout flowability and mechanical properties of TSC. FL model I was developed for data sets calculating the expected efflux time and the spread flow of a wide range of TSC grout mixtures. The database for training and testing this model contained 228 data points

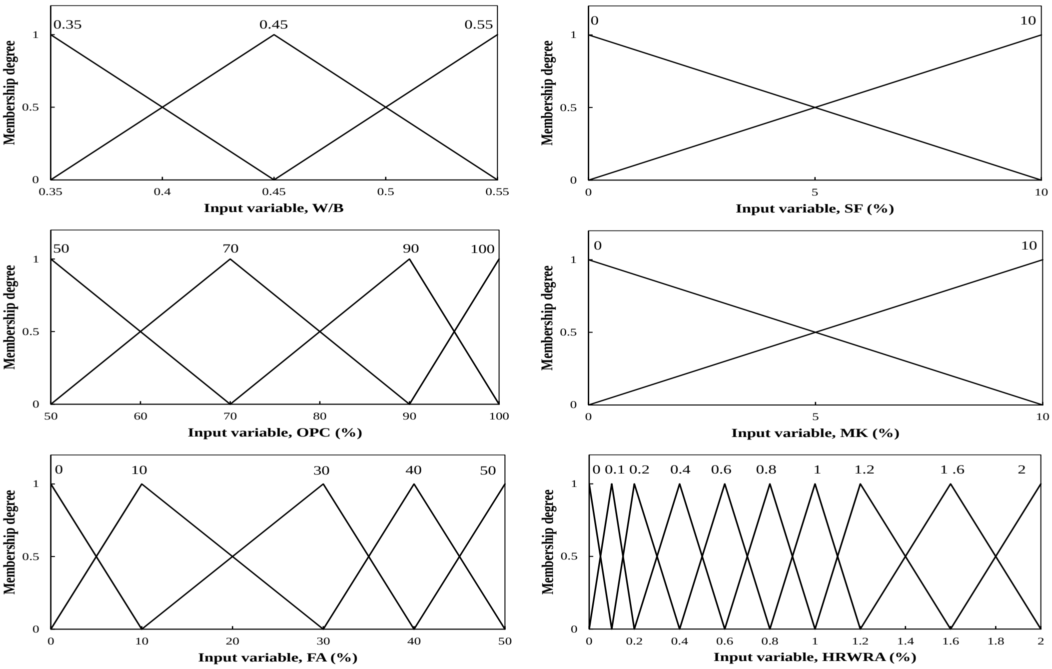

Fig. 3 Membership functions for input parameters of FL Model I

Table 7 Statistical analysis based on the ratio of experiential-to-predicted property

FL Model/Property	Training Data			Testing Data		
	Avg.	STDEV	COV(%)	Avg.	STDEV	COV(%)
I/Grout efflux time (sec)	1.00	0.06	5.79	1.02	0.07	7.35
I/Grout spread flow (cm)	1.00	0.05	4.99	0.97	0.06	5.84
II/Grout compressive strength (MPa)	1.02	0.04	4.30	1.03	0.05	5.15
II/TSC compressive strength (MPa)	1.01	0.04	3.49	1.03	0.03	3.14
II/TSC tensile strength (MPa)	1.01	0.04	3.77	1.03	0.05	4.57

Table 8 Comparison between experimental results collected from the literature and corresponding FL model II predictions

Ref.	OPC (%)	FA (%)	SF (%)	Steel dosage (%)	Age (days)	Grout compressive strength results (MPa)		
						Exp.	FL	COV(%)
(Abdul Awal 1984)	100	0	0	0	28	41.0	47.4	7.2
(Abdelgader 1999)	100	0	0	0	28	43.8	47.4	3.9
	OPC (%)	FA (%)	SF (%)	Steel dosage (%)	Age (days)	TSC compressive strength results (MPa)		
						Exp.	FL	COV(%)
(Abdul Awal 1984)	100	0	0	0	28	29.0	30.6	2.7
(Abdelgader 1999)	100	0	0	0	28	30.7	30.6	0.2
(Bayer 2004)	50	50	0	0	28	10.6	13.9	13.5
(Abdelgader *et al.* 2016)	94	0	6	0	28	22.6	32.8	18.4
	OPC (%)	FA (%)	SF (%)	Steel dosage (%)	Age (days)	TSC tensile strength results (MPa)		
						Exp.	FL	COV(%)
(Abdul Awal 1984)	100	0	0	0	28	3.1	3.6	7.5
(Abdelgader and Ben-Zeitun 2005)	100	0	0	0	28	3.0	3.6	9.1

associated with 24 grout mixtures. The model and database have 6 input variables: the *w*/*b* ratio and the OPC, FA, SF, MK, and HRWRA dosages. The efflux time and spread flow of the TSC grouts constituted the experimental output parameters of the database. Hence, they also were the output predicted by the FL model I. Fig. 1 illustrates the general structure of the developed FL model I. The database was divided randomly into 188 data sets for training and 40 for testing the model, respectively.

FL model II was then developed in order to predict the compressive and tensile strengths of a wide range of TSC mixtures. The database for training and testing this model contained 132 data points based on 19 TSC mixtures. The model and database have 7 input variables: the OPC, FA, SF, MK, short-steel fiber dosage, long-steel fiber dosage, and the age of the test specimen. The compressive and tensile strengths of the TSC mixtures constituted the experimental database parameters measured and were hence the output predicted by the FL model II. Fig. 2 illustrates the general structure of the developed FL model II. The database was divided randomly into 116 data sets for training and 16 data sets for testing the model, respectively. The range of input variables for models I and II is listed in Table 5. Furthermore, the properties of the training and testing data sets for models I and II are presented in Table 6.

4.2 Construction of fuzzy inference systems

The FL models were created in a MATLAB environment. The Mamdani inference method was used to develop these models. Partial belonging to a set was described numerically using a membership function that

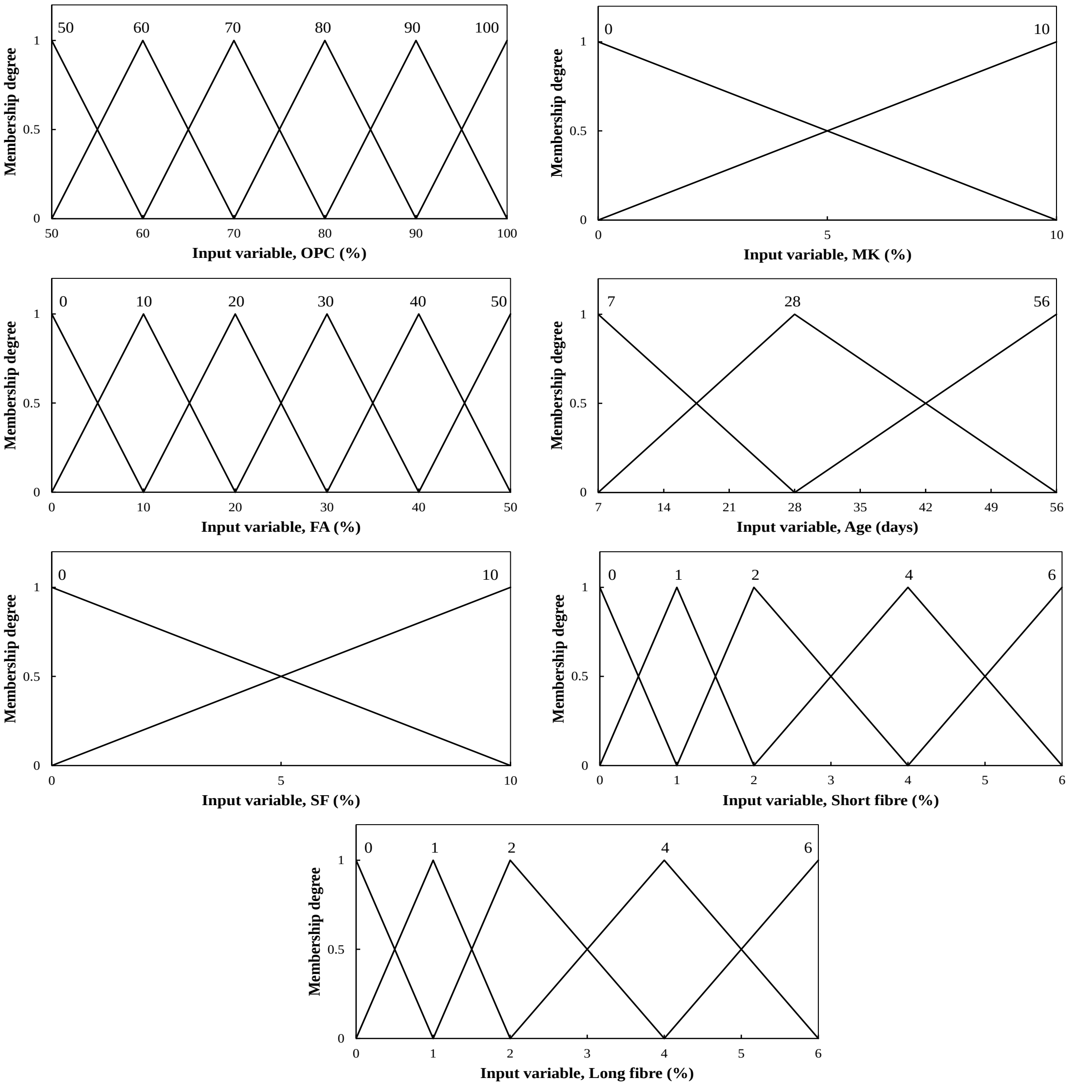

Fig. 4 Membership functions for input parameters of FL Model II

assumes values between 0 and 1. Triangular membership functions were used for fuzzy modeling. The membership functions for the input parameters used for the fuzzy modeling are illustrated in Figs. 3 and 4. After the membership functions were determined, rules were written based on the experimental results. The following are examples of the rules that were created:

For Model I: IF *w*/*b*=0.45 and *OPC*=50% and *FA*=40% and *SF*=0% and *MK*=10% and *HRWRA*=0.2% THEN grout efflux time=56 sec and grout spread flow is 17.5 cm.

For Model II: IF *OPC*=100% and *FA*=0% and *SF*=0% and *MK*=0% and short steel fibre=0%, and long steel fiber=0% and age of the test sample=28 days THEN grout compressive strength=50.4 MPa and TSC compressive strength=35.9 MPa, and TSC tensile strength=5.6 MPa.

In the final stage, the model results were obtained from the de-fuzzification monitor. The de-fuzzification was performed using the centroid of area method expressed in Eq. (2).

5. Analysıs, results and discussıon

5.1 Trained FL models

To evaluate the accuracy of the predictions of the trained system, the training data were revisited as a means of checking the trained FL models. The training data values predicted by the two FL models for the properties (i.e., grout efflux time, grout spread flow, grout compressive strength, TSC compressive strength, and TSC tensile strength) are shown in Fig. 5. It can be observed that the FL models have captured the input-output relations as the points located mostly on or slightly under/above the equity line between the experimental and predicted values. The performance of model I with respect to predicting the grout efflux time and the grout spread flow is also satisfactory.

These results are confirmed by the results of a statistical analysis of the training data with respect to the ratio of the experimental-to-predicted values for each property (P_{exp}/P_{pre}), as portrayed in Table 7. For example, the average, the standard deviation, and the coefficient of variation (COV) for the (P_{exp}/P_{pre}) of the grout spread flow training data were 1.00, 0.05, and 4.99%, respectively. These findings indicate that the performance of model I

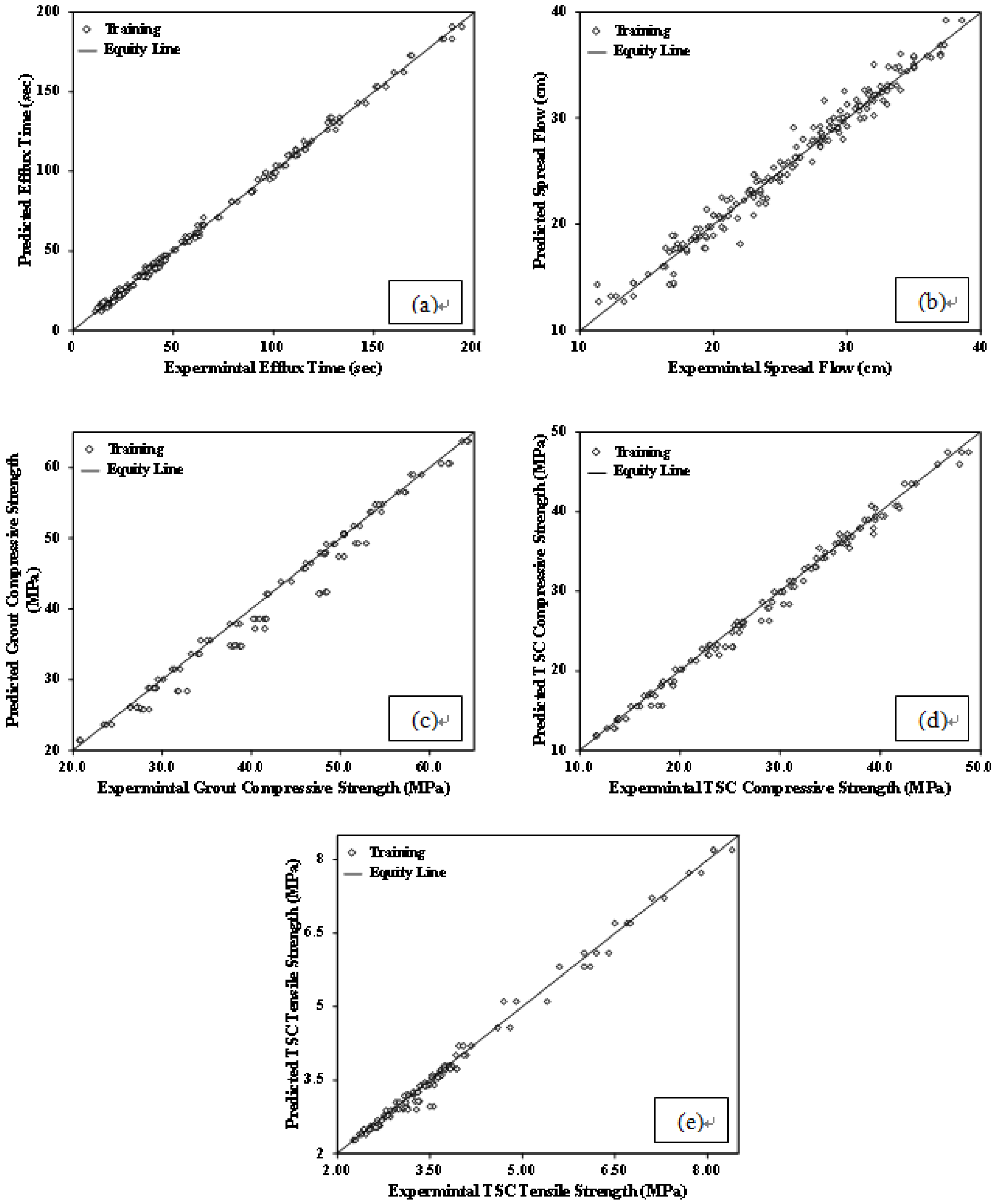

Fig. 5 Performance of FL models using training data in predicting: (a) grout efflux time, (b) grout spread flow, (c) grout compressive strength, (d) TSC compressive strength and (e) TSC tensile strength

with respect to predicting the spread flow is satisfactory and that the model exhibits good prediction accuracy.

5.2 Testing predictive capability of FL models

To examine the capacity of the FL model I and model II with respect to generalization, they were tested on 40 sets and 16 sets of test data, respectively. The values predicted by the two FL models for the properties of the test data (i.e., grout efflux time, grout spread flow, grout compressive strength, TSC compressive strength, and TSC tensile strength) are exhibited in Fig. 6. Similar to the case involving the training data points, FL models I and II produced reasonable predictions relative to the actual corresponding values measured experimentally. It can be observed in Fig. 6 that test data points were located mostly on or slightly deviating from the equity line.

Table 7 summarizes the statistical parameters pertaining to the responses of the FL models I and II with respect to the actual experimental test data. For example, the average, the standard deviation, and the coefficient of variation (COV) of the (P_{exp}/P_{pre}) values of the TSC compressive strength test data were 1.03, 0.03, and 3.14 %, respectively. Based on the statistical analysis of the (P_{exp}/P_{pre}) values for the test data, it can be concluded that FL models I and II are capable of effectively generalizing the relationships between the input variables and the output results and that the models yield reasonably accurate predictions.

Moreover, the performance of the FL model II was validated using data collected from the literature as reported in Table 8. It can be observed that the FL results were in agreement with the experimental results published by others. The slight variation between the experimental and FL results can be due to differences in the properties of the materials used in the various studies.

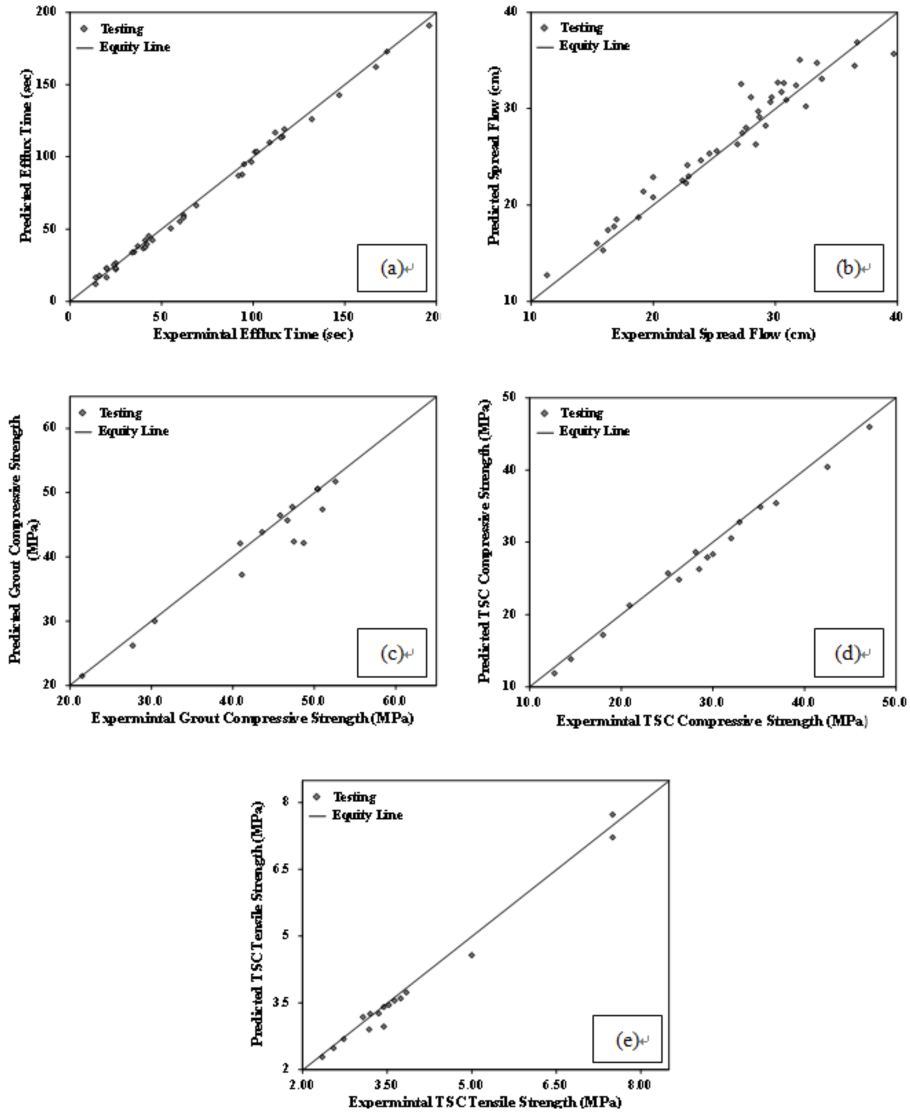

Fig. 6 Validation of FL models using testing data unfamiliar to the models in predicting: (a) grout efflux time, (b) grout spread flow, (c) grout compressive strength, (d) TSC compressive strength and (e) TSC tensile strength

Table 9 Performance of the developed FL models I and II

FL Model/Property	Training Data			Testing Data		
	RMSE	R^2	*MAPE(%)*	*RMSE*	R^2	*MAPE(%)*
I/Grout efflux time (sec)	2.068	0.999	4.322	3.139	0.999	5.894
I/Grout spread flow (cm)	1.068	0.998	3.361	1.753	0.996	5.205
II/Grout compressive strength (MPa)	1.847	0.998	2.873	2.539	0.997	3.649
II/TSC compressive strength (MPa)	0.922	0.999	2.474	1.243	0.998	3.943
II/TSC tensile strength (MPa)	0.142	0.999	2.586	0.209	0.997	4.087

5.3 Error analysis of FL models

The performance of both FL models thus developed was assessed based on the root-mean-square error (*RMSE*), the absolute fraction of variation (R^2), and the mean absolute percentage error (*MAPE*), using the following equations.

$$RMSE = \sqrt{\frac{1}{n}\sum\left|P_{exp} - P_{pre}\right|^2} \tag{3}$$

$$R^2 = 1 - \left(\frac{\sum\left(P_{exp} - P_{pre}\right)^2}{\sum P_{pre}{}^2}\right) \tag{4}$$

$$MAPE = \frac{1}{n}\sum\frac{\left|P_{exp} - P_{pre}\right|}{P_{exp}} \times 100 \tag{5}$$

Where (P_{exp}) and (P_{pre}) are the experimental and predicted values of the properties (i.e., grout efflux time, grout spread flow, grout compressive strength, TSC compressive strength, and TSC tensile strength), respectively, and (n) is the number of data points.

Table 9 presents the *RMSE*, R^2, and *MAPE* values derived for the training and testing data sets in order to evaluate the performance of the FL models. It can be observed that the developed FL models provide a high degree of accuracy and that their predictions of flowability and mechanical properties are very close to the actual experiment results. For example, the *RMSE*, R^2, and *MAPE* of the TSC tensile strength predicted by the FL model II using the test data were 0.209, 0.997, and 4.087, respectively.

6. Conclusıons

This paper reports on the development of fuzzy logic models for predicting the flowability and mechanical properties of two-stage concrete. Based on the results obtained in this study, the following conclusions can be drawn:

• The developed FL models offer simple and flexible tools for predicting the grout flowability and mechanical properties of TSC in which a variety of SCMs are incorporated. The properties predicted by the FL models were very close to the actual experimental results, providing evidence for the potential of these models as predictive tools.

• The models exhibit adequate capacity of generalization beyond the training stage, as verified by the fact that the predictions obtained for new test data that is unfamiliar to the models were within a similar range of accuracy to those obtained for the training database.

• The proposed FL models represent reasonably accurate tools for designing TSC mixtures in which several types and dosages of SCMs are incorporated; they can also save time as well as reduce wastage of materials and design costs.

• The FL models thus developed are flexible and can be easily updated and modified according to new findings and to accommodate data that might emerge in the future. Indeed, such models are adaptable and can encompass new parameters and new test data that becomes available in the future so that its predictive capability can be extended to include new materials, wider range of input parameters, or new test data such as on durability.

• It should be recognized that the accuracy of model predictions is normally limited to the range of data explored in this study. As indicated above, the models can be extended to cover a wider range should such data become available for training the model in the future.

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