Advances in prediction of the mechanical properties of self-compacting concrete by adaptive neuro-fuzzy systems

Dr Behnam Vakhshouri
Centre for Built Infrastructures (CBIR), Faculty of Engineering and Information Technology
University of Technology Sydney
Sydney, Australia
behnam.vakhshouri@student.uts.edu.au

A/Prof Shami Nejadi
Centre for Built Infrastructures (CBIR) Faculty of Engineering and Information Technology
University of Technology Sydney
Sydney, Australia
Shami.nejadi@uts.edu.au

***Abstract*: Many studies predict the compressive strength of conventional concrete from hardened characteristics; however, in the case of self-compacting concrete, these investigations are very rare. There is no study to predict the compressive strength of self-compacting concrete from mixture proportions and slump flow. This paper designs ANFIS models to establish relationship between the compressive strength as output, and slump flow and mixture proportions as input in eighteen combinations of input parameters. The applied dada is taken from 55 previously conducted experimental studies. Effect of each parameter on the compressive strength and its importance level in the developed model has been investigated. Based on the error size in each combination analysis, weighting factor and importance level of each parameter is evaluated to apply the correction of factors to get the most optimized relationship. Obtained results indicate that the model including all input data (slump flow and mixture proportions) gives the best prediction of the compressive strength. Excluding the slump flow from combinations affects the prediction of compressive strength, considerably. However it's not as much as the effect of the maximum aggregate size and aggregate volume in the mixture design. In addition, different values of powder volume, aggregate volume and paste content in the mixture reveal different ascending and descending effects on the compressive strength.**

Keywords:* *ANFIS, Compressive strength, Mixture proportion, Self-compacting concrete

1. INTRODUCTION

Self-Compacting Concrete (SCC) as new type of concrete has the capabilities of flowing easily, filling the formwork and making a full compaction, under its own weight. Using SCC in construction eliminates the vibration process, improves the sustainability and reduces the labor works. Additionally, SCC has proven advantages such as enhancing construction productivity, reducing the overall cost of the structure, achieving sustainable characteristics, increasing the practically allowable reinforcement rate, and increasing the construction rate and overall quality of the cast structures [1]. First studies in development of SCC was carried out by Okamura (1994) [2]and Okamura and Ouchi (2000) [3] in Japan. More recently, Su et al. (2001) [4] and Su and Miao (2003) [5] conducted studies to develop alternative compacting methods in SCC. Despite available studies for advantages of SCC associated to its high performance in the fresh state since its first developments in the late 1980s in Japan, there are less available results regarding the expected hardened properties for the mechanical response such as compressive strength [1]

SCC is highly sensitive to the changes in material properties and proportions and therefore, requires better quality control. The typical characteristics of SCC mixture proportions, which are necessary to ensure adequate fresh properties, can have significant consequences on hardened properties, including compressive strength, dimensional stability and durability [6].

Data-driven models including Artificial Neural Network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) are widely utilized in different engineering fields such as civil engineering. These models provide more accurate predictions of the relationships between the engineering experimental data and eliminate the need for extensive further laboratory and in-situ testing and better understanding of the materials performance [7]. Among the existing data-driven models, ANN and ANFIS give more reasonable predictions of the compressive strength of concrete [8].

Estimating the behavior of complex or unknown systems by input-output data is always of interest in the data-driven models among the researchers. Considering the complexities in mix components and proportions of concrete, and sensitivity of the concrete characteristic to the fresh state properties, prediction of the compressive strength of concrete is a complex problem. However, the literature review shows that compressive strength of the self-compacting concrete and its sensitivity to the mixture proportioning is not investigated, sufficiently [7, 9].

2. SIGNIFICANCE OF THE RESEARCH

Early evaluation of the hardened properties of SCC is crucial for the most design and application purposes. The compressive strength of SCC is a fundamental parameter to estimate its other mechanical properties. However, there is no direct relationship to obtain the compressive strength of SCC and it has to be predicted by experimental studies and destructive and non-destructive tests. Mechanical properties of SCC at hardened state directly come from its fresh properties. The problem is that following the hardening process, the quality and mechanical properties cannot improve. Structural behavior of concrete relies on mixture proportions and material properties of the composite system and these factors cannot change after hardening [10]. Consequently, obtaining a relationship to predict the hardening properties from fresh state and mixture proportions can be a useful achievement in widening of the SCC application in construction industry

Many approaches have been developed to estimate the compressive strength of conventional concrete related to its other hardened properties (Gupta et al. (2006) [11], Peng et al. (2009), Cevik and Ozturk (2009) [12], Sobhani et al. (2010)[13], Atici (2011)) [14]. In addition, some investigations have been conducted to predict the compressive strength of concrete from the fresh state properties such as slump (Chidiac et al.2005 [15], [16]; however, in self-compacting concrete there are very limited investigations to predict the compressive strength from its fresh or hardened properties.

Due to considerable abilities of the artificial intelligence in analyses of the unknown and complicated systems, they have been used to study the mechanical properties of concrete. Artificial intelligent-based modeling methods (artificial neural network, fuzzy systems, adaptive network-based inference system, neuro-fuzzy systems and genetic fuzzy systems) have been applied to simulate the non-linear and complex behavior of various properties of construction materials in recent years [17].

Nataraja et al. (2006) [18] designed a neuro-fuzzy model for mixture design of conventional concrete. Tesfamariam and Najjaran (2007) [19] designed adaptive network-fuzzy inference to estimate the compressive strength of concrete using the mixture design. Bilgehan (2010) [20] performed a comparative study to estimate the compressive strength of concrete using neural network and neuro-fuzzy modeling approaches. Nehdi and Bassuoni (2009) [21] found a fuzzy logic approach for estimating the durability of concrete. Tanyildizi and Qoskun (2007) [22] used fuzzy logic model to predict the compressive strength of lightweight concrete made with scoria aggregate and fly ash. Uyunoglu and Unal (2006) [23] proposed a new approach to determine the compressive strength of fly ash concrete using fuzzy logic. Yang et al. (2005) [24] studied the concrete strength evaluation by fuzzy neural networks.

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) which has the benefits of both artificial neural network and fuzzy systems is particularly useful in the engineering applications, where classical approaches fail or they are too complicated to be used [25].

Quantity and type of membership functions (triangular, trapezoidal, bell-shaped, Gaussian and sigmoid), types of output membership function (constant or linear), optimization methods (hybrid or back propagation) and number of epochs are five important adjustments in ANFIS to reach the most effective model by minimum errors size.

Figure (1) shows the general structure of ANFIS model including the number of rules and fuzzy clusters of each input and their relationship in the model.

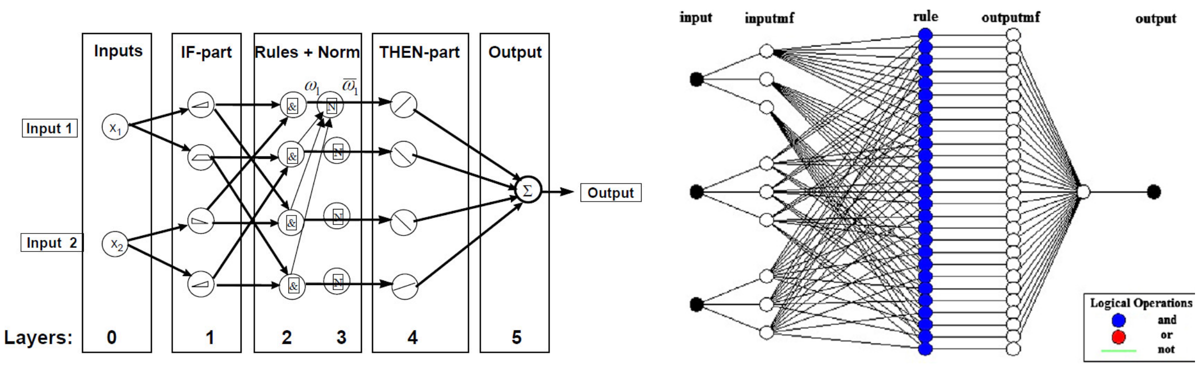


Fig.1 The structure of ANFIS network

Application of ANFIS was first proposed by Jang (1993). Ozel (2011) [10] used ANFIS to predict the compressive strength of high-performance conventional concrete from the fresh concrete properties based on the experimental data. He found very poor relation (R^2=0.262) between the real and predicted values of the compressive strength. Sadrmomtazi et al. (2013) [25] applied ANFIS analysis to study the relationship between the compressive strength of lightweight concrete and mixture proportions. They compared the results with the developed model of regression analysis and found that the accurate prediction of compressive strength needs more effective parameters to be included in the analysis.

Vakhshouri and Nejadi (2014) [16] investigated different combinations of membership functions, number of epochs, optimization method and classification method to get the most compatible results between the experimental data and ANFIS prediction of the compressive strength of high-strength concrete from the splitting tensile strength and the modulus of elasticity.

Self-compacting concrete poses a complex inherent and its nonlinear behavior after hardening increases the difficulty to predict their mechanical properties. This paper aimed to design the most known hybrid neuro-fuzzy network ANFIS models to predict the compressive strength of SCC. Consequently, various relationships between the mix proportions, fresh properties and hardened characteristics of SCC have been modeled. Moreover, different combinations of these effective parameters were also evaluated to find the importance and weight of each parameter to predict the compressive strength. A total number of 55 different mixture design proportions and fresh properties (slump flow) of SCC from previously conducted experimental studies in literature have been analyzed to determine the compressive strength.

The implemented data in ANFIS models are compiled to establish a fuzzy logic between the input and output values. The established logic between the complied (trained) data is verified by testing some other experimental data. Among the architecture type of ANFIS in the literature, the Mamdani and Sugeno arrangement has been implemented in the established models. This version is constructed so that it has five fuzzy "if-then" governing rules and processes a set of applied input variables to produce a single predicted output [26].

A trained three layer back propagation neural network is integrated in the model to remember the experimental data pertaining to fresh properties and mixture proportions versus the 28 days compressive strength of 55 sets of experimental data.

In order to analysis and defuzzification of the implemented data, the fuzzy algorithm classifies the information and assigns values to represent the degree of truth (degree of membership). The membership function represents this degree of truth in that classification in which, the members have smooth boundary rather than classical sets. Analytical data type and related uncertainties define the required type and shape of the membership functions [27].

Membership function has inevitable effect on the established neuro-fuzzy model to predict the comparable values with the implemented outputs. To construct the most reliable membership function for a series of complex data, especially the data from a new material with less supporting literature, it is crucial to have the basic knowledge about the general classification and nature of data and the effect of data variation on the interaction (response) between the input and output data.

Among the existing membership functions, the triangular or trapezoidal-shaped and Gaussian membership functions are generally utilized in the accelerated dynamic variation of data and high-accuracy requirements of the analytical data, respectively. The bell-shaped membership function is commonly used in the data related to the construction materials [28].

According to Sadrmomtazi et al. (2013) [25] the bell-shaped normalization method has been applied in this study in the ANFIS models with 3 membership functions by 500 epochs. Figure (2) presents the fuzzy domain decomposition using bell-shaped linguistic variables.

4. MATERIALS AND DATA COLLECTION

To carry out a precise prediction of the compressive strength of SCC, 55 sets of the mix proportions and fresh and hardened properties have been collected from different experimental studies presented by Domone (2006) [29]. Each dataset is a representative for a group of tests carried out by indicated researchers. Range and details of these sets of selected experiments are presented in Tables (1) and (2), respectively. To have a comprehensive comparison, according to Domone (2006) [29] almost all ranges of proportions and strengths are included in the study.

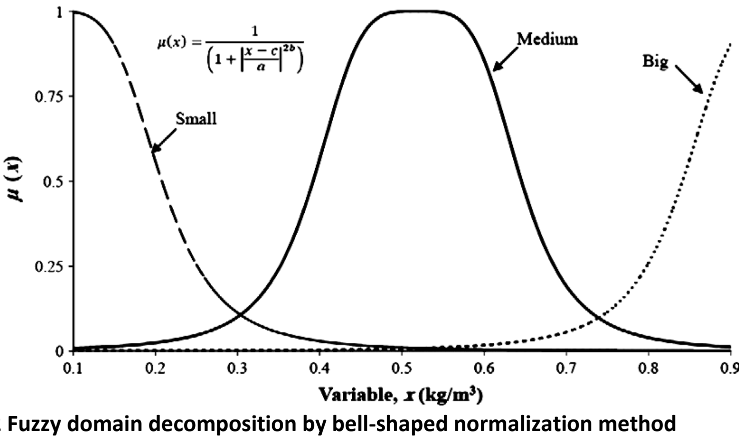


Fig.2 Fuzzy domain decomposition by bell-shaped normalization method

4.1. Mixture proportions

Volume and maximum size of coarse aggregate: Crushed rock is used in about 50% of the case studies, presenting the local availability, gravel (uncrushed) in about 15% and lightweight aggregate in about 3% of the case studies. No information is given about the aggregate type in the remaining 32% of the studies.

Powder: Majority of the powder types are Portland cement and limestone powder (in about 28% of the studies). Other components like ggbs, csf, Portland blast furnace cement, pfa and Portland fly ash cement are included in other case studies. In this study, the powder content (cement plus cementitious fillers) are included in the analysis in terms of the powder volume in unit volume of the concrete mix proportion and weight ratio of the water to powder (w/p by wt.).

Paste content in the concrete mix volume (past vol., %) and percentage ratio of the volume of fine aggregates to volume of mortar (V_f/V_m, %) are other key parameters of SCC mixes that are taken into the account.

4.2. Fresh properties

Slump flow as indicator of the fresh concrete flowability is considered to evaluate the effect of fresh state properties of SCC on the hardened characteristics. In 90% of the studies, the slump flow was in the range of 600-700 mm and only 10% was out of this range.

Table 1: Range of mix proportion, fresh and hardened properties of SCC

Property	Aggr.max size (mm)	Aggregate (vol. %)	Powder vol (kg/m3)	w/p by weight	Paste vol. (%)	V_f/V_m (%)	Slump flow (mm)	28d-f'c (MPa)
Range	10-40	28.1-42.3	385-635	0.26-0.48	29.6-40.4	38.1-52.9	500-790	22-95

Datasets of first 49 case studies out of 55 (89% of all) are selected as training data and the remaining datasets (11% of all) as the testing data to assess the accuracy of the ANFIS predictions after the training process.

According to Table (3), each set of training data includes 8 parameters; 7 parameters as input data and the compressive strength as output data. To evaluate the effect, weight and importance of each parameter on the compressive strength, 18 combinations of these parameters have been evaluated. Table (3) shows different combinations of 7 input parameters to produce the compressive strength.

Selection of the input and output data among a large number of data are based on the most important parameters in ANFIS. Input data can be categorized into hierarchical structure, however, there is no general automatic method to classify the data. Independence nature of the input data and equal priority assignment to the input variables are the common concept in application of the data of all engineering fields in ANFIS [30]. The input data in this study are independent and the most important variables in the mixture design of SCC. From the mathematical point of view, many combinations of the 7 input parameters can be established. However, the 18 combinations of the input parameters cover the most effective parameters and their possible combinations with the highest impact on the hardened properties of concrete.

5. RESULTS AND DISCUSSION

Figure (3) shows the results of training data of all combinations in ANFIS models to develop a neuro-fuzzy based model with the minimum error size. Succeeding this process, in Figure (4) the testing data are compared with predictions of the ANFIS after training the experimental input and output data to establish a neuro-fuzzy model. ANFIS model minimizes the error size by increasing the number of epochs to stabilize the process. Table (4) shows the training error size and the average size of testing errors for all 18 combinations of the input data in ANFIS models.

Table 2: Details of experimental data of mix proportions, slump flow and compressive strength of SCC

Year	Authors	aggr.max size	aggr.vol%	powder vol-kg/m3	w/p by wt	paste vol.%	vp/vm-vol.%	slumpflow-mm	28d-f'c-Mpa
1993	Hayakawa M, Matsuoka Y, Shindoh	20	32.1	500	0.34	34.6	46	650	60
1993	Sakamoto J, Matsuoka Y, Shindoh T, Tangtermsirikul S	20	34.2	500	0.34	34.6	44.3	650	53.7
1993	Sakamoto J, Matsuoka Y, Shindoh T, Tangtermsirikul S	20	34.9	500	0.34	34.7	45.5	650	44.2
1993	Miura N, Takeda N, Chikamatsu R, Sogo S	20	34.1	488	0.34	33.8	44.9	500	48
1993	Miura N, Takeda N, Chikamatsu R, Sogo S	20	30.6	500	0.34	34.6	48.1	650	39
1994	Furuya N, Itohiya T, Arima I	40	42.3	410	0.35	29.6	44.2	550	36
1993	Kuroiwa S, Matsuoka Y, Hayakawa M, Shindoh T	20	34.3	500	0.34	34.2	46	675	53
1994	Umehara H, Uehara T, Enomoto Y, Oka S	15	34.9	607	0.26	36	40.3	650	65
1996	Kosaka H, Higuchi M, Takeuchi H, Nanni A	20	31.2	470	0.35	34	48.4	620	55
1996	Kosaka H, Higuchi M, Takeuchi H, Nanni A	20	37.5	472	0.35	33.9	43.8	650	55
1995	Fukute T, Moriwake A, Sano K, Hamasaki K	20	30.9	385	0.48	31.2	51.8	645	41
1997	Fukute T, Hamada H, Sano K, Sueoka E, Moriwake A, Tkeichi H	20	31	448	0.4	32.7	48.7	647	56
1996	Sedran T, de Larrard F, Hourst F, Contamines C	20	35.2	484	0.35	33.1	49.8	650	50
1996	de Larrard F, Gillet G, Canitrot B.	20	32.9	473	0.38	33.5	50.8	640	94
1998	Khayat HK, Aitcin P-C	10	33.6	520	0.42	38.3	41.6	640	42
1998	Khayat HK, Aitcin P-C	25	32.5	466	0.45	37	43.5	580	45
1998	Khayat HK, Aitcin P-C	25	31.8	537	0.42	40.3	38.1	610	58
1998	Khayat HK, Aitcin P-C	14	29.6	532	0.41	40.4	38.8	615	35
1999	Sonebi M, Bartos PJM	20	28.3	525	0.38	38.3	46.5	650	47
1999	Sonebi M, Bartos PJM	10	28.3	530	0.37	36.9	47.6	690	80
1999	Billberg P, Petersson O, Osterber T	16	29.5	595	0.28	36.7	44.5	670	62.3
1999	Billberg P, Petersson O, Osterber T	16	31	526	0.31	33.7	47.9	700	69.3
1998	Petterson O	16	30.9	525	0.34	36.1	46.3	650	44
1998	Petterson O	10	31.1	480	0.35	32.6	50	710	70
1999	Nishizaki T, Kamada F, Chikamatsu R, Kawashima H	20	29.8	585	0.3	36.5	43.7	650	60
1999	Nagai T, Kojima T, Miura N.	15	33.3	580	0.32	37.4	47	695	73
2000	Henderson N.	20	30	550	0.35	38.4	43.4	625	75
1999	Mizobuchi T, Yania S, Takada K, Sakata N, Nobuta Y	20	32.9	533	0.3	32.9	47.5	650	32.5
1999	Mizobuchi T, Yania S, Takada K, Sakata N, Nobuta Y	20	32.6	625	0.27	38.8	39.7	650	24
1999	Mizobuchi T, Yania S, Takada K, Sakata N, Nobuta Y	20	33.4	635	0.26	39	40.6	700	24
1999	Mizobuchi T, Yania S, Takada K, Sakata N, Nobuta Y	20	31	554	0.32	35.7	45.9	650	30
1999	Wetzig V.	16	30.1	480	0.36	32.5	52.6	640	50
1999	Wetzig V.	16	31.3	460	0.4	33.3	52.9	670	50
1999	Wetzig V.	32	38.6	460	0.37	32.2	50	650	50
1999	Chikamatsu R, Shinkai C, Kushigemachgi H	20	31	501	0.33	33.4	48.5	605	39
1999	Maeda MK, Yamada K, Uchida A	20	30.9	529	0.34	35.6	46.9	700	25
1999	Maeda MK, Yamada K, Uchida A	20	29.5	462	0.35	33.2	50.2	650	22
2001	Tanaka M, Mori K	20	28.9	520	0.3	33.6	52.5	670	25
2001	Inoue H, Takeichi Y, Ohtomo T	20	31.8	500	0.32	33.8	48.8	650	25
2001	Johansen K, Kyltveit B-P	20	29.5	432	0.45	33.5	49.3	725	52
2001	Ohtomo T, Asaka S, Kim JY, Park CG, Beak SJ, Jung CS, et al	20	29.9	438	0.41	32.4	49	650	64
2001	Kubo M, Nakano M, Aoki H, Sugano S, Ouchi M	20	30.6	529	0.3	33.5	49.6	650	60
2002	Centing M, Jonsson U, Nilsson H, Tuutti K, Widenbrant K	16	29.8	538	0.33	36	48.8	700	78
2002	Centing M, Jonsson U, Nilsson H, Tuutti K, Widenbrant K	16	29.4	532	0.32	34.8	50.3	700	78
2001	Fleming D	20	37.7	450	0.4	32.3	48.8	630	62
2002	Khayat KH, Morin R	10	29.7	480	0.37	33.4	49.2	675	57
2002	Osterberg T.	16	30.5	600	0.28	38.4	45.3	740	75
2002	Lessard M, Talbot C, Baker D	19	34	450	0.42	33.7	48.5	660	28
2003	Collepardi M, Collepardi S, Ogoumah Ologat JJ, Troli R	16	31.3	500	0.36	34.5	50.5	700	43
2003	Collepardi M, Collepardi S, Ogoumah Ologat JJ, Troli R	22	34.5	530	0.33	35.2	43.7	730	95
2003	Collepardi M, Collepardi S, Ogoumah Ologat JJ, Troli R	20	31.1	435	0.41	33.2	52.8	790	42
2003	Fredvik TI, Gundersen NL, Johansen K	20	29.5	432	0.47	34	48.9	725	52
2003	Fredvik TI, Gundersen NL, Johansen K	16	32.1	474	0.38	34.8	48.5	650	50
2003	Ouchi M, Sada-aki N, Osterberg T, Hallberg S-E, Lwin M	20	31.7	470	0.33	30.4	52.3	630	74
2003	Ouchi M, Sada-aki N, Osterberg T, Hallberg S-E, Lwin M	20	28.1	575	0.3	37.3	46.4	665	71

Table 3: Different combinations of slump flow and mixture proportions of CSS

Comb.	Mixture proportion and slump flow	Output
A	Aggr.max size + aggr.vol% + powd. vol. + w/p by wt + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
B	aggr.vol% + powder vol + w/p by wt + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
C	aggr.max size + powder vol + w/p by wt + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
D	aggr.max size + aggr.vol% + w/p by wt + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
E	aggr.max size + aggr.vol% + powder vol + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
F	aggr.max size + aggr.vol% + powder vol + w/p by wt + vp/vm-vol.% + slump flow	f'_{c-28d}
G	aggr.max size + aggr.vol% + powder vol + w/p by wt + paste vol.% + slump flow	f'_{c-28d}
H	aggr.max size + aggr.vol% + powder vol + w/p by wt + paste vol.% + vp/vm-vol.%	f'_{c-28d}
I	powder vol + w/p by wt + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
J	w/p by wt + paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
K	paste vol.% + vp/vm-vol.% + slump flow	f'_{c-28d}
L	vp/vm-vol.% + slump flow	f'_{c-28d}
M	slump flow	f'_{c-28d}
N	aggr.max size + aggr.vol% + powder vol + w/p by wt + paste vol.%	f'_{c-28d}
O	aggr.max size + aggr.vol% + powder vol + w/p by wt	f'_{c-28d}
P	aggr.max size + aggr.vol% + powder vol	f'_{c-28d}
Q	aggr.max size + aggr.vol%	f'_{c-28d}
R	aggr.max size	f'_{c-28d}

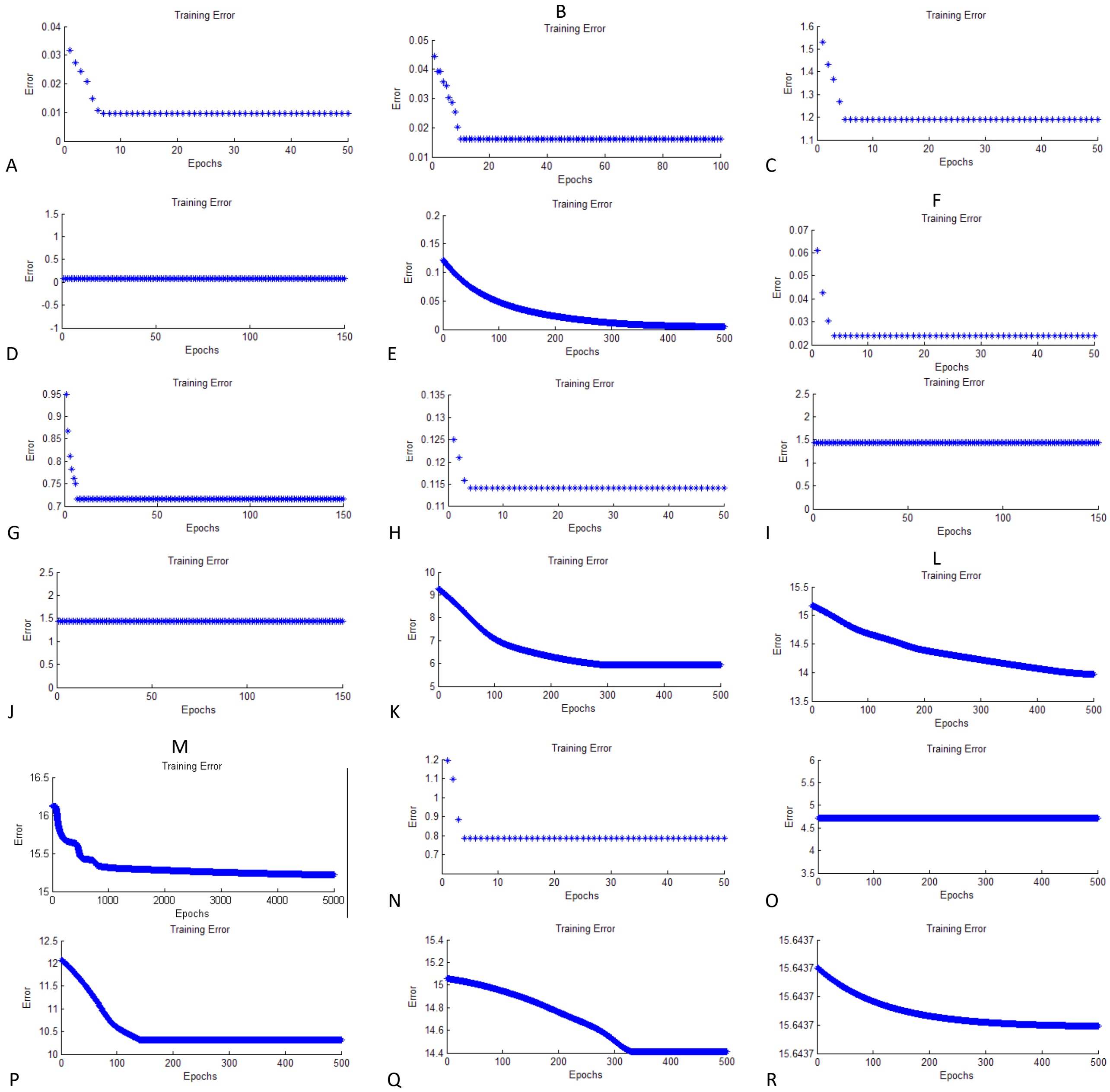


Fig. 3: Minimizing the error size by increasing the epochs to establish relation between the input and output data

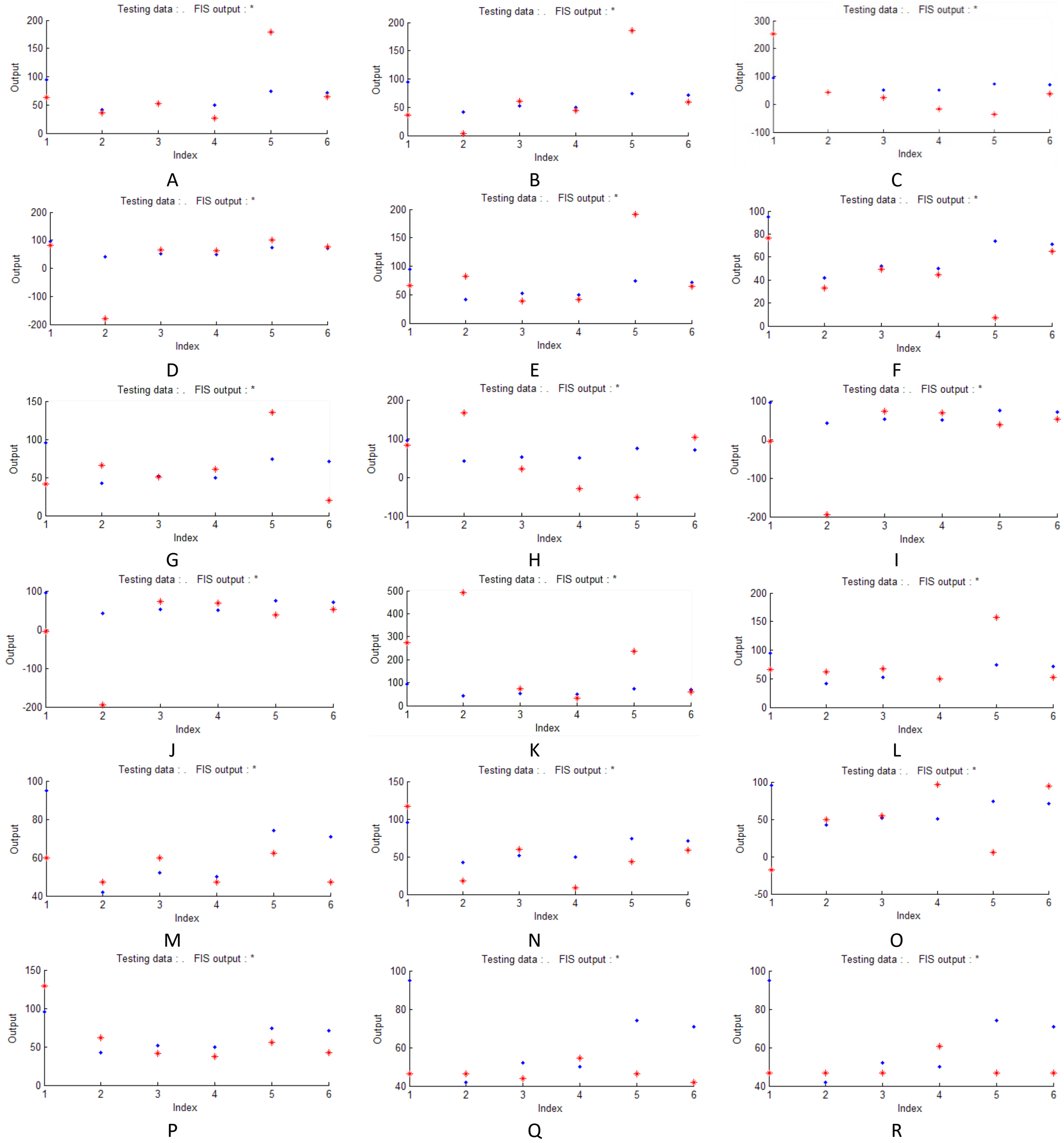


Fig. 4: Testing the trained data with some non-trained data to evaluate the accuracy of training process

According to Figure (4), the third, fourth and sixth case studies in the test data are compatible with predictions of the trained data in all combinations. The first case study (Collepardi M et al. 2003) has the main role to increase the errors in testing process of the trained data in combination G, M, O, P and Q. In addition, the second case study (Collepardi M et al. 2003) is not adjusted with the trained data in the combinations D, H, I, J and K. The fifth case study in testing data (Ouchi M et al. 2003) is not compatible with the trained data in the combinations A, B, C, E, F, G, H, L, N, O, Q and R. In the combination A and B with acceptable training error sizes, the fifth case study causes large error sizes. The main reason of incompatibility between the first and fifth case studies is the considerably higher values of the compressive strength of the self-compacting concrete type compared to the other experimental data. The second case study has the highest value of the slump flow that may be incompatible with that of the other normal strength SCC mixes.

As a sample of all combinations, Figure (5) shows the predicted values of ANFIS model versus the experimental compressive strength at the last epoch of training process in combinations B and L, respectively. As mentioned before, among the whole 55 case studies, 49 case studies were imported in the training process and the remaining 6 studies were imported in testing process.

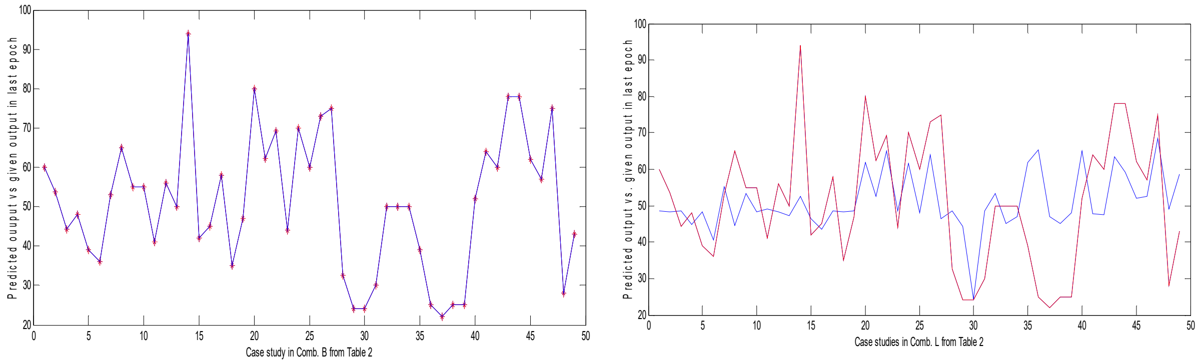
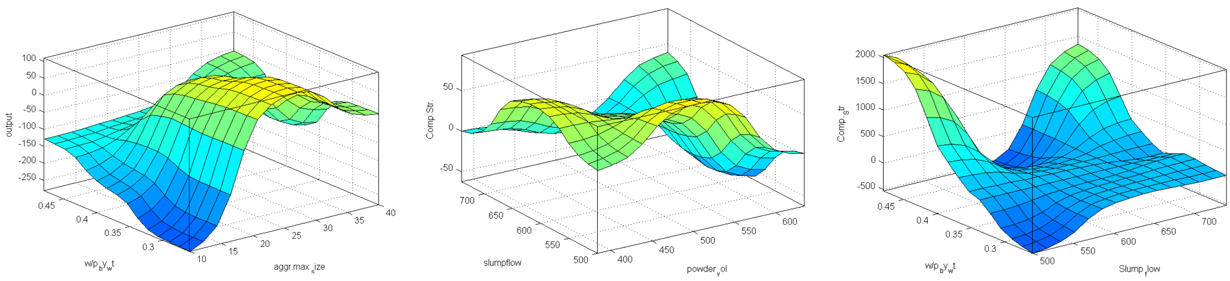


Fig. 5: Predicted values of last epoch in ANFIS vs experimental compressive strength in Table 2

Figure (6) shows some Three-Dimensional (3D) surface diagrams of the input and output parameters after analysis. To study the individual relationship of each input data with the output data, Figure (7) shows Two-Dimensional (2D) diagrams of the surface diagrams presented in Figure (6).

Theoretically, the relationship between each input data with the output data is constant and is independent from the other input data. However, it's not valid in the neuro-fuzzy logic environment of ANFIS. In other words, in the neuro-fuzzy system of ANFIS, the interaction between each input parameter with the output parameter is changing in different combinations. However, it follows a similar diagram in terms of the extreme points and curve shape. The reason is that each input data in the combination strongly influences the structure of the developed ANFIS model; that in turn, affects every singular sub-relation of the output with each input parameter.

The best prediction of the compressive strength comes from the combination including all 7 input parameters. While, the model excluding the slump flow and the ratio of powder volume resulted in the least accurate predictions. Concurrently, excluding the aggregate volume and slump flow from the model improves the predicted compressive strength values. The best-fitting model contains all the mixture proportions and slump flow to result the most compatible prediction of the compressive strength of SCC.



N B J

Fig. 6: 3D surface diagrams, combinations A (aggregate max size, w/p vs. f'_c), B (slump flow, powder volume vs. f'_c) and J (slump flow-w/p vs. f'_c)

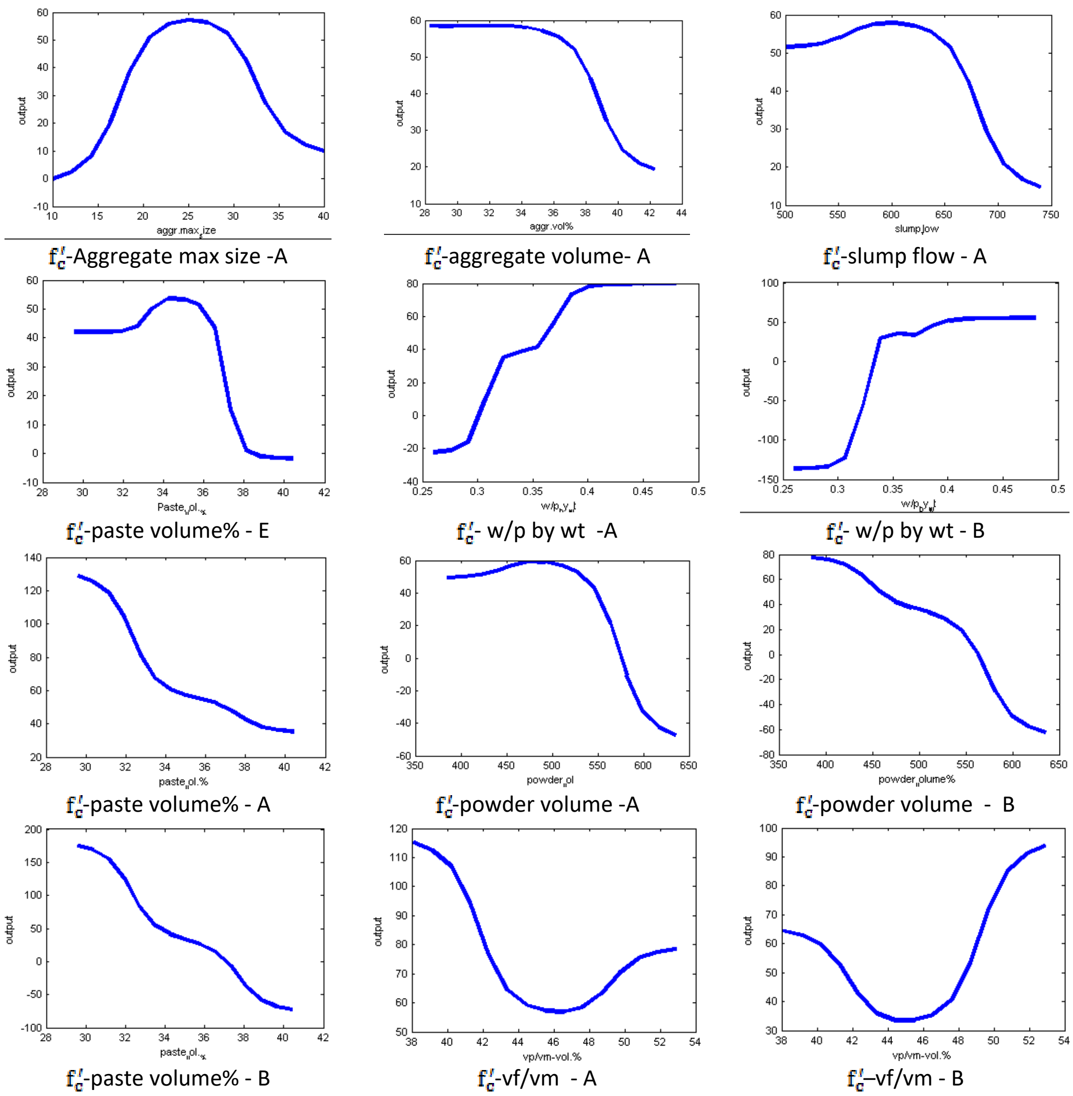


Fig. 7 Relationship between the mix proportion and slump flow with compressive strength in ANFIS model

Table 4: Training errors and average testing error in 18 combinations of input data to predict the compressive strength of SCC

Comb.	A	B	C	D	E	F	G	H	I
Training error	0.00955	0.01610	1.1917	0.0839	0.00463	0.0240	0.7157	0.1140	1.4406
Ave. Testing error	45.8998	54.2443	84.776	91.390	52.4694	28.773	40.8151	81.952	106.83

Comb.	J	K	L	M	N	O	P	Q	R
Training error	2.6487	5.9326	13.963	15.19	0.78403	4.7145	10.3084	14.410	15.643
Ave. Testing error	524.3267	208.338	37.990	18.479	25.5487	58.1361	22.2368	26.153	25.236

6. EFFECT OF ERROR SIZE

For the ANFIS-based soft sensor models, when estimation/prediction accuracy is concerned, it is assumed that both data which used to train the model and testing data to make the estimations, are free of errors. However, rarely a data set is clean and free of error before extraordinary effort having been put to clean the numbers [31]. Several studies have investigated the effect of error size on accuracy of the predictions of computer-based models. Bansel et al. (1993) [32] found a considerable effect of the testing data errors on the predictions made by neural network and linear regression models.

As presented in Table (3) and illustrated in Figures (3) and (5), the best fitting between the trained data versus the given output data are obtained in combinations A, B and E in which, the minimum error size tends to be zero. All combinations which include at least 6 out of 7 input data, give better estimation of the output data.

The models including less than 6 input parameters dramatically under or overestimate the compressive strength of SCC. However, as presented in Table (4), the effect of each input data on the compressive strength of SCC is totally changed in different combinations.

Combination E gives the least training error size and the best fitting of trained data with experimental data. Replacing paste volume with water/powder ratio in combination E (resulting the combination F) has minor effect on prediction of the compressive strength. It increases the training error size from 0.004 to 0.02. While, replacing powder volume with water/powder ratio increases the error size from 0.004 to 0.08.

By comparing the combinations C and D, compressive strength of SCC is more sensitive to the aggregate volume, rather than the powder volume. This conclusion is also evident in comparison of the combinations P, Q and R.

According to the results of ANFIS analysis, the least consistency in the models is observed between the maximum size of aggregate and the compressive strength of SCC. By combining the results, effect of the aggregate volume on the predicted compressive strength of SCC is higher than the effect of the maximum size of aggregate.

By analysis of the combinations H and L in ANFIS models, eliminating the slump flow from the general equation shows no considerable effect on the predicted compressive strength of SCC. While, including the slump flow in combinations L and M, causes higher error sizes in the predicted values. Therefore, the slump flow cannot be a reliable basis to estimate the compressive strength of SCC.

Combination E has the best-fitting of the experimental and predicted data in training process. Excluding the water/powder ratio from input parameters improves the predicted results. In addition, according to combinations O and P, including the water/powder ratio together with the aggregate volume and maximum size of the aggregate and the powder volume, improve the accuracy of the output data. The paste volume has certain effect on the predicted values of the compressive strength.

Despite a good fitting between the experimental and trained data in combination L, the 14th (Delarrad F. et al. (1996)), 35th (Chikamatsu et al. (1999)) and 36th (Maeda MK et al. (1999)) case studies of the training dataset cause the major error sizes in the training process. Depending on the research purposes, similar diagrams can be drawn for any other combinations of the input parameters.

The following interpretations can be drawn from the diagrams presented in Figure (7):

- In combination A that includes all the input parameters, the maximum size of aggregate up to 25 mm, increases the compressive strength. The maximum size of aggregate above 25 mm, decreases the compressive strength of SCC;
- Increasing the aggregate volume above 35% in the SCC mix, decreases the compressive strength of SCC;
- Increasing the powder volume over 500 kg/m^3 in the SCC mix, decreases the compressive strength of SCC. Meanwhile, increasing the water to powder ratio will enhance the compressive strength prediction.
- Increasing the ratio of fine aggregate volume to the mortar volume up to 45% decreases the compressive strength of SCC. Additionally, the ratio above 45% increases the compressive strength of SCC.
- Majority of the collected experimental data are from high-strength SCC. Although, some data for normal strength SCC are included in the training data; however, according to the results, predicting the compressive strength of normal-strength SCC from high-strength SCC is not recommended.
- Much the same conclusions can be made from the ANFIS analysis. Since they mostly rely on the fuzzy logic, some disagreements might be seen between the ANFIS analysis results with the mathematical and theoretical assumptions of the concrete technology as well.

7. CONCLUSIONS

Fifty five datasets of the previously conducted experimental studies on 28 days compressive strength of SCC have been analyzed in ANFIS models. To have a comprehensive study on the effects of mixture design proportions and fresh properties of SCC on the compressive strength, 18 combinations of these parameters have been analyzed and the results were compared. The following conclusions can be made from the results and comparison of the combinations:

ANFIS approves a strong relationship between the fresh state properties and mix proportions with the compressive strength as a representative of the hardened state characteristics of the self-compacting concrete;

The relationship between each input parameter and the compressive strength may change in different combinations. In spite of the constant values of each input parameter, their relationship with the compressive strength in different combinations is not similar with the theoretical relationship in the concrete technology. Effect of each parameter on the structure of ANFIS model is main reason to such differences.

In the ANFIS analysis, increasing the ratio of fine aggregate volume to the mortar volume up to 45%, decreases the compressive strength of SCC. The compressive strength is augmented by increasing the ratio above 45% (ratio of fine aggregate volume to the mortar volume).

Majority of the collected data are from high-strength self-compacting concrete and only minor part of the collected data are from normal-strength concrete, However, prediction of the compressive strength of the normal-strength SCC using this method is not reliable.

The results of this study can be assessed by other mathematical and artificial intelligent-based systems. Furthermore, for comprehensive evaluating of the self-compacting concrete, effect of fiber reinforcing and size effect should be included and investigated as well.

REFERENCES

1. Almeida Filho, F., et al., *Hardened properties of self-compacting concrete—a* statistical *approach.* Construction and Building Materials, 2010. **24**(9): p. 1608-1615.
2. Okamura, H. and K. Ozawa. *Self*-compactable *high-performance concrete in Japan*. in *International Workshop on High Performance Concrete (Edited by Paul Zia)*. 1994.
3. Okamura, H., K. Ozawa, and M. Ouchi, *Self*-compacting *concrete.* structural Concrete, 2000. **1**(1): p. 3-17.
4. Su, N., K.-C. Hsu, and H.-W. Chai, *A simple mix* design *method for self-compacting concrete.* Cement and concrete research, 2001. **31**(12): p. 1799-1807.
5. Su, N. and B. Miao, *A new method for the mix* design *of medium strength flowing concrete with low cement content.* Cement and Concrete Composites, 2003. **25**(2): p. 215-222.
6. Koehler, E.P., Aggregates *in self-consolidating concrete*. 2007: ProQuest.
7. Khademi, F., et al., *Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression.* International Journal of Sustainable Built Environment, 2016. **5**(2): p. 355-369.
8. Khademi, F., M. Akbari, and S.M. Jamal, *Prediction of compressive strength of concrete by data-driven models.* i-manager's Journal on Civil Engineering, 2015. **5**(2): p. 16.
9. Mansouri, I., et al., *Predicting behavior of FRP-confined concrete using neuro fuzzy, neural network, multivariate adaptive regression* splines *and M5 model tree techniques.* Materials and Structures, 2016. **49**(10): p. 4319-4334.
10. Özel, C., *Prediction of compressive strength of concrete from volume ratio and Bingham parameters* using *adaptive neuro-fuzzy inference system (ANFIS) and data mining.* International Journal of Physical Sciences, 2011. **6**(31): p. 7078-7094.
11. Gupta, R., M.A. Kewalramani, and A. Goel, *Prediction of concrete strength using neural-expert* system. Journal of materials in civil engineering, 2006. **18**(3): p. 462-466.
12. Cevik, A. and S. Ozturk, *Neuro-fuzzy model for shear strength of reinforced concrete beams without web reinforcement.* Civil Engineering and Environmental Systems, 2009. 26(3): p. 263-277.
13. Sobhani, J., et al., *Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models.* Construction and Building Materials, 2010. **24**(5): p. 709-718.
14. Atici, U., *Prediction of the strength of mineral admixture concrete using* multivariable *regression analysis and an artificial neural network.* Expert Systems with applications, 2011. **38**(8): p. 9609-9618.
15. Chidiac, S. and F. Habibbeigi, *Modelling the rheological behaviour of fresh concrete: An elasto-viscoplastic finite element approach.* Computers and Concrete, 2005. **2**(2): p. 97-110.
16. Vakhshouri, B. and S. Nejadi, *Application of Adaptive Neuro-Fuzzy Inference System in High* Strength *Concrete.* International Journal of Computer Applications, 2014. **101**(5): p. 39-48.
17. Neshat, M., et al., *A comparative study on ANFIS and fuzzy expert system models for concrete mix design.* IJCSI International Journal of Computer Science Issues, 2011. **8**(3): p. 196-210.
18. Nataraja, M., M. Jayaram, and C. Ravikumar, *Prediction of early strength of concrete: a fuzzy inference system model.* International Journal of Physical Sciences, 2006. **1**(2): p. 47-56.
19. Tesfamariam, S. and H. Najjaran, *Adaptive network–fuzzy inferencing to estimate concrete strength using mix design.* Journal of materials in civil engineering, 2007. **19**(7): p. 550-560.
20. Bilgehan, M. and P. Turgut, *The use of neural networks in concrete compressive strength estimation.* Comput Concr, 2010. **7**(3): p. 271-283.
21. Nehdi, M. and M. Bassuoni, *Fuzzy logic approach for estimating durability of concrete.* Proceedings of the Institution of Civil Engineers-Construction Materials, 2009. **162**(2): p. 81-92.
22. Tanyildizi, H. and A. Qoskun, *Int Earthquake Symp*. 2007, Kocaeli, Turkey.
23. Uygunoğlu, T. and O. Ünal, *A new approach to* determination *of compressive strength of fly ash concrete using fuzzy logic.* Journal of scientific & industrial research, 2006. **65**: p. 894-899.
24. Xiao-Feng, Y., et al., *Is decompressive craniectomy for malignant middle cerebral artery* infarction *of any worth?* Journal of Zhejiang University Science B, 2005. **6**(7): p. 644-649.
25. Sadrmomtazi, A., J. Sobhani, and M. Mirgozar, *Modeling compressive strength of EPS lightweight concrete using regression, neural* network *and ANFIS.* Construction and Building Materials, 2013. **42**: p. 205-216.
26. Vakhshouri, B. and S. Nejadi, *Predicition Of Compressive Strength In Light-Weight Self-Compacting Concrete By ANFIS Analytical Model.* Archives of Civil Engineering, 2015. **61**(2): p. 53-72.
27. Duch, W., *Uncertainty of data, fuzzy* membership *functions, and multilayer perceptrons.* IEEE transactions on neural networks, 2005. **16**(1): p. 10-23.
28. Vakhshouri, B. and S. Nejadi, *Application of adaptive neuro-fuzzy inference system in high* strength *concrete.* International Journal of Computer Applications, 2014. **101**(5).
29. Domone, P., *Self-compacting concrete: An analysis of 11 years of case studies.* Cement and Concrete Composites, 2006. **28**(2): p. 197-208.
30. Elena Dragomir, O., et al., *Adaptive Neuro-Fuzzy Inference Systems as a strategy for predicting and controling the energy produced from renewable sources.* Energies, 2015. **8**(11): p. 13047-13061.
31. Jassar, S., Z. Liao, and L. Zhao. *Impact of data* quality *on predictive accuracy of ANFIS based soft sensor models*. in *Proceedings of the World Congress on Engineering and Computer Science*. 2009.
32. Bansal, A., R.J. Kauffman, and R.R. Weitz, *Comparing the modeling performance of regression and neural networks as data quality* varies*: a business value approach.* Journal of Management Information Systems, 1993. **10**(1): p. 11-32.