Sensitivity of Compressive Strength of Self-Compacting Concrete to Mixture Proportions and Slump Flow in ANFIS Models

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***Abstract*—Self-compacting concrete is a new construction material and its mechanical properties are not completely understood in the literature. Compressive strength is representative of mechanical properties of hardened concrete; hence its prediction at the fresh stage can improve the final performance of structure. Sensitivity of compressive strength to the changes in mixture proportions, curing and environmental conditions together with the heterogeneous nature of the concrete complicates the problem. Considering the capabilities of artificial intelligent systems to discover any consistency between huge amounts of complex data, this study utilizes the ANFIS models to predict the compressive strength of Self-compacting concrete from mixture proportions and slump flow values. The empirical data from previously conducted 55 experiments have been implemented in 18 distinct models in ANFIS. The model including all input data (mixture components and slump flow) gives the best prediction. However eliminating the maximum size and volume of the aggregate from the input data results the least accurate ANFIS model. Any changes in the powder volume, paste content and slump flow also similarly affect the predictedvalue. Particular effect of each input data such as the interaction between the powder volume and the compressive strength are also investigated and compared with the basic concepts of concrete technology.**

***Index Terms*—ANFIS, self-compacting concrete, compressive strength, mixture proportion, slump flow, sensitivity, concrete technology**

I. Introduction

Self-Compacting Concrete (SCC) is a new type of construction materials and poses the capabilities of flowing easily, filling the formwork and making a full compaction under its own weight. SCC eliminates the vibration process, improves the environmental consideration and reduces the labor costs. Furthermore the sustainable characteristics, solving the congestion problems of the reinforcement in the section and increasing the construction speed and overall quality of the structures can be achieved by using SCC in the construction projects [1]. First studies in development of SCC was carried out by Okamura (1997), Okamura and Ouchi (1999) and Ouchi *et al*. (2003)) in Japan [2]. More recently, Su *et al*. (2001) and Su and Miao (2003) developed an alternative method for composing SCC [3].

Despite the studies on advantages of SCC associated to its high performance in fresh state, there are less available results regarding the expected hardened properties [4]. SCC is highly sensitive to the changes in the proportions of the mixture components and requires an increased quality control. The typical characteristics of SCC mixture proportions, which are necessary to ensure adequate fresh properties, can have significant effects on the hardened properties, including Compressive Strength (CS), dimensional stability against temperature and humidity, and durability [5].

Hardened concrete properties directly come from the fresh properties; the problem is that following the hardening process, the quality and mechanical properties cannot improve. In other words, structural behavior of the concrete relies on mixture and material properties and these factors cannot be changed after hardening [6].

Numerous studies have utilized different methods to estimate CS of conventional concrete (Chen *et al*., (2003), Han *et al*., (2003), Gupta *et al*., (2006), Peng *et al*., (2009), Sobhani *et al*. (2010) and Atici, (2011)). In addition, a few investigations such as Chidiac et al. (2005), Yeh (2008), Hsu *et al*. (2011) in the literature have tried to predict CS of concrete from the fresh properties like slump value [7]. In the case of SCC almost there is no similar study to predict CS from fresh properties [8], [9].

In recent years, artificial intelligence-based methods have been applied to simulate the non-linear and complex behavior of various properties of construction materials in recent years [10].

Nataraja *et al*. (2005) designed a neuro-fuzzy model for mixture design of conventional concrete.

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Tesfamariam and Najjaran (2006) designed the adaptive network-fuzzy inference to estimate CS of concrete from the mixture design. Bilgehan (2010) performed a comparative study to estimate CS of concrete by using the neural network and neuro-fuzzy modeling approaches. Nehdi and Bassuoni (2009) found a fuzzy logic approach for estimating the durability of concrete. Tanyildizi and Qoskun (2007) have utilized the fuzzy logic model to predict the CS lightweight concrete made with scoria aggregate and fly ash. Uyunoglu and Unal (2006) proposed a new method to determine CS of fly ash concrete by fuzzy logic models. Yang *et al*. (2005) have evaluated CS of concrete by fuzzy neural networks and found well predicted values of CS from the models [11], [12].

This study emphasizes on the followings items:

- Comparative collection of mixture design, slump flow and CS.
- Evaluating the individual or combined effects of mixture components and slump flow on CS.
- Simulating the relationship between slump flow and mixture proportions as with CS in ANFIS.
- Comparing the accuracy of the model predictions with the experimental values of CS.
- Comparing the developed euro-fuzzy model between each input and output data with the corresponding concepts of concrete technology.

II. Significance of the Research

SCC is a new construction material and the relationship between the properties in fresh and hardened stages is not completely understood in the literature. Reliable performance of neural networks and fuzzy systems in analyzing the multi-functional and complicated systems ensures to find a model to predict CS from the fresh state properties of SCC. The findings of this investigation can provide a platform to develop analytical and mathematical models to find out the hardened properties of SCC before hardening.

III. 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 [13].

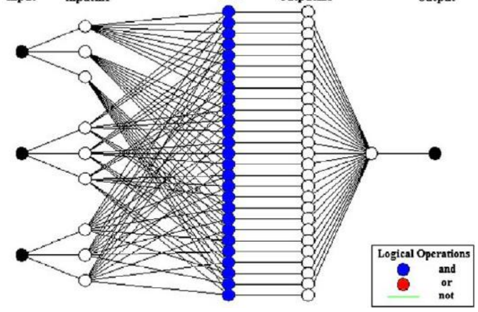


Figure 1. The structure of ANFIS network

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 the number of epochs are five important adjustments in ANFIS to reach the most effective model by minimum errors. Fig. 1 shows the structure of the best matching network for ANFIS model depicting on the number of rules, fuzzy clusters of each input and their relationship.

The main factor to evaluate the efficiency of the ANFIS models is the error size. For ANFIS-based soft sensor models, when estimation/prediction accuracy is concerned, it is assumed that both the data used to train the model and the testing the trained data to make the estimations are free of errors (Klein and Rosin, 1999). But rarely a data set is clean before extraordinary effort having been put to clean the data [11]. Bansel *et al*. (1993) studied the effect of errors in test data on the predictions made by neural network and linear regression models [14].

Application of ANFIS was first proposed by Jang (1993). Ozel (2011) used ANFIS to predict CS of high performance concrete from fresh properties based on the limited data of his research and found very poor relation between the real and predicted values [6]. Sadrmomtazi *et al*. (2013) [15] studied the relationship between CS of lightweight concrete and mixture proportions by ANFIS and regression modeling. They found that accurate prediction of CS needs more effective parameters to be included in analysis. Vakhshouri and Nejadi (2014) [7] investigated different combinations of membership functions, number of epochs, optimization and classification methods to reach the most compatible results between the test data and ANFIS prediction of CS of high strength concrete from splitting tensile strength and modulus of elasticity.

This study investigates the design of the most known hybrid neuro-fuzzy network ANFIS models to predict CS of SCC. Among the Mamdani and Sugeno type architectures, the later has been implemented. 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. A trained three layer back propagation neural network is integrated in the models to remember the experimental data pertaining to the slump flow and mixture proportions versus CS. The collected data include 55 sets of empirical investigations from the literature. The bell-shaped membership function normalization method with 3membership functions within 500 epochs has been applied to the ANFIS models.

IV. Materials and Data Resources

Total number of 55 sets of different mixture proportions and fresh property (slump flow) data of SCC from previously conducted experiments have been utilized [16]. Each dataset is representing a group of tests carried out by the indicated researchers. Range and details of these experimental data are presented in Tables respectively. The abbreviations presented in Table I and Table II are explained also.

TABLE I. DATA RANGE OF MIXTURE PROPORTION, FRESH AND HARDENED PROPERTIES OF SCC

property	aggr.max size (mm)	aggregate (vol. %)	powder vol (kg/m^3)	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

TABLE II. PREVIOUSLY CONDUCTED EXPERIMENTAL DATA OF MIXTURE PROPORTIONS, SLUMP FLOW AND COMPRESSIVE STRENGTH OF SCC

Year	Researcher(s)	Aggr.max size (mm)	Aggregate vol. (%)	Powder vol.(kg/m^3)	w/p by weight	Paste vol. (%)	vf/vm vol. (%)	Slump flow(mm)	f_c' (MPa)
1993	Hayakawa *et al.*	20	32.1	500	0.34	34.6	46	650	60
1993	Sakamoto *et al.*	20	34.2	500	0.34	34.6	44.3	650	53.7
1993	Sakamoto *et al.*	20	34.9	500	0.34	34.7	45.5	650	44.2
1993	Miura *et al.*	20	34.1	488	0.34	33.8	44.9	500	48
1993	Miura *et al.*	20	30.6	500	0.34	34.6	48.1	650	39
1994	Furuya *et al.*	40	42.3	410	0.35	29.6	44.2	550	36
1993	Kuroiwa *et al.*	20	34.3	500	0.34	34.2	46	675	53
1994	Umehara *et al.*	15	34.9	607	0.26	36	40.3	650	65
1996	Kosaka *et al.*	20	31.2	470	0.35	34	48.4	620	55
1996	Kosaka *et al.*	20	37.5	472	0.35	33.9	43.8	650	55
1995	Fukute *et al.*	20	30.9	385	0.48	31.2	51.8	645	41
1997	Fukute *et al.*	20	31	448	0.4	32.7	48.7	647	56
1996	Sedran *et al.*	20	35.2	484	0.35	33.1	49.8	650	50
1996	de Larrard *et al.*	20	32.9	473	0.38	33.5	50.8	640	94
1998	Khayat, Aitcin	10	33.6	520	0.42	38.3	41.6	640	42
1998	Khayat, Aitcin	25	32.5	466	0.45	37	43.5	580	45
1998	Khayat, Aitcin	25	31.8	537	0.42	40.3	38.1	610	58
1998	Khayat, Aitcin	14	29.6	532	0.41	40.4	38.8	615	35
1999	Sonebi, Bartos	20	28.3	525	0.38	38.3	46.5	650	47
1999	Sonebi, Bartos	10	28.3	530	0.37	36.9	47.6	690	80
1999	Billberg *et al.*	16	29.5	595	0.28	36.7	44.5	670	62.3
1999	Billberg *et al.*	16	31	526	0.31	33.7	47.9	700	69.3
1998	Petterson	16	30.9	525	0.34	36.1	46.3	650	44
1998	Petterson	10	31.1	480	0.35	32.6	50	710	70
1999	Nishizaki *et al.*	20	29.8	585	0.3	36.5	43.7	650	60
1999	Nagai *et al.*	15	33.3	580	0.32	37.4	47	695	73
2000	Henderson	20	30	550	0.35	38.4	43.4	625	75
1999	Mizobuchi *et al.*	20	32.9	533	0.3	32.9	47.5	650	32.5
1999	Mizobuchi *et al.*	20	32.6	625	0.27	38.8	39.7	650	24
1999	Mizobuchi *et al.*	20	33.4	635	0.26	39	40.6	700	24
1999	Mizobuchi *et al.*	20	31	554	0.32	35.7	45.9	650	30
1999	Wetzig	16	30.1	480	0.36	32.5	52.6	640	50
1999	Wetzig	16	31.3	460	0.4	33.3	52.9	670	50
1999	Wetzig	32	38.6	460	0.37	32.2	50	650	50
1999	Chikamatsu *et al.*	20	31	501	0.33	33.4	48.5	605	39
1999	Maeda *et al.*	20	30.9	529	0.34	35.6	46.9	700	25
1999	Maeda *et al.*	20	29.5	462	0.35	33.2	50.2	650	22
2001	Tanaka, Mori	20	28.9	520	0.3	33.6	52.5	670	25
2001	Inoue *et al.*	20	31.8	500	0.32	33.8	48.8	650	25
2001	Johansen,	20	29.5	432	0.45	33.5	49.3	725	52
2001	Ohtomo *et al.*	20	29.9	438	0.41	32.4	49	650	64
2001	Kubo *et al.*	20	30.6	529	0.3	33.5	49.6	650	60
2002	Centing *et al.*	16	29.8	538	0.33	36	48.8	700	78
2002	Centing *et al.*	16	29.4	532	0.32	34.8	50.3	700	78
2001	Fleming	20	37.7	450	0.4	32.3	48.8	630	62
2002	Khayat, Morin	10	29.7	480	0.37	33.4	49.2	675	57
2002	Osterberg	16	30.5	600	0.28	38.4	45.3	740	75
2002	Lessard *et al.*	19	34	450	0.42	33.7	48.5	660	28
2003	Collepardi *et al.*	16	31.3	500	0.36	34.5	50.5	700	43
2003	Collepardi *et al.*	22	34.5	530	0.33	35.2	43.7	730	95
2003	Collepardi *et al.*	20	31.1	435	0.41	33.2	52.8	790	42
2003	Fredvik *et al.*	20	29.5	432	0.47	34	48.9	725	52
2003	Fredvik *et al.*	16	32.1	474	0.38	34.8	48.5	650	50
2003	Ouchi *et al.*	20	31.7	470	0.33	30.4	52.3	630	74
2003	Ouchi *et al.*	20	28.1	575	0.3	37.3	46.4	665	71

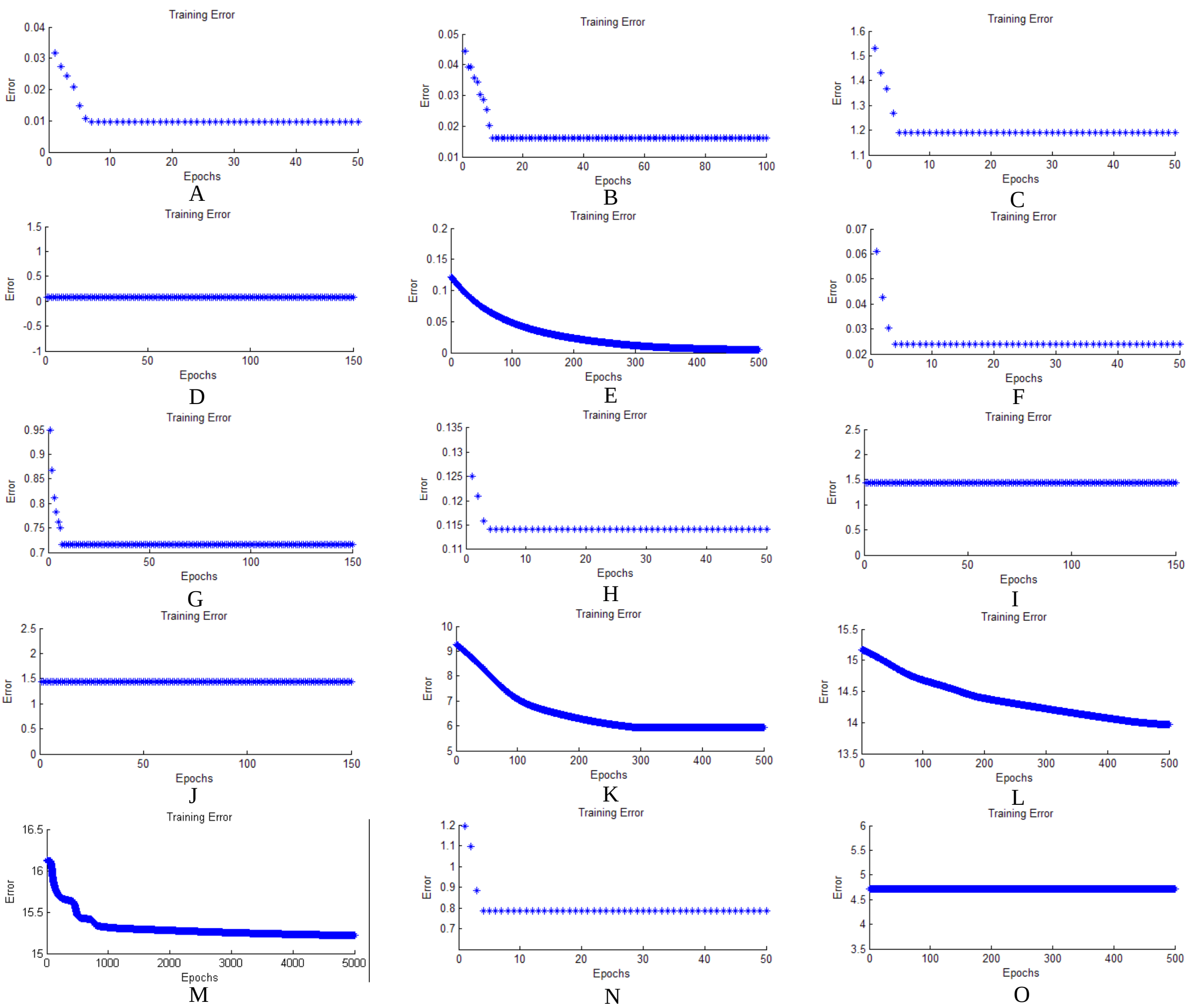
V. RESULTS AND DISCUSSION

Analysis of ANFIS model includes the training and testing steps. The training process attempts to develop a model between the series of input data with a single output in a neuro-fuzzy space. Generally the best matching model is achieved after great numbers of training epochs to minimize the error size. The error size is calculated based on the least square method by comparing the real and predicted values of CS.

After completion of the training step, the developed model in training process is verified by the testing process of data by different sets of data. Therefore the collected experimental data is classified into training and testing data sets. The testing data for verification of the trained model is about 10% of the total data and is selected to be representative for all ranges of CS, mixture proportions and slump flow as presented in Table II.

TABLE III. DIFFERENT COMBINATIONS OF SLUMP FLOW AND MIXTURE PROPORTIONS OF CSS

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



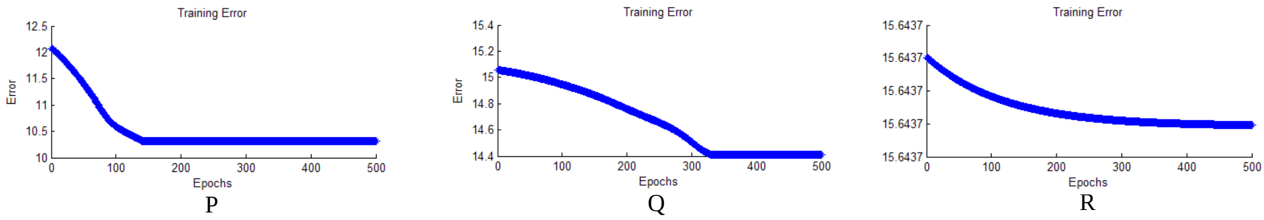


Figure 2. Minimizing the error sizeby increasing the epochs to develop aneuro-fuzzy model

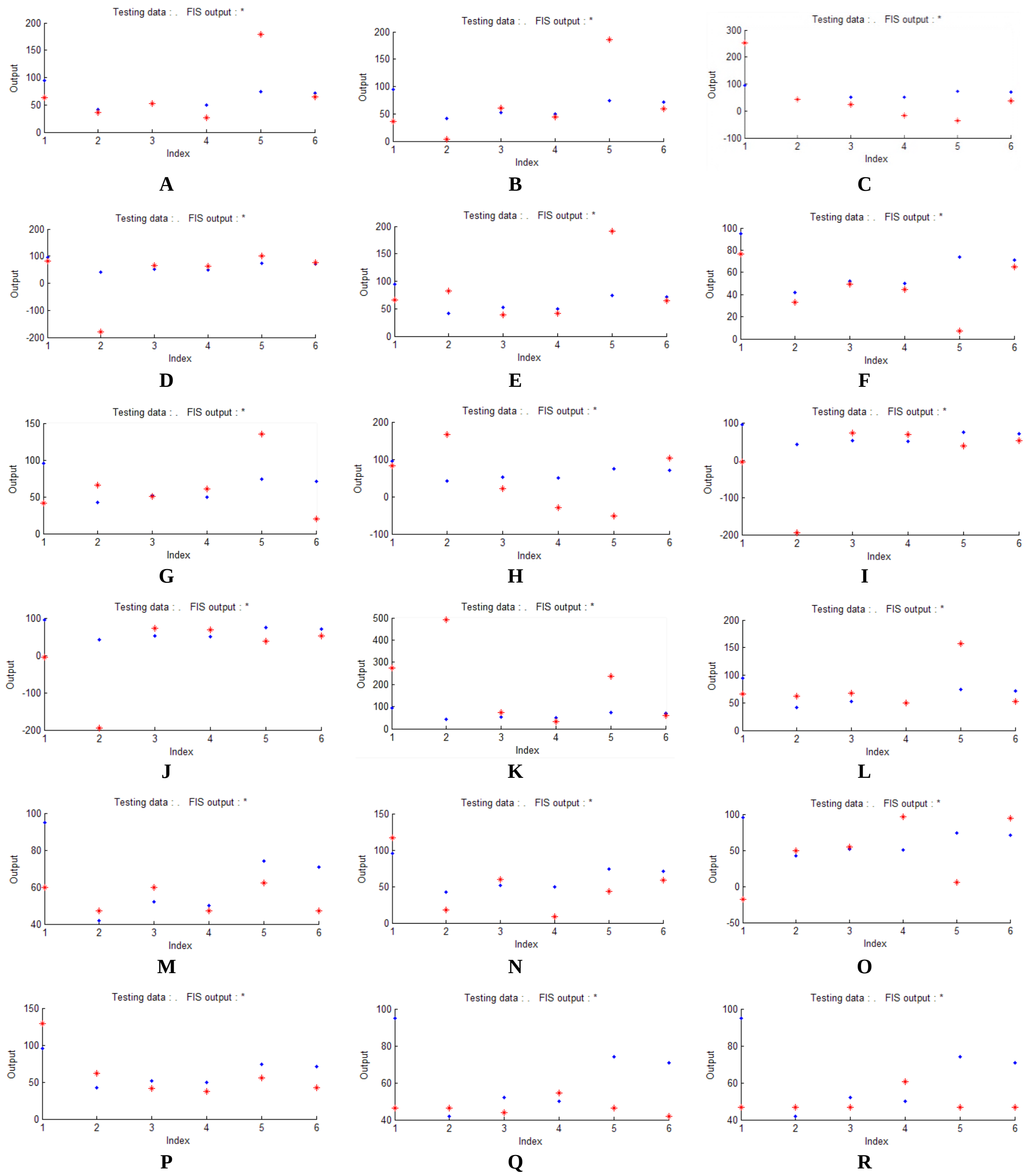


Figure 3. Testing the trained data with some non-trained data to evaluate accuracy and of each trained dataset in 18 combinations of training data

Fig. 2 shows the training results in ANFIS models in all combinations. The diagram is the developed model with minimum error size during the training process. Succeeding this process, the testing data are compared with the predicted values of trained model. Fig. 3 shows the results after verification process with testing data. ANFIS minimizes the error size in both the training and testing process by increasing the epoch numbers to reach a stable condition. Table IV shows the training error size and the average testing error size for all the 18 combinations of the input data.

The third, fourth and sixth case studies in the test data in Fig. 3 are compatible with the predicted values in the trained models. The first case study (Collepardi *et al*. 2003) has a significant effect on the increased error size in testing process in the combinations G, M, O, P and Q. In addition the second case study (Collepardi *et al*. 2003) is not matching in combinations D, H, I, J and K. The fifth case study in testing data (Ouchi *et al*. 2003) is not matching with the trained data in combinations A, B, C, E, F, G, H, L, N, O, Q and R.

In combinations A and B with acceptable error sizes after training, the fifth case study causes considerable increase in the error size. Higher value of CS in the first and fifth case studies can be a reason for the amplified error size. The highest value of slump flow is recorded in the second case study. This may cause some unexpected errors in the model in comparison with other similar normal strength SCC with less values of slump flow.

Fig. 4 shows the predicted values of ANFIS model in combinations B and L versus the experimental CS in the last epoch of training process respectively. It is also worth to mention that 49 out of 55 case studies have been selected as training case studies and the remaining 6 case studies are used in testing process.

Fig. 5 shows three dimensional diagram of parameters after completion of analysis and development of the ANFIS models in combinations N, B and J. Individual effect of each input parameter on CS is extracted from the combinations A and B and presented in Fig. 6 in a two dimensional diagram.

From the point of view of concrete technology, each component on the mixture has specific effect on CS. For instance, the cement content and the ratio of water to binder have increasing and decreasing effect on CS respectively. While the role of each component in the neuro-fuzzy based ANFIS models is changing in different combinations. However they follow a similar trend and the extreme points in the curves. Analysis of testing process, confirm that the best prediction of CS is obtained by combination of all 7 parameters in input data. Excluding the slump flow accompanied by the powder volume from the input data causes a considerable effect on the accuracy of the ANFIS model.

The least accurate ANFIS model was obtained by elimination the maximum size of the coarse aggregate and the volume of total aggregates from the input data; i.e. including them in input data considerably improves the efficiency of the model.

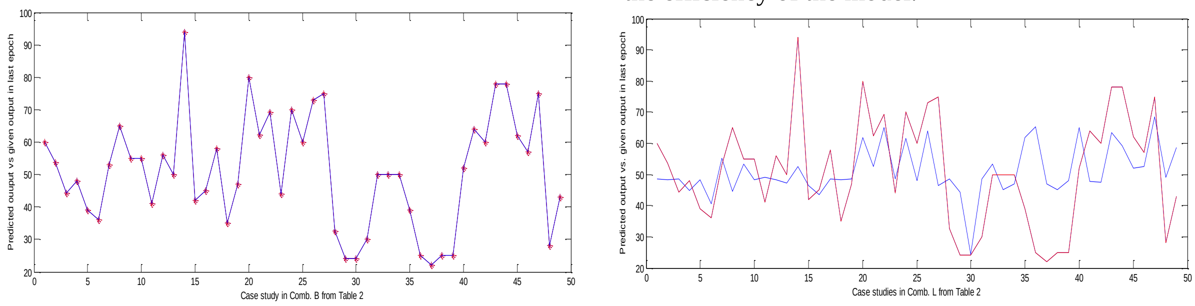
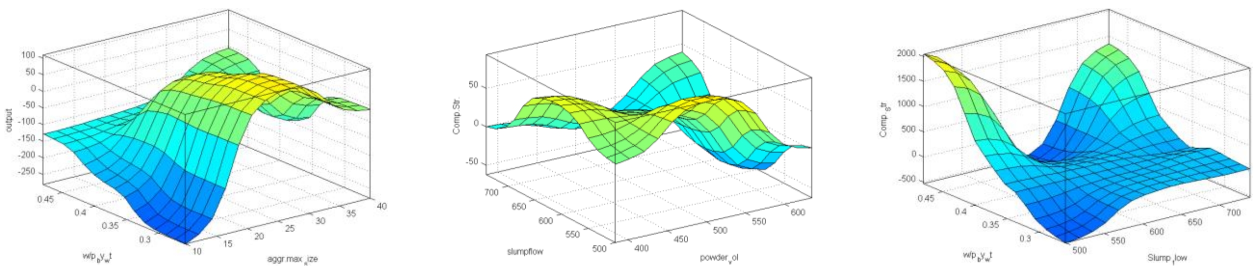
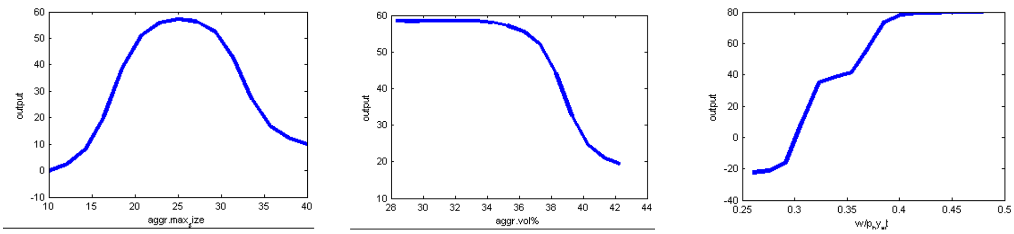


Figure 4. Predicted vs. real compressive strength at the last epoch in combinations A, B.



N B J

Figure 5. Three-dimensional surface diagrams of combination of parameters



f'_c-Aggregate max size -A | f'_c-aggregate volume- A | f'_c- w/p by wt. -A

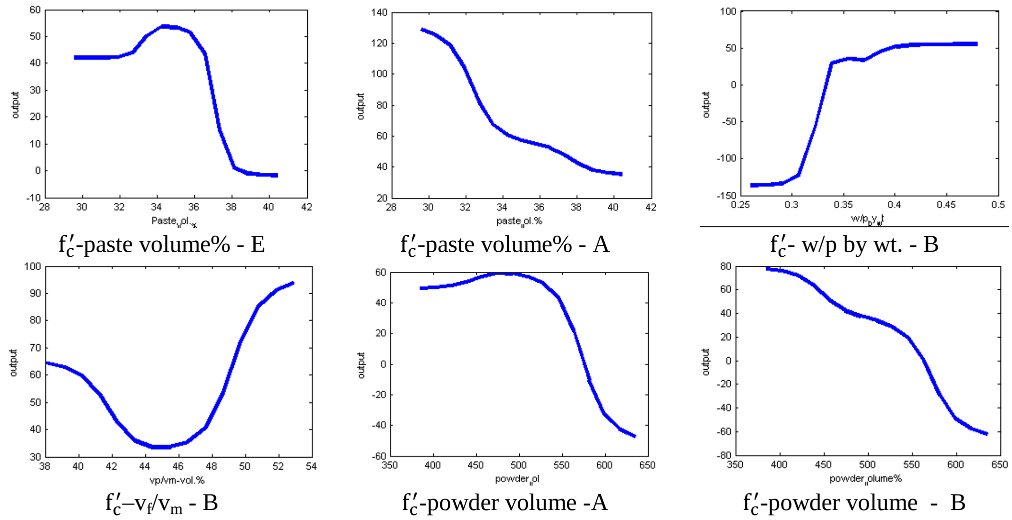


Figure 6. Particular neuro-fuzzy relationship of mixture proportion and slump flow with the compressive strength

The second least accurate model is the result of the removing of the slump flow and the volumetric ratio of powder from the input data. However, excluding the aggregate volume and slump flow from the model at the same time, improves the estimated value of CS in the ANFIS model.

According to Table IV, Fig. 2 and 4, the best fitting relationship in the training process is obtained in combinations A, B and E. In the developed models, the error size is almost zero. All combinations that include at least 6 out of 7 input data, give better estimation of CS. Decreasing the number of input data to less than 6 dramatically reduces the efficiency of the models.

Combination E makes the least training error size and the best prediction in training process. Replacing the paste volume with water to powder ratio in combination E, (resulting the combination F) has small effect on the predicted values of CS. It increases the size of training error from 0.004 to 0.02. While replacing the powder volume with water to powder ratio increases the error size up to 0.08. Comparing the combinations C and D, CS is more sensitive to the aggregate volume rather than powder volume. This conclusion is also obviously seen in comparing the combinations P, Q and R.

According to the ANFIS analysis, the least consistency is observed between the maximum size of aggregate and CS. This is to some extent in contrast with their relationship in concrete technology. In other words, the maximum size of aggregates has the least effect on CS. Effect of aggregate volume in CS is higher than the maximum size of aggregates.

According to H and L ANFIS models, excluding the slump flow from the combination A (which includes all the mixture proportions and slump flow), does not strongly affect the prediction of CS. While including the slump flow it in combinations L and M causes high error sizes in predicted values. Therefore the slump flow cannot be a good benchmark to estimate CS.

Combination E has the best fitting relationship between the predicted and experimental output data in the training process. In other words, in comparison with combination D, excluding the water to powder ratio from the input data improves the prediction of CS. In combinations O and P, including the water to powder ratio in accompany with the aggregate volume, maximum size of the coarse aggregate and the powder volume improve the precision of the output data. In addition the paste volume has unavoidable effect on the predicted values of CS.

Despite a good compatibility between the experimental and predicted data in training process of combination L, the case studies by Delarrad *et al*. (1996)), Chikamatsu *et al*. (1999) and Maeda *et al*. (1999) cause the major errors in the training process.

The diagrams in Fig. 6 extract the following conclusions:

In combination A, the maximum size of aggregate till 25 millimeters increases CS. Afterward, increasing the coarse aggregate size descends CS values. Moreover, increasing the aggregate volume beyond 35%of the SCC mixture will reduce CS.

The powder volume beyond 500 kg/m^3 decreases CS; while increasing the water to powder ratio will improve the precision of the prediction.

The volumetric ratio of fine aggregate to mortar up to 45%has a decreasing effect on CS of SCC, while exceeding this ratio above 45 increases the output value.

VI. Concluding Remarks

Fifty five datasets of previously conducted experimental studies on 28 days CS of SCC have been examined and analyzed. Combined effects of slump flow and mixture components on CS of SCC for 18 distinct combinations are simulated by ANFIS models. The following conclusions can be drawn from the study:

Verified type and number of input data strongly affect the mathematical or traditional models in studying the concrete properties. In this regard, the neuro-fuzzy models pose the capability of analysis of any type of data in fresh and hardened stages of SCC to discover and propose the possible relationships.

Including all the mixture components and slump flow as input data in ANFIS models gives the best prediction of CS of SCC as output data.

Combination of less than 6 input data will significantly decrease the accuracy of the developed model in ANSYS.

The volume of total aggregates and maximum size of coarse aggregate are two effective features of aggregates in the developed ANFIS models. Among all the input data, the maximum size of aggregate has the least effect on CS. Furthermore, the aggregate volume above 35% of the mixture volume has decreasing effect on CS.

Effect of the total aggregate volume on CS of SCC is higher than the effect of the maximum size of aggregates.

CS of SCC is more sensitive to the aggregate volume rather than powder volume in the mixture.

Exceeding the powder volume above 500 kg/m^3 will reduce CS. In addition slump flow cannot be a good benchmark to estimate CS of SCC.

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