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Long-term quality control of self-compacting semi-lightweight concrete using short-term compressive strength and combinatorial artificial neural networks

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Abstract. Artificial neural networks are used as a useful tool in distinct fields of civil engineering these days. In order to control long-term quality of Self-Compacting Semi-Lightweight Concrete (SCSLC), the 90 days compressive strength is considered as a key issue in this paper. In fact, combined artificial neural networks are used to predict the compressive strength of SCSLC at 28 and 90 days. These networks are able to re-establish non-linear and complex relationships straightforwardly. In this study, two types of neural networks, including Radial Basis and Multilayer Perceptron, were used. Four groups of concrete mix designs also were made with two water to cement ratios (*W/C*) of 0.35 and 0.4, as well as 10% of cement weight was replaced with silica fume in half of the mixes, and different amounts of superplasticizer were used. With the help of rheology test and compressive strength results at 7 and 14 days as inputs, the neural networks were used to estimate the 28 and 90 days compressive strengths of above-mentioned mixes. It was necessary to add the 14 days compressive strength in the input layer to gain acceptable results for 90 days compressive strength. Then proper neural networks were prepared for each mix, following which four existing networks were combined, and the combinatorial neural network model properly predicted the compressive strength of different mix designs.

Keywords: self-compacting semi-lightweight concrete; rheology; compressive strength; artificial neural network

1. Introduction

Concrete is the most widely used material for construction (after water), and effective steps are taken for optimum use of this product every day. For this purpose, weight reduction and correct implementation of concrete structures is taken into consideration which is also one of the ways to strengthen structures against earthquake. Various methods including the use of lightweight aggregates could produce lightweight concrete (Yasar *et al*. 2003).

The ACI 213R-87 (1998) regulations define Lightweight Concrete (LC) as a concrete with the 28 days compressive strength over 17 MPa, and the dry density should not exceed 1850 kg/m^3. Lightweight concrete has many advantages such as reducing both cross-sections of structural elements and dead load of buildings, making construction process easier than before (Yasar *et al*. 2003). Indeed, it decreases the cost of projects such as large spam bridges and tall buildings (Choi *et al*. 2006). Self-Compacting Concrete (SCC) is a new type with high performance, great plasticity, and resistance to segregation. It was developed for the first time in Japan by Okamura and fills the small distances between dense reinforcement and edges of molds without help of vibration (Okamura 1997, Okamura *et al*. 1993).

Increasing the speed of implementation, reducing manpower, ensuring of sufficient concrete density in places with high reinforcement density, reducing noise pollution, increasing the final quality of product, and economical savings can be mentioned as the advantages of SCC these days (Takada *et al*. 2001, Mazloom and Ranjbar 2010, Mazloom *et al*. 2015, Mazloom *et al*. 2017, Mazloom *et al*. 2018). The combination of Lightweight Concrete and Self-Compacting Concrete can be a good solution for solving the problems of LC such as low performance, pumping problems and compaction. In other words, it is possible to utilize the advantages of LC and SCC simultaneously (Mazloom and Hatami 2015). Recently, the use of Artificial Neural Networks (ANN) as a tool for prediction, specifically in pattern recognition and function estimation, plays an important role. These functions are non-linear and capable of finding complex relationships between input and output variables without any previous background of their relations (Fausett 1993).

Nehdi *et al.* (2001) showed that ANN method is capable of predicting the results of slump flow test, filling and segregation test for SCC. Oztas *et al.* (2006) used ANN modeling to estimate the results of slump flow test and compressive strength of High Performance Concrete (HPC). While parameters such as *W/C*, water content, proportion of fine aggregate, amount of fly ash and superplasticizer, and the percentage of silica fume were input parameters in their study, the outputs were slump flow test and compressive strength test results. Cheng (2007) modeled the slump of

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Table 1 LECA grading

Sieve size (mm)	LECA (%)
9.5	100
4.75	70
2.36	0

concrete by nonlinear regression as well as neural network and showed effectiveness of neural network. Altun *et al.* (2008) investigated lightweight aggregate concrete containing steel fibers. Steel fibers amount, *W/C*, cement, fine and coarse pumice and superplasticizer were the neural networks inputs. They found that the results of neural network are better than that of linear regression. Alshihri *et al*. (2009) modeled the compressive strength of LC with ANN. The input parameters included 8 variables, and two hidden layers were used. The outputs were 3, 7, 14 and 28 days compressive strength results. The feed-forward back propagation neural network model was used to determine compressive strength. Prediction of compressive strength of SCC containing fly ash was the name of the research done by Siddique *et al.* (2011), and two types of ANN were used. Six input parameters were used to predict the 28 days compressive strength in the first model, and eight parameters were used to predict the 7, 14, 28, 90 and 365 days compressive strength in the second one. Elshafey *et al*. (2013) used two kinds of neural networks, called Radial Basis Function (RBF) and the Feed-Forward Back Propagation, for studying the width of crack in concrete. It was found that the performances of both neural networks are better than the existing equations of valid rules and provided acceptable results. They also found that radial basis ANN requires less training time and gains better results than the feed-forward back propagation network.

The long-term strength of concrete should be determined to make the final decision about the projects. Although there are some papers about the estimation of compressive strength of SCC, to the authors' knowledge, there is no paper to do so about SCSLC. Therefore, the main purpose of this paper is to train combined Artificial Neural Networks (ANN) in order to estimate the long-term compressive strength of SCSLC, regarding the short-term compressive strength and the rheology of concrete.

2. Laboratory process

2.1 Materials and mixes

The cement used in this project was Portland cement type (I) produced in Tehran Cement Company and the sand was Shahriyar Sand with saturated surface dry density of 2.53 g/cm^2 and water absorption of 3.6%. In order to produce lightweight concrete, structural Lightweight Expanded Clay Aggregate (LECA), produced by LECA Company, was used. The LECA water absorption was 11.2%, grading of which is shown in Table 1. Low density, low thermal conductivity, fire resistance and lower water absorption compared with other lightweight aggregates are the most vital properties of LECA (Demirboğa *et al*. 2001).

Table 2 Self-compacting semi-lightweight

Group	*W/C*	Water (kg/m^3)	Cement (kg/m^3)	Silica fume (%)	Limestone Powder (kg/m^3)	LECA (kg/m^3)	Sand (kg/m^3)
1	0.35	207	591	0	250	294	743
2	0.35	207	531.9	10	250	294	743
3	0.4	236.4	591	0	300	280	704
4	0.4	236.4	531.9	10	300	280	704

It is really important how to use LECA in concrete. Since most lightweight aggregates are able to absorb water for long time, it is really vital how to add them to mixes. Some researchers considered its one hour water absorption in mix designs. In Norway, for instance, they considered 90 to 100 percent of one hour water absorption for calculating effective water to cementitious materials ratio. Some investigators emphasized on using saturated surface dry LECA (Yi *et al*. 2003). It means lightweight aggregates should be submerged in water before using in concrete with dried surface. Firstly, the LECA was submerged in water for 1 hour in this study, and then the surface was dried and used in concrete. Stone powder was used as fine filler, and the use of fillers such as limestone powder brings stability for concrete mixture. Limestone used in this study was produced in Qom Factory sifted through the sieve number 100. Because of lightness, LECA tends to segregate from other components of the mix, and the possibility of segregation rises as the slump flow time increases. In order to solve the problem, silica fume with proper amounts of superplasticizer can be used to improve concrete uniformity. More explanation about silica fume can be seen in the previous papers of Afzali Naniz and Mazloom (Afzali Naniz and Mazloom 2019a, Afzali Naniz and Mazloom 2019b, Afzali Naniz and Mazloom 2018). Silica fume used in this study is prepared from the Iran Ferrosilicon Company. Polycarboxylicether type superplasticizer (SP) is also used in the mixtures. Generally, 4 mix groups are constructed in this study, each of which contains 4 mixes, and only superplasticizer amount is the variable in each group. The details of the mixes are listed in Table 2.

2.2 Workability of fresh concrete

Neither a single test nor few tests can fully cover the properties of SCSLC, so various tests should be carried out for each mix. In this research, slump flow, V-funnel, and L-box tests are considered to control the mixtures, and they are performed on fresh concrete according to EFNARC standard (2002).

2.2.1 Slump flow test

This test is one of the standard tests for evaluating SCC and is defined in order to determine the deformation of concrete under its own weight without any barrier except the friction of the plate. The test shows the fluidity of concrete and its ability to fill the molds (EFNARC 2002). More explanation about slump flow and other test methods for SCLC can be seen in the previous paper of the authors (Mazloom and Mahboubi 2017). The results of this test can be seen in Table 3. According to EFNARC (2002), almost

Table 3 Properties of fresh self-compacting semi-lightweight concrete

Group	Mix No.	Superplasticizer (%)	Slump flow (mm)	V-funnel (s)	L-box (H2/H1)
1	1	2	720	15.2	0.84
	2	2.2	755	14.4	0.87
	3	2.4	780	13.2	0.91
	4	2.6	805	12.9	0.92
2	5	2	670	17.8	0.81
	6	2.2	705	16.5	0.84
	7	2.4	735	15.3	0.89
	8	2.6	750	11.2	0.9
3	9	0.8	680	14.7	0.85
	10	1	700	11.6	0.88
	11	1.2	735	10.9	0.89
	12	1.4	770	10.7	0.92
4	13	0.8	625	15.9	0.75
	14	1	650	12.8	0.8
	15	1.2	685	11.4	0.86
	16	1.4	750	9.7	0.9

all the mixtures are in the range of SCC, and the test shows how silica fume decreases workability of SCSLC and improved its viscosity instead.

2.2.2 V-funnel test

This test was invented and developed in Japan by Ozawa *et al*. (1995). A V-shaped funnel mold is used, and filling ability of SCLC and its rheology is investigated by means of measuring the time that concrete needs to pass the mold. Table 3 shows the results of the test. Some of the test results are more than the 12 second limit of EFNARC 2002 for SCC. These results are mainly due to lower W/C ratios as well as lightweight aggregates used in the mentioned mixtures (Mazloom and Mahboubi 2017). It is worth adding that the earlier effects of using silica fume on the concrete fluidity can be seen in this test too.

2.2.3 L-box test

This test is used and developed by Petersson (1996), based on a Japanese design for SCC. It demonstrates passing ability of concrete through reinforcement (EFNARC 2002). The ratio of the height at the end to that before the bars of the *L*-shape mold is measured in this test (H2/H1). The higher the ratio shows the more fluidity of SCSLC. The results of all tests conducted on SCSLC are listed in Table 3. EFNARC (2002) limitations accept almost all the mixtures as self-compacting; in fact, only one of the mixes had the H2/H1 ratio of a bit lower than 0.8. It is clear that silica fume marginally increased this ratio in all the mixes.

2.2.4 Compressive strength test

In this test, cubical samples with 100 mm dimensions were made, and compressive strength tests are carried out at ages 7, 14, 28, 90 days. Karamloo and his colleagues have offered three papers regarding the fracture behaviors of SCLC (Karamloo *et al*. 2016a, Karamloo *et al*. 2016b, Karamloo *et al*. 2017). Salehi and his coworker have worked in this field too (Salehi and Mazloom 2018a, Salehi and Mazloom 2018b, Salehi and Mazloom 2019). The compressive strength test results on samples and their dry density are listed in Table 4. It is clear that the density of the samples changed from 1747 to 1922 kg/m^3. Also the 90 days compressive strength test results were between 33.5 to 49 MPa, which were quite high for SCSLC. Apart from that, different specifications of high strength concrete are presented earlier (Mazloom 2008, Mazloom *et al*. 2004). It is clear that silica fume had a considerable positive role for improving the long-term strength of SCSLC. This is in agreement with previous finding in different mixtures (Mazloom and Miri 2017). In other words, it is possible to make high strength SCSLC through the use of LECA aggregate, superplasticizer and silica fume. Also, according to Table 4, it is necessary to decrease the amount of superplasticizer in order to increase the compressive strength of SCSLC.

Table 4 Self-compacting semi-lightweight concrete compressive strength test results

Group	Mix No.	Compressive strength (MPa)				Dry density, ρ_d (kg/m^3)
		7 days	14 days	28 days	90 days	
1	1	28.7	36.2	41.3	44.1	1922
	2	27.2	33.6	38.5	40.5	1913
	3	25.6	32	36.4	38.5	1906
	4	24	30.1	34.3	37.6	1897
2	5	31.5	39.6	45.7	49	1891
	6	29.7	38.5	43.6	46.7	1884
	7	27.9	36.4	41.5	44.2	1879
	8	26.4	34.2	39.6	42.4	1875
3	9	24.4	30.2	33.7	37.1	1825
	10	23.5	28.8	32.9	35.8	1819
	11	23	27.4	30.5	34.5	1792
	12	22.4	24.7	39.8	33.5	1779
4	13	27.3	34.3	37.8	40.9	1797
	14	26.3	32.4	35.9	39.7	1786
	15	25.9	31.1	33.4	36.8	1767
	16	24.5	29.7	31.8	35.2	1747

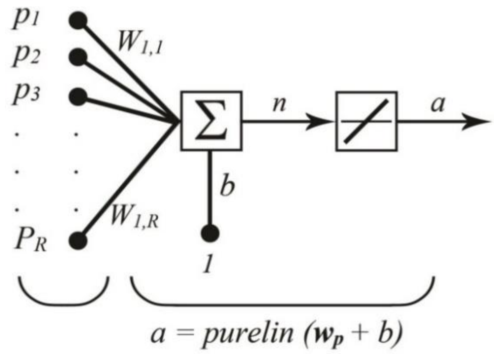


Fig. 1 Simple neuron model with a linear transfer function

3. Artificial neural networks

Artificial neural networks (ANN) modeling is a new topic which computer scientists have been interested in and spent a lot of time and money on for more progresses. It was formed with the idea of getting the nervous system and developed with the purpose of simulating of human brain with computer.

The purpose of using ANN for solving a problem is to achieve appropriate output according to the input data. The difference between achieved output and the actual result depends mostly on network training as well as selection of network weights and biases of the layers. A network is trained in a way that the desired outputs will be obtained using a set of inputs. Each of these sets of inputs and outputs can be considered as a vector. Training is done by applying input vectors sequentially and setting network weights according to a predetermined procedure. During network training, the weights gradually converge to values, and the desired output vector is produced via applying the input vector for them (Kaveh and Servati 2011). Design of network includes the number of layers and neurons, the transfer function of each layer, and the way they are connected to each other that depends on the type of problem. The number of independent variables determines the number of inputs while the number of dependent variables determines the number of neurons in the output layer. The output value of the system is a function of input neurons and the transfer function used (Mamdoohi and Ardeshiri 2013). Fig. 1 shows a model of a simple neuron whose output (*a*) is a value of both its input (*P*) and the utilized linear transfer function (Purelin). Besides, *W* is a weight for each input of the linear function and *b* is a bios for weighted matrix.

In this study, two kinds of simple ANN were used. The first one was supervised feed-forward back propagation Multi-layer Perceptron. The Tan-sigmoid and Levenberg-Marquardt functions were used as stimulation function and optimization algorithm respectively, used for suitable weight setting of neural networks. In fact, if the output of each neuron connects only to those neurons in the next layer of a neural network system, it will be called feed-forward.

The second utilized neural network was Radial Basis. These networks are the most common basis functions, and their fundamental advantages are ability to learn, main structure, and various usages. These functions are also superior to multi-layer networks mainly because of their significant higher learning speed (Pedrycz 1998). Theoretical principles of Radial Basis neural networks are based on Functions Approximation Theory. In these networks, Gauss Exponential Function is used instead of Sigmoid and Hyperbolic Tangent.

The most common evaluation criterion in neural networks training algorithms is Mean Squared Error (MSE) index, explaining the difference between the observations and the results of the models. It is clear that the lower value indicates the better function of the network. In both utilized ANN, the errors are obtained from the Eq. (1) as follows.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}[t\arg eg(i) - estimate(i)]^2 \qquad (1)$$

Where MSE is Mean Squared Error of the network, (n) is the total number of output data of network given for comparison to the network. Target (i) is the real answer of test number (i), and estimate (i) is the result of test number (i) obtained by ANN.

4. Regression functions to collect neural networks training data

Regression functions are used to obtain required data for network training. Since the neural network is a processor which stores the knowledge acquired through experience for other uses, numerous input data is required to create neural network so that it can gain necessary experience through the use of inputs and predict newer cases. According to tests results, variable amounts of superplasticizer had no effect on mix proportions, whereas it had direct effects on the test results. Therefore, the regression functions of the existing tests were obtained according to the superplasticizer amounts. By increasing the percentage of superplasticizer (x), the results of the tests (y) changed linearly. Also the (R^2) is the correlation coefficient of the equations and shows their accuracy, after all. Regression functions of relevant tests are listed in Tables 5 to 8. The numbers of data for each group as well as all four groups are 81 and 324, respectively.

5. Neural networks for estimating the compressive strength of SCSLC

As mentioned earlier, two kinds of neural networks known as Multi-Layer Perceptron (MLP) and Radial Basis Functions (RBF), which are denoted by Newff and Newrb in MATLAB, are used in this research. It should be noted that these methods were compared in SCC earlier (Mazloom and Yoosefi 2013). While the amounts of water to cementitious materials ratio (*W/C*), superplasticizer, silica fume, *V*-funnel test result, the 7 and 14 days compressive strength test were considered as input data for all groups, the 28 and 90 days compressive strengths were outputs. In order to have acceptable predictions for 90 days compressive strengths, it was necessary to use the 14 days compressive strengths in the input layers. After evaluating and comparing the results using evaluation criteria, Newff

Table 5 Regression functions for group 1

Test	Function	R^2
Slump flow	y=140x+443	0.994
V-funnel	y=-4.05x+23.24	0.9571
L-box	y=0.14x+0.563	0.9561
7 days Compressive strength	y=-7.85x+44.43	0.9998
14 days Compressive strength	y=-9.95x+55.86	0.9897
28 days Compressive strength	y=-11.55x+64.19	0.9945
90 days Compressive strength	y=-13.75x+71.3	0.9886

Table 6 Regression functions for group 2

Test	Function	R^2
Slump flow	y=135x+404.5	0.972
V-funnel	y=-10.5x+39.35	0.9015
L-box	y=0.16x+0.492	0.9481
7 days Compressive strength	y=-8.55x+48.54	0.9982
14 days Compressive strength	y=-9.15x+58.22	0.9799
28 days Compressive strength	y=-10.2x+66.06	0.9994
90 days Compressive strength	y=-11.15x+71.22	0.9959

Table 7 Regression functions for group 3

Test	Function	R^2
Slump flow	y=152.5x+553.5	0.9857
V-funnel	y=-6.49x+19.091	0.7869
L-box	y=0.11x+0.764	0.968
7 days Compressive strength	y=-3.25x+26.9	0.9837
14 days Compressive strength	y=-8.95x+37.62	0.9693
28 days Compressive strength	y=-7.05x+39.48	0.9478
90 days Compressive strength	y=-6.05x+41.88	0.9963

Table 8 Regression functions for group 4

Test	Function	R^2
Slump flow	y=205x+452	0.9524
V-funnel	y=-9.97x+23.422	0.966
L-box	y=0.255x+0.547	0.9946
7 days Compressive strength	y=-4.4x+30.84	0.9548
14 days Compressive strength	y=-7.55x+40.18	0.9924
28 days Compressive strength	y=-10.25x+46	0.9936
90 days Compressive strength	y=-10x+49.15	0.9761

Table 9 Specifications of final model of the Newff Network

Repetitions number	Data number	Output layer	Middle layer	Number of Layers
250	81	linear	Tan-sig	2

network model with its structural specifications in Table 9 was chosen as the superior network. Indeed, the numbers of hidden layer neurons for each group are 6, 7, 3 and 6, respectively.

In the Newrb method (Radial Basis), the number of middle layer is 1, and that of neurons of the middle layer is 81. The figures for convergence radius of each group are listed in Table 10. Additionally, MSE for both types of Newff and Newrb methods is given in Table 11. It is evident that Newff was more successful for long-term mechanical control of SCSLC. Also according to the results, it is advisable to use more improved ANN through training to have better predictions in this field.

Table 10 Convergence Radius values for each mix design

Group	1	2	3	4
Radius	1.305	7.95	6.025	5.95

Table 11 Comparison of mean squared error

Group	1	2	3	4
Newff	0.4023	0.0127	0.0545	0.0412
Newrb	0.3928	0.0659	0.0652	0.3527

Table 12 Mean squared error for combining neural networks

Function	Newff	Newrb
First method	0.1651	0.2281
Second method	0.1218	0.2025

6. The combination of artificial neural networks

The designed artificial networks for each group of the mix designs could predict the compressive strengths of SCSLC with great approximation; nevertheless, the purpose of this article is to predict the results of all possible mixes made with available materials. It was not possible, for instance, to predict the compressive strength of mixes comprising 8 percent silica fume with the ANN designed in the previous part, so decision was made to combine neural networks of the four mix designs. Increasing the network safety factor, reducing the network error, integrating different neural networks working individually, and increasing the scopes of applications are the benefits of combining ANN (Kardos *et al*. 2012). Two methods were used to combine neural networks in this article as follows.

6.1 First method: Results combination

This method is also known as weighting results, and neural networks of each group of mixes are considered as a part of a whole network. Input data are entered in all four neural networks, and each network is weighted separately. Eventually, the results of all four neural networks are combined. The Newff and Newrb functions are used in this method as well.

6.2 Second method: Stacked generalization

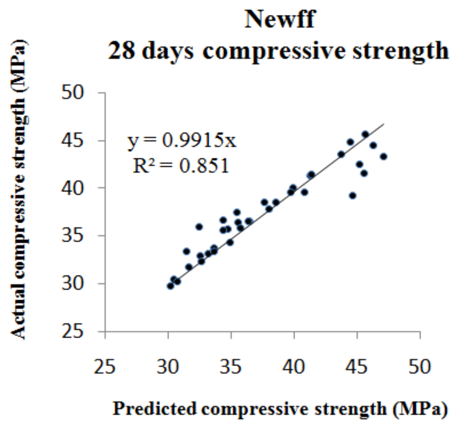
The structure of the stacked generalization algorithm consists of two levels for composing neural networks. In the first level, there are classifiers trained by means of learning set data. Once the training has been completed, the outputs of the first layer classifier collected for all learning set data, are gathered and put in a new set. This set is given as an input to the second level classifier, and the same training vector of the original learning data set will be peer to peer to train these inputs. In this method, groups of classifiers are made whose outputs act as inputs for the next layer

Table 13 Properties of extra mixes of self-compacting semi-lightweight concrete

Group No.	*W/C*	Water (kg/m^3)	Cement (kg/m^3)	Silica fume (%)	Limestone Powder (kg/m^3)	LECA (kg/m^3)	Sand (kg/m^3)	Superplasticizer (%)
1	0.35	207	561.5	5	250	294	743	2
2	0.4	236.4	561.5	5	300	280	704	0.8
3	0.35	207	543.7	8	250	294	743	2
4	0.4	236.4	543.7	8	300	280	704	0.8
5	0.37	218.7	591	0	250	294	743	2
6	0.38	224.6	591	0	250	294	743	1.2
7	0.37	218.7	561.5	5	250	294	743	2
8	0.38	224.6	561.5	5	250	294	743	1.2
9	0.37	218.7	543.7	8	250	294	743	2
10	0.38	224.6	543.7	8	250	294	743	1.2
11	0.37	218.7	531.9	10	250	294	743	2
12	0.38	224.6	531.9	10	250	294	743	1.2
13	0.35	207	591	0	250	294	743	2.1
14	0.35	207	591	0	250	294	743	2.5
15	0.35	207	531.9	10	250	294	743	2.1
16	0.35	207	531.9	10	250	294	743	2.5
17	0.4	236.4	591	0	300	280	704	0.9
18	0.4	236.4	531.9	0	300	280	704	1.3
19	0.4	236.4	531.9	10	300	280	704	0.9
20	0.4	236.4	531.9	0	300	280	704	1.3

Table 14 Results of self-compacting semi-lightweight concrete tests for neural network testing

Mix no	Slump flow (mm)	*V*-funnel (s)	Compressive strength (MPa)			
			7 days	14 days	28 days	90 days
1	695	16.3	29.8	37.5	43.3	46.4
2	655	15.3	26	32.1	35.6	38.8
3	680	16.9	30.5	38.4	44.5	47.3
4	640	15.7	26.5	33	36.5	39.7
5	760	16.8	26.9	32.8	38.5	41.7
6	690	13.6	24.1	29.7	33.4	36.7
7	745	17.3	28.5	34.3	39.2	42.7
8	670	14.1	25.3	31.9	36	38.4
9	730	18.2	29	35.5	41.6	44.9
10	655	14.5	26.2	32.7	36.7	39.8
11	720	18.9	29.7	37.5	42.5	45.3
12	640	14.7	26.9	33.6	37.5	41.2
13	740	14.9	28	35.1	39.6	42.7
14	790	12.7	25.1	31	35.7	37.9
15	680	17	31	39.1	44.9	48
16	745	13.8	27.2	35.9	40	43.5
17	695	13.5	24.1	29.3	33.2	36.4
18	750	10.8	22.6	25.6	30.2	34
19	640	13.4	26.9	32.9	36.5	40.1
20	720	10.5	24.8	30.4	32.3	36.5



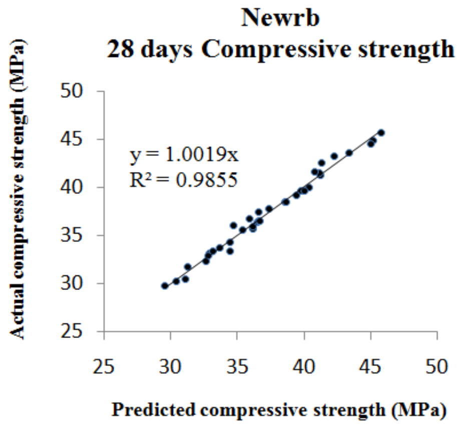


Fig. 2 the 28 days compressive strengths estimated graphs and actual laboratory results comparison for Results Combination method

classifier. These classifiers learn the mapping between the output of each normal classifiers of first layer and the real output classes (Khasheie and Bijary 2010). In other words, in this method, simulated outputs of each trained neural network have been collected, all of which are put in a matrix. This matrix plays the role of an input for the new neural network. The favorable outputs of the previously designed networks are located in a matrix, so it continues to play the desired output of the new neural network. In Stacked Generalization of Newff method, the number of neurons in the middle layer is 1 for Newff, and the obtained convergence radius is 9.15 for Newrb. The Mean Squared

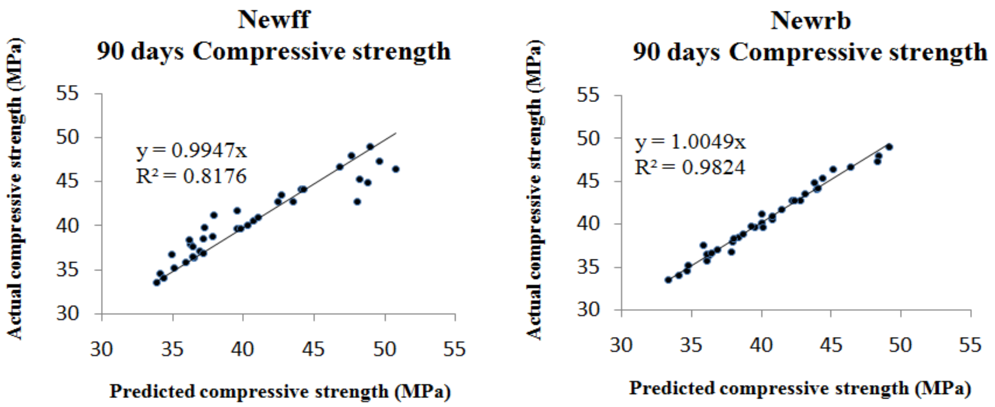


Fig. 3 the 90 days compressive strengths estimated graphs and actual laboratory results comparison for Results Combination method

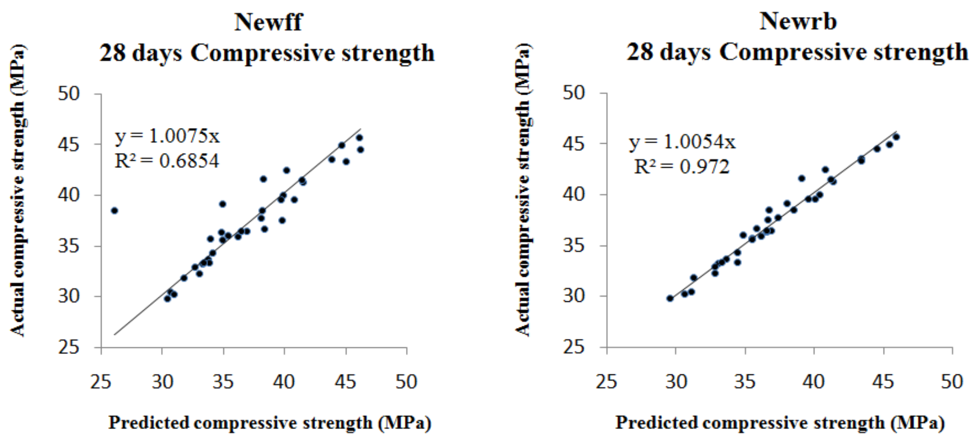


Fig. 4 the 28 days compressive strengths estimated graphs and actual laboratory results comparison for Stacked Generalization method

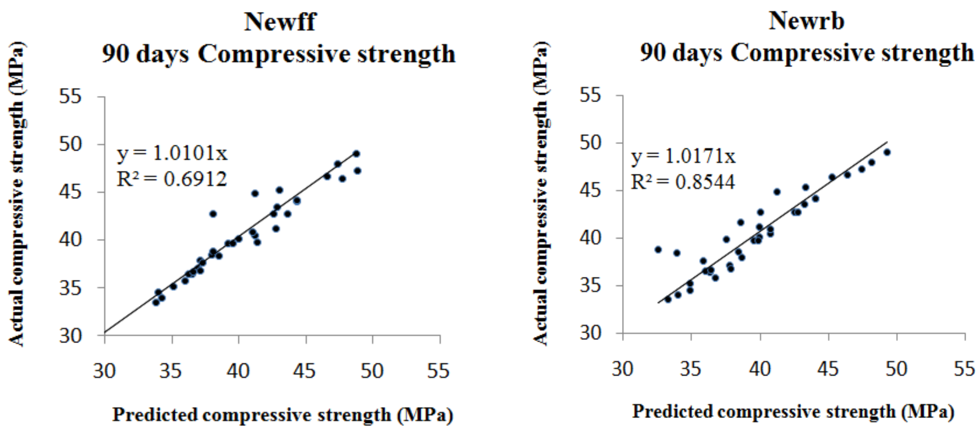


Fig. 5 the 90 days compressive strengths estimated graphs and actual laboratory results comparison for Stacked Generalization method

Error for both combining methods is given in Table 12. It is clear that both Stacked Generalization and Results Combination methods are acceptable.

7. Verification of the combined artificial neural networks

After designing the compound neural networks, 20 extra mix designs were made to ensure the trustiness of the networks. These results are listed in Table 13 and 14. Apart from that, the comparisons of ANN and laboratory test results for main 16 mixes are shown in Figs. 2 to 5. It is clear that by combining different neural networks, the performance of the networks increases for estimating the compressive strength of SCSLC with different mix designs. Also according to these figures, both Stacked Generalization and Results Combination methods gave acceptable estimation of long-term strength of SCSLC. In other words, both of them can be used for long-term mechanical control of SCSLC.

8. Conclusions

Regarding the use of different dosages of superplasticizer in the mix designs of Self-Compacting Semi-Lightweight Concrete (SCSLC), the main results are:

- Using silica fume as a partial replacement of cement reduced the rheology and also increased the viscosity of SCSLC.
- In addition to reducing the segregation of SCSLC through the use of Silica Fume, the stability, and specifically, the strength of the concrete increased. Moreover, to increase the compressive strength of SCSLC, it was necessary to decrease the dosage of superplasticizer as much as possible.
- Although both Multi-layer Perceptron and Radial Basis neural networks were applicable, in combination of neural networks, the former were more precise for estimating the compressive strength of SCSLC.
- By combining different Artificial Neural Networks (ANN), the performance of the networks increased for estimating the long-term quality of SCSLC with different mix designs.
- Both Stacked Generalization and Results Combination methods gave acceptable estimation of long-term strength of SCSLC, so both of them can be used for long-term mechanical control of SCSLC; however, the latter showed superior performance than the former by a narrow margin.
- It is better to utilize Radial Basis neural networks firstly and then Multi-layer Perceptron on condition that proper network is not obtained by means of the first method.

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