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Application of Neural Networks for Predicting the Workability of Self-Compacting Concrete

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Author's contribution

Author MM designed the study, wrote the protocol, and wrote the first draft of the manuscript. He managed the literature searches, analyses of the study performed the spectroscopy analysis and he managed the experimental process and he identified the species of plant. Author read and approved the final manuscript.

Research Article

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ABSTRACT

Self-compacting concrete (SCC) is a complex material and modeling its workability is a complicated task. To evaluate the workability of SCC, five different tests have been conducted, which are slump flow, V-funnel, J-Ring, L-box and U-box. In fact, executing L-box and U-box tests are more difficult than the other ones, especially on sites. Therefore, this research studies the possibility of predicting the results of L-box and U-box tests from the results of the other tests utilizing artificial neural networks (ANN). For this purpose, multi layer perceptron (MLP) networks and radial basis (RB) networks were chosen. The conclusion was that the MLP networks could foresee the L-box and U-box test results in all situations.

Keywords: Concrete; self-compacting; workability; neural networks; perceptron; radial basis.

1. INTRODUCTION

With the introduction of the new generation of superplasticizers, self-compacting concrete (SCC) is industrialized. This type of concrete having superior viscosity and workability properties can simply fill the molds without the obligation of utilizing vibrators [1-4]. High quantity of mineral powders is a requirement for designing a suitable SCC. It is worth adding

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that Ho et al. have investigated the use of quarry dust in SCC [5]. Moreover, the influence of limestone powder on SCC is investigated recently [6]. For this purpose, natural or artificial mineral additives such as fly ash, silica fume, blast furnace slag, and limestone powder can be used too. In this study, the effects of replacing 10% of cement by silica fume on fresh and hardened properties of SCC have been investigated.

The importance of workability in concrete technology is quite apparent. It is one of the main properties that have to be satisfied. A concrete mixture that cannot be placed simply or compacted completely is not likely to yield the required strength and durability characteristics [7]. It is worth noting that extensive investigations on the workability of SCC have been made recently [8-10]. Kayat et al. reported that the J-ring, U-box and L-box tests can be used to estimate the passing ability of SCC and resistance to segregation [8]. The combination of slump flow and L-box tests is very appropriate for the quality control of SCC on sites [11]. It is worth noting that Bui et al. have introduced a rapid testing method for segregation resistance of SCC [12]. In this research, to evaluate the workability of SCC, five different tests have been conducted, which are slump flow, V-funnel, J-Ring, L-box and U-box.

An artificial neural network (ANN) model, which is a computer model, imitates the learning ability of the human brain. In recent years, the applications of ANN in modeling the behaviors of materials have been considered widely [13-18]. Nevertheless, small research has been done on modeling the workability of concrete using neural networks [19]. Nehdi et al. [20] confirmed that ANN methods can precisely predict the segregation, filling capacity and slump flow test results of SCC. Bai et al. [21] developed reliable and accurate ANN models for predicting the workability of concrete. Ji et al. [22] used the following parameters to build ANN models for predicting the strength and slump of concrete: nominal water to cement ratio, equivalent water to cement ratio, average paste thickness, fly ash-binder ratio, and grain volume fraction of fine aggregates. Yeh [23] established the capabilities of ANN to show the effects of each material component on concrete slump. This research concentrates on utilizing ANN for predicting the L-box and U-box test results from slump flow, V-funnel and J-Ring experimental outcomes. In fact, executing L-box and U-box tests are more difficult than the other ones on sites, and this paper investigates how to replace ANN to a portion of these complex tests.

2. MATERIAL PROPERTIES

The cementitious materials utilized were silica fume (SF) and ordinary Portland cement (OPC). Their physical properties and chemical components can be seen in Table 1. Details of the mix proportions for the concrete containing different dosages of superplasticizers with and without silica fume are given in Table 2. The control mixes were prepared using OPC, while the other mixes were cast by replacing 10% of the cement with silica fume on mass-for-mass basis. The water/binder ratios were 0.35 and 0.45 respectively. The effect of water to cement ratio on the properties of SCC is studied recently [24]. The same mix proportions were used for the concrete mixes with the dosages of 0.4%, 0.8%, 1.2%, and 1.6% of a kind of carboxylic based superplasticizer. As a result of using different dosages of the superplasticizer, the fresh and hardened properties of the mixes were quite different. It is worth noting that the effects of superplasticizers on the mechanical strength of mortars have been studied recently [25]. Also, the application of carboxylic based superplasticizers in SCC is investigated [26]. The effects of chemical admixtures and mineral additives on SCC are studied too [27]. It is worth adding that Su and Miao have introduced a method for the mix design of flowing concrete [28].

3. COMPRESSIVE STRENGTH OF SELF-COMPACTING CONCRETE

It is crucial to attain a maximum possible density in concrete because its strength is considerably and adversely affected by the existence of voids in the compacted mixture [29]. This maximum density needs an adequate workability or almost full compaction. Obviously, the existence of voids in concrete decreases its strength seriously, which means the presence of 5 percent of voids in concrete can lower the strength by 30 percent [29]. This research compares the compressive strengths of self-compacting and standard concrete mixtures having the same ingredients and different dosages of superplasticizers. It is worth noting that the hardened mechanical properties of SCC have been reviewed recently [30].

For the cubic concrete specimens stored in water, the development of compressive strength with age is presented in Table 3. It is clear that the compressive strength development of concrete mixtures containing different dosages of the utilized superplasticizer were quite different. However, the comparison between the mixes containing silica fume and the similar ones without silica fume shows the first group had lower workability and higher compressive strength. The reason for this phenomenon can be the pozzolanic activities of silica fume.

Table 1. Physical Chemical compositions and physical properties of cementitious materials

Item	Ordinary Portland cement	Silica fume
SiO2	21.9	91.5
Al2O3	4.48	0.9
Fe2O3	3.4	1
CaO	64.7	1.9
MgO	2.1	1.5
Cl	___	0.1
Na2O	0.12	___
K2O	0.55	___
SO3	1.42	1
LOI	1.3	2.1
Compounds		
C3S	57.9	___
C2S	19.2	___
C3A	6.13	___
C4AF	10.3	___
Fineness		
SSA(m2/kg)	308	14,400

4. WORKABILITY OF SELF-COMPACTING CONCRETE

The definition of workability is the total of useful internal work essential to create complete compaction. This internal work, which is a physical property of concrete, is the necessary work or energy to conquer the internal friction between the particles of the mixture. Because of the very high workability of SCC, it requires no external vibration for spreading into place, filling the framework and encapsulating reinforcement without any segregation and bleeding. Furthermore, the aggregate particles in SCC should have homogeneous distribution in the specimen and the minimum segregation risk ought to be existed during the process of carrying and placement.

Table 2. Mix proportions of concrete containing different water to cementitious materials ratios

Concrete Mixes	Mix 1	Mix 2	Mix 3	Mix 4
W/b	0.35	0.35	0.45	0.45
SF/(SF+C)%	0	10	0	10
Cement or C (kg/m^3)	500	450	400	360
Silica fume or SF (kg/m^3)	-	50	-	40
Gravel (kg/m^3)	867	867	833	833
Sand (kg/m^3)	668	668	722	722
Water (kg/m^3)	175	175	180	180
Rock flour (kg/m^3)	155	155	150	150
Super plasticizer (kg/m^3)	2 to 8	2 to 8	1.6 to 6.4	1.6 to 6.4

Table 3. Development of compressive strength with age

Concrete Mixes	Superplasticizer Dosage	Compressive Strength (MPa)
		28 Days
Mix 1	0.4%	61
	0.8%	58
	1.2%	58
	1.6%	56
Mix 2	0.4%	69
	0.8%	62
	1.2%	60
	1.6%	58
Mix 3	0.4%	47
	0.8%	42
	1.2%	40
	1.6%	37
Mix 4	0.4%	48
	0.8%	45
	1.2%	46
	1.6%	41

It is clear that workability depends on a number of interacting issues such as aggregate type and grading, aggregate to cement ratio, the fineness of cement, water content, and the dosage and kind of superplasticizers. The main factors on SCC are the superplasticizer and water contents of the mix because by increasing them the inter particle lubrication is improved. As explained earlier, in this research, the water contents of the mixes having the same water to binder ratios were constant and the dosages of the superlasticizer were 0.4%, 0.8%, 1.2%, and 1.6% of the weight of cement. Moreover, to attain optimal conditions for minimum voids with no segregation, the effects of the aggregate type and grading should be considered. In this study, the quality and grading of the aggregates in all the mixtures were the same. In other words, the main objective of this research was to find the effect of the dosages of superplacticizers on the fresh and hardened properties of the mixes.

To estimate the workability of SCC, static and dynamic stability tests are generally essential [8,9]. Static stability tests handle the properties of SCC during the phase from casting to initial set whereas dynamic stability tests concern the properties of SCC during the processes of mixing, transportation, and casting. This research concentrates on dynamic stability tests as follows.

4.1 Slump Flow Test

Only the slump test results of the mixes having the superplasticizer dosage of 0.4% can be seen in Table 4. The other superplasticizer dosages produce SCC, and because the slump test is not appropriate for the analysis of the fluidity of SCC, the slump flow test is approved. It should be noted that computational modeling of concrete flow has been overviewed recently [31]. The slump flow testing equipment has a normal slump cone and a steel plate with the size of 900 × 900 mm. The time taken for SCC to spread to 500 mm in diameter, T500, and the final slump flow diameters in the two orthogonal directions can be measured with this equipment. According to EFNARC [32], for class 1 SCC the slump flow diameter is 550-650 mm and T500≤2 s; for class 2 SCC the slump flow diameter is 600-750 mm and T500≥2 s; for class 3 self-compacting concrete the slump flow diameter is 760-850 mm, but no condition for T500 is specified. It is worth noting that the slump flow test is recently modeled using artificial neural networks [19]. The results of slump flow tests of the present research are given in Table 5.

4.2 V-Funnel Test

The equipment for V-funnel test is expressed by Wu et al. [11]. The entire time for SCC to flow through the V-funnel, can be measured with this equipment. The V-funnel flow test is useful for estimating the fluidity of SCC to alter its path and to pass through narrow regions. According to EFNARC [32], for class 1 SCC, Tv is smaller than 8 s and for class 2 SCC, Tv is 9-25 s. The measured values of Tv of the present research can be observed in Table 5.

4.3 J-Ring Test

J-ring test consists of the slump cone located inside a 300 mm diameter steel ring, which is attached to vertical reinforcing bars at proper spacing [33]. The number of bars should be chosen according to the maximum size of aggregates in SCC mixes. The variation of the height of a SCC before and after the bars is measured in this test. Clearly, as the workability of the mix is superior, the result of J-ring test is lesser. The results of J-ring tests of the present research can be observed in Table 5.

4.4 L-Box Test

The L-box test is utilized to estimate the fluidity of SCC and its capability to pass through steel bars [34]. The L-box involves a “chimney” section and a “channel” section as explained by Wu et al. [11]. The height of concrete in chimney, h1, the height of concrete in the channel section, h2, and the time taken for SCC to reach 40 mm from three steel bars, T400, can be measured with the L-box. According to EFNARC [32], when the ratio of h2 to h1 is bigger than 0.8, SCC has fine passing skill. However, no specification for T400 is specified in EFNARC. In most previous investigations on SCC, T400 is employed to approximate the flow velocity of SCC [11]. The measured values of h2/h1 of the present research are given in Table 6.

4.5 U-Box Test

The U-box test is utilized to estimate the passing ability and filling ability of SCC in jam-packed reinforcement. The key factor to be considered is the height difference of concrete between the two boxes, ∆h. According to EFNARC [32], once the height difference of concrete is lesser that 30 mm, SCC has good passing and filling abilities. The measured height differences of the investigated concrete mixtures are presented in Table 6.

Table 4. Workability of the concrete mixes containing the superplasticizer dosages of 0.4%

Concrete Mixes		Slump (mm)
W/c = 0.35	Mix 1 (OPC)	238
	Mix 2 (SF10)	215
W/c = 0.45	Mix 3 (OPC)	216
	Mix 4 (SF10)	185

Table 5. Input data gathered from the lab for testing the ANN

Concrete mix	Superplasticizer dosage, %	Slump flow (mm)	V-funnel (sec)	J-ring (mm)
Mix 1 (OPC)	0.8%	730	6.5	12
	1.2%	785	5.4	6.3
	1.6%	825	4.8	4
Mix 2 (SF10)	0.8%	550	8	14.5
	1.2%	670	6.2	8
	1.6%	780	5.3	5.5
Mix 3 (OPC)	0.8%	730	4	14
	1.2%	810	3.6	6.5
	1.6%	830	3.3	4.2
Mix 4 (SF10)	0.8%	530	4.8	17
	1.2%	760	4.2	12
	1.6%	770	3.8	11

Table 6. Output data gathered from the lab for testing the ANN

Concrete mix	Superplasticizer dosage, %	L-box (ratio)	U-box (mm)
Mix 1 (OPC)	0.8%	0.86	12
	1.2%	0.90	7
	1.6%	0.95	3
Mix 2 (SF10)	0.8%	0.62	36
	1.2%	0.82	18
	1.6%	0.90	5
Mix 3 (OPC)	0.8%	0.88	8
	1.2%	0.96	4
	1.6%	0.98	1
Mix 4 (SF10)	0.8%	0.57	24
	1.2%	0.86	13
	1.6%	0.90	6

5. EFFECT OF SILICA FUME ON WORKABILITY

The definition of workability is the total of useful internal work essential to create complete compaction. This internal work, which is a physical property of concrete, is the necessary work or energy to conquer the internal friction between the particles of the mixture. Because of the very high workability of SCC, it requires no external vibration for spreading into place, filling the framework and encapsulating reinforcement without any segregation and bleeding. Furthermore, the aggregate particles in SCC should have homogeneous distribution in the specimen and the minimum segregation risk ought to be existed during the process of carrying and placement.

6. APPLICATION OF ARTIFICIAL NEURAL NETWORKS

The greater part of researchers that used artificial neural networks to model material behaviors are the ones who have utilized back-propagation networks for minimizing the error coefficients. The back-propagation networks discover the material behaviors by matching the output of each input pattern with the target output of that pattern. Afterward, the error coefficient backward through the net should be calculated. The essential regulations of back-propagation algorithm is covered widely [36,37].

6.1 Data sets

Table 2 presents the details of the concrete mixes investigated in this study. It should be mentioned that for generating enough data for training the ANN, regression analyses were used and about 400 various data were generated for training each network. The results of regression analyses and the equations for data generations can be seen in Table 7. Finally, the 12 experimental data were utilized for testing the exactness of the trained networks.

Table 7. Regression functions used for generating the training data

Concrete Mixes	Experiment	Regression Function*	R2
Mix 1 (OPC)	L-box (ratio)	Y=0.1125(x)+0.7683	0.9959
	U-box result (ratio)	Y=-11.55(X)+20.839	0.9959
	Slump flow (mm)	y = 118.7(x)+ 637.5	0.991
	J-ring (mm)	y = 10.62(x2) – 35.5(x)+ 33.6	1
	V-funnel (sec)	y = -2.125(x)+ 8.116	0.972
	L-box (ratio)	Y=0.35(X)+0.36	0.9423
Mix 2 (SF10)	U-box result (ratio)	Y=-38.75(X)+66.167	0.9914
	Slump flow (mm)	y = 287.5(x) + 321.6	0.999
	J-ring (mm)	y = 12.5(x2)- 41.25x + 39.5	1
	V-funnel (sec)	y = -3.375(x) + 10.55	0.964
	L-box (ratio)	Y=0.125(X)+0.79	0.8929
Mix 3 (OPC)	U-box result (ratio)	Y=-8.75(X)+14.893	0.9932
	Slump flow (mm)	y = 125(x) + 640	0.892
	J-ring (mm)	y = 16.25(x2) - 51.25(x) + 44.6	1
	V-funnel (sec)	y = -0.875(x) + 4.683	0.993
Mix 4 (SF10)	L-box (ratio)	Y=0.35(X)+0.36	0.9423
	U-box result (ratio)	Y=-38.75(X)+66.167	0.9914
	Slump flow (mm)	y = 300(x) + 326.6	0.781
	J-ring (mm)	y = 12.5(x2) – 37.5(x) + 39	1
	V-funnel (sec)	y = -1.25(x) + 5.766	0.986

** X= superplasticizer percentage and Y= test result*

According to Tables 5 and 6, the database was split in four different groups; therefore, four ANN models were trained for them. The four models had the same architecture, but different regression coefficients for regression analyses and different connection weights for neural networks since each of the networks was trained using a partially different set of data.

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6.2 Modeling the Workability of SCC using Artificial Neural Networks

The neural networks developed in this investigation were divided in two groups of multi layer perceptron (MLP) and radial basis (RB) networks, which are presented in MATLAB software by the names of newff and newrb respectively. All of the networks had three units in the input layer, which were the results of slump flow, V-funnel and J-ring tests, and two units in the output layer, which were the results of L-box and U-box tests. In newff, which is multi layer perseptron (MLP), the relations between the input and hidden layers and also the relations between the hidden and output layers are presented by some equivalent weights. The values of MLP network parameters considered in this approach were as follows: number of hidden layers = 1 and 2; number of hidden neurons = from 3 to 12; number of epochs (learning cycles) = 300, 500 and 1000. Based on the error of primary testing set, the best network parameters are as follows: number of hidden layers = 1; number of hidden neurons = 6 or 7; number of epochs = 500. To choose the number of hidden neurons, the value of error coefficient (e), which is presented in Eq. 1, is utilized.

$$e = \Sigma[(\text{target}(i)-\text{estimate}(i)]^2 \quad (1)$$

where target(i) and estimate(i) are the experimental and the estimated values in ith event respectively. In fact, Table 8 shows the average of e value of the first mixture (OPC and w/c=0.35). According to this table, six hidden units should be chosen for having the minimum average e value. Only in the last mix (SF10 and w/c=0.45), one hidden unit is added to the six units above for training the related network. Tables 9 and 10 show the exactness of the ANN in predicting the L-box and U-box test results respectively. It is clear that ANN models are quite successful in predicting the L-box and U-box results from the other workability tests. The mean square error coefficients (mse) of each mix, which is presented in Eq.2, can be seen in Table 11.

$$mse = 1/n.\Sigma[(\text{target}(i)-\text{estimate}(i)]^2 \quad (2)$$

where n is the number of tests or estimations.

Table 8. Average e value after 10 repetitions of mix one (w/c=0.35, OPC)

Number of hidden units	e value
3	1.73
4	1.66
5	2.05
6	0.79
7	1.68
8	1.81
9	1.95
10	1.12
11	1
12	0.96
13	1.66
14	1.17

Table 9. Comparing the experimental and estimated values of L-box test using newff networks

Concrete Mixes	Superplasticizer Dosage	L-box result (ratio)	
		Experimental result	Estimated result
Mix 1 (OPC)	0.8%	0.86	0.8555
	1.2%	0.90	0.9078
	1.6%	0.95	0.9462
Mix 2 (SF10)	0.8%	0.62	0.6211
	1.2%	0.82	0.8277
	1.6%	0.90	0.8941
Mix 3 (OPC)	0.8%	0.88	0.8793
	1.2%	0.96	0.9510
	1.6%	0.98	0.9841
Mix 4 (SF10)	0.8%	0.57	0.5635
	1.2%	0.86	0.8093
	1.6%	0.90	0.9386

Table 10. Comparing the experimental and estimated values of U-box test using newff networks

Concrete Mixes	Superplasticizer Dosage	U-box result (ratio)	
		Experimental result	Estimated result
Mix 1 (OPC)	0.8%	12	11.7849
	1.2%	7	7.1676
	1.6%	3	3.0294
Mix 2 (SF10)	0.8%	36	36.7886
	1.2%	18	17.9030
	1.6%	5	5.0784
Mix 3 (OPC)	0.8%	8	8.0889
	1.2%	4	3.5406
	1.6%	1	1.2506
Mix 4 (SF10)	0.8%	24	23.6649
	1.2%	13	13.4157
	1.6%	6	5.4046

Table 11. Comparing the mean square error coefficients of newff and newrb networks

Concrete mixes	mse value	
	newff network	newrb network
Mix 1 (OPC)	0.0126	0.0056
Mix 2 (SF10)	0.1061	0.3456
Mix 3 (OPC)	0.0470	0.2322
Mix 4 (SF10)	0.1071	2.8083

In newrb method, which is radial basis (RB), the relations between the input and hidden layers are presented by some mathematical equations, but the relations between the hidden and output layers are presented by some equivalent weights. It should be mentioned that the number of hidden neurons in this method are chosen by the software and they are much more than the number of neurons used by the newff method. The values of RB network parameters considered in this approach are as follows: number of hidden layers = 1; number of hidden units = 100. It should be mentioned that working with newrb networks is much easier than working with newff networks and also newrb networks converge to the final solutions faster. Table 12 shows the radius (R) values of the newrb networks of each mix.

Table 12. Radius values of newrb networks in different mixes

Concrete Mixes	Radius
Mix 1 (OPC)	1.4
Mix 2 (SF10)	2.1
Mix 3 (OPC)	2.04
Mix 4 (SF10)	3.975

The mean square error coefficients (mse) of each mix can be seen in Table 11. It is clear that in most cases, the mse of newff networks were lower the ones of newrb networks, and the newff networks were more exact than the newrb ones. Table 13 shows the newrb method is exact enough in predicting the L-box test results; however, according to Table 14, the newrb network could not predict the results of U-box tests with acceptable exactness in mix four. To solve this problem, it was decided to train a different network for estimating the U-box test results separately. The results can be observed in Table 15. The R and mse values of this network were 4.1 and 3.0327 respectively. In fact, Table 15 shows the network was not exact enough for predicting the U-box test results, and producing a different RB network for predicting the U-box test results independently did not work either. In other words, although RB networks were more users friendly and they converged to the final results quicker than MLP networks, they could not properly predict the workability of SCC in some circumstances.

Table 13. Comparing the experimental and estimated values of L-box test using newrb networks

Concrete Mixes	Superplasticizer Dosage	L-box result (ratio)	
		Experimental result	Estimated result
Mix 1 (OPC)	0.8%	0.86	0.8581
	1.2%	0.90	0.9074
	1.6%	0.95	0.9459
Mix 2 (SF10)	0.8%	0.62	0.6402
	1.2%	0.82	0.7863
	1.6%	0.90	0.9181
Mix 3 (OPC)	0.8%	0.88	0.8786
	1.2%	0.96	0.9328
	1.6%	0.98	0.9799
Mix 4 (SF10)	0.8%	0.57	0.5771
	1.2%	0.86	0.8611
	1.6%	0.90	0.8909

Table 14. Comparing the experimental and estimated values of U-box test using newrb networks

Concrete Mixes	Superplasticizer Dosage	U-box result (ratio)	
		Experimental result	Estimated result
Mix 1 (OPC)	0.8%	12	11.8488
	1.2%	7	6.9274
	1.6%	3	3.0747
Mix 2 (SF10)	0.8%	36	35.1497
	1.2%	18	18.9712
	1.6%	5	4.3775
Mix 3 (OPC)	0.8%	8	8.6298
	1.2%	4	4.84
	1.6%	1	1.5390
Mix 4 (SF10)	0.8%	24	25.22
	1.2%	13	9.6934
	1.6%	6	8.1042

Table 15. Comparing the experimental and estimated values of U-box test in mix four (w/c=0.45, SF10)

	U-box test		
Experimental results	24	13	6
Estimated results	25.6293	9.6657	8.1034

7. CONCLUSIONS

From the results presented in this paper, the main conclusions are:

- MLP networks could predict the L-box and U-box test results from the flump flow, J-ring and V-funnel test results in all circumstances.

- RB networks were not exact enough for predicting the U-box test results from the flump flow, J-ring and V-funnel test results in some circumstances. In this condition, training a different network for predicting the U-box test results separately was not successful too.
- RB networks are quite easy to work with and they touch to the final solutions faster than MLP networks. However, RB networks cannot solve the problems in some circumstances, and it is necessary to use MLP networks in these circumstances.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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