Computers and Concrete, *Vol. 12, No. 3 (2013) 285-301*
DOI: http://dx.doi.org/10.12989/cac.2013.12.3.285

Predicting the indirect tensile strength of self-compacting concrete using artificial neural networks

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(Received March 3, 2011, Revised March 7, 2013, Accepted March 29, 2013)

Abstract. This paper concentrates on the results of experimental work on tensile strength of self-compacting concrete (SCC) caused by flexure, which is called rupture modulus. The work focused on concrete mixes having water/binder ratios of 0.35 and 0.45, which contained constant total binder contents of 500 kg/m^3 and 400 kg/m^3, respectively. The concrete mixes had four different dosages of a superplasticizer based on polycarboxylic with and without silica fume. The percentage of silica fume that replaced cement in this research was 10%. Based upon the experimental results, the existing equations for anticipating the rupture modulus of SCC according to its compressive strength were not exact enough. Therefore, it is decided to use artificial neural networks (ANN) for anticipating the rupture modulus of SCC from its compressive strength and workability. The conclusion was that the multi layer perceptron (MLP) networks could predict the tensile strength in all conditions, but radial basis (RB) networks were not exact enough in some circumstances. On the other hand, RB networks were more users friendly and they converged to the final networks quicker.

Keywords: concrete; tensile strength; self-compacting; neural networks; perceptron; multi layer perceptron (MLP) and radial basis (RB) networks

1. Introduction

It is not straightforward to test concrete in direct tension because there must be no eccentricity of the applied load and also because of the difficulty of gripping the sample acceptably. Therefore, direct tensile test is not standardized, and it is seldom used. The standards ASTM C 78-84, ASTM C 496-90 and BS 1881: 1383 recommend other methods of determining the tensile strength that are in indirect tensile and flexure, which are called splitting and modulus of rupture, respectively. Moreover, a new biaxial flexure test method has been developed to measure the biaxial tensile strength of concrete recently (Zi *et al*. 2008). The different test methods give dissimilar results numerically, ordered as follows: direct tension < splitting tension < flexural tension. In fact, in the order presented above, the volume of concrete subjected to tensile stress and the chance of existing weak points in this part decreases statistically. Therefore, failure occurs in the larger volume than in the smaller one. Also the flexural and splitting test methods involve non-uniform stress distributions, which delay both the spread of cracks and the ultimate failure. On the other hand, in

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http://www.techno-press.org/?journal=cac&subpage=8 ISSN: 1598-8198(Print), 1598-818X (Online)

the direct test, the stress distribution is uniform and if a crack creates, it can spread rapidly through the section of the specimen. In other words, the tensile behaviour of concrete is similar to that of rock specimens (Vasconcelos *et al*. 2008).

The compressive strength of normal-strength concrete is eight times bigger than the tensile strength theoretically (Neville and Brooks 1990). In fact, experimental results show that there is a close relation them but not a direct proportionality; the ratio of the two strengths depends on the level of strength of the concrete. Normally, the ratio of tensile to compressive strengths is lower if the compressive strength is higher. Thus the tensile strength increases with age at a minor speed than the compressive strength. Nevertheless, there are several other factors that affect the relation between the two strengths. The key ones are the technique of testing the concrete in tension, the size of specimen, the shape and surface texture of gravel, and the moisture condition of the concrete. The relation between bending and compressive strengths (Arias *et al*. 2008) as well as the correlation of tensile and flexural strengths (Soranakom and Mobasher 2008) have been studied recently.

Angular crushed aggregate increases the flexural strength of concrete because the superior bond of crushed aggregate holds the material together. But there is little influence of the type of the aggregate on the splitting and direct tensile strengths. The ratio of flexural strength to compressive strength is bigger for angular crushed aggregate because the compressive strength is little affected by the shape and surface texture of the aggregate. The moisture condition of concrete influences the relation between the compressive and flexural strengths. The compressive strength of drying concrete is larger than the continuously wet-stored ones but the splitting and direct tensile strengths are not affected in a similar manner. The flexural strength of drying concrete is lesser than that of wet concrete, possibly because of sensitivity of this test to the existence of shrinkage cracks.

2. Modulus of rupture

The hypothetical maximum tensile stress at the bottom fiber of a flexural specimen is known as the modulus of rupture, which is related to the design of aircraft pavements and highways. The test is approved as a observance test by BS 5328: 1991, but in the US the test is thought to be inappropriate for observance purposes because of its relative difficulty (Neville and Brooks 1990). The modulus of rupture depends on the arrangement of loading and the dimensions of the beam. Two-point loading at third points of the span is used both in the UK and the US, which produces a constant bending moment between the load points. Therefore, one third of the span is subjected to the maximum stress, and cracking is likely to take place there. To improve the flexural behaviour of concrete, different kinds of polymer-based fibers can be used (Pham and Al-Mahaidi 2008, Kim *et al*. 2008, Gravina *et al*. 2008, Bogas and Gomes 2008, Campione and Mangiavillano 2008).

According to BS 1881: Part 118 1983, the favorite size of beam is 150 × 150 × 750 mm. However, once the maximum size of aggregate is less than 25 mm, 100 × 100 × 500 mm beams may be used. The making and curing of the beams is covered by BS 1881: Part 3: 1970 and the use of swan samples is acceptable by Bs 1881: Part 118: 1983. In relation to the as-cast position, the beams are tested on their side. The rate of raise in stress in the bottom fiber is between 0.02 and 0.1 MPa/second, and the higher rate is for high strength concrete. ASTM C78-84 recommends a parallel flexure test except that the loading rate is between 0.0143 and 0.02 MPa/second and the size of the beam is 150 × 150 × 500 mm.

If breakage happens within the middle one-third of the beam, the modulus of rupture is calculated on the basis of ordinary elastic theory as follows

$$f_t = (P.L)/(bd^3) \tag{1}$$

If breakdown takes place outside the middle one-third, according to BS 1881: Part 118: 1983, the test result should be rejected. Conversely, ASTM C 78-84 allows for failure outside the load points at an average distance k from the adjacent support, by the following equation:

$$f_t = (3P.k)/(bd^3) \tag{2}$$

However, if failure arise at a section such that (L/3-k) > 0.05L, the result should not be accepted. In this research, the size of the beam was 150 × 150 × 400 mm, and the failure results outside the middle one-third of the beams were not accepted. It should be noted that in case of fiber reinforcement multiple cracking and crack formations out of the middle one-third of the beam may be observed.

A number of experiential equations have been suggested to relate tensile (f_t) and compressive (f_c) strengths. Most of them are of the type

$$f_t = a.\, f_c^{\,n} \tag{3}$$

The expressions by the ACI 318-05 (2005), ACI 318-89 (1992) and Iranian concrete building code (2009) are of interest

$$f_t = 0.75\sqrt{f_c}\ \text{(ACI-2005)} \tag{4}$$

$$f_t = 0.63\sqrt{f_c}\ \text{(ACI-1389)} \tag{5}$$

$$f_t = 0.6\sqrt{f_c}\ \text{(Iranian Code 2009)} \tag{6}$$

where f_c and f_t are in MPa and the compressive strength is on standard cylindrical specimens.

3. Self-compacting concrete

Self-compacting concrete (SCC) has been industrialized with the introduction of the new generation of superplasticizers to the market. This type of concrete can simply fill the molds without the need of using vibrators because of having advanced viscosity and workability properties (Okamura and Ouchi 1999, Jianxiong *et al*. 1999, Sari *et al*. 1999, Felekoglu 2003). High amount of mineral powder is a requirement for designing a suitable SCC. It is worth adding that Ho *et al*. (2002) investigated the use of quarry dust in SCC (Ho *et al*. 2002) Moreover, the influence of limestone powder on SCC is investigated recently (Ye *et al*. 2007) For this purpose, natural or artificial mineral additives such as limestone powder, fly ash, silica fume and blast furnace slag can be used too. In this study, the effects of replacing 10% of cement by silica fume on fresh and hardened properties of standard and self -compacting concrete have been investigated.

It is worth noting that wide researches on the workability of SCC have been made recently (Khayat *et al*. 2004, Assaad *et al*. 2004, Ding *et al*. 2008) Khayat *et al*. (2004) reported that the L-box, U-box, and J-ring tests can be used to assess the passing capability of SCC, the resistance to

Table 1 Mix proportions of concrete containing different water to cementitious materials ratios

Mix components	Concrete Mixes			
	W/*C*=0.35		*W*/*C*=0.45	
	OPC	SF10	OPC	SF10
Cement (kg/m^3)	500	450	400	360
Silica Fume	-	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
Superplasticizer (kg/m^3)	2 to 8	2 to 8	1.6 to 6.4	1.6 to 6.4

segregation and deformability (Khayat *et al*. 2004). The combination of slump flow and L-box tests is very appropriate for the quality control of on-site SCC (Wu *et al*. 2009) It is worth noting that Bui *et al*. have introduced a rapid testing method for segregation resistance of SCC (Bui *et al*. 2002)

Workability depends on a number of interrelating factors such as water content, aggregate to cement ratio, dosage and kind of superplasticizers, the fineness of cement, and aggregate type and grading. The main factors on SCC are the superplasticizer and water contents of the mixture because they increase the interparticle lubrication. 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 achieve maximum density with no segregation, or with optimum conditions for minimum voids, the influence of the aggregate grading and type has to 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.

4. Materials and mix proportions

This part of the paper presents the specifications of the mixes used for obtaining the workability, compressive strength and tensile strength of SCC. The cementitious materials used were ordinary Portland cement (OPC) and silica fume (SF). The strength grade of OPC was 42.5 MPa. Natural river sand and quartzite crushed gravel with a nominal maximum size of 14 mm were used as the aggregates. The control mixes were cast using OPC, while the other mixes were prepared 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 (Felekoglu *et al*. 2007). 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 polycarboxylate-based superplasticizer. It is worth noting that the effects of superplasticizers on the mechanical strength of mortars have been studied recently (Pei 2008). Also, the application of policarboxylic based superplasticizers in SCC is investigated recently (Felekoglu and Sarikahya 2008). The effects of chemical admixtures and mineral additives on SCC are studied too

Table 2 Workability of the concrete mixes

Concrete mixes		Superplasticizer dosage	Workability tests			
			Self-compacting concrete			Standard concrete
			Slump flow (mm)	V- funnel (second)	J-ring (mm)	Slump (mm)
W/C = 0.35	OPC	0.4%	460	---	---	238
		0.8%	730	6.5	12	---
		1.2%	785	5.4	6.3	---
		1.6%	825	4.8	4	---
	SF10	0.4%	410	---	---	215
		0.8%	550	8	14.5	---
		1.2%	670	6.2	8	---
		1.6%	780	5.3	5.5	---
W/C = 0.45	OPC	0.4%	410	---	---	216
		0.8%	730	4	14	---
		1.2%	810	3.6	6.5	---
		1.6%	830	3.3	4.2	---
	SF10	0.4%	320	---	---	185
		0.8%	530	4.8	17	---
		1.2%	760	4.2	12	---
		1.6%	770	3.8	11	---

(Sahmaran *et al*. 2006). It is worth noting that Su and Miao have introduced a method for the mix design of flowing concrete (Su and Miao 2003). The details of the mix proportions of the present research are given in Table 1. As a result of using different dosages of the superplasticizer, the fresh and hardened properties of the mixes were quite different.

5. Experimental results

In this part of the paper, the experimental results of self-compacting and standard concrete mixes on compressive strength, tensile strength and workability are discussed. The workability tests performed in this research were ordinary slump, slump flow and J-ring.

5.1 Workability of fresh concrete

There is not any satisfactory test, which can straightforwardly determine the workability of SCC. The following techniques give a measure of workability indirectly. Actuality, these methods have found worldwide approval because of their capability to distinguish the variations in the uniformity of a mix, and their simplicity.

To better assess the workability of SCC, both static and dynamic stability tests are usually necessary (Khayat *et al*. 2004, Assaad *et al*. 2004) Static stability handle the properties of SCC during the period from casting to initial set while dynamic stability deals with the properties of

SCC during the process of mixing, transportation, and casting. This research concentrates on dynamic stability tests as follows. It should be noted that computational modeling of concrete flow has been overviewed recently (Roussel 2007)

Slump flow test

Because the slump test is not appropriate for the analysis of the fluidity of SCC, the slump flow test is accepted. The testing tools consists of a steel plate with the dimensions of 900 × 900 mm and a normal slump cone., The time for SCC to extend to 500 mm in diameter, T500, and the final slump flow diameters in the two orthogonal directions can be measured with this apparatus. According to EFNARC (European Project Group 2002)for class 1 SCC, the slump flow diameter is T500 ≤ 2 s and 550-650 mm; for class 2 SCC T500 ≥ 2 s and the slump flow diameter is 600-750 mm; for class 3 SCC no specification for T500 is given and the slump flow diameter is 760-850 mm. It is worth noting that the slump flow test is recently modeled using ANN (Yeh 2007). The results of slump flow tests are presented in Table 2.

V-funnel test

The equipment for V-funnel test is expressed by Wu *et al*. (2009). The total time for SCC to flow through the V-funnel can be measured with this apparatus. The V-funnel flow test evaluates the fluidity of SCC to pass through a tighten area and to change its path. According to EFNARC (European Project Group 2002), Tv is smaller than 8 s for class 1 SCC, and Tv is 9-25 s for class 2 SCC. The measured values of Tv are shown in Table 2.

J-ring test

J-ring test involves the slump cone located inside a 300 mm diameter steel ring that is attached to vertical bars at suitable spacing (Druta 2003). The number of bars should be adjusted according to the maximum size of aggregates in the SCC mix. In this test, the variation of the height of the mix before and after the bars is measured. It is obvious that as the result of this test is lower, the workability of the mix is higher. The results of J-ring tests can be observed in Table 2.

Effect of silica fume on workability

As described earlier, all of the results of workability tests on SCC are shown in Table 2. This table includes the results of the slump tests of the standard concrete mixes too. It can be observed that the standard mixes incorporating silica fume content tended to have lower workability. This finding is obvious in the self-compacting mixes as well. The reason for declining the workability of the mixes can be endorsed to the very fine particle size of silica fume that causes some of the superplasticizer being adsorbed on its surface (Khatri and Sirivivatnanon 1995). It is worth adding that mixes including silica fume were more cohesive, which is in agreement with the findings of Khatri and Sirivivatnanon (1995).

5.2 Compressive strength

For concrete stored in water, the development of compressive strength with age is shown in Table 3. It is clear that the compressive strength development of concrete mixtures containing different dosages of the utilized superplasticizer were quite different. According to Tables 2 and 3, it can be said that as the workability of the mixes improved, the compressive strength of the SCC mixes decreased. This may be because of wider spread of the air-voids in the mixtures as a result of higher dosages of the superplasticizer. Moreover, 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 too. It is clear that the effects of silica fume and the dosage of the superplasticizer were higher on changing the compressive strength when the w/c ratio was lower.

Table 3 Development of compressive strength with age

Concrete Mixes		Superplasticizer Dosage	Compressive strength (MPa)	
			7 Days	28 Days
W/*C*=0.35	OPC	0.4%	44	61
		0.8%	40	58
		1.2%	39	58
		1.6%	35	56
	SF10	0.4%	46	69
		0.8%	42	62
		1.2%	40	60
		1.6%	38	58
W/*C*=0.45	OPC	0.4%	32	47
		0.8%	30	42
		1.2%	30	40
		1.6%	27	37
	SF10	0.4%	34	48
		0.8%	31	45
		1.2%	30	46
		1.6%	28	41

Table 4 Development of tensile strength with age

Concrete mixes		Superplasticizer dosage	Tensile strength (MPa)		
			7 Days	14 Days	28 Days
W/*C* = 0.35	OPC	0.4%	4.19	5.03	5.14
		0.8%	3.87	4.77	5.05
		1.2%	3.79	4.75	5.00
		1.6%	3.47	4.43	4.87
	SF10	0.4%	4.30	5.14	5.47
		0.8%	4.02	4.89	5.18
		1.2%	3.87	4.79	5.10
		1.6%	3.74	4.72	5.05
W/*C* = 0.45	OPC	0.4%	3.3	3.93	4.36
		0.8%	3.24	3.69	3.96
		1.2%	3.26	3.68	3.86
		1.6%	3.19	3.46	3.67
	SF10	0.4%	3.4	4.26	4.22
		0.8%	3.27	3.73	4.22
		1.2%	3.24	3.76	4.27
		1.6%	3.19	3.58	3.91

5.3 Tensile strength

For concrete stored in water, the development of tensile strength with age is shown in Table 4. It is clear that the tensile strength development of concrete mixtures containing different dosages of the superplasticizer were not constant. According to Tables 3 and 4, there was a logical relation between the compressive and tensile strengths of the mixes. Table 5 shows the results of the American, Canadian and Iranian prediction equations for anticipating the tensile strengths of the mixes from their compressive strengths. It is worth noting that the compressive strength of cylindrical specimens should be substituted in these equations. Because 100 mm cube specimens were utilized to measure the compressive strength, the factors suggested by the Iranian concrete building code 2009 is utilized for estimating the compressive strength of cylindrical specimens of 150 × 300 mm height. According to this standard, the factor of 0.95 is used for finding the equivalent compressive strength of 150 mm cubes from 100mm cubes. Afterwards, Table 6 is utilized for estimating the strengths of 150 × 300 mm cylinders from 150 mm cubes. It is worth noting that the effects of shape and size of specimens on the compressive strength high strength concrete have been studied recently (Del Viso 2008) In fact, Table 5 shows that none of the presented equations is exact enough for anticipating the tensile strengths of the mixes; therefore, it is decided to use ANN for this purpose.

Table 5 Prediction of 28-day tensile strength of concrete

Concrete mixes		Superplasticizer dosage	Tensile strength (MPa) Test result	Eq. (4) (ACI-05)	Eq. (5) (ACI-89)	Eq. (6) (Iranian)
W/*C* = 0.35	OPC	0.4%	5.14	5.45	4.58	4.36
		0.8%	5.05	5.32	4.47	4.25
		1.2%	5.00	5.32	4.47	4.25
		1.6%	4.87	5.25	4.41	4.20
	SF10	0.4%	5.47	5.80	4.90	4.64
		0.8%	5.18	5.50	4.62	4.40
		1.2%	5.10	5.40	4.54	4.32
		1.6%	5.05	5.32	4.47	4.25
W/*C* = 0.45	OPC	0.4%	4.36	4.72	4.00	3.77
		0.8%	3.96	4.44	3.73	3.55
		1.2%	3.86	4.34	3.64	3.50
		1.6%	3.67	4.17	3.50	3.34
	SF10	0.4%	4.22	4.52	3.79	3.61
		0.8%	4.22	4.62	3.88	3.70
		1.2%	4.27	4.67	3.92	3.74
		1.6%	3.91	4.39	3.70	3.51

Table 6 Comparison of strength of cubes and cylinders

Compressive strength of cube specimens (MPa)	≤ 25	30	35	40	45	50	55
Cylinder/cube strength ratio	0.8	0.833	0.857	0.875	0.889	0.9	0.909
Compressive strength of cylinder specimens (MPa)	According to the ratio	25	30	35	40	45	50

6. Artificial neural networks

Artificial neural networks (ANN) can be trained to find the input-output mappings of complex problems. The mappings are learned, but not definite. The learning procedure is applied to establish appropriate interconnection weights, and the network is trained to suitably connect the inputs with their equivalent outputs. The fundamental policy for introducing a neural network model of material behaviors is to train the network on a series of experimental results on a material. If the results include appropriate information about the material behaviors, the trained neural network will have adequate quality for predicting the necessary information about the

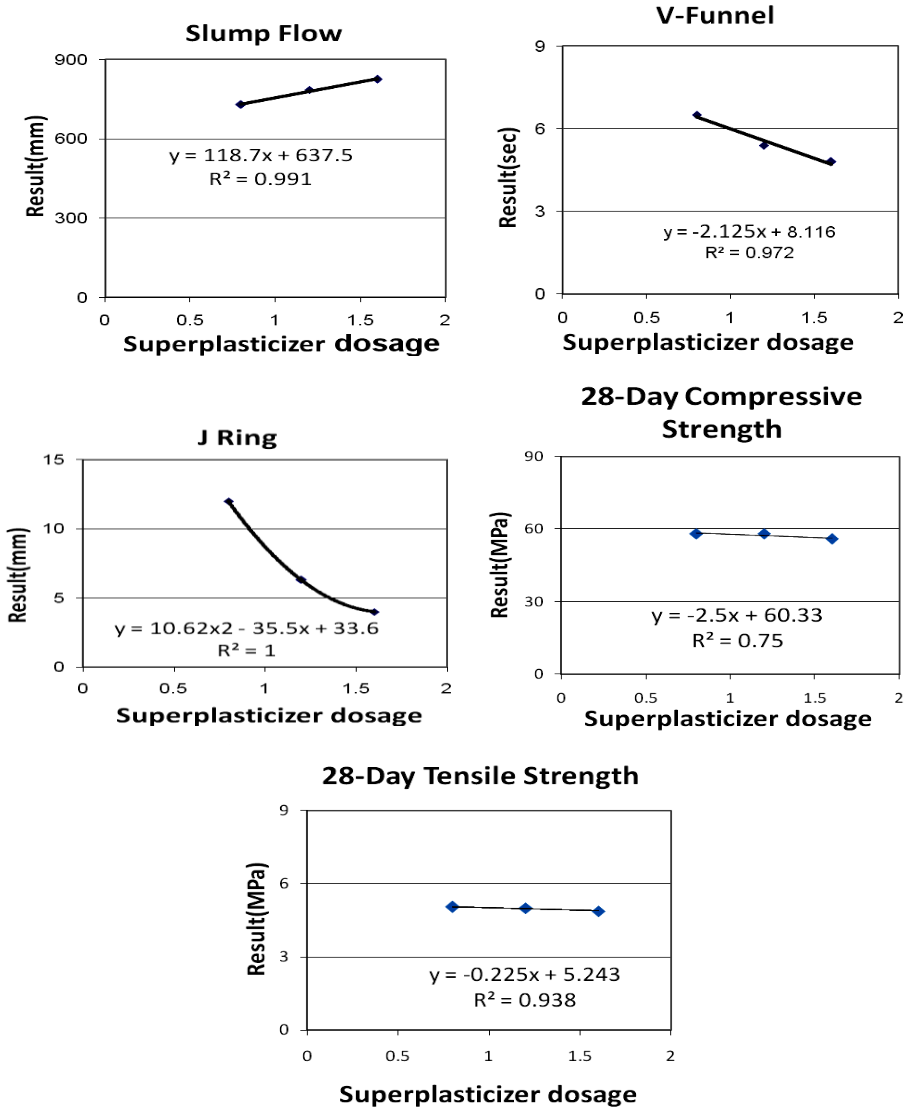

Fig. 1 Test results versus superplasticizer dosage of concrete mix one (*W*/*C* = 0.35, OPC)

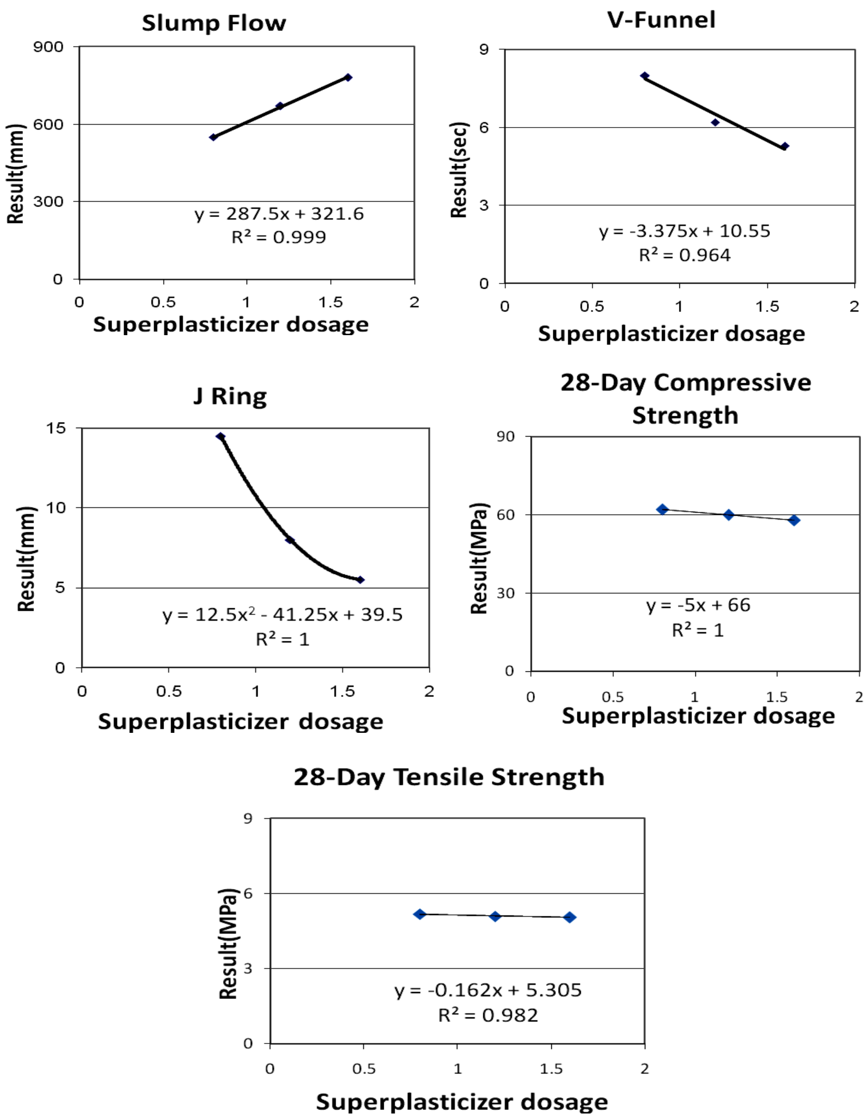

Fig. 2 Test results versus superplasticizer dosage of concrete mix two (W/C = 0.35, SF10)

material. This trained network is able to reproduce the experimental results it was trained on. Also the trained network should be capable of approximating the results of other experiments through its generalization ability (Ghaboussi 1991).

The majority of researchers that used ANN to model material behaviors are the ones who have utilized back-propagation networks (BPN) for minimizing the error coefficients. The BPN learns the material behaviors by balancing the output of each input pattern with the target output of thatpattern. Then, the error coefficient and propagating an error function backward through the net should be calculated. The basic rules of back-propagation algorithm is covered extensively (Rumelhart *et al*. 1986, Welstead 1994).

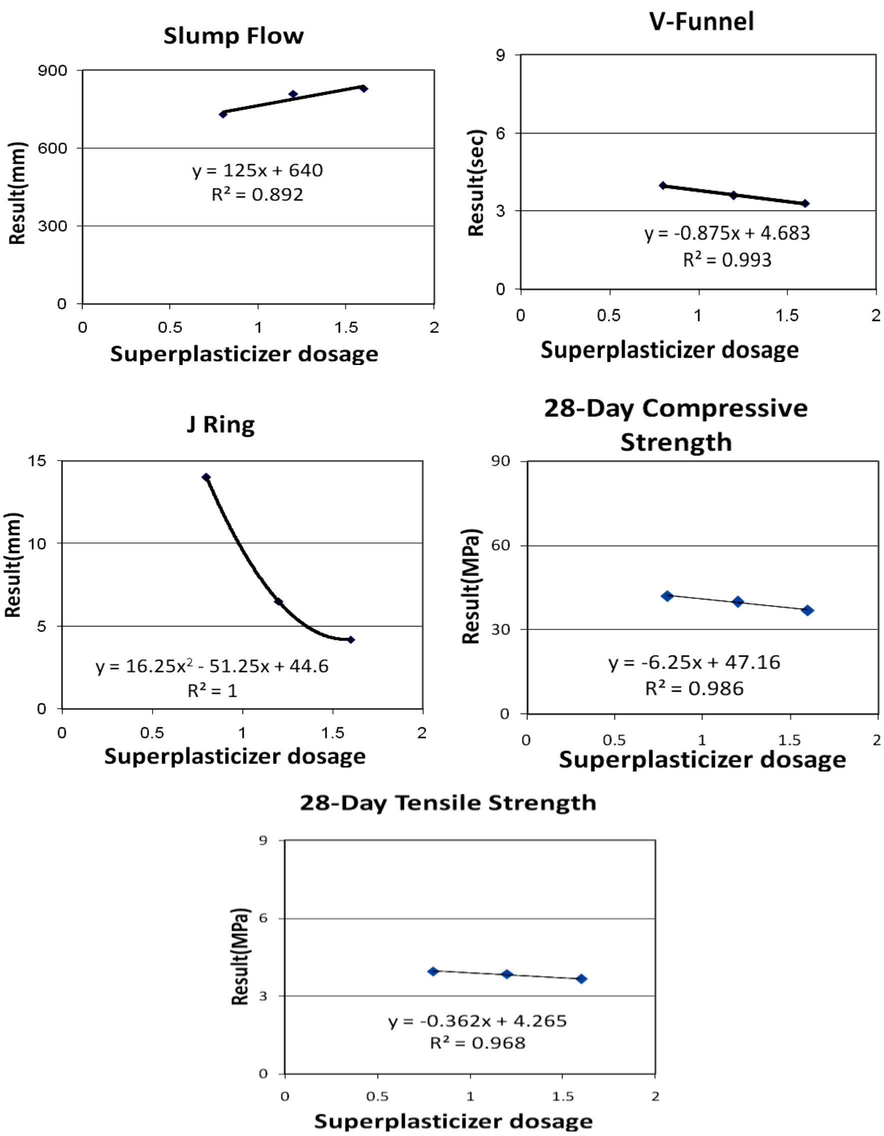

Fig. 3 Test results versus superplasticizer dosage of concrete mix three (W/C = 0.45, OPC)

6.1 Data sets

Because superplasticizers with different chemical compositions have various effects on the workability of the mixtures, the data for modeling the workability of SCC were gathered using the same polycarboxylate-based superplasticizer in all the mixes. 16 mixtures were studied in this research and 12 of them, which were SCC, were used to make the workability models. Table 1 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

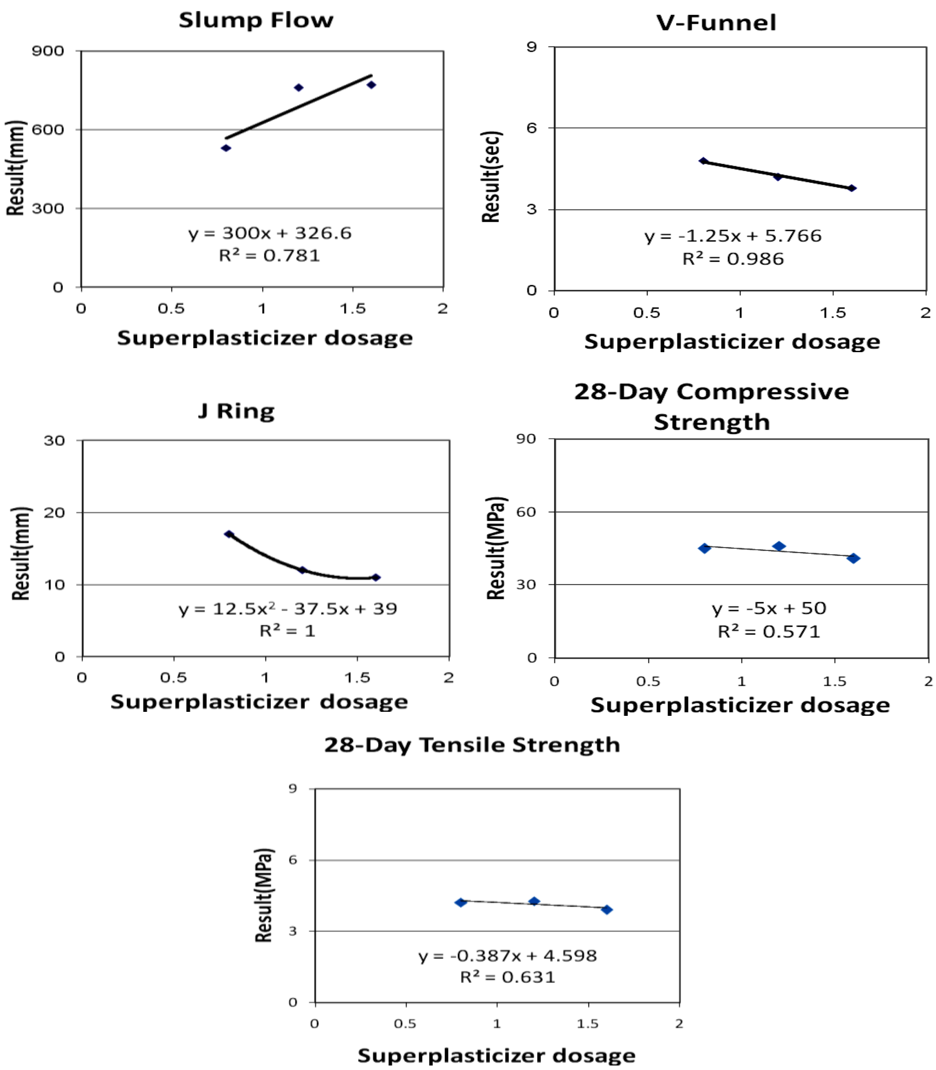

Fig. 4 Test results versus superplasticizer dosage of concrete mix four (*W*/*C*=0.45, SF10)

for data generations can be seen in Figs. 1 to 4. Finally, the 12 experimental data were utilized for testing the exactness of the trained networks.

According to Tables 7 and 8, 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.

6.2 Modeling the tensile strength 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 four units in the input layer, which were the results of slump flow, V-funnel, J-ring and 28-day compressive strength tests, and one unit in the output layer, which was the result of rupture modulus test. 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 14; 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 = 300. To

Table 7 Input data gathered from the lab for testing the ANN

Concrete mix		Superplasticizer dosage	Input data			
			28-Day compressive strength (MPa)	Slump flow (mm)	V-funnel (sec)	J-ring (mm)
W/*C* = 0.35	OPC (mix 1)	0.8%	730	730	6.5	12
		1.2%	785	785	5.4	6.3
		1.6%	825	825	4.8	4
	SF10 (mix 2)	0.8%	550	550	8	14.5
		1.2%	670	670	6.2	8
		1.6%	780	780	5.3	5.5
W/*C* = 0.45	OPC (mix 3)	0.8%	730	730	4	14
		1.2%	810	810	3.6	6.5
		1.6%	830	830	3.3	4.2
	SF10 (mix 4)	0.8%	530	530	4.8	17
		1.2%	760	760	4.2	12
		1.6%	770	770	3.8	11

Table 8 Output data gathered from the lab for testing the ANN

Concrete mix		Superplasticizer dosage, %	Output data
			28-Day tensile strength (MPa)
W/*C* = 0.35	OPC (mix 1)	0.8%	5.05
		1.2%	5.00
		1.6%	4.87
	SF10 (mix 2)	0.8%	5.18
		1.2%	5.10
		1.6%	5.05
W/*C* = 0.45	OPC (mix 3)	0.8%	3.96
		1.2%	3.86
		1.6%	3.67
	SF10 (mix 4)	0.8%	4.22
		1.2%	4.27
		1.6%	3.91

Table 9 Average e value after 10 repetitions of mix one (W/C = 0.35, OPC)

Number of hidden units	*e* value
3	0.02289
4	0.02094
5	0.00983
6	0.009245
7	0.010000
8	0.013359
9	0.009854
10	0.024333
11	0.022670
12	0.019710
13	0.018428
14	0.019770

Table 10 Comparing the experimental and estimated values of 28-day tensile strength test using newff networks

Concrete mixes		Superplasticizer dosage	28-day tensile strength (MPa)	
			Experimental result	Estimated result
W/C =0.35	OPC (mix 1)	0.8%	5.05	5.033
		1.2%	5.00	5.026
		1.6%	4.87	4.882
	SF10 (mix 2)	0.8%	5.18	5.169
		1.2%	5.10	5.121
		1.6%	5.05	5.045
W/C =0.45	OPC (mix 3)	0.8%	3.96	3.987
		1.2%	3.86	3.858
		1.6%	3.67	3.681
	SF10 (mix 4)	0.8%	4.22	4.243
		1.2%	4.27	4.228
		1.6%	3.91	3.933

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

Concrete Mixes		*mse* value	
		newff network	newrb network
W/C = 0.35	OPC (mix 1)	0.000372	0.000523
	SF10 (mix 2)	0.000199	0.000353
W/C = 0.45	OPC (mix 3)	0.000281	0.002100
	SF10 (mix 4)	0.000944	0.013300

Table 12 Radius values of newrb networks in different mixes

Concrete Mixes		Radius
W/C = 0.35	OPC (mix 1)	2.98
	SF10 (mix 2)	3.64
W/C = 0.45	OPC (mix 3)	2.79
	SF10 (mix 4)	3.41

choose the number of hidden neurons, the value of error coefficient (e), which is presented in Eq. 7, is utilized.

$$e = \Sigma\ [(\text{target } (i) - \text{estimate } (i)]^2 \tag{7}$$

where *target(i)* and *estimate(i)* are the experimental and the estimated values in i^{th} event respectively. In fact, Table 9 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. Table 10 shows the exactness of the ANN in predicting the rupture modulus test results respectively. It is clear that ANN models are quite successful in predicting the rupture modulus results from the other tests. The mean square error coefficients (*mse*) of each mix, which is presented in Eq. (8), can be seen in Table 11.

$$mse = 1/n.\Sigma[(\text{target}(i)\text{-estimate}(i)]^2 \tag{8}$$

where n is the number of tests or estimations.

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. 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 rupture modulus test results in most circumstances; however, according to this table, the newrb network could not predict the results of rupture modulus tests with acceptable exactness in mix four. 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 rupture modulus of SCC in some circumstances.

7. Conclusions

From the results presented in this paper, using concrete mixes containing different dosages of a kind of polycarboxylate-based superplasticizer, the main conclusions are:

• In the mixes containing constant dosage of superplasticizer, the ones containing silica fume had lower workability.

• For improving the compressive strength of the mixes without changing the mix design, it is necessary to reduce the dosage of polycarboxylate-based superplasticizer as much as possible.

• Moreover, the utilization of air-detraining agents with polycaboxylate-based superplasticizers is advised in order to prevent strength loss due to high admixture dosage.

• Silica fume increased the compressive strength of the mixes.

• Multi layer perceptron networks could predict the rupture modulus test results from the flump flow, J-ring, V-funnel and 28-day compressive strength test results in all circumstances.

•Radial bases networks were not exact enough for predicting the rupture modulus test results from the flump flow, J-ring, V-funnel and 28-day compressive strength test results in some circumstances.

•Although radial basis networks are more users friendly and they converge to the final solutions faster than multi layer perceptron networks, they can not solve the problems in some circumstances, and it is necessary to utilize multi layer perceptron method in these conditions

References

ACI Committee 318-05 (2005), *Building code requirements for structural concrete*, American Concrete Institute.

ACI Committee 318-89 (1992), *Building code requirements for reinforced concrete*, American Concrete Institute.

Arias, A., Forquin, P., Zaera, R. and Navarro, C. (2008), "Relationship between static bending and compressive behaviour of particle-reinforced cement composites", *Compos. Part B*, **39**(7-8), 1205-1215.

Assaad, J., Khayat, K.H. and Daczko, J. (2004), "Evaluation of static stability of self-consolidating concrete", *ACI ACI Mater. J.*, **101**(3), 207-215.

Bogas, J.A. and Gomes, A. (2008), "Analysis of the CFRP flexural strengthening reinforcement approaches proposed in Fib bulletin 14", *Construct. Build Mater.*, **22**(10), 2130-2140.

Bui, V.K., Montgomery, D., Hinczak, I. and Turner, K. (2002), "Rapid testing method for segregation resistance of self-compacting concrete", *Cement Concrete Res.*, **32**(9), 1489-1496.

Campione, G. and Mangiavillano, M.L. (2008), "Fibrous reinforced concrete beams in flexure: experimental investigation, analytical modeling and design considerations", *Eng. Struct.*, **30**(11), 2970-2980.

Del Viso, J.R., Carmona, J.R. and Ruiz, G. (2008), "Shape and size effects on the compressive strength of high-strength concrete", *Cement Concrete Res.*, **38**(3), 386-395.

Ding, Y.N., Liu, S.G., Zhang, Y. and Thomas, A. (2008), "The investigation on the workability of fibre cocktail reinforced self-compacting high performance concrete", *Construct. Build Mater.*, **22**(7), 1462-1470.

Druta, C. (2003), "Tensile strength and bonding characteristics of self-compacting concrete", M.Sc. Thesis in Engineering Science, Polytechnic University, Bucharest.

European Project Group (2002), *Specification and guidelines for self-compacting concrete*, United Kingdom, EFNARC.

Felekoglu, B. (2003), "Investigation on mechanical and physical properties of SCC", M.Sc. Thesis in Civil Engineering, Dokus Eylul University, Izmir.

Felekoglu, B., Turkel, S. and Baradan, B. (2008), "Effect of chemical structure of polycarboxylate-based superplasticizers on workability retention of self-compacting concrete", *Construct. Building Mater.*, **22**(9), 1792-1980.

Gravina, R.J. and Smith, S.T. (2008), "Flexural behaviour of indeterminate concrete beams reinforced with FRP bars", *Eng. Struct.*, **30**(9), 2370-2380.

Ghaboussi, J., Garrett, J.H. and Wu, X. (1991), "Knowledge-based modeling of material behaviour with neural networks", *J. Eng. Mech.*, **117**(1), 129-134.

Ho, D.W.S., Sheinn, A.M.M., Ng, C.C. and Tam, C.T. (2002), "The use of quarry dust for SCC applications", *Cement Concrete Res.*, **32**(4), 505-511.

Iranian National Building Code (2009), *Design and Construction of Reinforced Concrete Buildings*.

Jianxiong, C., Xincheng, P. and Yubin, H. (1999), "A study of self-compacting HPC with superfine sand and pozzolanic additives", *Proceedings of the First International RILEM Symposioum*, 549-560.

Kim, D.J., Naaman, A.E. and El-Tawil S. (2008), "Comparative flexural behaviour of four fiber reinforced cementitious composites", *Cement Concrete Compos.*, **30**(10), 917-928.

Khatri, R.P. and Sirivivatnanon, V. (1995), "Effect of different supplementary cementitious materials on mechanical properties of high performance concrete", *Cement Concrete Res*., **2**(1), 209-220.

Khayat, K.H., Assaad, J. and Daczko J. (2004), "Comparison of field-oriented test methods to assess dynamic stability of self-consolidating concrete", *ACI Mater*. *J*., **101**(2), 168-176.

Neville, A.M. and Brooks, J.J. (1990), *Concrete Technology*, Longman, United Kingdom.

Okamura, H. and Ouchi, M. (1999), "Self-compacting concrete: development, present use and future", *Proceedings of the First International RILEM Symposioum*, 3-14.

Pei, M., Wang, Z., Li, W., Zhang, J., Pan, Q. and Qin, X. (2008), "The properties of cementitious materials superplasticized with two superplasticizers based on aminosulfonate-phenol-formaldehyde", *Construct*. *Build Mater*., **22**, 2382-2385.

Pham, H.B. and Al-Mahaidi, R. (2008), "Reliability analysis of bridge beams retrofitted with fibre reinforced polymers", *Composite Structures*, **82**, 177-184.

Roussel, N., Geiker, M.R., Dufour, F., Thrane, L.N. and Szabo, P. (2007), "Computational modeling of flow concrete: General overview", *Cement Concrete Res*., **37**(9), 1298-1307.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986), "Learning internal representation by error propagation", Eds. Rumelhant, D.E., McClelland, J.L., *Parallel Distributed Processing*, Vol. 1, MIT Press.

Sahmaran, M., Christianto, H.A. and Yaman, I.O. (2006), "The effect of chemical admixtures and mineral additives on the properties of self compacting mortars", *Cement Concrete Compos*., **28**(5), 432-440.

Sari, M., Prat, E. and Labastire, J.F. (1999), "High strength self-compacting concrete-original solutions associating organic and inorganic admixtures", *Cement Concrete Res*., **29**(6), 813-818.

Soranakom, C. and Mobasher, B. (2008), "Correlation of tensile and flexural responses of strain softening and strain hardening cement composites", *Cement Concrete Compos*., **30**(6), 465-477.

Su, N. and Miao, B. (2003), "A new method for mix design of medium strength flowing concrete with low cement content", *Cement Concrete Compos*., **25**(2), 215-222.

Vasconcelos, G., Lourenco, P.B., Alves, C.A.S. and Pamplona, J. (2008). "Experimental characterization of the tensile behaviour of granites", *Int*. *J*. *Rock Mech*. *Mining Sci*., **45**(2), 268-277.

Welstead, S.T. (1994), *Neural network and fussy logic applications in C/C++*, John Wiley and Sons, New York, USA.

Wu, Z., Zhang, Y., Zheng, J. and Ding, Y. (2009), "An experimental study on the workability of self-compacting lightweight concrete", *Construct*. *Build Mater*., **23**(5), 2087-2092.

Ye, G., Liu, X., Schutter, G.D., Poppe, A.M. and Taerwe, L. (2007), "Influence of limestone powder used as filler in SCC on hydration and microstructure of cement pastes", *Cement Concrete Compos*., **29**(2), 94-102.

Yeh, I.C. (2007), "Modeling slump flow of concrete using second-order regressions and artificial neural networks", *Cement Concrete Compos*., **29**(6), 474-480.

Zi, G., Oh, H. and Park, S.K. (2008), "A novel indirect tensile method to measure the biaxial tensile strength of concretes and other quasibrittle materials", *Cement Concrete Res*., **38**(6), 751-756.

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