

# Modeling the effects of additives on rheological properties of fresh self-consolidating cement paste using artificial neural network

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**Abstract.** The main purpose of this study includes investigation of the rheological properties of fresh self consolidating cement paste containing chemical and mineral additives using Artificial Neural Network (ANN) model. In order to develop the model, 200 different mixes are cast in the laboratory as a part of an extensive experimental research program. The data used in the ANN model are arranged in a format of fourteen input parameters covering water-binder ratio, four different mineral additives (calcium carbonate, metakaolin, silica fume, and limestone), five different superplasticizers based on the poly carboxylate and naphthalene and four different Viscosity Modified Admixtures (VMAs). Two common output parameters including the mini slump value and flow cone time are chosen for measuring the rheological properties of fresh self consolidating cement paste. Having validated the model, the influence of effective parameters on the rheological properties of fresh self consolidating cement paste is investigated based on the ANN model outputs. The output results of the model are then compared with the results of previous studies performed by other researchers. Ultimately, the analysis of the model outputs determines the optimal percentage of additives which has a strong influence on the rheological properties of fresh self consolidating cement paste. The proposed ANN model shows that metakaolin and silica fume affect the rheological properties in the same manner. In addition, for providing the suitable rheological properties, the ANN model introduces the optimal percentage of metakaolin, silica fume, calcium carbonate and limestone as 15, 15, 20 and 20% by cement weight, respectively.

**Keywords:** self consolidating cement paste; rheological properties; ANN; additive; flow behavior.

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## 1. Introduction

Self Compacting Concrete (SCC) is a new kind of high performance concrete with distinctive deformability (Okamura and Ouchi 2003). SCC has three abilities, which characterize it from the other concretes, including flowing and passing ability, filling ability and segregation resistance (EFNARC 2005). Therefore, it is a flowing concrete without segregation and bleeding, capable of filling spaces in dense reinforcement or inaccessible voids without hindrance or blockage (Prasad *et al.* 2008).

In order to achieve these unique characteristics for SCC fresh state, a comprehensive investigation on fresh self consolidating cement paste should be conducted. It is important to understand the fresh

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properties of cement paste in order to evaluate the flow behavior of SCC. It has been known that the rheological properties and consistency of cement paste play an important role on controlling the rheology and consistency of concrete (Lachemi *et al.* 2004). Also, low time consuming and easy of handling make it reasonable to perform tests on cement paste instead of self compacting concrete. Furthermore, some reliable equations have been developed to relate the cement paste properties to the fresh rheology of self compacting concrete (Lachemi *et al.* 2007). Therefore, it is required to carry out a series of experiments for analyzing the rheological properties of self consolidating cement paste such as yield stress and plastic viscosity. It should be noted here that in this investigation these properties were indirectly measured through the mini slump and slump cone tests. The rheological parameters, i.e. yield stress and plastic viscosity, can be physically interpreted as the stress needed to be applied to a material to initiate flow and the resistance of a fluid to move which is the slope of the shear stress-shear rate plot, respectively.

In the conventional material modeling process, different statistical tools such as regression analysis are utilized for developing models. In the last two decades, the different modeling methods based on Artificial Neural Network (ANN) approach have become popular and have been used by many researchers in a huge variety of engineering applications (Topcu and Saridemir 2008). Basically, the processing elements of a neural network are quite similar to the neurons in the brain, which consist of many simple computational elements arranged in layers (Yeh 1998). The ANN is able to solve very complex problems with the help of interconnected computing elements (Prasad *et al.* 2008). It is also considered as a powerful data analysis tool that is able to capture and represent complex input/output relationships. The real power of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships from the data being modeled (Perlovsky 2000). Traditional linear models are simply inadequate when it comes to modeling data containing non-linear characteristics.

The review of the previous accomplished researches reveals that application of the ANN models in cementitious material has been restricted in the hardened properties of concrete or cement paste such as compressive strength (Saridemir 2009, Zarandi *et al.* 2007, Altun *et al.* 2007, Pala *et al.* 2007, Tang *et al.* 2007, Hossain *et al.* 2006, Tang 2006). The rheological properties of fresh concrete, however, have not been deeply addressed using the ANN method. There are few published papers investigating the workability of traditional concrete using this method (Yeh 2008).

The main objective of this study includes presenting a methodology for predicting the rheological properties of fresh self consolidating cement paste as well as investigation on the performance of four different types of mineral additives (silica fume, metakaolin, calcium carbonate, and limestone powder) and different types of superplasticizers and VMAs based on the results of two experimental tests i.e., the mini slump and flow cone. The rheological properties are modeled using the ANN method. The proposed ANN model for self consolidating cement paste is expected to appraise the influence of water/Binder ratio on the fresh cement paste characteristics and determine the optimal percentage of additives needed to obtain cement paste with the proper rheological properties. Therefore, in the first part of this paper, experimental tests have been performed to evaluate the effects of various additives on rheological properties of cement paste. These data are used to validate the ANN model. In the next part, the rheological properties of several cement paste mixes which have not been cast are predicted using the proposed ANN model. Different steps of this study are shown in Fig. 1.

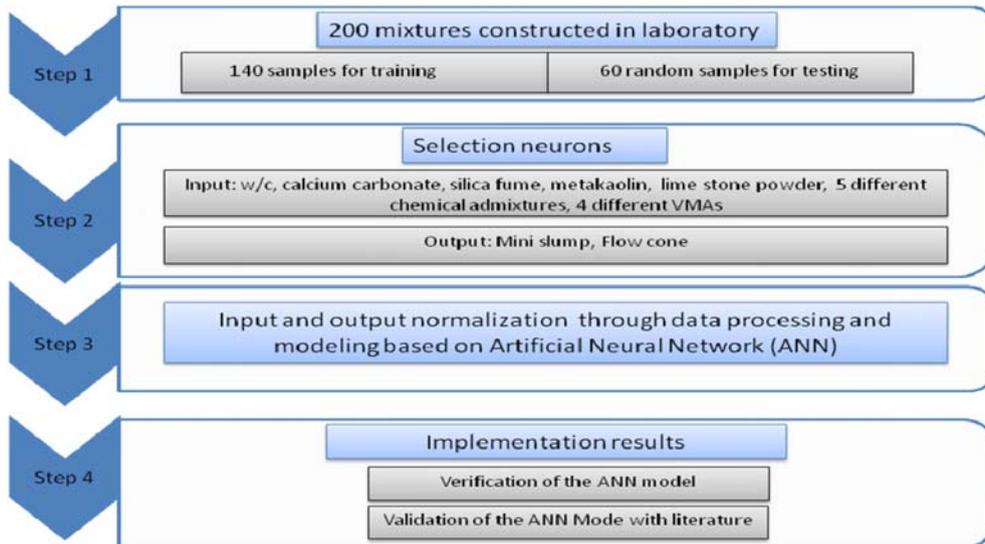


Fig. 1 Steps of this study

## 2. Theoretical aspect

### 2.1 Rheological properties of self consolidating cement paste

SCC is an emerging technology that enables the casting of concrete without any mechanical compaction which would be required when traditional concrete is used (Sonebi and Cevik 2009). Since SCC has been defined as a concrete exhibiting high deformability and excellent resistance to segregation, it has gained wide applications especially in the case of difficult casting conditions such as heavily congested reinforced sections.

Fresh SCC should be stable to ensure the homogeneity of mechanical properties. However, several problems like bleeding, blockage, settlement, or segregation can occur, sometimes simultaneously on construction sites (Cussigh *et al.* 2003). Avoiding segregation is a matter of cement paste rheology and granular characteristics. The cement paste has to be sufficiently fluid with appropriate yield stress to ensure the fluidity of concrete itself and sufficiently “viscous” to maintain the coarse aggregates stable (Schwartzentruber *et al.* 2006). So, the relation between stress and strain is defined as the main behavior of rheological researches. Many qualitative and quantitative mathematical approaches have been presented by several researchers in order to define properties of flow curve of cement paste. All of the quantitative mathematical approaches (except the Newtonian liquid) employ at least two parameters to describe the flow behavior.

### 2.2 Artificial neural network

A neural network model is a computer model, whose architecture essentially mimics the learning capability of the human brain (Yeh 2007). It can also exhibit a surprising number of human brains characteristics, e.g. learning from experience and generalizing from previous examples to solve new problems. ANN can provide meaningful answers even when the data to be processed include errors

or are incomplete, and also can process information extremely rapidly when applied to solve real world problems (Lippman 1988, Rafiq *et al.* 2001). The neural network based modeling process involves five main aspects: (a) data acquisition, analysis and problem representation; (b) architecture determination; (c) learning process determination; (d) training of the networks; and (e) testing of the trained network for generalization evaluation (Saridemir 2009, Wu and Lim 1993). The error incurred during the learning process can be expressed as mean square error (MSE) or root-mean-squared (RMS) as given in the Eqs. (1) and (2).

$$\text{MSE} = \frac{1}{p} \sum_j (O_j - t_j)^2 \quad (1)$$

$$\text{RMS} = \sqrt{\left(\frac{1}{p}\right) \times \sum_j |t_j - O_j|^2} \quad (2)$$

In addition, the absolute fraction of variance ( $R^2$ ), and sum of the squares error (SSE) can be calculated by utilizing the Eqs. (3) and (4), respectively.

$$R^2 = 1 - \left( \frac{\sum_j (t_j - O_j)^2}{\sum_j (O_j)^2} \right) \quad (3)$$

$$\text{SSE} = \sum_j (O_j - t_j)^2 \quad (4)$$

where  $t_j$  represents target value of node  $j$ ,  $O_j$  is the output value of node  $j$ , and  $p$  denotes patterns.

The multi-layer perceptron (MLP), radial basis function network (RBFN), probabilistic neural network (PNN), cascade correlation neural network (Casacor), learning vector quantization (LVQ), and self-organizing feature map (SOM) are among the popular neural network architectures widely used. They differ in various aspects including the type of learning, node connection mechanism and training algorithm. The most common neural network model employed in the engineering fields is the multilayer perceptron (MLP). This type of neural network is known as a supervised network since it requires a desired output in order to be learned. The goal of this type of network is to create a model that correctly maps the inputs to the outputs using historical data, so that the model can later be used to predict the output when the desired output is unknown.

### 3. Experimental program

An extensive experimental study was performed at the University of Tehran to determine the behavior of fresh self consolidating cement paste. The additives and ingredients' type in the mixed proportion of self consolidating cement paste plays an important role in modeling of the rheological properties. Hence, for designing the architecture of ANN, appropriate separation among self consolidating cement paste ingredients should be considered. Here, 14 input parameters including W/B ratio, mineral additives and superplasticizers content are used to propose the ANN model. The material properties, mixed proportions, and test methods are discussed in the next subsections.

Table 1 Chemical analysis of the cement and powders

Material	Chemical analysis (% mass)								
	SiO <sub>2</sub>	Al <sub>2</sub> O <sub>3</sub>	Fe <sub>2</sub> O <sub>3</sub>	CaO	MgO	SO <sub>3</sub>	K <sub>2</sub> O	Na <sub>2</sub> O	Ignition loss
Cement	23.4	5.1	3.15	60.4	3.45	1.95	0.36	0.65	1.4
Silica fume	98.78	0.27	0.52	0.2	-	-	0.01	0.1	0.07
Metakaolin	51.8	43.8	0.99	0.2	0.18	-	0.12	0.01	0.57
Calcium carbonate	1.36	0.10	0.2	50.96	2.6	-	0.4	0.11	44.4
Limestone	2.74	0.25	0.34	50.98	1.4	-	0.42	0.12	43

### 3.1 Material properties

The materials used in this study, are tried to be locally available. So, we used five different superplasticizers based on poly carbocsilate and naphthalene, four different mineral additives and four different VMAs. Poly carboxylate based and naphthalene based admixtures are conforming to ASTM C494. Cement, which corresponds to ASTM C594, is also used in all mixtures. Physical and chemical properties of the cement and powders used in the mixes are given in Table 1 while the characteristics of the powders are discussed below:

Silica fume consists of very fine vitreous particles with a surface area of 20,000 m<sup>2</sup>/kg with particles approximately 100 times smaller than the average cement particle (Emdadi *et al.* 2007). Specific gravity of silica fume given by the factory is 2.2 gr/cm<sup>3</sup>. Limestone powder is a sedimentary rock composed largely of the mineral calcite. Density of the powder used in the experiments is 2.6 gr/cm<sup>3</sup>. In this study, limestone powder passed from sieve #100 and remained on sieve #200. Thus, diameter of particles lies between 0.15 mm and 0.075 mm.

Calcium carbonate powder is a synthetic material with specific gravity of 2.8 gr/cm<sup>3</sup>, consisting of trigonal calcite crystals with cube-shaped particles or ortho-rhombic aragonite crystals with a needle-like structure (Emdadi *et al.* 2007). Metakaolin is a white pozzolan made by heating kaolin clay up to 600-800°C. It reacts rapidly with the calcium hydroxide in the cement paste (Bonakdar *et al.* 2005). According to the factory data sheet, the specific gravity and specific surface of metakaolin are 2.6 gr/cm<sup>3</sup> and 14 m<sup>2</sup>/g, respectively.

Densities of Viscorecte, Rheobuild, Glenium 51, ACR 303, Powerflow, VMA-BASE, VMA-FOS, VMA Stream2 and VMA structor480 are 1.09, 1.09, 1.08, 1.06, 1.09, 1.00, 1.03, 1.02 and 1.05, respectively.

### 3.2 Mixed proportion

All Mixtures were proportioned on the way to reach the defined rheological properties of self consolidating cement paste. The mixtures are made by four different mineral powders, e.g. calcium carbonate, limestone, metakaolin and silica fume with 10% to 30% of cement weight replacement, 5 different types of superplasticizers, with 0% through 2.5% of cement content, and 4 different kinds of VMA with 0% through 2% of cement content. Mini slump in terms of centimeters and flow cone in terms of second are separately measured. Therefore, fourteen input and two output variables as shown in Table 2 are considered in the ANN model. The Table also shows the minimum and maximum values of these parameters used in the experiments. It should be noted that these ranges

Table 2 Range of input-output parameters in databases (in percent by cement mass)

		Input parameters	Minimum	Maximum
	W/B	Water/Binder	0.15	0.75
Powders (%)	P <sub>1</sub>	Calcium carbonate	10	30
	P <sub>2</sub>	Metakaolin	10	30
	P <sub>3</sub>	Silica fume	10	30
	P <sub>4</sub>	Limestone	10	30
Superplasticizer (%)	SP <sub>1</sub>	Viscocrete	0	2.5
	SP <sub>2</sub>	Power flow	0	2.5
	SP <sub>3</sub>	Rheobuild 1100	0	2.5
	SP <sub>4</sub>	Glenium 51	0	2.5
	SP <sub>5</sub>	ACR 303	0	2.5
VMAs (%)	V <sub>1</sub>	VMA-BA	0	2
	V <sub>2</sub>	VMA-FOS	0	2
	V <sub>3</sub>	VMA-Stream2	0	2
	V <sub>4</sub>	VMA-Structor 480	0	2
		Output parameters	Minimum	Maximum
		Mini slump (cm)	0	30
		Flow cone (sec)	8	800=block

were precisely selected regarding to their extensive usage in the concrete industry.

### 3.3 Experimental tests

Different test methods are available in order to measure the rheological properties of fresh self consolidating cement paste. As it was mentioned earlier, in this research, mini slump and flow cone tests are chosen regarding to their worldwide acceptance and easy of application.

**Mini-slump test**, which was originally developed by Kantro (1980) and later modified by Zhor and Bremner (1998), measures the consistency of cement paste. The mini-slump cone is simply a small version of the slump cone. It has a bottom diameter of 38 mm, a top diameter of 19 mm, and a height of 57 mm. The cone is placed in the center of a square piece of glass on which the diagonals and medians are traced. The cone is lifted then the average spread of the paste, as measured along the two diagonals and two medians, is recorded (Eric *et al.* 2003). The mini slump test has been used to investigate the effect of admixtures on the yield stress of the paste. Generally speaking, increase in mini slump leads to reduction of yield stress of the paste (Roussel 2006).

**Flow cone test** (Scanlon 1994) is intended for measuring the flow properties of grout. The test is standardized in ASTM C939 and appropriate for use in both the field and the lab (Eric *et al.* 2003). To perform the test, grout is poured into the flow cone before the opening at the bottom of the cone is opened. Discharge time of the grout from the cone is accurately recorded as the output value of the flow cone test. In a general manner, higher flow time value shows higher plastic viscosity of the paste (Roussel 2005).

#### 4. Proposed neural network model

The basic strategy for developing a neural network model for material behavior includes training a neural network using the obtained results from experiments. If the experimental results contain the relevant information about the material behavior, the trained neural network will contain sufficient information about material behavior to qualify as a material model (Lee 2003). The ANN model developed in this study can be used to evaluate the rheological properties of self-consolidating cement paste.

In order to produce an effective ANN model, it is vital to properly train the network. The back propagation (BP) algorithm is used to train and construct the present ANN model and the hyperbolic tangent sigmoid transfer function is adopted. The tangent function is nonlinear and, therefore, the original data before training the network are normalized. The overall architecture of the proposed ANN is illustrated in Fig. 2. Herein, 200 cement paste mixtures are prepared in the laboratory. As mentioned before, 14 input variables including W/B ratio, mineral additives and

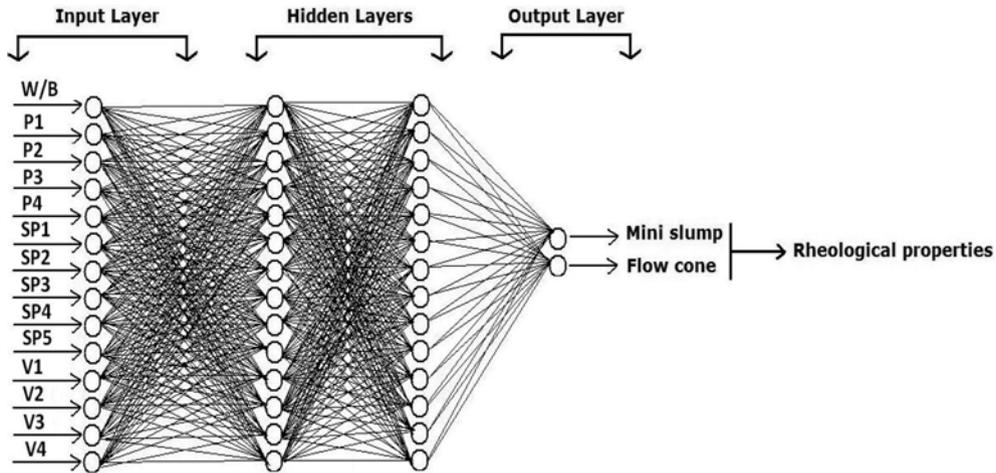


Fig. 2 Proposed ANN architecture

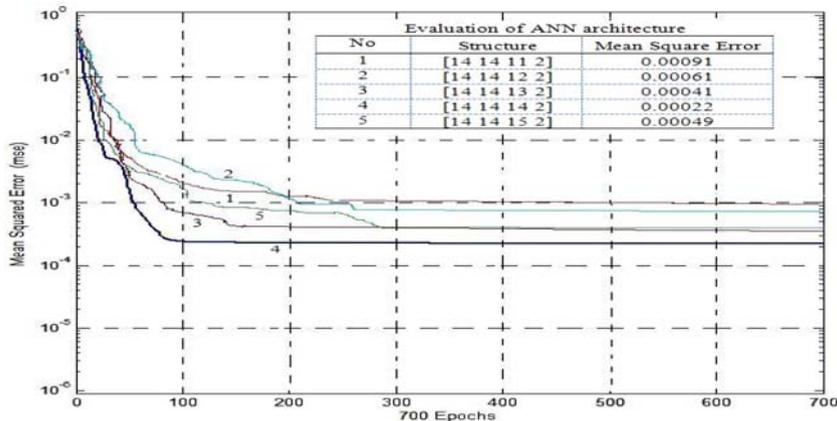


Fig. 3 Comparison of ANN architecture based on MSE

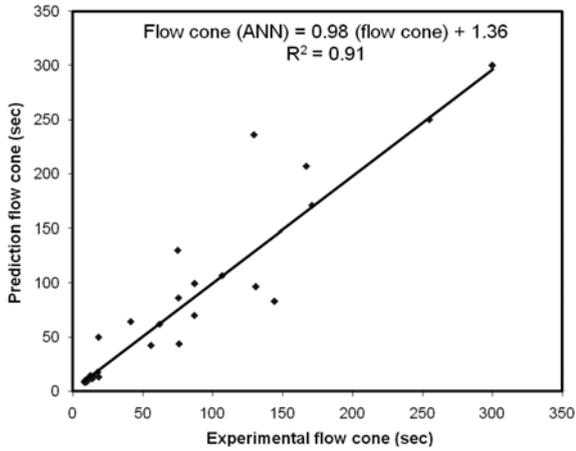


Fig. 4 Comparison of ANN results with respect to experimental data for the flow cone test

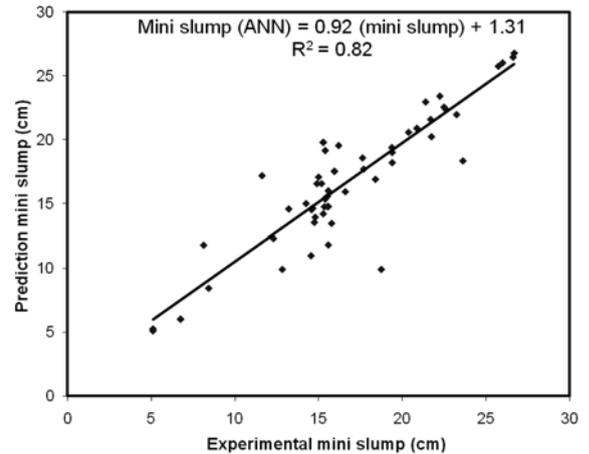


Fig. 5 Comparison of ANN results with respect to experimental data for the mini slump tests

superplasticizer and 2 different outputs i.e. mini slump and flow cone values are considered. In order to determine the best accurate structure, five different architectures [14-14-11-2 to 14-14-15-2] are considered where based on MSE criteria [14 14 14 2] structure is selected as the best accurate architecture. Fig. 3 presents the obtained result for each structure. To test the reliability of the proposed ANN model, the results of 60 mixtures are randomly selected as the test set, while the remaining 140 samples were used to train the network.

Here, the Matlab software is used as a tool to construct and train the supervised network. In training process of a supervised ANN, weights of the links between the neurons are adjusted to minimize output error. The numbers of the parameters used in the model are:

- Number of input layer units = 14
- Number of hidden layer = 2
- Number of output layer units = 2
- Learning cycle = 700

The parameters used in this figure are the same as the parameters described in Table 2.

The difference between the predicted value by the ANN model and the experimental data for the flow cone and mini slump tests are plotted in Figs. 4 and 5, respectively. Indeed, the obtained regression coefficient ( $R^2$ ) for the flow cone and mini slump tests (0.91 and 0.82) demonstrates that the developed ANN model can properly predict the rheological properties of self consolidating cement paste. It means that the learning process and generating the relationship between input variables and two output parameters were reasonably performed.

## 5. Implementation results

By feeding the various input parameters into the developed ANN model, the optimum percentages of the admixtures can be determined for achieving the appropriate mini slump value and flow cone time. Therefore, more mixes were virtually designed (no mixes have been cast in this section) to

gain the optimum percentage of the admixtures when the combination of powders, VMAs and superplasticizers are used. Notably, huge number of mixes can be designed due to the existence of large number of inputs (14). However, in this study the limited number of mixes has been selected and their results were compared to the results of other studies.

These new mix designs were divided into the three segments. Evaluating the influence of W/B ratio on the parameters indirectly related to the yield stress and viscosity of fresh self consolidating cement paste was the objective of the first segment. While the other two segments were designed to investigate the effect of the superplasticizer and VMA on results of the mini slump and flow cone testes. In each segment, the results were compared with the existing studies in the literature to be validated. It should be reminded that in all segments powder, VMA and superplasticizer were simultaneously used to assess the combination's effect of these materials on the fresh properties.

### 5.1 Segment I: Effect of W/B ratio

The mixtures, in this segment, were designed to investigate the effect of W/B ratio on the rheological properties of fresh self consolidating cement paste. W/B ratio changed between 30% to 60% and Viscocrete (SP1) was used in 1% of cement weight in all mixes. Limestone (LS) and silica fume (SF) were replaced by 10, 20 and 30 % of cement weight. In two different series, 0 and 1% of Stream 2 as VMA were also used to assess the effect of combination of materials on the rheology. Again, it should be noted that no experiment has been performed in the following

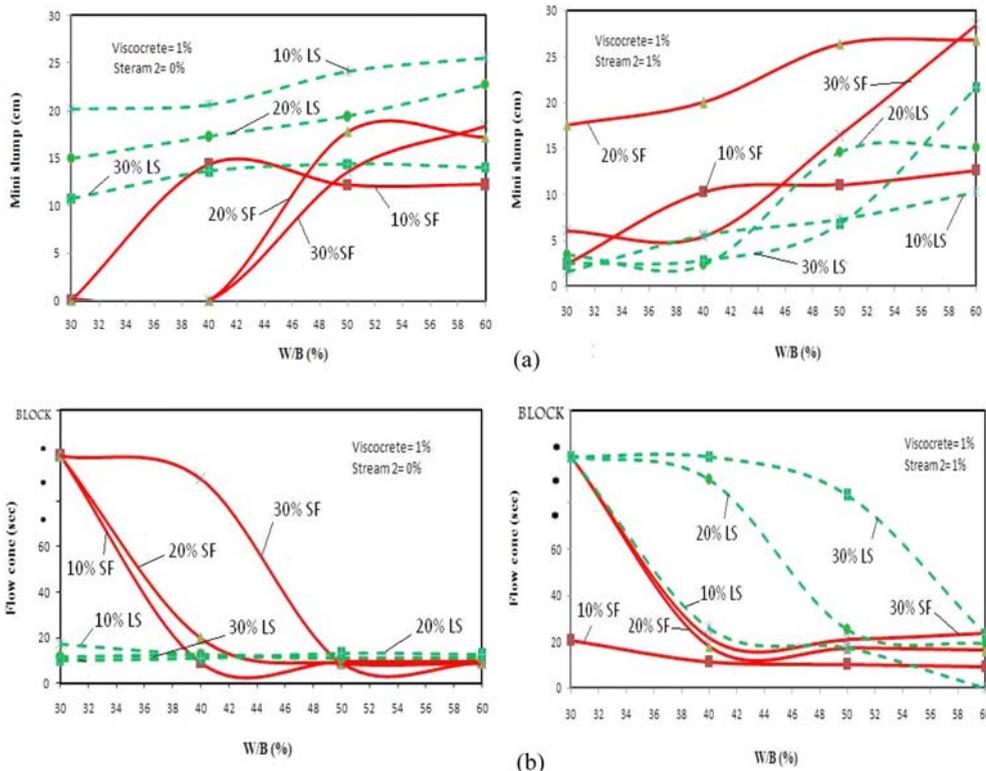


Fig. 6 Effect of W/B ratio on: (a) mini slump value and (b) flow cone time predicted by the ANN model

segments (I-III) and the results were obtained based on the developed ANN model.

As illustrated in Fig. 6, increase of W/B ratio increased the mini-slump value (Fig. 6(a)) while it reduced the flow time (Fig. 6(b)). These outcomes come from the ANN model were compatible with the experimental results reported by Libre *et al.* (2010), Emdadi *et al.* (2007) and Svermova *et al.* (2003). According to Emdadi *et al.* (2007), the mini slump value and flow time are highly sensitive to W/B ratio. Also, they showed that the value of the flow cone test for cement paste with W/B ratio of 50% and higher is about eight seconds which is in agreement with the predicted results. The results of ANN model also indicate that the effect of VMA on the mini slump value was negligible while VMA increased the flow time of cement paste containing both powder and superplasticizer. Finally, it can be concluded that the type and percentage of powers have not changed the flow time values in mixes with W/B ratio of 50% and higher.

### 5.2 Segment II: Effect of superplasticizer

The mixtures, in this segment, were virtually designed to determine the influence of the superplasticizer on the rheological properties of the fresh self consolidating cement paste. Two series of mixes were designed. In the first series, W/B ratio was 40% and VMA-FOS (V2) was used. In the second series, W/B ratio was increased to 45% and no VMA was added. Similar to the

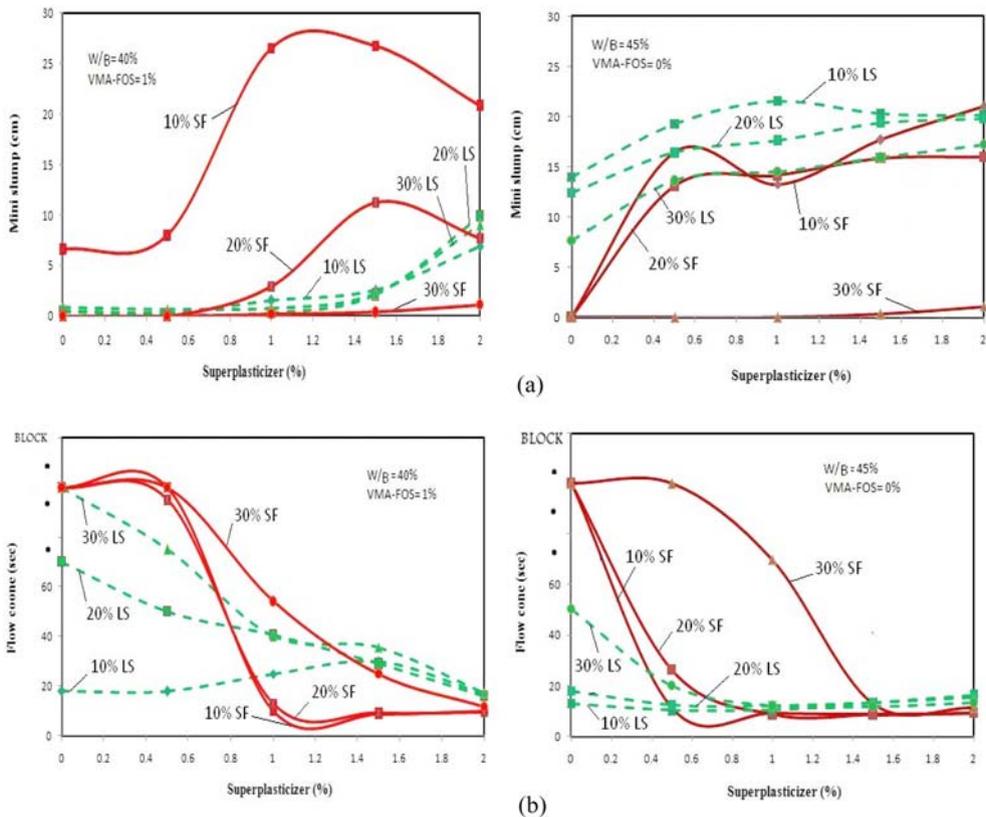


Fig. 7 Influence of the superplasticizer on: (a) mini slump value and (b) flow cone time predicted by ANN

segment I, silica fume and limestone were replaced by 10, 20 and 30% of cement weight. In both series, the percentage of Viscocrete (SP1) has been changed to observe its effect on the mini slump value and flow time. The ANN model outputs are shown in Fig. 7.

As shown in Fig. 7, increase of superplasticizer increased the mini slump value and decreased the flow time in both W/B ratios. In other words, both yield stress and viscosity of the paste have decreased. The same conclusion has been also observed by Svermova *et al.* (2003).

In mixes with W/B ratio of 45%, increase of silica fume and limestone from 10% to 30% has decreased the mini slump values. For W/B ratio of 40%, this trend is only valid for silica fume and no distinct trend can be observed for limestone. Park *et al.* (2005) also revealed that an increase in silica fume increases the yield stress and mini slump value. By taking an accurate look at the ANN prediction results it can be observed that the optimal percentage of superplasticizer is 1.5% of cements content where powder, VMA and superplasticizer are combined to make self consolidating cement paste.

### 5.3 Segment III: Effect of VMA

The mixtures, in this segment, were virtually designed to demonstrate the influence of VMA on the rheological properties of fresh self consolidating cement paste. The application of VMA has been proved to be very effective in stabilizing the rheological properties and consistency of SCC (Lachemi *et al.* 2003). In this experiment, the W/B ratio was kept constant for all mixtures (45%) and the VMA-Stream 2 contents has varied from 0.0% to 2.0% of cement weight. In all mixes 1% of Power flow (SP2) was used. To investigate the effect of combination of the ingredients (VMA, superplasticizer and powder), silica fume and limestone in 10, 20 and 30% of cement weight were also used. The prediction results of the ANN model are shown in Fig. 8.

As illustrated in Fig. 8(a), when VMA content was higher than 0.5%, it had no considerable influence on the mini slump value. This result coincides with the experimental results reported by Libre and Vahdani (2008) and it is against the Svermova *et al.* (2003) conclusion. However, flow time increased by increasing the VMA percentage which is in agreement with Leemann and Winnefeld (2007) results. Results also reveals that flow time values of mixes containing limestone

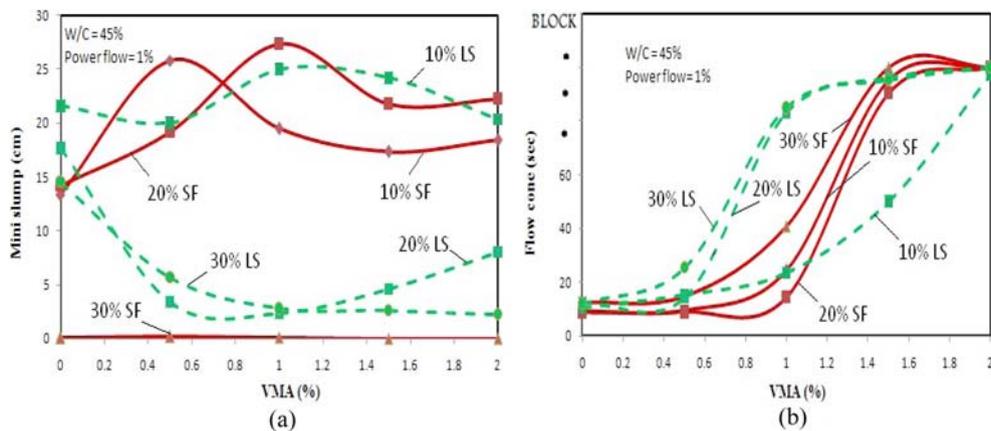


Fig. 8 Influence of the VMAs on (a) mini slump value and (b) flow cone time predicted by ANN

were higher compared to silica fume. Generally speaking, it can be concluded that increase of powder content in mixes with both VMA and superplasticizer reduced the mini slump value and increased the flow time. The results of Yahia *et al.* (2005) study validate this conclusion. They demonstrated that after limestone reaches to a critical percentage, the flow time increases quickly. By focusing on the results of flow cone obtained from the ANN prediction it can be concluded that the optimal percentage for VMA is 1.0% of cements content when the combination of powder, VMA and superplasticizer is employed.

## 6. Conclusions

This study was aimed at demonstrating possibilities of adopting artificial neural networks to predict the rheological properties of self consolidating cement paste. The network presented in this research unlike the previous studies, which most evaluated the harden properties of concrete or cement paste such as compressive strength, can predict the rheological properties of fresh self consolidating cement paste based on the mini slump and flow cone tests. These tests can indirectly evaluate the yield stress and the viscosity of paste as the known fundamental rheological parameters. The results elicited from this research lead and/or help to reach to the best possible stability of coarse and fine aggregates in self-compacting concrete. The main findings of the experimental and analytical study are outlined below:

1. Using the results of 200 data obtained from the experimental studies performed at the University of Tehran, the best structure for the artificial neural network model was determined as [14 14 14 2].

2. Increase of W/B ratio increases the mini-slump value while it reduces the flow time of mixes containing powder, VMA and superplasticizer. Also. It was observed that the type and percentage of powers have not changed the flow time values in mixes with W/B ratio of 50% and higher.

3. Increase of superplasticizer increases the mini slump value and decreases the flow time. In mixes with W/B ratio of 45%, increase of silica fume and limestone from 10% to 30% drops the mini slump values. Also, the optimal percentage of superplasticizer was found as 1.5% of cements content when powder, VMA and superplasticizer are involved in making self consolidating cement paste.

4. VMA has no considerable influence on the mini slump value. However, flow time increases by increasing the VMA percentage. It can be concluded that flow time values of mixes made with limestone are higher compared to mixes containing silica fume. Generally speaking, increase of powder content in mixes containing both VMA and superplasticizer reduces the mini slump value and increase the flow time. Finally, the optimal percentage for VMA is proposed as 1.0% of cements content when the combination of powder, VMA and superplasticizer is employed.

## References

- Altun, F., Kisi, O. and Aydin, K. (2008), "Prediction the compressive strength of steel fiber added lightweight concrete using neural network", *Comp. Mater. Sci.*, **42**, 259-265.
- Bager, H., Geiker, R. and Jensen, M. (2001), *Rheology of self-compacting mortars Influence of particle grading*, Nordic Concrete Research, Publ. No. 25.

- Bonakdar, A., Bakhshi, M. and Ghalibafian, M. (2005), "Properties of high performance concrete contain high reactivity metakaolin", *7th International symposium on utilization of high strength/high performance concrete*, Washington DC, USA, 228-232.
- Cussigh, F., Sonebi, M. and De Schutter, G. (2003) "Project testing SCC segregation test methods", in: O. Wallevik, I. Nielson (Eds.), *Self compacting concrete, Third International RILEM Symposium*, RILEM Publications, 311-322.
- EFNARK, (2005), *The European guidelines for self-compacting concrete, specification, production and use*.
- Emdadi, A., Mohebbi, A.R., Yekta, S., Libre, N.A. and Mahoutian, M. (2007), "Self compacting concrete incorporating high volume of raw materials", *Struct. Eng. Mech. Comp.*, 1611-1616, Belgium.
- Emdadi, A., Libre, N.A., Mehdipour, I. and Vahdani, M. (2007), "Investigation on the parameters that influence viscosity of cement paste", *Advances in Cement Based Materials and Applications to Civil Infrastructure (ACBM-ACI)*, Pakistan.
- Ferraris, C.F. (1999), "Measurement of the rheological properties of high performance concrete", *J. Res. Natl. Inst. Stan.*, **104**(5), 461-478.
- Hossain, K.M.A., Lachemi, M. and Easa, S.M. (2006), "Artificial neural network model for the strength prediction of fully restrained RC slabs subjected to membrane action", *Comput. Concrete*, **3**(6), 439-454.
- Koehler, E. and Fowler, D. (2003), "Summary of concrete workability test methods", RESEARCH REPORT ICAR-105-1, International center for aggregate research, The University of Texas, USA, 1-57.
- Lachemi, M., Hossain, K., Lambrosa, V., Nkinamubanzib, P. and Bouzoubaa, N. (2004) "Performance of new viscosity modifying admixtures in enhancing the rheological properties of cement paste", *Cement Concrete Res.*, **34**, 185-193.
- Lachemi, M., Hossain, K., Patel, R., Shehata, M. and Bouzoubaa, N. (2007) "Influence of paste/mortar rheology on the flow characteristics of high-volume fly ash self consolidating concrete", *Mag. Concrete Res.*, **59**, 517-528.
- Lee, S. (2003), "Prediction of concrete strength using artificial neural networks", *Eng. Struct.*, **25**, 849-857.
- Leemann, A., Winnefeld, F. (2007), "The effect of viscosity modifying agents on mortar and concrete", *Cement Concrete Comp.*, **29**, 341-349.
- Libre, N.A., Khoshnazar, R. and Shekarchi, M. (2010) "Relationship between fluidity and stability of self-consolidating mortar incorporating chemical and mineral admixtures", *Constr. Build. Mater.*, **24**, 1262-1271.
- Libre, N.A. and Vahdani, M. (2008), "Rheological properties of grout incorporating different dosage of viscosity modified agent", *3rd ACF International Conference-ACF/VCA*, Vietnam.
- Lippman, R.P. (1988), "An introduction to computing with neural nets. In: *Artificial neural networks*", *Computer Society Theoretical Concepts*, Washington, 36-54.
- Okamura, H. and Ouchi, M. (2003), "Self-compacting concrete", *J. Adv. Concrete Tech.*, **1**(1), 5-15.
- Pala, M., Ozbay, E., Oztas, A. and Yuce, M. (2007), "Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks", *Constr. Build. Mater.*, **21**, 384-394.
- Park, C.K., Noh, M.H. and Park, T.H. (2005), "Rheological properties of cementitious materials containing mineral admixtures", *Cement Concrete Res.*, **35**, 842-849.
- Perlovsky, L.I. (2000), *Neural networks and intellect: using model based concepts*, Oxford University Press.
- Prasad, B., Eskandari, H. and Venkatarama, B. (2008), "Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN", *Constr. Build. Mater.*, **23**(1), 117-128.
- Roussel, N. (2006), "Correlation between yield stress and slump: comparison between numerical simulations and concrete rheometers results", *Mater. Struct.*, **39**, 501-509.
- Rafiq, M., Bugmann, G. and Easterbrook, D. (2001), "Neural network design for engineering applications", *Comput. Struct.*, **79**, 1541-1552.
- Roussel, N. and Roy, R. (2005), "The marsh cone: a test or a rheological apparatus", *Cement Concrete Res.*, **35**, 823-830.
- Saridemir, M. (2009), "Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks", *Adv. Eng. Softw.*, **40**, 350-355.
- Schwartzentruber, L. Roy, R. and Cordin, J. (2006), "Rheological behavior of fresh cement pastes formulated from a Self Compacting Concrete (SCC)", *Cement Concrete Res.*, **36**, 1203-1213.
- Svermova, L., Sonebi, M. and Bartos, P.J. (2003), "Influence of mix proportions on rheology of cement grouts containing limestone powder", *Cement Concrete Comp.*, **25**, 737-749.

- Sonebi, M. and Cevik, A. (2009), "Genetic programming based formulation for fresh and hardened properties of self-compacting concrete containing pulverized fuel ash", *Constr. Build. Mater.*, **23**, 2614-2622.
- Tang, C. (2006), "Using radial basis function neural networks to model torsional strength of reinforced concrete beams", *Comput. Concrete*, **3**(5), 335-355.
- Tang, C., Lin, Y. and Kuo, S.F. (2007), "Investigation on correlation between pulse velocity and compressive strength of concrete using ANNs", *Comput. Concrete*, **4**(6), 477-497.
- Tattersall, G. (1991), *Workability a quality-control on concrete*, E & FN SPON, London, pp. 262.
- Topcu, I. and Saridemir, M. (2008), "Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic", *Comp. Mater. Sci.*, **41**, 305-311.
- Wu, X. and Lim, S. (1993), Prediction maximum scour depth at the spur dikes with adaptive neural networks", *Neural networks and combinatorial optimization in civil and structural engineering*, Edinburgh: Civil-Comp Press, 61-66.
- Yahia, A., Tanimura, M. and Shimoyama, Y. (2005), "Rheological properties of highly flowable mortar containing limestone filler-effect of powder content and W/C ratio", *Cement Concrete Res.*, **35**, 532-539.
- Yeh, I.C. (1998), "Modeling of strength of high-performance concrete using artificial neural networks", *Cement Concrete Res.*, **28**(12), 1797-1808.
- Yeh, I.C. (2007), "Modeling slump flow of concrete using second-order regressions and artificial neural networks", *Cement Concrete Comp.*, **29**, 474-480.
- Yeh, I.C. (2008), "Prediction of workability of concrete using design of experiments for mixtures", *Comput. Concrete*, **5**(1), 1-20.
- Yeh, I.C. (2008), "Modeling slump of concrete with fly ash and superplasticizer", *Comput. Concrete*, **5**(6), 559-572.
- Yücel, K.T. (2004), "Theoretical and experimental expression of rheology of cement, mortar and concrete in fresh state", *2<sup>nd</sup> International Aegean Physical Chemistry*, Turkey.
- Zarandi, F., Turksen, M., Sobhani, I. and Ramezani-pour, J. (2008), "Fuzzy polynomial neural network for approximation of the compressive strength of concrete", *Appl. Soft. Comput.*, **8**, 488-498.