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ARTICLE

Simulation of Self-compacting Concrete Properties Containing Silica Quicksand Using ANN Models

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ABSTRACT

Self-compacting concrete (SCC) mix designs demonstrate complexities in their mechanical properties due to natural compounds of the material and the diversity and abundance of factors that affect the properties. In this paper, a set of SCC mix designs is made using silica quicksand (as a filler) instead of rock powder with other required materials. The tests of fresh concrete such as the slump flow, J-ring, V-funnel, L-box tests and the hardened concrete tests are investigated and considered. The test results are shown that, a high quality has been achieved for SCC mixture contains the quicksand and silica fume contents with low lubricant admixture dosage. The research is embodied the use of a branch of Artificial Neural Networks (ANN) as a quick and reliable method of such concrete experimental testing. The results confirm that the ANN technique can perform as a satisfactory algorithm to provide speedy prediction of optimum silica quicksand content must be added prior to SCC mix design. Carry out experiments are usually costly and time consuming, therefore, the proposed algorithm can be used as an approximate method.

1. Introduction

Self-Compacting Concrete or SCC was carried out by Okamura for the first time in late 1980 in Japan for earthquake-prone buildings that were located in areas with a high density of reinforcement.[1,2] Recently, this type of concrete is widely applied in many countries in order to vary the shape of the structure has been used.

Self-Compacting Concrete or SCC is treated as a mix of lubricant admixtures such as rock powder, silica fume (SF), fly ash (Fly-Ash) and superplasticizer (SP) contents and a very low water to cement ratio. Granulometry and heat treatment have been optimized to obtain excellent mechanical and durability properties. Starting point of the SCC mix design is the packing theory. These types of concrete are very smooth and without undergoing any significant separation that can be spread readily into place and fill the framework without any consolidation, thus SCC mixes, which requires less-skilled workers, in construction's development can be found.[3]

The strength and durability of SCC as the main criteria for success are the properties of fresh concrete mixes, but it is much wider than conventional concrete is compacted by vibration. In general the relation between compacting and mechanical properties of concrete is known, and usually a granulometric curve of the solid components such as gravel, sand, filler (rock powder, fly ash and silica fume) and cement is selected. These mixes are extensive-

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ly tested, both in fresh and hardened states, and meet all practical and technical requirements such as a low cement and admixtures.[4]

However, SCC mixture should maintain continuity and no separation between aggregate grains occur. The Japanese method suggest that the coarse aggregate content in the SCC mix corresponds to generally fixed at 50 percent of the total solids volume, the fine aggregate content is fixed at 40 percent of the mortar volume and the water / powder ratio is assumed to be 0.9-1.0 by volume depending on the properties of the powder and the SP contents. In many countries, the Japanese method has been adopted and used as a first step for training on the development of the SCC mix design.[5]

A new mix design method developed for creating SCC, henceforth was referred to as Chinese method.[5] First, in this recent method the amount of all aggregates requirement is determined, and the paste is then filled into the void space of the grading aggregates to guarantee that the concrete thus obtained has flowability, compactability, without segregation and other desired SCC properties.
Recently, several researchers follow that the particle size distribution (PSD) of all aggregates in the concrete mix should follow the grading line of the modified Andreasen and Andersen (A&A) model. This line grading comprises the fine aggregate and goes down to a particle size of typically 150μm. In order to model the SCC mix design, all solid components should be considered, so also the cement and the filler.[5] This modified model verifies the positive relation between the rheological properties and the compacting of the SCC mix: accomplishing full compacting, the enough water is available to perform as lubricant for the solid components, and the better flowability. Both the Japanese and Chinese methods do not consider the PSD values of the aggregates.[6]

The amount of aggregates, powders, water/filler ratio and water/cement ratio, as well as type and dosage of superplasticizer to be used are the major factors influencing the properties of SCC mixture.[7,8]

The principal consideration of the SCC mix design method is that the void space of the aggregate is filled with paste requirement (cement, water and rock powder). Further, the grading of the fine and coarse aggregates is an important characteristic because it determines the paste to obtain suitable workability. Further, the paste is the factor calculating the price, since the increase of the cost of paste is use of higher powder content and it can also be reduced by use of various mineral materials such as rock powder, fly ash, metakaolin etc., as partial replacement of cement. However, it is generally noted that, the mineral materials also improve the mechanical properties and durability of the SCC [9,10]. It is therefore desirable to accomplish, the more aggregate, the less paste and consequently, less flowability. Subsequently, the cement content is evaluated. This quantity is assessed by the required mechanical properties and durability of the hardened concrete stage.[11]

A serious lack of the mineral material resources (such as rock powder and fly ash) increases the cost of SCC production. Therefore, in some countries natural substitute materials such as quicksand can be used. Mineral materials which are also known as mineral admixtures have been used as replacement cements for a long time ago. There are two types of materials crystalline and non-crystalline. Micro silica (or called silica fume) is very fine of non-crystalline type. But it should be noted that the use of the micro silica has led to an increase in the cost of filler, and the price of SCC.

Over the last two decades, the development of an acceptable artificial neural network (ANN) model is necessary for the prediction of reliable results for a problem such as mechanical properties of concrete.[12]

In the literature, many researchers either selected the different data mining methods to input the variables for their ANN models in studying the compressive strength of concrete [13-17]. Therefore, the correct selection of the input and output of ANN algorithms can be likely to be impressive. Thus do the steps of data preparation and training/testing are very sensitive and important. To achieve an optimal result, several iteration steps are usually required. Usually the Backpropagation (BP) layout of neural network model is used. In fact, BP is kind of the training algorithm in which pattern provided direction of the data flow, either forward or backward. BP requires at least three layers in order to predict correctly, and training is conducted in a supervised processes. Training of a BP neural network occurs in two steps.[18]

The purpose of this study was to examine tiny silica quicksand (at Kerman desert) as filler for a broad range of SCC concrete mixes. This was achieved by mix the quicksand ratio for 5, 10, 15 and 20% by weight, as a substitute for concrete rock powder. The quicksand is considered as filler and its price is about 1/4 the price of the rock powder. The natural silica quicksand is usually a gray colored powder somewhat similar to some micro silica and they are generally classified as filler content.

The empirical studies show that, the quicksand treats as rock powder and fly ash and it was initially suitable as cement replacement material and sometimes it can view as an alternative to micro silica. As known that, micro silica content may be used as costly pozzolanic admixtures. Following the previous references methods, the concrete paste lines are considered for significant water/powders

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(cement, fly ash and rock powder). A general relation is achieved between the compacting and specific surface area of each solid, and the water required for bleeding, flowing and deformability of paste phase. The effects of quicksand content in addition to rock powder, silica fume (SF) and superplasticizer (SP) dosage on fresh and hardened concrete properties of SCC are considered. This mix is introduced all practical and technical requirements such as a low cement and powder content, therefore the experimental results are illustrated that the mix design has the high compressive strength and low cost.

As mentioned, due to the variation in the SCC concrete constituents has different behavior. As a result, it is necessarily the view of the mechanical properties such as compressive strength and workability is reviewed. In this research the objective goal was not the evaluation of concrete durability. Therefore, the two artificial neural network (ANN) models that were selected for the present study are predictions of SCC mechanical properties. These two models are developed to predict the following attributes of the SCC mix design: 1) mechanical property, 2) rheological property.

In order to present study, the results of forty-five experimental samples are utilized to develop these two ANN models, incorporating some of the effective parameters on their mechanical properties.

2. Experimental Stage

The experiment stage is consisted of six studies on forty-five full scale mixes. Each study is built upon techniques and observations as the SCC mix designs are limited to standard mix designs at a constant, moderate level of workability. Furthermore, the studies are statistically designed to estimate all of the possible properties variation that might occur in SCC preparation, as explained in the next sections. The materials used are chosen to allow the optimal use of standard requirements, which proved to be vital in extracting information from the data in the previous studies.

2.1. Materials

Cement:The cement used was type II of Portland cement with a specific gravity 3.15*ton/m*^{3}, produced by Kerman cement factory. The XRD test results show that chemical characteristics of the cement satisfy the ASTM C150 Standard Specification.

Fine aggregate:The fine aggregate (sand) used in the samples was the natural siliceous clean and free of impurities crushed stone sand with a specific gravity 2.7*ton/m*^{3}. It was obtained from Kerman aggregate mine in eastern south of Iran. Its maximum nominal size (4.75*mm*) is suitable to be used in SCC and absorption of the sand found 0.7%. Granulometric curve of the used fine aggregate is shown in Fig. 1. Sieved sand over sieve of size 0.6*mm* was discarded as impurities. This indicates that the fine aggregate is unstable and contains void. Adequate grading and packing is therefore required to obtain workable fresh concrete.

Coarse aggregate: Two types of coarse aggregates used to make mix design were obtained from Kerman crushed aggregate mines. Maximum size of the coarse aggregate used in concrete was 19*mm*.

Specific gravity and water absorption of the coarse aggregates (gravels) under examination are determined using ASTM standard C127. The values of specific gravity and water absorption of aggregates are found 2.7*ton/m*^{3}and 0.7%, respectively. Sieve testing results of the used coarse aggregates are shown in Fig. 1.

Silica fume (SF): It is a product of micro silica consisting mainly of amorphous silica (SiO_2) and non-combustible particles. It was produced by Ferro Alloys Corporation Ltd. The main constituent material in SF is silica (SiO_2), the content of which is normally over 90%. Table 1 shows chemical components obtained by the XRD test of a commercially available silica fume. The silica fume used was

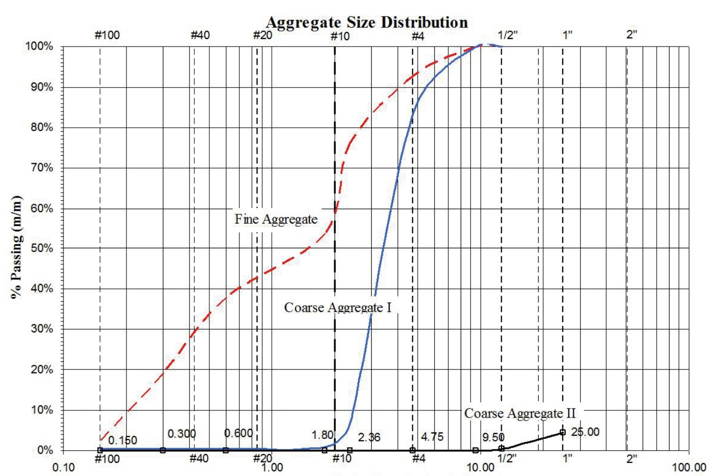

Figure 1. Sieve analysis of fine and two types of coarse aggregates

Table 1. The chemical components of the silica fume

Chemical Composition	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	K_2O	Na_2O	N_2O	P_2O_5	Cl
Average (%)	93.6	1.32	0.87	0.49	0.97	0.87	0.50	1.01	0.16	0.04

satisfied with the main requirements of ASTM C1240.

Superplasticizer: In order to improve the workability of fresh phase without an additional amount of water, the high-range water-reducing admixtures, often referred to as superplasticizer was added to the mixture. In this study a naphthalene sulphonate group based superplasticizer, supplied by Chemical Supply Manufactory was used. The main properties of the used superplasticizer were conformed to ASTM C494-Type F.

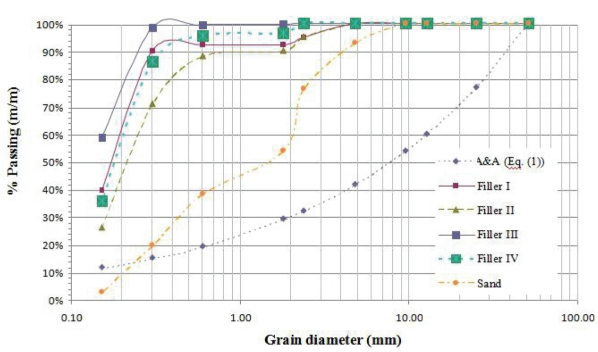

Figure 2. Particle Size Distribution(PSD) of fillers and sand

Quicksand: Because of its unique nature, some of the silica quicksand has the potential to significantly reduce SCC costs. There is not currently an exact standard requirements regard to proportioning of the quicksand in the SCC mixes.

In this study, the clean silica quicksand materials as filler were prepared from deserts around Kerman province. The physical properties (granulometric tests and SE) have been used as examples of fine aggregate (sand). As the A&A model accounts for fillers (<250μm) better, it is better suited for designing SCC and when the cumulative PSD satisfies equation as follows [6],

$$P(D) = \left(\frac{D}{D_{\max}}\right)^q \quad (1)$$

The parameter P is a fraction that is based on the size of sieve D, $D_{\max}$ is the maximum particle size of the aggregate components and q has a value between 0 and 1. Based on Andreasen and Andersen (A&A) research, the optimum packing will be obtained when value of $q \approx 0.37$.

The sieve analysis results of the used fillers and the fine aggregate are compared in Fig. 2. The results are implied that all of the quicksand materials (Type I to IV) are within the specified limit and these values are suitable as filler for construction work (see Fig. 2).

2.2. Mix design

In present study, the effects of the quicksand (as filler) instead of the rock powder content are investigated for a broad range of SCC concrete mixes. This was achieved by mixing the quicksand ratio for 5, 10, 15 and 20% by weight, as a substitute for concrete rock powder.

At first step, the most important consideration is that the voids between incompact aggregates are filled with paste, and that the packing of the aggregates is minimized.

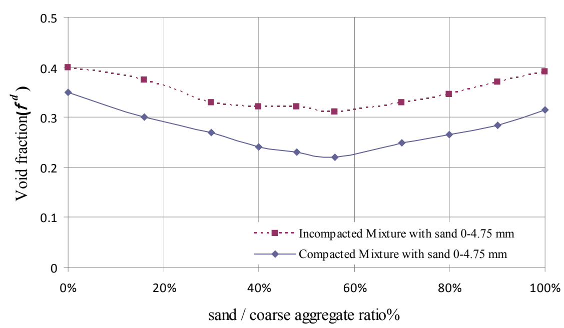

Figure 3. Void fraction of aggregates mixes, before and after compaction process

Therefore, the locally fine aggregate (sand) and a gapped grading has been used for the coarse aggregates (2 types) made by combining what has been retained on the sieve #4. Hence, the density of the aggregate components depends on the sand/coarse ratio, and not only to the value of sand or gravel alone.

The void fraction of the densely packed aggregate is determined as follow [5],

$$\varphi^d = 1 - \frac{\rho_a^d}{\rho_a} \quad (2)$$

where ρ_a^d and ρ_a are density of the compacted aggregate (referred to apparent density) and its specific density (or particle), respectively.

Fig. 3 shows the void fraction values with sand/coarse (mass) ratios of both in loose and compacted situation. As shown in this figure, the fine aggregate (sand 0-4.75*mm*) achieves a minimum value of the void fraction when its content is 56% in combination with coarse aggregate.

The second step is the addition of the powders (cement and filler) contents. The concrete samples are carried out based on replacement of powder by the quicksand as filler material. The required cement content is directly related to the desired compressive strength. In the most previous researches, a linear relation between the mechanical properties of the hardened concrete and the cement content is assumed. Furthermore, the quantity of water for the cement and the powders follows from the flowability requirement. Then the mix designs were carried out according to number of trail mixes to produce SCC without segregation and bleeding. In the trail mixes, it can be noted that the quan-

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tity of water for the cement and the filler can be achieved in fresh mix according to the flowability requirement. For this study, SCC mixes were prepared with a different filler ratio.

These mix designs are introduced in detail here, whereby the quicksand and other supplementary cementitious materials are now also included as filler content.

As shown in Table 2 the more details on the preparation procedure of the SCC mixes have been contained the following specifications, Mix QS expresses a concrete with just quicksand content, Mix RP and Mix SF represent mixes create just containing rock powder and Silica Fume, respectively, Mix RP + SF and Mix QS + SF concretes related to mix design by rock powder plus silica Fume and mix using quicksand in combination with silica Fume, respectively, and Mix RP + QS introduce mix include rock powder and quicksand as filler material content.

Table 2. Dosage of developed SCC mixes

Material (kg/m^3)	Mix QS	Mix RP	Mix RP + QS	Mix RP + SF	Mix QS + SF	Mix SF
Cement	450	450	450	450	450	450
Rock powder	--	250	125	120	--	--
Fine aggregate (sand)	850	800	850	850	850	850
Coarse aggregate I	450	450	450	450	450	450
Coarse aggregate II	400	400	400	400	400	400
Quicksand	250	--	125	--	125	--
Water	170	140	170	130	145	145
Silica Fume (SF)	--	--	--	50	125	250
Superplasticizer (SP)	20	20	20	20	15	10
Water/cement ratio	0.38	0.31	0.38	0.29	0.32	0.32
Water/(QS+SF) ratio	0.68	0.56	0.68	0.77	0.58	0.58

Finally, the plastic and hardened properties of the SCC were monitored and measured.

2.3. Fresh Concrete Experiments

Several tests for the fresh properties (paste phase) of SCC have been proposed [19]. Tests was included density, air content, slump flow and passing ability that are measured by L box, V-funnel time and J-ring. Further, characterizing method for the mortar properties were proposed and the indices for deformability and viscosity were defined as Γ_m and R_m [4].

$$\Gamma_m = (d_1 d_2 - d_0^2) / d_0^2 \quad (3)$$

$d_{1,} d_2$: Measured flow diameter through slump flow

d_0: Flow cone diameter

$$R_m = 10/t \quad (4)$$

t (sec): Measured time (sec) for mortar to flow through the V-funnel

In Eqs. (3) and (4) a larger Γ_m shows higher deformability and a smaller R_m indicates higher viscosity.

The test results of the fresh concrete are given in Table 3 according to the different standard reference methods.

Table 3. Results of fresh SCC tests according to standards

Result	Mix QS	Mix RP	Mix RP + QS	Mix RP + SF	Mix QS + SF	Mix SF
Slump (mm)	665	631	684	671	709	720
Slump flow time T_{50}(sec)	4.9	4.7	4.5	4.6	4	2.8
L-Box (h_2/h_1)%	81	76	80	79	89	90
V-funnel time (mm)	12	13	12	9	10	8
J-ring diameter (cm)	64.5	61	66.1	66.3	69.9	71.2
J-ring ($h_2 - h_1$) (mm)	11	13	11	7	7	5
Superplasticizer (kg/m^3)	20	20	20	20	15	10
Superplasticizer/powder (%)	8	8	8	11.8	6	4
Air content (%)	1	1	1	1	1	1
Density (kg/m^3)	2590	2510	2590	2470	2560	2555

The properties of the freshly-prepared SCC mixes are tested including density as the specified limit by European standard.

Table 4. Results of hardened SCC tests

Result (kg/cm^2)	Mix QS	Mix RP	Mix RP + QS	Mix RP + SF	Mix QS + SF	Mix SF
28 days compressive strength	300	480	380	585	820	660
modulus of elasticity ($\times 10^5$)	2.60	3.29	2.92	3.63	4.20	3.85

2.4. Hardened SCC Experiments

Hardened concrete tests on SCC included compressive strength and modulus of elasticity.

The six different mixes have been cast in standard cubes of 150×150×150 mm^3 for the compressive strength testing at 28 days, (standard BS EN 12350-1). At ages of 7, 14 and 28 days, four cubes per mix QS+SF with a quicksand ratio as much as 5% to 20% (of the weight) are tested, and the mean values of the tests results are represented in Fig. 4.

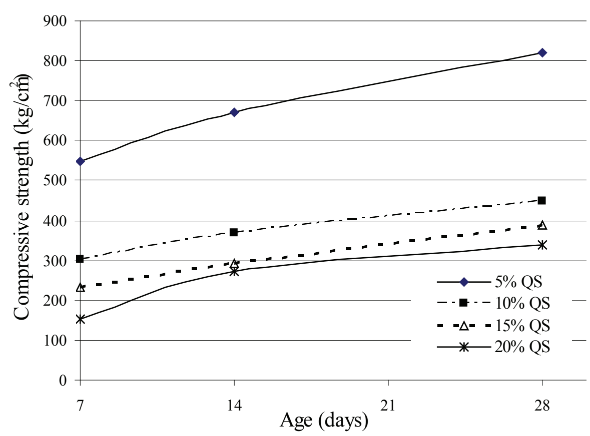

Figure 4. Compressive strength versus age (Mix QS+SF)

The data regarding the compressive strength for all the mixes is presented in Table 4 and indicates that average 28 days strengths of 820 kg/cm^2 obtained for 5% quicksand content (Mix QS + SF).

Based on results of hardened concrete tests, using the quicksand (as filler) instead of the rock powder, decreases the amount of SP. Additionally, there is a consistent behavior for both 7 and 28 days compressive strengths have been observed. When the amount of the quicksand content exceeds 5%, the compressive strength is decreased with the same SP dosage. Further, a condition of good dispersion of mortar with more content of the quicksand (greater than 5%) due to high SP dosage could increase the amount of weak zones, interfacial transaction zone. thereby decrease the compressive strength of mortar. More importantly, the experimental results pointed out that there exists a critical unit quicksand volume for mortar with W/C = 0.32 of the Mix QS + SF included content of SP dosage. The compressive strength of mortar would be affected when the content of quicksand exceeded this critical volume. It was due to the differences of effective thickness of paste around aggregates. The maximum compressive strength has been achieved for this critical volume (see Fig. 4).

3. Investigating the Alkali-Silica Reaction (ASR)

In this section, standard test method for evaluating the potential Alkali-Silica Reactivity of combinations of the pozzolan and the aggregates is investigated. Materials required for the Accelerated Mortar-Bar Method (AMBM) are selected based on the norm ASTM C 1260recommendation. In all tests, to determine the effect of pozzolanic activity on the ASR, the rate of deformation of specimens from concrete components (with constant value) containing different percentages of the pozzolan to the cement was observed over a period of approximately 14 days and compared to the control specimen reviewed.

Table 5. Mortar-Bar mixing with different pozzolan replacement ratios

Specimen No.	Oven-dry aggregate (kg)	Cement (kg)	Water (kg)	(w/c)	Special Weight (kg/m^3)	Pozzolan (%)	Air-Entrained (%)
P-1	878	350	200	0.47	2274.3	0	2.49
P-2	878	350	200	0.47	2251.9	5	0.48
P-3	878	350	200	0.47	2237.6	10	1.11
P-4	878	350	200	0.47	2224.1	20	1.71
P-5	878	350	200	0.47	2215.7	35	1.89
P-6	878	350	200	0.47	2054.8	50	1.70

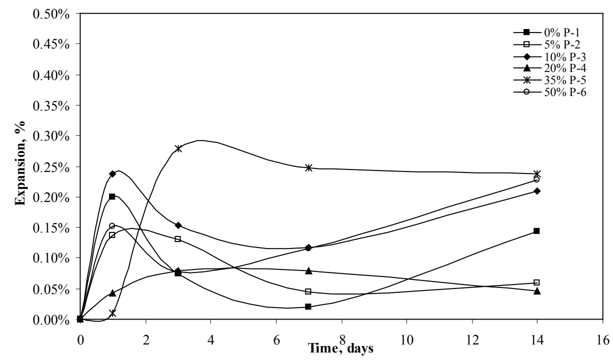

Figure 5. Specimens expansion containing Pozzolan for a period of 14 days

It should be noted that, in the AMBM test, expansion of specimens is considered to be more than 0.1% for 14 days as ASR criteria.Fig. 5 show the expansion rate of specimens against the alkali solution. Figure demonstrated that mortar with 20% pozzolan replacement (instead of cement) are activated with an alkali solution and expand less than 0.1% after almost 14 days.

4. ANN modeling stage

Experimental studies of engineering issues are time-consuming and expensive. Particularly in concrete mixing designs, the selection of suitable components may be due to an error. So using simulation methods to predict results can be very useful. One of the most commonly used simulation methods in engineering issues is artificial neural network (ANN). In this section, application of artificial neural network (ANN) to develop two models for predicting SCC mix design properties is presented. These two models are developed to predict the following attributes: 1) mechanical property (ANN1), 2) rheological property (ANN2). In this study, two proposed ANN models are initially converted into an input layer, multi-hidden layers, and an output layer. The final layers for these two models are as shown in Fig. 6. As seen in the figure, in the multi-hidden layer case, the output of each hidden layer is used as an input for the next hidden layer. In fact, in ANN1 model, the inputs are the values of concrete components and the output is an estimate of the compressive strength of different ages. In ANN2 model, inputs are the same values as components, and the output represents the parameters that illustrate the workability of fresh concrete phase.

In this research, in both ANN1 and ANN2 models, the tansig transfer function in the hidden and output layer was used. Furthermore, the feed-forward Back propagation (BP) learning algorithm is used to find a local minimum of the error functions of the training data set.

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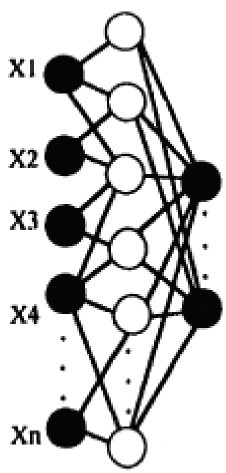
Results from two models were evaluated based on three error functions: the square of the correlation coefficient (R^2), root mean squared error (RMSE), and mean absolute error (MAE). If the calculated error of the test set was less than the previous optimal network, the current network would be saved; these steps would continue until no upgrading in the current network occurred. An average error for all training cases would then be calculated for comparison purposes. However, a lower calculated error would indicate that the network performance is better.

4.1. ANN steps

After modeling, its computational operations are carried out in two basic steps:1) The preparation of the training data; and 2) training/testing.

Inputs
X1: Cement
X2: Rock powder
X3: Fine aggregate (sand)
X4: Coarse aggregate I
X5: Coarse aggregate II
X6: Quicksand
X7: Silica Fume (SF)
X8: Superplasticizer (SP)
X9: Water/cement ratio
X10: Water/powder ratio



Outputs
ANN1 model:
O1: 3 days compressive strength
O2: 7 days compressive strength
O3: 14 days compressive strength
O4: 28 days compressive strength
O5: 42 days compressive strength

ANN2 model:
O1: Γ_m deformability index
O2: R_m viscosity index

Figure 6. The basic structure of the created two ANN models

① The preparation of the training data
As shown in Fig. 6, the parameters for input (X1 to X10) and output (O1 to O5 in ANN1 model and O1 to O2 in ANN2) was introduced to the network. In order for the architecture design of the network, 70% of experimental data for training, 15% for validation and 15% for testing was chosen. Selecting the data was random using the software. In the architecture of neural networks, the number of neurons in the input layer is similar to the number of the input parameters, i.e. number 10. The number of neurons in the hidden layer neurons initially was considered 10 and then the optimum number of the neurons was determined. Also, the number of the output layer neurons depends on the number of the output parameters of each model. According to the Fig. 6, the output data of ANN1 and ANN2 models was 6 and 2, respectively.

The training process was set for 100 epochs (or in order to modify the values of the weight are 100 times the all data entered) and the best case was obtained nearly in 20 times. This process is repeated until the error reaches the priority level. Recent step is very time-consuming and reduces the efficiency of the ANN method. A common way to select the appropriate number of neurons in each hidden layer is to perform a parametric analysis of the network and check the accuracy of the results. In each iteration step using Eq. (5) between the input data will be summed together with their weight values and with the bias,

$$\Delta W(t) = -\eta(error) + \alpha \Delta W(t-1 \tag{5}$$

where η, α are training rate and momentum factor, respectively.

The parameters η, α both are in the range 0 to 1. The weight and bias values will be initially selected as random numbers and then adjusted according to the obtained results of the training process. This method causes the model to become agile and decreases during the execution of the operation.

② The training/testing

The validity of the proposed ANN models is then tested by applying training/testing on the results of the experimental data. So that, 30% of the experimental data results were initially set aside for simulation purposes at this step. It should be noted that, these data are not used for training step, and if they can accurately predict the results, then it can be said that the network is reliable and usable.

5. Results and Discussion

To determine the optimum number of neurons in the hidden layer, with neural network architecture is mentioned only by the number of different neurons from 1 to 30 was created by neurons and minimum RMSE, MAE and R^2 of each of the two obtained the network that the results shown in Table 6. Results shown that, the maximum errors for 45 test results are about less than 20%, on the other hand, it can be seen that 98% of the output results has errors less than 15%.

Table 6. Performance results for the two ANN models

Model	Network Architecture	Maximum error (%)	R^2	RMSE	MAE
ANN1	Backpropagation	14.5	0.925	3.972	3.521
ANN2	Backpropagation	15.3	0.928	3.859	3.126

According to Table 6, the minimum error and the maximum correlation coefficient in 11 neurons was happened. The value of the squared error has decreased for 1 to 11 neurons and then increased. Also, the value of the correlation coefficient has increased slowly with increasing the number of the neurons. Meanwhile, with the increase in the number of neurons to more than 11, the value of the squared error has increased sharply and the value of the correlation coefficient with large slope is reduced. This means that, increasing the number of neurons is not always improves network performance, but also the number of neurons is dependent on the number of all input data of a neural network. In this research the number of all input data is 45 and the number of the appropriate neurons in the hidden layer is 11. Therefore, the number of neurons in the hidden layer must be approximately 1/4 to 1/5 of the number of all input data.

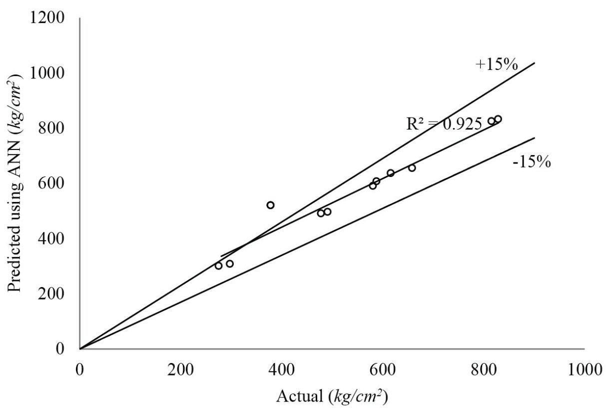


Figure 7. Actual v/s predicted results of the 28-day compressive strength(kg/cm^2) using ANN1

Fig. 7 shows a plot of actual compressive strength against corresponding ANN1 model predication for testing data. A linear correlation can be observed and the square of the correlation coefficient is found to be 0.925. Thus it can be concluded that the model successfully predicted the compressive strength of concrete in good manner.

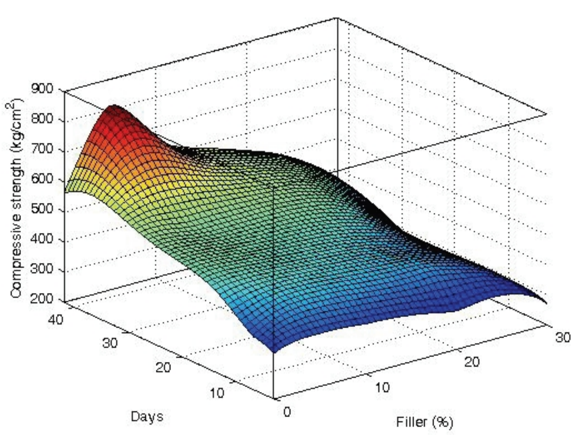


Figure 8. Predicted results of the comprehensive strength (kg/cm2) using ANN1

Fig. 8 shown that, the results suggest that ANN, can effectively be used to predict the compressive strengths of the SCC included different percent of the filler content.

There is a wide variation of two parameters i.e. the concrete age (days) and the percent of quicksand content (filler %) which can be used.

The second model (ANN2) involved choosing the ideal model for the rheological property of the SCC, again by minimizing the weighed errors produced for model and by also evaluating the ability of the network to produce results for deformability and viscosity indices. The results for the optimum model for ANN2 are shown in Fig.9. The results are suggested the prediction of the rheological property based on characterizing method for the mortar properties were proposed using the Γ_m and R_m indices. Hence the square of the correlation coefficient was found to be 0.928.

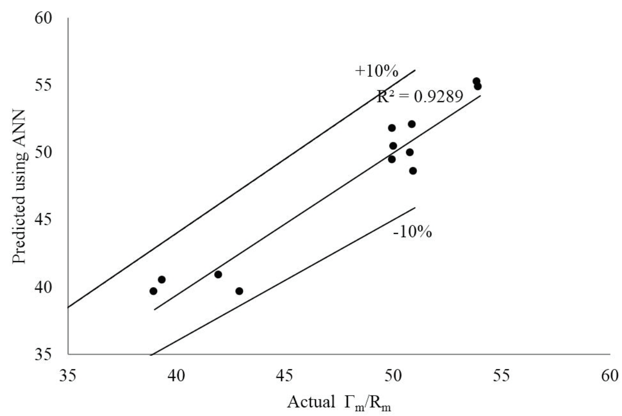


Figure 9. Actual v/s predicted results of the deformability and viscosity indices using ANN2

As shown in Fig. 10, separate training and testing was conducted for rheological property model (ANN2 model) which predicted the deformability and viscosity for different percentage of the filler content.

It is anticipated that the results for both networks could only improve with the addition of further experimental data for training and testing the networks.

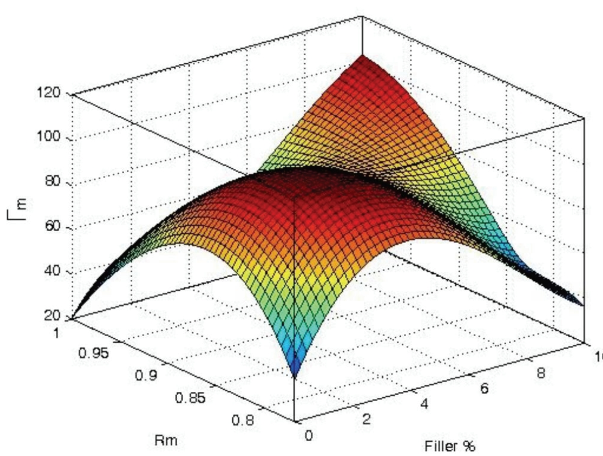


Figure 10. Predicted results of the deformability and viscosity using ANN2

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6. Conclusions

The process of choosing a suitable silica quicksand content material to make SCC is considered with the aim of determining the relative amounts of concrete produced economically as possible and with the maximum of required properties, particularly compressive strength, compactability and flowability. Based on these considerations, increasing the amount of quicksand (as filler) instead of rock powder samples of SP is reduced.

Characteristics of fresh SCC tests show that, high compactability and restrained flowability is usually depends on the shape, size and quantity of the aggregate, and the friction between the solid particles, which would be reduced by adding the amount of quicksand to the mortar. It was due to the quicksand act as a roller between the aggregates. Further, the segregation phenomena is usually related to the cohesiveness of the paste of the fresh concrete, which can be improved by some combination of increasing the volume of paste, reducing the free water content and the coarse aggregate, which would be achieved by adding the quicksand content to the SCC mixture.

Further, adding silica quicksand as much as 5% (of the weight of the cement) in the concrete, the concrete strength will be seen, as 28-day compressive strength increased by 40% compared to the control sample (using both rock powder and silica fume materials). Slump flow, V-funnel, L-flow, J-ring tests were carried out to examine the performance of fresh concrete, and the results indicate that using the quicksand in the mixture could produce successfully SCC of high flowability, without segregating and saves cost. Mortar with 20% pozzolan (instead of cement) are activated with an alkali solution and expand less than 0.1% after almost 14 days.

Two ANN models for both mechanical and rheology properties of SCC containing silica quicksand (as filler) have been developed. The optimal network is a three-layer network with 11 neurons in the hidden layer. The use of the Levenberg-Marquardt training function and the tansig transfer function in the hidden and output layers and the number of neurons between 1/5 to 1/8 of the input data will have the suitable results for predicting the properties of the self-compacting concrete. Results of each model were trained with input and output experimental data. Statistical values such as the square of the correlation coefficient, RMSE and MAE that are calculated for comparing experimental data with two ANN models. Consequently, compressive strength and flowability properties of SCC can be predicted in the two models without attempting any experiment al program.

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