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Research paper

Performance evaluation of mechanical properties of self-compacting concrete using artificial neural network

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Abstract

This experimental study was undertaken to investigate the effects of using local materials (cement, fly ash, super-plasticizer, coarse aggregate, and sand) on the mechanical properties of Self-Compacting Concrete (SCC). For this purpose, a total of 31 mixtures of SCC were prepared by the neural network design methods. Furthermore, based on the experimental results, the neural network model-based clear formulations were developed to predict the mechanical properties of SCC. The test results have shown that mineral admixtures were very effective on hardened properties of SCC. In addition, it was found that the developed model by using neural network appeared to have a high predictive capacity of hardened properties of SCC with respect to regression and experimental results.

Keywords: *Hardened Properties; Self-Compacting Concrete; Neural Network; Experimental; Regression.*

1. Introduction

Mehta and Monteiro [1] stated that the static elasticity modulus under compression using uniaxial loading force is given by the slope of the stress-strain curve. The initial tangent, secant, and chord modulus are used for the calculation.

Vengala et al. [2] found that the addition of fly ash in SCC results in an increase in the 28 days compressive strength of concrete by nearly 38%. SCC was achieved when the volume of paste was between 0.43 and 0.45.

Alqadi et al. [3] studied the proportions of the four factors (cement, water-powder ratio, fly ash and superplasticizer) that will increase the compressive strength of SCC by using factorial design and response surface methodology. The method of the two levels was used with 16 factorial points. It was concluded that the interactions of the factors of a coupling effect of the parameters in good significant models is a full quadratic model and the assumptions of the analysis are satisfied. Cement, water-powder ratio, fly ash, and superplasticizer dosage should be at a high level of significance in maximizing compressive strength and the process is relatively robust to superplasticizer.

Arabi et al. [4] carried out statistical models to model the influence of key mixture factors (cement, water-powder ratio, fly ash, and superplasticizer) on mechanical properties that affect the enhancement of SCC. The valid models were used for a wide range of mixture constituent. The useful derived numerical models are to reduce the test procedures and the number of trials of mix constituting of SCC. It was concluded that full quadratic models were shown to be the best models.

Arabi et al. [5] studied the effect of the addition of different factors on the fresh and hardened properties of SCC using a central composite design method and response surface procedure. SCC mixes were made with the addition of materials such as cement, aggregate (coarse, sand), fly ash and superplasticizer in different constituents and their results from fresh properties (V-funnel, segregation resistance, and J-ring) and hardened properties at 28 days (compressive strength and elasticity modulus) were recorded. The results of the models were predicting the independent variables on the responses by using regression analysis. It was concluded that full quadratic models can be used to study the influence of proportional materials on the properties of SCC. Optimizations of the responses were done. Also, fresh properties resulted were 17.8% segregation resistance, 18.3 seconds V-funnel, 849 mm J-ring flow, and the hardened properties were 27.214 to 39.026 MPa for the modulus of elasticity and 35.254 to 48.174 MPa for the compressive strength.

Osman et al. [6] investigation on the concrete properties showed that increasing the Coleman ratio by volume of the mix has affected the engineering properties up to 30% as replacement materials.

Ji et al. [7] neural network results are excellent in terms of regression and genetic programming, except when used in the form of estimation of the function. They are non-linear and can handle complex interactions among input/output variables in a system without any interactions.

Oztas et al. [8] explained the probable applicability of neural network to estimate the compressive strength and the slump flow of high enhancement concrete.

The current study provides guidelines on the procedure for mix proportions of SCC. For this purpose, a total of 31 mixtures of SCC were prepared using local materials. Using the experimental database, the neural network model-based definite formulations were derived to predict the mechanical properties of SCCs as a function of the concrete mixture constituent.
The organization of this paper is as follows. The experimental program is explained as a feature selection method. The intelligent classification system and the structures of the six types of ANNs are presented. The study area, descriptions on the factor extraction, and data collection are given. The results of the feature selection and classification of performance are presented and the conclusions are drawn.

2. Multilayer perception neural network

Bauer et al. [9] studied the Multilayer Perceptron (MLP) network which has been the most common ANN used for pattern recognition and classification in recent years.
Mitra et al. [10] fed the forward artificial neural network model which consists of one input layer, multi hidden layers, and one output layer. As shown in Figure 1, the output of the MLP network with m outputs and n_h hidden nodes can be expressed by Eq. (1):

$$\tilde{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 F\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i(t) + b_j^1\right); \text{For } 1 \le j \le n_h \text{ and } 1 \le k \le m \tag{1}$$

Where w^1_{ij} and w^2_{jk} denotes to the weights of the connection between the input and the hidden layers, and the connections between the hidden and output layers; respectively, x_i and b_j^1 denote to the values of input nodes and the thresholds in hidden nodes, respectively; n_i and n_h is the number of input nodes and hidden nodes respectively, and finally $F(*)$ is a transfer function that is normally selected as a sigmoidal and linear functions for the input and output layer; respectively.
Al-Batah et al. [11] studied the MLP network which is a highly non-linear neural network. In a linear system case, the system has to be approximated by using the non-linear MLP network model.

3. Materials used

Materials properties: The materials implemented in the research are:

3.1. Cement

Ordinary Portland cement available in the local market is used in the investigation. The Cement used has been tested for various proportions as per (ASTM C150-85A) [12]. The specific gravity was 3.15 and fineness was 2091cm^2/gm.

3.2. Coarse and fine aggregates

Coarse aggregate: Crushed angular granite material of 20 mm max size from a local source was used as coarse aggregate. The specific gravity was 2.45, absorption value was 1.5%., fineness modulus was 6.00, and bulk density of 1480 kg/m^3 (conforms to ASTM C 33-86) [13]. The fine aggregates consisted of river sand with a maximum size of 4.8 mm, with a modulus of the fineness equal to 4.2 normal grading. The specific gravity was 2.6 and absorption value was 6.4%.

3.3. Fly ashes (FA)

Type-II fly ash from Thermal Power Station was used as cement replacement material; Fly Ash for use as Pozzolana and Admixture. Class F fly ash was obtained which had a specific gravity of 2.32 and a fineness of 2423 cm^2/g (conforms to ASTM C 618) [14].

3.4. Super plasticizer (SP)

Polycarboxylicether (PCE) based super-plasticizer which is Brown Colour, free-flowing liquid, have a relative density of 1.15. The Super Plasticizer confirms to ASTM C 494-92 [15]. Type A and Type F are in the aqueous form to enhance workability and water retention. A sulfonated, naphthalene-formaldehyde superplasticizer and a synthetic resin type air-entraining admixture (AEA) were used in all the concrete mixtures.

3.5. Mixing water

Potable water that conforms to ASTM D 1129 [16] is used for mixing the concrete and curing of the reaction.

4. Mixture proportioning

All concrete has been mixed in 40-L batches in a planetary mixer with the proportions mentioned in [3]. The batching arrangement consisted of homogenizing the sand and coarse aggregate for the 30s, then add about half of the mixing water into the mixer and continue to mix for one more minute. A plastic cover was used at the mixer to minimize the evaporation of the mixing water and let the dry aggregates in the mixer absorb the water. After 5 min, the cement and fly ash were added and mixed for another minute. At the end, the SP and the remaining water were poured, and the concrete was mixed for 3 minutes. Thirty one mixes were tested for the hardened properties: compressive strength and elasticity modulus at 28 days. A total of 93 cubic specimens, (100 x 100 x 100) mm, were tested while taking the average of results (3 specimens per mix).

5. Neural network design method

Villiers and Barnard [17] indicated that the neural networks are made up of three layers which are the input, hidden and output layers. There is one input node for every input on the input layer. The hidden layer is the middle layer connecting the input layer and the output layer, the purpose of which is to build up the weight of the input factors and to minimize the error rate.
Furthermore, a neural network with one hidden layer is enough to solve the most complicated situations. However, certain conditions need to be made about the hidden layer. Firstly, the number of neurons to be used in this layer and secondly, the type of suitable transfer function would need to be determined. For that, experiments were carried out by varying the number of hidden neurons from 1 to 100. For each number of a hidden neuron, the network was trained by varying the transfer function from the tan-sigmoid to log-sigmoid function. Transfer function tan-sigmoid is chosen in this study. The optimum hidden neuron and transfer function which produced the highest accuracy was determined. As the output layer represents the target variables in the model, it is fully connected to the hidden layer and the purlin was used as the transfer function of this layer.
In addition to that, the learning rate, which is constant, can affect the speed of the neural network learning process. Large learning rates lead to an unstable neural network. On the other hand, if the learning rate is too small, the learning algorithm will take a longer time to converge. For this study, the learning rate was chosen to be 0.1 based on a trial and error basis.
Neural network design was employed to limit the number of experimental runs compared to regression and experimental design. This would enable modeling of mixture proportions involving interaction. These models were used for optimization as shown in Fig.1 and Fig.2 of self-compacting concrete mixes. For a six-factor experiment, the neural network design are shown.

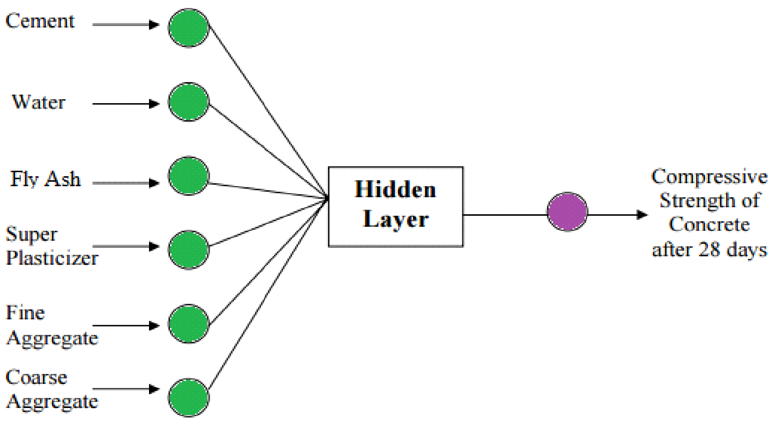

Fig. 1: The Output of the MLP Network with m Outputs and n_h Hidden Nodes.

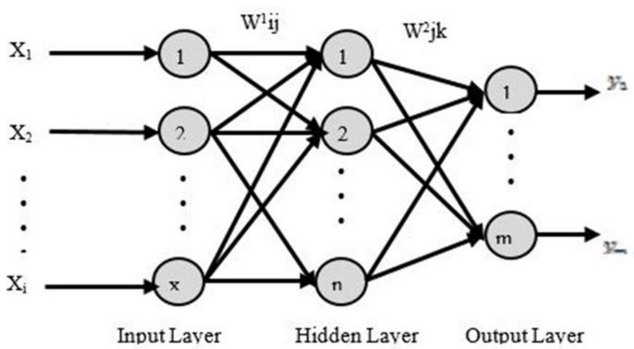

Fig. 2: Initial Neural Network Structure.

Sonebi [18] studied a 31-statistical experimental design with 6 factors and 31 points which were used to evaluate the influence of two different levels of each variable on the relevant concrete properties.
In the fact that the expected responses do not vary in a linear manner with the selected variable to enable the quantification of the prediction of the responses, the response could be modelled in a linear manner to estimate the degree of experimental error for the modelled of responses.
MINITAB Handbook [19], a commercial software was used for the statistical analysis of the results. Six key parameters that can have a significant influence on the mix characteristics of SCC were selected to derive the mathematical models for evaluating relevant properties. The experimental levels of the variables (maximum and minimum), the boundary of fly ash content, superplasticizer dosage, cement content, sand, coarse aggregate and water to powder ratio are defined.
The modelled experimental region consisted of mixes ranging between the coded variables. The derived statistical models are valid for mixes with w/p ranging from 0.30 to 0.38, quantities of Super-Plasticizer ranging from 7.2 to 10.8kg/m^3, cement content ranging from 400 to 450 kg/m^3 and fly ash content ranging from 110 to 150 kg/m^3. The modelled SCC responses were the compressive strength and modulus of elasticity at 28 days as listed in Table 1 and Table 2.

Table 1: Comparison of Experimental of Compressive Strength Results with ANN Predicted and Regression Value

Test run	Experimental Compressive Strength (MPa)	ANN prediction (MPa)	Regression results (MPa)
1	35.254	27.8900	38.4436
2	47.095	32.8620	45.4494
3	36.235	31.9500	37.1823
4	46.484	34.9260	46.8588
5	44.307	37.8650	45.6614
6	45.216	38.9430	45.0657
7	48.975	37.4940	42.5658
8	44.543	32.7520	42.5658
9	45.102	30.4730	42.5658
10	48.174	32.0960	48.3962
11	47.181	28.8860	48.4516
12	41.927	32.3200	43.6341
13	39.152	33.7980	39.5636
14	45.997	30.5890	44.7764
15	37.573	31.5760	42.6847
16	40.747	36.9310	40.9952
17	38.587	34.1380	39.3929
18	44.732	38.4010	39.8529
19	43.337	29.9390	42.5658
20	37.051	39.0260	38.3246
21	41.055	30.7420	43.8270
22	42.657	34.3450	46.1858
23	42.433	29.2840	43.7081
24	40.734	31.2880	43.4729
25	46.833	36.2340	42.5658
26	47.752	34.7890	42.5658
27	46.2	33.7160	42.5658
28	41.056	27.2140	40.9730
29	41.451	29.8150	41.4423
30	38.457	38.4570	40.3000
31	35.995	35.9950	39.2317

Table 2: Comparison of Experimental of Modulus of Elasticity Results with ANN Predicted and Regression Values

Test run	Experimental Modulus of Elasticity (GPa)	ANN Prediction (GPa)	Regression Results (GPa)
1	27.89	32.6437	27.8900
2	32.862	30.0336	32.8620
3	31.95	35.1193	31.9500
4	34.926	32.2341	34.9260
5	37.865	38.1278	37.8650
6	38.943	35.1370	38.9430
7	37.494	33.4300	37.4940
8	32.752	33.4300	32.7520
9	30.473	33.4300	30.4730
10	32.096	32.1133	32.0960
11	28.886	32.4134	28.8860
12	32.32	31.8535	32.3200
13	33.798	31.0501	33.7980
14	30.589	31.3430	30.5890
15	31.576	31.4649	31.5760
16	36.931	34.3336	36.9310
17	34.138	33.0323	34.1380
18	38.401	34.8442	38.4010
19	29.939	33.4300	29.9390
20	39.026	34.6088	39.0260
21	30.742	30.9543	30.7420
22	34.345	33.5435	34.3450
23	29.284	32.9194	29.2840
24	31.288	34.9577	31.2880
25	36.234	33.4300	36.2340
26	34.789	33.4300	34.7890
27	33.716	33.4300	33.7160
28	27.214	33.2507	27.2140
29	29.815	34.0495	29.8150
30	38.457	34.5601	38.4570
31	35.995	36.1365	35.9950

5.1. Applying artificial neural network

An artificial neural network (ANN) was created with the following specification:
Number of inputs are six parameters (Cement, W/P, FA, SP, Sand, and CA); number of outputs are two (compressive strength and modulus of elasticity at 28 days); the architecture of ANN is constructed by using one input layer with 6 neurons, one hidden layer with 36 neurons, and one output layer with two neurons.
The following parameters were chosen for ANN: goal = 0, training ratio = 0.01 and number of epochs = 1500. ANN was trained using the input data in listed Table 1 and output data (as a target) in listed Table 2.

The previous ANN was tested using experimental data for the six inputs, the outputs obtained by ANN were very close to the experimentally obtained outputs (error leads to zero) as shown in Fig. 3 and Fig. 4. Also, the final architecture of the developed artificial neural network is shown in Fig. 5.

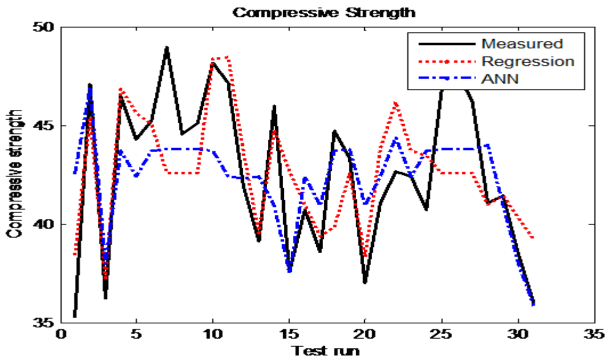

Fig. 3: Relationship between Compressive Strength for Experimental Measured, Regression Analysis, and ANN Curves.

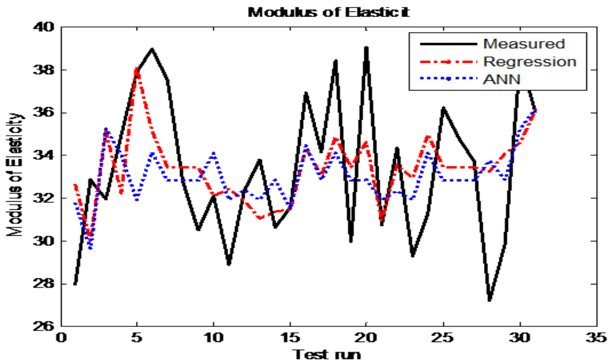

Fig. 4: Relationship between Modulus of Elasticity for Experimental Measured, Regression Analysis, and ANN Curves.

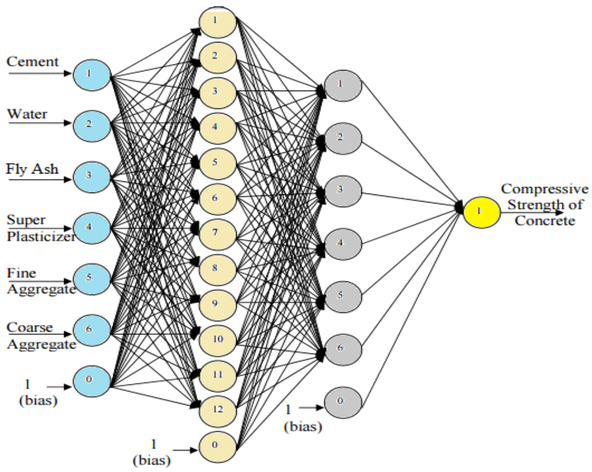

Fig. 5: Final Architecture of the Developed Artificial Neural Network.

5.2. Applying regression analysis

A Matlab multiple regression was applied using the input/output data in Table 1 and Table 2. From these, the relationships between the outputs and the inputs were obtained as shown in the following equations (2) and (3):

$$F1 = -819.3178 + 0.567X1 + 278.4565X2 + 0.6757X3 - 0.0765X4 + 0.4505X5 + 0.0518X6 \quad (2)$$

$$F2 = 1.0e + 003 * (-1.0520 + 0.0005X1 + 0.5043X2 + 0.0007X3 + 0.0010X4 + 0.0007X5 - 0.0000X6 \quad (3)$$

Where F1: compressive strength; F2: modulus of elasticity; X1: Cement; X2: W/p; X3: FA; X4: SP; X5: sand; X6: CA

Applying these equations to calculate the compressive strength and modulus of elasticity mathematically shows that there is an error with maximum value equal 4.2% as shown in Fig. 3 and Fig. 4. Also, it is shown that the modulus of elasticity does not depend on CA.

6. Conclusions

- Applying ANN to obtain the values of compressive strength and modulus of elasticity is an efficient tool forcing the error move to a small value. However, it needs more efforts for training and testing.
- Numerical models established for the SCC mixtures can be useful in the design of concrete and selection of constituent materials on hardened properties of SCC.
- Applying multiple regressions is a simple way to obtain the equations of compressive strength and modulus of elasticity and to use these equations to obtain their values in case the error of 4.2 is acceptable.

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