**Prediction of silica fume concrete strength by artificial neural networks**

Muhannad Ismeik

Department of Civil Engineering, Australian College of Kuwait, Safat 13015, Kuwait

**Abstract**

Artificial neural network (ANN) models have been widely used in materials modeling, inter-correlations, as well as behavior and trend predictions when the nonlinear relationship between system parameters cannot be quantified explicitly and mathematically. In this study, an ANN model was proposed to predict the compressive strength of silica fume concrete. Various amounts of silica fume were added at different water/cementitious ratios. Concrete specimens were tested and compared with plain concrete specimens at different ages. The ANN training, testing, and validation results indicated that the concrete strength was predicted accurately with ANN techniques. The reliability between the predicted outputs and the experimental data was high as suggested by several statistical indices. With new ingredients, the proposed ANN model is an alternative reliable and efficient approach to estimate the strength of silica fume concrete as a rapid inexpensive substitute for cumbersome experimental testing.

**Keywords**

Concrete, silica fume, compressive strength, modeling, artificial neural networks.

**1. Introduction**

Large quantities of waste materials and by-products (silica fume, fly ash) are generated from manufacturing processes and service industries. As a result, proper disposal of such materials become one of the major environmental concerns in the world. With the increasing awareness about the environment, scarcity of landfill space and due to its ever increasing cost, waste utilization has become an attractive alternative to disposal.

Silica fume (SF) is generally used as a replacement of cement, as an admixture in concrete, and in manufacturing of cement. Economic and environmental considerations played a great role in advancing its usage. SF, composed of submicron particles of silicon dioxide, is produced by electric arc furnaces as a by-product waste of the production of metallic silicon or ferrosilicon alloys. SF incorporation could enhance the concrete basic properties in both the fresh and hardened states. It improves compressive strength, durability, depletion of cement alkalis, resistance to chloride and sulphate penetration, and continued micro structural development through a long-term hydration and pozzolanic reaction (Gonen and Yazicioglu 2007, Sata et al. 2007, Yazici 2008).

Artificial neural networks (ANN) have been used successfully to model a wide variety of complex and highly nonlinear problems in civil engineering. ANN operate without detailed information about the system with an attempt to capture the association between model inputs and outputs. Unlike classical regression models, they have the ability to learn about the system that can be modeled without advanced knowledge of potential relationships. The prediction by an ANN model is usually precise compared to traditional simulation programs as no iterative calculations are needed to solve complex equations with advanced numerical techniques (Fausett 1994).

Although the literature is rich with standard codes of practice, guidelines, and prediction linear models to estimate the compressive strength of SF concrete (Zelic et al. 2004, Holland 2005, Bhikshma et al. 2009, Ismeik 2009, Ashteyat et al., 2012), there exists limited number of statistical models for predicting the strength of silica fume concrete using ANN (Bilim et al. 2009, Gregor et al. 2009). Thus, the aim of this investigation is to develop a reliable ANN model that could be employed reliability for estimating strength of silica fume concrete using key input variables.

**2. Experimental procedure**

Ordinary Portland cement (C) type I was used with properties listed in Table 1. Properties of SF are shown in Table 2. Physical properties of aggregate are listed in Table 3 with grading shown in Figure 1. Concrete mix proportions are summarized in Table 4. Three series of tests designated as series I (mix A, B, C, and D), series II (mix E, F, G, and H), and series III (mix I, J, K, and L) were prepared with three water-to-cement (W/C) ratios of 0.50, 0.55, and 0.60, respectively. In each series, the replacement level (R) of fine aggregate with silica fume, was 0, 5, 10, and 15% by weight. The cement content (C) varied from 400 to 433 kg/m3. The cementitious materials content (CM = C + SF) varied between 385 and 450 kg/m3 resulting in four water-to-cementitious materials (W/CM) ratios of 0.50, 0.48, 0.46, and 0.44 for test series I, of 0.55, 0.53, 0.51, and 0.49 for test series II, and of 0.60, 0.58, 0.55, and 0.53 for test series III. All experiments were conducted in a laboratory under a controlled environment and were properly monitored. Specimens used were standard cylinders of 150 x 300 mm. Specimens were kept for 24 hours in molds at a temperature of 23º C in the casting room; and then cured in a water tank for the specified time at a temperature of 23º ± 1º C. Compressive strength tests were performed at age of 7, 28, and 56 days. The specimens were tested in a dry state following the moist curing. The compressive strength of specimens was recorded as load was gradually applied until failure. The average of 3 specimens was used to report the compressive strength of each mix, F. High quality control requirements in terms of mixing, curing, and testing of specimens were strictly followed during the experimental phase and according to ASTM (2012) standards. Further details about the experimental program are given by Ismeik 2010 and Ashteyat et al. 2012.

**3. Artificial Neural Networks**

ANN are computational data-processing techniques inspired by biological neural system in which they have an inherent tendency for storing experimental knowledge and making it available for use. Usually an ANN architecture in its basic form is composed of an input layer, at least one hidden layer, and an output layer as shown in Figure 2. The hidden layer is made of a large number of interconnected neurons linked to the input and output variables. A neuron consists of weight, bias, and a nonlinear transfer function mainly. The number of hidden layers used depends on the degree of problem complexity. Typically, one hidden layer, with adequate number of hidden neurons, is found to be sufficient for most engineering problems (Fausett 1994).

The interest in ANN is due to their capability to simulate natural intelligence in its learning from past experience. The method generally relies on experimental results, which are used to train the ANN model so that it can precisely predict the system performance at other conditions. The back-propagation algorithm, which is the most widely used training algorithm in analytical applications, is usually employed to minimize the error for a particular training process. For a given input data, a flow of activation is usually passed between the input and output layers via hidden layers. Then the error in the output is initiated. The algorithm is then used to adjust incrementally the weights and biases in a way that decreases the error. The training of a network is typically achieved by modifying the weights and is carried out through thousands of cycles until the error is minimized across all sets.

The learning procedure usually employs two types of independent datasets. Training data used to train the network and test data used to monitor the ANN performance during training process. The objective of the learning process is to determine specific set of weights that would produce the right output for a certain input. Then, the output of the model is compared with actual data to validate the prediction. When the error falls below a specified tolerance or the maximum number of epochs are exceeded, the training process is terminated. If convergence occurs, then the trained network can be used for modeling system outputs for new input data.

The performance of an ANN-based prediction is evaluated by a regression analysis between the predicted outputs and the corresponding actual values. Among several criterions, R2 and mean-square-error (MSE) values are used for measuring the prediction performance of an ANN model. R2 assesses the strength of the relationship between the predicted and target results. The value of R² ranges from zero for poor model performance to unity for perfect performance.

**4. Results and Statistical analyses**

Compressive strength for all concrete mixes was determined at 7, 28, and 56 days of curing as shown in Table 4. Figures 3, 4, and 5 show the variation of compressive strength with SF replacement levels for test series I (W/C = 0.50), II (W/C = 0.55), and III (W/C = 0.60), respectively. Test results show that the compressive strength of concrete mixes with 5, 10, and 15% replacement levels (mix B, C, and D), (mix F, G, and H), (mix J, K, and L), were higher than their corresponding control concretes, (mix A, E, and I), respectively. The maximum value of 28-day compressive strength was obtained as 35.11 MPa at 5% replacement level with a W/C ratio of 0.50 and W/CM ratio of 0.48 (mix B), and the minimum was obtained for the control specimens at a W/C ratio of 0.60 and W/CM ratio of 0.60 as 21.88 MPa (mix I). The maximum value of 56-day compressive strength was obtained as 39.62 MPa at 5% replacement level with a W/C ratio of 0.50 and W/CM ratio of 0.48 (mix B), while the minimum value was 27.13 MPa obtained at the control specimens at a W/C ratio of 0.60 and W/CM ratio of 0.60 (mix I). When the W/CM ratio decreased, the compressive strength of concrete increased for all ages and replacement levels compared to the corresponding control mix. The results indicated that the strength benefits were increased as the age increased.

The input variables a strength results were used for ANN modeling. A multi layered feed forward neural network, with back propagation algorithm, was used during the analysis. The number of neurons, in the hidden layer, was determined by training a large number of networks with different numbers of hidden neurons while comparing the predicted results with the experimental values to obtain the optimum structure. A source code was used to develop a relatively large number of different ANN configurations. With a trial-and-error approach, the code optimized the number of neurons and the selection of transfer functions.

The estimation of strength was developed using the experimental database. Input parameters were W/C, R, P, W/CM, SF, C, CM, W, FA, CA, and T, while the output variable was the strength F. As seen in Table 5, the 11-3-1 structure (eleven input neurons, three neurons in one hidden layer, one output neuron) was found to be the optimal architecture. The momentum term and learning rate were taken as 0.3 and 0.1, respectively. The input and output transfer functions were tangent hyperbolic as shown in Table 5 while the biases and connection weights were listed in Table 6. The developed model was evaluated for statistical performance using the coefficient of determination R2, and mean square error MSE. The strength of the model was measured for the training, testing, and validation datasets as shown in Table 5. It was observed that a high prediction capability was achieved for the dataset as demonstrated by the statistical indices. The R2 and MSE values were 0.9630 and 0.0003. Thus, the proposed ANN model offered excellent performance capability of predicting the silica fume concrete strength accurately with the selected input variables.

To have a more precise investigation into the model, a comparison between the experimental outputs and predicted values for dataset was plotted. As illustrated in Figures 6, an excellent agreement existed between the experimental outputs and predicted values. This demonstrated that the suggested ANN model was successful in learning the relationship between the input and out parameters.

**6. Summary and conclusions**

Efforts were made to develop an artificial neural network model that can be employed feasibly for estimating the strength of silica fume concrete using mix properties based on a reliable experimental data. Multi layered feed forward neural network, with back propagation algorithm, was used during model development. One hidden layer with three neurons was used in constructing the model. The strength values predicted using the proposed model were very close to the experimental results as illustrated by statistical parameters. R2 value was 0.9630 and MSE was 0.0003 for the dataset.

The present study shows that the strength determination of silica fume concrete can be predicted accurately and reliably using the proposed artificial neural network model. Although the prediction capability of the suggested model is limited to the boundaries of the used data, the model can be retrained to include a wider range of input variables by providing additional data covering the new range. Considering experimental laboratory tests to be cumbersome, expensive, and time intensive, the use of the proposed model can be a viable and powerful alternative for estimating the compressive strength of silica fume concrete easily and efficiently.

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Table 1. Properties of ordinary Portland cement

|  |  |
| --- | --- |
| Property | Value |
| Fineness (90-m sieve) | 8.3 |
| Specific surface (m2/kg) | 281 |
| Normal consistency (%) | 28 |
| Vicat setting time (min) |  |
| Initial | 145 |
| Final | 260 |
| Specific gravity | 3.15 |

Table 2. Properties of silica fume

|  |  |
| --- | --- |
| Property | Value |
| SiO2 Content (%) | 90 |
| Surface Area (m2/kg) | 20,000 |
| Specific gravity | 2.2 |
| Unit weight (kg/m3) | 245 |
| Fineness (45-m sieve) | 5.1 |

Table 3. Physical properties of aggregate

|  |  |  |
| --- | --- | --- |
| Property | Fine  aggregate | Coarse  aggregate |
| Specific gravity | 2.46 | 2.75 |
| Specific gravity (SSD) | 2.50 | 2.78 |
| Apparent relative density | 2.56 | 2.83 |
| Los Angeles abrasion (%) | N/A | 20.50 |
| Absorption (%) | 1.62 | 1.05 |
| Fineness modulus | 2.73 | 6.53 |
| Voids (%) | 36.7 | 38.1 |
| Unit weight (kg/m3) | 1705 | 1617 |

Table 4. Concrete mix proportions and experimental results

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Series | Mix | W/C | R | P | W/CM |  | Weight (kg/m3) | | | | | |  | Compressive strength (MPa) | | |
| SF | C | CM | W | FA | CA |  |  |  |
| I | A | 0.50 | 0 | 0.000 | 0.50 | 0 | 400 | 400 | 200 | 340 | 1360 | 19.67 | 31.95 | 33.81 |
| B | 5 | 0.041 | 0.48 | 17 | 400 | 417 | 200 | 323 | 1359 | 27.04 | 35.11 | 39.62 |
| C | 10 | 0.078 | 0.46 | 34 | 400 | 433 | 200 | 306 | 1358 | 25.56 | 34.92 | 39.52 |
| D | 15 | 0.113 | 0.44 | 51 | 399 | 450 | 200 | 288 | 1357 | 25.38 | 34.46 | 37.49 |
| II | E | 0.55 | 0 | 0.000 | 0.55 | 0 | 392 | 392 | 216 | 333 | 1334 | 17.84 | 26.39 | 30.04 |
| F | 5 | 0.041 | 0.53 | 17 | 391 | 409 | 216 | 317 | 1333 | 21.97 | 32.88 | 37.21 |
| G | 10 | 0.078 | 0.51 | 33 | 391 | 425 | 215 | 300 | 1332 | 21.50 | 32.60 | 38.18 |
| H | 15 | 0.113 | 0.49 | 50 | 391 | 441 | 215 | 283 | 1331 | 21.23 | 30.46 | 33.71 |
| III | I | 0.60 | 0 | 0.000 | 0.60 | 0 | 385 | 385 | 231 | 327 | 1308 | 14.37 | 21.88 | 27.13 |
| J | 5 | 0.041 | 0.58 | 16 | 384 | 401 | 231 | 310 | 1307 | 17.02 | 27.31 | 30.37 |
| K | 10 | 0.078 | 0.55 | 31 | 384 | 417 | 231 | 294 | 1306 | 19.03 | 28.89 | 32.46 |
| L | 15 | 0.113 | 0.53 | 49 | 384 | 433 | 230 | 277 | 1305 | 18.57 | 27.14 | 31.49 |

W/C = water-to-cement ratio, R = silica fume replacement level of fine aggregate, P = silica fume-to-cementitious materials ratio (SF/CM), W/CM = water-to-cementitious materials ratio, SF = silica fume, C = cement, CM = cementitious materials (SF+C), W = water, FA = fine aggregate, CA = coarse aggregate. , and = compressive strengths of concrete at 7, 28, and 56 day, respectively.

Table 5. Structure and performance of the ANN model

|  |  |  |  |
| --- | --- | --- | --- |
| Model properties | | | |
| Output | Input | Structure | Function |
| F | W/C, R, P, W/CM, SF, C, CM, W, FA, CA, T | 11-3-1 | Tanh-Tanh |
|  |  |  |  |
| Model parameters | | | |
| R2 | | MSE | |
| 0.9630 | | 0.0003 | |
|  | |  | |

Table 6. Biases and connection weights of the ANN model (11-3-1)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | N1 | N2 | N3 | F |
| W/C | 0.5169 | 0.6599 | -0.4807 |  |
| R | 0.9067 | -0.5552 | 0.5400 |  |
| P | 0.0790 | -0.4035 | -0.1915 |  |
| W/CM | -0.5330 | -0.2054 | -0.6107 |  |
| SF | 0.5718 | 0.4802 | -0.2124 |  |
| C | 0.4128 | -0.5978 | 0.3507 |  |
| CM | -0.5552 | -0.7530 | 0.0458 |  |
| W | 0.3913 | -0.1413 | 0.1097 |  |
| FA | 0.4591 | -0.3856 | -0.4945 |  |
| CA | -0.0117 | 0.0801 | -0.1829 |  |
| T | 0.1732 | 0.1140 | -1.5488 |  |
| F | -2.0374 | -0.6912 | -0.7412 |  |
| Bias | 0.2527 | -1.0939 | 0.1474 | 0.6727 |

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Figure 1. Grain size distribution of aggregates

Hidden layer

Yk

Y1

Xi

X1

Input layer

Output layer

Figure 2. A typical structure of an artificial neural network



Figure 3. Concrete compressive strength development of test series I (W/C = 0.50)



Figure 4. Concrete compressive strength development of test series II (W/C = 0.55)



Figure 5. Concrete compressive strength development of test series III (W/C = 0.60)

Figure 6. Comparison of predicted and experimental strength values