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MODELING OF STRENGTH OF HIGH-PERFORMANCE CONCRETE USING ARTIFICIAL NEURAL NETWORKS

I.-C. Yeh
Department of Civil Engineering, Chung-Hua University, 30 Tung Shiang, Hsin Chu, 30067, Taiwan, Republic of China

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ABSTRACT

Several studies independently have shown that concrete strength development is determined not only by the water-to-cement ratio, but that it also is influenced by the content of other concrete ingredients. High-performance concrete is a highly complex material, which makes modeling its behavior a very difficult task. This paper is aimed at demonstrating the possibilities of adapting artificial neural networks (ANN) to predict the compressive strength of high-performance concrete. A set of trial batches of HPC was produced in the laboratory and demonstrated satisfactory experimental results. This study led to the following conclusions: 1) A strength model based on ANN is more accurate than a model based on regression analysis; and 2) It is convenient and easy to use ANN models for numerical experiments to review the effects of the proportions of each variable on the concrete mix. © *1998 Elsevier Science Ltd*

Introduction

High-performance concrete (HPC) is a new terminology used in the concrete construction industry. In addition to the three basic ingredients in conventional concrete, i.e., Portland cement, fine and coarse aggregates, and water, the making of HPC needs to incorporate supplementary cementitious materials, such as fly ash and blast furnace slag, and chemical admixture, such as superplasticizer (1,2). High-performance concrete is such a highly complex material that modeling its behavior is a difficult task.

The Abrams' water-to-cement ratio (w/c) pronouncement of 1918 has been described as the most useful and significant advancement in the history of concrete technology. His most important formulation was the inverse proportionality between the w/c ratio and the strength of concrete. The generally accepted Abrams rule is a formulation of the observation that an increase in the w/c decreases the concrete strength, whereas a decrease in the w/c ratio increases the strength. The implication, therefore, is that the strengths of various but comparable concrete are identical as long as their w/c ratios remain the same, regardless of the details of the compositions (3). The Abrams rule implies that only the quality of the cement paste controls the strength of comparable cement. The paste quantity does not matter. Analysis of a variety of experimental data shows that this is not quite true. For instance, if two comparable concrete mixtures have the same w/c ratio, the strength of the concrete with the higher cement content is lower (4).

Several studies independently have shown that concrete strength development is determined not onlyby the w/c ratio, but that it is also influenced by the content of other ingredients (3). Therefore, although experimental data have shown the practical acceptability of this rule within wide limits, a few deviations have been reported. The current empirical equations presented in the codes and standards for estimating compressive strength are based on tests of concrete without supplementary cementitious materials. The validity of these relationships for concrete with supplementary cementitious materials (fly ash, blast furnace slag, etc.) should be investigated. The more we know about the concrete composition versus strength relationship, the better we can understand the nature of concrete and how to optimize the concrete mixture (4).

Artificial neural networks are a family of massively parallel architectures that solve difficult problems via the cooperation of highly interconnected but simple computing elements (or artificial neurons). Basically, the processing elements of a neural network are similar to the neurons in the brain, which consist of many simple computational elements arranged in layers. Interest in neural networks has expanded rapidly in recent years. Much of the success of neural networks is due to such characteristics as nonlinear processing, parallel processing, etc.

Most neural network applications are based on the back-propagation paradigm, which uses the gradient-descent method to minimize the error function (5). A back-propagation neural network consists of a number of interconnected processing elements (artificial neurons). The elements are arranged logically into two or more layers and interact with each other via weighted connections. These scalar weights determine the nature and strength of the influence between the interconnected elements. Each element is connected to all of the neurons in the next layer. There is an input layer where data are presented to the neural network, and an output layer that holds the response of the network to the input. It is the intermediate layers (hidden layers) that enable these networks to represent the interaction between inputs as well as the nonlinear property between inputs and outputs. Traditionally, the learning process is used to determine proper interconnection weights, and the network is trained to make proper associations between the inputs and their corresponding outputs. Once trained, the network provides rapid mapping of a given input into the desired output quantities.

The basic strategy for developing a neural-based model for material behavior is to train a neural network on the results of a series of experiments using that material. If the experimental results contain the relevant information about the materials behavior, then the trained neural network will contain sufficient information about the material's behavior to qualify as a material model. Such a trained neural network not only would be able to reproduce the experimental results it was trained on, but through its generalization capability it should be able to approximate the results of other experiments (6).

In the area of material modeling, Ghaboussi et al. (6) modeled the behavior of concrete under a state of plane stress using monotonic biaxial loading and compressive uniaxial cycle loading with a back-propagation neural network. Their results look very promising. Brown et al. (7) demonstrated the applicability of neural networks to composite material characterization. In their approach, a back-propagation neural network had been trained to accurately predict composite thermal and mechanical properties when provided with basic information concerning the environment, constituent materials, and component ratios used in the creation of the composite. Kasperkiewicz et al. (8) demonstrated that the fuzzy-ARTMAP neural network can model the strength properties of HPC mixes and optimize the concrete mixes. Yeh (9) proposed a modified neural network architecture for modeling the strength of normal strength concrete and optimize the mix proportions. The main benefits in using a neural network approach are that all of the behavior of a material can be represented within the unified environment of a neural network, and the neural network-based model is built directly from experimental data using the learning capabilities of the neural network. The methodology of an artificial neural network has been described in many papers and books, and will not be discussed here. The purpose of this article is to provide a methodology for predicting the compressive strength of HPC. In the following sections, section 2 describes the artificial neural network. Section 3 examines the network in modeling the compressive strength of concrete. Section 4 examines the model with several proportioning parameters to observe the strength behavior of the HPC. Section 5 uses a series of experiments to verify the proposed method. Finally, Section 6 gives a summary and conclusions.

Architecture of Artificial Neural Networks

Artificial neural networks are a family of massively parallel architecture that can solve difficult problems by cooperating with highly interconnected but simple computing elements (or artificial neurons). Most research is based on back-propagation neural networks (5).

To train the network, the weights of connections are modified according to the information it has learned. The network learns by comparing its output for each input pattern with a target output for that pattern, then calculating the error and propagating an error function backward through the net.

To run the network after it is trained, the values for the input parameters for the project are presented to the network. The network then calculates the node outputs using the existing weight values and thresholds developed in the training process. The process for running the network is extremely rapid, because the system only calculates the network node values once.

To test the accuracy of a trained network, the coefficient of determination R^2 is adopted. The coefficient is a measure of how well the independent variables considered account for the measured dependent variable. The higher the R^2 value, the better the prediction relationship.

A thorough treatment of back-propagation networks is beyond the scope of this paper. The basic algorithms for back-propagation neural network have been covered widely (5,10–12).

Modeling of Strength of High-Performance Concrete

System models

Although each component is described using only a single term, these terms actually represent a variety of forms. For example, a cement can be powdered to various degrees of finenesses and composed of several different chemical compositions. Apart from the component types, the properties of concrete are influenced by the mixing proportions and by the mixing preparation technique. Although technical references consist of experimental data describing thousands of different mixes, no one has yet made a composite of this information. Moreover, a mix is almost never described with all of the important details indicated; thus,

TABLE 1
Ranges of components of data sets.

Component	Minimum (kg/m^3)	Maximum (kg/m^3)	Average (kg/m^3)
Cement	71	600	232.2
Fly ash	0	175	46.4
Blast furnace slag	0	359	79.2
Water	120	228	186.4
Superplasticizer	0	20.8	3.5
Coarse aggregate	730	1322	943.5
Fine aggregate	486	968	819.9

a strength prediction from the available data is a highly uncertain task (8). Therefore, in this approach, the compressive strength of concrete is a function of the following eight input features:

1. Cement (kg/m^3)
2. Fly ash (kg/m^3)
3. Blast furnace slag (kg/m^3)
4. Water (kg/m^3)
5. Superplasticizer (kg/m^3)
6. Coarse aggregate (kg/m^3)
7. Fine aggregate (kg/m^3)
8. Age of testing (days).

Data sets

Experimental data from 17 different sources was used to check the reliability of the strength model (1,13–28). Test data were assembled for concrete containing cement plus fly ash, blast furnace slag, and superplasticizer. A determination was made to ensure that these mixtures were a fairly representative group governing all of the major parameters that influence the strength of HPC and present the complete information required for such an evaluation.

In all about 1000 concrete samples from the above investigations were evaluated. During the evaluation, some of the concrete samples were deleted from the data due to larger size aggregates (larger than 20 mm), special curing conditions, etc. About 700 concrete samples made with ordinary Portland cement and cured under normal conditions were evaluated. Different studies used specimens of different sizes and shapes. All of these specimen types were converted into 15-cm cylinders through accepted guidelines. Tables 1 and 2 present the general details of the concrete evaluated in this study. The data base often contain unexpected inaccuracies, for instance, the class of fly ash is sometimes not reported. The greatest difficulty seems to be related to the application of superplasticizers. They are from different manufacturers, of different chemical compositions, and without details concerning the solid contents in the suspension (8).

TABLE 2
Ranges of ratio of data sets.

Ratio	Minimum	Maximum	Average
Water to cement	0.24	2.73	0.97
Water to binder	0.24	0.87	0.56
SP to binder	0.00	0.040	0.009
Fly ash to binder	0.00	0.50	0.13
Slag to binder	0.00	0.70	0.23
(Fly ash + slag) to binder	0.00	0.70	0.35

A data base of 727 records, each containing the eight components for the input vector and the one output value (compressive strength), was split in such a way that the vectors from the different references were divided into four data sets: set A, set B, set C, and set D. To test the reliability of the methodology, we selected three sets as a training set, and the remaining set was used to test the accuracy of the method. Alternatively, all of the records were combined and simply shuffled using random sampling, dividing them into training and testing groups. The numbers of training and testing examples for these experiments are listed in Table 3.

Network parameters

The neural network developed in the investigation has eight units in the input layer and one unit in the output layer. Training means to present the network with the experimental data and have it learn, or modify its weights, such that it correctly reproduces the compressive strength when presented with the mix proportion and age.

The values of network parameters considered in this approach are as follows:

TABLE 3
Training set and testing set.

Experiment	Training set	Test set	No. of training examples	No. of testing examples
S1	B, C, D	A	527	200
S2	A, C, D	B	516	211
S3	A, B, D	C	527	200
S4	A, B, C	D	611	116
R1	Random 3/4	The rest 1/4	545	182
R2	Random 3/4	The rest 1/4	545	182
R3	Random 3/4	The rest 1/4	545	182
R4	Random 3/4	The rest 1/4	545	182

TABLE 4
Results of neural networks.

Experiment	R^2 of training set	R^2 of testing set
S1	0.917	0.855
S2	0.929	0.814
S3	0.935	0.895
S4	0.933	0.859
R1	0.923	0.916
R2	0.933	0.908
R3	0.945	0.922
R4	0.932	0.911

- Number of hidden layers = 1
- Number of hidden units = 8
- Learning rate = 1.0
- Momentum factor = 0.5
- Learning cycles = 3000

Training results

Table 4 shows the training results. It appears that the following conclusions can be drawn:

1. When the data base was divided into four data sets based on the source of the vectors, the coefficients of determination R^2 were 0.855, 0.814, 0.895, and 0,859, respectively. These coefficients indicate a significant enough correlation.
2. If all the records were used in combination and simply shuffled using random sampling, the result was even better. The coefficients of determination R^2 were 0.916, 0.908, 0.922, and 0,911, respectively.

The predicted values of the best experiment compared with values actually observed in the laboratory for the testing examples are shown in Figure 1.

Comparison with statistical techniques

In the conventional material modeling process, regression analysis is an important tool for building a model. In this study, w/c and water-to-binder ratios were used to build the regression formulas. The types of regression formulas adopted were as in the following equation:

$$f'_c(t) = aX^b \cdot [c \ln(t) + (d)]$$

where t = age at test; X = w/c or water-to-binder ratio; and a, b, c, and d are regression coefficients.

Tables 5 and 6 show the coefficients of determination and regression coefficients. They also verify that when the water-to-binder ratio is used instead of the w/c ratio as the basis for

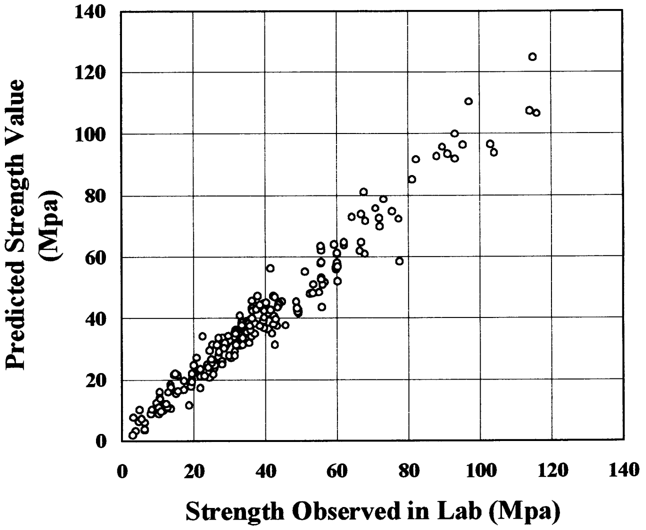

FIG. 1.
Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples.

modeling strength behavior, the prediction becomes more accurate for most of the experiments used in this study. The predicted values of the best experiment compared with the values actually observed in laboratory for the testing examples are shown in Figure 2.

The comparison between Tables 4 and 6 shows that the neural network models are supported better by experimental data than the regression analysis. It is shown that although the use of the models is not as simple as that of the basic formula, they provide a more accurate tool for the prediction of concrete strength.

TABLE 5
Results of regression analysis based on water-to-cement ratio and age.

	Coefficients of determination R^2		Regression coefficient			
Experiment	Training set	Testing set	a	b	c	d
S1	0.564	0.537	30.283	−0.6755	0.2673	0.1638
S2	0.587	0.583	29.215	−0.7281	0.2807	0.0901
S3	0.552	0.515	26.913	−0.6333	0.2674	0.1122
S4	0.463	0.432	26.952	−0.5351	0.2647	0.1056
R1	0.588	0.573	28.801	−0.6906	0.2627	0.1289
R2	0.579	0.584	28.898	−0.6815	0.2669	0.1196
R3	0.583	0.576	27.862	−0.7314	0.2660	0.1306
R4	0.582	0.563	28.898	−0.6815	0.2668	0.1354

TABLE 6
Results of regression analysis based on water-to-binder ratio and age.

	Coefficients of determination R^2		Regression coefficient			
Experiment	Training set	Testing set	a	b	c	d
S1	0.745	0.726	13.780	−1.3084	0.2707	0.1564
S2	0.753	0.734	13.812	−1.3173	0.2657	0.0891
S3	0.713	0.683	14.267	−1.1730	0.2688	0.0523
S4	0.742	0.721	13.251	−1.3258	0.2519	0.0986
R1	0.782	0.773	13.744	−1.2648	0.2688	0.1408
R2	0.772	0.768	13.865	−1.2712	0.2758	0.1307
R3	0.792	0.779	13.859	−1.2749	0.2583	0.1377
R4	0.769	0.759	13.838	−1.2673	0.2702	0.1359

Effects of Water-to-Binder Ratio and Age

The neural network model is built based on the data over the experimental domain. The modeling and prediction of the response of other experimental points in the experimental domain were therefore possible.

To evaluate the effects of water-to-binder ratio and age on concrete strength, one diagram

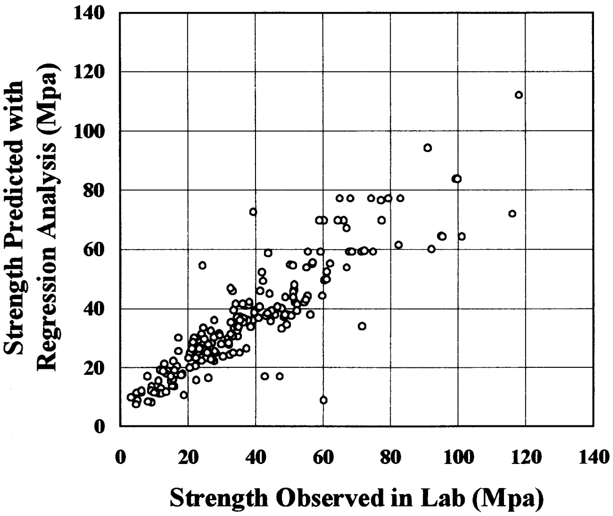

FIG. 2.
Predicted values of regression analysis compared with values actually observed in laboratory for the testing examples.

TABLE 7
Data of analysis for strength–age curves.

Component	Mix proportion				
	Mix 1	Mix 2	Mix 3	Mix 4	Mix 5
Water-to-binder ratio	0.3	0.4	0.5	0.6	0.7
Cement (kg/m^3)	200	180	160	155	150
Fly ash (kg/m^3)	160	140	120	100	80
Slag (kg/m^3)	210	151	133	103	90
Water (kg/m^3)	160	180	200	210	220
Superplasticizer (kg/m^3)	11	8.5	6.5	4.5	3.5
Coarse aggregate (kg/m^3)	1000	950	900	850	800
Fine aggregate (kg/m^3)	647.7	746.3	805.5	889.8	956.0

was produced based on the data listed in Table 7. Figure 3 shows the water-to-binder ratio–strength curves at various concrete ages (3, 14, 28, and 90 days).

Experimental Program

To demonstrate the utility of the proposed methodology, experimental results from several different mix proportions based on various water-to-binder ratios are presented.

The materials used in the experimental program were as follows:

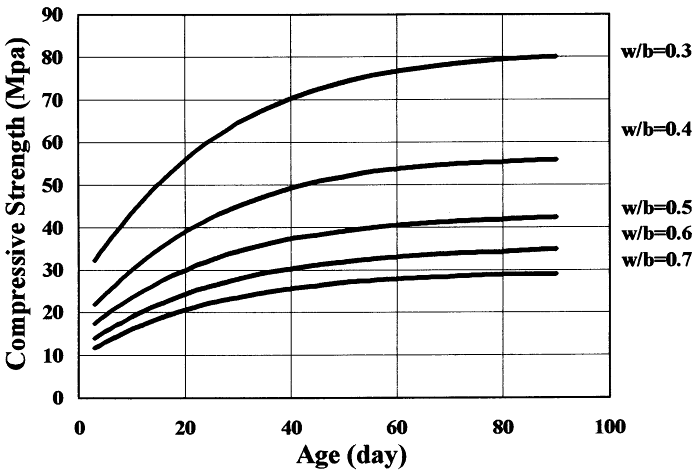

FIG. 3.
Predicted age–strength curves under various water/binder ratios (w/b = 0.3, 0.4, 0.5, 0.6, 0.7).

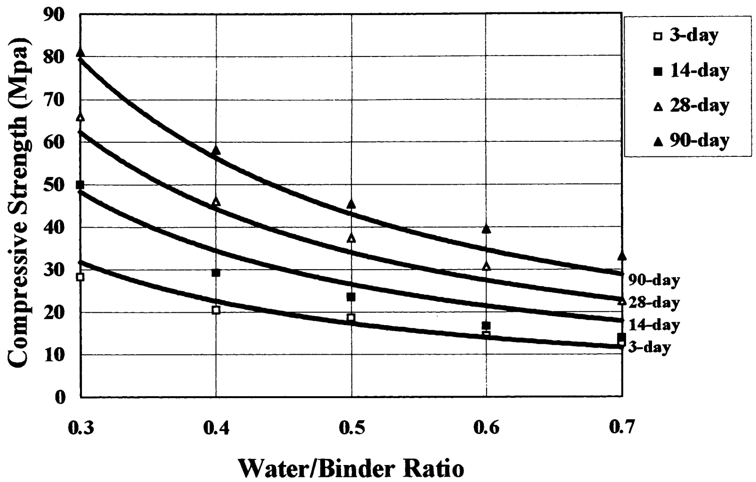

FIG. 4.
Experimental strength values compared with predicted water/binder ratio–strength curves (age = 3, 14, 28, 90 days).

1. Cement—Portland cement (ASTM type I)
2. Fly ash—manufactured by power plant
3. Water quenched, blast furnace slag powder—supplied by a local steel plant
4. Water—ordinary tap water
5. Chemical admixture—a superplasticizer that meets ASTM C494 type G with main ingredients of naphthalene-formaldehyde condensate and fatty acid copolymer
6. Coarse aggregate—crushed natural rock with a 10-mm maximum size.
7. Fine aggregate—washed, natural river sand with a fineness module of 3.0.

To achieve mixtures of high workability, a superplasticizer (trade name HICON) was used in all of the mixes to obtain a slump of 125 to 175 mm.

Mixing was carried out in a laboratory pan mixer. The superplasticizer was premixed with water to ensure consistency of action throughout the test program. The mixing procedure used is as follows:

1. Two thirds of water and superplasticizer was added at the beginning of the mixing together with cement and slag and mixed for 1 min.
2. One third of water and superplasticizer was added together with the aggregates and mixed for 1 min;
3. Fly ash was added and mixed for 1 min.

The fresh concrete was assessed using a slump test. This convenient and simple test was adequate to quantify the fresh properties of the concrete for the purposes of this program. All compressive strengths were measured using 15-cm cylinders, whicn were moist cured for 24 h, demolded, and cured in water until testing. Each quoted strength value is the average of the strengths from five cylinders.

To demonstrate the prediction capacity of the proposed methodology, experimental results from five different mix proportions listed in Table 7 using the same materials are presented. Experimental results for 3-day, 14-day, 28-day, and 90-day concrete compressive strengths are shown in Figure 4. Obviously, the strengths of the these mix proportions meet the predicted values obtained from the strength model.

Conclusions

High-performance concrete is a highly complex material that makes modeling its behavior a difficult task. This study was aimed at demonstrating the possibilities of adapting neural networks to predict the compressive strength of concrete. A set of trial batches of HPC was produced at the laboratory and showed satisfactory experimental results. However, the method is not applicable to extrapolation beyond the domain of the data accumulated in the past.

This study led to the following conclusions:

1. The strength model based on the artificial neural network is more accurate than the model based on regression analysis.
2. The compressive strength can be calculated using the models built with this methodology. It is convenient and easy to use these models for numerical experiments to review the effects of each variable on the mix proportions. For example, the strength model can be used to study the strength effects of age or water-to-binder ratio.

References

1. T.-P. Chang, F.-C. Chung, and H.-C. Lin, J. Chin. Inst. Eng. 19, 645 (1996).
2. P.L.J. Domone and M.N. Soutsos, Concr. Int. October 1994, 26 (1994).
3. F.A. Oluokun, ACI Mater. J. 91, 362 (1994).
4. S. Popovics, ACI Mater. J. 87, 517 (1990).
5. D.E. Rumelhart, G.E. Hinton, and R.J. Williams. Parallel Distributed Processing, D.E. Rumelhart and J.L. McClelland (eds.), p. 318, M.I.T. Press, Cambridge, MA, 1986.
6. J. Ghaboussi, J.H. Garrett, and X. Wu, J. Engng. Mech. ASCE. 117, 129 (1991).
7. D.A. Brown, P.L.N. Murthy, and L. Berke, Microcomput. Civil Engng. 6, 87 (1991).
8. J. Kasperkiewicz, J. Racz, and A. Dubrawski, J. Comput. Civil Engng. ASCE. 9, 279 (1995).
9. I.-C.Yeh, J. Mater. Civil Engng. ASCE. (1998). (Accepted)
10. S.T. Welstead, Neural Network and Fuzzy Logic Applications in C/C++, John Wiley & Sons, New York, 1994.
11. I.-C.Yeh, Y.-H. Kuo, and D.-S. Hsu, Expert Syst. Applic. 5, 59 (1992).
12. I.-C. Yeh, Y.-H. Kuo and D.-S. Hsu, J. Comput. Civil Engng. ASCE. 7, 71 (1993).
13. C.Z. Chang, Research on the mix proportion of high flowing eugenic concrete, Master's thesis, Department of Civil Engineering, Chung Hua University, Hsin Chu, Taiwan, 1997.
14. F.C. Chung, Study on characteristic of coarse aggregate in high-performance concrete, Master's thesis, Department of Construction Engineering, National Taiwan Institute of Technology, Taipei, Taiwan, 1995.
15. G. Giaccio, C. Roccd, D. Violini, J. Zappitelli, and R. Zerbino, ACI Mater. J. 89, 242 (1992).
16. O.E. Gjorv, P.J.M. Monterio, and P.K. Metha, ACI Mater. J. 87, 573 (1990).
17. T.S. Hwang, Compressive strength of blast furnace slag concrete, Master's thesis, Department of Civil Engineering, National Chiao Tung University, Hsin Chu, Taiwan, 1966.

18. G.E. Hwang, A study on blast furnace slag concrete, Master's thesis, Department of Civil Engineering, National Chiao Tung University, Hsin Chu, Taiwan, 1991.
19. W.S. Langley, G.S. Garette, and V.M. Malhotra, ACI Mater. J. 85, 507 (1989).
20. C.F. Lee, A study on dry shrinkage and creep property of HPC, Master's thesis, Department of Construction Engineering, National Taiwan Institute of Technology, Taipei, Taiwan, 1994.
21. M. Lessard, O. Chaallal, and P.C. Aitcin, ACI Mater. J. 90, 303 (1993).
22. F.Y. Lin, Mixture proportion and quality of HPC, Master's thesis, Department of Construction Engineering, National Taiwan Institute of Technology, Taipei, Taiwan, 1994.
23. H.L. Mo, A study on high performance concrete, Master's thesis, Department of Construction Engineering, National Taiwan Institute of Technology, Taipei, Taiwan, 1995.
24. T.R. Naik and B.W. Ramme, ACI Mater. J. 87, 619 (1990).
25. T.Z. Pon, Modeling of strength of high performance concrete using artificial neural networks, Master's thesis, Department of Civil Engineering, Chung Hua University, Hsin Chu, Taiwan, 1998.
26. S.L. Sarkar and P.C. Aitcin, Cem. Concr. Aggr. 9, 57 (1987).
27. V. Sivasundaram, G.G. Garette, and V.M. Malhotra, ACI Mater. J. 88, 407 (1991).
28. R.N. Swamy and A. Bouikni, ACI Mater. J. 87, 210 (1990).