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COMPARISON OF CONCRETE STRENGTH PREDICTION TECHNIQUES WITH ARTIFICIAL NEURAL NETWORK APPROACH

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Prediction of concrete strength is an important issue in ready-mixed concrete industry, especially, in proportioning new mixtures and for the quality assurance of the concrete produced. In this paper, it is aimed to illustrate that the artificial neural networks can be used for predicting the 28-day strength of low to medium strength concretes. The compositional, fresh concrete and early strength data obtained from different batching plants of a ready-mixed concrete company have been defined in terms of ten independent variables that are grouped in five different system models to which neural network and multiple linear regression models have been applied. The accuracies of prediction by artificial neural network and multiple linear regression models as well as by Abrams' law are compared on the basis of the coefficient of determination. It appears that the best results are obtained by the artificial neural network models using data for fresh concrete and early strength simultaneously.

Keywords: Abrams' law; Artificial neural networks; Compressive strength; Multiple linear regression; Ready-mixed concrete; Strength prediction

1 Introduction

Strength, in almost all cases, is considered to be the most important property of concrete, because it usually indicates the overall quality of the concrete. Although the strength of concrete can be measured at different ages, codes usually specify standard 28-day testing. Earlier testing at such as seven days, on the other hand, may be useful for the prediction of the 28-day strength of concrete. When no specific data are available, 28-day strength may be assumed to be 1.5 times the 7-day strength whereas this ratio was shown to vary generally from 1.3 to 1.7 (Neville, 1986).

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Strength of a fully compacted concrete at a given age may be estimated by the well known Abrams' law (Abrams, 1927) which states that the strength of concrete is inversely proportional to the water-cement ratio. Several researchers, on the other hand, showed that the compressive strength of concrete was determined not only by the water-cement ratio, but it was also affected by the content of other constituents of the concrete (Popovics, 1990; Oluokun, 1994). Strength of concrete may also be estimated through its compositional properties by empirical relationships built through a statistical approach such as multiple linear regression (MLR). However, considering that concrete is a highly nonlinear material, modeling its behavior would be highly difficult. An alternative method to estimate the strength of concrete is the artificial neural network (ANN) approach. ANNs may be trained on the available experimental data describing the behavior of the material to predict its behavior from the results of other experiments using that material. Most research in this area used the backpropagation networks (Yeh, 1999; Lai and Serra 1997; Nehdi et al., 2001a; Dias and Pooliyadda, 2001; Yeh, 1998a) to design concrete mixtures and/or to predict its strength whereas some modifications to the standard backpropagation network (Yeh, 1998b) and other ANN techniques (Kasperkiewicz et al., 1995) were reported in the literature.

Yeh (1998a) showed that ANNs could easily be adapted to predict the compressive strength of high performance concrete from the mix proportions of the concrete ingredients based on a large set of experimental data obtained from literature to be more accurate than a model based on regression analysis. Yeh (1999) extended the application of ANNs together with nonlinear programming to the optimization of high performance concrete mix proportioning for a given workability and compressive strength. Lai and Serra (1997) developed an ANN model for predicting the compressive strength of concretes with varying aggregate properties based on data from intensive experimental measurements and concluded that the ANN performance was independent of the number of neurons in the hidden layer within the range of 4 – 8. Kasperkiewicz et al. (1995) demonstrated that an ANN of the fuzzy-ARTMAP type could be used for predicting strength properties of high performance concrete and for searching for optimal concrete mixes. In their work, they obtained significant correlations between the actual strength values and the values predicted by the ANN based on data from various publications and concluded that the most rational approach to applying learning and predicting techniques was using data from a single source.

Dias and Pooliyadda (2001) used backpropagation networks to predict the strength and slump of ready mixed concrete and high strength concrete with chemical and/or mineral admixtures. They tried various data transforms and concluded that models based on raw data gave the best results and that the ANN models performed better than the multiple regression models in reducing the scatter of predictions. Yeh (1998b) proposed an augmented ANN to improve the efficiency and accuracy in modeling highly complex and nonlinear concrete behavior using experimental data from 15 different sources. Nehdi et al. (2001a) demonstrated that ANNs could be used to accurately predict the slump flow, filling capacity, segregation and

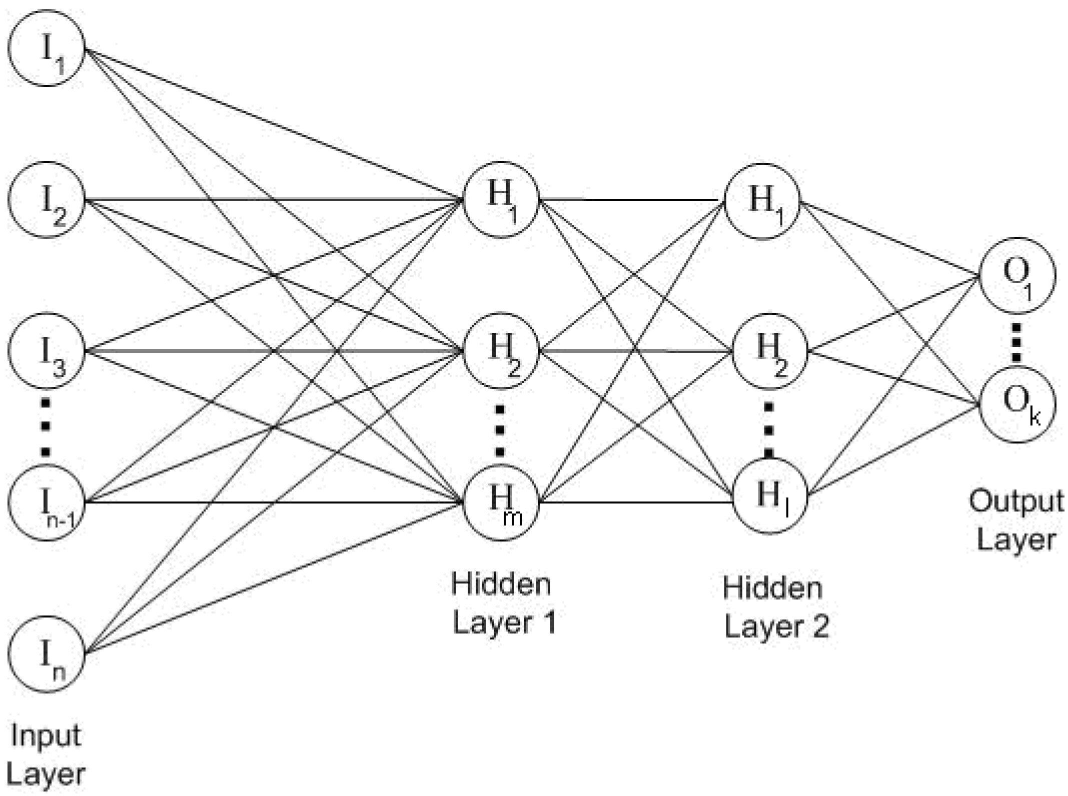

Figure 1. 2-hidden layer network with n inputs and k outputs

28-day compressive strength of self compacting concrete mixtures made by various researchers with an average absolute error of 4, 5, 7 and 7 %, respectively.

2 Artificial Neural Network Approach

Machine learning approach is appealing for artificial intelligence since it is based on the principle of learning from training and experience. Connectionist models, such as neural networks, are well suited for machine learning where connection weights are adjusted to improve the performance of a network. A neural network consists basically of a number of simple processing units called neurons. Typically, the neurons are organized logically into groupings called layers. The network is hierarchical, consisting of three or more layers: the input layer, one or more hidden layers, and the output layer (Fig. 1). Each neuron in a given layer is connected to all the neurons in the next layer. The neurons in each layer interact with neurons in other layers through weighted connections.

Each unit in the network receives an input from the lowest-level units and computes a weighted sum. The input data are propagated through the network by multiplying the values of the neurons in the input layer by the connecting weights. The weights should be randomized initially in order to avoid the system to be locked at the starting point (Baxter, 2001). These products are summed at the target neurons in the first hidden layer. The summed products are operated on by a transfer function to determine the output level of each neuron. A linear sigmoid could be used as the transfer function producing an analog output with values ranging from 0 to 1 (Deboeck, 1994). The signals from the first hidden layer are propagated to the following hidden layers, if they exist, and to the output layer in a similar fashion.

Although in theory a single hidden layer is sufficient to solve any function approximation problem, some problems might be easier to solve using more than a single hidden layer, especially two hidden layers (Partovi and Anandrajan, 2002; Carsten and Thorstein, 1993). The number of neurons in a hidden layer was usually determined via a trial and error procedure (Nehdi et al., 2001b). There were many specified empirical criteria for the number of neurons in the first hidden layer as a function of the number of input (NI) and output (NO) variables as given in Table 1. The optimum ratio of neurons in the first hidden layer to the second hidden layer was recommended to be 3 : 1 (Kudrycki, 1988).

Table 1 Empiricial Criteria for the Number of Neurons in the First Hidden Layer

Number of Nuerons in the First Layer	Reference(s)
2*NI	[6]
NI+NO	[10]
0.75*NI	[13]
2*NI+1	[13]
NI	[5, 9]
(NI+NO) / 2	[16]

(NI: Number of Inputs, NO: Number of Outputs)

The above mentioned networks are also called layered feed forward networks because the connections are unidirectional and they are typically trained with static back propagation. While using back propagation, it was stated that the network could learn by comparing its output for each input pattern with a target output for that pattern and then by calculating the error and propagating an error function backward through the net (Yeh, 1999). The Generalized Feed Forward (GFF) network is a generalization of the layered feed forward networks such that the connections can jump over one or more layers. These networks are usually preferred since they solve problems much more efficiently.

Training of the network can be performed using gradient descent approach with a constant learning rate of which the stepsize is controlled by a parameter ρ greater than zero. When ρ is chosen too large, the algorithm may become unstable and fail to converge at all. Gallant (1993) stated that it was probably the best to set it to a value not greater than 0.1. This approach minimized the sum of squared errors and the training process was carried out until one of the following conditions was met (Yeh, 1999; Lai and Serra, 1997; Nehdi et al., 2001a; Gallant, 1993; Baxter, 2001; Teh et al., 1997): a) a sufficiently small predetermined testing error was reached, b) the testing error began to increase, c) a predetermined number of learning cycles had passed. The error is multi-dimensional and may contain many local minima. A momentum factor is usually added to the weight adjustment in order to avoid a local minima or slow convergence. Momentum factor varies from 0.1 to 1. In prediction studies of concrete strength by ANNs, 0.5 was a commonly used value for momentum factor (Yeh, 1998a; Yeh, 1998b; Yeh, 1999).

Teh et al. (1997) affirmed that after the training process was completed, the network with specified weight factors could be used for testing a set of inputs different than the inputs used for training. Testing was then carried out using a separate set of data to validate whether the neural network could produce correct responses for patterns that only broadly resemble the data in the training set. Neural networks should be trained on a wide enough set of input data to generalize from their training sets (Nagendra, 1998). The ratio of training set to test set varied from 1 : 9 to 5 : 5 in related studies (Yeh, 1998a; Yeh, 1998b; Yeh, 1999; Kasperkiewicz et al., 1995; Baxter, 2001; Carsten and Thorstein, 1993; Nehdi et al., 2001b).

R^2 (coefficient of determination) is usually used to test the accuracy of the trained network. The coefficient of determination is a measure of how well the independent variables considered account for the measured dependent variable. A higher R^2 value indicates a better prediction relationship. Predictive capability of the method on the other hand was within the range of data employed for model fitting (Yeh, 1999).

3 Research Significance

The objective of this paper is to illustrate that the ANNs can be used to predict the 28-day compressive strength of ready-mixed concrete through a comparative analysis by ANN, MLR and Abrams' prediction models. Data are gathered directly from a ready-mixed concrete company for low to moderate strength concrete mixtures produced over a period of six months at its different batching plants using the same type of constituent materials. Various sets of combinations of available data are considered for prediction modeling. Supervised learning models have been utilized in which certain output nodes are trained to respond to certain input patterns and the changes in connection weights due to learning have caused those same nodes to respond to more general classes of patterns.

4 Modeling of the Prediction of 28-day Compressive Strength of Concrete

4.1 System Models

Strength of concrete is mostly defined by its components with regard to their mass contents in unit volume of concrete and individual characteristics. Additional factors related to the batching, mixing, placing and curing procedures affect the strength development of concrete. Although experimental data available in the literature provide a great deal of information, some important details might be lacking in many situations, making the strength prediction a highly uncertain task.

Therefore, in this study the following input variables obtained through different stages of the ready-mixed concrete production are considered to ultimately affect the 28-day compressive strength of the concrete, f_{C28} (MPa).

Cement, C (kg/m^3)
Water, W (kg/m^3)
Crushed Limestone I (5-10 mm), CLI (kg/m^3)
Crushed Limestone II (10-20 mm), CLII (kg/m^3)
Natural Sand, NS (kg/m^3)
Crushed Sand, CS (kg/m^3)
Water Reducing Admixture, WRA (kg/m^3)
Slump, S (cm)
Fresh Density, FD (kg/m^3)
7-day Compressive Strength, f_{C7} (MPa)

Considering the input variables, five different system models (M1 to M5) consisting of different sets of these input variables are considered for the prediction of 28-day compressive strength of concrete:

System Model 1, M1 : $f_{C28} = f_{Model1}$ (C, W, CLI, CLII, NS, CS, WRA)
System Model 2, M2 : $f_{C28} = f_{Model2}$ (C, W, CLI, CLII, NS, CS, WRA, S, FD)
System Model 3, M3 : $f_{C28} = f_{Model3}$ (f_{C7})
System Model 4, M4 : $f_{C28} = f_{Model4}$ (C, W, CLI, CLII, NS, CS, WRA, f_{C7})
System Model 5, M5 : $f_{C28} = f_{Model5}$ (C, W, CLI, CLII, NS, CS, WRA, S, FD, f_{C7})

Thus, the effectiveness of different combinations of compositional, fresh concrete and early strength data has been investigated for the strength prediction.

4.2 Data Sets

Experimental data collected from five different batching plants of a ready-mixed concrete company for a period of six months for a specified strength concrete, produced with the same type of materials, are used to train and test the strength prediction models without normalization. Statistical analysis of the data set based on normal distribution is given in Table 2. The data set of 111 records indicate that the workability range from stiff to plastic and even fluid consistencies, depending on the casting and compacting conditions at the site. Statistical analysis of the 28-day 150 mm cube compressive strength indicates a mean value of 26.2 MPa and standard deviation of 3.0 MPa for 111 test results. Statistical evaluation of concrete strength based on EN206-1 conformity criteria for the mean strength and the minimum individual value reveals a characteristic strength of 21.8 MPa and 23 MPa, respectively. This evaluation indicates a C16/20 quality for the concrete. Moreover, a coefficient of variation of 11.5 % indicates a moderate degree of quality control.

Table 2. Statistical analysis of data set (n = 111)

Variable	Minimum	Maximum	Mean	Standard Deviation
Cement (kg/m^3)	268	307	286	12
Water (kg/m^3)	81	213	154	24
Crushed Limestone I (kg/m^3)	391	610	494	89
Crushed Limestone II (kg/m^3)	563	787	657	58
Natural Sand (kg/m^3)	398	590	474	77
Crushed Sand (kg/m^3)	172	437	326	69
Water Reducing Admixture (kg/m^3)	0.54	1.54	0.69	0.17
Slump (cm)	5.0	19.5	12.7	3.2
Fresh Density (kg/m^3)	2 311	2 451	2 374	21
7-day Concrete Strength (MPa)	15.0	28.9	20.6	2.8
28-day Concrete Strength (MPa)	19	35	26.2	3.0

From this data set, 100 cases are taken as training and 11 as testing (9 : 1 ratio) examples by systematic sampling where every tenth case is chosen for testing group from the list of data sorted in the ascending order of 28-day compressive strength of concrete. Thus, it has been possible to test the reliability of the prediction model over the full range of strength data.

4.3 Network Parameters

For each system model described before, the Generalized Feed Forward Artificial Neural Network model is applied for two different numbers of hidden layers (HL = 1, 2) at six different numbers of first hidden layer neurons as stated before for the data set. Thus, 12 different ANN models have been used for each system model. For all of those ANN models, the following network parameters are taken the same:
Learning rule: Momentum (momentum factor = 0.5)
Stopping criteria: Mean Square Error (minimum MSE = 0.005)
Learning rate: 0.1
Activation function: Linear Sigmoid
Initial weight: Randomized

4.4 Training Results

In this study, 12 ANN models are applied to each of the five system models, using NeuroSolutions ANN software package. Thus, a total of 60 strength prediction models have been tried. ANN models' performances are measured by the coefficient of determination (R^2). Table 3 shows the ANN models with the highest R^2 values among the 12 GFF network models applied to each system model.

Table 3. Results of artificial neural network models

	GFF – One Hidden Layer			GFF – Two Hidden Layers		
System Model	R^2	# of Neurons in the Hidden Layer (1)	Learning Cycles	R^2	# of Neurons in the Hidden Layers (1 –2)	Learning Cycles
M1	0.423	14	22 660	0.504	5 – 2	28 451
M2	0.120	5	29 991	0.410	7 – 2	19 105
M3	0.790	3	37	0.790	1 –1	3 844
M4	0.884	6	44	0.903	17 – 6	207
M5	0.884	8	26	0.919	11 – 4	116

4.5 Comparison with Multiple Regression Model and Abrams' Law

The ANN performances are compared with MLR approach and the results obtained from the Abrams' formula. The general regression expression is shown in Eq.(1). Regression coefficients of the expression are obtained by fitting the training set data for each system model, and the model is evaluated by comparing the predicted and measured strength values of the testing set data. Table 4 shows the coefficients of determination for the MLR models. Experimental parameters of the Abrams' formula (Eq.2) are obtained by fitting it to the training set data after converting to a linear form (Eq.3) by taking the logarithm of both sides.

$$f_{C28} = a_0 + a_1 x_1 + \ldots\ldots + a_n x_n \tag{1}$$

$$f_{C28} = \frac{A}{B^{w/c}} \tag{2}$$

$$\log f_{C28} = \log A - \left(w/c\right)\log B = a_0 + a_1\left(w/c\right) \tag{3}$$

The Abrams' law is evaluated by comparing the predicted and measured strengths of the testing set data. The w/c values vary from 0.27 to 0.75 with a mean value of

0.54 and a standard deviation of 0.09. The coefficient of determination (R^2) for the Abrams' law is also shown in Table 4.

Table 4 Results of multiple linear regression models and Abrams' law

System Model	MLR	Abrams' Law
M1	R^2 = 0.550	
M2	R^2 = 0.469	
M3	R^2 = 0.786	R^2 = 0.351
M4	R^2 = 0.885	
M5	R^2 = 0.903	

5 Evaluation

The accuracy of the prediction for each approach has been evaluated by the coefficient of determination. Tables 3 and 4 verify that the best solution (R^2 = 0.919) for the prediction models considered in this study is achieved by the ANN model of 2 hidden layers with 11 neurons in the first layer and 4 neurons in the second layer for M5. On the other hand, lower R^2 coefficients have been determined for M1 and M2 models in all techniques which indicate that the input variables included in these models alone have not been sufficient enough for the prediction of concrete strength.

It has been also observed that MLR models are much more successful for predicting the strength of concrete than ANN models for M1 and M2. However, the inclusion of early strength data as in M4 and M5 causes an improvement in the prediction accuracy of the ANN models compared to the MLR models. Thus, ANN models are generally better than the MLR models for M4 and M5. ANN and MLR models, on the other hand, are equally successful in predicting the 28-day strength of concrete for M3 which include only early strength as the input variable. Both ANN and MLR models have much higher prediction accuracies than the Abrams' law in all five system models.

Fig. 2 shows the predictions of the 28-day strength of the concrete based on the validation data through the learning process for M5. The coefficients of determination are 0.919, 0.903 and 0.351 for ANN, MLR and Abrams' models, respectively, indicating better accuracy of prediction for the ANN model. Fig. 3, on the other hand, shows the predictions of the 28-day strength of the concrete based on all data for M5. It is observed that the coefficients of determination are reduced to 0.623, 0.692 and 0.113 for ANN, MLR and Abrams' models, respectively, as the prediction of the concrete strength has been extended to all data. It is observed that the accuracy prediction was slightly better for the MLR model than ANN model when all data are considered.

Abrams' law which predicts the concrete strength based on its w/c gives a considerably low coefficient of determination. This may be due to the fact that

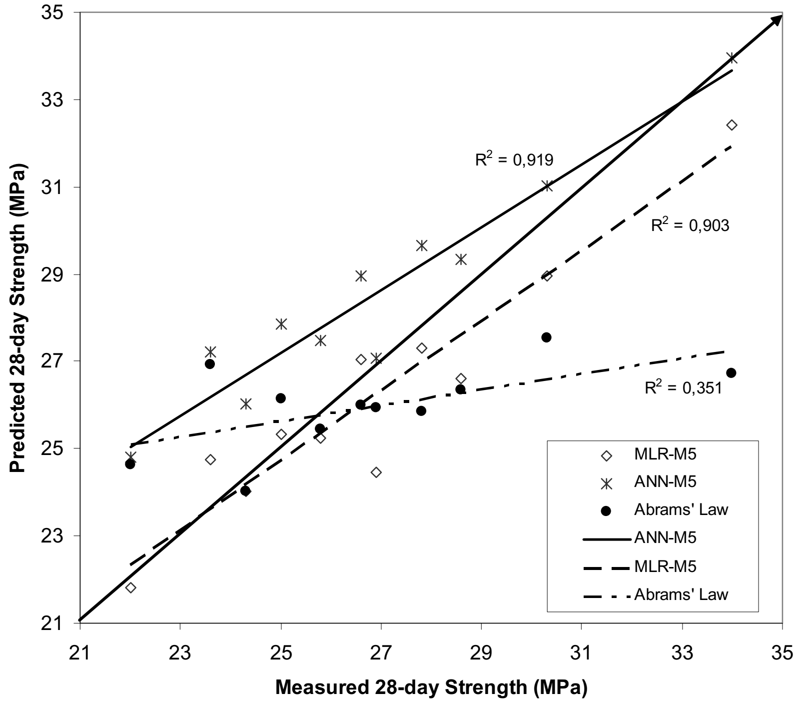

Figure 2. Predicted concrete strengths compared with measured strengths (test data)

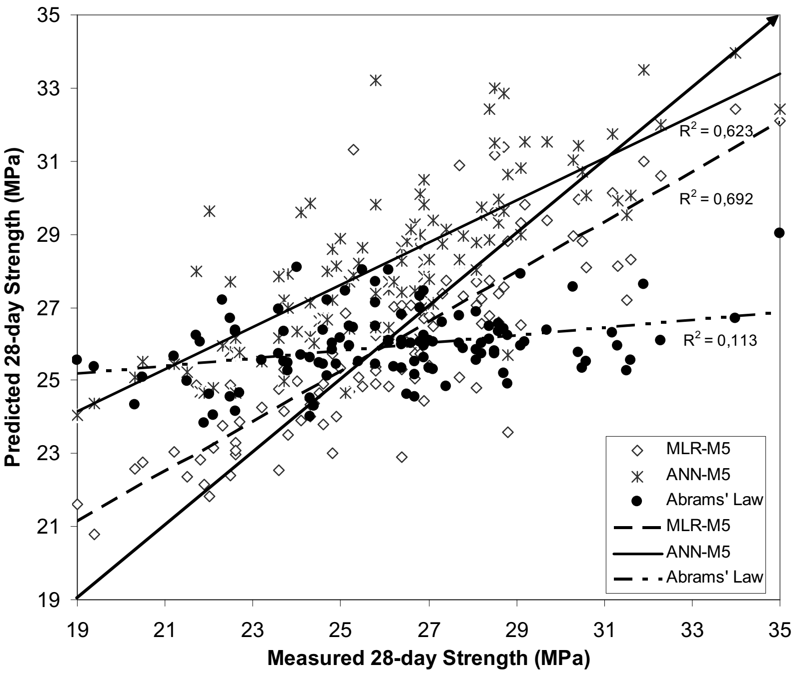

Figure 3. Predicted concrete strengths compared with measured strengths (all data)

water reducing and plasticizing admixtures may interfere with the hydration of cement and may cause some changes in the microstructure of the cement paste affecting the strength development of concrete. This indicates that the Abrams' formula should be augmented with terms representing the concrete composition as mentioned by Popovics (1990).

As shown in Table 3 the accuracy of ANN models, on the other hand, varies with the number of hidden layers and the number of neurons in the hidden layers. In all system models, higher accuracies are obtained with two hidden layers but it has been observed that no specified empirical criteria common to all system models is found for determining the number of neurons in the first hidden layer and implicitly in the second hidden layer. It is also seen in Table 3 that the compositional data alone (M1) or together with fresh concrete data (M2) require much higher number of training iterations with a relatively lower accuracy independent of the layer structure of the ANN. Inclusion of the early strength data, f_{C7}, on the other hand, considerably increases the speed of learning process and the accuracy of prediction as it can be seen in Table 3 when the results of M1 are compared with M4 and M2 with M5.

Considering the different data sets for training the ANN and regression models, the use of fresh concrete data together with the compositional data as in M2 compared to M1 causes a reduction in the prediction accuracy whereas equal or slightly higher accuracies are obtained in M5 compared to M4 where the fresh concrete data are included in the presence of the early strength data. As it is seen in Tables 3 and 4 the use of early strength in data set increases the accuracy of the prediction considerably. Although the use of early strength alone is not sufficient to create the best solution, the early strength seems to be the most effective among all data items in achieving higher accuracies. However, observing that the highest prediction accuracy in all ANN models and the regression model is obtained in M5, it is appropriate to conclude that the best result for prediction by ANN models will be obtained when all the information available will be utilized. This is also in agreement with the findings of Yeh (1998b). Moreover, the coefficient of determination values obtained in this study are comparable to the ones obtained in the previous studies (Lai and Serra, 1997; Dias and Pooliyadda, 2001; Yeh, 1998a; Yeh 1998b; Kasperkiewicz et. al., 1995).

Fig. 4 is based on the measured strength data and the predicted strength values by the artificial neural networks for M5 to evaluate the effects of w/c ratio on the concrete strength. It is clearly observed that the trend being modeled by the ANNs appears to be meaningful also from a physical stand point. However the very low correlation coefficients may be due to the rather large scatter in the compositional data for the concretes tested.

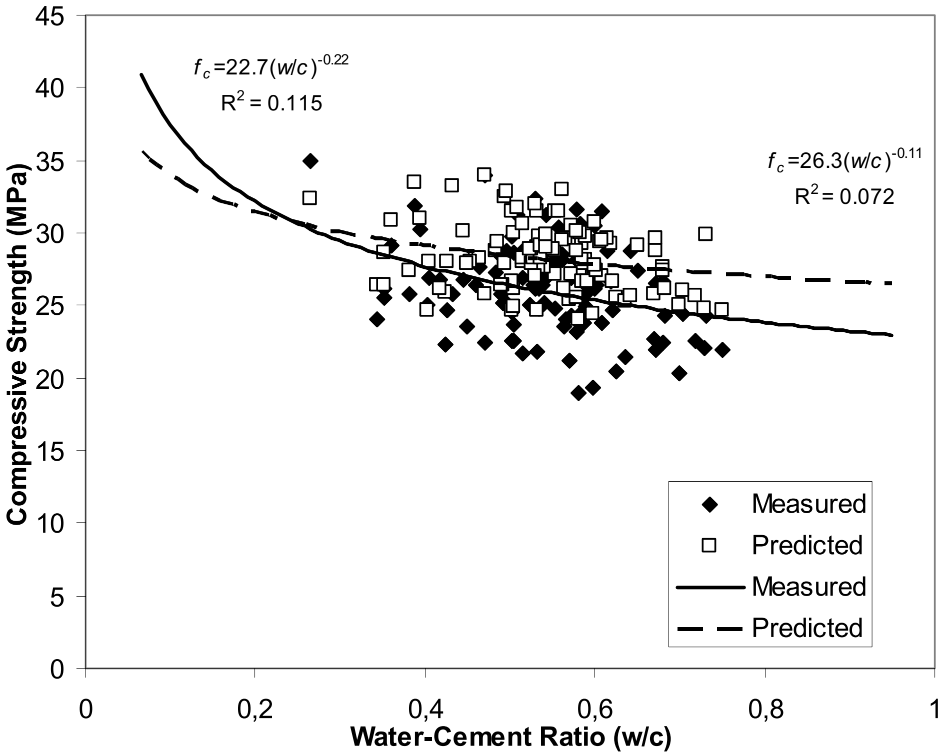

Figure 4. Measured strength and strength predicted by ANN (M5) versus water-cement ratio

6 Conclusions

This study is aimed at finding the best system model for the prediction of the 28-day compressive strength of concrete through a comparative analysis by ANN, MLR and Abrams' prediction models. A total of 65 sets of predictions, which result from the application of 12 ANN models and one MLR model to five system models, are produced. Abrams' law is also considered for predicting the strength on w/c basis. All of those results are compared using the coefficients of determination calculated for the models with highest R^2 values for each system model to be more confident about the results.

Based on the findings of this study it can be concluded that:

1. MLR models are better in predicting the strength of concrete than ANN models for M1 and M2 which include only the constituent materials and fresh concrete data. However, the inclusion of early strength data in M4 and M5 results in better prediction of strength by the ANN models. Both ANN and MLR models, on the other hand, show almost the same performance for M3 which included only the early strength data.
2. Although the inclusion of the early strength data, f_{C7}, increases the speed of learning process and the accuracy of prediction, best results for each of the pre-

diction models are obtained when all of the input variables defined in this study have been considered (M5).

3. Accuracy of the ANN models varies with the number of hidden layers and the number of neurons in the hidden layers. For all system models better accuracies are obtained with two hidden layers but no specified empirical criteria common to all system models is found for determining the number of neurons in the first hidden layer and implicitly in the second hidden layer.
4. Abrams' law, predicting the strength based on w/c, gives considerably low coefficient of determination which may be due to the effect of plasticizing admixture on the microstructure of the concrete. Thus, it may state that an empirical equation for determining strength must include terms representing concrete composition.
5. Plot of compressive strengths predicted by ANN models as function of w/c shows a trend similar to the one obtained from the real data indicating that the ANN prediction makes sense also from a physical stand point.

REFERENCES

[1] ABRAMS, D. A. (1927), „Water-Cement Ratio as a Basis of Concrete Quality", ACI Journal Proceedings 23, 452–457.

[2] BAXTER, C. W. (2001), Modelling Heuristics from Literature, CIV E 729 Course Notes, Department of Civil and Environmental Engineering. University of Alberta, Edmonton, Canada, www.civil.ualberta.ca/courses/cive729/lectures/lecture5.ppt, retrieved on 2004.

[3] CARSTEN, P. and THORSTEIN R. (1993), Jetnet 3.0: A Versatile Artificial Neural Network Package, Sweden, http://www.thep.lu.se/activities/jetnet_30_manual/jetnet_30_manual.html, retrieved on 2007.

[4] DEBOECK, G. J. (1994), Trading on the Edge, John Wiley and Sons Inc., New York.

[5] DIAS, W. P. S. and POOLIYADDA, S. P. (2001), "Neural Networks for Predicting Properties of Concretes with Admixtures", Construction and Building Materials 15, 371–379.

[6] GALLANT, S. I. (1993), Neural Network Learning and Expert Systems, MIT Press, Cambridge.

[7] KASPERKIEWICZ, J., RAEZ, J. AND DUBRAWSKI, A. (1995), „HPC Strength Prediction Using Artificial Neural Network", Journal of Computing in Civil Engineering 9(4), 279–284.

[8] KUDRYCKI, T. P. (1988), „Neural Network Implementation of a Medical Diagnostic Expert System", Master's Thesis, College of Engineering, University of Cincinnati.

[9] LAI, S. and SERRA, M. (1997), „Concrete Strength Prediction by Means of Neural Network", Construction and Building Materials 11(2), 93–98.

[10] NAGENDRA, S. (1998), Practical Aspects of Using Neural Networks: Necessary Preliminary Specifications, Technical Paper, GE Research and Development Center.

[11] NEHDI, M., EL CHABIB, H. and EL NAGGAR, H. (2001a), „Predicting Performance of Self-Compacting Concrete Mixtures Using Artificial Neural Networks", ACI Materials Journal 98(5), 394–401.

[12] NEHDI, M., DJEBBAR, Y. and KHAN, A. (2001b), „Neural Network Model for Preformed-Foam Cellular Concrete", ACI Materials Journal 98(5), 402–410.

[13] NEVILLE, A. M. (1986), Properties of Concrete, Longman Scientific and Technical, Third Edition.

[14] OLUOKUN, F. A. (1994), „Fly Ash Concrete Mix Design and the Water-Cement Ratio Law", ACI Materials Journal 91(4), 362–371.
[15] PARTOVI, F. Y. and ANANDRAJAN, M. (2002), „Classifying Inventory Using an Artificial Neural Network Approach", Computers and Industrial Engineering 41, 389–404.
[16] POPOVICS, S. (1990), „Analysis of Concrete Strength versus Water-Cement Ratio Relationship", ACI Materials Journal 87 (5), 517–529.
[17] TEH, C. I., WONG, K. S., GOH, A. T. C. and JARITNGAM, S. (1997), „Prediction of Pile Capacity Using Neural Networks", Journal of Computing in Civil Engineering, 129–138.
[18] YEH, I. C. (1999), „Design of High-Performance Concrete Mixture Using Neural Networks and Nonlinear Programming", Journal of Computing in Civil Engineering 13(1), 36–42.
[19] YEH, I. C. (1998a), „Modeling of Strength of High-Performance Concrete Using Artificial Neural Networks", Cement and Concrete Research 28(12), 1797–1808.
[20] YEH, I. C. (1998b), „Modeling Concrete Strength with Augment-Neuron Networks", Journal of Materials in Civil Engineering 10 (4), 263–268.