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Full Length Research Paper

Prediction of the compressive strength of vacuum processed concretes using artificial neural network and regression techniques

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Concrete which is a composite material is one of the most important construction materials. For the improvement of concrete quality some advanced technologies are used for curing and placement of concrete. Vacuum processing is one of these technologies. With the vacuum application, water content of the mixture is decreased and by this way a better water/cement ratio is obtained. Since most of the empirical equations which use nondestructive test results are developed for normal concretes, their prediction performance for vacuum processed concrete is unclear. In this study regression equations and an artificial neural network (ANN) were developed for the estimation of compressive strength of vacuum processed concrete. For the experimental set up, three different concretes were prepared by applying variable vacuum application duration. On these concrete samples, Windsor probe penetration tests, Schmidt hammer tests, pulse velocity determination tests, were performed. In addition to these; densities, void ratios, water absorption values and capillary water absorption values of extracted core samples were determined. Several equations using single independent variables for the estimation of compressive strength were developed, a multi linear regression equation which uses Windsor probe exposed length, pulse velocity, density and water absorption ratio as predictor variables was developed. A neural network was developed for the estimation of compressive strength. Finally prediction performances of previously published empirical equations, single and multiple variable regression equations developed during this study and ANN were compared. According to this comparison, best prediction performance belongs to ANN.

Key words: Artificial neural network, vacuum processed concrete, nondestructive testing, statistical analysis.

INTRODUCTION

Concrete is the most important material for construction. Materials used in concrete, mix ratios, mixing process, transportation and placements of concrete are all important parameters defining concrete performance. For the improvement of concrete quality, advanced techniques are used during the placement and curing of fresh concrete. Vacuum processing is one of these techniques. Water and air voids within 15 cm depth from surface are removed by vacuum application. By this way a better water/cement ratio is obtained that causes improvements of physical and mechanical properties of concrete. With the application of vacuum, 100% compressive strength increase can be achieved for 3 day aged concrete, 50% of compressive strength increase can be achieved on 28 day aged concrete. In addition to strength increase, erosion, abrasion and freeze-thaw resistance of concrete are also obtained using vacuum application. With the early strength gain obtained using vacuum application, formworks can be removed within a shorter time (Neville, 1993). Vacuum processed concrete is used in wide pavements, roads, terminals, car parks and whenever an abrasion resistant pavement is needed (Neville, 1993; Simsek, 2005).

Compressive strength is one of the commonly used parameter for the assessment of concrete quality. Although destructive methods of compressive strength determination in which cube or cylindrical samples prepared from fresh concrete or core samples extracted from structural concrete members are the most accurate ways, they have their own shortcomings. Cube or cylindrical samples casted from fresh concrete may not be identical to *in-situ* concrete because of curing and placement differences. Coring process is time consuming, uneconomical and this process may damage the structural member (Mehta, 1986). Because of these disadvantages of destructive test methods, nondestructive test methods are also preferred. Schmidt hammer test in which surface hardness is indirectly measured is widely used for compressive strength estimation and it has the advantage of being economical, fast and non-destructive. However this test only reflects the surface properties of concrete and it may not accurately estimate the internal strength. Because vacuum processed concrete has a higher surface hardness, perfor-mance of Schmidt hammer tests should be even worse for vacuum processed concrete (Mehta, 1986; Erdal and Simsek, 2006).

Another popular nondestructive test method for the determination of compressive strength of concrete is the pulse velocity test. In this method the velocity of sound waves transmitted though the concrete specimen is measured. This velocity is dependent on the stiffness of the concrete specimen (Bungey, 1989; Malhotra and Carino, 2004).

In addition to these popular nondestructive test methods, a relatively new technique called as Windsor probe penetration test is also utilized for the estimation of compressive strength. In this method, compressive strength is indirectly estimated using the penetration of a probe in to the concrete which is charged with explosives. Lesser the depth of penetration of the probe means the higher the compressive strength of concrete (Mallick, 1983; Windsor Probe Test System Inc., 1994).

Many empirical equations based on regression technique in which the results of nondestructive tests are used, were developed for the estimation of compressive strength of concrete. Users of nondestructive tests are faced with the problem of choosing the empirical equation which has the highest estimation performance.

In this study, performance of previously developed empirical equations for the estimation of compressive strength of concrete was compared. In addition to this, new empirical equations and ANN are proposed for this purpose.

Recent researches are performed for the usability of ANN in the civil engineering field and especially for the concrete technology (Subasi and Beycioglu, 2008; Sancak, 2009). Lee (2003) utilized ANN's for the determination of concrete compressive strength. Lee (2003) suggested that ANN has a good predictive capacity. Topcu and Saridemir (2008) utilized ANN and Fuzzy Logic for the determination used of compressive strength of fly ash added concretes. Topcu and Saridemir (2008) concluded that both ANN and Fuzzy Logic methods have high predictive performance. Altun et al. (2008) used ANN and multiple linear regression techniques for the estimation of compressive strength of steel fiber reinforced concrete. Subasi (2009) developed on ANN for the estimation of mechanical properties of fly ash added cement paste and he concluded that ANN has better performance than multiple linear regression technique.

Table 1. Amount of materials used for fresh concrete production (1m³).

Mix proportion	Amount
Crushed coarse aggregate (16 - 25 mm)	334 kg
Crushed medium aggregate (4 - 16 mm)	632 kg
Crushed fine aggregate (0 - 4 mm)	761 kg
Cement (CEM I 42.5)	426 kg
Water	190 lt

Figure 1. Compaction of concrete with vibrating screed

EXPERIMENTAL STUDIES

Experimental studies consist of sample preparation, curing, application of nondestructive tests, coring, compressive strength determination by destructive tests.

In this study, crushed limestone aggregate whose grain size distribution is given in Table 1, CEM I 42.5 Portland cement and ordinary water are used for sample preparation. Table 1 presents the grain size distributions of aggregate, cement and water amount for 1 m³ fresh concrete.

Concrete mix was prepared according to C 20 type concrete, and slump of fresh concrete was about 20 cm. Prior to concrete placement a polyethylene membrane was laid to the bottom surface in order to apply vacuum properly and to prevent fractures due to ground surface. After the placement of fresh concrete to formworks, compaction was achieved using a vibrating screed (Figure 1). After the compaction stage, vacuum sheet was placed to concrete surface. Duration of vacuum application was 34 min to first formwork, 17 min to second formwork. Vacuum was not applied to third formwork (Figure 2).

After 28 day period, core samples having 75 mm diameter were extracted from concrete slabs according to ASTM C 42/C 42M (1999). Length to diameter ratio of core samples was about 2. Densities, void ratios, water absorption, capillary water absorption value of core samples were determined according to ASTM C 138/C138M (2001). After the determination of physical properties,

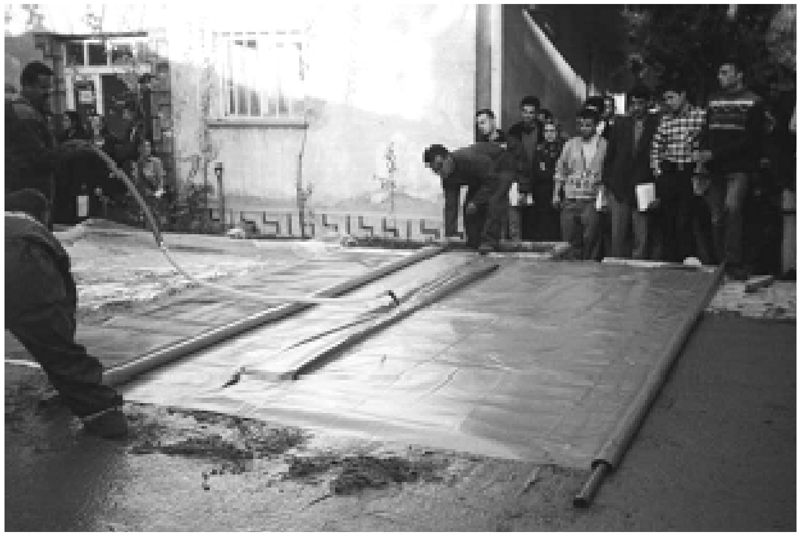

Figure 2. Application of vacuum process.

compressive strength values of core samples were determined using a stress controlled compression machine according to ASTM C 39 (2001). Windsor probe penetration tests (ASTM C 803/C 803M, 1999), Schmidt hammer tests (ASTM C 805, 1997) and pulse velocity tests (ASTM C 597, 1998) were performed directly on concrete slabs prior to coring.

REGRESSION EQUATIONS FOR THE ESTIMATION OF COMPRESSIVE STRENGTH OF CONCRETE

Some of the empirical equations used for the estimation of compressive strength of concrete were reviewed. These equations and predictor variables are summarized in Table 2.

In order to compare the performance of existing single and multi variable equations database determined in this study was employed. To compare prediction performances of existing equations root mean square error (RMSE) term was utilized. Equation 1 presents the calculation of RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(f_{c_{est}} - f_{c_{mea}})^2} \tag{1}$$

RMSE values of existing equations are also given in Table 2. In order to visually compare the prediction performance of existing equations, predicted versus measured compressive strength values are plotted together with 1:1 line (Figure 3 - 7).

The performances of single variable equations are compared in the following paragraph. Kheder 1 (1998) under predicts the compressive strength (Figure 3). The predictive equations proposed by NDT Windsor System Inc. (1994) mainly under predicts the compressive strength values lower than 30 MPa where as it over predicts the compressive strength values higher than 30 MPa. The performance of predictive equation of Kheder 2 (1998) is better compared to that proposed by Kheder 1 (1998) and NDT Windsor System Inc. (1994). RMSE values of these equations are also display in this situation (Table 2).

Similar to that of Kheder's 1 (1998) equation, the relationship proposed by Qasrawi 1 (2000) is also under predicts of the compressive strength (Figure 4). The equation proposed by Qasrawi 2 (2000) show a better prediction capacity with a RMSE of 2.8152, similarly relationship of Malhotra et al. (2004) shows a good performance with a RMSE equal to 2.2128 (Table 2).

As previously stated, there are multi variable equations used for the prediction of compressive strength of concrete. All of these equations use the pulse velocity and Schmidt hammer rebound value as predictor variables. The equation proposed Tanigawa et al. (1984) has the best prediction performance with a RMSE equal to 2.1000. The equation proposed by Kheder 3 (1998) has also a very low RMSE (2.1375). Both Kheder 3 (1998) and Tanigawa et al. (1984) seem to have superior prediction performance compared to single variable equations.

According to Figure 5 both Bellander (1979) and Meynink et al. (1979) equations significantly over predicts the compressive strength values, on the other hand data points which belong to Tanigawa et al. (1984) are evenly distributed around the 1:1 line showing this equation has a very good prediction performance.

The equations proposed by Postacioglu (1985) and Arioglu et al. (1991) are under estimated the compressive strength values lower than about 30 MPa (Figure 6). The equation proposed Arioglu et al. (1991) slightly over predicts the compressive strength (Figure 6).

It is clear from Figure 7 that the equations belong to Ramyar et al. (1996) and Arioglu et al. (1996) significantly

Table 2. Equations of existing relationship used for compressive strength estimation of concrete and their performances.

Eq. No.	Equations	Explanations	Reference	RMSE
Single-variable equations				
1	$f_c = 21.575 \times L - 72.276$	f_c [MPa], L [cm]	NDT Windsor Sys. Inc. (1994)	3.7813
2	$f_c = 1.2 \times 10^{-5} \times V^{1.7447}$	f_c [MPa], V [km/s]	Kheder 1 (1998)	6.0974
3	$f_c = 0.4030 \times R^{1.2083}$	f_c [MPa]	Kheder 2 (1998)	2.1651
4	$f_c = 36.72 \times V - 129.077$	f_c [MPa], V [km/s]	Qasrawi 1 (2000)	3.6981
5	$f_c = 1.353 \times R - 17.393$	f_c [MPa]	Qasrawi 2 (2000)	2.8152
6	$f_c = -5333 + 5385 \times L$	f_c [MPa], L [in]	Malhotra et al. (2004)	2.2128
Multi-variable equations				
7	$f_c = -25.568 + 0.000635 \times R^3 + 8.397V$	f_c [MPa], V [km/s]	Bellander (1979)	13.2794
8	$f_c = -24.668 + 1.427 \times R + 0.0294V^4$	f_c [MPa], V [km/s]	Meynink at al. (1979)	7.0654
9	$f_c = 0.745 \times R + 0.951 \times V - 0.544$	f_c [MPa] , V [m/s]	Tanigawa et al. (1984)	2.1000
10	$f_c = [R/(18.6 + 0.019 \times R + 0.515 \times V)]$	f_c[kg/cm^2], V [km/s]	Postacioglu (1985)	3.7617
11	$f_c = 18.6 \times e^{(0.019 \times R + 0.515 \times V)}$	f_c[kg/cm^2], V [km/s]	Arioglu et al. (1991)	2.9205
12	$f_c = 10^{3.119\sqrt{\log(R^3 \times V^4)} - 5.890}$	f_c[kg/cm^2], V [km/s]	Arioglu et al. (1994)	4.2305
13	$f_c = -39.570 + 1.532 \times R + 5.0614 \times V$	f_c [MPa] , V [km/s]	Ramyar et al. (1996)	7.5910
14	$f_c = 0.00153 \times (R^3 \times V^4)^{0.611}$	f_c [MPa] , V [km/s]	Arioglu et al. (1996)	11.1623
15	$f_c = 0.0158 \times V^{0.4254} \times R^{1.1171}$	f_c [MPa], V [km/s]	Kheder 3 (1998)	2.1375

f_c = Compressive strength, V=ultrasonic pulse velocity, R=rebound number, L=exposed probe length.

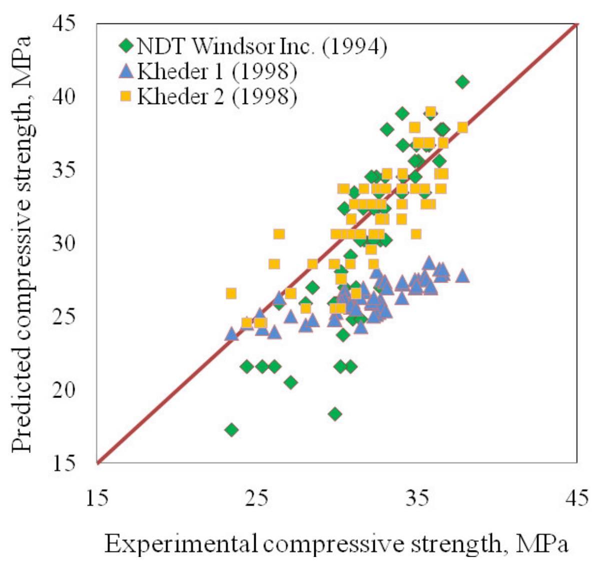

Figure 3. Performance comparison of equations proposed by NDT Windsor System Inc. (1994), Kheder 1 (1998) and Kheder 2 (1998).

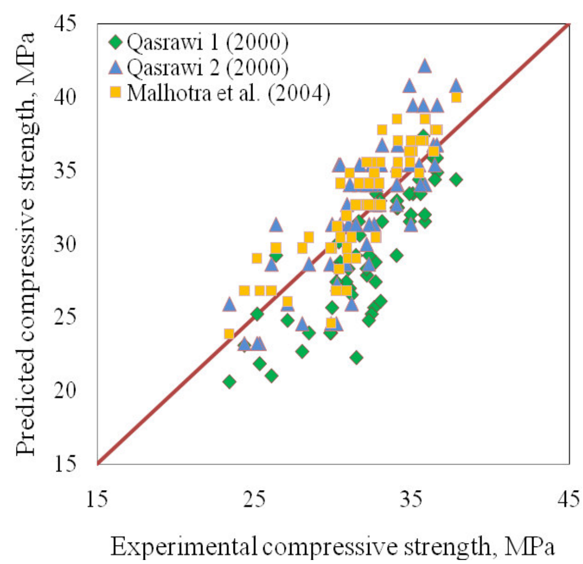

Figure 4. Performance comparison of equations proposed by Qasrawi 1 (2000), Qasrawi 2 (2000) and Malhotra et al. (2004).

over predicts of the compressive strength. Similar to the equation of Tanigawa et al. (1984), the equation proposed by Kheder 3 (1998) has a very high prediction performance; this is also displayed on Figure 7.

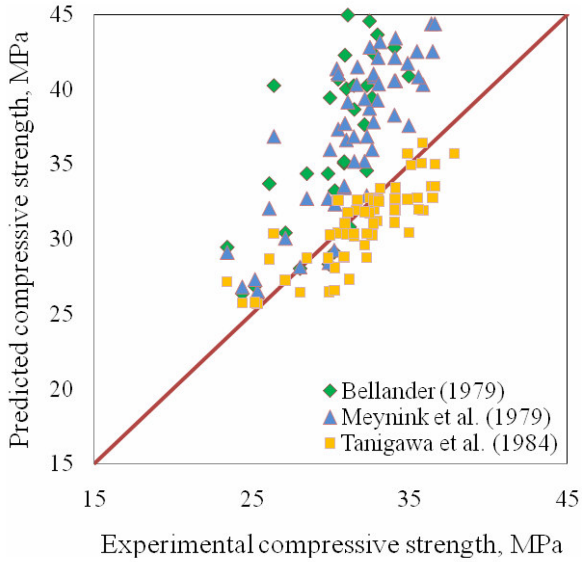

Figure 5. Performance comparison of equations proposed by Bellander (1979), Meynink et al. (1979) and Tanigawa et al. (1984).

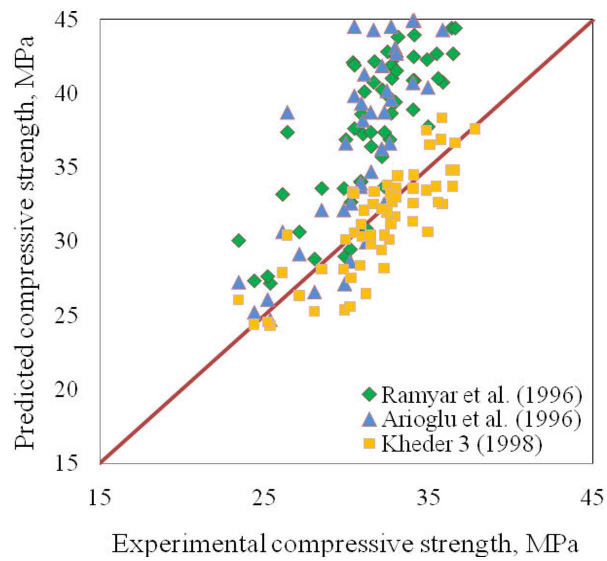

Figure 7. Performance comparison of equations proposed by Ramyar et al. (1996), Arioglu et al. (1996) and Kheder 3 (1998).

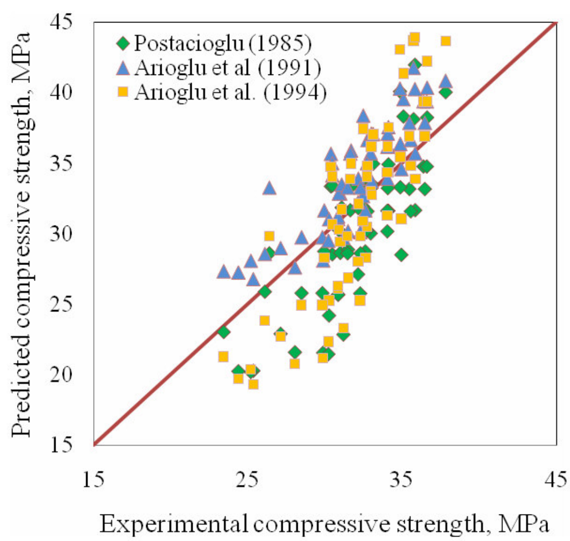

Figure 6. Performance comparison of equations proposed by Postacioglu (1985), Arioglu et al. (1991) and Arioglu et al. (1994).

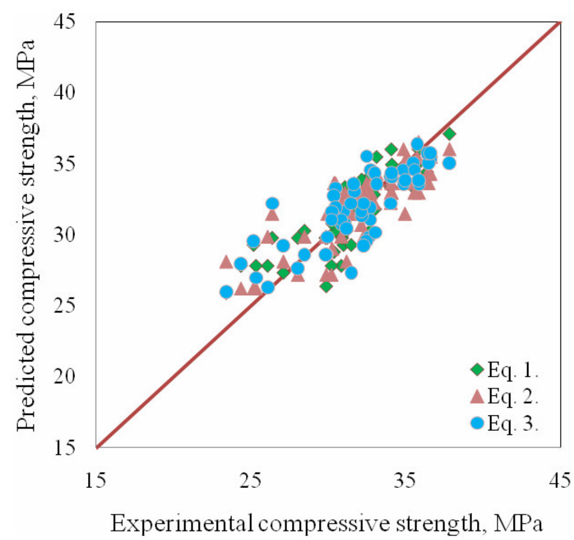

Figure 8. Measured versus predicted compressive strength values of single variable equations proposed in this study

Although the multi variable equations proposed by Tanigawa et al. (1984) and Kheder 3 (1998) present a very good prediction performance, new single and multi variable equations were developed in this study for the prediction of compressive strength values of vacuum processed concrete using least squares regression technique. The equations of proposed relationships, their regression coefficients (R) and RMSE values are listed in Table 3. RMSE values of these proposed equations are lower than that of previously proposed equations. The performance of multi variable equations using R and L (Equation 6), L and V, Land R are better than single variable equations. Only the multi variable equation which uses R and V as predictor variables displays a worse prediction performance than that of single variable equations using L as predictor variable. The probable reason for this situation is that Windsor probe is a better non-destructive test for compressive strength determination than Schmidt hammer.

Figure 8 and 9 present the measured versus predicted

Table 3. The equations, regression coefficients (R) and RMSEs of relationships developed in this study.

Eq. No.	Equations	Explanations	R	RMSE
Single-variable equations				
1	$f_c = 0.697 \times L^2 + 3.6521 \times L - 1.2982$	f_c [MPa], L [cm]	0.8602	1.6407
2	$f_c = -0.0177 \times R^2 + 2.0481 \times R - 19.303$	f_c [MPa]	0.8099	1.8874
3	$f_c = -16.777 \times V^2 - 167.29 \times V - 377.18$	f_c [MPa], V [km/s]	0.8134	1.8712
Multi-variable equations				
4	$f_c = 0.42 \times R + 13.166 \times V - 40.255$	f_c [MPa], V [km/s]	0.8570	1.6567
5	$f_c = 0.319 \times R + 7.058 \times L - 13.411$	f_c [MPa], L [cm]	0.8850	1.4997
6	$f_c = 6.871 \times L - 0.127 \times V + 43.454$	f_c [MPa] , V [m/s], L [cm]	0.8900	1.4687
7	$f_c = 5.665 \times L - 0.095 \times V + 0.206 \times R + 30.578$	f_c [MPa] , V [m/s], L [cm]	0.8980	1.4161

f_c = Compressive strength, V=ultrasonic pulse velocity, R=rebound number, L=exposed probe length

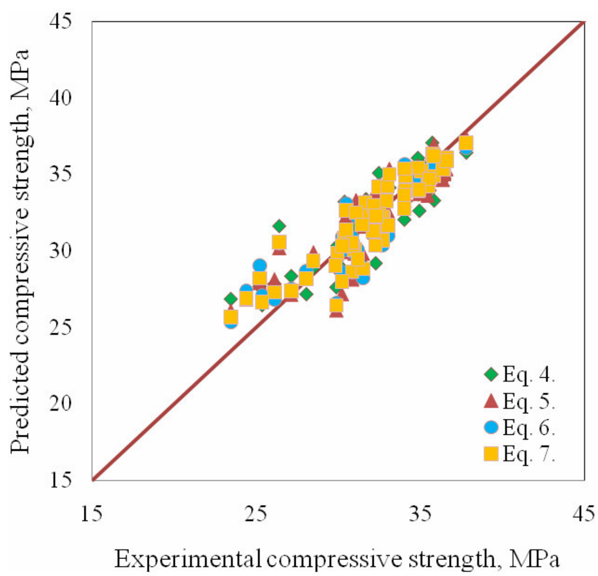

Figure 9. Measured versus predicted compressive strength values of multi variable equations proposed in this study

compressive strength values of equations proposed in this study.

ARTIFICIAL NEURAL NETWORK ASSESSMENT OF COMPRESSIVE STRENGTH OF CONCRETE

In this study, in addition to regression equations an artificial neural network consisting of 1 hidden layer and 5 dependent variables was developed. Artificial neural networks can solve complex problems with the help of interconnected computing elements. 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 (Raghu et al., 2009). In recent studies, artificial neural networks (ANNs) have been applied to many civil engineering tasks and have demonstrated some degree of success. The purpose of ANNs is to set a relationship between model inputs and outputs by continuously updating connection weights according to inputs-outputs. The main advantage of ANNs is that they are very flexible, and complex relationships between inputs and outputs can be discovered by changing the model structure and connection weights. However, ANNs have an important disadvantage why they are not transparent as a closed form equation (Ozer et al., 2008).

An artificial neural network model is developed in six main stages: first input and output variables are defined; database is grouped into two as training and validating datasets; network structure is selected; connection weights are optimized, optimization is terminated according to stopping criteria; and finally neural network is validated.

It is common practice to divide the available data into two subsets; a training set to construct the neural network model and an independent validation set to estimate model performance (Twomey and Smith 1997). Approximately 80% of the data were used for training and 20% for validation. The validation data were selected to cover a wide range of compression strength values. Hornik et al. (1989) showed that a network with one hidden layer can approximate any continuous function provided that sufficient connection weights are used; therefore, in this study a network with one hidden layer is used and the number of hidden layer nodes was increased until a good model was achieved. Back propagation is a frequently used training algorithm. Important factors that affect the ANN performance can be listed as the number of input neurons, hidden neurons, output neurons and activation function. In this study a back propagation algorithm was used during training with a 0.6 momentum and 0.8 learning rate. Stopping criteria are used to decide whether to stop the training process or not; in this study the training process was stopped when error of the each of

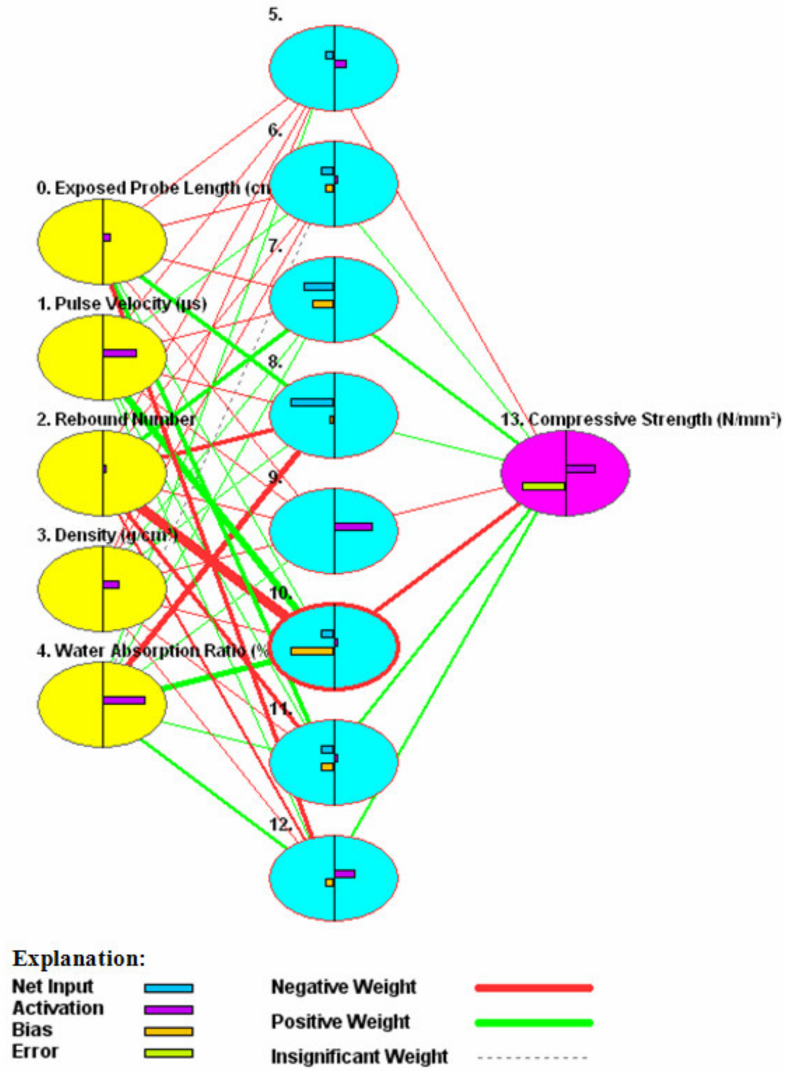

Figure 10. Architecture of the neural network and relative connection weights.

the training data set is less than 10%.

Figure 10 displays the architecture of the neural network for prediction of the compressive strength and the relative connection weights. Figure 11 presents the experimenttally determined scaled compressive strength values versus the ANN predicted scaled compressive strength values of training and validating data. The RMSE of the training and validation data was calculated as 0.9113, which is better than the RMSE of regression equations (Figure 12).

Conclusions

In this study performances of previously suggested single and multi variable equations used for the estimation of compressive strength of concrete utilizing nondestructive test results were compared. Among the single variable equations Kheder 2 (1998) equation showed best performance. Multi variable equations suggested by Tanigawa et al. (1984) and Kheder 3 (1998) were also presents good prediction performances.

In addition to performance comparison of existing equations, seven new equations were suggested. Windsor probe penetration test results were very well correlated with the compressive strength therefore the prediction peformance of single variable equation which uses exposed probe length is very good. Among the multi variable equations, equation using exposed probe length, pulse velocity and Schmidt hammer rebound value has the best prediction performance.

Finally an artificial neural network with single hidden layer and six input layer nodes was developed and trained for the estimation of compressive strength of vacuum processed concrete. It has found that the prediction performance of ANN is superior to regression

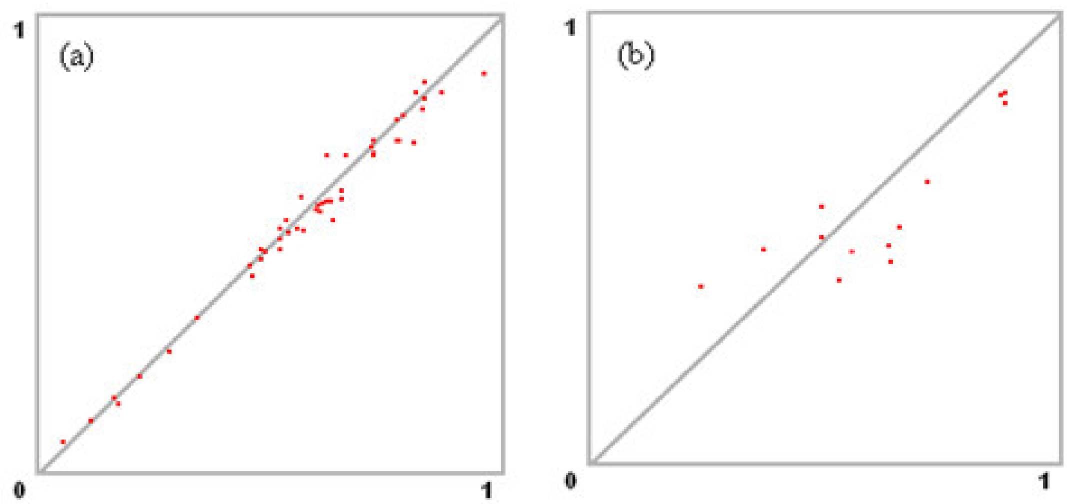

Figure 11. Experimentally determined scaled compressive strength values versus the ANN predicted scaled compressive strength values of a) training and b) validating data.

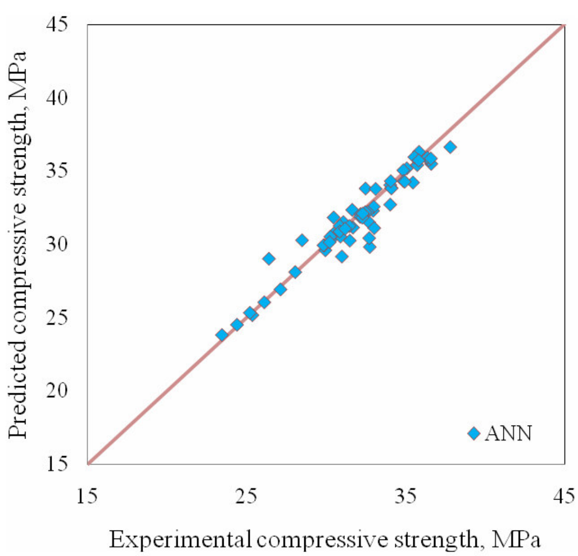

Figure 12. Experimentally determined compressive strength values versus the ANN predicted compressive strength values of all data.

equations.

REFERENCES

Altun F, Kisi O, Aydin K (2008). Predicting the compressive strength of steel fiber added lightweight concrete using neural network. Computat. Mat. Sci. 42(2): 259-265.

Arioglu E, Koyluoglu O (1996). Discussion of prediction of concrete strength by destructive and nondestructive methods by Ramyar and Kol, Cement and Concrete World, (in Turkish). 3: 33-34.

Arioglu E, Manzak O (1991). Application of “Sonreb” method to concrete samples produced in Yedpa construction site. Prefabrication Union. (in Turkish) pp. 5-12.

Arioglu E, Odbay O, Alper H, Arioglu B (1994). A new formula and application results for prediction of concrete compressive strength by combined non-destructive method. Assoc. of Prefabrication Manufacturers, Concrete Prefabrication, (in Turkish). 28: 5-11.

ASTM C 138/C 138M (2001). Standard test method for density (unit weight), yield, and air content (gravimetric) of concrete. ASTM. USA.

ASTM C 39/C (2001). Standard test method for compressive strength of cylindrical concrete specimens. ASTM, USA.

ASTM C 42/C 42M (1999). Standard test method for obtaining and testing drilled cores and sawed beams of concrete. ASTM. USA.

ASTM C 597 (1998). Standard test method for pulse velocity through concrete. ASTM. USA.

ASTM C 803/C 803M (1999). Standard test method for penetration resistance of hardened concrete. ASTM. USA.

ASTM C 805 (1997). Standard test method for rebound number of hardened concrete. ASTM. USA.

Bellander U (1979). NTD testing methods for estimating compressive strength in finished structures evaluation of accuracy and testing system. RILEM Symp. Proc. on Quality Control of Concrete Structures, Session 2.1, Swedish Concrete Research Institute Stockholm. Sweden. pp. 37-45.

Bungey JH (1989). Testing of concrete in structures. Surrey University Press. New York pp. 65-75.

Erdal M, Simsek O (2006). Investigation of the performance of some non-destructive tests on the determination of compressive strength of vacuum processed concrete. J. Fac. Eng. Arch. Gazi Univ. (in Turkish) 21(1): 65-73.

Hornik K, Stinchcombe M, White H (1989). Multilayer feed forward networks are universal approximators. Neural Netwk. 2: 359-366.

Kheder GF (1998). A two stage procedure for assessment of in-situ concrete strength using combined non-destructive testing. Mat. Structures 32: 410-417.

Lee SC (2003). Prediction of concrete strength using artificial neural networks. Eng. Structures 25: 849-857.

Malhotra VM, Carino NJ (2004). Handbook on nondestructive testing of concrete. CRC Press. Florida.

Mallick DV, Ben-Zeitun A (1983). UPV method of testing in-situ concrete. Proceedings of the First International Conference on Concrete Technology for Developing Countries. Amman. Libya.

Mehta PK (1986). Concrete Structure, Properties and Materials. Prentice-Hall, Inc., New Jersey, USA.

Meynink P, Samarin A (1979). Assessment of compressive strength of concrete by cylinders, cores and non-destructive tests. RILEM Symp. Proc. on Quality Control of Concrete Structures, Session 2.1, Swedish Concrete Research Institute Stockholm, Sweden pp. 127-134.

Neville AM (1993). Properties of Concrete. Longman Scientific and Technical. New York, U.S.A.
Ozer M, Isik NS, Orhan M (2008). Statistical and neural network assessment of the compression index of clay bearing soils. Bull. Eng. Geol. Environ. 67: 537-545.
Postacioglu B (1985). Nouvelle significations de l'indice Sclerometrque Schmidt et de la Vitesse de Propogation des Ultra-Sons. Mat. Structures pp. 447-451.
Qasrawi HY (2000). Concrete strength by combined nondestructive methods simply and reliable predicted. Cement and Concrete Res. 30: 739-746.
Raghu P, Eskandari BK, Venkatarama H, Reddy BV (2009). Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN. Construction Build. Mat. 23: 117-128.
Ramyar K, Kol P (1996). Destructive and non-destructive test methods for estimating the strength of concrete. Cement and Concrete World (in Turkish) (2): 46-54.
Sancak E (2009). Prediction of bond strength of lightweight concretes by using artificial neural networks. Sci. Res. Essay 4(4): 256-266.
Simsek O (2005). Effects of vacuum processing on strength and surface hardness properties of concrete. J. ASTM Int. 2(2): 1-8.
Subasi S (2009). Prediction of mechanical properties of cement containing class C fly ash by using artificial neural network and regression technique. Sci. Res. Essay 4(4): 289-297.
Subasi S, Beycioglu A (2008). Determining the compressive strength of crushed limestone aggregate concrete using different prediction methods. e-J. N. World Sci. Acad. 3(4): 580-589.
Tanigawa Y, Baba K, Mori H (1984). Estimation of concrete strength by combined nondestructive testing method. ACI SP 82: 1: 57-65.
Topcu IB, Saridemir M (2008). Prediction of compressive strength of concrete containing fly ash using artificial neural network and fuzzy logic. Computat. Mat. Sci. 41(3): 305-311.
Twomey JM, Smith AE (1997). Validation and verification. In: Kartam N, Flood I, Garrett JH (eds). Artificial neural networks for civil engineers: fundamentals and applications. ASCE. New York pp. 44-64
Windsor Probe Test System Inc. (1994). WPS 500 Windsor Probe Test System Operating Instructions. Chicago. USA.