Scientific Research and Essay Vol. 4 (4), pp. 256-266, April, 2009
Available online at http://www.academicjournals.org/SRE
ISSN 1992-2248 © 2009 Academic Journals

Full Length Research Paper

Prediction of bond strength of lightweight concretes by using artificial neural networks

Emre Sancak

Construction Education Department, Technical Education Faculty, Suleyman Demirel University, Batı Kampus-Cunur, Isparta, 32260, Turkey. E-mail: esancak@tef.sdu.edu.tr. Tel: +90 542 486 3823. Fax: +90 246 237 1283.

Accepted 6 March, 2009

In the scope of this study, concrete samples planned to be used as load-bearing concrete were produced by using pumice aggregate and silica fume. Cement was replaced by silica fume, as the mineral additive, by 5 and 10% of its weight. First of all, fresh concrete properties of the produced samples were evaluated. Then, compressive strength tests were conducted on the 28th and 90th days. In addition, pull-out tests were carried out on cubic samples of 150 mm^3 on the 90th day so as to detect the reinforcing steel-concrete bond strength. The data obtained at the end of the tests were used as input to the Artificial Neural Networks (ANN) method to predict bond strength values. Bond strength values predicted via the ANN method were found to be close to the bond strength values obtained via tests. In conclusion, it can be quite beneficial to predict the bond strength of normal and lightweight concrete via the ANN method by using a high number of parameters as input. Thus, it will be possible to detect the reinforcing steel-concrete bond strength in a faster and reliable manner and by doing less laboratory work.

Key words: Artificial neural networks, structural lightweight concrete, pumice, bond strength.

INTRODUCTION

The low density of lightweight aggregate concrete made with pumice aggregates results in a reduction in the weight of the structures and the foundations and in considerable savings in thermal and sound insulation (Topcu, 1997; Mor, 1992).

Lightweight concrete (LWC) has also been employed more recently to make structural elements, in particular in the field of precast concrete structures. Maintaining an adequate strength level, LWC, with respect to normal weight concrete, among other things permits a reduction in the horizontal inertia actions on structures in seismic regions, exerts a favourable effect on the foundations of buildings supported by soil having low bearing capacity, and facilitates the carriage of precast concrete elements (Campione et al., 2005). For long-span bridges, the live load is a minor part of the total load and a reduction in density is translated into reductions in not only mass, but also in section size (Chandra and Berntsson, 2002; Popovics, 1992). When structural LWC is proportioned with cement paste binder amounts similar to those required for normal aggregate concretes, the shrinkage of LWC is generally, but not always, slightly greater than that of NWC due to the lower aggregate stiffness (Holm and Bremner, 2000).

Silica fume used as an admixture in a concrete mix has significant effects on the properties of the resulting material. These effects pertain to the strength, modulus, ductility, abrasion resistance, and air void content, shrinkage, bonding strength with reinforcing steel, permeability, chemical attack resistance, alkali-silica reactivity reduction, and corrosion resistance of embedded steel reinforcement. In addition, silica fume addition degrades the workability of the mix (Xu and Chung, 2000).

Previous studies via ANN

Yeh (1998), Kasperkiewics (1995), Lai and Serra (1997) and Lee (2003) applied a different predicting method based on NNs for predicting properties of conventional concrete and high performance concretes.

Dias and Pooliyadda (2001) used back propagation neural networks to predict the strength and slump of ready mixed concrete and high strength concrete, in which chemical admixtures and/or mineral additives were used. According to the authors, the neural network models also performed better than the multiple regression ones, especially in reducing the scatter of predictions.

Oztas et al. (2006) studied with the NN for developing a methodology for predicting compressive strength of HSC with suitable workability. They arranged to the data used in NN model in a format of seven input parameters that cover the water-to-binder ratio, water content, fine aggregate ratio, fly ash content, air entraining agent content, and silica fume replacement. The proposed NN model predicts the compressive strength and slump value of HSCs.

Baykasoglu et al. (2004) used the soft computing techniques which were gene expression programming and neural networks, for predicting the 28 day compressive strength of Portland composite cement. Besides, they used the stepwise regression analysis to have an idea about the predictive power of the soft computing techniques in comparison to classical statistical approach. Baykasoglu et al. (2004) reported that the results obtained from the computational tests showed that GEP was a promising technique for the prediction of cement strength.

The ANN-based model was developed by Lee (2003) for predicting the concrete strength development. According to conclusions of the study, ANN-based model was predicted well than traditional maturity method within the cylinder test data used in this study. Modular neural networks were more suitable rather than single one for predictting the concrete strength. Multiple architectures composed of five ANNs solved the problem occurred in single one.

Pala et al. (2005) focused on studying the effects of fly ash and silica fume replacement content on the strength of concrete cured for a long term period of time by using neural networks (NNs). The NN model arranged was composed of eight input parameters that cover the fly ash replacement ratio (FA), silica fume replacement ratio (SF), and total cementitious material, fine aggregate, coarse aggregate, water content, high rate water reducing agent and age of samples and an output parameter that is compressive strength (fc). The authors explained that NNs have strong potential as a feasible tool for evaluation of the effect of cementitious material on the compressive strength of concrete.

In other study performed as the experimental analysis, two steel beams with eight distributed surface-bonded electrical strain gauges and an accelerometer mounted at the tip were used to obtain modal parameters such as resonant frequencies and strain mode shapes. The authors applied the trained feed-forward back propagation ANNs by using the data obtained from the experimental damage case (Sahin and Shenoi, 2003).

In the study performed by Kelesoglu et al. (2005), the thickness of the insulation material was fixed by using a multi-layer feed-forward artificial neural network. A back propagation training algorithm was used in training of the network. A brick wall for the structural component was considered and whether or not this wall needed insulation was analyzed and min thickness of this material was determined by ANN. The results obtained from the network were determined compared with the numerical result and it was seen the results sensitive enough.

In a study by Ozsoy and Firat (2004) conducted, it was struggled to estimate the horizontal displacement values depend on various parameters by artificial neural networks. The authors have defined that the feed forward artificial neural network gives the best results in the studies of estimation. In the NN model constructed by the researchers, height of structure, height of floor, slab thickness and weight of structures were used as input parameters and the displacement which occured in structure was used as output parameter. As a result of this study, they were reported that lateral displacements can be predicted by using artificial neural networks.

A neural network-based concrete mix optimization methodology is proposed and is verified to be a promising tool for mix optimization in the study conducted by Yeh (1998).

Peng et al. (2002) studied the feasibility of using a neural network as an adaptive synthesizer as well as a predicttor to meet such a requirement. The authors reported that the predictions given by the cascade-correlation algorithm were in good agreement with the test results in both steady and unsteady states. Besides, it has the potential of becoming an effective tool in the prediction of durability problems.

Kim et al. (2004) applied neural network-based system identification techniques to predict the compressive strength of concrete based on concrete mix proportions. They developed, trained, and tested the back-propagation neural networks using actual data sets of concrete mix proportions provided by two ready-mixed concrete companies. According to this study, the neural network techniques are effective in estimating the compressive strength of concrete based on the mix proportions. Some studies have been conducted on the relationship between concrete strength and the chloride in concrete structures.

Artificial neural network

A first wave of interest in neural networks (also known as 'connectionist models' or 'parallel distributed processing') emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks. When Minsky and Papert published their book Perceptions in 1969. They showed the deficiencies of perception models, most neural network funding was redirected and researchers left the field. Only a few researchers continued their efforts, most notably Teuv O. Kohonen, Stephen Grossberg, James Anderson and Kunihiko Fukushima. The interest in neural networks re-emerged only after some important theoretical results were attained in the early eighties (most notably the discovery of error back-propagation) and new hardware developments increased the process-ing capacities (Krose and Smagt, 1996).

According to Zurada (1992), artificial neural systems or neural networks are physical cellular systems which can acquire, store and utilize experiential knowledge.

An Artificial Neural Network (ANN) is an information

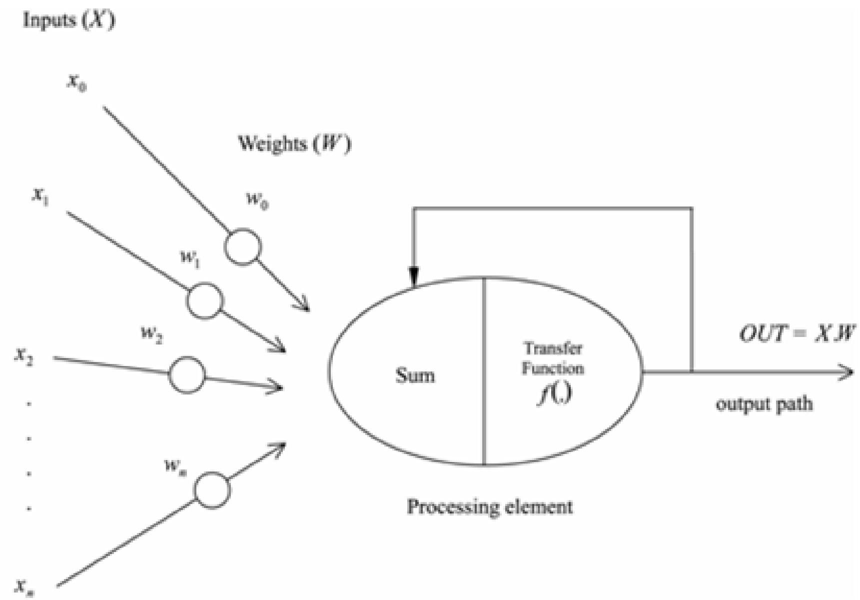

Figure 1. A simple artificial neuron (Sinanoglu, 2006).

processing paradigm that is inspired by the way biological nervous systems such as the brain and process information. Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin stand known as an axon which splits into thousands of branches.

At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurones. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes. It is composed of a large number of neuron elements working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classifycation, through a learning process. Learning in biological systems involves adjust-ments to the synaptic connections that exist between the neurones.

The neuron has two modes of operation: the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. Most NNs have some sort of "training" rule whereby the weights of connections are adjusted on the basis of data. If trained carefully, NNs may exhibit some capability for generalization beyond the training data, that is, to produce approximately correct results for new cases that were not used for training (Fausett, 1994; Civalek and Ulker, 2004).

A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions (Civalek and Ulker, 2004; Aleksander and Morton, 1995). A simple artificial neuron is shown in Figure 1.

The back-propagation algorithm

Among several architectures and paradigms, the back-propagation network is one of the simplest and most applicable networks being used in performing higher level human task such as diagnosis, classification, decision making, planning and scheduling (Sohabhon and Spethen, 1999). Back-propagation can be considered a generalization of the delta rule for onlinear activation functions and multilayer networks.

In a back-propagation neural network, the learning algorithm has two phases. First, a training input pattern is presented to the network input layer. The network propagates the input pattern from layer to layer until the output pattern is generated by the output layer. If this pattern is different from the desired output, an error is calculated and then propagated backward through the network from the output layer to the input layer. The weights are modified as the error is propagated (Jung and Wang, 2008). Figure 2 shows single-layer back- propagation network algorithms.

The learning procedure involves the presentation of a set of pairs of input and output patterns. The system first uses the input vector to produce its own output vector and then compares this with the desired output, or target vector. If there is no difference, no learning takes place. Otherwise, the weights are changed to reduce the diffe-

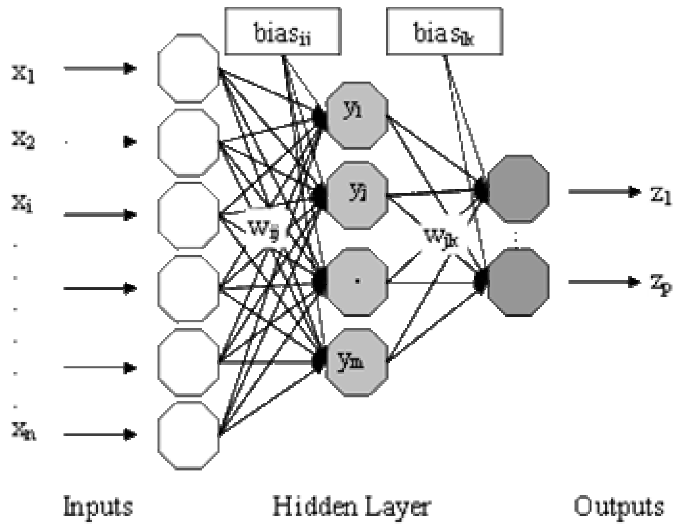

Figure 2. A single-layer back-propagation network algorithm.

rence. In this case, with no hidden units, this generates the standard delta rule. The delta rule for changing weights following presentation of an input/output pair p is given by equation (1):

$$\Delta_p w_{ji} = \eta(t_{pj} - o_{pj})i_{pi} = \eta\delta_{pj} i_{pi} \quad (1)$$

where t_{pj} is the target input for the jth component of the output pattern for pattern p, o_{pj} is the jth element of the actual output pattern produced by the presentation of input pattern p, i_{pi} is the value of the ith element of the input pattern, $\delta_{pj} = t_{pj} - o_{pj}$, and $\Delta_p w_{ji}$ is the change to be made to the from the *ith* to the jth unit following presentation of pattern *p.* There are many ways of deriving the delta rule. In this network, the input units are the bottom layer and the output units are the top layer. There can be many layers of hidden units in between, but every unit must send its output to higher layers than its own and must receive its input from lower layers than its own. Gi-ven an input vector, the output vector is computed by a forward pass that computes the activity levels in the earlier layers. The back-propagation algorithm performs the steepest descent on a surface in a weight space whose height at any point in weight space is equal to the error measure. In order to show the algorithm, let

$$E_p = \frac{1}{2}\sum_j (t_{pj} - o_{pj})^2 \quad (2)$$

be the measure of the error on input/output pattern *p* and let $E = \sum E_p$ be the overall measure of the error. Here, it defines the weighted sum of the output of the previous layer,

$$net_{pj} = \sum_i w_{ji} o_{pi} \quad (3)$$

as the state of the unit.

$$o_{pj} = f_j(net_{pj}) \quad (4)$$

uses the sigmoid function, which is non-decreasing and the differentiable function. To implement a gradient descent in *E*, we should make the weight changes according to:

$$\Delta_p w_{ji} = \eta\delta_{pj} o_{pi} \quad (5)$$

Just as in the standard delta rule. In this equation $w_{ji}(t)$ is the weight, η is a gain term which is called learning rate and δ_{pj} is an error term of unit j. The interesting result is that there is a simple recursive computation of this *δ's* that can be implemented by propagating an error signal backward through the network.

If the unit j is an output unit, then the error signal (δ_{pj}) is given by:

$$\delta_{pj} = (t_{pj} - o_{pj})\, f_j^{\prime}(net_{pj}) \quad (6)$$

Take as the activation function f_j the 'sigmoid' function,

$$o_{pi} = \frac{1}{1 + e^{-(net_{pj}) + \theta_j}} \quad (7)$$

Where θ_j is abias similar in function to a threshold. The sigmoid function performs a sort of 'soft' threshold that is rounded (and differentiable) compared with other transfer functions (Judith, 1990). If unit j is a hidden unit, the δ_{pj} can be computed by

$$\delta_{pj} = f_j^{\prime}(net_{pj}) \sum_k \delta_{pk} w_{kj} \quad (8)$$

The error signal for an output unit can be written as:

$$\delta_{pj} = (t_{pj} - o_{pj}) o_{pj}(1 - o_{pj}) \quad (9)$$

The error signal for a hidden unit determined recursively in terms of error signals of the units to which it directly connects and the weights of those connections. For the sigmoid activation function (Rumelhart et al., 1986; Fukuda and Shibata, 1992):

$$\delta_{pj} = \mathrm{o_{pj}}(1 - \mathrm{o_{pj}}) \sum_k \delta_{pk} w_{kj} \quad (9)$$

Learning rate and momentum

The learning procedure requires that the change in weight is proportional to $\partial E^p / \partial w$. True gradient descent requires that infinitesimal steps are taken. The constant of proportionality is the learning rate. For practical purposes we choose a learning rate that is as large as possible without leading to oscillation. One way to avoid oscillation at large is to make the change in weight dependent of the past weight change by adding a momentum term:

$$\Delta w_{jk}(n+1) = \eta(\delta_{pj} o_{pi}) + \alpha \Delta w_{ji}(n) \qquad (10)$$

Where n indexes the presentation number and α is a constant which determines the effect of the previous weight change (Rumelhart et al., 1986; Fukuda and Shibata, 1992).

Bond strength and development length

The bond feature between reinforcing bar-concrete is one of most important properties in reinforced concrete structures. Steel-concrete bond is the combination of adhesion, friction and support of the ribs in deformed steel. The adhesion mechanism is the first property activated by the load. Adhesion is partly microscopic interlock of paste into imperfections of the steel surface and partly a possible chemical interaction between surfaces.

The two other mechanisms, friction and rib support, go into action when adhesion fails and some relative movement begins between concrete and steel. Then, this time significant slip may be observed, as well as the formation and growth of cracks. There is little knowledge on the mechanical interaction (“bond”) between reinforcing bars and natural lightweight aggregate con-crete as pumice etc. Some studies were performed in terms of bond strength between reinforcing bars and concrete with artificial lightweight aggregate (Mor, 1992; Cox et al., 2000; Chent et al., 2004)

Field performance has demonstrated satisfactory performance LDC with strength levels of 20 to 35 MPa with respect to bond and development length. Because of the lower particle strength, LDC have lower bond splitting capacities and a lower post-elastic strain capacity than NDC. Unless tensile splitting strengths are specified, ACI 318 requires the development lengths for low-density concrete to be increased by a factor of 1.3 over the lengths required for normal-density concrete (Holm and Bremner, 2000).

In one study, Yerlici et al. (1995) examined the bond behaviors of high-strength concretes (HSC) with mineral additives. The results of the said study showed that required anchorage lengths of HSCs were shorter than those of normal-strength concretes (NSCs) and that crack widths of HSCs were smaller than those of NSCs.

In the scope of the study “Bond Strength of HSC Elements” conducted by Yerlici and Ozturan (2000), single-reinforced and double-reinforced concrete elements were subjected to eccentric, single-load pull-out bond tests. It was observed that the increase in compressive strength of concrete, the thickness of concrete cover and the amount of body reinforcement resulted in an increase in the bond strength while the increase in the reinforcement diameter resulted in a decrease in the same. Moreover, bond fracture was detected to be sudden and brittle in HSC elements.

Depending on the amount of the additive, silica fume (SF) can increase reinforcement bond by 3 - 5 times in lightweight aggregate concretes (Robins and Austin, 1986; Bürge, 1983). The studies about the reinforcement- concrete bond properties of lightweight concretes showed that these concretes showed sufficient site performance and that the bond strength of lightweight aggregate concretes was lower than that of gravel-sand concretes for the same compressive strength when flat and round reinforcements were used. In addition, the anchorage strength of the ribbed reinforcements was found to be generally the same as that of normal-density concretes (Slate, 1986).

Since it decreases sweating and turns cement paste into a harder and stronger structure, SF increases the bond between the concrete and the reinforcement. This positive effect can be observed more clearly at additive rates above 20%. Some studies have been conducted on the relationship between concrete strength and the chloride in concrete structures (Khayat, 1992).

The actual compressive strength of concrete is unknown during the early life of the structure. Also, the concrete market is generally very competitive and it turns out that concrete companies have only restricted budgets to spend in mix-design, although from this fundamental stage comes a great deal of consequences for the site operations and for the structure to be built (Oztas et al., 2006).

Tanyildizi (2007) made a study to determine the fuzzy logic prediction model of the reinforcement-concrete bond strength of lightweight concrete prepared by using three different mixtures kept under different cure conditions. Concrete samples were produced by using three different mixtures: control concrete prepared by using only Portland cement, produced by mixing cement with fly ash (in an amount corresponding to 15% of the weight of the cement) and a serial produced by mixing cement with silica fume (in an amount corresponding to 10% of the weight of the cement). The concrete samples were subjected to compressive strength and bond strength tests. At the end of the study, it was suggested that the fuzzy logic method could be used in the prediction of the bond strength of lightweight concrete.

Research significance

For design purposes, the tensile strength of concrete is assumed to be zero. Generally, the bond between steel and concrete is related to the quality of the concrete and the bond strength is approximately proportional to the compressive strength of the concrete (Gani, 1997). Concrete is, on the other hand, a heterogeneous material made up of cement, mortar and aggregates. Its mechanical properties scatter more widely and cannot be defined easily.

For the convenience of analysis and design, however, concrete is often considered a homogeneous material in the macroscopic sense. Many mathematical models of the mechanical behavior of concrete are currently being used in the analysis of reinforced concrete structures. For many years, researchers have proposed various methods for predicting concrete strength (Snell et al., 1989; Popovics, 1998).

Such traditional prediction models have been developed with a fixed equation form based on a limited number of data and parameters. If new data are quite different from original data, then the model should update not only its coefficients but also its equation form. Artificial Neural Network (ANN) does not need such a specific equation form. Instead, it needs sufficient input-output data. Also, it can continuously re-train the new data, so that it can conveniently adapt to new data (Lee, 2003).

Therefore, silica fume proportion and 28th and 90th day compressive strength data were used with the aim of predicting the bond strength between the “pumice aggregate lightweight concrete including silica fume and super plasticizer” and “reinforcing steel” via the artificial neural networks approach, which can be used without need for mathematical modeling and which produces values quite close to experimental values. Taking into consideration the importance of the bond strength in designing reinforced concrete structures, this method will greatly facilitate practical predictions of bond strength by using compressive strength values. The present study is the first study using the artificial neural networks (ANN) method in predictting bond strength.

EXPERIMENTAL DETAILS

Materials

Pumice aggregates obtained from Isparta province, Turkey, were utilized to prepare structural lightweight concrete specimens. The aggregates were used after washing and sieving. The particle size ranged as 0 - 4 mm, 4 - 8 mm and 8 - 16 mm. Grain size distribution curve of the pumice aggregate used was provided that complied with border curves to the requirements of ASTM C 330. The specific gravity factors of pumice aggregate were obtained to determine concrete mixture proportion according to ACI 211 as 2.09, 1.75 and 1.50 kg/dm^3 respectively.

The bulk density was around 0.650, 0.738 and 0.893 kg/dm^3 respectively. Specific gravity of pumice was 2.47. The water absorption rate of pumice was 12, 19 and 42% on the grain interval of 8-16 mm, 4-8 mm and 0-4 mm respectively. The porosity of pumice was 29, 70 and 68% respectively on the same grain interval.

An ASTM Type I Ordinary Portland Cement (OPC), having a 28 day compressive strength of 42.5 N/mm^2 (MPa) was used in this study. Its specific gravity and Blaine specific surface area were 3.15 kg/dm^3 and 3350 cm^2/g respectively. Initial and final setting times of the cement were 150 and 196 min. respectively. The 7 day and 28 day compressive strengths of PC were 41.3 and 51.2 MPa respectively. The required cement dosages which had been found to obtain C 20 were determined in a previous study. Silica fume (SF) used in concrete production was obtained from Antalya Electro Ferro-Chrome Company in Turkey. The regular tap water was used in the whole tests. The nominal diameter of rebar was 14 mm. For the mechanical characterization of six steel bar specimens tensile tests were carried out using the tensile testing machine according to ASTM A615M. For the reinforcing bars yielding stress *fy* and ultimate stress *ft* values of 104 and 679 MPa respectively were recorded.

Testing details

“The compressive strength test specimens were 100 mm cubes as per ASTM C 192. The used pullout specimens were modified ASTM C 234 specimens. The reinforcing bars have diameter of 14 mm instead of no.6 (19mm) bars specified in ASTM C234. The produced concrete was placed in standard cube (150 x 150 x 150 mm) moulds. The mix proportions and some fresh properties of the lightweight concrete specimens are shown (Table 1).”

Prediction of bond strength of lightweight concrete via the ANN method

Forty-eight tests were conducted to determine via the ANN method the effects of silica fume and the age of the concrete on the bond strength of reinforced lightweight concrete. The neural network developed in the scope of the present study consisted of 3 neurons (variables) in the input layer and 1 neuron in the output layer. Since minimum error percentage was achieved, 2 hidden layers composed of 4 and 3 neurons were used in the network design. The developed ANN model is presented in figure 3.

Silica fume proportion (in terms of weight and expressed in %) and compressive strength values obtained on the 28th and 90th days were used as input to the model. Bond strength was predicted in the output layer. The test process was started after the values used for training purposes were compared with the values in the ANN model. In the testing phase, data were input to the model in order to predict bond strength values. The Easy NN-Plus program using the back propagation artificial neural network model was preferred in the study. The results were detected at a 1.6% error rate.

FINDINGS AND DISCUSSION

The relationship between compressive strength and bond strength

Results obtained from compressive strength tests and bond strength tests were analyzed via regression analysis to find any relationship between the two variables. This process aimed at testing the accuracy of the bond strength values obtained via the artificial neural networks method and determining the usability of artificial neural networks to this end.

Regression analysis was made to examine the relationship between the results of the compressive strength test conducted on the 28th day and the bond strength results obtained via ANN (Figure 4). The determination coefficient shows that there is a strong relationship (R^2 = 0.937). The regression curve of the relationship between the experimental bond strength value obtained on the 90th day and the experimental compressive strength value obtained on the 28th day and the related determination coefficient are presented in Figure 5 (R^2 = 0.9453).

The relationship between experimental compressive strength and experimental bond strength was found not to be quite different from the relationship of the experimental compressive strength and the bond strength obtained via ANN (R^2 = 0.937 and R^2 = 0.9453). In light of this data, it can be suggested that ANN can reliably predict the value of the reinforcement-concrete bond strength of lightweight concrete. These values remained within the

Table 1. Mix proportions (for $1/m^3$) and some fresh properties of the SLWAC.

Concrete	Cement (kg)	Water (kg)	w/c	Aggregate (kg)			SF (kg)	Slump (cm)	Fresh unit weight (kg/m^3)
				0 - 4 mm	4 - 8 mm	8 - 16 mm			
L - 0	430	199	0.46	730	550	52	---	8.4	1809
L – 5	408.5	202	0.49	729	549	52	21.50	7.2	1792
L – 10	387	202	0.52	729	549	52	43	6.8	1772

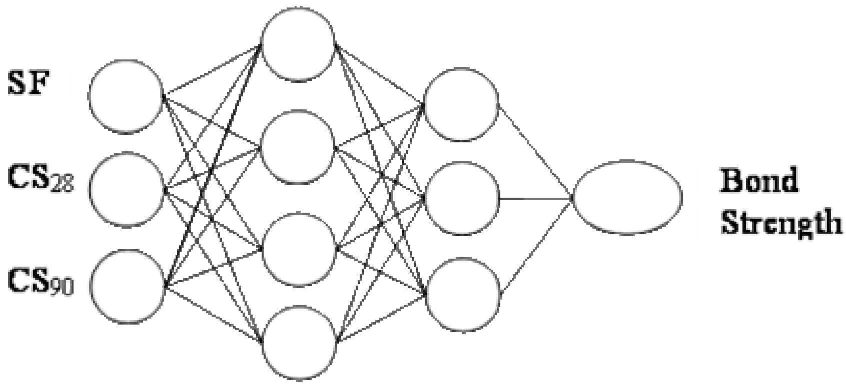

Figure 3. ANN model developed to predict bond strength by using compressive strength values.

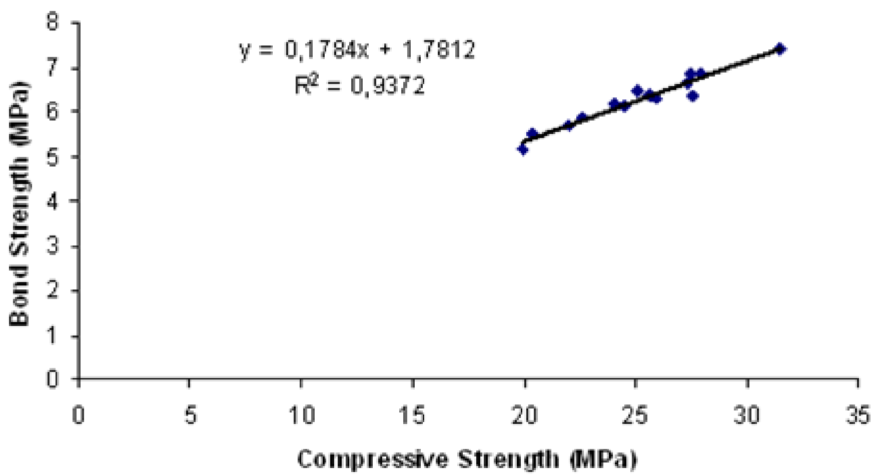

Figure 4. The relationship between the compressive strength values obtained on the 28th day and the bond strength predicted by ANN.

range of the determination coefficients found in previous studies which used ANN to predict the compressive strength of normal and high-strength concretes by using mixture parameters as inputs (R^2 = 0.615 - 0.99) (Yeh, 1998; Kasperkiewics et al., 1995; Lee, 2003; Dias et al., 2001; Pala et al., 2005). In another study, the determination coefficient between the reinforcement-concrete bond strength value obtained on the 28th day and compressive strength value (R^2 value) was calculated as 0.77 (Tanyildizi, 2007).

In addition, the same analysis was also made between compressive strength values obtained on the 90th day and the bond strength predicted by ANN. The resulting graphic is presented in figure 6.

The relationship between the values obtained from the tests conducted on the 90th day to determine reinforcement-concrete bond strength and the values obtained from the compressive strength tests conducted on the date is

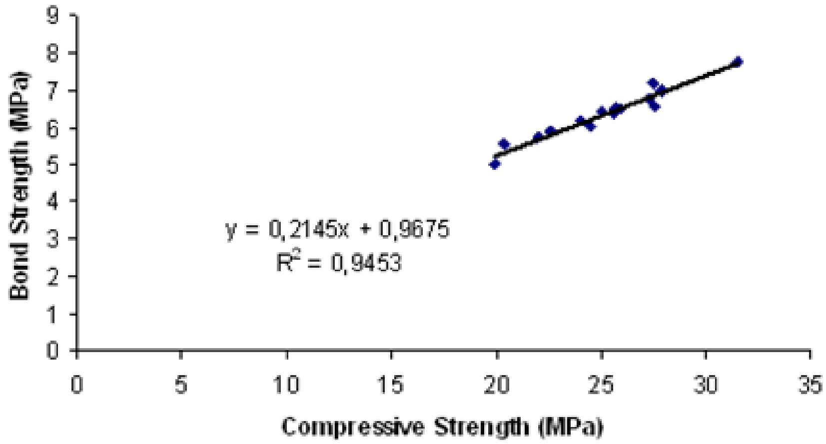

Figure 5. The relationship between the compressive strength value obtained on the 28th day and experimental bond strength.

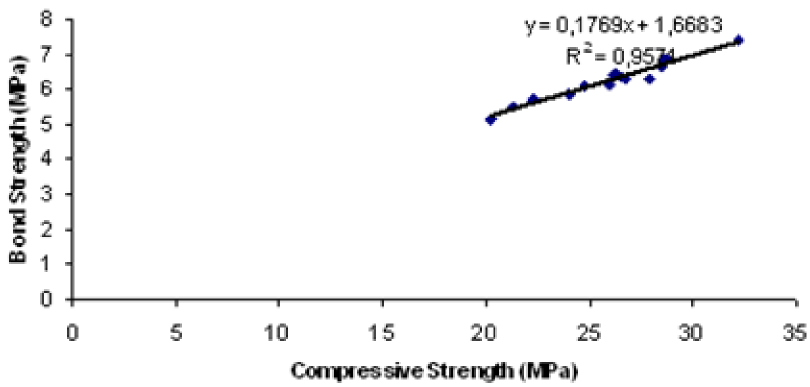

Figure 6. The relationship between compressive strength values obtained on the 90th day and bond strength values predicted by ANN.

same date is presented in Figure 7.

A quite high correlation was detected between these values. The determination coefficient between experimental bond strength and compressive strength was calculated to be R^2 = 0.9601. The correlation between bond strength values predicted by ANN and compressive pressure values obtained on the 90th day was found to be considerably high (R^2 = 0.9571). Bond strength values predicted via ANN and the bond strength values obtained experimentally run parallel with each other. ANN proved to be a very useful tool in the prediction of bond strength values.

Since linear regression was preferred for the statistical analysis done in this study, the coefficient R^2 = 0.9601 was produced via the equation $\tau_b = 0.2122(f_{ck}) + 0.8469$. Comparison of the experimental results with related studies in the existing literature showed that the study conducted by Yerlici and Ozturan (2000) suggested the following equation to determine the relationship between bond strength and compressive strength in high-strength concrete elements:

$$\tau_b = 0.44(f_{ck})^{0.78}$$

The equation obtained in this study can be expressed as an exponential function as $\tau_b = 0.63(f_{ck})^{0.714}$. Thus, the determination coefficient of this equation turns out to be R^2 = 0.9395.

In another study, the highest mean bond strength value was calculated as $\tau_{b\max} = 1.38\sqrt{f_{ck}}$ (Robins and Austin, 1986). Yerlici and Ozturan (2000) stated that the bond strength value produced by their equation remained within the limits specified in the 1990 CEB/FIB Specifications Model: $\tau_{b\max} = 2.0\sqrt{f_{ck}}$ for good anchorage conditions and 1.0 $\sqrt{f_{ck}}$ for all other anchorage conditions for the normal-strength concretes. The equation of the present study stayed within the limits stipulated

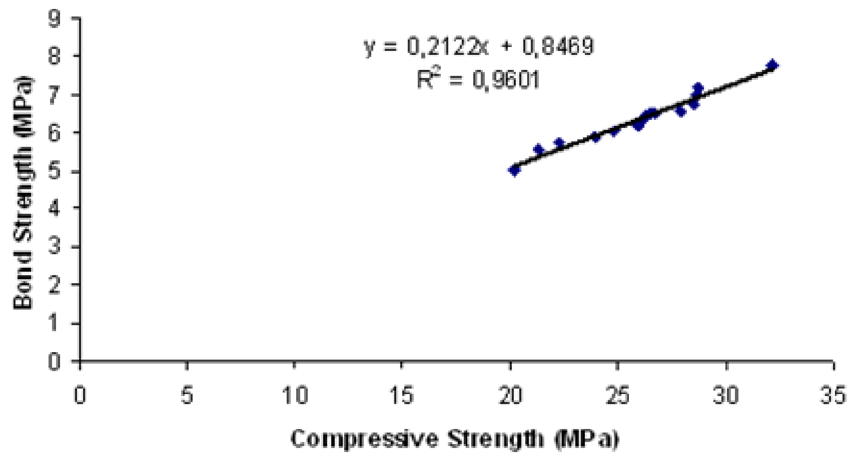

Figure 7. The relationship between the compressive strength values and bond strength values obtained on the 90th day.

Table 2. Experimental and predicted results via ANN.

Sample Code	SF rate (%)	Compressive Strength at 28th day (MPa)	Compressive Strength at 90th day (MPa)	Predicted Bond strength via ANN (MPa)	Experimental bond strength (MPa)
L-0	0	19.92	20.23	5.03	5.16
L-0	0	24.5	24.79	6.03	6.12
L-0	0	22.61	23.95	5.89	5.86
L-0	0	27.53	27.93	6.58	6.32
L-0	0	25.61	26.22	6.38	6.39
L-5	5	20.34	21.30	5.54	5.51
L-5	5	24.06	25.97	6.17	6.17
L-5	5	25.91	26.70	6.53	6.29
L-5	5	27.51	28.73	7.20	6.85
L-5	5	27.34	28.51	6.73	6.63
L-10	10	22.02	22.28	5.74	5.70
L-10	10	25.69	26.51	6.53	6.33
L-10	10	31.48	32.16	7.76	7.42
L-10	10	27.89	28.63	6.97	6.85
L-10	10	25.1	26.25	6.40	6.46

in the specifications as well. Table 2 presents the testing results and predicted results via ANN. The relationship between the values predicted via the model and the experimental results is presented in figure 8.

It was found that there was a high correlation bet-ween the experimental bond strengths and the bond strengths predicted by ANN ($r = 0.9861$; $R^2 = 0.9725$). Bond strength predictions made via ANN for the pumice aggregate light weight concrete were found to be similar to the experimental bond strength results. Accordingly, useful findings can be obtained via ANN analysis of the experimental bond strengths by using more parameters. Thus, ANN can not be suggested as an alternative for experimental studies. However, it can be stated that ANN can be used successfully in the prediction of bond strength.

Conclusion

The results obtained in this study are as follows:

i) Bond strength tests conducted on pumice aggregate light weight concretes can be successfully predicted via ANN by using more parameters.

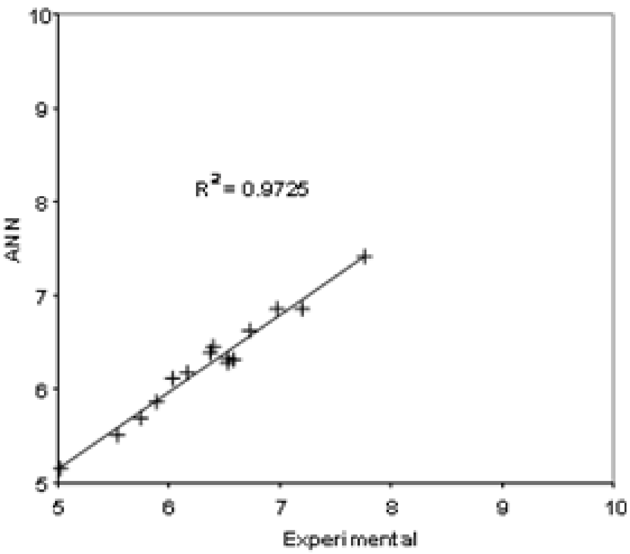

Figure 8. The relationship between the values predicted via the model and the experimental bond strength test results.

ii) Bond strength value is an important datum for calculations related to reinforced concrete structures and can be predicted via ANN in a short time.
iii) A similar study should be conducted by using a higher number of parameters and tests for the normal aggregate concretes.
iv) Since normal aggregate concrete is widely used, it is likely that ANN could be used to predict its bond strength as well.

Normal aggregate concrete and particularly light weight aggregate concrete, do not exhibit a linear relationship with the loads applied to them due to their brittle micro-structure. Therefore, analytical formulas remain insufficient in modeling the general behavior of these concretes. On the other hand, thanks to improvements in ANN, it is regarded as an appropriate tool for the prediction of concrete behavior.

REFERENCES

Aleksander I, Morton I (1995). An introduction to neural computing. International Thomson Computer Press.
Baykasoglu A, Dereli T, Tanış S (2004). Prediction of cement strength using soft computing techniques. Cement Concrete Res. 34: 2083-2090.
Bürge TA (1983). High strength lightweight concrete with condensed silica fume. ACI, SP-79. pp. 731-745.
Campione G, Cucchiara C, La Mendola L and Papia M (2005). Steel–concrete bond in lightweight fiber reinforced concrete under monotonic and cyclic actions. Engineering Structures 27(6): 881-890.
Chandra S, Berntsson L (2002). Lightweight aggregate concrete: science, technology, and applications. Noyes Publications, pp. 1-18.
Chent HJ, Huangt CH, Kaot ZY (2004). Experimental investigation on steel-concrete bond in lightweight and normal weight concrete. Struct. Eng. Mech. 17(2): 141-152.
Civalek Ö, Ülker M (2004). Dikdörtgen plakların doğrusal olmayan analizinde yapay sinir ağı yaklaşımı, İMO Teknik Dergi, 3171-3190.
Cox JV, Bergeron K, Malvar J (2000). A combained experimental and numerical study of the bond between lightweight concrete and CFRP bars. Sessions on Interface Degradation 14th ASCE Engineering Mechanics Conference, The University of Texas at Austin. pp. 1-5.
Dias WPS, Pooliyadda SP (2001) Neural networks for predicting properties of concretes with admixtures. Constr. Build. Mater. 15: 371-379.
Fausett L (1994). Fundamentals of neural networks, architectures, algorithms, and applications., Prentice-Hall, Inc., New-Jersey.
Fukuda T, Shibata T (1992). Theory and applications of neural networks for industrial control systems. IEEE Transactions on industrial electronics. 39(6): 472-489.
Gani MSC (1997). Cement and concrete. Chapman & Hall, London, p. 205.
Holm TA, Bremner TW (2000). State-of-the-art report on high-strength, high-durability structural low-density concrete for applications in severe marine environments. U.S. Army Engineer Research and Development Center p. 116.
Judith ED (1990). Neural Network Architectures. Van Nostard Reinhold: New York.
Jung I, Wang GN (2008). Pattern classification of back-propagation algorithm using exclusive connecting network. Int. J. Comp. Sci. Eng. 2 (2): 76-80.
Kasperkiewics J, Racz J, Dubrawski A (1995). HPC strength prediction using ANN. ASCE J. Comp. Civil Eng. 9(4):279-284.
Kelesoglu Ö, Ekinci CE, Fırat A (2005). The using of artificial neural networks in insulation computations. J. Eng. Natural Sci. Sigma, 3: 58-66.
Khayat KH, Aitcin PC (1992). Silica fume in concrete-an overview. ACI SP-132, pp. 835-865.
Kim JI, Kim DK, Feng MQ, Yazdani F (2004). Application of neural networks for estimation of concrete strength. J. Mater. Civil Eng. 16 (3): 257-264.
Krose B, Smagt P (1996). An introduction to neural networks. Eighth edition, The University of Amsterdam, pp. 1-2.
Lai S, Serra M (1997). Concrete strength prediction by means of neural network. Constr. Build. Mater. 11(2): 93-98.
Lee SC (2003). Prediction of concrete strength using artificial neural networks. Eng. Struct. 25: 849-857.
Mor A (1992). Steel-concrete bond in high-strength lightweight concrete. ACI Mater J., 89 (1): 76-82.
Özsoy İ, Firat M (2004). Estimation of lateral displacements in a reinforced concrete structure with flat slabs by using artificial neural networks. Dokuzeylül University Faculty of Engineering, J. Sci. Eng. 6 (1): 51-63.
Oztas A, Pala M, Özbay E, Kanca E, Çağlar N, Bhatti MA (2006). Predicting the compressive strength and slump of high strength concrete using neural network. Constr. Build. Mater. 20: 769-775.
Pala M, Özbay E, Öztaş A, Ishak YM (2005). Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks. Constr. Build. Mater. doi:10.1016/j.conbuildmat. 08.009.
Peng J, Li Z, Ma B (2002). Neural network analysis of chloride diffusion in concrete, J. Mater. Civil Eng. 14 (4): 327-333.
Popovics S (1992). Concrete materials properties, specifications and testing, Second Edition, Noyes Publications, USA. pp. 513-527.
Popovics S (1998). History of a mathematical model for strength development of Portland cement concrete. ACI Mater. J. 95 (5): 593-600.
Robins PJ, Austin SA (1986). Bond of lightweight aggregate concrete ıncorporating condensed silica fume. Publication SP - American Concrete Institute, 2: 941-958.
Rumelhart DE, Hinton GE, Williams RJ (1986). Learning internal representation by error propagation. in parallel distributed processing: Explorations in the microstructures of cognition, MIT Press, Cambridge, MA.
Sahin M, Shenoi RA (2003). Quantification and localisation of damage in beam-like structures by using artificial neural networks with experimental validation. Eng. Struct. 25: 1597-1610.
Sinanoglu C (2006). The analysis of effects of shaft surface porosity on journal bearing using experimental and neural network approach. Industrial Lubrication Tribology. 58 (1):15- 31.

Slate FO, Nilson AH, Alou F (1986) Mechanical properties of high strength lightweight concrete. ACI Mater. J. 83 (4): 606-613.
Snell LM, Van Roekel J, Wallace ND (1989). Predicting early concrete strength. Concrete Int. 11(12): 43-47.
Sohabhon B, Spethen OO (1999). Application of ANN to forecast construction duration of buildings at the predesign stage. Eng. Constr. Architect Manage. 6 (2):133-44.
Tanyildizi H (2007). Fuzzy logic model for the prediction of bond strength of high-strength lightweight concrete. Advances in Engineering Software, doi:10.1016/j.advengsoft. 05.013.
Topçu IB (1997). Semi-lightweight concretes produced by volcanic slags. Cement Concrete Res. 27: 15-21.
Xu Y, Chung DDL (2000). Improving silica fume cement by using silane. Cement Concrete Res. 30: 1305-1311.
Yeh IC (1998). Modeling concrete strength with augment-neuron networks. J Mater Civil Eng. 10 (4): 263-268.
Yerlici V, Ersoy U, Özturan T, Türk M, Özden Ş (1995). Anchorage of reinforcement in high-strength concrete elements. İMO Teknik Dergi. 6 (3): 1007-1026.
Yerlici VA, Ozturan T (2000). Factors affecting anchorage bond strength in high-performance concrete. ACI Struct. J. 97 (3):499-507.
Zurada, JM (1992). Introduction to artificial neural Networks. Boston: PWS Publishing Company. p. XV.