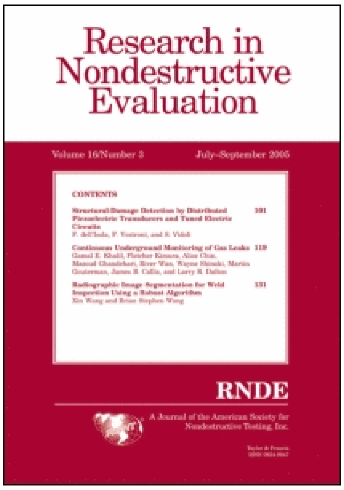

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ARTIFICIAL NEURAL NETWORK APPROACH TO PREDICT COMPRESSIVE STRENGTH OF CONCRETE THROUGH ULTRASONIC PULSE VELOCITY

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Plenty of efforts to use ultrasonic pulse velocity (UPV) as a measure of concrete compressive strength have been implemented in the recent years due to obvious advantages of nondestructive testing methods. In this article, an artificial neural network (ANN) approach has been proposed for the evaluation of relationship between concrete compressive strength and UPV values by using the data obtained from many cores taken from different reinforced concrete structures having different ages and unknown ratios of concrete mixtures. The presented approach enables to practically find concrete strengths in the existing reinforced concrete structures, whose records of concrete mixture ratios are not available or present. Thus, researchers can easily evaluate the compressive strength of concrete specimens by using UPV values. The method can also be used in conditions such as too many numbers of the structures and examinations to be done in a restricted time. The comparison of the results clearly shows that the ANN approach can be used effectively to predict the compressive strength of concrete by using UPV values.

Keywords: artificial neural networks, concrete, compressive strength, ultrasonic pulse velocity, nondestructive testing

1. INTRODUCTION

The nondestructive testing (NDT) of concrete bears a great scientific and practical importance. The subject of using NDT methods has received growing attention during recent years, especially during the rising need for quality characterisation of damaged constructions made of concrete (Turgut, 2004). Malhotra (1976) presented a comprehensive literature survey for the nondestructive methods normally used for concrete testing and evaluation. Leshchinsky (1991) summarized the advantages of nondestructive tests, compared to core testing, as reduction in the labor consumption of testing, a decrease in labor consumption of preparatory work, a smaller amount of structural damage, a possibility of testing concrete strength in structures where cores cannot be drilled, and application of less expensive testing equipment. These advantages signify no value if the results are not reliable, representative, and as close as possible to the actual strength of the tested

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part of the structure. Quality of concrete in structures is generally determined by standard cubes or cylinders supplied to the construction site (Neville, 1995). Therefore, the determination of the compressive strength of concrete requires preparation, curing, and testing of special specimens. Although this is well accepted by the construction industry, some differences do exist between the cube or cylinder strength and actual strength of concrete in the structure (Bungey and Soutsos, 2001). These differences generally arise from the possibility of different curing and compaction of concrete in the structure. There are quantities of destructive and nondestructive methods for in-situ concrete strength. The UPV test is one of the most popular nondestructive techniques used in the assessment of concrete properties in structures (Neville, 1995). The interpretation of the test results, however, is very difficult since UPV values are influenced by a number of factors although the UPV test is fairly simple and easy to apply (Ohdaira and Masuzawa, 2000; Davis, 1977). Longitudinal ultrasonic waves are an attractive tool for investigating concrete. Such waves have the highest velocity so it is simple to separate them from the other wave modes. The equipment is portable, usable in the field for in-situ testing, truly nondestructive, and has proven successful for testing materials other than concrete. In addition, none of the available nondestructive methods for testing concrete strength is better. Nevertheless, there are intrinsic and practical factors that may interfere with the determination of concrete strength by ultrasonic means. Concrete is a composite material consisting of Portland cement, mineral aggregate, water, and air. This complexity makes the behavior of ultrasonic waves in concrete highly irregular, which in turn hinders nondestructive testing. In view of the complexities of the problem, it would appear to be overly optimistic to attempt to formulate an ultrasonic test method for the determination of concrete strength. On the other hand, major advancement is desperately needed to improve the current situation considering the seriousness of the infrastructure problem and the enormity of the cost for rehabilitation. For instance, it has been demonstrated repeatedly that the standard ultrasonic method, using longitudinal waves, for testing concrete can estimate the concrete strength only with ±20% accuracy under laboratory conditions (Popovics, 1998).

In this research, the concrete core samples were taken from existing reinforced concrete structures, ranging in age from 28 days to 36 years. Their concrete mixture ratios were not known. An unknown concrete mixture ratio in existing reinforced concrete structures is one of the most frequent issues that cause difficulties to determine the concrete compressive strength–UPV relationship. In this respect, the strength of concrete cannot be determined appropriately caused by the nongeneral pattern in the variability in the concrete mixture ratio findings obtained from laboratory researches. Thus, these findings cannot represent a general pattern for analysis as well. In this study, a new approach is presented by considering the compressive strength–UPV relationship of concrete cores taken from existing reinforced concrete structures. In other words, an ANN approach for the estimation of the compressive strength of concrete specimens, using UPV values, is utilized in the study. Compressive strength of concrete prediction was implemented using ANN models, consisting of one input layer, one hidden layer and one output layer, for each data set. The analysis was then conducted for cylinder specimens with different compressive strength due to wide variation in their UPV.

2. ULTRASONIC PULSE VELOCITY (UPV)

The UPV technique is one of the most popular nondestructive techniques used in the assessment of concrete properties. Nevertheless, it is very difficult to accurately evaluate the concrete compressive strength with this method since UPV values are affected by a number of factors, which do not necessarily influence the concrete compressive strength in the same way or to the same extent (Trtnik, 2009). The UPV testing is the most commonly used one in practice among the other available nondestructive methods. The UPV test is described in ASTM C597 (1991) and BS 1881-203 (1986) in detail.

The longitudinal waves travel faster than the transverse waves. For this reason, the longitudinal waves are called primary or P waves, and the transverse waves are called secondary or S waves. The dynamic modulus of elasticity of a homogenous and isotropic material can be determined by measuring the P and S wave velocities.

The compression wave velocity can be expressed in terms of dynamic modulus of elasticity E_d and poisson's ratio ν as in the following equations:

$$V_P = \sqrt{\frac{E_d(1-\nu)}{\rho(1-2\nu)(1+\nu)}} \tag{1}$$

$$V_S = \sqrt{\frac{E_d}{2\rho(1+\nu)}}, \tag{2}$$

where ρ is density of material, and V_P and V_S are primary and secondary wave velocities of material, respectively.

Relationships between the pulse velocity of concrete, the strength of concrete, and the dynamic modulus of elasticity of concrete are given in references (Nilsen and Aitcin, 1992; Philleo, 1955; Sharma and Gupta, 1960; ACI 318-95, 1995; Mehta and Monteiro, 2006). V_P primary longitudinal wave velocity of material is determined in this study. The time the pulses take to travel through concrete is recorded in the test. The velocity is then calculated as:

$$V_P = \frac{L}{T}, \tag{3}$$

TABLE 1 Quality of Concrete as a Function of the UPV

UPV (m/s)	>4500	3500–4500	3000–3500	2000–3000	<2000
Concrete quality (compressive strength of concrete)	Excellent	Good	Doubtful	Poor	Very Poor

where V_P is the pulse velocity (m/s), L is the length (m), and T is the effective time (s), which is the measured time minus the zero time correction. Numerous experimental data and the correlation relationships between strength and pulse velocity of concrete have been presented and proposed. Table 1, suggested by Whitehurst (1951), shows the use of velocity obtained to classify the quality of concrete.

Tharmaratnam and Tan (1990) and Bungey and Miller (2004) gave the relationship between UPV in a concrete, V, and concrete compressive strength, f_{cube}, based on experimental results, as follows:

$$f_{\mathrm{cube}} = ae^{bV_P}, \tag{4}$$

where a and b are parameters dependent upon the material properties.

The ultrasonic pulse is created by applying a rapid change of potential from a transmitter-driver to a piezoelectric transformation element that

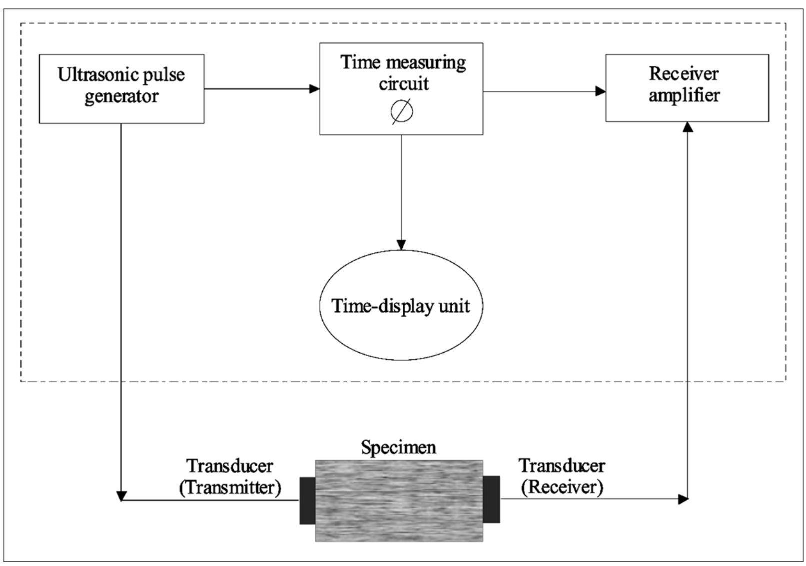

FIGURE 1. Schematic diagram of ultrasonic pulse velocity testing circuit.

causes it to vibrate at its fundamental frequency. The transducer is placed in contact with the material so that the vibrations are transferred to the material. The vibrations travel through the material and are then picked up by the receiver. The wave velocity is calculated using the time taken by the pulse to travel the measured distance between the transmitter and the receiver. If only very rough concrete surface is available for use, it is then required to smoothen and level the surface where the transducer is to be placed. The transducers are held tight on the surfaces of the specimens, and the display indicates the time of travel of the ultrasonic wave. This is a very convenient technique for evaluating concrete quality since the pulse velocity depends only on the elastic properties of the material and not on the geometry (Kewalramani and Gupta, 2006). Equipment, such as shown schematically in Fig. 1, is actually used to determine the UPV through a known thickness of concrete.

3. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANNs are based on the present understanding of the biological nervous system although much of the biological detail is neglected. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights. The backpropagation network is by far the most popular among the many ANN models (Lippman, 1987; Kisi, 2008). These networks are similar to the biological neural networks in the sense that functions are performed collectively and parallel with the units, rather than having a clear description of subtasks to which various units are assigned. The term ANN currently tends to refer mostly to neural network models employed in statistics and artificial intelligence. ANN models are designed with emulation of the central nervous system in mind, which makes also them subjects of theoretical neuroscience (Tapkin, 2004; Tapkin et al., 2006).

The neural network is created for two different phases in the most general sense. The first phase is the training phase and the second phase is the testing (simulation) phase (Tapkin et al., 2006). ANNs have the ability of performing with a good amount of generalization from the patterns on which they are trained. Training consists of exposing the neural network to a set of known input–output patterns (Kartam, Flood, and Garrett, 1997; Rafiq, Bugmann, and Easterbrook, 2001; MathWorks Inc., 1999; Ashour and Alqedra, 2005). Several methods do exist to train a network. One of the most successful and widely used training algorithms for multilayered perceptron (MLP) is the backpropagation (Kartam, Flood, and Garrett, 1997; Flood and Kartam, 1994).

The neural network is operated using backpropagation training algorithm in this study. Backpropagation neural networks generally have a layered structure with an input layer, an output layer, and one or more hidden layers (Kewalramani and Gupta, 2006). As represented by Kewalramani and Gupta

(2006), in general, each neuron j^l in layer l receives multiple inputs X_i^{l-1} from neurons in layer l–1 to which it is connected, and then performs a simple computation to form a single net input U_j^l presented by

$$U_j^l = \sum_{i=1}^{n} W_{ji}^l X_i^{l-1} + \theta_j^l, \tag{5}$$

where W_{ji}^l is the connection strength (weight) that connects neuron j in layer l to neuron i in layer l–1, n is the number of neurons in layer $l-1$, θ_j^l is a threshold value assigned to neuron j in layer l, and X_i^{l-1} is the input coming from neuron i in layer l–1 to neuron j in layer l. The net input U_j^l is then modified by an activation function ϕ to generate an output value Y_j^l as shown in Fig. 2 and presented by

$$Y_j^l = \phi(U_j^l), \tag{6}$$

where ϕ is a nonlinear activation function assigned to each neuron in the network. A continuous nonlinear sigmoid function, commonly used as an activation function in ANN because it meets the differentiability requirement needed in the backpropagation algorithm, is represented by

$$\phi_j^l = \frac{1}{1 + e^{-(U_j^l - \theta_j^l)}}. \tag{7}$$

The modification process is continued in the output layer, where the error between the network outputs and desired targets is calculated, and then propagated back to the network through a learning mechanism. The generalized delta rule is a widely used learning mechanism in backpropagation

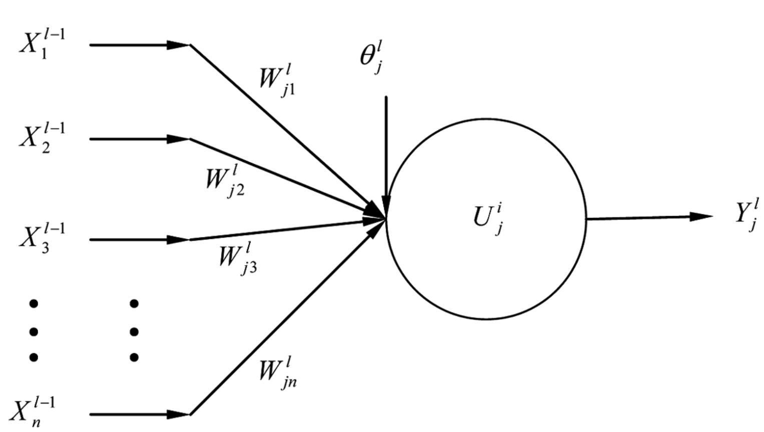

FIGURE 2. Simplified model of an artificial neuron.

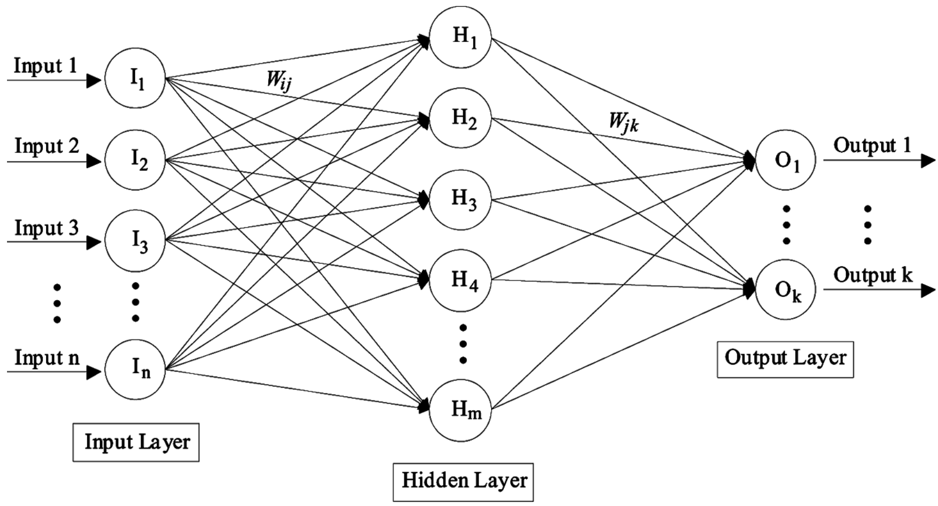

FIGURE 3. A typical ANN topology with n input nodes, m hidden nodes, and k output nodes.

neural networks (Rajagopalan, Prakash, and Naramimhan, 1973). The implementation of such algorithm updates the network weights and biases in the direction in which the performance function decreases most rapidly (reduces the total network error in the direction of the steepest descent of error) (Kewalramani and Gupta, 2006).

The network consists of layers of parallel processing neuron elements with each layer being fully connected to the proceeding layer by interconnection strengths, or weights, *W* (Kisi, 2005). Figure 3 illustrates a three-layer neural network consisting of layers *i, j*, and *k*, input layer, hidden layer and output layer, respectively.

ANN modelling is getting more popular and has been commonly used in engineering tasks (Shahin, Jaksa, and Maier, 2001). ANNs have been applied to many civil engineering problems with some degree of success in the recent years (Kewalramani and Gupta, 2006). Modelling of material behavior and characteristics plays a significant role in these applications (Tapkin et al., 2006). This study also covers the contents of characteristics of concrete specimens and determination of material properties.

4. ANN APPLICATION AND RESULTS

A total of 238 concrete core samples, obtained from 30 reinforced concrete structures, with ages varying between 28 days to 36 years old, were tested for this study. Eight core samples were taken from each of these structures on avarage. Two-hundred thirty-eight independent sets of data were available for the ultrasonic and the compressive strength of the core testing in the laboratory. Thirty-two batches of data, which have very close values, were eliminated from data set, and a total of 206 data were used in the ANN analyses. Records containing the aggregate proportions, the water-cement ratio, and strength value for tested concretes were not available for structures tested in this study. The cores were obtained from columns, shear, or retaining walls in the reinforced concrete structures. The size of cores was 100×200 mm. No reinforcement existed in the cores. All cores were drilled horizontally through the thickness of the concrete elements. BS 1881 (1983) and ASTM C 42-90 (1992) procedures were used for determining the compressive strength of the cores. The cores were tested using ultrasound for the determination of the velocities of the longitudinal ultrasonic waves before the execution of destructive compressive test. The velocity of the propagation of ultrasound pulses was measured by direct transmission using a Controls E–48 ultrasound device. This device measured the time of propagation of ultrasound pulses with a precision of 0.10 μs. The transducers used were 50 mm in diameter, and had maximum resonant frequencies, as measured in laboratory conditions, of 54 kHz. The compressive strengths of the concrete cores were then converted to those of a cubical sample with 15 mm side length, according to BS 1881 (1983), by using Eq. (8):

$$f_{\text{cube}} = \frac{D}{1.5 + \frac{1}{\lambda}} \times f_{\text{core}}, \tag{8}$$

where D is 2.5 for cores drilled horizontally and 2.3 for cores drilled vertically, and λ signifies length (after end preparation)/diameter ratio of the core.

The values of the ultrasonic pulse velocities were observed to be lying within 1900 and 5100 m/s, and the concrete cube compressive strengths varied between 4.00 and 79.00 MPa. The test setups under compression and ultrasound are shown in Figs. 4 and 5, respectively.

The typical multilayer feedforward neural networks are used in the current application. The problem in this study can be defined as a nonlinear input–output relation among the influencing factors, which are ultrasonic pulse velocity and compressive strength of concrete values, for neural network analyses. The backpropagation algorithm and construction of the neural network model were carried out in the conceptual ANN simulation. There was one node in the input layer, corresponding to UPV of concrete specimens, and one node in the output layer, corresponding to compressive strength of concrete. All data was divided into two sets: one for the network learning named the training set, and the other for testing the network named the testing set. Each set was composed of 118 and 88 pairs of input and output vectors in training and testing sets, respectively.

The methodology used here for adjusting the weights is called momentum backpropagation, based on the generalized delta rule presented by Rumelhart et al. (1986). The learning rates were used for increasing the convergence

FIGURE 4. The test setup related to compression testing.

velocity throughout all ANN simulations. The sigmoid function and linear function were additionally used for the activation functions of the hidden and output nodes, respectively. The hidden layer node numbers of each model were determined after trying various network structures since no theory yet exists clarifying the number of hidden units needed to approximate a given function. The training of the networks was stopped after 5000 epochs, when the variation of error became sufficiently small. The error graph for an ANN model during training is shown in Fig. 6, where it can be seen that the necessary epochs to reach the training goal was approximately 5000. This

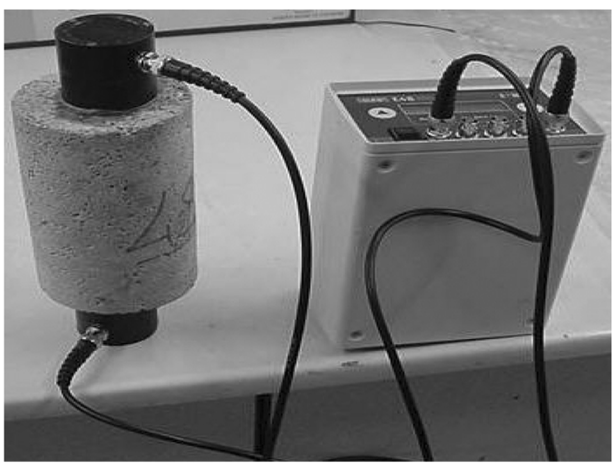

FIGURE 5. The test setup related to the UPV testing.

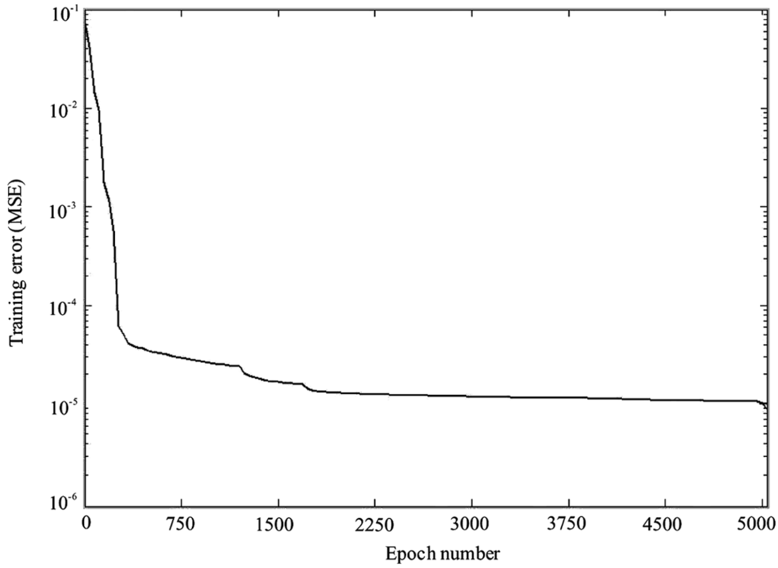

FIGURE 6. Training error versus epoch number for the neural network model.

shows the training of the network was carried out on a sensitive manner enabling to determine the mean squared error on a dependable basis. In other words, this high epoch number signified the acuteness in the carried calculations.

The computer program code for the ANN simulation, including neural networks toolbox, was written in MATLAB language. Different ANN architectures were tried using this code, and then the appropriate model structure was determined for data sets. Numerous trials were carried out in the neural network environment to determine neuron number of the hidden layers. Optimum hidden neuron numbers were obtained for different cases. The ANN model was then tested, and the results were compared by means of root mean squared error (RMSE) and coefficient of determination, R^2, statistics. The neurons of neighbouring layers were fully connected in this study.

The network parameters, number of input layer neurons was one, number of hidden layer neurons was 25, number of hidden layers was one, and number of output layer neurons was also one. Moreoever, type of backpropagation learning rule was gradient descent algorithm, activation functions were tangent sigmoid (tansig) and logarithmic sigmoid (logsig), learning rate was 0.4, and training performance goal was 10^{-6}. Different combinations of the number of hidden neurons and activation functions for the training of the neural network architecture were actually used to have the optimum number of hidden neurons.

The testing set was exploited to evaluate the confidence in the performance of the trained network. The training data set was normalized before the analyses, and the predictive capabilities of the feedforward backpropagation neural network were examined. The basis of this procedure was to demonstrate the prediction performance of these models. The prediction performances were then compared with the RMSE values. The lesser the RMSE, the better the estimates were found to be.

RMSE values can be computed by the following formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(p_i - o_i)^2}{n}}, \tag{9}$$

where p_i is the predicted value by ANN, o_i is the calculated value, and n is the number of data. The unit of measurement for RMSE is MPa.

The correspondence of all of the data set has been ensured by using the RMSE approach. The behavior of all of the system, rather than just data set, can be monitored by this way. Therefore, it is much easier to determine the number of hidden neurons that can be utilized in the hidden layers. This calculation is solely done on an RMSE minimization basis so that when the value of the RMSE for the whole set of data is minimum, the optimum number of hidden neurons could be determined (Tapkin, 2004; Tapkin et al., 2006).

Any difference between the output and expected values from the input pattern is interpreted as an error in the system. Weights of the networks are then used to adjust the using error backpropagation and gradient descent techniques aiming to minimize the error. The weight update is calculated from the partial derivative of the error function multiplied by a constant known as the learning rate. The input training patterns are propagated forward through the network; the mean squared error is summed; and the error is then backpropagated through each layer until the input layer is reached to calculate the above-mentioned last term (Todd and Challis, 1999). The training performance goal is the best yield which can be reached. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm can then oscillate and become unstable. If the learning rate is too small, however, the algorithm then takes too long to converge. The gradient is computed by summing the gradients calculated at each training example, and the weights are only updated after all training examples, termed as epoch, have been presented (MathWorks Inc., 1999).

Lots of trials were carried out to determine the optimum number of hidden neurons in the ANN simulation. The ANN models by applying the cross validation process have been analyzed. As a result of this process, the optimum number of hidden neurons has been obtained as 25 for the training set of data. Figure 7 shows the RMSE values for different hidden

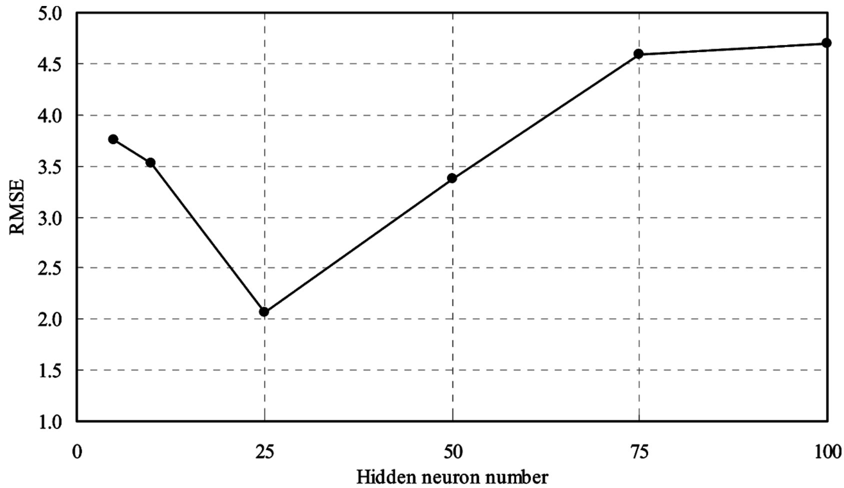

FIGURE 7. The performances of the network architecture for different hidden neuron numbers.

neuron numbers. It can be seen that the smallest RMSE and the highest R^2 values were obtained by having 25 hidden neurons in hidden layer. The only variable was hidden neuron number in these analyses. In this respect, the analyst had the optimum flexibility to be able to determine the number of hidden neuron numbers solely on a RMSE basis. Further similar analyses were also undertaken for different learning rate values as presented in Fig. 8. The optimum learning rate was found to be 0.4 for the concrete specimens.

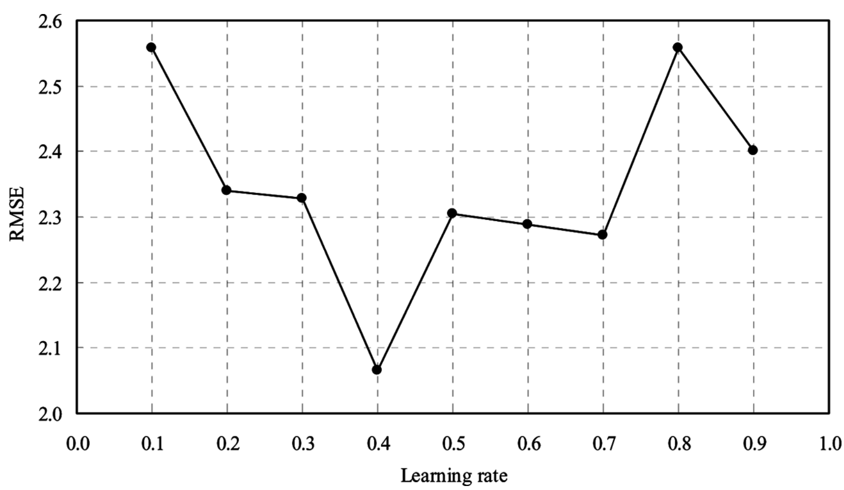

FIGURE 8. The performances of the network architecture for different learning rate.

Many studies suggest UPV as a measure of concrete quality assessment (Kewalramani and Gupta, 2006). Figure 9 shows a relationship among compressive strength of concrete and corresponding UPV for the concrete specimens tested in the laboratory. The data in Fig. 9 contains all of the training and testing data used in this study. It is clearly depicted in the figure that UPV values, ranging of 1900 to 5100 m/s, suggest a good quality control. The best fit-curve representing UPV-compressive strength of concrete relationship is given as

$$f_{\text{cube}} = 0.8822e^{0.0008V_P}. \tag{10}$$

It is observed that the trend obtained from data in Fig. 9 is similar to studies of Soshiroda and Voraputhaporn (1999), Trezos et al. (1993), and Bungey (1980) (see Fig. 10).

The obtained results were graphically plotted showing comparison of predictions through ANN analysis method. Figure 11 shows predicted compressive strengths of concrete through ANN. The predictions on Fig. 11 are based on data from the testing set implemented to samples that were not in the training set. The figures clearly show that experimentally evaluated values of compressive strength of concrete are in strong consistency with the values predicted through ANN for most of the specimens. Figure 11 clearly depicts the comparison of results in prediction of compressive strengths based on UPV, using ANN, for concrete specimens.

The RMSE values of each model with different hidden neuron number in the testing period are given in Fig. 7. It can be seen from the figure that the

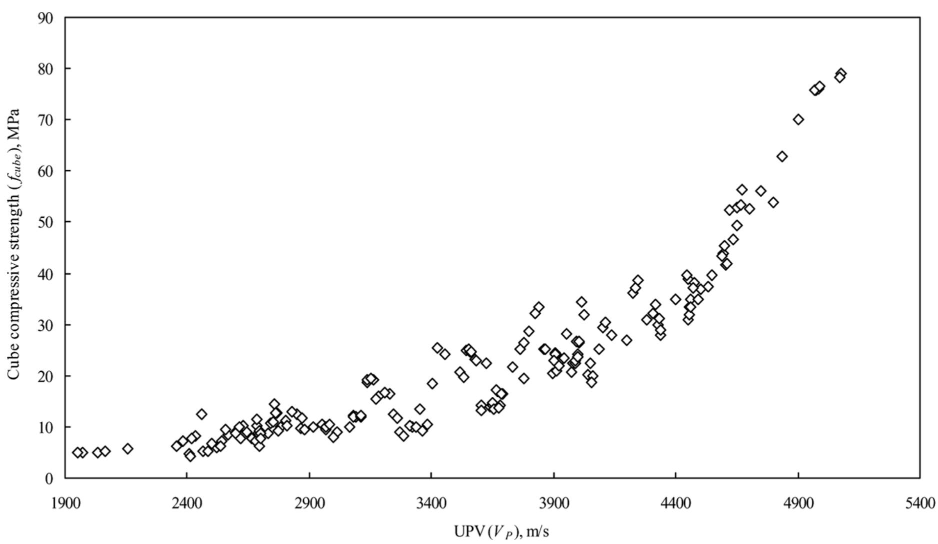

FIGURE 9. The UPV versus cube compressive strength of concrete specimens.

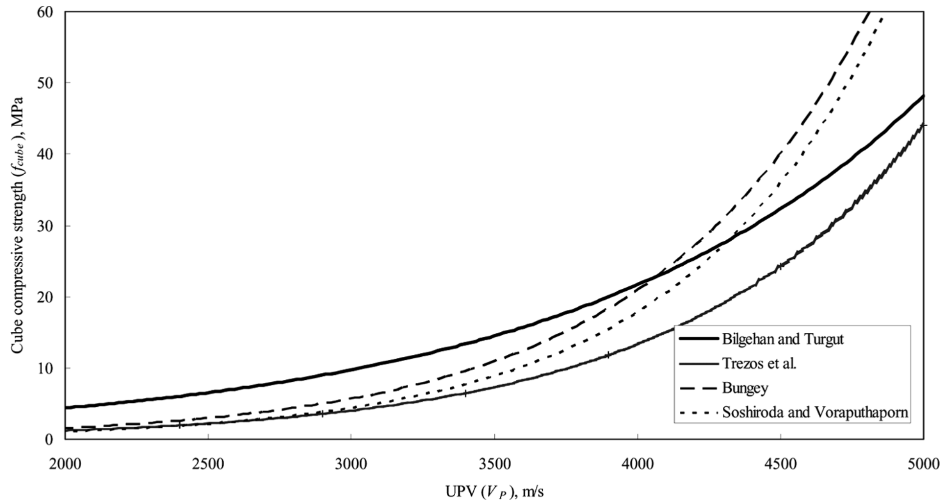

FIGURE 10. Comparison of UPV-compressive strength trends from some earlier researches.

model of hidden layer with 25 neuron has the smallest RMSE (2.06577 MPa), and it has the highest R^2 (0.9915). RMSE value of 2.06577 is fairly representative for specimens. It is not surprising to observe some fluctuations in the mean squared errors due to the nature of the backpropagation algorithm. This fact is also depicted visually in Fig. 6. On the other hand, it was observed that the modelling results were exceptionally close to the real

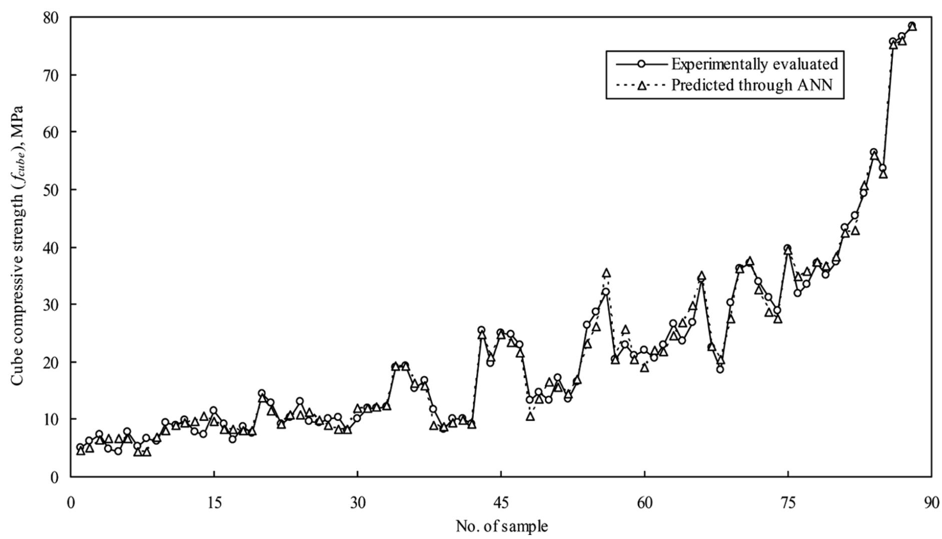

FIGURE 11. Predicted cube compressive strengths through ANN for concrete specimens.

compressive strength test results; therefore, there was no doubt regarding the accuracy of the RMSE values. The RMSE values ranged between 2.06577 and 2.55885, according to Fig. 8. This was really a narrow range, and the existence of a regular pattern of spread in the RMSE values can be visualized as the graph is analyzed. The optimum hidden neuron number for specimens was found to be 25 since the minimum RMSE value was important. Further analyses were carried on neural network architecture with the 25 hidden neuron, and it was found out that the optimum learning rate was 0.4. This presentation of error type is more realistic and meaningful. A more visual insight to the whole data set's performance can be obtained and analyzed this way. A new point of view to the neural network training and testing can also be drawn with the help of the RMSE and learning rate graphs. Lastly, the performance of the overall system with such a big amount of input data for concrete core strength can be more meaningful and easier to analyze by this method of analysis.

5. SUMMARY AND CONCLUSIONS

This study indicates the ability of the multilayer feedforward backpropagation neural network model as a good technique for determining the concrete compressive strength. The ANN model performs sufficiently well in estimation of concrete compressive strength. Gradient descent algorithm and one hidden layer were employed in the analysis. Analyzing the results obtained at the end of the study has shown that using UPV data and ANNs, particularly by the gradient descent algorithm and one hidden layer architecture, was a suitable method to estimate the compressive strength of concrete specimens. The calculation of RMSEs for the gradient descent network, determination of the optimum number of hidden neurons, optimum learning rate, and the relevant analyses also supported this conclusion. The RMSE values were reasonably small indicating that the estimates were fairly accurate and the trained network yielded superior results.

Carrying out destructive tests is generally not possible, especially on concrete elements which are in service. Therefore, using the help of UPV test results and material properties of concrete for the estimation by utilizing the neural network techniques help the site engineer to make reasonable estimates about the concrete compressive strength of these structural members. An ANN model can be constructed in order to provide a quick and dependable means of predicting the compressive strengths of concrete of structural elements. Neural networks would be useful to civil engineers especially dealing with concrete engineering, as an estimation method for compressive strengths of concrete by using UPV data, and also would provide a sound basis for these and similar types of analyses. Approximate value of compressive strength in any point of concrete can then be practically found, by ignoring the mixture ratio of concrete through and using only longitudinal velocity variable, with the ANN modelling.

The neural network model to predict compressive strength based on UPV of concrete specimens is utilized in this study. The prediction made using ANN shows a high degree of consistency with experimentally evaluated compressive strength of concrete specimens used. Thus, the present study suggests an alternative approach of compressive strength assessment against destructive testing methods.

Neural networks can indicate correlations between sets of data. If these correlations are significant, then the results imply that there are underlying physical processed which bring about the observed correlations. Therefore, it would be reasonable to propose a further study in which the underlying physical phenomena are investigated. The problem of the relevant elastic modulus (see Section 2) should be considered as well. This current study only used data sets which were composed of limited pairs of input and output vectors. Additional works using more data sets from various areas could be needed to generalize the conclusions in this study. Different factors which affect compressive strength of concrete such as density and so forth should also be considered in future studies.

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