

# ESTIMATION OF CONCRETE COMPRESSIVE STRENGTH BY USING ULTRASONIC PULSE VELOCITIES AND ARTIFICIAL NEURAL NETWORKS

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## ABSTRACT

*Ultrasonic pulse velocity is one of the most popular non-destructive techniques used in the assessment of concrete properties. However it is very difficult to evaluate the test results since the ultrasonic pulse velocity values are affected by a number of factors. In this study a neural network approach has been proposed for the evaluation of concrete compressive strength by the use of ultrasonic pulse velocity values and some other factors. By this tool, researchers can easily evaluate the compressive strength of concrete specimens by using the ultrasonic pulse velocity value and some material properties. The neural network toolbox of MATLAB has been utilised in order to estimate the compressive strength of concrete specimens without carrying out real tests, using the predetermined test data. The results for predicted compressive strength values are analysed in a root mean squared error basis.*

**Keywords:** Ultrasonic pulse velocity, concrete, artificial neural networks, MATLAB

## 1. INTRODUCTION

Quality of concrete in structures is generally determined by standard cubes or cylinders supplied to the construction site [1]. 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, there exist some differences between the cube or cylinder strength and actual strength of concrete in the structure [2]. This is generally arisen from possible different curing and compaction of concrete in the structure. For in-situ concrete strength, there are some destructive and non-destructive methods. Ultrasonic pulse velocity (UPV) test is one of the most popular non-destructive techniques used in the assessment of the concrete properties in structures [1]. Although the UPV test is very simple and easy to apply, the interpretation of the test results is very difficult since the UPV values are influenced by a number of factors [3,4]. In this study, a neural network approach for the estimation of the compressive strength of concrete specimens by using the ultrasonic pulse velocity values and some material properties is utilised.

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## **2. ARTIFICIAL NEURAL NETWORKS**

An artificial neural network, also called a simulated neural network or commonly just neural network is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation [5]. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. In more practical terms neural networks are non-linear statistical data modelling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. There is no precise agreed definition among researchers as to what a neural network is, but most would agree that it involves a network of simple processing elements (neurons) which can exhibit complex global behaviour, determined by the connections between the processing elements and element parameters. The original inspiration for the technique was from examination of the central nervous system and the neurons (and their axons, dendrites and synapses) which constitute one of its most significant information processing elements. In a neural network model, simple nodes are connected together to form a network of nodes, hence the term neural network. While a neural network does not have to be adaptive, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

These networks are also similar to the biological neural networks in the sense that functions are performed collectively and in parallel by the units, rather than there being a clear description of sub-tasks to which various units are assigned. Currently, the term artificial neural network tends to refer mostly to neural network models employed in statistics and artificial intelligence. Neural network models designed with emulation of the central nervous system in mind are a subject of theoretical neuroscience [6].

In modern software implementations of artificial neural networks the approach inspired by biology has more or less been abandoned for a more practical approach based on statistics and signal processing. In some of these systems neural networks, or parts of neural networks (such as artificial neurons) are used as components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such adaptive systems is more suitable for real-world problem solving, it has far less to do with the traditional artificial intelligence connectionist models. What they do however have in common is the principle of non-linear, distributed, parallel and local processing and adaptation [7].

Artificial neural networks have been applied to many civil engineering problems in recent years [8]. In these applications, modelling of material behaviour and characteristics plays an important role. This study is also about the determination of material characteristics of concrete specimens.

## **3. ARTIFICIAL NEURAL NETWORK APPLICATION**

In the most general sense, the neural network is created for two different phases. The first phase is the training phase and the second phase is the testing (simulation) phase. In this study, the network architecture that is being used is proposed in Figure 1.

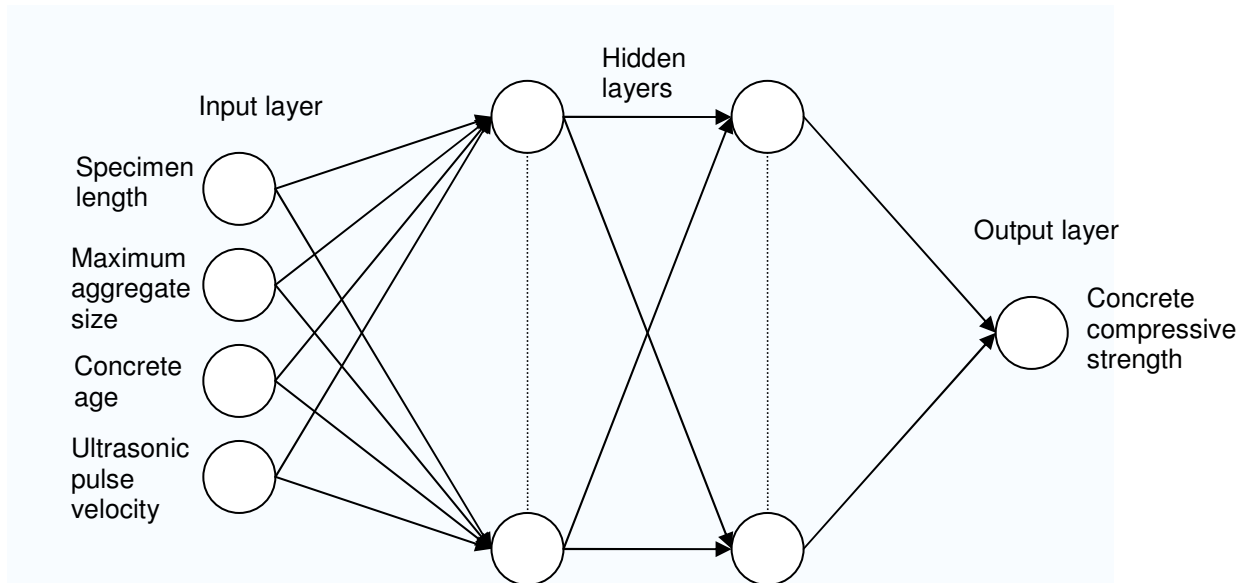


Figure 1. Neural network architecture

Ultrasonic Pulse Velocity (UPV) tests were performed on 250x300x650 mm beam specimens prepared by eight different concrete mixtures in which two different aggregates of four different maximum aggregate sizes ranging from 10 mm to 30 mm were utilised. The compressive strength test was applied on cubes and UPV tests were performed on beams. The tests were performed at the ages of 7, 28, and 90 days. For each age, six cubes were crushed and the average of these was taken as the cube compressive strength. The UPV measurements were applied through 9 paths by direct transmission and the average of these was taken as UPV for the corresponding beam. Three beams were prepared from each mixture and the average of these was recorded as test result.

In neural network analyses, the problem can be defined as a nonlinear input-output relation between the influencing factors (specimen length, maximum aggregate size, age of concrete and ultrasonic pulse velocity) and compressive strength values. Figure 1 illustrates the architecture of the neural network applied in the study. There are four nodes in the input layer corresponding to specimen length, maximum aggregate size, age of concrete and ultrasonic pulse velocity and one in the output layer corresponding compressive strength. Lots of trials were carried out in the MATLAB neural network toolbox environment for the determination of hidden neuron number of the hidden layers. Different optimum hidden neuron numbers were obtained for different cases. In this study, the neurons of neighbouring layers were fully connected.

Each batch of data was divided into two sets, one for the network learning called training set, and the other for testing the network called testing set. Each set was composed of 144 pairs of input and output vectors. Each input pair was calculated by taking the average of at least six specimens. An input vector consisted of four components and an output vector had only one component. The backpropagation algorithm and construction of the neural network model was carried out in the neural network toolbox of MATLAB.

In general, the network parameters; number of training samples for each concrete core sample property was 144, number of input layer neurons was 4, number of hidden layer neurons ranging between 25 to 500, number of hidden layers between 1 to 4, number of output layer neurons was 1, type of back-propagation learning rule was gradient descent algorithm, activation functions were logarithmic sigmoid and tangent sigmoid, learning rate was changing between 0.1 and 0.9, training goals were  $10^{-6}$  and  $10^{-7}$  and number of epochs, normally, varied from training to training. Actually, the number of training samples was more

than 72 and different combinations of the number of hidden neurons and activation functions for the training of the neural network architecture were used in order to have the optimum number of hidden neurons.

After carrying out numerous trainings in the neural network toolbox of MATLAB, the optimum hidden neuron number, hidden layer number, training goal and learning rate was determined as, 25, 1,  $10^{-7}$  and 0.4 respectively. Also the activation function was determined as tangent sigmoid. Therefore it can be concluded that the network used throughout the entire study is a 4-25-1 type.

Figure 2 shows a typical sample training session performed in this study. This sample training was for one hidden layer, 25 hidden neurons, a learning rate of 0.4, logarithmic sigmoid activation function and  $10^{-7}$  training goal. As can be visualised from Figure 2, the training goal was selected as  $10^{-7}$ . For the sake of correctness of the training session, a training goal of this small has been selected. In Figure 2, it can be seen that the necessary epochs to reach the training goal is approximately 200000. This shows the training of the network was carried out on a sensitive manner in order to be able to determine the Root Mean Squared Error on a dependable basis. In other words, this high epoch number shows the acuteness in the carried calculations.

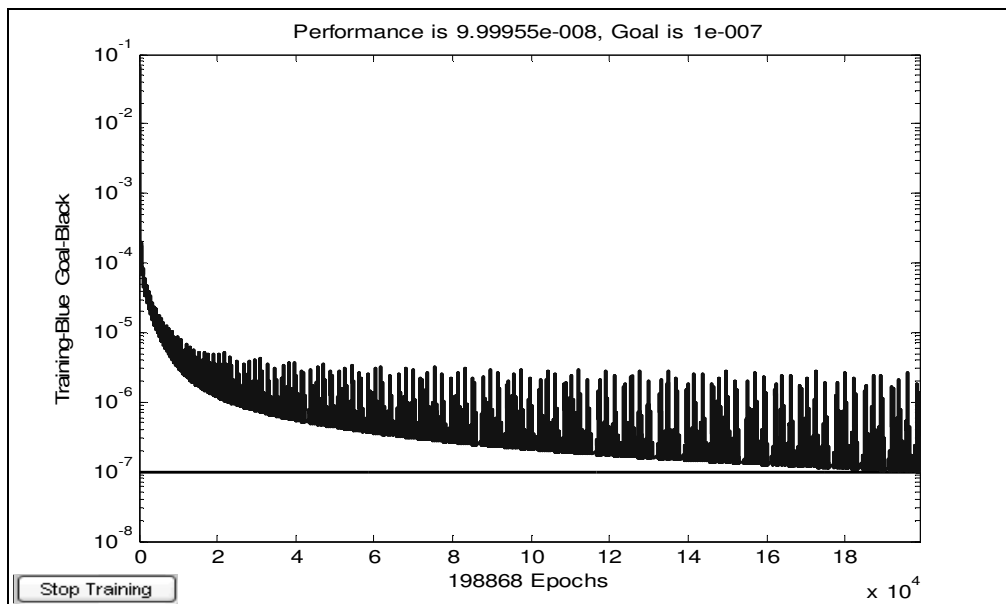


Figure 2. Sample training performed through the analyses

The testing set was employed to evaluate the confidence in the performance of the trained network. 144 testing vectors of the batch of data were used to test the neural network model. The training was conducted on by the crushed limestone aggregate and the testing was performed by the natural aggregate data sets. This is a regular procedure that is undertaken by all of the similar studies that can be found in the literature regarding neural network analyses.

The training data set was normalised before the analyses and the predictive capabilities of the feedforward back-propagation neural network were examined. The basis of this discussion was to demonstrate the prediction performance of these models by comparing their levels of prediction rather than to illustrate how well the models predict a given set of data. The prediction performances were compared with the Root Mean Squared Error (RMSE) values. The lesser the Root Mean Squared Error, the better the estimates were. RMSE values can be obtained by the following standard formula:

$$RMSE = \sqrt{\frac{\sum_{j=1}^N (X_j - \bar{X})^2}{N}} \quad (\text{Equation 1})$$

where;

$N$  = number of observations,

$X_j$  = Predicted values, and

$\bar{X}$  = Observed values

The correspondence of all of the data set has been ensured by using RMSE approach. By this way, the behaviour of all of the system, rather data set can be monitored. Therefore, it is much easier to decide the number of hidden neurons that can be utilised in the hidden layers. This is solely done on a root mean squared error minimisation basis. This means, when the value of the root mean squared error for the whole set of data is minimum, the optimum number of hidden neurons is determined. Lots of trials were carried out in order to determine the optimum number of hidden neurons in the MATLAB neural network toolbox environment. It was found that the optimum number of hidden neurons was 25 for the training set of data. By the way, after obtaining the number of hidden neurons, some further analyses were also carried out to determine the optimum learning rate. Figure 3 shows the RMSE values for different hidden neuron numbers. It can be seen that the smallest RMSE value was obtained by 25 hidden neurons. In these analyses, the activation function was logarithmic sigmoid, the error gradient was set to  $10^{-7}$ , the hidden layer number was 1 and the only variable was hidden neuron number. From this point of view, the analyst has the optimum flexibility to be able to determine the number of hidden neuron numbers, solely on a Root Mean Squared Error Basis.

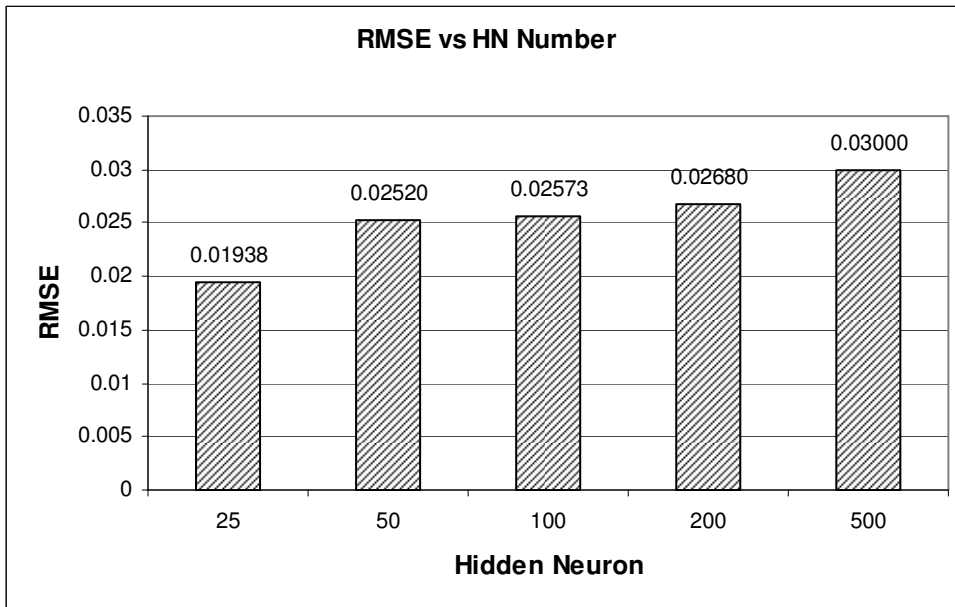


Figure 3. RMSE values vs. hidden neuron number for natural aggregate containing specimens

Also, further analyses were undertaken and for different learning rate values, similar analyses were carried out. The optimum learning rate was found to be 0.4 for natural aggregate containing specimens. This is presented in Figure 4. Figures 3 and 4 solely

seem to represent only one feature of the data set, but in fact, the analyses carried out to plot these graphs are really cumbersome.

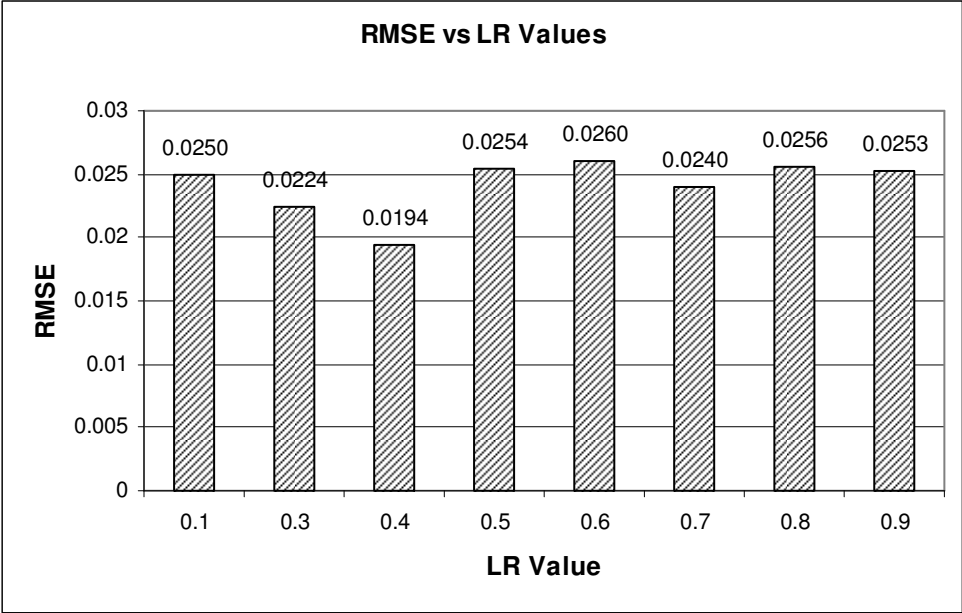


Figure 4. Different learning rate values for 25 hidden neurons for natural aggregate containing specimens

When the simulation results for the optimum hidden neuron numbers were further analyzed, it can be seen that the modelling results are reasonably good for such a big data set. RMSE value of 0.019382 is fairly representative for natural aggregate containing specimens. It is not surprising to observe some fluctuations in the root mean squared errors due to the nature of the backpropagation algorithm. This fact is also depicted visually in Figure 2. However, it was observed that the modelling results were very near to the real compressive strength test results, therefore there was no doubt for the sake of correctness of the RMSE values.

According to Figure 4, the RMSE values range between 0.019382 and 0.026019. This was really a narrow range and as the graph was analyzed, it can be visualized that there was a regular pattern of spread in the RMSE values. Since the minimum RMSE value was important, the optimum hidden neuron number for specimens prepared from natural aggregate-containing concrete specimens was twenty-five. Further analyses were carried on the twenty-five hidden neuron neural network architecture and it was found out that the optimum learning rate was 0.4.

This type of error presentation is more realistic and meaningful. In this way, a more visual insight to the whole data set's performance can be obtained. By the help of the RMSE and learning rate graphs, a new point of view to the neural network training and testing can be drawn. By this type of analysis, 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 analyse.

**4. CONCLUSIONS**

In this study, the ultrasonic pulse velocity test results and concrete compressive strength values were analyzed by means of multi layer feedforward backpropagation neural network model. By the virtue of these results, the compressive strengths of an entirely different set of specimens were estimated using the ultrasonic pulse velocity test results and some material properties. In the analysis, gradient descent algorithm and one hidden layer was employed. The following conclusions may be drawn from this study;

1. Analyzing the results obtained at the end of the study has shown that, by using the ultrasonic pulse velocity data, using artificial neural networks 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 gives rise to this result. Determination of the optimum number of hidden neurons and the relevant analyses arise this result.

2. Compared to other studies in the literature, the RMSE values are reasonably small which means that the estimates are fairly good and the trained network yields superior results.

3. Sometimes, it is not possible to carry out destructive tests, especially on concrete elements which are in service and therefore, the estimation of compressive strengths by the help of ultrasonic pulse velocities, and utilising the neural network techniques, help the site engineer to make reasonable estimates about the compressive strength of these structural members.

By utilising these RMSE values, reasonable predictions can be made for the compressive strength values of different types of concrete elements by using ultrasonic pulse velocity test results and some material properties. A neural network model can be constructed in order to provide a quick and dependable mean of predicting the compressive strengths of these elements. As an estimation method for concrete compressive strengths by using the ultrasonic pulse velocity data, neural networks will be useful to civil engineers especially dealing with concrete engineering and will provide a sound basis for these and similar types of analyses.

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## VITA

Serkan Tapkın was born in Ankara, Turkey on 7 October 1973. He completed his secondary education in 1990 at T.E.D. Ankara College. He graduated in 1994 from Middle East Technical University with the B.Sc. degree in Civil Engineering followed by M.Sc. degree in 1998 and Ph.D. degree in 2004 from the same University. He has become an Assistant Professor in April 2004 and is working in the Civil Engineering Department of Anadolu University, Eskişehir, as the Head of Transportation Division and Vice Chair.