

## The use of neural networks in concrete compressive strength estimation

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**Abstract.** Testing of ultrasonic pulse velocity (UPV) is one of the most popular and actual non-destructive techniques used in the estimation of the concrete properties in structures. In this paper, artificial neural network (ANN) approach has been proposed for the evaluation of relationship between concrete compressive strength, UPV, and density values by using the experimental data obtained from many cores taken from different reinforced concrete structures with different ages and unknown ratios of concrete mixtures. The presented approach enables to find practically concrete strengths in the reinforced concrete structures, whose records of concrete mixture ratios are not yet available. Thus, researchers can easily evaluate the compressive strength of concrete specimens by using UPV values. The method can be used in conditions including too many numbers of the structures and examinations to be done in restricted time duration. This method also contributes to a remarkable reduction of the computational time without any significant loss of accuracy. Statistic measures are used to evaluate the performance of the models. 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 and density data. In addition, the model architecture can be used as a non-destructive procedure for health monitoring of structural elements.

**Keywords:** concrete; density; compressive strength; ultrasonic pulse velocity; non-destructive testing; artificial neural networks.

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### 1. Introduction

The subject of using non-destructive testing (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 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 as compared to core testing. These advantages are of no value if the results are not reliable, representative, and as close as possible to the actual strength 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 concrete compressive strength 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

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strength of concrete in the structure (Bungey and Soutsos 2001). 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. UPV test is one of the most popular non-destructive techniques used in the assessment of the 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).

Determination of the concrete strength using NDT methods has been intensively investigated (Malhotra 1976, Leshchinsky 1991, Turgut 2004, Del Rio *et al.* 2004, Popovics 2001, Popovics and Popovics 1992, Ferreira and Castro 2000, Castro 2000, Yaman *et al.* 2006). The ultrasonic method is one of the most widely used nondestructive methods. Despite the positive results obtained in some studies (Turgut 2004, Del Rio *et al.* 2004, Popovics 2001, Popovics and Popovics 1992), there is no completely acceptable method for the nondestructive determination of concrete strength using ultrasonics. This is because the complexities of the produced waveform, structure, and the material. In this way, continued research toward the development of a concrete strength versus ultrasonic pulse velocity relationship is justified (Popovics 2001).

Concrete is a mixture of four materials, namely, 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 the view of the problem complexities it would appear extremely optimistic to formulate an ultrasonic test method for the concrete strength determination. However, considering the seriousness of the infrastructure problem and the magnitude of the cost of rehabilitation, major advancement is desperately needed to improve the current situation. 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  $\pm 20$  percent accuracy under laboratory conditions (Popovics 1998).

The ages of existing reinforced concrete structures, which was taken concrete core samples, ranged between 28 days to 36 years; and their concrete mixture ratios were not known in this research. 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 can not be determined appropriately caused by the non-general pattern in the variability in the concrete mixture ratio findings obtained from laboratory researches. Thus, these findings can not represent a general pattern for analysis as well.

It is the main purpose of this study, an effective approach is presented by considering the compressive strength-UPV and density 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 and density values, is utilized in the study. Prediction of concrete compressive strength is implemented using ANN models, consisting of one input layer, one hidden layer and one output layer, for each data set. The analysis is then conducted for cylinder specimens with different compressive strengths due to wide variation in their UPV and density.

## 2. Non-destructive testing (NDT) of concrete using ultrasound

The UPV technique is one of the most popular non-destructive methodology 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 *et al.* 2009). Among the available nondestructive methods, the ultrasonic pulse velocity tester is the most commonly used one in practice. 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 ( $P$ ) waves and the transverse waves are called secondary ( $S$ ) 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  $\nu$  as follows

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

where  $\rho$  is density of material;  $V_p$  is primary wave velocity of the material. Relationships between the pulse velocity of concrete, the strength of concrete and the dynamic modulus of elasticity are given in references (Nilsen and Aitcin 1992, Philleo 1995, 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 and subsequently the velocity is calculated as

$$V_p = \frac{L}{T} \quad (2)$$

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. For instance, concrete with a velocity of 5000 m/s falls in the excellent class, whereas generally good, doubtful, generally poor and very poor classes have ranges as 3500-4500, 3000-3500, 2000-3000 and below 2000 m/s, respectively.

Based on experimental results, Tharmaratnam and Tan (1990), and Bungey and Millard (2004) gave the relationship between the UPV in a concrete,  $V_p$ , and concrete compressive strength,  $f_{cube}$ , as an exponential function.

$$f_{cube} = ae^{bV_p} \quad (3)$$

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

Table 1 Quality of concrete, compressive strength of concrete, as a function of the UPV

Group velocity, m/s	Concrete quality
Above 4500	Excellent
3500-4500	Generally good
3000-3500	Questionable
2000-3000	Generally poor
Below 2000	Very poor

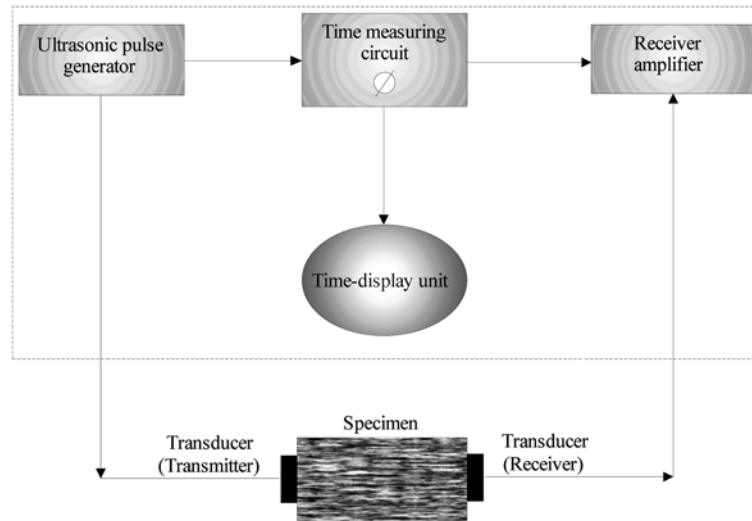


Fig. 1 Schematic diagram of UPV testing circuit

a piezoelectric transformation element that 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 network

ANNs are based on the present understanding of the biological nervous system, though much of the biological detail is neglected. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights. Of the many ANN paradigms, the multi-layer backpropagation network is by far the most popular (Lippman 1987). The basic element of a neural network is the artificial neuron which is actually the mathematical model of a biological neuron. A biological neuron is made up of four main parts: dendrites, synapses, axon and the cell body (Tapkin *et al.* 2010). ANNs are data processing paradigms made up of highly interconnected nodes, called neurons. Even though there are various types of neural networks they differ in the architecture and the learning rules. A multilayer feed-forward ANN model is the most commonly used architecture for its efficient generalization capabilities (Kartam *et al.* 1997, Flood and Kartam 1994a, Flood and Kartam 1994b).

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 (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 *et al.* 1997, Rafiq *et al.* 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 multi-layered perceptron (MLP) is the backpropagation (Kartam *et al.* 1997, Flood and Kartam 1994a). The neural network is operated using backpropagation training algorithm in this study. Backpropagation neural networks generally have a layered structure with an input, an output, and one or more hidden layers.

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 back-

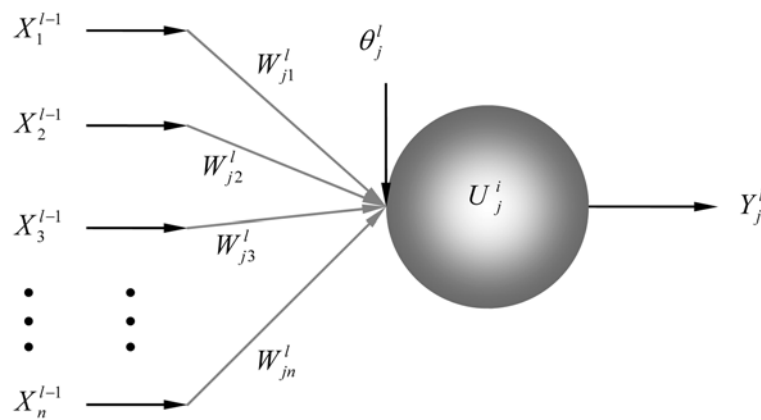


Fig. 2 Simplified model of an artificial neuron

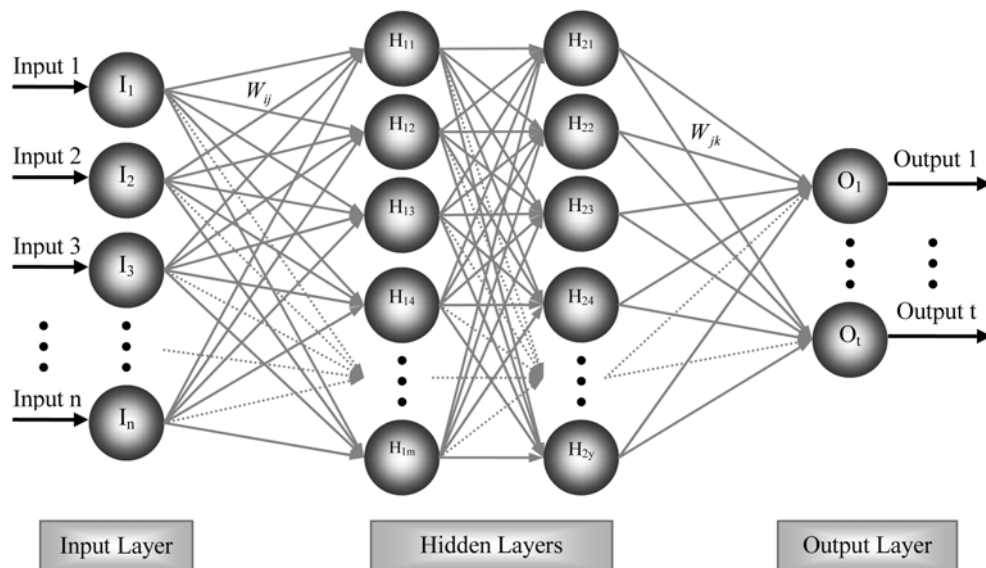


Fig. 3 A typical ANN topology with  $n$  input nodes,  $m$  and  $y$  hidden nodes, and  $t$  output nodes

propagation neural networks (Rajagopalan *et al.* 1973). The implementation of such algorithm updates the network weights 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). Fig. 3 illustrates a three-layer neural network consisting of layers  $i$ ,  $j$  and  $k$ ; input layer, hidden layer and output layer, respectively, with the interconnection weights  $W_{ij}$  and  $W_{jk}$  between layers of neurons. Initially estimated weight values are progressively corrected during a training process that compares predicted outputs with known outputs, and backpropagates any errors (from right to left in Fig. 3) to determine the appropriate weight adjustments necessary to minimize the errors.

Many applications of neural networks in civil and structural engineering are available. Recently, ANNs have been used for the estimation of concrete compressive strength based on ultrasonic pulse velocity (Bilgehan and Turgut 2010, Kewalramani and Gupta 2006, Hola and Schabowicz 2005a, Hola and Schabowicz 2005b, Trtnik *et al.* 2009). In this study, neural network approach for prediction of the concrete compressive strength, using UPV and density values, has also been utilized.

#### 4. Experimental method

A total of 238 concrete core samples are tested using ultrasound for the determination of the velocities of the longitudinal ultrasonic waves before the execution of destructive compressive test for this study. Records containing the aggregate proportions, the water-cement ratio, and strength value for tested concretes are not available for structures tested in this study. The cores are obtained from columns, shear or retaining walls in the reinforced concrete structures. The size of cores is 100×200 mm and no reinforcement existed in the cores, which are drilled horizontally through the thickness of the concrete elements. BS 1881 (1983) and ASTM C 42-90 (1992) procedures are used for determining the compressive strength of the cores. The velocity of the propagation of ultrasound pulses is measured by direct transmission using a Controls E-48 ultrasound device, which measured the time of propagation of ultrasound pulses with a precision of 0.10  $\mu$ s. The transducers used are 50 mm in diameter, and had maximum resonant frequencies, as measured in laboratory conditions, of 54 kHz. The compressive strengths of the concrete cores are then converted to those of a cubical sample with 15 mm side length, according to BS 1881 (1983), by using the following expression

$$f_{cube} = \frac{D}{1.5 + \frac{1}{\lambda}} \times f_{core} \quad (4)$$

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

The values of the UPV are observed to be lying within 1951 m/s and 5217 m/s; and the concrete core densities varied between 1.88 g/cm<sup>3</sup> and 2.67 g/cm<sup>3</sup>; and the concrete cube compressive strengths varied between 4.35 MPa and 81.38 MPa.

The problem can be defined as a nonlinear input-output relation among the influencing factors which are UPV, density of concrete specimens and compressive strength of concrete values, for ANN analyses. The typical multi-layer feed-forward ANNs consist of an input layer, one or more

hidden layer(s) and an output layer. This type of ANNs are used in the current application. All of data is divided into two sets; one for the network learning (training) set and the other for testing set. Each of training and testing set covers approximately 50% of the total data. The data set is normalised before the analyses and the predictive capabilities of the feedforward back-propagation ANN are examined.

The methodology used here for adjusting the weights is the momentum back-propagation with a delta rule, as presented by Rumelhart *et al.* (1986). Throughout all ANN simulations, the learning rates are used for increasing the convergence velocity. The sigmoid and linear functions are used for the activation functions of the hidden and output nodes, respectively. The hidden layer node numbers of each model are determined after trying various network structures since no theory yet exists to clarify the number of hidden units needed to approximate a given function. The training phase is stopped after 5000 epochs; when the variation of error became sufficiently small.

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

Gradient descent algorithm back-propagation learning rule is employed with activation functions as tangent sigmoid (tansig) and logarithmic sigmoid (logsig). Learning rate is 0.4 with training performance goal  $10^{-5}$ , momentum constant 0.9 and maximum number of epochs 5000. After carrying out numerous trainings in the neural network simulation, the optimum hidden neuron number and hidden layer number are determined as 50 and 1, respectively.

The testing set is employed to evaluate the confidence in the performance of the trained network. The prediction performances are compared using two global statistics; the coefficient of determination ( $R^2$ ) and the root mean squared error (RMSE), where the smaller the RMSE, the better are the estimates. RMSE and  $R^2$  values can be computed by the following standard formulas

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (P_i - A_i)^2}{N}} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (A_i - P_i)^2}{\sum_{i=1}^N (A_i - \tilde{A}_i)^2} \quad (6)$$

where  $P_i$ ,  $A_i$  and  $\tilde{A}_i$  are the predicted, actual and averaged actual output of the network, respectively, and  $N$  is the total number of training patterns. The unit of measurement for RMSE is MPa.

Any difference between the output values and expected 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 back propagated through each layer until the input layer is reached to calculate the abovementioned last term (Todd and Challis 1999). The training performance goal is the best yield, which could 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 then the algorithm can 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).

## 5. Results

Fig. 4 shows the RMSE and  $R^2$  values for different hidden neuron numbers. It can be seen that the smallest RMSE and the highest  $R^2$  values are obtained by 50 hidden neurons in hidden layer. The analyst had the optimum flexibility to be able to determine the number of hidden neuron numbers, on a RMSE basis (Table 2). The optimum learning rate is found to be 0.4 for the concrete specimens as presented in Fig. 5 and Table 3.

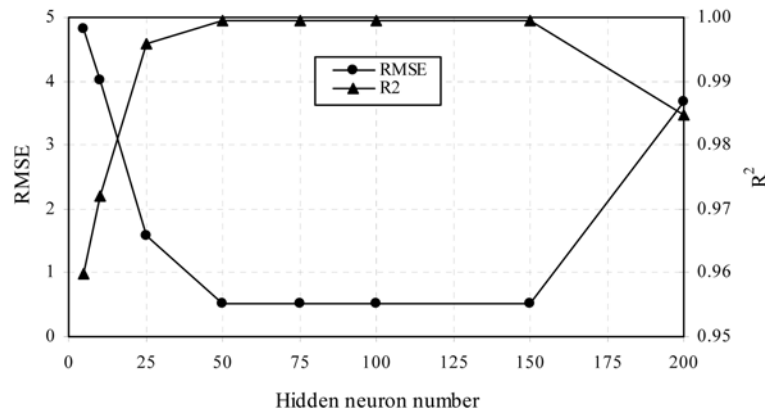


Fig. 4 RMSE and  $R^2$  values versus different hidden neuron number for specimens

Table 2 The performances of the network architecture for different hidden neuron numbers

Hidden neuron number	Learning rate	Epoch number	RMSE	$R^2$
5	0.4	5000	4.81635	0.9598
10	0.4	5000	4.01344	0.9721
25	0.4	5000	1.57694	0.9958
50	0.4	5000	0.51699	0.9995
75	0.4	5000	0.51706	0.9994
100	0.4	5000	0.51702	0.9994
150	0.4	5000	0.51705	0.9994
200	0.4	5000	3.67182	0.9847



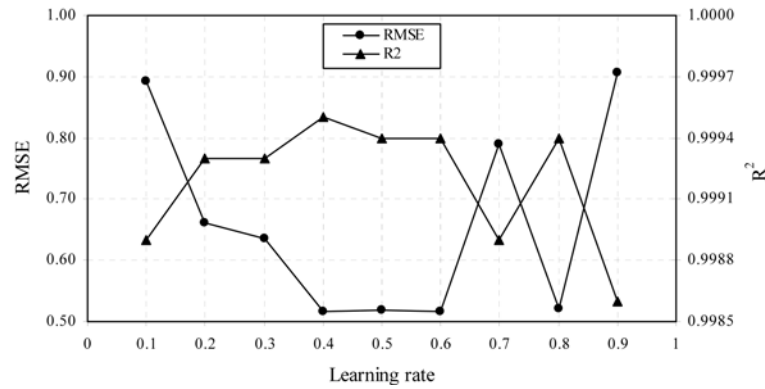
Fig. 5 RMSE and  $R^2$  values versus different learning rate for specimens

Table 3 The performances of the network architecture for different learning rate

Hidden neuron number	Learning rate	Epoch number	RMSE	$R^2$
50	0.1	5000	0.89367	0.9989
50	0.2	5000	0.66108	0.9993
50	0.3	5000	0.63668	0.9993
50	0.4	5000	0.51699	0.9995
50	0.5	5000	0.51759	0.9994
50	0.6	5000	0.51700	0.9994
50	0.7	5000	0.78934	0.9989
50	0.8	5000	0.52062	0.9994
50	0.9	5000	0.90677	0.9986

Fig. 6 shows a relationship among compressive strength of concrete, density of specimen and corresponding UPV for all concrete specimens tested in the laboratory. It is seen that UPV values are in a range of 1900–5300 m/s suggesting a good quality control.

The obtained results are graphically plotted showing comparison of predictions through ANN analysis method. Fig. 7 shows predicted compressive strengths of concrete through ANN. The predictions on Fig. 7 are based on data from the testing set implemented to samples that are not in the training set. These figures clearly show that experimentally evaluated values of concrete compressive strength are in strong consistency with the values predicted through ANN for most of the specimens. Fig. 7 clearly depicts the comparison of results in prediction of compressive strengths based on UPV, using ANN, for concrete specimens.

The RMSE and  $R^2$  values of each model with different hidden neuron number in the testing period are given in Fig. 4. It can be seen from the figure that the model of hidden layer with 50 neurons has the smallest RMSE (0.51699 MPa), and it has the highest  $R^2$  (0.9995). The RMSE value of 0.51699 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. However, it is observed that the modelling results are exceptionally close to the real compressive strength test results; therefore there is no doubt regarding the accuracy of the RMSE values.

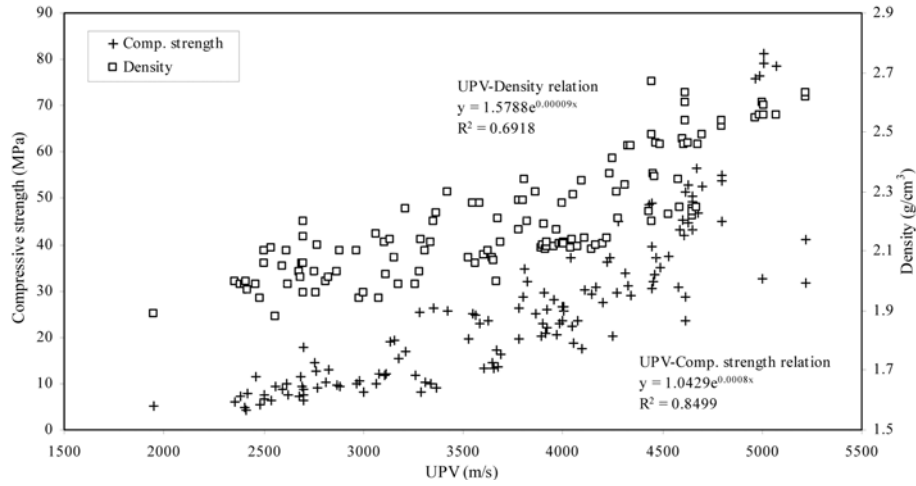


Fig. 6 UPV versus compressive strength and density of concrete specimens

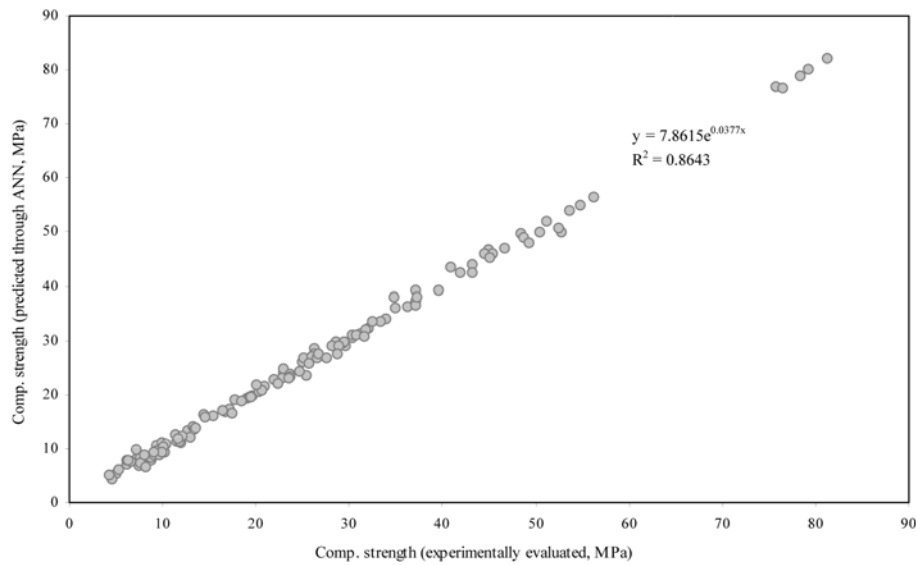


Fig. 7 Predicted compressive strengths through ANN for concrete specimens

The RMSE values range between 0.51699 and 0.90677 according to Fig. 5. This is 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 is found to be fifty since the minimum RMSE value is important. Further analyses are carried on neural network architecture with the fifty hidden neurons and it is found out that the optimum learning rate is 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 by 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.

## 6. Conclusions

This study indicates the ability of the multilayer feedforward backpropagation neural network as a good technique for model the concrete compressive strength-UPV and density relationship. The ANN model performs sufficiently in the estimation of concrete compressive strength. Gradient descent algorithm and one hidden layer are employed in the analysis. Analyzing the results obtained at the end of the study has shown that using UPV and density data, and ANNs, particularly by the gradient descent algorithm and one hidden layer architecture, is 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 support this conclusion. The RMSE values are reasonably small indicating that the estimates are fairly accurate and the trained network yield superior results.

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. When the density increases, the pulse velocity in concrete increases, in other words pulse transition time is shorter. This case shows that concrete compressive strength is higher. In this research, next to the UPV parameter to estimate the compressive strength, density parameter has also been taken into consideration. When the density, which can be easily determined, has been taken into account, it has been useful for more accurate prediction of concrete strength.

This current study employed data set which is composed of limited pairs of input and output vectors. Therefore, it would be reasonable to propose a further works using more data sets from various areas could be needed to generalize the conclusions in this study.

## Notations

The following notations are used in the present paper.

*ANN* : Artificial neural network

*RMSE* : Root mean squared error

*UPV* : Ultrasonic pulse velocity

*NDT* : Non-destructive testing

*MLP* : Multi layered perceptron

$P_i$  : Predicted value

$A_i$  : Actual value

$\bar{A}_i$  : Averaged actual value

$N$  : Number of data

$L$  : Path length (m)

$T$  : Effective time (s)

$E_d$  : Dynamic modulus of elasticity (kN/m<sup>2</sup>)

$\rho$  : Density of material (kN/m<sup>3</sup>)

$f_{cube}$  : Concrete compressive strength (kN/m<sup>2</sup>)

$a, b$  : Parameters dependent upon the material properties

$U_j^l$  : Net input of neuron  $j$  in layer  $l$

- $X_i^{l-1}$  : Input coming from neuron  $i$  in layer  $l-1$   
 $\phi$  : Nonlinear activation function  
 $\phi_j^l$  : Nonlinear activation function for neuron  $j$  in layer  $l$   
 $Y_j^l$  : Output of neuron  $j$  in layer  $l$   
 $\theta_j^l$  : Threshold value  
 $W_{ji}^l$  : Weight between neuron  $j$  in layer  $l$  and neuron  $i$  in previous layer  
 $V_P$  : Primary (longitudinal) wave velocity; pulse velocity (m/s)  
 $\nu$  : Poisson's ratio

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