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Artificial Neural Network Model for Predicting the Compressive Strength of Concrete using Ultrasonic Pulse Velocity

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ABSTRACT

This paper presents the results of study conducted with artificial neural networks (ANN) to determine the effects of the variations of concrete constituents on ultrasonic pulse velocity (UPV) and developed mathematical model to predict the compressive strength of concrete. The proposed input parameters are major factors that affect (UPV), such as cement content, water–cement ratio (W/C), the aggregate–cement ratio (A/C), maximum aggregate size, and age of concrete. The output parameter is the (UPV). The results show that (UPV) increased with the increase in concrete age. Increasing the cement content caused a rapid pulse in velocity readings, and (UPV) increased with the increase in maximum aggregate size. Aside from these factors, (W/C) negatively affected pulse velocity. Also, the ANN model was built to predict the compressive strength of the concrete using pulse velocity and the age of concrete. The results showing good rapprochement between experimental value of compressive strength with predicated value of compressive strength.

نموذج الشبكات العصبية الاصطناعية للتنبؤ بمقاومة الانضغاط للخرسانة باستخدام سرعة الموجات فوق الصوتية

الكلمات المفتاحية
عناصر الخرسانة، سرعة النبضة للموجات فوق الصوتية، الشبكات العصبية الاصطناعية، مقاومة الضغط للخرسانة

الخلاصة

يقدم هذا البحث نتائج الدراسة التي أجريت باستخدام الشبكات العصبية الاصطناعية لدراسة مدى تأثير تغاير مكونات الخرسانة على سرعة الموجات فوق الصوتية و ايجاد معادلة رياضية للتنبؤ بمقاومة الانضغاط للخرسانة. إذ أن المدخلات المقترحة شملت العوامل الرئيسية المؤثرة على سرعة الموجات فوق الصوتية والتي تتضمن محتوى السمنت، نسبة (الماء\السمنت)، نسبة (الركام\السمنت)، المقاس الاقصى للركام وعمر الخرسانة، بينما كانت المخرجات هي سرعة الموجات فوق الصوتية. أظهرت النتائج أنه بزيادة عمر الخرسانة، تزداد سرعة الموجات فوق الصوتية. كما أنه بزيادة محتوى السمنت، يؤدي ذلك الى موجة أسرع في قراءات السرعة. وقد وجد أن سرعة الموجات فوق الصوتية تزداد بازدياد المقاس الاقصى للركام. الى جانب هذه العوامل فإن نسبة (الماء\السمنت) تؤثر سلباً على السرعة الموجية. وكذلك تم بناء نموذج الشبكة العصبية الاصطناعية للتنبؤ بمقاومة الانضغاط للخرسانة من خلال سرعة الموجات فوق الصوتية وعمر الخرسانة. اظهرت النتائج تقاربا جيدا لقيم مقاومة الخرسانة المختبرية مع النتائج التي تم التنبؤ بها من خلال نموذج الشبكة العصبية الاصطناعية.

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Introduction:

The use of non-destructive testing (NDT) methods has received growing attention in recent years, especially due to the rising need for quality characterization of damage constructions made of concrete [1]. The use of (NDT) leads to increased safety and allows better scheduling of construction, thus making it possible to progress faster and more economically. Broadly speaking, these tests can be categorized into those that assess the strength of the concrete in situ, and those that determine characterizations of the concrete [2]. Among the available methods of (NDT), ultrasonic pulse velocity (UPV) can be considered one of the most promising methods for the evaluation of concrete structures, once an examination of material homogeneity is made possible [3]. This long-established method has been used on concrete for more than (60) years.

International Atomic Energy Agency [4] give the longitudinal pulse velocity in (km/s) or in (m/s) as follows:

$$V = L / T \tag{1}$$

where

(V) is the longitudinal pulse velocity

(L) is the path length

(T) is the time taken by the pulse to traverse that length.

ASTM C597-83 and BS 1881: part 203: 1986 [2] prescribes the test method (reapproved 1991). This method is based on the fact that the velocity of sound in a material is related to the elastic modulus of (E) by the expression [5].

$$V = \sqrt{E(1-\mu) / \rho(1+\mu)(1-2\mu)} \tag{2}$$

Where

(E) is modulus of elasticity

(ρ) is density of the material

(μ) is dynamic Poisson's ratio.

The pulse velocity depends only on the elastic properties of the material and not on the geometry, making this technique very convenient for the evaluation of concrete quality. To carry out the test under optimum conditions, access is required on opposite sides of the test member (direct method), but usable results may be obtained with a semi-direct method (pulse passing between adjacent faces) or an indirect method (pulse passing between transducers placed on the same face); however, the amplitude of the received signal decreases in both cases, particularly in the latter [6].

Although the (UPV) test is very simple and easy to apply, the interpretation of the test results is difficult because the (UPV) values are influenced by a number of factors [7], such as cement content, water–cement ratio (W/C), aggregate–cement ratio (A/C), maximum aggregate size, and age of concrete. These factors directly influence the UPV and make the identification of concrete properties difficult. This study aims to demonstrate the possibilities of adapting the artificial neural network (ANN) for the prediction of (UPV) based on these factors.

Artificial Neural Network

An (ANN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases, an (ANN)'s structure changes according to the external or internal information that flows through the network [7]. In more practical terms, neural networks are non-linear statistical data modeling tools. They may be used to model complex relationships between inputs and outputs or to find patterns in a set of data. (ANN) involves a network of simple processing elements (neurons) that can exhibit complex global behavior, and is determined by the connections between the processing elements and element parameters. The original inspiration for the technique was from the examination of the central nervous system and its neurons (and their axons, dendrites, and synapses), which constitute one of the most significant information processing elements. In a neural network model, simple nodes are connected to form a network of nodes, hence the term neural network. Although 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 the units perform functions collectively and in parallel, rather than having a clear description of sub-tasks to which various units are assigned [7]. Currently, the term (ANN) tends to refer mostly to neural network models used in statistics and artificial intelligence. Neural network models designed to emulate the central nervous system are a subject of theoretical neuroscience.

In the construction of any given (ANN), we can identify three kinds of computational neurons, namely, input, output, and hidden, depending on their locations in the network. The input nodes, as their name indicates, serve as the entrance to the network and obtain information from their surroundings. They can have any sensor as origin or come from other system sectors. The units of the output nodes transmit the answer of the (ANN) to the exterior (output network). They can be used to control a system directly. Finally, the hidden units are those whose entrances and exits are inside the net; they do not have any contact with the exterior. Fig.(1) shows the architecture of the (ANN).

Validation of experimental Data

The most important and crucial part of data preparation is the process of selecting the right variables with strong effects on the desired output results. A total of (380) concrete specimen data were collected locally [8]. The proposed input values were considered major factors that greatly affected the UPV of concrete. Five input variables were included (cement content, water cement ratio (W/C), aggregate cement ratio(A/C), maximum aggregate size, and age of concrete). Table (1) shows the ranges of the input parameters. The output variable was the UPV that ranged from (3.66 km/s to 5.19 km/s).

Table (1): Range of Input Parameters in Database

Input Parameter	Min.	Max.
Cement Content (kg/m^3)	168	558
W/C	0.4	0.9
A/C	2.83	11.97
Maximum Aggregate Size (mm)	10	37.5
Age of Concrete (days)	7	150

Results and Discussion

A methodology for concrete pulse velocity neural identification was developed. In the most general sense, a neural network is created for two different phases: the training phase and the testing or simulation phase. The training and testing procedures are followed according to the selected architecture, which is the back-propagation network. Therefore, the algorithm of a multi-layered feed-forward neural network simulator must follow the back-propagation learning algorithm, which is represented by the Levenberg–Marquardt (LM) back propagation algorithm. The (ANN) was developed using the popular MATLAB software package (MATLAB R2009b) [9]. The most used activation function is sigmoid because it squashes very well, is expressible in closed form, its modifications lead to or are related to other activation functions, and its derivative is easy to form. Training and testing the neural network started immediately prior to the completion of the development of the architecture and data preparation. The neural network model for the (UPV) of the concrete was developed to perform prediction of the amounts of mixed proportions and other variable factors that can affect the (UPV) of concrete.

A total of (380) concrete specimen data were used to train and test the neural network. Of these, (342) pairs were used for the training of the model, whereas the remaining (38) pairs were used for testing the (ANN) model.

The error incurred during the learning process may be expressed in terms of the mean squared error (MSE) [7]. The (LM) algorithm is significantly faster than the more traditional gradient descent type algorithms for training neural networks.

It is, in fact, the fastest method for training moderately sized feed-forward neural networks [7]. Although the iteration of the (LM) algorithm tends to take longer than that of other gradient descent algorithms, it yields far better results using far less iteration. This result leads to a net saving in computer processor time over other methods. One concern, however, is that it may over fit the data. The network should be trained to recognize general characteristics, rather than variations specific to the dataset used for training.

To avoid the slow rate of learning near the ends, specifically the output range due to the property of the sigmoid function, the input and output data were scaled between intervals (0.1) and (0.9). The scaling of the training data sets was carried out using the following equation:

$$y = (0.8/\Delta)x + (0.9 - 0.8x_{max}/\Delta) \qquad (3)$$

where

y = Scaled value

x = input value before scaling

$\Delta = x_{max} - x_{min}$

x_{max} = Largest value of data set

x_{min} = Smallest value of data set

After several trials, the best network architecture and parameters to minimize the (MSE) error in the training data were selected, as shown in table (2).

Table (2): Properties of (ANN) Model

Architecture	5-8-1
Training Function	LM
Activation Function	Log Sigmoid
Number of Epochs	1052
Mean Squared Error (MSE)	0.001

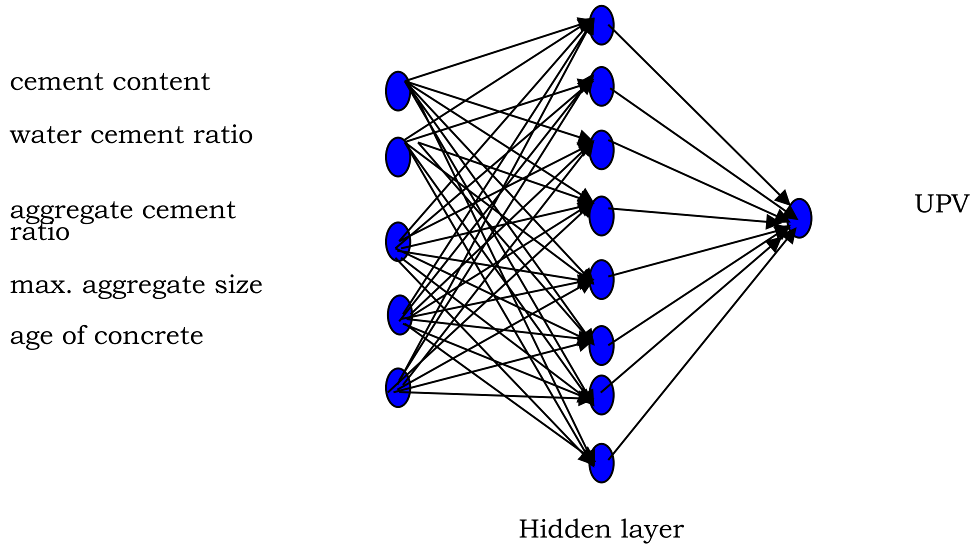

Figure 1: Architecture of neural network model

The relationship between the destructively determined experimental values of (UPV) and its predicted values identified by the neural network for concrete specimens is shown in Figs. (2) and (3), respectively. The results show that the network correctly maps the training data and correctly identifies the testing data. These results are proven by the ideal mapping and the very highly correlated coefficient (R) values [10]. Clearly, the network has learned the relationship between the concrete mixture variables and their respective (UPV) values effectively. The correlation coefficient was (0.94), making the model performance on the training data satisfactory. Thus, the testing points in Fig. (3) are located within the cluster of the (ANN)-predicted data points and slightly over or under the equity line measured and predicted values. The correlation coefficient was (0.93). Therefore, the model successively predicted the (UPV) of the concrete in a precise manner.

Pulse velocity tests need to be conducted, such that the pulse velocity readings are reproducible and are affected only by the properties of the concrete under investigation, rather than other factors. The factors affecting pulse velocity can be divided into two categories as follows [11]:

(a) Factors that affect pulse velocity, regardless of concrete properties, including concrete temperature, moisture content, path length, specimen size and shape, level of stress, and reinforcing steel.

(b) Factors that affect concrete properties, which affect pulse velocity, including aggregate (size, grading, type, and content), cement content, (W/C), admixtures, degree of compaction, curing, and age of concrete.

One advantage of neural network models is that parametric studies are easily done by simply varying one input parameter while all other input parameters are set to constant values. Parametric studies can verify the performance of the (ANN) model in simulating the physical behavior of the (UPV) of the concrete.

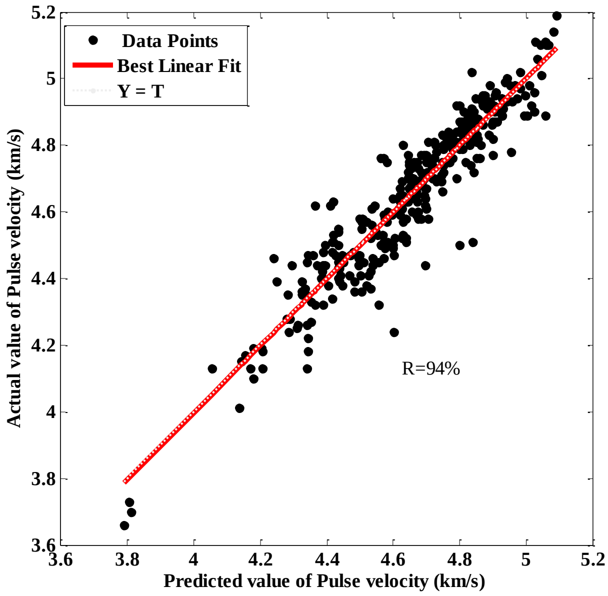

Figure 2: Actual Trained and Corresponding (ANN) Pulse Velocity

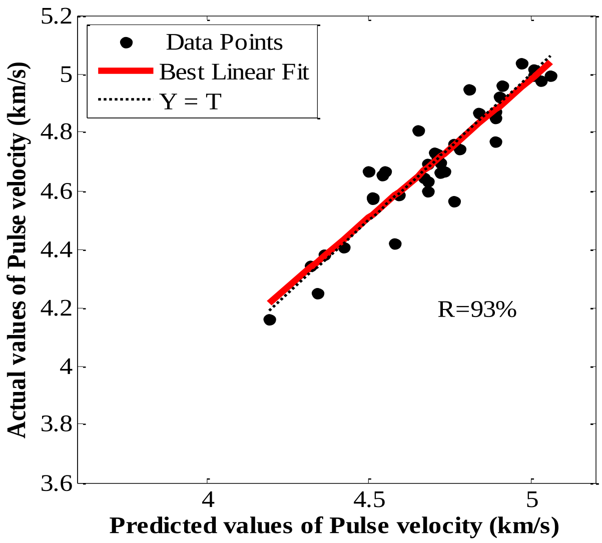

Figure 3: Actual Tested and Corresponding (ANN) Pulse Velocity

Figs. (4 to 7) explain the relationships between (UPV) and (W/C) under the effect of the other main factors (age of concrete, (A/C), cement content and maximum aggregate size). In general, mixtures with higher W/C have lower values of pulse velocity due to decreasing density, porosity, and compressive and flexural strengths. Kaplan studied the effect of (W/C) on pulse velocity. He found that as (W/C) increases, the compressive and flexural strengths and the corresponding pulse velocity decrease, assuming there are no other changes in the composition of the concrete [12]. Therefore, the values for the (UPV) of mixtures with lower (W/C) are higher due to the higher amount of solid materials in the system.

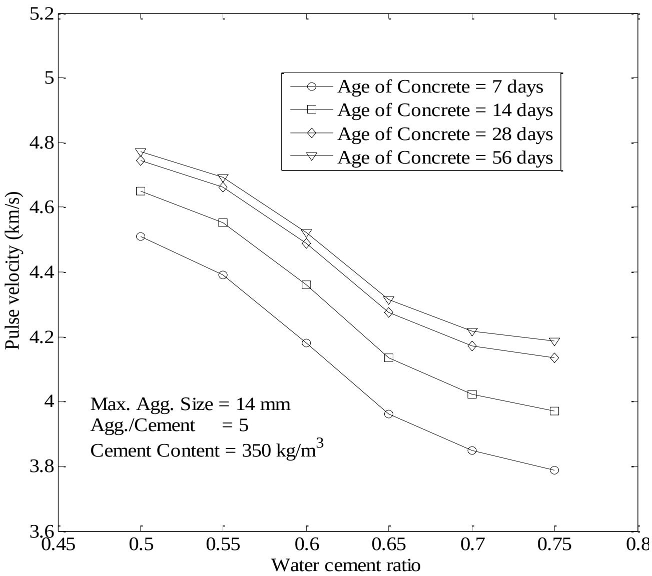

Figure 4: Effect of Age of Concrete and (W/C) on the Pulse Velocity

The test results of the pulse velocity at different ages for concrete mixtures are shown in Fig. (4). The effect of age of the concrete on the pulse velocity is similar to the effect on the strength development of the concrete. The pulse velocity of concrete at its early ages can reach more than (80% to 90%) in (28) days, which is consistent with the function of compressive strength of concrete with age [13].

Many investigators have found that pulse velocity is significantly affected by the type and amount of aggregate. In general, the pulse velocity of cement paste is lower than that of the aggregate. For the same concrete mixture at the same compressive strength level, concrete with rounded gravel has the lowest pulse velocity, whereas crushed limestone has the highest; crushed granite has a velocity whose value is between the previous two [12]. The ratio between cement and aggregate also has a strong influence on the definition of the pore structure and the material capacity [3].

Fig. (5) shows the (ANN) prediction of the variation of pulse velocity and (W/C) for a concrete with maximum aggregate size = 14 mm, age = 28 days, cement content = 350 kg/m^3, and different values of (A/C). As shown in the figure, for a given value of (W/C), the higher the (A/C), the lower the pulse velocity. The presence of aggregate affects the relationship between pulse velocity and compressive strength of concrete. At the same cement content, the concrete with the highest aggregate content has the lowest pulse velocity.

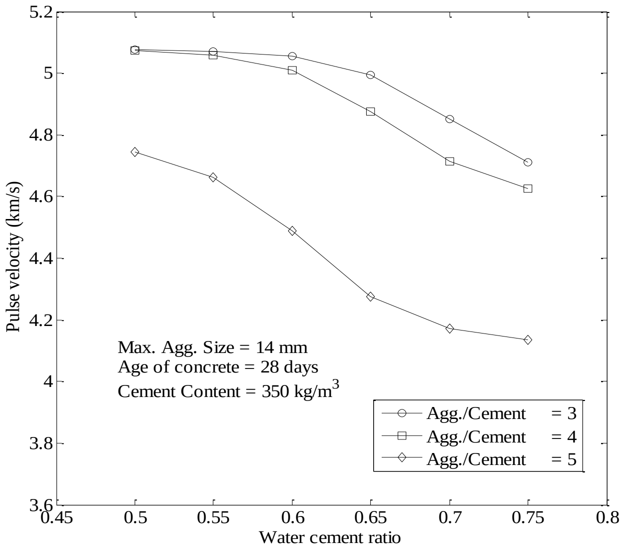

Figure 5: Effect of (A/C) and (W/C) on the Pulse Velocity

Fig. (6) shows that a given value of (W/C) and (A/C) = 5 results in higher cement content and lower pulse velocity. However, for a given aggregate and a given richness of the mixture, the (UPV) of the concrete is affected by changes in the hardened cement paste, such as a change in the (W/C), which affects the modulus of elasticity of the hardened cement paste. For concrete with (A/C) = 5 and low cement content (200 and 250 kg/m^3), the change in W/C does not significantly affect the pulse velocity of the concrete. However, the effect of (W/C) on the pulse velocity of the concrete with (300 and 350 kg/m^3) cement content is very clear.

About Fig. (7), for a given (W/C), the concrete with a larger maximum aggregate size has higher pulse velocity, which may be related to the reduction of the number of interfaces in each path length. The same is true for a (W/C < 0.6). On the other hand, with a (W/C > 0.6), the mixtures with aggregate size ≤ 20 mm have the same value as the pulse velocity.

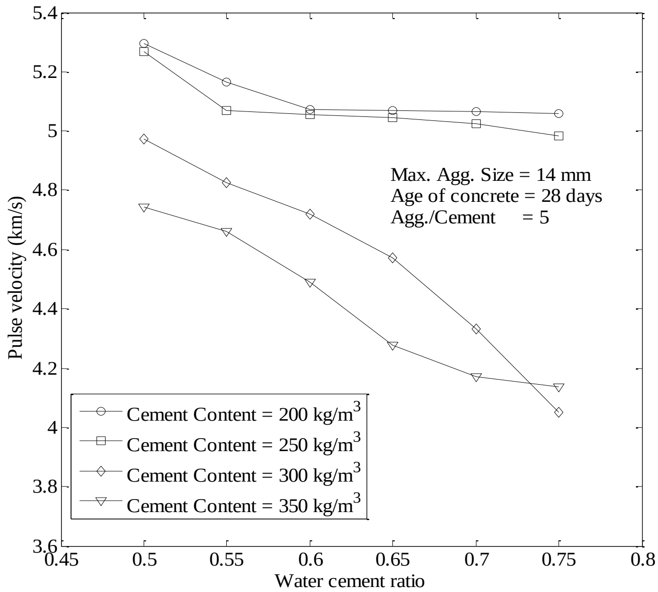

Figure 6: Effect of Cement Content and (W/C) on the Pulse Velocity

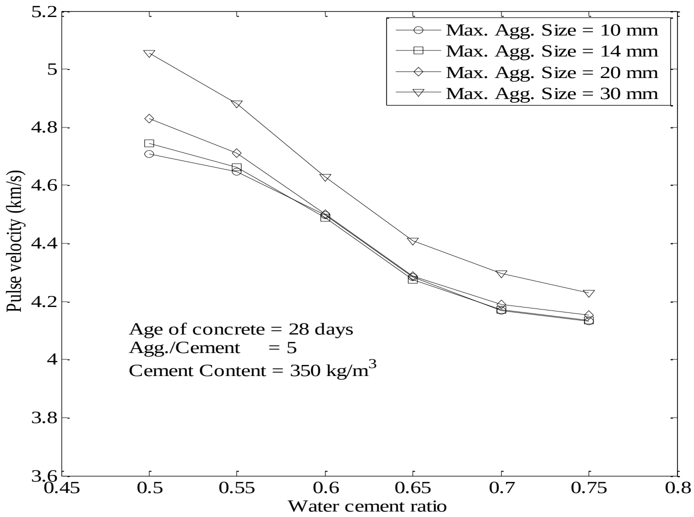

Fig. (7): Effect of Maximum Aggregate Size and (W/C) on the Pulse Velocity

Model Developments for Compressive Strength of Concrete

Another application of ANNs is in building a mathematical model. The present study contains five input and one output parameters. A model equation can be established using the weights as the model parameters [14].

The equation length depends on the number of nodes in the input and hidden layers. To simplify the equation, the most importance input parameters, which are the pulse velocity and the age of concrete, were used in training the second ANN model with one node in the hidden layer. The result was the development of an ANN model with a regression of 0.925 (Fig. 8). The small number of connection weights of the neural network enables the ANN model to be translated into a relatively simple formula in which the compressive strength of the concrete (*Fc*) can be expressed as follows:

$$\mathbf{F_c} = \frac{\mathbf{1}}{\mathbf{1+ e^{1.03-\frac{2.7}{1+e^{-x}}}}} \qquad (4)$$

Where

$\mathbf{x = 10.8 + 15\,v + 0.7\,a}$

$\mathbf{F_c = Compressive\ strength\ (MPa)}$ (5)

$\mathbf{v = pulse\ velocity\ (km/s)}$

$\mathbf{a = age\ of\ concrete\ (days)}$

Before using Eqs.4 and 5, all input variables must be scaled between 0.1 and 0.9 using Eq. 3 for the data ranges shown in Table 1. The predicted values obtained from Eqs. 4 and 5 are scaled between 0.1 and 0.9. To obtain the actual values, these had to be unscaled using Eq. 3.

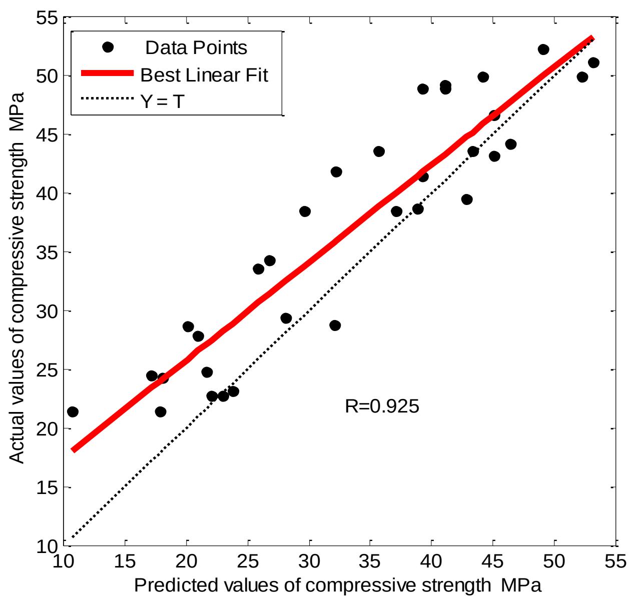

Figure 8: Actual and corresponding predicted compressive strength of the test data

Conclusions

This study presents the ability of the (ANN) as a good technique for modeling the (UPV) of concrete. The (ANN) model performs sufficiently in the estimation of the (UPV) of concrete in the training and testing process. The (ANN) model predicts the (UPV) based on main factors related to concrete mixtures. These factors include cement content, (W/C), (A/C), maximum aggregate size, and age of concrete. The prediction using (ANN) shows high consistency with the experimentally evaluated (UPV) of concrete specimens used. The results show that velocity speed increases with increase in concrete age. Moreover, an increase in cement content causes a rapid pulse in the velocity readings. Large concrete maximum aggregate size is confirmed to increase pulse velocity. Aside from these factors, (W/C) negatively affects pulse velocity. Also, the ANN model predicts the compressive strength of the concrete using pulse velocity and the age of concrete. The results showing good rapprochement between experimental value of compressive strength with predicated value of compressive strength.

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