PREDICŢIA REZISTENŢEI LA COMPRESIUNE A BETONULUI PRIN TESTARE UPV (ULTRASONIC PULSE VELOCITY) ȘI MODELARE CU REŢELE NEURONALE ARTIFICIALE

PREDICTION OF CONCRETE COMPRESSIVE STRENGTH USING ULTRASONIC PULSE VELOCITY TEST AND ARTIFICIAL NEURAL NETWORK MODELING

FAEZEHOSSADAT KHADEMI[1]* , MAHMOOD AKBARI[2], SAYED MOHAMMADMEHDI JAMAL[3]
[1]Department of Civil, Architectural, and Environmental Engineering, Illinois Institute of Technology, Chicago, USA.
[2]Civil Engineering Faculty, University of Kashan, Kashan, Iran.
[3]Civil Engineering Department, University of Hormozgan, Hormozgan, Iran.

Ultrasonic pulse velocity (UPV) test method is used in this study for evaluating the compressive strength of concrete. A series of UPV tests were performed to evaluate the 28-day compressive strength of concrete and examine the effect of concrete mixture parameters on the UPV of concrete. It was found that concrete with higher 28-day compressive strength gives higher UPV and that an exponential relationship exists between the UPV and 28-day compressive strength of concrete. The results showed that the aggregate size has a significant effect on the strength of concrete. Concrete with larger aggregate size was found to give lower UPV and compressive strength. UPV results also indicated that the UPV and compressive strength of concrete consistently decrease with increase in water-cement ratio of concrete. The effect of using microsilica (Silica fume) in concrete is also studied. It was found that as the microsilica to cement ratio increases in concrete, the UPV and compressive strength of concrete increase. The effects of the ingredient materials on UPV were analyzed and potential mechanisms were proposed. To make the results applicable, the artificial neural network (ANN) method was used to predict the compressive strength of concrete based on the evaluated concrete mix parameters and ultrasonic pulse velocity. The ANN analysis demonstrated high reliability in predicting the compressive strength values of concrete.

Keywords: *Concrete, Compressive Strength, Ultrasonic Pulse Velocity, Aggregate, Water-Cement Ratio, Microsilica, Artificial Neural Network*.

1. Introduction

Resistance of the concrete is assumed as one of the most important characteristics that are almost regularly required in concrete. Compressive strength of concrete at the age of 28 days is most of the time used to characterize the concrete properties. The compressive strength is one of the most important properties of concrete, which is the most controlled parameter during quality control. Several attempts to utilize the ultrasonic pulse velocity V_p(km/s) as a determination of the compressive strength of concrete f'_c (MPa) has been prepared, due to its distinct advantages over conventional compression measurements. Scientists have examined the application of the UPV to the evaluation of the concrete quality for decades. These types of measurements have considered to be of real significance as a useful implement for examining the concrete quality and mechanical properties in concrete structures. The most attractive aspect of this method is to prevent the damaging of concrete while being tested. Additionally, using this method is both quick and simple. Furthermore, test results are available on the site and the less expensive equipment can be used for this purpose [1 - 5]. The concrete compressive measurement is generally based on empirical relations between strength and UPV. These relationships are not appropriate for every kind of concrete, and hence, the manufactures typically give such correlation for their own testing. As a result, they need to be calibrated for different mixtures. The conventional approach to derive a mathematical correlation using ultrasonic pulse velocity and compressive tests on concrete specimens by means of regression analysis has not been very successful [3, 6, 7]. Numerous data and the relationship between the compressive strength and the ultrasonic pulse velocity of concrete have been suggested and presented.

Rajagopalan et al. studied the relationship of concrete compressive strength and ultrasonic pulse velocity for some typical mixes. The report evaluated simultaneous measurements of compressive strength and ultrasonic pulse velocity at different ages of 1 day to 28 days which resulted in the linear relationship between the velocity and compressive strength of concrete [7]. Galan presented a regression analysis to depict compressive strength of concrete based on acoustic characteristics like UPV and damping constant [8].

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* Autor corespondent/*Corresponding author*,
E-mail: Faezehossadat_khademi@yahoo.com, fkhademi@hawk.iit.edu

Sahu and Jain used the ultrasonic pulse velocity as measure of assessment of concrete quality for different components like shell beams, shell roof, columns, roof beams, and crane girders [9]. Lin et al. showed an experimental study to prove the mathematical models for predicting concrete pulse velocity based on water-cement ratio an aggregate content [10]. Therefore, most of the literature reports ultrasonic pulse velocity as a predictor of concrete compressive strength based on a very few parameters through linear regression analysis.

The first objective of this study is to identify the effect of concrete mix parameters, including the aggregate ratio, water-cement ratio, and microsilica ratio on a compressive strength and ultrasonic pulse velocity of concrete. Second, in this paper, it is found that there is exponential relationships between the ultrasonic pulse velocity and 28 days compressive strength of concrete which is shown in Eq. (1). In this formula, A and B are experimental parameters and V is the ultrasonic velocity. In addition, the specific numbers for constants A and B are obtained with respect to the used mix designs in this experimental work.

$$f_c = Ae^{Bv} \qquad (1)$$

The next objective of this study is to establish a numerical model to evaluate the compressive strength of concrete as a function of the ultrasonic pulse velocity and concrete mix parameters. The artificial neural network (ANN) was used for this purpose. The privilege of the ANN model in comparison to the other traditional models is that there is no concern about the amount of input. In addition, it can continuously re-train the new data, so that it can conveniently adapt to new data. To overall, the artificial neural network is a very strong model of solving difficult problems by conventional techniques such as a multiple regression model.

The experimental study incorporated 90 different concrete mix designs. The study was conducted on two specimens of each mix design with the cubic size of 15 cm*15 cm*15 cm. Concrete specimens were tested in laboratory for ultrasonic pulse velocity and compressive strength at a period of 28 days.

2. Experimental Program

2.1. Concrete mixing and compositions

In order to investigate the objectives of this study, various concrete specimens are constructed with different mix designs in the laboratory. The specimens are designed with varying amount of different constituents namely cement, water, gravel, sands, and microsilica. The weight ranges of concrete mix constitutes are shown in Table 1. The mix designs differed in terms of type, different amount of cement and different amount of water which lead to different water to cement (W/C) ratio (0.43-0.51), different amount of gravel and sands, and different amount of microsilica (0.05-0.15 weight of cement). The total number of mix designs used in this study was equal to 90 with respect to varying amount of different constituents.

Table 1. The weight ranges of concrete mix constitute

Materials in the specimens	Weight ranges (Kg/m^3)
water	100 to 250
cement	200 to 390
microsilica	2 to 60
gravel	750 to 950
sand	900 to 1300

2.2. Ultrasonic Testing Method

The ultrasonic pulse velocity method works based on the transit time of the ultrasonic wave through the concrete. The signal velocities passing through the concrete depends on both the density and elasticity of the materials [3, 11].On the other hand, the sound velocity is independent of the excitation frequency that leads to the agitation. Based on the wave type (transverse or longitudinal), in order to determine the Poisson`s ratio and elastic modulus of concrete, a specific transducer must be used. The device used for this experiment was the portable ultrasonic non-destructive digital indicating tester (PUNDIT).

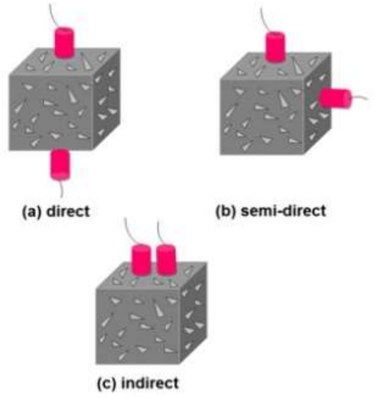

Fig. 1- Three Different Modes of Ultrasonic Test; Direct, Semi-Direct, and Indirect.

According to Figure 1, the positions of pulse velocity measurements are divided into three different categorization; (a) Opposite faces (direct transmission); (b) Adjacent faces (semi-direct transmission); and (c) Same face (indirect or surface transmission). In this study, the opposite faces mode was used for measuring the ultrasonic pulse velocity as the most accurate mode, because the longitudinal pulses leaving the transmitter are propagated in the direction normal to the transducer face.

In this method an ultrasonic pulse is produced using a pulse generator and transmitted to the surface of concrete through the transmitter transducer. The pulse traveling time through the concrete is measured by the receiver transducer on the opposite side. The transducers were placed in the center of each opposing face, orthogonal to the direction of concreting. Then, the ultrasonic device recorded the propagation time while the ultrasonic waves were transmitting through the 15 cm cubic specimens. A digital readout is demonstrated in a 4-digit LCD.

The pulse velocity can be defined from equation (2) where V is the pulse velocity (km/s), L is the path length (cm), and T is the transit time (μs).

$$V=L/T \qquad (2)$$

According to Eq (2), the ultrasonic device measures the passing time of the waves in the concrete. Then, by having the dimensions of the concrete cube, the ultrasonic pulse velocity can be measured.

This method is based on the fact that the velocity of sound in a material is based on the elastic modulus of E by the expression presented in equation (3) where E is the modulus of elasticity and ρ is the density of the material.

$$V=\sqrt{\frac{E}{\rho}} \qquad (3)$$

To overall, the ultrasonic pulse velocity method is a very suitable technique for investigating the quality of the concrete, since according to equation (3) the pulse velocity just depends on the elastic properties of the concrete.

2.3. Concrete 28 Days Compressive Strength

The compressive strength is the result of breaking cubic concrete specimens in a compression-testing machine. This strength is resulted from dividing the failure load by the cross-sectional area resisting the load.

In a compression strength test, there is a linear region which the concrete follows Hooke's Law. The Hook's Law is presented in equation (4). Compressive strength is widely used for specification requirement and quality control of concrete.

$$\sigma=E\varepsilon \qquad (4)$$

3. Results and Discussions

3.1. Effect of Aggregate Size on Ultrasonic Pulse Velocity

According to Figures 2 - 4, the effect of aggregate size on the ultrasonic pulse velocity of concrete for three different ratios of microsilica and three different water-cement ratios is studied. According to these Figures, as the ratio of small to large aggregate increases, the wave velocity increases.

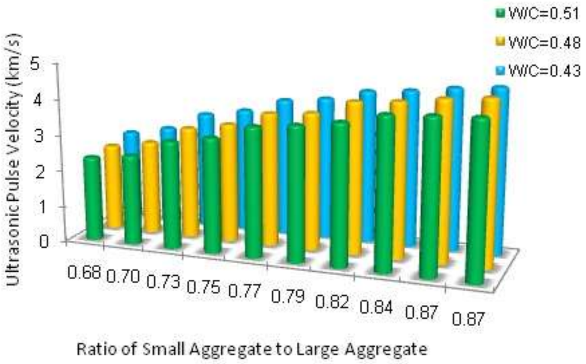

Fig. 2 - Effect of Aggregate Size on UPV for the 5% Microsilica& Three Different Water to Cement Ratios of 0.43 and 0.48 and 0.51.

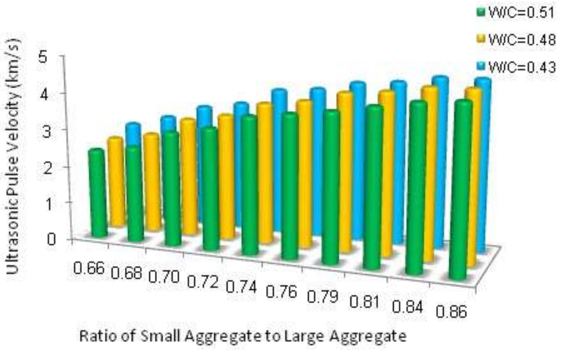

Fig. 3- Effect of Aggregate Size on UPV for the 10% Microsilica& Three Different Water to Cement Ratios of 0.43 and 0.48 and 0.51.

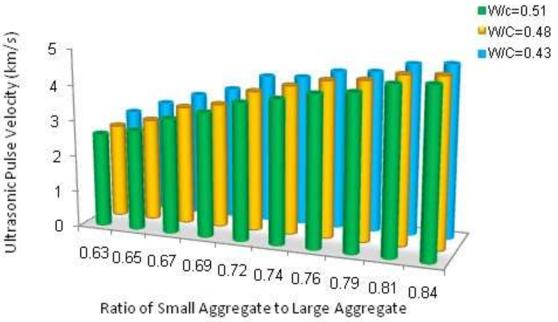

Fig. 4 - Effect of Aggregate Size on UPV for the 15% Microsilica& Three Different Water to Cement Ratios of 0.43 and 0.48 and 0.51.

In this study, the ultrasonic pulse velocity values have the higher amount in comparison with many studies. Three reasons can lead the ultrasonic waves to have the higher velocity which are; (1) the first reason for the higher ultrasonic velocity is that utilizing the direct transmission method to evaluate the velocity of the waves leads to the higher velocity. Results generated by Akhras illustrates the fact that the direct transmission method will increase the measured velocity by about 20% [12], (2) the velocity will be higher when the material molecules are closer to each other. As the ultrasonic test was performed right after the time that concrete specimens were taken out of the water pool after 28 days, the pores in concrete were completely saturate with water, and hence the measured ultrasonic pulse velocity had the higher value, (3) Law wave frequency lead to the higher ultrasonic pulse velocity

3.2. Effect of Aggregate Size on 28 days Compressive Strength of Concrete

According to Figures 5 - 7, the effect of aggregate size on the 28 days compressive strength of concrete for three different ratios of microsilica and three different water-cement ratios is studied.

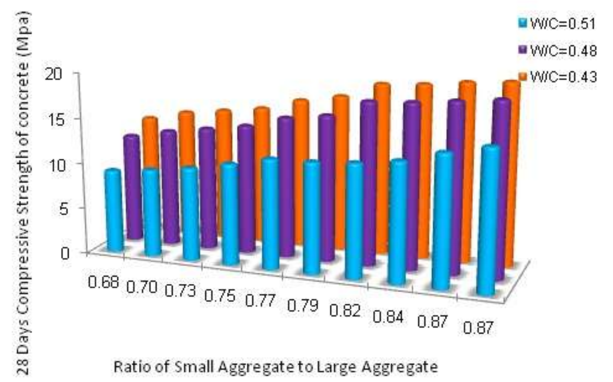

Fig. 5- Effect of Aggregate Size on f'c for the 5% Microsilica& Three Different Water to Cement Ratios of 0.43 and 0.48 and 0.51.

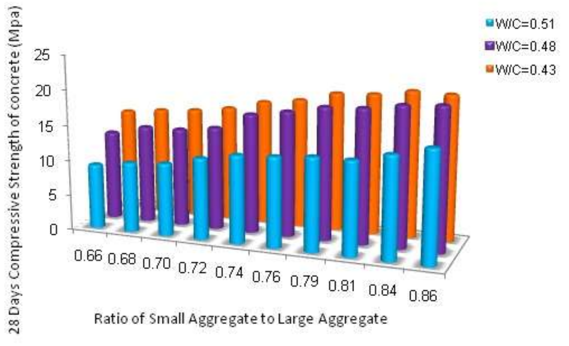

Fig. 6 - Effect of Aggregate Size on f'cfor the 10% Microsilica& Three Different Water to Cement Ratios of 0.43 and 0.48 and 0.51.

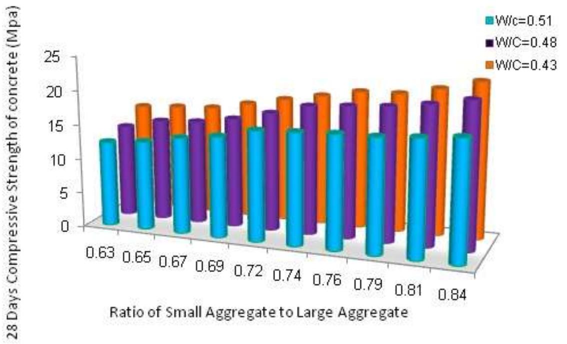

Fig. 7 - Effect of Aggregate Size on f'c for the 15% Microsilica& Three Different Water to Cement Ratios of 0.43 and 0.48 and 0.51.

Concrete properties are strongly related to the characteristics of the solid aggregate, the performance of the cement paste, and the interfacial region as well. Since approximately 75% of the concrete volume is engrossed by the aggregates, it is perceived that the aggregate size forcefully influence the compressive strength of concrete [13].

To overall, for the same W/C ratio, mixtures with the lowest and the highest nominal aggregate size have the highest and the lowest compressive strengths, respectively.

3.3. Effect of Water to Cement Ratio on Ultrasonic Pulse Velocity.

According to Figures 8 - 10, the effect of water to cement ratio on the ultrasonic pulse velocity of concrete for three different ratios of microsilica and ten different aggregate ratios is studied. It can be concluded that for the constant amount of microsilica and aggregate ratio, increasing in the water-cement ratio leads to the decrease in the ultrasonic pulse velocity of concrete.

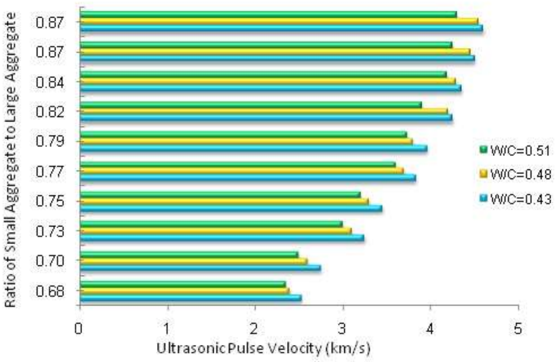

Fig. 8- Effect of water to Cement Ratio on Ultrasonic Pulse Velocity of Concrete for the 5% Microsilica& Ten Different Aggregate Ratios.

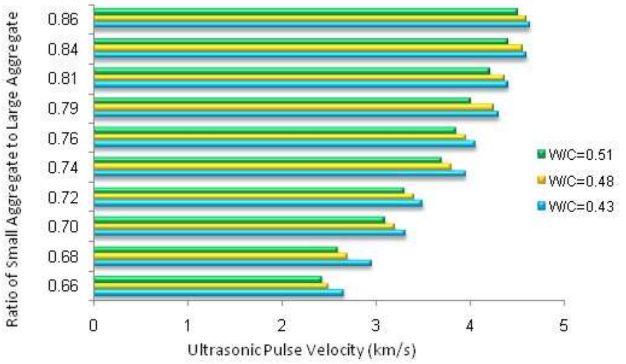

Fig. 9- Effect of water to Cement Ratio on Ultrasonic Pulse Velocity of Concrete for the 10% Microsilica& Ten Different Aggregate Ratios.

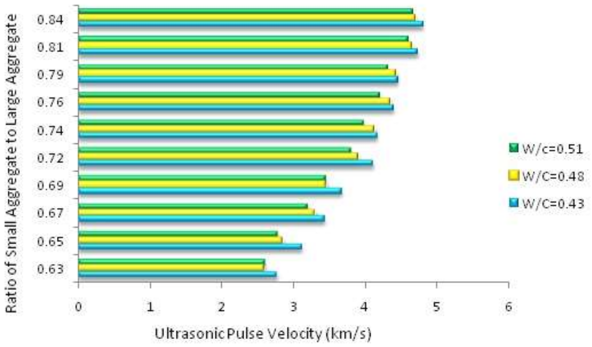

Fig. 10- Effect of water to Cement Ratio on Ultrasonic Pulse Velocity of Concrete for the 15% Microsilica& Ten Different Aggregate Ratios.

The reduction on ultrasound wave velocity as water–cement ratio increases can be explained by the fact that increasing the concrete water–cement ratio will cause an increase in the volume of capillary voids and micro cracks in the concrete transition zone, causing reduction in the concrete capability to transfer ultrasonic waves.

3.4. Effect of Water to Cement Ratio on 28 Days Compressive Strength of Concrete

According to Figures 11 - 13, the effect of water to cement ratio on the 28 day compressive strength of concrete for three different ratios of microsilica and ten different aggregate ratios is studied. It can be concluded that the higher the initial water content, the higher the average spacing between the cement particles will be. When the initial Water-Cement ratio is high, the resulting pore structure within the hydrates is interconnected and the concrete specimen has low strength.

3.5. Relationship between the Ultrasonic Pulse Velocity and 28 Days Compressive Strength of Concrete

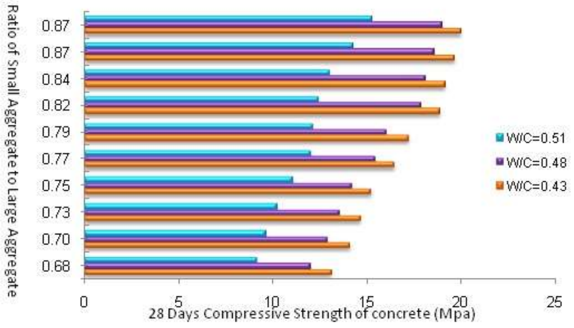

Fig. 11- Effect of water to Cement Ratio on the 28 Days Compressive Strength of Concrete for the 5% Microsilica& Ten different Aggregate Ratios.

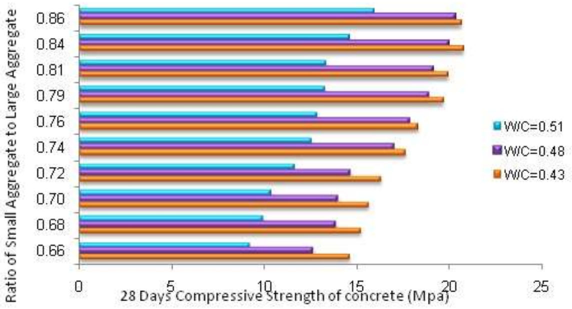

Fig. 12 -. Effect of water to Cement Ratio on the 28 Days Compressive Strength of for the 10% Microsilica& Ten different Aggregate Ratios.

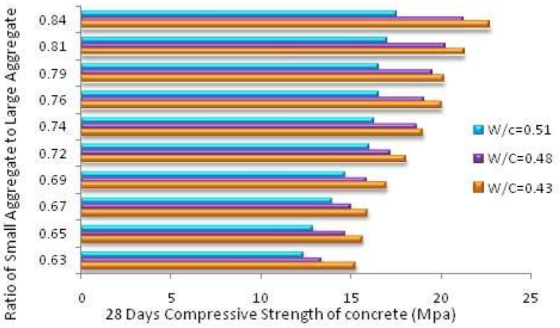

Fig. 13- Effect of water to Cement Ratio on the 28 Days Compressive Strength of Concrete for the 15% Microsilica& Ten different Aggregate Ratios

Figures 14 - 16 show the relationship between the ultrasonic pulse velocity and 28 days compressive strength of concrete for 3 different microsilica to cement percentage and three different water to cement ratios.

In earlier investigations [14 - 16] there is not a unique formula representing the relationship between the ultrasonic pulse velocity and

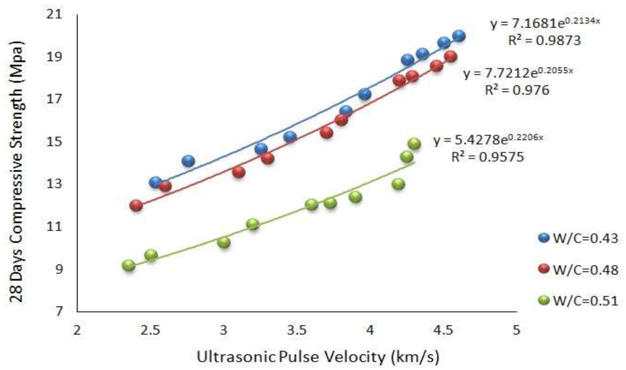

Fig. 14- Relationship between the Ultrasonic Pulse Velocity and 28 Days Compressive Strength of Concrete for the 5% Microsilica& three Different Water to Cement Ratios of 0.43, 0.48 and 0.51.

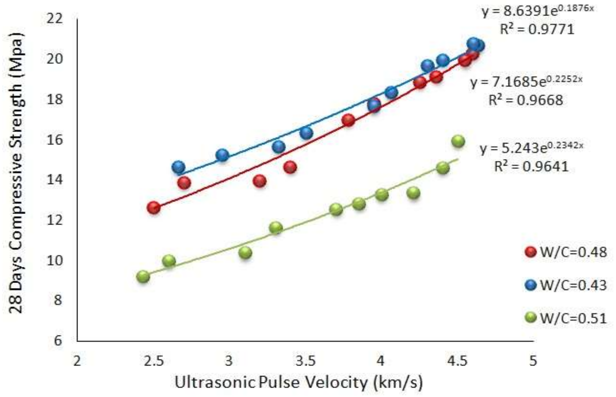

Fig. 15- Relationship between the Ultrasonic Pulse Velocity and 28 Days Compressive Strength of Concrete for the 10% Microsilica& three Different Water to Cement Ratios of 0.43, 0.48 and 0.51.

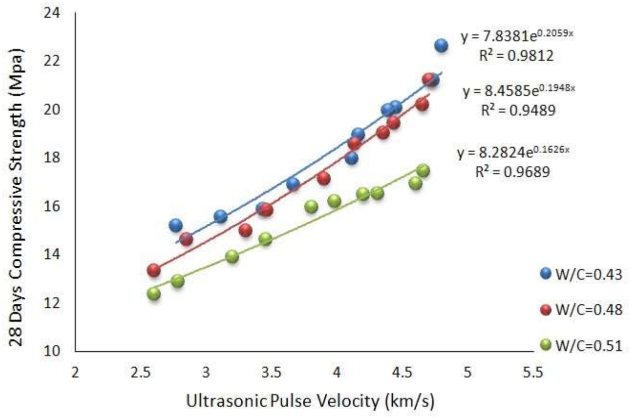

Fig. 16 - Relationship between the Ultrasonic Pulse Velocity and 28 Days Compressive Strength of Concrete for the 15% Microsilica& three Different Water to Cement Ratios of 0.43, 0.48 and 0.51

compressive strength of concrete. It is worth mentioning that the researches which has done by now on UPV strongly depends on the material characteristics, and hence, each study leads to finding a different UPV and compressive strength correlations. This variation in their correlations is because the specimens experimented in the laboratory have different concrete mix designs.

According to Figures, it can be concluded that for constant microsilica to cement ratio and constant water to cement ratio there is an exponential relationship between the ultrasonic velocities and concrete 28 days compressive strengths. Each three Figures in this part show a high ability of modeling the experimental data. It is explicit that the constant parameters in each exponential formula varies for different concrete mix designs, while in all of them the relationship between the UPV and compressive strength is in the form of exponential formula. The exponential relation was selected as the final equation when it was the best in terms of R^2 among some linear and nonlinear equations.

3.6. Predicting the 28 days Compressive Strength of Concrete using the Neural Network

Neural networks are data processing systems containing the artificial neurons which are a large number of simple, highly interconnected processing elements and inspired by the structure of the central cortex of the brain. These neurons have the ability to learn from the experience In order to gain the better performance. Neural networks are the simulation of a human brain and most of the times they are able to find the solution for the problems that conventional methods were not able to solve. In order to solve a specific problem, the neurons which are highly interconnected processing elements work in unison [17 - 20].

Numerous statistical goodness-of-fit criteria have been proposed in the literature for evaluating data driven modeling results. We consider the coefficient of determination (R^2) as it is presented in equation (5):

$$R^2 = \frac{\left[\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})\right]^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2} \tag{5}$$

In the equations (n) is the number of specimens, (y_i) is the experimental strength of ith specimen, ($\bar{y}$) is the averaged experimental strength, ($\hat{y}_i$) is the calculated compressive strength of i th specimen, and ($\bar{\hat{y}}$) is the averaged calculated compressive strength.

The R^2 coefficient which ranges from 0 to 1 provides a measure of how well observed outcomes are replicated by the model, as the proportion of total variation of outcomes explained by the model. The best model is the one which demonstrates a higher quantity of R^2.

In recent years, scientists have performed different investigations on various types of civil engineering materials, specially concrete and cement [21-26]. Numerous studies [27 - 30] have applied artificial intelligence techniques for predicting concrete properties profitably. However, none of them have been able to presents an equation that can be used in practice. In all cases, it is essential to use specific software to run the ANN. In this study, the Matlab software was used to program the ANN model [31].

Since the network topology directly affects its computational complexity and its generalization capability, determining a proper architecture of a neural network for a specific problem is an undeniable task. The use of a single hidden layer is generally recommended [32] and this recommendation has been adopted in the present study as well as in many of the applications of the ANNs. The structure of the ANN model in Matlab software is presented in Figure 17.

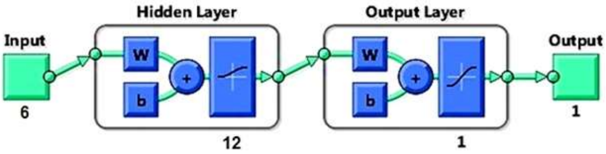

Fig. 17- Modeling the Neural Network in Matlab Software.

In the ANN model the input parameters are the quantity of water, cement, microsilica, gravel, sand, and ultrasonic pulse velocity. In this study, the artificial neural network has been programmed for the 28 days compressive strength of concrete in which 60% of total data (i.e. 60 samples) were used as the training data, 10% (i.e. 10 samples) as the validation data and remaining data (i.e. 30 samples) were used as the test data. Figure 18 shows the relationship between the experimental compressive strength and ANN predicted compressive strength for test data.

As a matter of fact, there is no particular way to anticipate the compressive strength of concrete based on all the concrete mix designs and in all the weight ranges, but there can be ways to predict it for specific range of concrete mix designs. In this study, with respect to Table 1, the parameters` weights has been introduced for a specific range. In addition, the concrete mixture consists of five different parameters which are water, cement, gravel, sand, and microsilica. Furthermore, in addition to 5 different concrete constitutions, ultrasonic pulse velocity of concrete was selected as another input variable. For this situation, neural network in Matlab software was modeled for predicting the 28 days compressive strength of a definite concrete mix designs.

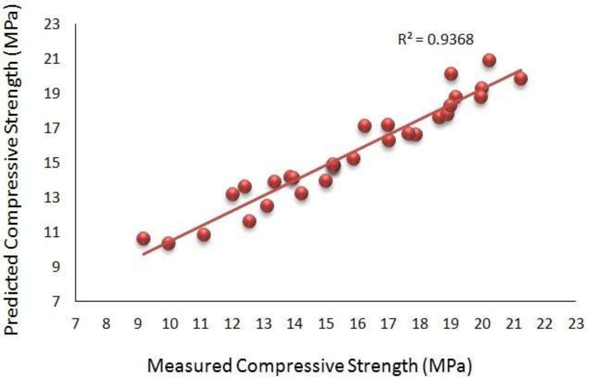

Fig. 18 - The Relationship between the Experimental Compressive Strength and ANN Predicted Compressive Strength for Test Data.

It can be concluded that the neural network modeling in Matlab clearly predicts that experimental values are in strong coherence with the depicted values. . This is evidenced by the fact that the lozenges lie close to the center line, corresponding to the ideal mapping, as well as by the relatively high correlation coefficient value R^2. The nearer the points gather at the diagonal, the better are the results. As it is shown in Figure 18, the value of R^2 for the relationship between the experimental compressive strength and ANN predicted compressive strength for test data is 0.936. The statistical parameter values of both models R^2, have shown obviously this situation that artificial neural networks is a practicable methods for predicting compressive strength values of concretes based on the specific concrete mix designs and ultrasonic pulse velocities used in this research.

4. Conclusion

In this study, the effect of the concrete parameters on the strength of concrete was investigates. It was concluded that there is a decrease in the 28 days concrete compressive strength with increase in aggregate size for the specific water to cement ratio and also the specific microsilica to cement ratio. In addition, increasing in the water to cement ratio for the specific amount of aggregate and microsilica to cement ratio leads to the decrease in the 28 days compressive strength of concrete. Furthermore, the amount of microsilica has a direct effect on the strength of concrete. The more the microsilica to cement ratio is, the more the 28 days compressive strength of concrete would be.

In addition, the effect of concrete mix parameters on ultrasonic pulse velocity was studied. It can be concluded that the aggregate size has the revers effect on the ultrasonic pulse velocity for this range of concrete mix design and for the constant ratio of water to cement and the constant ratio of microsilica to cement. In addition, increase in the water to cement ratio leads to the decrease in the ultrasonic pulse velocity of concrete for the specific aggregate ratio and a specific microsilica to cement ratio. Moreover, the effect of microsilica on the UPV indicates that there is a ascending relationship between the amount of the microsilica to cement ratio with the ultrasonic pulse velocity. In other words, when the amount of microsilica to cement ratio increases in the concrete mixture, the ultrasonic pulse velocity increases.

It can be mentioned that by the concrete parameters effect the same on both the concrete compressive strength and ultrasonic pulse velocity. So, it can be concluded that there is a ascending relationship between these two parameters. In this paper, it was resulted that there is exponential relationships between the ultrasonic waves and compressive strengths for different w/c ratios and different microsilica to cement ratios. It was concluded that the constant parameters of the exponential formula varies with the change in the concrete mixtures, although the exponential relationship is always preserved.

Finally, the artificial neural network was used for predicting the 28 days compressive strength of concrete using concrete mix parameters and ultrasonic pulse velocity. The results have represented that artificial neural networks is a practicable methods for predicting the compressive strength values of concretes with the weight ranges presented in this article. The statistical parameter values of the model, R^2have shown this situation clearly.

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