Evaluating the Compressive Strength of Concrete Exposed to Elevated Temperatures Using Ultrasonic Pulse Velocity and Artificial Neural Networks

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ABSTRACT

The objective of this study is to construct artificial neural networks for evaluating the compressive strength of concrete subjected to elevated temperature by using ultrasonic pulse velocity technique. The experiments were performed with different mixture proportions of concrete at temperature ranging from 200 to 800 degrees Celsius. For each test, the ultrasonic pulse velocity and compressive strength were measured. The multi-layer feed-forward neural network was used in this study. The input features to the neural networks were ultrasonic pulse velocity, feature extraction of ultrasonic waveform and mix parameters of concrete. Based on the experimental results, the proposed neural network was successfully used in modeling the ultrasonic pulse velocity and compressive strength relationship. Therefore, the proposed neural network can be utilized for predicting the compressive strength of concrete exposed to elevated temperatures.

INTRODUCTION

Concrete at elevated temperature may cause considerable changes in the physical and mechanical properties. The properties of concrete retained after a fire are important for determining the load carrying capacity and for reinstating fire-damaged constructions. The compressive strength of concrete is significantly reduced when it is exposed to evaluated temperature that may result in undesirable structure failures [1-4]. Ultrasonic pulse velocity is used for assessment of residual compressive strength of concrete after exposure to elevated temperature. The previous studies showed that the ultrasonic pulse velocity decreases by increasing the exposure temperature for all the concrete specimens with different mixture proportions [1]. However, the composition and damage of concrete influence the relationship between pulse velocity and the compressive strength [5]. Therefore, there is ambiguity in the interpretation of the ultrasonic pulse velocity for residual compressive strength prediction.

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The objective of this study is to investigate the feasibility to use ultrasonic pulse velocity, feature extraction of ultrasonic waveform and mix parameters of concrete to train and test the neural network for predicting the residual compressive strength. The three-layer feed-forward neural network architectures were designed with the different groups of input features. Ultrasonic waveforms were extracted as input features of root mean square (RMS) voltages of the decomposed waveform by wavelet packet transform (WPT).

EXPERIMENTAL PROCEDURE

Five different concrete mixtures were prepared by using ordinary Portland cement (Type I), crushed limestone aggregate, river sand and fly ash. Concrete mixture proportions are given in Table 1. Twenty-four concrete specimens were produced for each mixture proportion. All specimen were cast in cubed steel mold of 150×150×150 mm and cured in water for 28 days. Afterwards, they were placed in ambient air for 7 days.

Specimens were heated in an electric furnace at elevated temperatures of 200, 300, 400, 500, 600, 700 and 800^{o}C for 2 hours. The heating rate used in the experiment was 5^{o}C/min. After exposing to the elevated temperature, the specimens were cooled down in the ambient air for 1 day until testing. For each test, the ultrasonic pulse velocity and compressive strength of specimens were measured according to the specification of ASTM C597 and ASTM C39, respectively.

Ultrasonic pulse velocities were measured by pulse meter (V-Meter MKII, NDT James Instruments Inc.) with longitudinal wave transducer (nominal frequency of 54 kHz) in transmission mode of direct, semi-direct and indirect method as illustrated in Figure 1. In addition, the ultrasonic pulse waveforms were fed to the digital oscilloscope with sampling rate of one million samples per second. After ultrasonic testing, compressive strength of all specimens were measured by compressive testing machine (ADR 3000, ELE). For comparison, three unheated specimens of each mixture also were tested to investigate the changes in the ultrasonic pulse velocity and compressive strength of concrete at elevated temperatures.

Table 1. Mixture proportions of concrete specimens.

Mixture No.	**W/C ratio**	**F/C ratio**	**Mixture proportion (kg/m^3)**				
			Sand	Limestone	Cement	Water	Fly Ash
C1W40	0.4	0	776	1025	435	174	0
C1W50	0.5	0	776	1025	382	191	0
C1W60	0.6	0	776	1025	340	204	0
C1F20W50	0.5	0.2	776	1025	295	185	74
C1F40W50	0.5	0.4	776	1025	215	179	143

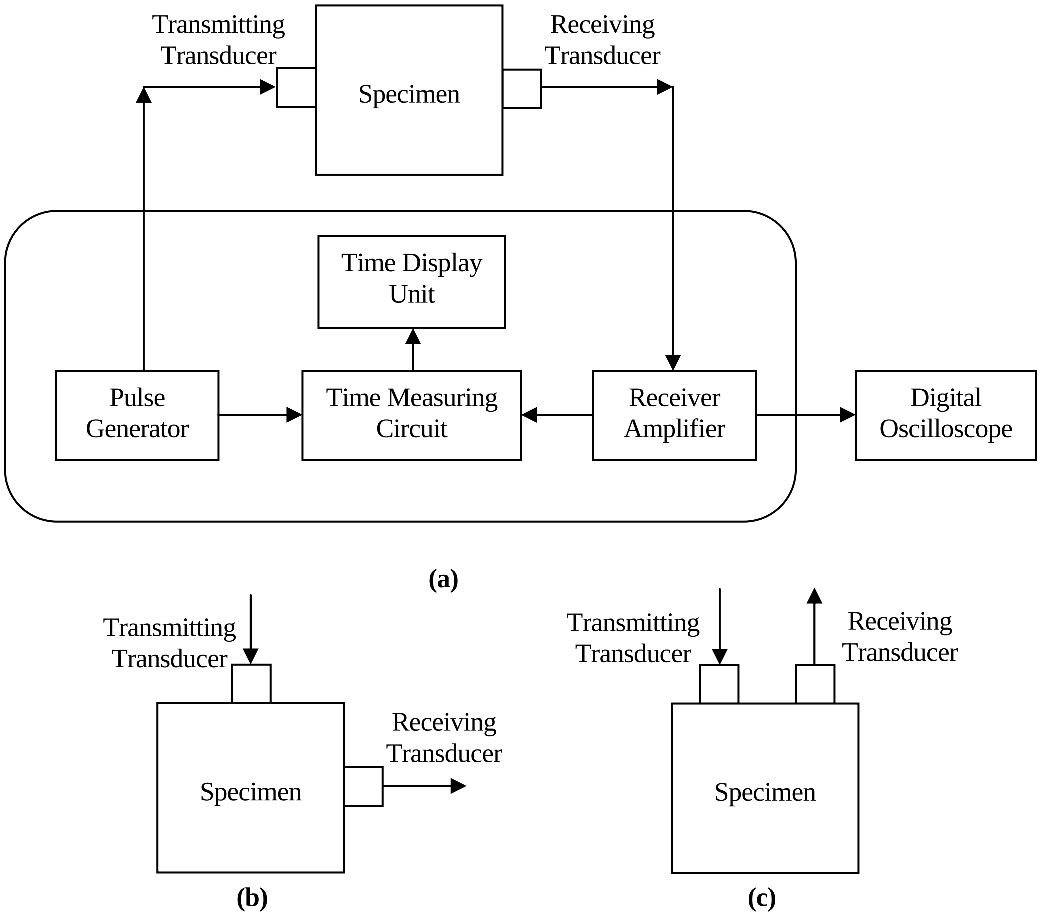


Figure 1. Schematic diagram of pulse velocity measurement:
(a) direct method; (b) semi-direct method;(c) indirect method.

EXPERIMENTAL RESULTS

Relationship between the compressive strength and ultrasonic pulse velocity of concrete at elevated temperature

Figure 2 shows the relationship between compressive strength and exposure temperature. It indicates that the compressive strength decreases by increasing the exposure temperature for all the concrete specimens with different mixture proportions. Figure 3 shows the relationship between compressive strength of concrete specimen and ultrasonic pulse velocity for all concrete specimens. It indicated that the compressive strength decreases with ultrasonic pulse velocity. Figure 3(a) clearly demonstrates that there are only one half of data compared with Figure 3(b) and 3(c) because ultrasonic pulse velocity cannot be measured for above 400^{o}C exposed specimens. Thus, in this study, the neural network analysis for direct method is not developed.

The statistical analysis of the regression models is given in Table 2. The coefficient of correlation (R^2) values indicated that the relationship between pulse velocity and compressive strength is low because the elevated temperature changed the cement properties and also the effect of concrete mixture. This shows that the ultrasonic pulse velocity is not sufficiently sensitive to the change of cement properties and concrete composition. Figure 4 shows samples of ultrasonic waveform and their corresponding fast Fouier transform (FFT). The FFT analysis shows that the frequency distribution of waveform changes magnitude and shifts location of spectral peaks as the compressive strength changes. For more comprehensive health monitoring, the ultrasonic pulse waveform should be extracted by wavelet packet.

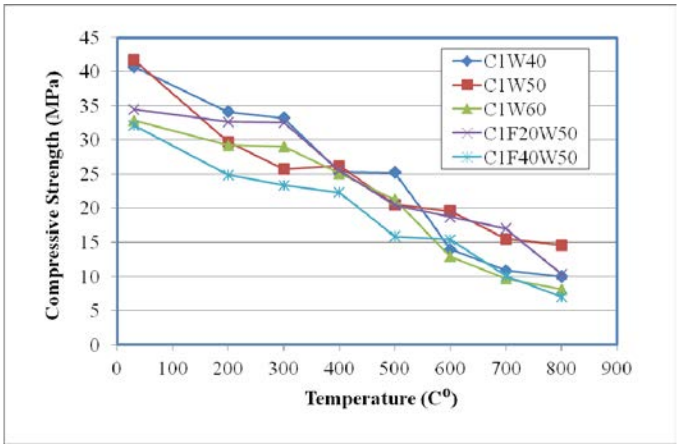
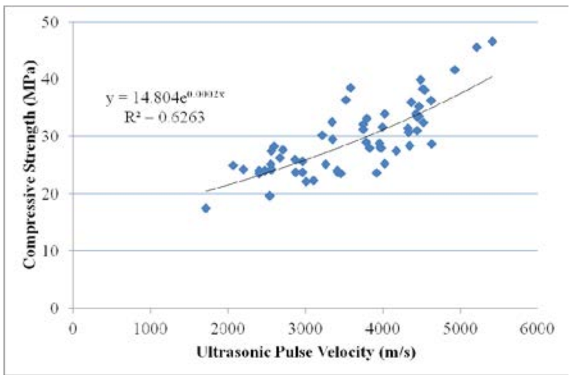
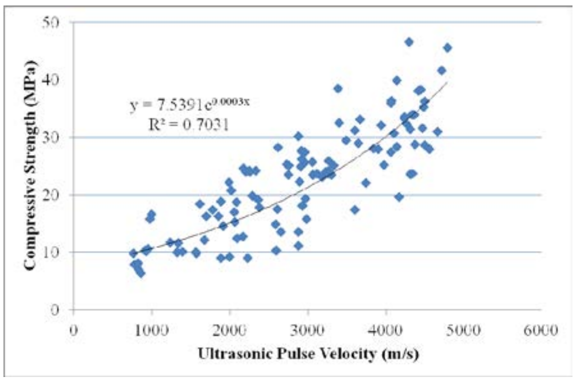
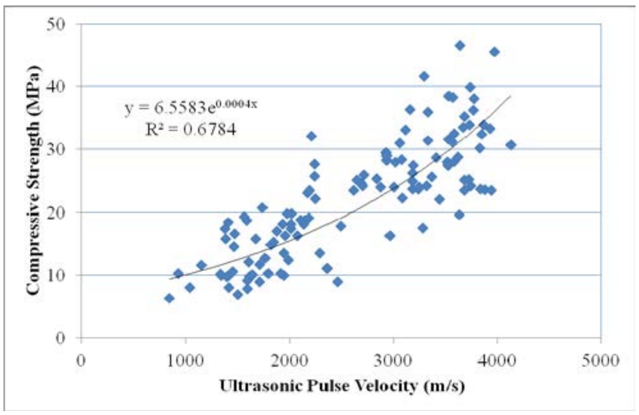


Figure 2 Relationship between compressive strength and exposure temperature.





(a) **(b)**



(c)

Figure 3. Relationship between compressive strength and ultrasonic pulse velocity for all data: (a) direct method; (b) semi-direct method;(c) indirect method.

Table 2. Statistical analysis of the regression models.

Method	R^2	**Regression model**
Direct	0.63	$y=14.804e^{0.0002x}$
Semi-Direct	0.70	$y=7.5391e^{0.0003x}$
Indirect	0.68	$y=65583e^{0.0004x}$

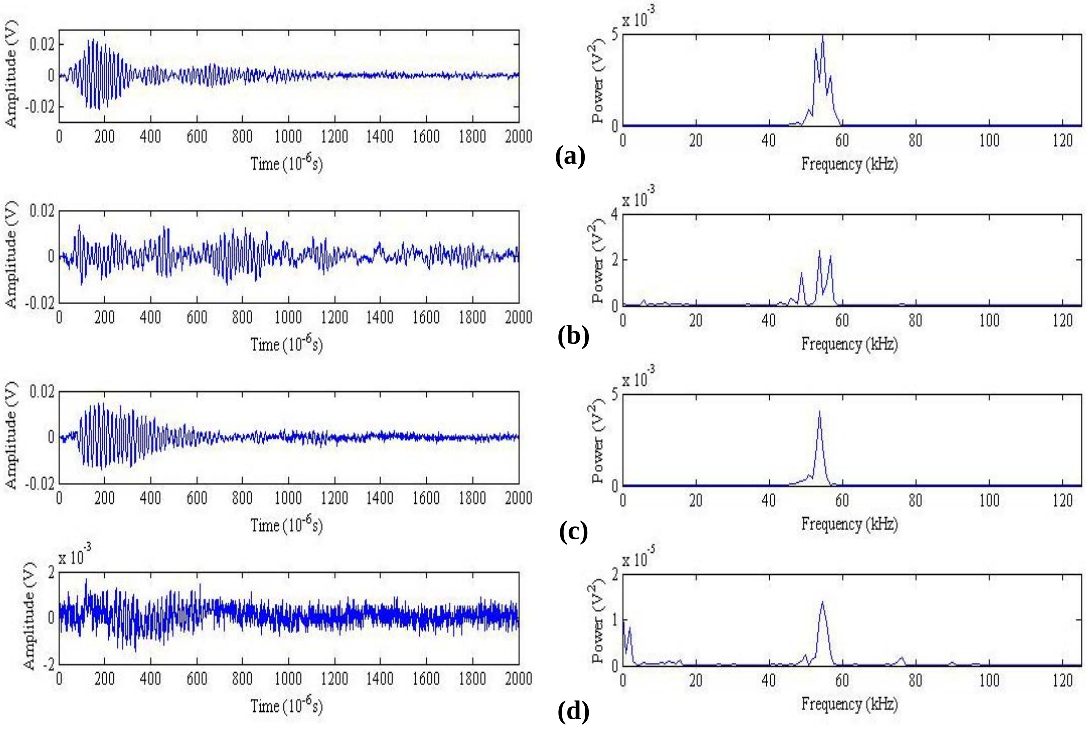


Figure 4. The ultrasonic waveforms and their FFT plots for semi-direct method of C1W60: (a) 200°C; (b) 400°C; (c) 600°C; (d) 800°C.

Frequency band-RMS analysis based on wavelet packet transform

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. The complete binary tree is produced as shown in the following Figure 5. The idea of this decomposition is to start from a scale-oriented decomposition, and then to analyze the obtained signals on frequency subbands. In this study, the name of wavelet packet are named by numbers of level and order enclosed in parentheses, for example, wavelet packet (3,0), (3,1), ..., and (3,7) respectively.

For ultrasonic signal, each waveform was decomposed to 32 wavelet packets, namely wavelet packet (5,0), (5,1),…, (5, 31) which are represented at frequency band [0-15.625], [15.625-31.25], …, [484.375-500] kHz, respectively. Frequencies up to 500 kHz were considered because the ultrasonic waveforms were acquired at sampling rate of 1 MHz. Obviously, the wavelet packet (5,0), (5,1), …, (5,7) correspond frequency band of 0-125 kHz which cover the ultrasonic signal frequency in this study and were used for waveform decomposition as shown in Figure 6. The family of Daubechies wavelets was chosen because it is compactly supported orthonormal wavelets, thus making wavelet packet analysis practicable.

The root mean square (RMS) of correspond wavelet packets were used to describe the changing feature of the ultrasonic waveforms which are influenced by the composition and damage of concrete.

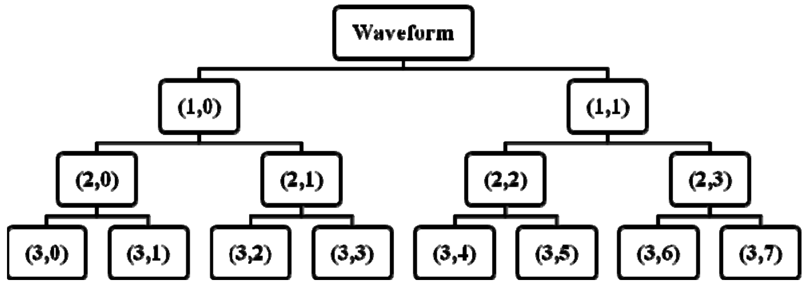


Figure 5. Wavelet packet decomposition tree at level 3.

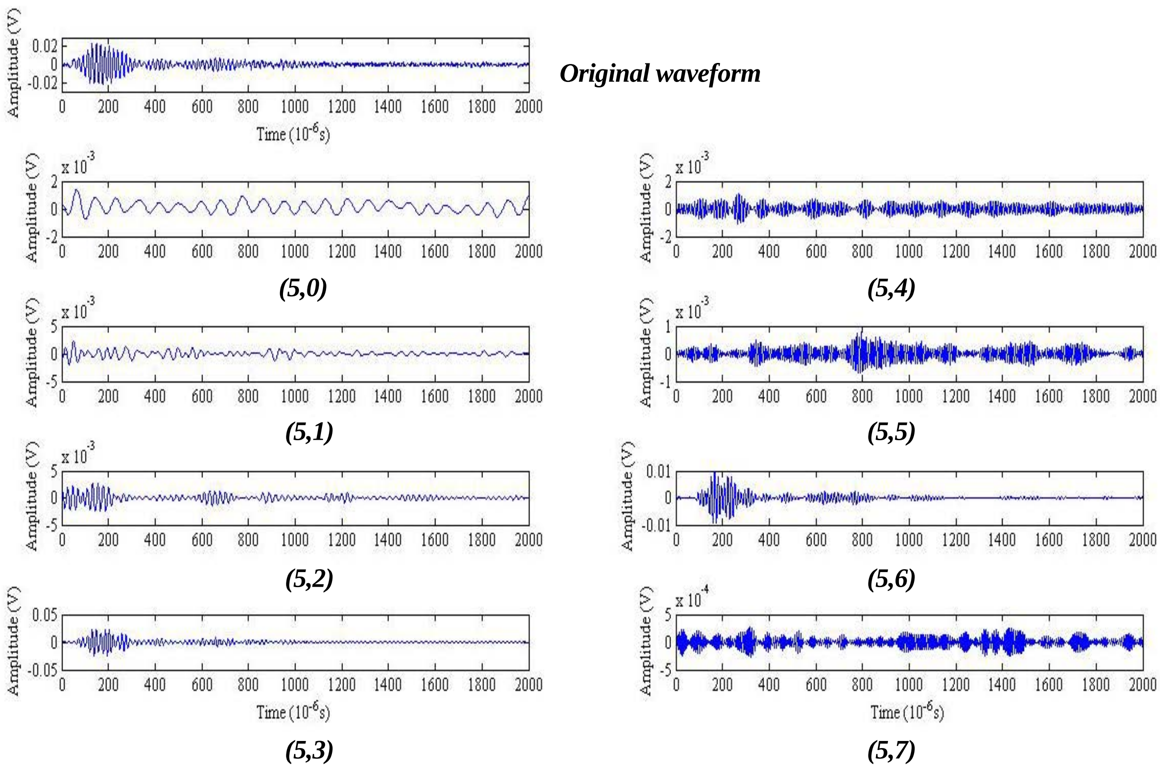


Figure 6. Five-level wavelet packet decomposition of ultrasonic waveform (semi-direct method of C1W60 exposed to 200^{o}C).

Neural networks

The architecture of a three-layer feed-forward neural network was used in this study. This neural network used a linear transfer function. The Bayesian regularization is used in training neural networks in order to obtain neural networks with good generalization capability. The structure of proposed neural network is shown in Figure

7. Input layer was modeled with 11 input features of 8 wavelet packet-RMS, W/C ratio, F/C ratio and ultrasonic pulse velocity. The output layer was represented by one output of compressive strength.

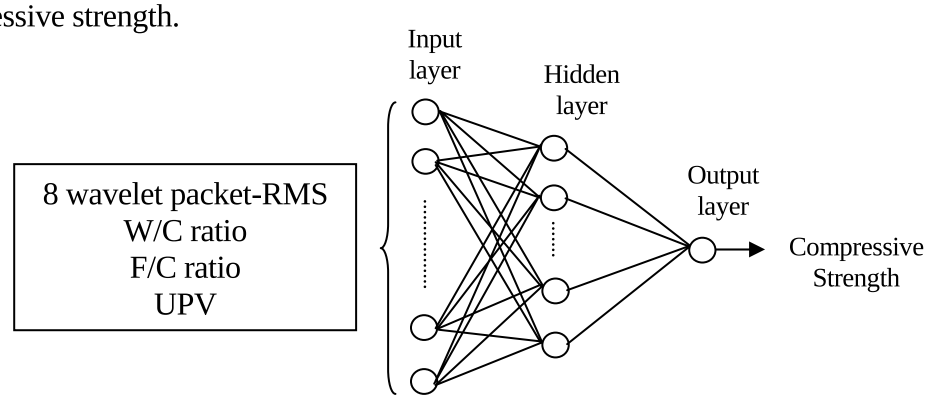
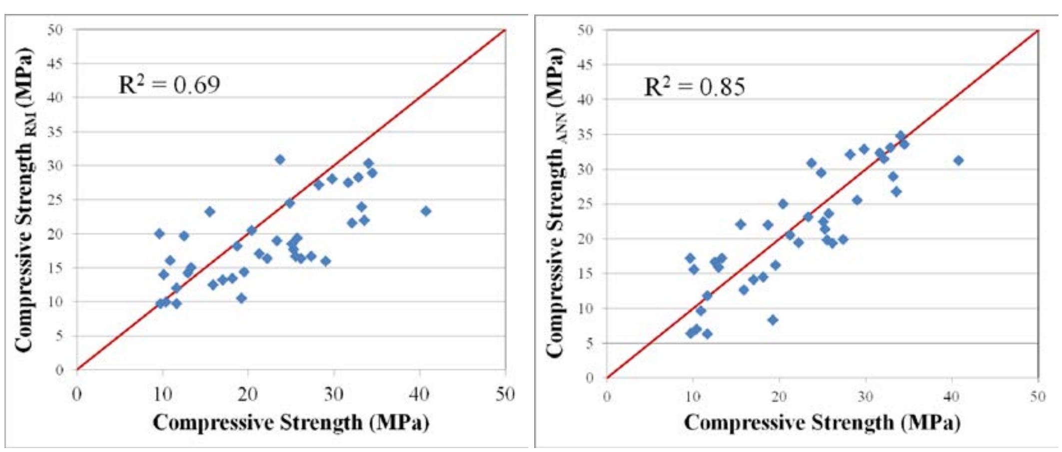


Figure 7. Feed-forward neural network architecture.

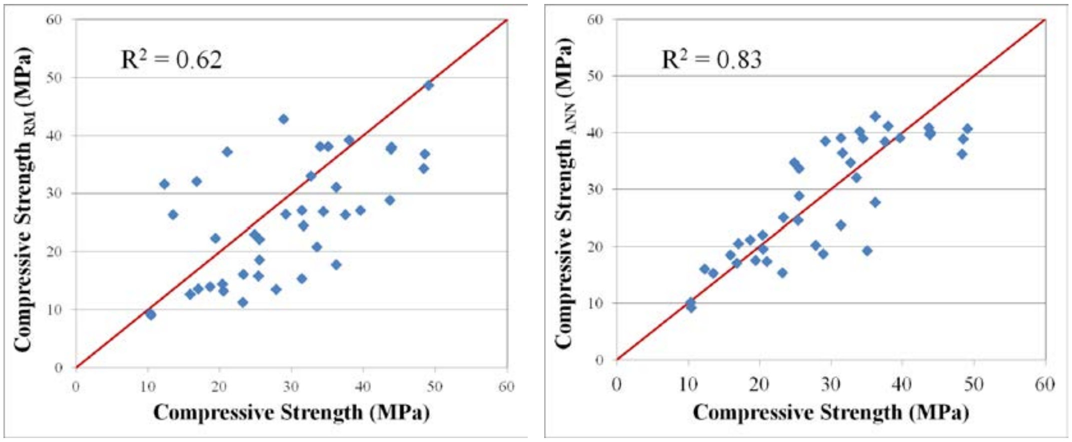
Each test forms a pattern of input and output parameters; such 120 patterns were used in the training phase of each ultrasonic testing method. There is no single rule to determine the optimum number of neurons in the hidden layer required for optimum performance. However, number of hidden layer neurons is usually found with trial-and-error approach. Consequently, the number of hidden neurons 9 and 10 were chosen for architectures of semi-direct and indirect method, respectively. The coefficient of correlation between actual and estimated value belonging to the training set were R^2 = 0.92 and 0.89 for architectures of semi-direct and indirect method, respectively. Forty additional specimens were prepared in order to validate proposed neural network model. The additional specimens were same five mixtures in Table 1. Eight concrete specimens were produced for each mixture proportion and were heated in an electric furnace at elevated temperatures of 200, 250, 350, 450, 550, 650, 750 and 800^{o}C.

Figure 8 and 9 show the correlation between CS-CS$_{RM}$ and CS-CS$_{ANN}$ values of both semi-direct and indirect method, respectively for additionally prepared concrete specimens. The significant difference between R^2 values between CS-CS$_{RM}$ and CS-CS$_{ANN}$ can be clearly observed in both indirect and semi-direct methods.



(a) **(b)**

Figure 8. Efficiency of the proposed model for additionally prepared specimens: (a) CS-CS$_{RM}$; (b) CS-CS$_{ANN}$ of semi-direct method.



(a) **(b)**

Figure 9. Efficiency of the proposed model for additionally prepared specimens: (a) CS-CS_{RM} ; (b) CS-CS_{ANN} of indirect method.

CONCLUSIONS

A three-layer feed-forward neural network with Bayesian regularization training was developed for predicting the residual compressive strength of concrete after exposing to elevated temperature. The performance of neural network architectures was tested and found to be sensitive to the input features. The ultrasonic signal features extracted by RMS-WPT analysis, W/C ratio, F/B ratio and pulse velocity as the input resulted in good performance at the coefficient of correlation between actual and estimated compressive strength of 0.85 and 0.83 for semi-direct and indirect method of ultrasonic testing, respectively. To expanding the range of suitability of proposed neural network, this neural network should be retrained with more pattern data of additional concrete proportions. Once the neural network was properly trained, it could be a powerful and reliable tool to solve the classification and pattern recognition problems of structural health monitoring applications.

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