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Artificial neural network model using ultrasonic test results to predict compressive stress in concrete

Jason Ongpeng[*1], Marcus Soberano[1a], Andres Oreta[1b] and Sohichi Hirose[2c]

[1]*Department of Civil Engineering, De La Salle University, Manila, Philippines*
[2]*Department of Civil Engineering, Tokyo Institute of Technology, Tokyo, Japan*

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Abstract. This study focused on modeling the behavior of the compressive stress using the average strain and ultrasonic test results in concrete. Feed-forward backpropagation artificial neural network (ANN) models were used to compare four types of concrete mixtures with varying water cement ratio (WC), ordinary concrete (ORC) and concrete with short steel fiber-reinforcement (FRC). Sixteen (16) 150 mm×150 mm×150 mm concrete cubes were used; each contained eighteen (18) data sets. Ultrasonic test with pitch-catch configuration was conducted at each loading state to record linear and nonlinear test response with multiple step loads. Statistical Spearman's rank correlation was used to reduce the input parameters. Different types of concrete produced similar top five input parameters that had high correlation to compressive stress: average strain (ε), fundamental harmonic amplitude (A1), 2nd harmonic amplitude (A2), 3rd harmonic amplitude (A3), and peak to peak amplitude (PPA). Twenty-eight ANN models were trained, validated and tested. A model was chosen for each WC with the highest Pearson correlation coefficient (R) in testing, and the soundness of the behavior for the input parameters in relation to the compressive stress. The ANN model showed increasing WC produced delayed response to stress at initial stages, abruptly responding after 40%. This was due to the presence of more voids for high water cement ratio that activated Contact Acoustic Nonlinearity (CAN) at the latter stage of the loading path. FRC showed slow response to stress than ORC, indicating the resistance of short steel fiber that delayed stress increase against the loading path.

Keywords: artificial neural network; linear ultrasonic test; nonlinear ultrasonic test; concrete; fiber-reinforced concrete

1. Introduction

In today's infrastructure development, structural health monitoring is crucial in assessing existing bridges against man-made and natural disasters. Accurate assessment after an event in preparation for repair, rehabilitation, or retrofitting is the common problem. Most of the existing structures are made out of complex material known as concrete. Concrete can be assessed in many ways where factors to be considered in the test are cost, time, idle period during assessment, and degree of uncertainty. Development of this accurate assessment can be made with rapid assessment using non-destructive testing. Non-destructive test in concrete is complex due to its inhomogeneous ingredients and its particle sizes which experiences clapping of cracks and friction present inside the material. In this paper, ultrasonic test is used as a non-destructive assessment in concrete under uniaxial compressive test in concrete cubes. This ultrasonic test method is divided into two tests, linear and nonlinear.

From references, there are numerous linear ultrasonic testing procedures in concrete. Past researches use combination of linear ultrasonic test using ultrasonic pulse velocity and rebound hammer to test on site strength of concrete (Breysse 2012). Another example is the combination of ultrasonic pulse velocity and ultrasonic pulse amplitude to predict the compressive strength of concrete (Liang and Wu 2002). Researchers use combinations to improve the prediction of the behavior of concrete. Still, ultrasonic pulse velocity is limited due to its insensitivity to the changes in load (Daponte *et al.* 1995). Previous researches also uses air-coupled impact echo, infrared, and sounding through chain drag method as a non-destructive method to test concrete (Oh *et al.* 2013).

In linear ultrasonic testing, the received waveform shares the same amplitude as that of the transmitted waveform. Thus, no harmonics is generated during linear ultrasonic testing. An illustration of this is the ultrasonic pulse velocity test (ASTM C597) wherein time of wave traveling a particular distance are the parameters measured during testing as shown in Eq. (1). This parameter is shown in Fig. 1 where the time to travel of the longitudinal wave from transmitter to receiver is used to compute the ultrasonic pulse velocity. It is worth noting that in this test, it is not essential to measure the wave amplitude. In other study, it is observed that cracks of size greater than 100 mm are the only ones detected by longitudinal ultrasonic pulses (Komlos *et al.* 1996). Further study claimed that cracks are undetectable especially if it is filled up with fluids.

In relation to Fig. 1, Peak to Peak Amplitude (PPA) of the received waveform is also used as a measurement in

∗Corresponding author, Assistant Professor
E-mail: jason.ongpeng@dlsu.edu.ph
[a]Student
[b]Professor
[c]Professor

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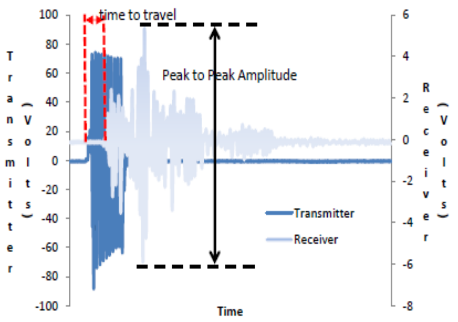


Fig. 1 Linear ultrasonic test using UPV and PPA in time-domain recorded from the transmitter and receiver

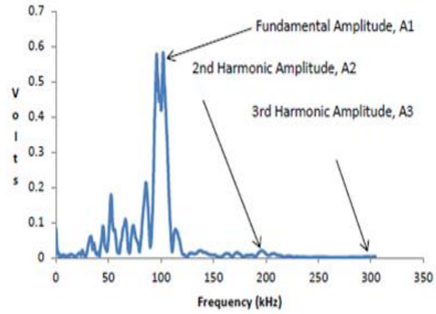


Fig. 2 Nonlinear ultrasonic test using higher harmonic generations A1, A2, and A3 in frequency-domain recorded from the receiver

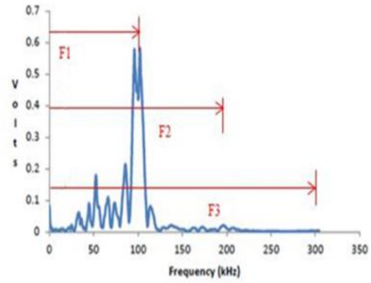


Fig. 3 Nonlinear ultrasonic test using frequency F1, F2, and F3 at each harmonic amplitude in frequency-domain recorded from the receiver

damage detection. Peak to peak amplitude can be taken from the time domain spectra. Peak to peak amplitude is the vertical distance from the highest point of the wave form to the lowest point of the waveform. In another study, PPA has also been one of the significant parameters in estimating the residual strength of concrete (Shah and Ribakov 2008) (Shah *et al.* 2012).

$$\text{UPV} = \text{distance of transmitter to receiver} \,/\, \text{time to travel} \quad (1)$$

For the aforementioned methods, nonlinear ultrasonic provides to be promising due to its sensitivity in damage and micro- crack detection. Nonlinear ultrasonic waves proves to be sensitively interacting with contact-type defects (Yim *et al.* 2012) (Shah and Hirose 2010a). This includes the opening/closing of cracks formed when loading and unloading occurs. Ultrasonic waves passing thru damaged concrete interacts with micro cracks that result to generation of higher harmonics. In particular, harmonic ratio generated from damaged concrete is sensitive to micro structural changes and micro-cracking in the interfacial transition zone (Shah and Ribakov 2009). Concrete mixture content also influences the generation of higher harmonics. Increase in water-cement ratio proves to be increasing the nonlinear parameter. From a previous study, third harmonic ratio is sensitive compared to the second harmonic ratio (Shah *et al.* 2009). In addition, 2nd higher harmonics become large, if crack opening displacement is small (Hirose and Achenbach 1993). The sensitivity of the A2 and A3 depends on the type of loading pattern as single loading pattern or multiple step loading pattern (Ongpeng 2016a). It is found out that 2nd harmonic amplitude is sensitive to any load pattern introduced for low and high water cement ratio. It is also suggested that the amplifier be triggered at high power level in experiments to produce better sensitivity in the higher harmonics generation (Shah *et al.* 2013). Advancement in non-destructive test uses combination of acoustic emission with nonlinear ultrasonic test in concrete to evaluate damage gives good relation in damage detection (Shah and Ribakov 2010b).

In this paper, nonlinear ultrasonic test method focused on spectral frequency analysis. Frequency domain graphs focused on harmonic generation that was used as parameters in the model. This was a phenomenon resulting from interaction between concrete and ultrasonic wave (Zheng *et al.* 1999). During this nonlinear interaction, a portion of the fundamental frequency gets converted to higher harmonics as shown in Fig. 2 where A1, A2 and A3 were observed. Harmonic generation will not occur without attenuation. Attenuation is the reduction in intensity in any kind of flux during its travel through a medium. Moreover, internal friction contributes to the attenuation. Higher harmonic generation occurrence is due to contact of crack interfaces called Contact Acoustic Nonlinearity (CAN) (Solodov *et al.* 2002) (Korshak, *et al.* 2002) (Solodov 1998) (Solodov *et al.* 2011). Opening and closing of cracks and/or frictional forces acting on the interfaces between cement paste and the aggregates were experienced when concrete was loaded. The higher harmonics generated depended on the behavior of the cracks forming inside when corresponding compressive load was applied (Solodov and Chin 1993). This non-classical acoustic nonlinearity in solids reveal subharmonic and harmonic generations, evident hysteresis, and instability effects. Concrete also contributed to complex behavior like dynamic characteristics where an amplitude jump right beyond the CAN threshold was evident.

Another method is the non-linear wave modulation spectroscopy (NWMS) which is centered on studying the non-linear wave mixing happening in the material (Johnson 2006). This method measures the modulation of the ultrasonic using a low frequency vibration. This method is best used in comparing damaged and undamaged materials. Additionally, non-linear resonant ultrasound spectroscopy (NRUS) is centered on measuring the shift of resonance frequency and the material dumping as a function of the

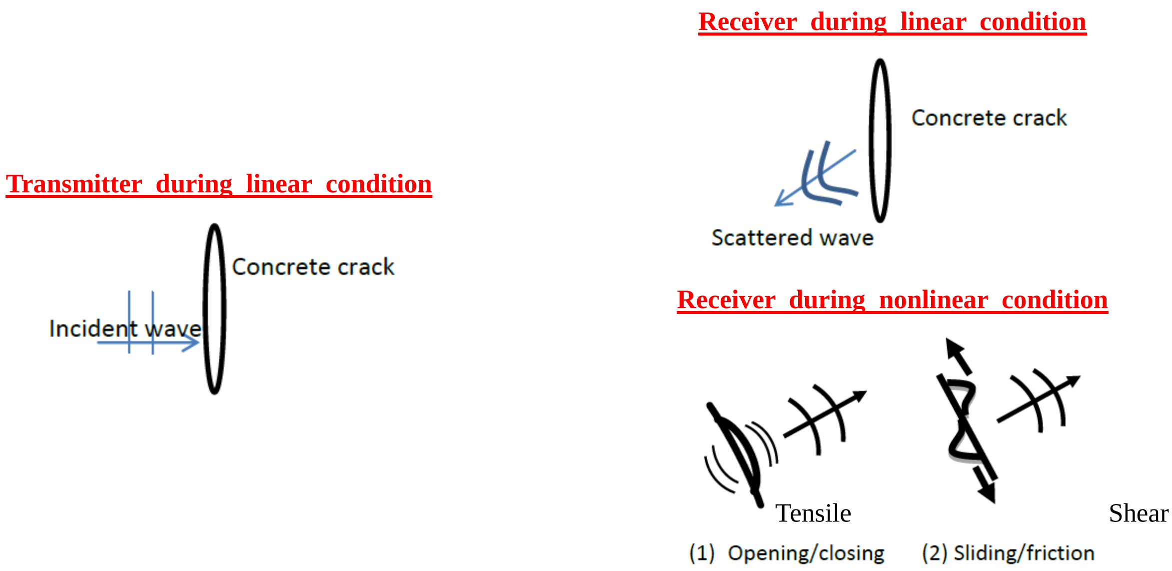


Fig. 4 Ultrasonic wave passing through concrete in linear and nonlinear condition

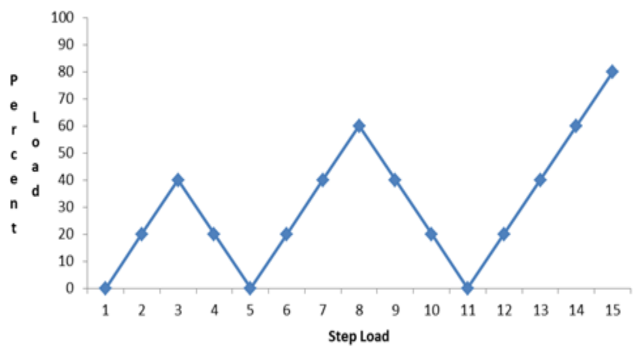


Fig. 5 Compression loading and unloading of specimen

Table 1 Design mix for the different materials

Item	Max. aggregate size (mm)	W/C (%)	Unit quantity (kg/m^3)				
			Cement	Sand	Gravel	Water-Reducing Agent	Fiber Content
ORC FRC	20mm	40 60	344	761	1038	0.69	ORC=0 FRC=78.5

resonance peak amplitude. The NRUS is a branch of the Resonant Ultrasound Spectroscopy (RUS) that is utilized in the industrial non-destructive evaluation. The shift of frequency is also used in this paper as a parameter to be considered as shown in Fig. 3 where F1, F2, and F3 and the changes of frequency corresponding to the maximum amplitude for A1, A2, and A3, respectively. In addition, micro-cracking corresponds to the non-linear softening of the modulus of elasticity with increasing level in resonance experiments which can be seen with strain as low as 10^{-8}. When the resonance frequency shifts, higher harmonics are produced and damping is observed (Van den Abeele *et al.* 2000). These phenomena can be observed significantly in damaged materials.

Determining the efficiency of linear and nonlinear ultrasonic showed that the wave attenuation and harmonic generation are sensitive to different damage level. It is proven experimentally that efficiency and sensitivity of nonlinear ultrasonic method to detect damages in concrete are higher than that of linear ultrasonic (like pulse velocity method) for all damage levels.

Seen in Fig. 4 is the incident wave and transmitted wave for two conditions. In linear condition, the incident wave when passing through cracks in concrete will be scattered. In nonlinear condition, as seen in this paper's experimental procedure, the transmitted wave reacted to two types of mechanism-opening/closing and sliding/friction of cracks.

Aside from microscopic and macroscopic scale damage level assessment, Nonlinear Mesoscopic Elastic (NME) theory can also be used in concrete. This is a scale in between micro and macro where dimensions are preferred by some researchers as vital to the study of concrete materials. Several important properties such as shift of resonance frequency, generation of higher harmonics, and the phenomenon known as slow dynamics (Johnson and Sutin 2005), can be observed in a heterogeneous material in this case, concrete. These effects are called non-classical non-linear where there are softer regions inside a hard material. Some examples of failure are micro cracks in soft bonding regions between grains. In particular, the presence of cement paste in concrete served as a soft bonding region binds with aggregates of different sizes together which serves as a hard material in the matrix. If external forces are applied to a concrete specimen, some weak joints may be broken since it is relatively weaker than the coarse aggregates. For weak joints, non-linear behavior sets in at an earlier stage. For strong joints, it behaves linearly and then non-linearly.

Artificial Neural Network (ANN) is a tool available in MATLAB that is capable of modelling nonlinear systems. It is a data mining tool that is based on the neural structure of the brain. This means that the ANN is modeled so that it can learn from experience. A Neural Network basically consists

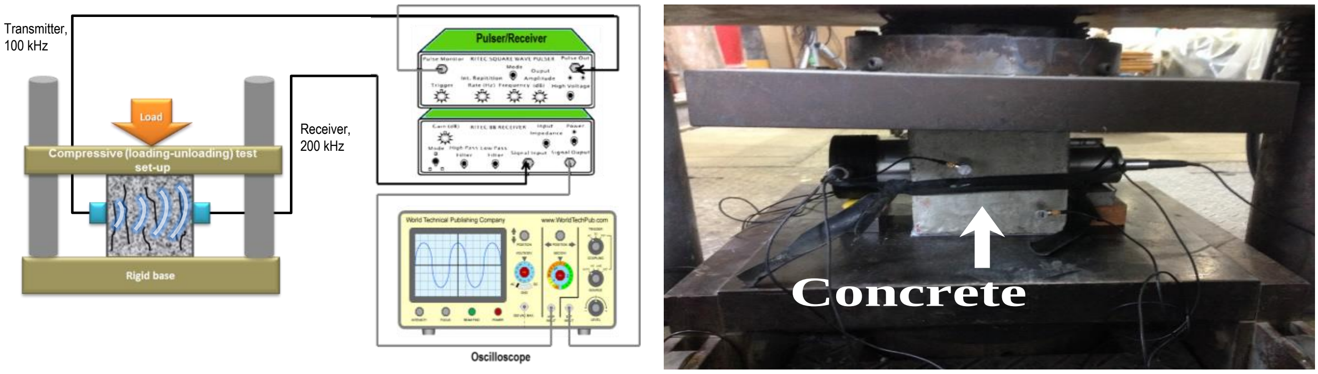
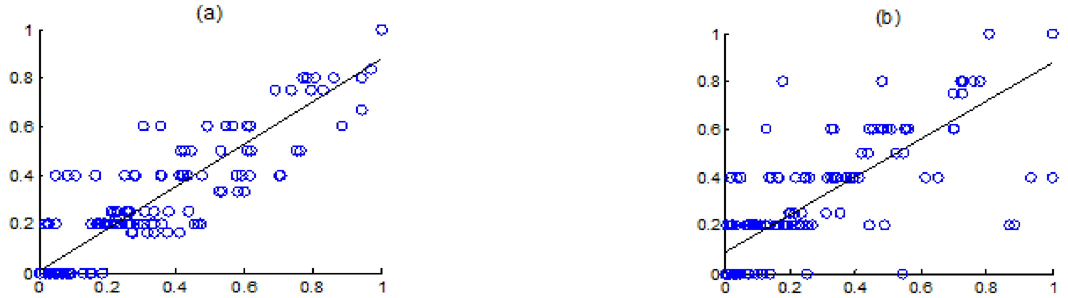


Fig. 6 Compressive testing procedure by loading and unloading setup using ultrasonic testing



(a) and (b) WC40 and WC60 normalized stress directly proportional to ε

(c) and (d) WC40 and WC60 normalized stress inversely proportional to A2

Fig. 7 Parameters with the highest spearman's rank correlation

of input layer, hidden layer and output layer. Each node from the input layer is connected to a node from a hidden layer and the node in the hidden layer is connected to the node in the output layer. Weights and Biases are present in each node connection. The higher the weights, the higher the impact of the input node. It uses algorithms in adjusting weights and biases and this process is called training. It determines the relationship of the input nodes and the output nodes of the model using transfer functions. It is used in modelling confined compressive strength of hybrid circular concrete columns (Oreta and Ongpeng 2011) and prediction of hybrid fibre-added concrete strength (Ali Demir 2015). There are also studies which focus on neural network algorithm development. An example is the study of decomposition techniques for multilayer perceptron training (Grippo *et al.* 2016). A fast and efficient method for training categorical radial basis function network is also studied (Alexandridis *et al.* 2016). The role of synchronized and chaotic spiking neutral ensembles in neural information processing (Rossello *et al.* 2014) and a neural network for learning the meaning of object and word from feutural representation (Ursino *et al.* 2015) are also being developed.

In this paper, average strain and linear/nonlinear ultrasonic test results were used as input parameters in the development of ANN models to predict stress in concrete. The ANN model was advantageous to generalize complex behavior of concrete combining its microscale, mesoscale, and macroscale properties. The ANN model learns from experimental data similar to a human brain learning from its experience. The input parameters initially considered were: strain (ε), Ultrasonic Pulse Velocity (UPV), Peak to Peak Amplitude (PPA), Fundamental Harmonic Amplitude (A1), Second Harmonic Amplitude (A2), Third Harmonic Amplitude (A3), Fundametal Frequency (F1), Second Harmonic Frequency (F2), and Third Harmonic Frequency (F3). Prior to ANN modeling, statistical Spearman' rank correlation was used to reduce the input parameters in the ANN modeling stage.

Table 2 Spearman's correlation coefficient

Correlation	WC40	WC60
Very strong	ε	
Strong		ε
Moderate	A1, A2, A3, PPA	A1, A2, A3, PPA
Very weak	UPV, F1, F2, F3	UPV, F1, F2, F3

2. Experimental procedures

A total of 16 cubic specimens were casted for concrete specimens. The size of the specimen is 150 mm×150 mm×150 mm. Specimens are designed at ultimate load of 900 kN and 1,200 KN for WC60 and WC40, respectively. The design of the multistep loading pattern is shown in Fig. 5. The sand-total aggregate ratio is 45%. Shown in Table 1 is the design mix for the four types of concrete.

A universal testing machine was used to subject each specimen through step loading after standard wet curing for 28 days. Simultaneously, at every step load, specimens were assessed using linear and nonlinear ultrasonic testing. In addition, two strain gauges were placed vertically along two faces of the concrete cube to measure its contraction against load. The designed step load was used to examine the behavior of the harmonics generated when crack opened and closed with load.

The experiment consisted of tone-burst pulser supplied with voltage amounting up to 1800 V. Its output was aimed to a single frequency which drove the nonlinear range response of the specimen. Another device used was the high gain broadband receiver that could be tuned to the desired frequency. This device effectively eliminated the noise frequencies that affect the recorded measurements. The pulser-receiver unit have built in modern facilities such as low pass filter set at 3 MHz and high pass filter set at 50 KHz, and input impedance of 50 Ω.

Transducers were connected to the tone-burst pulser and broadband receivers. It was carefully aligned, centered and bonded to the concrete specimen using a couplant. A transducer with 100 kHz generating frequency capacity was used to transmit the signal through the damaged concrete with a receiver of 200 kHz on the opposite end as shown in Fig. 6.

Four cube specimens were tested for each type of sample. In every step load, time-domain waveform data for each specimen were obtained from the ultrasonic test equipment. These were converted to frequency spectra using Fast Fourier Transform (FFT) to acquire the input parameters needed in this paper.

Shown in Fig. 7(a) and 7(b) are scatter plot of the linearly normalized stress strain for WC40 and WC60. This input parameter, strain, is considered since this shows the highest correlation among all other parameters that influence the stress. Additionally, it shows that the stress is directly proportional to the strain experienced in Fig. 7(a) and 7(b) experienced in the multiple step loading pattern as presented by the regression lines formed in the graphs. On the other hand, Figs. 7(c) and illustrates the second harmonic amplitude of WC40 and WC60. The A2 is

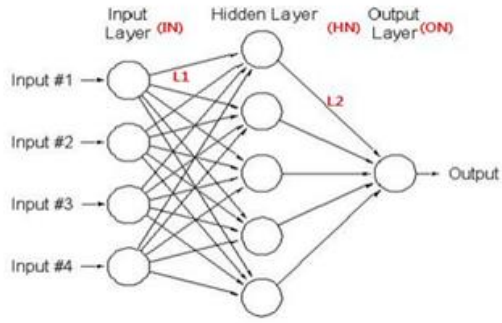


Fig. 8 ANN model with 4 IN-5 HN-1 ON with L1 and L2 as transfer functions

inversely proportional to stress as presented by the regression lines in each plot. The behavior of the datasets when stress is plotted according to single independent variable can be difficult to model using statistical regression due to wide spread of data sets. In this paper, ANN is used as a model that can be developed using multiple input parameters with non-linear relationship based from the training, validating, and testing stages.

3. Artificial neural network models

A previous study used ultrasonic testing and ANN was used to develop a model that would predict the residual strength of the concrete (Shah *et al.* 2012). The parameters used were peak to peak, strength of the concrete (*fc'*), velocity of the wave, input voltage, arrival time and water to cement ratio (WC). It was also observed in the parametric study that the voltage input, peak to peak and arrival time were the most significant parameters in predicting the residual strength of the concrete. The average pulse velocity which was used in the linear ultrasonic method did not appear to be important in the damage detection.

In this paper, multistep loading pattern was used to consider the damping effect of concrete when subjected to repeated load. The input parameters initially considered were: strain (ε), Ultrasonic Pulse Velocity (UPV), Peak to Peak Amplitude (PPA), Fundamental Harmonic Amplitude (A1), Second Harmonic Amplitude (A2), Third Harmonic Amplitude (A3), Fundamental Frequency (F1), Second Harmonic Frequency (F2), and Third Harmonic Frequency (F3). Prior to ANN modeling, statistical Spearman's rank correlation was used to reduce the input parameters in the ANN modeling stage. The software SPSS statistics was used in doing this process of pre-elimination. The Spearman's rank correlation was used because it measured the strength and direction of the monotonic relationship of the two parameters involved rather than their linear relationship. The Spearman's rank order correlation had already been used in studying the relationship of the input parameters to further support the result of the network (Osman *et al.* 2016) and it had also been used in selecting the input parameters that would be used in ANN to enhance the performance of the network. (Kumar and Anamika 2016). The parameters were arranged from highest

Table 3 Trained, validated, and tested ANN models for WC40 concrete

IN-HN-ON	IN parameters	X (varying HN)	L1	L2	Pearson correlation coefficient (R) Training data	Validating data	Testing data
4–xHN-1	ε A2 A3 ORC/FRC	3	LOGSIG	PURELIN	0.96	0.91	0.93
		4			0.95	0.93	0.95
		5			0.85	0.86	0.98
		9			0.94	0.96	0.92
5–xHN-1	ε A2 A3 PPA ORC/FRC	3			0.94	0.93	0.98
		4			0.93	0.95	0.96
		5			0.95	0.95	0.93
		6			0.94	0.95	0.96
		11			0.94	0.91	0.93
6–xHN-1	ε A1 A2 A3 PPA ORC/FRC	4			0.95	0.94	0.94
		5			0.94	0.97	0.93
		6			0.94	0.95	0.95
		7			0.96	0.98	0.93
		13			0.95	0.94	0.95
4–xHN-1	ε A2 A3 ORC/FRC	3	TANSIG	PURELIN	0.94	0.93	0.95
		4			0.95	0.94	0.86
		5			0.96	0.95	0.96
		9			0.95	0.94	0.95
5–xHN-1	ε A2 A3 PPA ORC/FRC	3			0.93	0.92	0.95
		4			0.94	0.96	0.98
		5			0.95	0.97	0.92
		6			0.94	0.94	0.96
		11			0.96	0.92	0.96
6–xHN-1	ε A1 A2 A3 PPA ORC/FRC	4			0.94	0.95	0.94
		5			0.95	0.98	0.85
		6			0.96	0.96	0.90
		7			0.95	0.92	0.87
		13			0.95	0.96	0.95

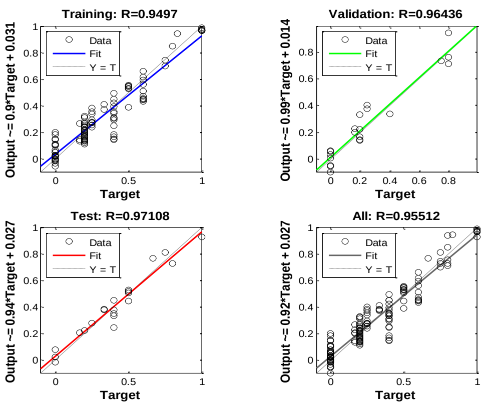


Fig. 9 Simulated output VS Target output for WC40

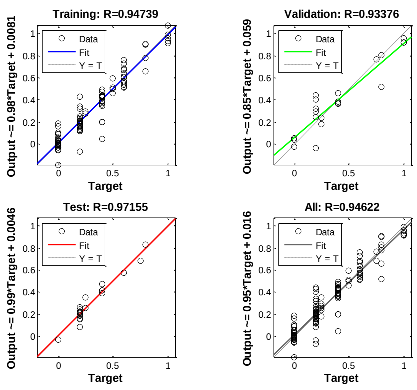


Fig. 10 Simulated output VS Target output for WC60

correlation to lowest correlation. It was observed that there was a strong correlation between the average strain (ε) and the stress. It is noticeable that A1, A2, A3, and PPA were moderately correlated with the stress. The parameters F1, F2, F3, and UPV had very weak correlation with the stress. All the weak correlation was discarded in the ANN modeling. The remaining input parameters that were used in training, validating, and testing the ANN model were ε,

Table 4 Trained, validated, and tested ANN models for WC60 concrete

IN-HN-ON	IN parameters	X (varying HN)	L1	L2	Pearson correlation coefficient (R)		
					Training data	Validating data	Testing data
4–xHN-1	ε A2 A3 ORC/FRC	3	LOGSIG	PURELIN	0.80	0.91	0.86
		4			0.87	0.89	0.86
		5			0.86	0.91	0.81
		9			0.84	0.83	0.89
5–xHN-1	ε A2 A3 PPA ORC/FRC	3			0.84	0.89	0.84
		4			0.90	0.88	0.91
		5			0.86	0.94	0.83
		6			0.86	0.78	0.93
		11			0.86	0.82	0.95
6–xHN-1	ε A1 A2 A3 PPA ORC/FRC	4			0.84	0.89	0.87
		5			0.88	0.91	0.93
		6			0.88	0.86	0.93
		7			0.90	0.89	0.94
		13			0.95	0.93	0.95
4–xHN-1	ε A2 A3 ORC/FRC	3	TANSIG	PURELIN	0.83	0.90	0.81
		4			0.85	0.76	0.86
		5			0.85	0.88	0.81
		9			0.89	0.91	0.92
5–xHN-1	ε A2 A3 PPA ORC/FRC	3			0.88	0.89	0.93
		4			0.85	0.93	0.88
		5			0.88	0.86	0.83
		6			0.82	0.91	0.89
		11			0.87	0.88	0.88
6–xHN-1	ε A1 A2 A3 PPA ORC/FRC	4			0.87	0.91	0.79
		5			0.90	0.93	0.90
		6			0.87	0.91	0.94
		7			0.93	0.92	0.94
		13			0.93	0.85	0.90

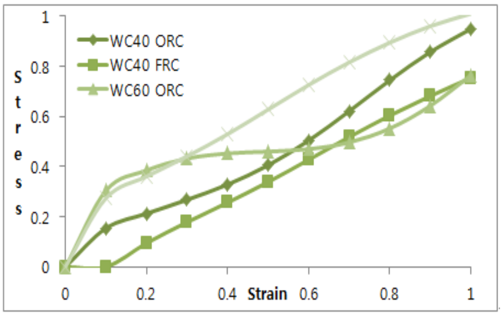


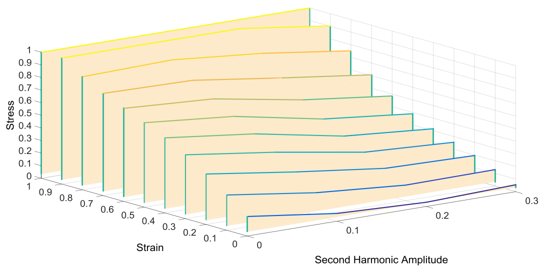
Fig. 11 Parametric study using the chosen model (Varying ε with constant input parameters)

PPA, A1, A2, and A3. Shown in Table 2 was the result of the Spearman's correlation ranking.

After the reduction of parameters, linear normalization of data was done. This normalization converted minimum values for each parameter as zero, and maximum values for each parameter as one. The reason for linear normalization was to eliminate the scale factor between parameters with small and large values. Artificial Neural Network (ANN) was then used as a tool that is capable of modelling nonlinear systems. It is a data mining tool that is based on the neural structure of the brain. This meant that the ANN was modeled so that it can learn from experience. A Neural Network basically consisted of input layer, hidden layer and output layer. Each node from the input layer was connected to a node from hidden layer and the node in the hidden layer was connected to the node in the output layer. Weights and biases were present in each node connection. To get the desired output, the weight of the node must be adjusted. It used algorithms in adjusting weights and biases under training stage where the performance goal was measured using mean square error. It determined the relationship the input and the output of the model using transfer functions.

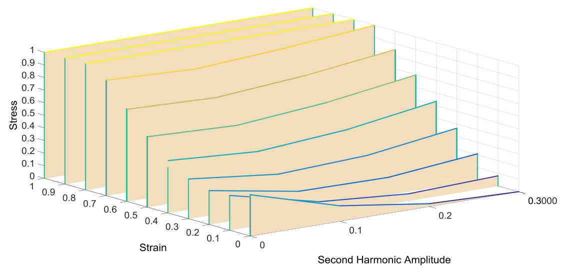
The ANN was utilized in numerous prediction problems many times in researches. The author used ANN in modelling the confined compressive strength of hybrid

(a) ORC40



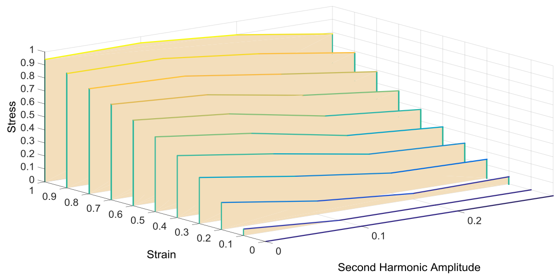
(a) 4-5HN-1 where A3 is constant at median value

(b) ORC60



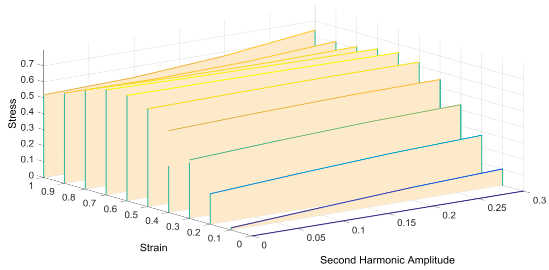
(b) 6-13HN-1 where A1, A3, PPA are constants at median value

(c) FRC40



(c) 4-5HN-1 where A3 is constant at median value

(d) FRC60



(d) 6-13HN-1 where A1, A3, PPA are constants at median value

Fig.12 Parametric study using the chosen model with varying strain and 2nd harmonic amplitude

circular concrete columns (Oreta and Ongpeng 2011) from previous studies which showed accurate prediction model tools. Recent studies also used ANN in the prediction of hybrid fibre-added concrete strength (Ali Demir 2015). A new method in determining the three point bending strength of concrete mortars in non-destructive manner was also predicted using ANN (Alexandridis *et al.* 2015). Estimation of the compressive strength of concrete using the ultrasonic pulse velocity and the ANN which can be used in health monitoring of concrete structures was also done (Bilgehan and Turgut 2010). Another study in damaged concrete was predicting the residual strength of concrete using non-linear ultrasonic testing and artificial neural network. Peak to peak, strength of the concrete (*fc'*), velocity of the wave, input voltage, arrival time and water to cement ratio (w/c) were the input parameters that were used in this study. In the results, the voltage input, peak to peak and arrival time were the most significant parameters in predicting the residual strength of the concrete. Shown in Fig. 8 is an example ANN model with 4 IN-5 HN-1 ON, where "IN" represented the number of input nodes, "HN" represented the number of hidden nodes, and "ON" represented the number of output node. The network architecture used in this paper was defined as "IN-HN-ON". Transfer function for each layer was also varied where "L1" is the 1st layer transfer function and "L2" is the 2nd layer transfer function. In particular, LOGSIG and TANSIG was varied in L1 to arrive at a model.

Data from the experiment were processed from eight cube specimens that contain 144 datasets per water cement ratio. In the neural network, the data were divided into training (60%), validating (20%) and testing (20%). When training networks, the training subset was used in updating the weights and biases of the network. The validation subset was used to validate that the network was generalizing. The validation subset was also used to stop the training of the network before overfitting. The testing subset was used to measure on how good the model could generalize. The network training function used in this paper was Levenberg-Marquardt optimization in updating the weight and biases with a target performance goal measured using mean square error. This function is one of the fastest backpropagation algorithms available. This algorithm was proven to give good results in mechanics of materials like quality control in resistance spot welding (Martin *et al.* 2007), prediction of the strength of mineral admixture concrete (Atici 2011), and predicting residual strength of non-linear ultrasonic evaluated damaged concrete (Shah *et al.* 2012). The ANN network when trained, validated, and tested to attain a performance goal produced stochastic results. Each run of the model produced unique weights and biases that were saved for further analysis.

Variation of the number of input nodes, hidden nodes, and transfer functions was done to come up with twenty-eight distinct models per WC ratio was trained, validated, and tested. The transfer function was varied for the first layer using TANSIG or LOGSIG, while the second layer transfer function was PURELIN.

Single hidden layer was used throughout the modeling in this paper to arrive at the simplest model in predicting compressive strength. Varying number of hidden nodes was designed to model as many possible networks. A previous study gave good estimate of the number of hidden nodes needed (Oreta and Kawashima 2003). It was suggested that it will be between the average and the sum of nodes on the input and output layers (Hecht-Nielsen 1998).

From the 28 ANN models trained, validated, and tested, a model was chosen for each WC having the highest Pearson correlation coefficient (R) in testing, and the soundness of the behavior for the input parameters in relation to the compressive stress of concrete. Some of the models had its R=0.98, but these models may tend to overfit. In order to avoid overfitting, the soundness of models was checked by having simulations attuned to theory. As an example, increasing axial strain led to increasing compressive stress. In this way, it prevented the trained ANN models to overfit even if it has the most desirable R. Shown in Tables 3 and 4 are the ANN model with transfer function at the first layer, R for the training, validating and testing data for WC40 and WC60, respectively.

Based from Table 3, model for WC40 is taken as 4 IN-5 HN-1 ON with L1 as TANSIG and L2 as PURELIN transfer function. This model has the highest Pearson correlation coefficient (R) in testing, and the soundness of the behavior for the input parameters in relation to the compressive stress of concrete. On the other hand, the model for WC60 as shown in Table 4 is 6 IN-13 HN-1 ON with L1 as LOGSIG and L2 as PURELIN transfer function. The highest R values in training do not arrive at models. The ANN model can overfit its data when R value in training is very high and R value in testing is relatively low.

In this paper, careful analysis of R values was used to arrive at models without overfitting of ANN to its datasets presented. As seen in Figs. 9 and 10 are the R values with residual errors. Residual errors of WC40 and WC60 for the training, validating, and testing data give a good measurement of the accuracy of ANN model in predicting non-linear relationship of parameters to determine the stress in concrete.

Based from the models, parametric study is used to analyze and compare the four types of concrete with the highest Spearman's rank correlation which is the strain. Seen in Fig. 11 is the behavior of increasing strain for models having other input parameters taken as the median of the dataset. It is noted that the WC40 FRC has delayed stress response and behaves linearly compared to the others. The WC60 ORC on the other hand behaves nonlinear than the rest. This indicates that the higher water cement ratio behaves nonlinear in its stress strain diagram.

Another parametric study is used to analyze and compare the four types of concrete. Seen in Fig. 12 is the behavior of the stress against the input parameters ε and A2. The other parameters in each corresponding chosen model is made constant using their median value. Strain is selected for the parametric study since it gives high correlation to all models, while A2 was chosen to be another parameter where previous studies show that A2 is sensitive to the changing load in concrete (Ongpeng *et al.* 2016a) (Ongpeng *et al.* 2016b). The models give good agreement to theory that increasing strain increases its stress. The varying A2 parameters are limited to the values 0 to 0.30. This is to prevent extrapolation of the prediction model out of the training data. In Fig. 12(a) and (c), it shows that low water-cement ratio with decreasing A2 in a particular strain level produces increase in stress. For high water-cement ratio seen in Fig. 12(b) and (d), changes in A2 in a particular strain level is not significant. In addition, all FRCs in low and high water-cement ratio show slow response to stress than the ORC. This indicates the resistance of short steel fiber that significantly delays stress increase.

4. Conclusions

The feed-forward backpropagation artificial neural network (ANN) models were used to compare four types of concrete mixtures with varying water cement ratio (WC), as ordinary concrete (ORC) and concrete with short steel fiber-reinforcement (FRC). The models showed promising results comparing four types of mixtures for the concrete cubes ORC WC40, ORC WC60, FRC WC40, and FRC WC60. Prior to ANN modeling, statistical Spearman's rank correlation was used to reduce the input parameters in the ANN model. In general, different types of concrete produced similar top five input parameters that had high correlation to compressive stress. These were average strain (ε), fundamental harmonic amplitude (A1), 2nd harmonic amplitude (A2), 3rd harmonic amplitude (A3), and peak to peak amplitude (PPA).

The model was chosen for each WC model having the highest Pearson correlation coefficient in testing, and the soundness of the behavior for the input parameters in relation to the compressive stress of concrete. The ANN model showed that increasing WC produced delayed response to stress at the initial stages, followed by abrupt response after 40%. This was due to the presence of more voids for high water cement ratio that activated Contact Acoustic Nonlinearity (CAN) at the latter stage of loading path. In addition, FRC showed slow response to stress than the ORC. This indicated the resistance of short steel fiber that significantly produced delayed stress increase against the loading path. Moreover, residual errors of WC40 and WC60 for the training, validating, and testing data gave a good measurement on the accuracy of ANN model in predicting non-linear relationship of the parameters presented to determine the stress in concrete.

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