Structural Engineering and Mechanics, *Vol. 74, No. 4 (2020) 559-565*
DOI: https://doi.org/10.12989/sem.2020.74.4.559

Displacement prediction of precast concrete under vibration using artificial neural networks

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(Received August 14, 2018, Revised May 14, 2019, Accepted January 4, 2020)

Abstract. This paper intends to progress models to accurately estimate the behavior of fresh concrete under vibration using artificial neural networks (ANNs). To this end, behavior of a full scale precast concrete mold was investigated numerically. Experimental study was carried out under vibration with the use of a computer-based data acquisition system. In this study measurements were taken at three points using two vibrators. Transducers were used to measure time-dependent lateral displacements at these points on mold while both mold is empty and full of fresh concrete. Modeling of empty and full mold was made using ANNs. Benefiting ANNs used in this study for modeling fresh concrete, mold design can be performed. For the modeling of ANNs: Experimental data were divided randomly into two parts such as training set and testing set. Training set was used for ANN's learning stage. And the remaining part was used for testing the ANNs. Finally, ANN modeling was compared with measured data. The comparisons show that the experimental data and ANN results are compatible.

Keywords: modeling; artificial neural networks (ANNs); precast concrete mold; compaction of fresh concrete; vibration

1. Introduction

Although a lot of efforts have been used to find different methods, vibration still remains the dominating procedure in molding and compacting concrete compositions. That is, external vibrators are commonly used in compacting fresh concrete in the production of precast concrete members.

The purpose of compaction is to get rid of the air voids that are trapped in loose concrete. Two types of vibrators are common on building sites-poker (immersion) vibrators and surface vibrators. The poker vibrator is the most popular of the appliances used for compacting concrete. This is because it works directly in the concrete. A third type is clamp-on vibrators (external vibrators). External vibrators consist of an electrically or pneumatically operated motor with an eccentric component. They work by vibrating the mold to which they are fixed. These vibrations are transmitted to the concrete. This vibrator is fundamentally for precast concrete work, but it is sometimes also used on site concrete, especially where there is congested reinforcement.

Wenzel (1986) examined principles, practices and some specific problems associated with compaction of fresh concrete. The study introduced that, vibrations of external vibrators used for concrete compaction in production of precast concrete products cannot penetrate deeper than 200 mm from the mold surface, so vibrators should be placed on both sides in cross-sections wider than this. He also defined that vibrators running at 6000 rpm, corresponding to a frequency of 100 Hz, represent a compromise, a sort of middle way in terms of technical equipment and of compaction achieved.

There is a limited number of theoretical and / or experimental studies in the literature to determine the behavior of fresh concrete subjected to vibration. In most of the studies, fresh concrete has been defined to be a non-Newtonian fluid and commit Bingham model without vibration. Tattersall and Baker(1988) stated flow behavior of non-vibrated fresh concrete by the Bingham model as follows

$$\tau = \tau_o + \mu\dot{\gamma} \tag{1}$$

where τ is shear stress, τ_o is yield stress, μ is plastic viscosity and $\dot{\gamma}$ is shear rate. Furthermore, they remarked that yield stress lost its value through measurements. Consequently, fresh concrete gained Newtonian fluid (zero yield stress) properties, and its plastic viscosity decreased. Shear strength characteristics of fresh concrete was studied by using a three-axis compression device by Alexandridis and Gardner (1981). Experimental results were compared by Mohr-Coulomb and Rowe shear strength theories. Comparing of "angle of internal friction" of fresh concrete by Mohr-Coulomb theory gave the result as a constant for concrete mix between 37°-41°. Analysis by Rowe theory indicated that this parameter is between 18°-21°. Larrard *et al.* (1997), using a device named 'BTRHEOM', indicated that yield stress of fresh concrete was halved under vibration, in some cases even was near zero. It also

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http://www.techno-press.com/journals/sem&subpage=7 ISSN: 1225-4568 (Print), 1598-6217 (Online)

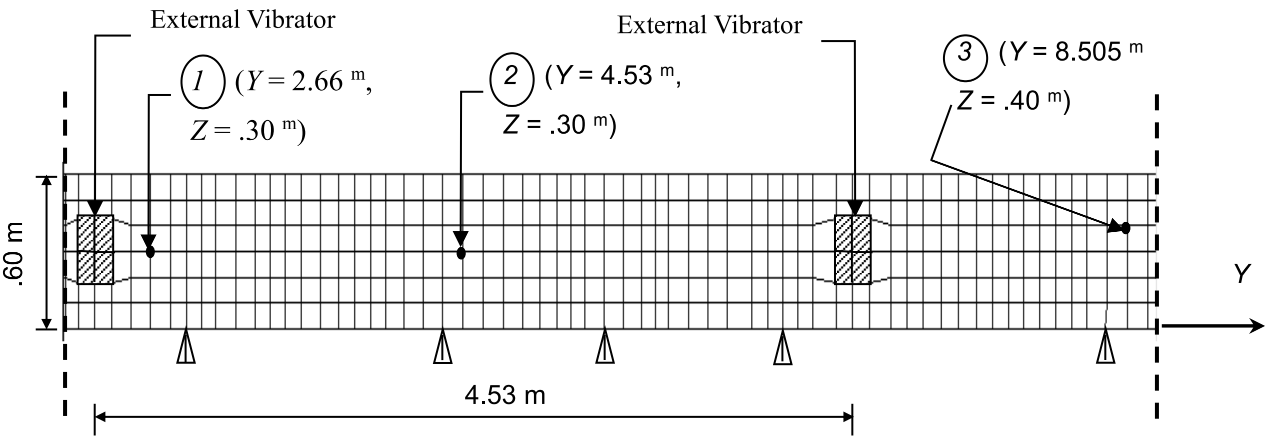


Fig. 1 Measurement surface of finite element mesh of Column mold (Y-Z Plane, X = .30 m)

remarked that plastic viscosity was not affected by vibration.

The “Poisson's ratio” of fresh concrete was described by an equation using a software named HIPERPAV by United States Department of Transportation (2003). Using this equation, Poisson's ratio was found between 0.40-0.42 in the plastic state. As a function of time, Poisson's ratio was described as follows

$$\upsilon(t) = -0.05\, ln(t + 1.11) + 0.425 \le 0.42 \qquad (2)$$

where t is time passed after preparation of concrete (hour). Thomas and Harilal (2014) stated the properties of fresh and hardened concrete made using three types of artificial cold bonded aggregates.

Experimental studies have shown that the sufficient compaction of the fresh concrete depends on configuration of the vibrators defined with number and location (two parameters) of external vibrators (Aktas *et al.* 2014). In the mentioned article, the fresh concrete is modeled using mass and time-dependent function for computer-aided mold design (CAMD). Aktas (2016) examined numerically the behavior of fresh concrete subjected to vibration using mass-spring model, and obtained results were compared with experimental data.

Nowadays, artificial neural networks (ANNs) are extensively applied in the field of structural elements due to their advantageous properties. Some significant studies can be listed as follows: Onat and Yon (2019) proposed a model to predict the missing eigenvector values with a robust Adaptive-Network Based Neuro Inference System (ANFIS) model to present failure mode of infill wall. Ashteyat and Ismeik (2018) proposed a model that is an efficient approach to estimate the residual compressive strength of self-compacted concrete as a substitute for sophisticated laboratory procedures. Cascardi *et al.* (2017) proposed a model might be used for an accurate prediction of the compressive strength of Fiber Reinforced Polymers-confined concrete. Chithra *et al.* (2016) proposed an ANN model to predict the compressive strength of High Performance Concrete containing nano silica and copper slag as partial cement and fine aggregate replacement respectively. The model results were compared with Multiple Regression Analysis results. Zhou *et al.* (2016) proposed the use of ANN sand adaptive neuro-fuzzy i nference systems for estimating the compressive strength of hollow concrete block masonry prisms.

Kao and Yeh (2014) expressed that there had been many packages that could be employed to analyze plane frames. They recommended a possible alternative, DAMDO, which integrate Design, Analysis, Modeling, Definition, and Optimization phases into an integrative environment. The DAMDO methodology utilizes neural networks to integrate structural analysis package and optimization package so as not to need directly to integrate these two packages. Demir (2015) studied the compressive and bending strengths of hybrid fibre-added and non-added concretes using ANNs.

The main goal of this paper is to provide a new approach using ANNs for behavior of fresh concrete subjected to vibration in precast concrete elements. This paper contains experimental and numerical studies. The experimental studies were carried out in the production workshop of Kambeton Company (Adana/Turkey). ANNs modeling were used to simulate the behavior of the fresh concrete in full scale test specimen. In this study, the ANNs results for mold displacement data under vibration are compared with the measured data.

2. Experimental study

In the content of current study, a full scale mold of precast concrete member having geometry of real sizes was utilized. The view of the mold (Column) used in the experiment is shown in Fig. 1 (Aktas, 2016). 1, 2 and 3 points are measurement points in Fig. 1. The length and height of Column mold is 9.0 m and 600 mm. Using this mold, manufacturing was made for real engineering applications in the precast concrete production workshop. The mold used for test specimen is made of steel plates of 5 mm thickness. Steel profiles in various size and sections are connected to the mold in horizontal, vertical and diagonal directions in order to strengthen the system. Boundary conditions of Column mold is given by Aktas (2016).

The external vibrator employed in the experiment is attached to a steel plate having dimensions of 200x250 mm. The cyclic frequency of the external vibrator utilized in this

Table 1 Specifications of external vibrator

Mechanical Features					Electrical Features	
Vibrat. range	Centrifugal force		Weight	Max. input power	Max. current A (100Hz)	
Vibr./min	kg	kN	Kg	W	42V	250V
6000 (200 Hz)	1157	11.30	25	1200	23	-

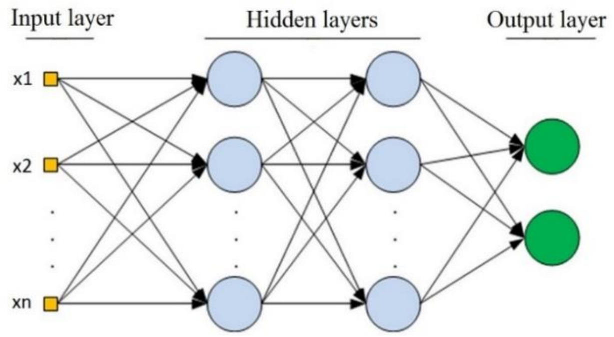


Fig. 2 Structure of ANN model

study is 100 Hz. The properties of the external vibrator are given in Table 1.

Experimental measurements were made at the surface of the mold vibrated by two vibrators for a precast concrete element using a computer based data collection system. Measurement locations were selected near and away from the vibration points to see their differences and effects. The calibration of the displacement transducer was performed using a dial gauge with a sensitivity of 0.01 mm. Displacements measured by the transducers were recorded simultaneously with 0.5 ms (millisecond) of sampling rate for a duration of 4.096 sec. Data collection system including instrumentation, hardware and software utilized in this study is given in detail (Aktas e tal., 2014; Aktas and Karasin, 2014).

3. Model determination with Artificial Neural Networks (ANNs)

ANNs are data processing systems inspired by the way the human brain functions and are used to model complex relationships between inputs and outputs. ANN is basically made of simple processing units (neurons) which are identified as the highly interconnected processing constituents acting altogether to achieve a specific problem (Khademi and Jamal, 2016). An ANN model consists of number of interconnected group of processing units, each of which is fully connected to the through connection weights and receives an input signal from processing units linked to it. Generally, ANNs are used in complex problems where the customary computational techniques are not efficient enough to resolve them (Khademi *et al.*2016).The structure of ANNs is layered such as input, hidden and output layers. The general structure of ANN is shown in Fig. 2.In this structure, information is transmitted from input to output layer, along with which learning process is conducted to minimize the deviation between the actual values and output values (Duan *et al.* 2013). The back-propagation (BP) is one of the most popular learning algorithms andis based on minimization of the quadratic cost function by tuning the network parameters. If the ANN correctly determines the training data and correctly identifies the testing data, it is considered that the learning stage of the ANN is completed (Aktas and Ozerdem, 2016). For testing the accuracy of the trained network, the mean square error (MSE) and the correlation coefficient (R^2) can be used. MSE and $R^2$are computed by Eq. (3) and Eq. (4), respectively.

$$MSE = \frac{1}{p}\sum_{i}(t_i - o_i)^2 \tag{3}$$

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right) \tag{4}$$

where t and o are the predicted and actual output of network, respectively, and p is the total number of training and testing patterns (Erdem 2010).

4. Prediction of behavior of fresh concrete with proposed ANNs model

In this study, ANN model was employed to predict the behavior of fresh concrete exposed to vibration. For the proposed network, time information was used as an input parameter and mold displacement data under vibration is used as the output parameter. The structure was designed with one hidden layer. In this manner, the structure of ANN becomes 1xnx1, where n is the number of neurons in the hidden layer. Hidden layer makes the ANN structure more flexible for the model. However, there is no any rule for determining the number of hidden layer and the number of neurons in the hidden layer(s). So, these parameters are usually determined via trial and error procedures or suggested rules. In this research, different ANN architectures were created and tested using neuron numbers in hidden layer from 5 to70 with the increment value of 5. The proposed ANN model is shown in Fig. 3.

ANN model was used to estimate the behavior of fresh concrete under vibration in three points using two vibrators as shown in Fig.1. There are two models created with respect to concrete form for each point as shown in Table 2.

Time-dependent lateral displacements were measured at three points and these measured values called patterns were used for training network. Separating data into training and testing sets is an important part of evaluating data in ANN models. The experimental data set includes 1000 patterns, of which 500 patterns were used for training the network and remaining patterns were selected randomly to test the performance of the trained network. Data normalization is the process of transforming all variables in the data to a specific range. So, all the input and output values of data sets were normalized between 0.01 and 0.99 by using linear scaling. The tan-sigmoid and log-sigmoid transfer functions were used in the hidden and output

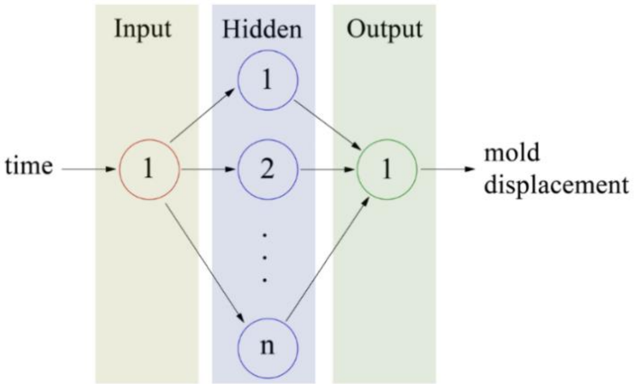


Fig. 3 Proposed structure of ANN Model. Number of Neurons in Hidden Layer Is N=5:5:70

Table 2 Labels of modeling points with Concrete form

Place	Concrete Form
Point 1	With concrete
Point 1	Without concrete
Point 2	With concrete
Point 2	Without concrete
Point 3	With concrete
Point 3	Without concrete

layer, respectively. It is observed that MSE decreased with increasing number of iteration during the training period.

To minimize training error in this study, different training algorithms such as scaled conjugate gradient (trainscg), resilient back propagation (trainrp) and Levenberg-Marquardt back-propagation (trainlm) were used and the best result was obtained with the trainlm training algorithm. The same performance of the trainlm training algorithm was obtained in the previous study (Aktas and Ozerdem, 2016). In the mentioned article, measurements had been taken at two points using a vibrator. In this study, unlike the previous study, measurements were taken at three points employing two vibrators. So, the result of trainlm training algorithm was presented in this paper. More detailed information about training algorithms can be found (Beale 2014).

The values of network parameters considered in this approach are as follows: Number of hidden neurons=5:5:70, learning rate=0.1, learning cycle=5000 and default learning momentum values (mu_dec=0.1, mu_inc=10, mu=0.002) were used. Each ANN structure was repeated 20 times because of that initial weights are randomly selected before learning stage by software. To get the accuracy result, this trial process was repeated and the best performances of ANN structures with different number of hidden neurons were determined.

For the testing set, the relationship between the number of hidden neurons and MSE is illustrated in Fig.4(a). Also, the relationship between the number of hidden neurons and R^2 is illustrated in Fig. 4(b). The both Figures showed that the performance increases with increasing of hidden neurons. So, in the testing stage, the ANN structures having best performances for predicting the mold displacement is illustrated in Table 3. As shown in the table, the correlation coefficient is in the range of (0.8815 - 0.9947) for the testing stage. It is clear to point out from the performance and generalization capacity of ANN that the proposed model is consistent to predicting the mold displacement.

Table 3 In testing stage, the ANN structures having best performances for predicting the mold displacement

Data	ANN structure having the best performance	min. MSE	R2
Point 1 without concrete	1x70x1	0.0060	0.9578
Point 1 with concrete	1x70x1	0.0012	0.9947
Point 2 without concrete	1x70x1	0.0052	0.9649
Point 2 with concrete	1x70x1	0.0076	0.9398
Point 3 without concrete	1x70x1	0.0101	0.8815
Point 3 with concrete	1x65x1	0.0032	0.9789

Comparison of the experimental data of mold displacement with the predicted mold displacement is made and shown in Fig. 5 as scatter-plots. It can be seen from the scatter diagrams that the slope and intercept of the regression equations for the outputs are significantly near to 1 and 0, respectively.

The relationship between experimental and predicted mold displacement obtained from ANN model is illustrated in Fig. 6.

5. Results and discussion

The aim of this section of the paper is to examine, discuss and compare the results obtained from experiments and ANNs model. As previously mentioned, developed ANNs model were tested with experimental data.

The ANNs models were created for three points both with concrete and without concrete cases. The best ANNs models were determined for point 1 – with and without concrete, point 2 – with and without concrete and point 3 – with and without concrete.

The correlation coefficient of point 1 with concrete model has the highest performance among the models. On the other hand, the correlation coefficient of point 2 without concrete model has the highest performance among the models having without concrete. The correlation coefficients are obtained as 95.78% and 99.47% at point 1 without concrete and at point 1 with concrete respectively. The correlation coefficients are obtained as 96.49% and 93.98% at point 2 without concrete and at point 2 with concrete respectively. The correlation coefficients are obtained as 88.15% and 97.89% at point 3 without concrete and at point 3 with concrete respectively (Table 3). These values indicate that the proposed ANN models are successful and the test results also show that the generalization ability of ANNs are well.

For the testing set, mean square error was decreased while the number of hidden neurons were increased. And

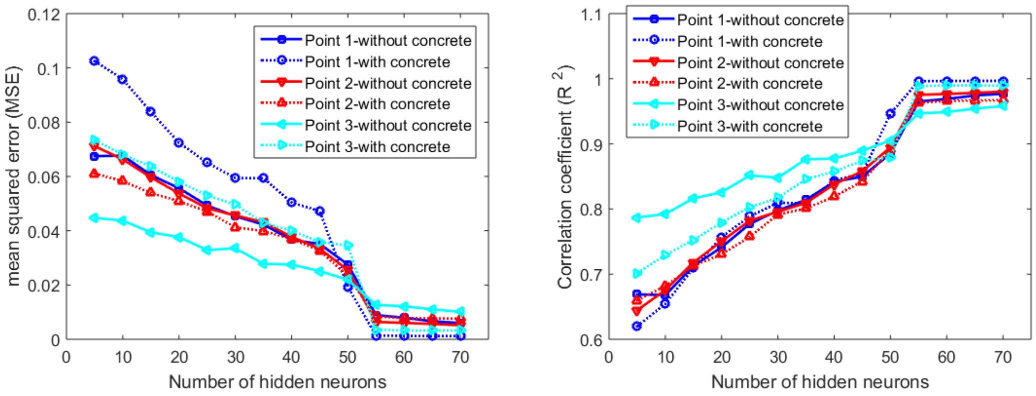


Fig. 4 The Performance of ANN structures with different number of hidden neurons. Each result in the graph is the best result for its ANN structure determined over 20 Trials. (A) Changing of MSE with respect to number of hidden neurons (B) Changing of coefficient with respect to number of hidden neurons

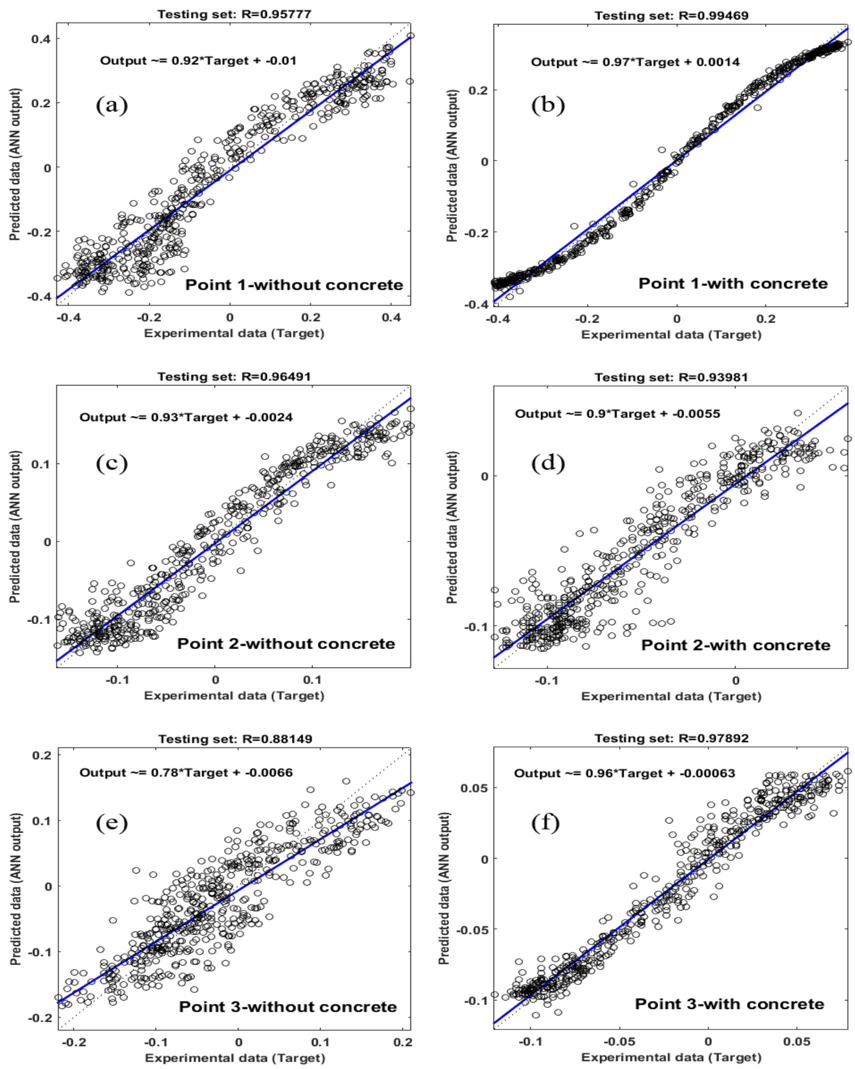
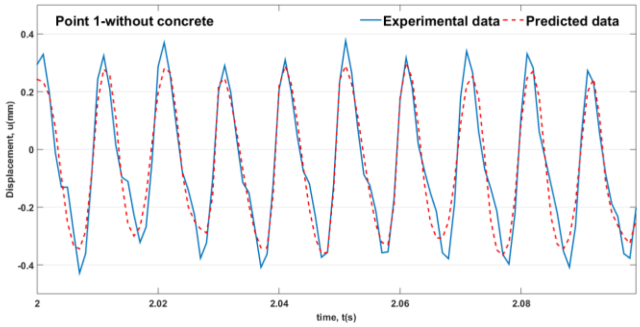
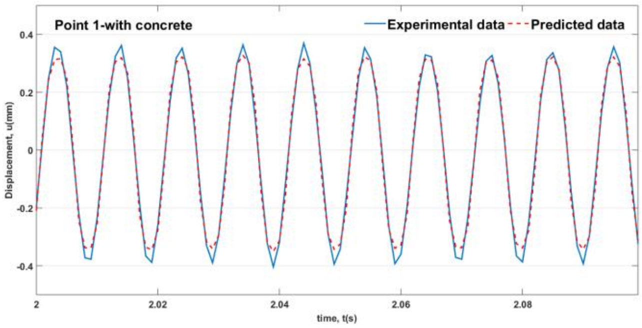


Fig. 5 Comparison of experimental and predicted mold displacement data in the testing stage

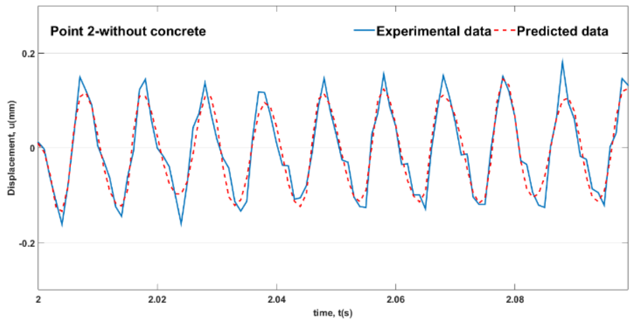
also, correlation coefficient was increased while the number of hidden neurons were increased. So, the performances of ANN models increase with increasing of hidden neurons. The best model of ANNs was observed as 1x65x1 for point 3 with concrete and the best model of ANNs was 1x70x1 for the remain points such as point 1 with concrete, point 2 with and without concrete and point 3 without concrete.



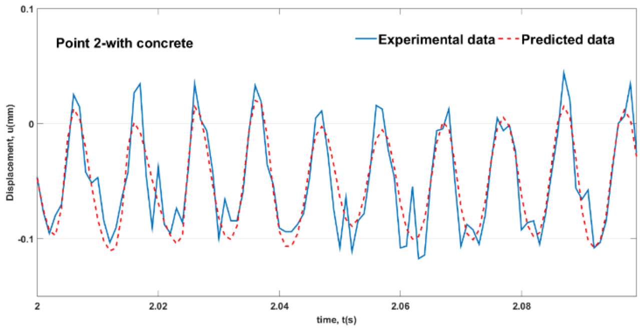
(A)



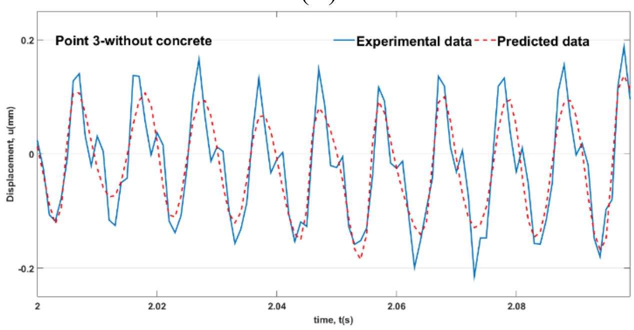
(B)



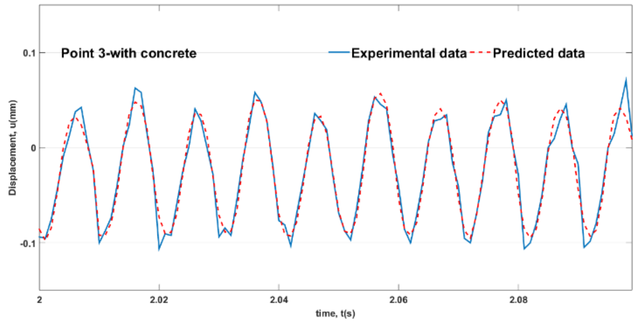
(C)



(D)



(E)



(F)

Fig. 6. Comparison of experimental and predicted mold displacement data in the testing stage (A,B,C,D,E,F).

6. Conclusions

The aim of this paper is to develop a model for predicting the behavior of fresh concrete exposed to vibration using ANNs. Time-dependent lateral displacements were measured at three points on mold while both mold is empty and full of fresh concrete, using 1000 experimental data for this study.

It was concluded that the ANN models used in this study gives good accuracy of prediction for the behavior of fresh concrete exposed to vibration.

This study aims to demonstrate that the behavior of different materials can be modeled with the use of ANNs. Taking advantage of ANNs used in this study for modeling fresh concrete, mold design can be performed.

The predicted values based on ANN model were compared with time-dependent lateral displacements values. The comparisons show that the experimental data and ANN results are compatible.

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