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Prediction of behavior of fresh concrete exposed to vibration using artificial neural networks and regression model

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Abstract. This paper aims to develop models to accurately predict the behavior of fresh concrete exposed to vibration using artificial neural networks (ANNs) model and regression model (RM). For this purpose, behavior of a full scale precast concrete mold was investigated experimentally and numerically. Experiment was performed under vibration with the use of a computer-based data acquisition system. Transducers were used to measure time-dependent lateral displacements at some points on mold while both mold is empty and full of fresh concrete. Modeling of empty and full mold was made using both ANNs and RM. For the modeling of ANNs: Experimental data were divided randomly into two parts. One of them was used for training of the ANNs and the remaining part was used for testing the ANNs. For the modeling of RM: Sinusoidal regression model equation was determined and the predicted data was compared with measured data. Finally, both models were compared with each other. The comparisons of both models show that the measured and testing results are compatible. Regression analysis is a traditional method that can be used for modeling with simple methods. However, this study also showed that ANN modeling can be used as an alternative method for behavior of fresh concrete exposed to vibration in precast concrete structures.

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

1. Introduction

Although numerous endeavors have been used to find alternative methods, vibration still remains the dominating procedure in molding and compacting concrete compositions. Namely, external vibrators are commonly used in compacting fresh concrete in the production of precast concrete elements.

The aim 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

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component. They work by vibrating the formwork to which they are fixed. These vibrations are transmitted to the concrete. This vibrator is mainly for precast concrete work, but it is sometimes also used in cast-in-place concrete, especially where there is congested reinforcement.

Wenzel (1986) investigated principles, practices and some specific problems related to compaction of fresh concrete. The study revealed 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, thus vibrators should be placed on both sides in cross-sections wider than this. He also stated 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.

In the literature, there are available a limited number of theoretical and/or experimental studies aiming to determine the behavior of fresh concrete exposed to vibration. In most of the studies, fresh concrete has been described to be a non-Newtonian fluid and commit Bingham model without vibration. Tattersall and Baker (1988) defined flow behavior of non-vibrated fresh concrete by the Bingham model given below as

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

where τ is shear stress, τ_o is yield stress, μ is plastic viscosity and $\dot{\gamma}$ is shear rate. Moreover; they indicated that yield stress lost its value through measurements, therefore; fresh concrete gained Newtonian fluid (zero yield stress) properties, and its plastic viscosity decreased.

Alexandridis and Gardner (1981) investigated shear strength characteristics of fresh concrete by using a three-axis compression device. Experimental results were analyzed by Mohr-Coulomb and Rowe shear strength theories. Analysis of "angle of internal friction" of fresh concrete by Mohr-Coulomb theory gave the result as a constant for concrete mix between 37^o-41^o. Analysis by Rowe theory showed that this parameter is between 18^o-21^o. Larrard, Hu *et al*. (1997), using a device called 'BTRHEOM', showed that yield stress of fresh concrete was halved under vibration, in some cases even was close to zero. It also pointed out that plastic viscosity was not affected by vibration.

United States Department of Transportation (2003) described the "Poisson's ratio" of fresh concrete by an equation using a software called HIPERPAV. Poisson's ratio was found between 0.40-0.42 in the plastic state. As a function of time, Poisson's ratio was described by using following equation

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

where t is time passed after preparation of concrete (hour). Thomas and Harilal (2014) determined 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, Tanrikulu *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) investigated numerically the behavior of fresh concrete exposed to vibration using mass-spring model, and obtained results were compared with experimental data.

There are some studies performed in recent years related to structural elements using artificial neural networks (ANNs). Garzón-Roca, Adama *et al*. (2013) investigated the load eccentricity, wall slenderness ratio and stiffness and masonry tensile strength for estimation of the axial

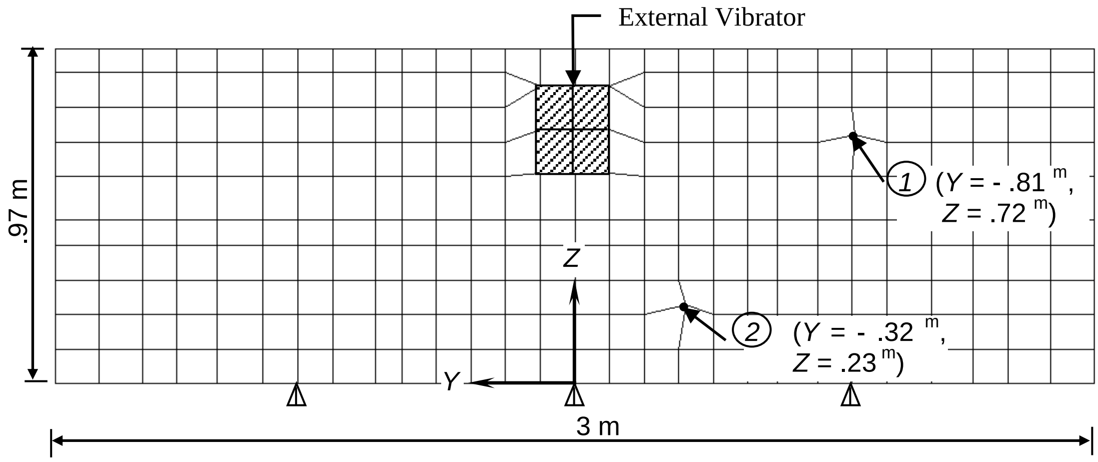


Fig. 1 Measurement surface of Box culvert mold

behavior of masonry walls using ANNs. Kardan, Abiri *et al.* (2013) proposed a recurrent neural network structure for the modeling of the behavior of shape memory alloy (SMA) springs. Numerous mathematical modeling and experimental evaluations showed that the force exerted by SMAs, aside from their length and applied voltages, depends on the loading path.

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

The main aim of this study is to provide a new approach using ANNs and RM for behavior of fresh concrete exposed to vibration in precast concrete structures. This paper contains experimental and numerical studies. The experimental studies were performed in the production workshop of Kambeton Company (Adana/Turkey). ANNs and regression modeling were used to simulate the behavior of the fresh concrete in full scale test specimen. In this study, both the ANNs and RM results for mold displacement data under vibration are compared with the measured data separately. Finally, the performances of both models were compared with each other.

2. Experimental investigation

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 (Box culvert) used in the experiment is shown in Fig. 1 (Aktas 2016). 1 and 2 points are measurement points in Fig. 1. The size of Box culvert mold with 200 mm thickness in *X* direction and 250 mm in Y direction is 3.0×2.9 m. And, its height is 970 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,

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	-

vertical and diagonal directions in order to strengthen the system. Reinforcing steel profiles located at the bottom of the mold are assumed to be simply supported in the model. Boundary conditions of molds for Box culvert element is given by Aktas (2016)**.**

The external vibrator used in the experiment is connected to a steel plate having dimensions of 200×250 mm. The cyclic frequency of the external vibrator used in this study is 100 Hz. The features of the external vibrator are introduced in Table 1.

The experimental measurements were taken on the surface of the mold for precast concrete structural member by using a computer-based data acquisition system. The location of measurement points were selected near and far from vibration points to see their differences and effect. The calibration of the displacement transducer was carried out 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 acquisition system including instrumentation, hardware and software used in this study is described in detail (Aktas, Tanrikulu *et al*. 2014, Aktas and Karasin 2014).

3. Artificial Neural Networks (ANNs) model

ANNs were inspired by the way the human brain functions and are used to model complex relationships between inputs and outputs. ANNs are parallel and distributed systems, composed of simple processing units (neurons) which calculate specific mathematical functions, similar to the structure of human brain (Dantas, Leite *et al*. 2013). 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. The structure of ANNs is layered. These are input, hidden and output layers. 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, Kou *et al*. 2013). The back-propagation (BP) is one of the most popular learning algorithms and is 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. The mean square error (MSE) and the correlation coefficient (R^2) can be used to test the accuracy of the trained network (Erdem 2010). 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.

4. Regression model

Regression analysis is used to: (a) Predict the value of a dependent variable based on the value of at least one independent variable, (b) Explain the impact of changes in an independent variable on the dependent variable. In simple linear model, only one independent variable, x, is used and the relationship between x and y is described by a linear function. In this study, sinusoidal function was used for RM to describe the relationship between time and measured data. Since it was observed that measured data changes as a sinusoidal function of time, the basic sinusoidal function was used for regression modeling. To obtain accurate regression model, Least-Squares method can be used to calculate the model parameters (amplitude, period, phase, offset) of sinusoid function with reducing of residual, which is the difference between the experimental and the predicted data (Robeyst, Grosse *et al*. 2011). The regression equation form used in this study is given below

$$y = a \sin (bx + c) + d \tag{5}$$

The sinusoidal regression equations (models) for the measured data (points: 1 and 2, form: with and without concrete) were obtained with least squared method and obtained parameters were given in the Table 2.

The performances of regression models are given in the Table 2. For comparison of performances of both models, the sinusoidal regression models developed in this study were given in the following section with ANN models.

Table 2 Sinusoidal regression model parameters for experimental data

Place	Concrete Form	Amplitude (a)	Period (b)	Phase (c)	Offset (d)
Point 1	With concrete	0.3219	20.1027	-0.6038	-0.0869
Point 1	Without concrete	0.3685	20.0907	-0.2773	0.0071
Point 2	With concrete	-0.0516	20.0846	-0.9261	-0.0688
Point 2	Without concrete	0.1624	20.0748	-0.5991	0.0009

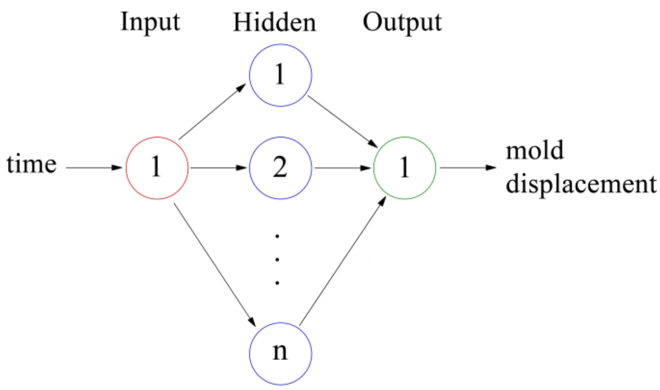


Fig. 2 Proposed ANN model. Number of neurons in hidden layer is n=5:5:70

5. Prediction of behavior of fresh concrete with ANNs model

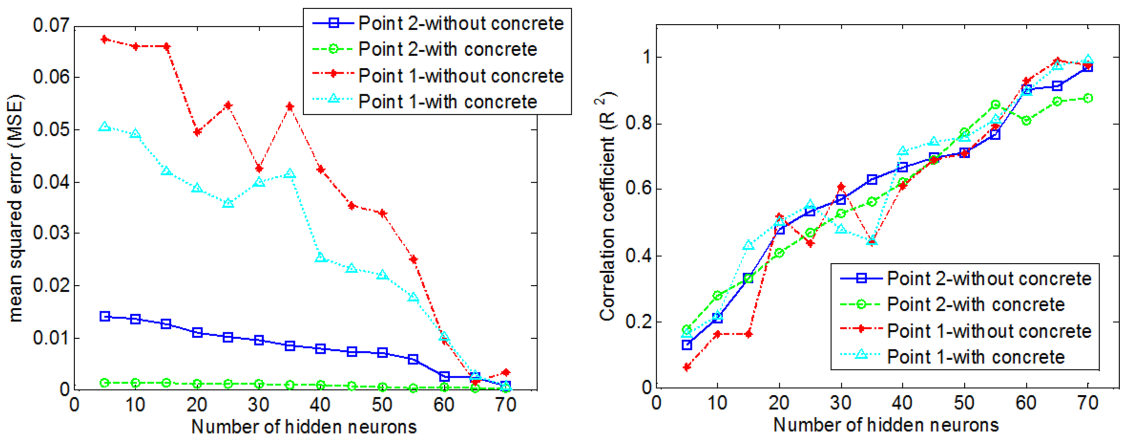
The aim of employing an ANN model is to predict the behavior of fresh concrete exposed to vibration. The time information is the input parameter for the network and mold displacement data under vibration is the output parameter. So, the architecture of ANN becomes $1\times n\times 1$. n is the number of neurons in the hidden layer. The number of hidden layers and number of neurons in hidden layers 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. 2.

ANN model was employed to predict the behavior of fresh concrete exposed to vibration in two points using a vibrator as shown in Fig. 1. There are two models developed with respect to concrete form for each point. So, the developed ANN models are namely; point 1 with concrete, point 1 without concrete, point 2 with concrete and point 2 without concrete (Table 2).

The experimental data set includes 1000 patterns, of which 500 patterns were used for training the network and 500 patterns were selected randomly to test the performance of the trained network. All the input and output values 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 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 backpropagation (trainlm) were used and the best result was obtained with the trainlm training algorithm. So, in this paper the result of this algorithm was presented. 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=0.001) were used. Each ANN structure was repeated 20 times



(a) (b)

Fig. 3 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

Table 3 In testing stage, the ANN structures having best performances for predicting the mold displacement and the performance of sinusoidal regression model for predicting the mold displacement

Data	ANN Model			Regression Model	
	ANN structure having the best performance	min. MSE	R^2	min. MSE	R^2
Point 1 without concrete	1×65×1	0.0016	0.9882	0.0017	0.9875
Point 1 with concrete	1×70×1	0.0007	0.9933	0.0002	0.9980
Point 2 without concrete	1×70×1	0.0008	0.9696	0.0009	0.9648
Point 2 with concrete	1×70×1	0.0004	0.86005	0.0004	0.8845

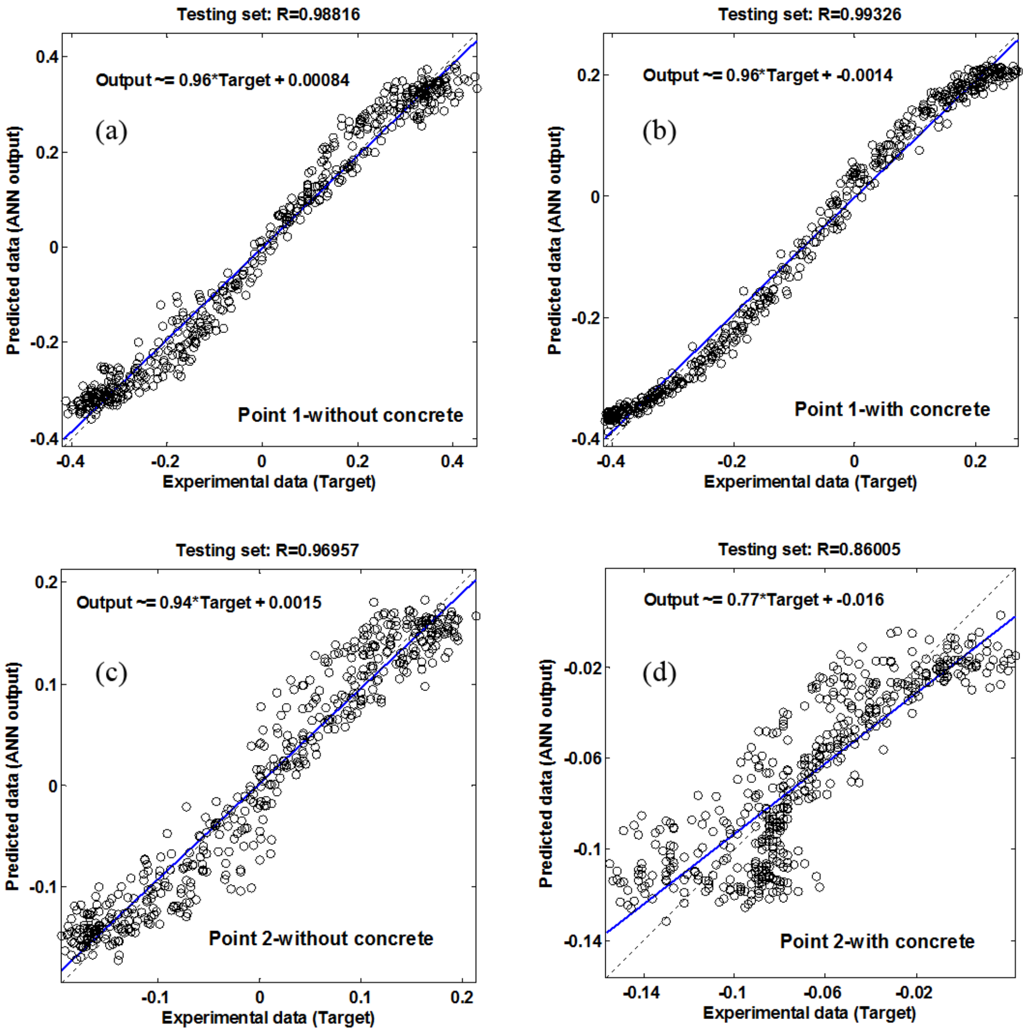


Fig. 4 Comparison of experimental and predicted mold displacement data in the testing stage

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. 3(a). Also, the relationship between the number of hidden neurons and R^2 is illustrated in Fig. 3(b). The both Figs. 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 (0.8601-0.9933) 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.

Comparison of the experimental data of mold displacement with the predicted mold displacement is made and shown in Fig. 4 as scatterplots. 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

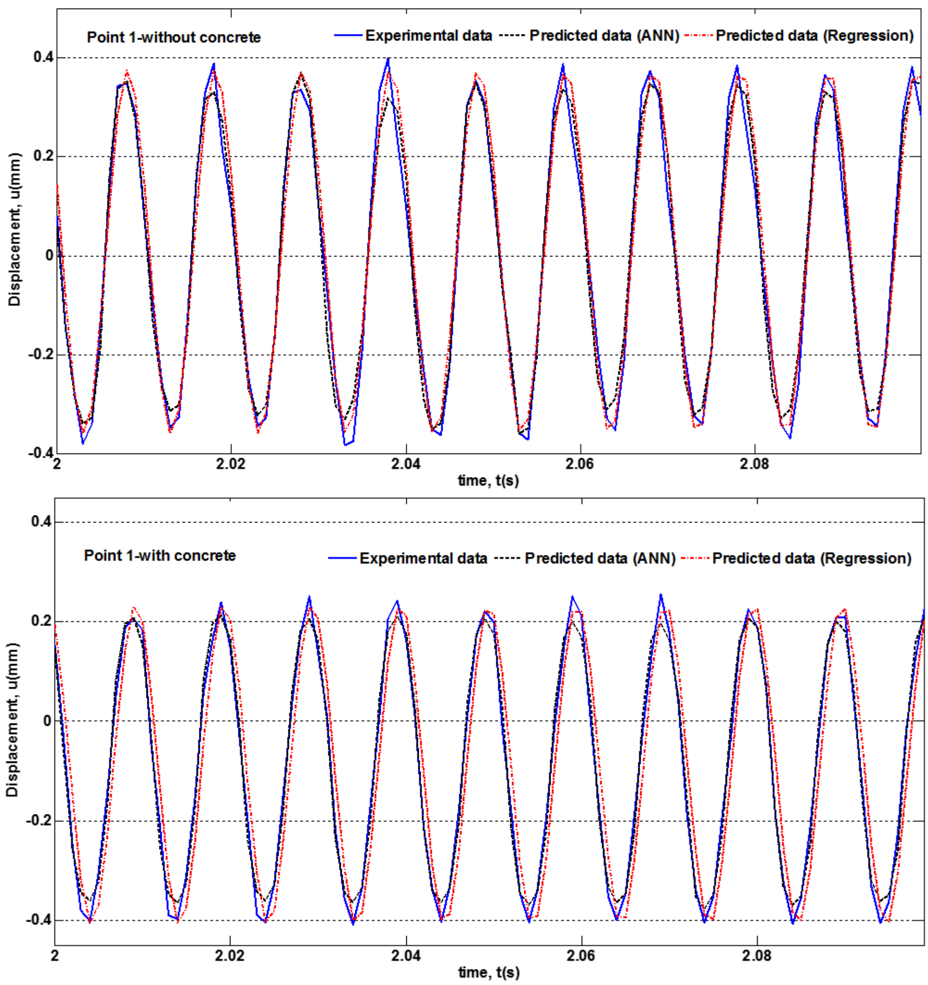


Fig. 5 Comparison of experimental and predicted mold displacement data in the testing stage

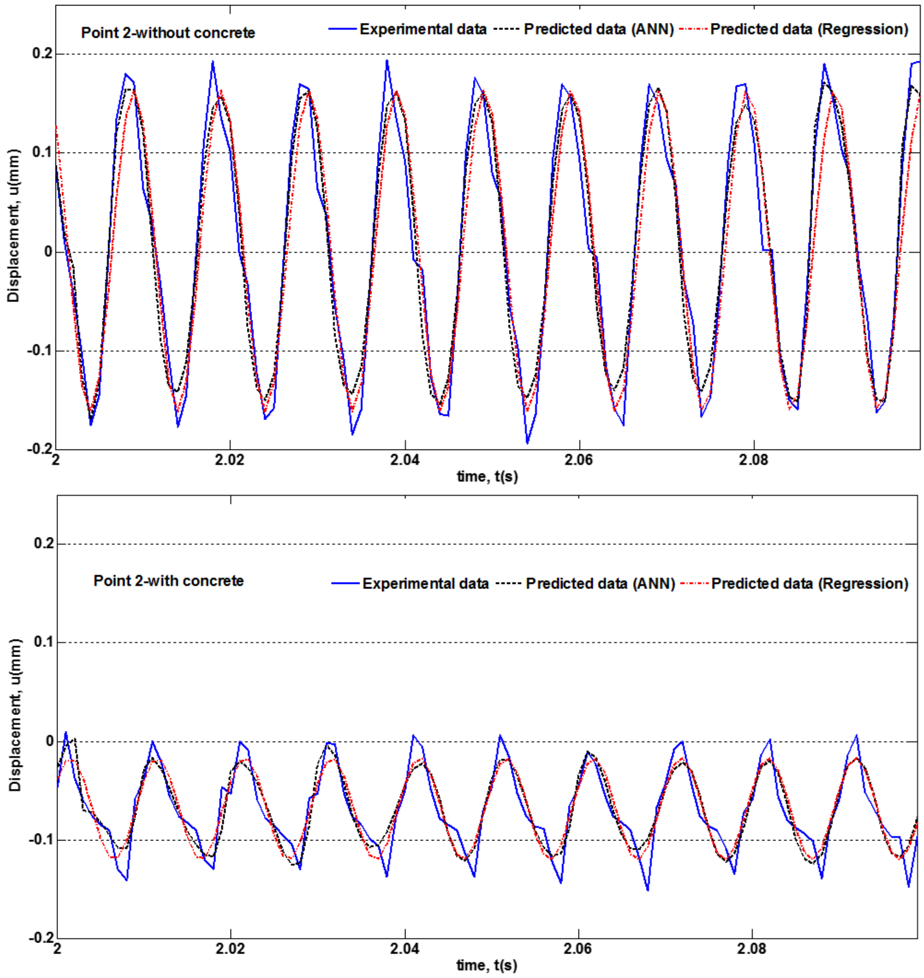


Fig. 5 Continued

model is illustrated in Fig. 5.

6. Results and discussion

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

The ANNs models were developed for two points both with concrete and without concrete cases. The best ANNs models were determined for point 1 - with and without concrete and point 2 - with and without concrete.

The correlation coefficients of the ANNs models having with and without concrete for point 1 were higher than the correlation coefficients of models having with and without concrete for point 2. The correlation coefficients are obtained as 98.816% and 99.326% at point 1 without concrete and at point 1 with concrete respectively. The correlation coefficients are obtained as 96.957% and

86.005% at point 2 without concrete and at point 2 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 also, correlation coefficient increased while the number of hidden neurons increased. So, the performances of ANN models increase with increasing of hidden neurons. The best model of ANNs was observed as 1×65×1 for point 1 without concrete and the best model of ANNs was 1×70×1 for the remain points such as point 1 with concrete, point 2 with and without concrete.

The RM models were developed for two points both with concrete and without concrete cases. The comparisons of RM models show that the measured and testing results are compatible. Regression analysis is a traditional method that can be used for modeling with simple methods such as Least-Squares method. However, this study also showed that ANN modeling can be used as an alternative method for behavior of fresh concrete exposed to vibration in precast concrete structures.

Traditional regression analysis containing sinusoidal regression models has been made and regression models results were compared with ANNs models (Fig. 5). For the regression model, one suitable function is determined and the parameters of function are calculated with Least-Squared method based on measured data. After this calculation, model parameters are obtained as fixed values. So, the predicted data is obtained with fixed values of model.

For the ANNs model, the data is divided into two parts such as training and testing sets. In the learning stage of ANN, the learning set is used. After the learning stage, the ANN is tested with testing sets. In the learning stage, ANN learns the behavior of variable such as fresh concrete exposed to vibration in precast concrete structures. As shown in Fig. 5, the amplitude of each oscillation is different and this difference was learned by ANN. However, this difference cannot be adopted into regression model because of that regression model predicted data with fixed parameters values.

7. Conclusions

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

The correlation coefficient is lower than others at point 2 with concrete (Table 3). The reason of this may be the non-uniformity of the mold behavior (lack of good connections) at the bottom of mold system where point 2 is located, in which concrete applies more pressure to mold.

It was concluded that the ANN and regression models used in this study gives good accuracy of prediction for the behavior of fresh concrete exposed to vibration. Regression analysis is a traditional method that can be used for modeling with simple methods. However, this study also showed that ANN modeling can be used as an alternative method for behavior of fresh concrete exposed to vibration in precast concrete structures.

The amplitudes of oscillation of regression analysis are obtained equally, whereas amplitudes of oscillation obtained from ANNs are not equal. Namely, amplitude obtained from ANNs resembles experimental amplitude.

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

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