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Determining the Drift in Reinforced Concrete Building Using ANFIS Soft Computing Modeling

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ABSTRACT

Earthquakes are considered as one of the most significant natural disasters that can potentially cause significant damages to structures. Displacement of buildings' floors is one of the serious failures in structures caused by earthquakes. In this paper, the drift of a concrete frame with the shear wall is estimated using ANFIS modeling. A dataset of 300 measured data points was used herein as the inputs for the ANFIS model. The dataset has six input parameters including frequency, magnitude, peak ground acceleration (PGA), and shear wave velocity (Vs) of an earthquake and the distance from the earthquake epicenter to use in the ANFIS model, while the model has just one output. Moreover, a sensitivity analysis was performed on the dataset in order to determine the efficiency of the individual input variables on the accuracy of the results. The results demonstrate that the ANFIS model is an effective model for predicting the drift in reinforced concrete structures. Finally, according to sensitivity analysis, the acceleration and shear wave velocity of an earthquake have the highest and lowers impacts on the accuracy of the results, respectively.

1. Introduction

Earthquake is one of the most significant factors in the decision making of buildings after natural disasters. Therefore, researchers have always been concerned about the condition of the structure

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after the earthquake [1–3]. The main goal of the performance-based design of structures is to reduce the damage level and increase the safety of residents under the predicted earthquakes [4–7]. Several factors have been proposed to quantify the performance level of structures including displacement, which is one of the most critical factors in designing earthquake resistance structures. Among all the techniques of determining the displacement of building after the earthquake, data-driven modeling is considered as the most suitable one due to being both economical and time-saving [8].

Data-driven methods, such as machine learning techniques, have been used widely in various civil engineering studies [9–12]. This increase in attention is due to their robustness to data clarification. Khademi et al. have used three different data-driven models, i.e., artificial neural network, ANFIS, and multiple linear regression in predicting the strength of recycled aggregate concrete. They have claimed that artificial neural network and ANFIS are strong prediction tools in estimating the concrete strength. They have also claimed that multiple linear regression is not a skilled model for predicting the compressive strength of concrete [13]. Topcu and Saridmehr have successfully used the neural network and ANFIS in approximating the concrete compressive strength [14]. Sadowski and Nikoo have reported the imperialist competitive algorithm an efficient estimation technique in determining the corrosion current density of reinforcement concrete [15]. Yadollahi et al. have used the application of neural network in estimating the optimal mixture of radiation shielding concrete [16]. Khademi and Jamal have determined the compressive strength of concrete using multiple linear regression and ANFIS models. They have reported ANFIS as a capable model in prediction, on the other hand, they have reported multiple linear regression a weak model for estimating the concrete compressive strength [17]. Jang et al. have successfully used the artificial neural network (ANN) in simulating the random emission concentration of granulated blast furnace slag mortar [18]. Khademi et al. have successfully approximated the compressive strength of concrete using ANN modeling [19]. Finally, Keshavarz provided a summary of the literature in which the civil engineering characteristics were predicted through soft computing models [20]; afterward, Keshavarz and Torkian investigated soft computing methods for determining the compressive strength of concrete using two soft computing techniques (i.e., Artificial Neural Network, ANN, and Adaptive Neuro-Fuzzy Inference System, ANFIS) [21]. Keshavarz and Torkian results show that both of ANN and ANFIS models are successful models for predicting the compressive strength of concrete. However, ANFIS is more capable of predicting the compressive strength of the concrete in comparison to the ANN [21].

In this research work, the ANFIS model is used as the data-driven model for estimating the drift in a reinforced concrete building. Moreover, the Sensitivity Analysis (SA) was performed on the dataset for all six input variable to investigate the impacts of changes in the input variables on the accuracy of the model results.

2. Data preparation

In order to determine the drift in the concrete frame with the shear wall, 300 data points were collected from the existing literature [22,23]. Six variables including acceleration, frequency, magnitude scale (in Richter), peak ground acceleration (PGA), and shear wave velocity (Vs) of an earthquake and the distance from the earthquake epicenter were used as the input parameters in the ANFIS models. A concrete frame with a shear wall containing 4-stories and four bays were considered herein as a base structure for the model. The concrete frame characteristics are summarized in Table 1. Although Nikoo and Zarfam conducted the concrete frame design and analysis within elastic limit, the Non-Linear Dynamic Analysis Software for Reinforced Concrete buildings (IDARC Software) was applied to explore the structure performance within nonlinear limit [22]. Finally, all of the spectral dynamic modes were also considered in the modes analysis [22,24].

Table 1.
Characteristics of concrete frame with a shear wall containing 4-stories and 4 bays [22,24].

Name	Characteristic or Description
Frame	Special reinforced concrete
Structure loading	Standard 519-2800- third edition
Live load of the stories	200 Kg/m^2
Dead load of the roof	600 Kg/m^2
Live load of the roof	175 Kg/m^2
Yield stress	F_y=3000 Kg/cm^2
Stories height	3.2 m
Dead load of stories	500 Kg/m^2
Steel ratio in the structure	$0.015 \leq \rho \leq 0.035$
28-day resistance of concrete sample in a concrete pillar	F_c=240 Kg/cm^2
Bays in each frame	5 m

3. ANFIS model

In the past couple of years, experts have performed several studies on various fields of civil engineering, and among all of them, a large number have used the application of estimation techniques in their studies [12,20,21,25–31]. Normally, in complex problems where the traditional statistical tools are not able to solve the problem, the application of some more progressive prediction techniques like artificial neural network and ANFIS show better results. In this study, the adaptive neuro-fuzzy inference system is used as a data-driven model to determine the displacement in a reinforced concrete building.

One of the most effective estimation techniques for complex problems is adaptive neuro-fuzzy inference system, also known as ANFIS. It is one of the most important intelligent models, which is the combination of fuzzy model and neural network. ANFIS offers the learning ability of the artificial neural network to define and utilize the correlation between input and output elements. In ANFIS, the correlations between elements are shown by fuzzy If-Then rules [13,32]. In the architecture of the adaptive neuro-fuzzy inference system, the number of membership functions, type of membership function, and the optimization method play important roles. The number of membership functions is chosen as 3 for each input. The sub-clustering is chosen for the type of membership function. Also, In order to train the model, the hybrid training algorithm was used. Figure 1 shows the architecture of ANFIS modeling chart.

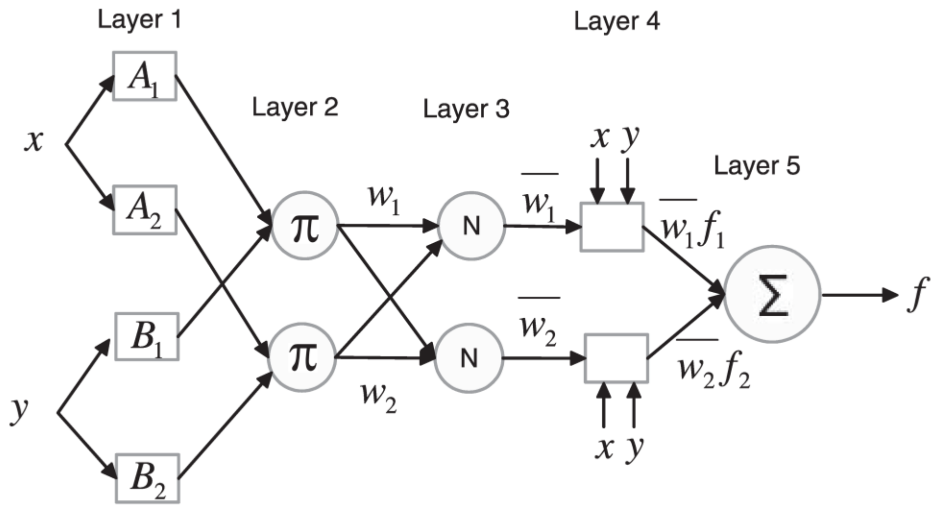

Fig. 1. Structure of ANFIS model [adapted from [13].

The description of each layer is explained comprehensively in the following [12,13]:

Layer (1): This layer is called the fuzzy layer. The node functions in this layer are shown in Equation (1).

$$O_i^1 = \mu_{A_i}(x) \tag{1}$$

In which x is the input to node i and A_i is the linguistic label associated with this node function.

Layer (2): Any nodes in this layer is a fixed node, with the node function to be multiplied by input signals and result in the output signal. The example for this layer is shown in Equation (2).

$$w_i = \mu_{A_i}(y) \times \mu_{B_i}(y) \quad , \quad i = 1,2 \tag{2}$$

Layer (3): Any nodes in this layer is a fixed node which is labeled as N. The ith node determines the ratio of the rule's firing strength to the sum of all the rule's firing strength, as shown in Equation (3):

$$\overline{w}_i = \frac{w_i}{(w_1+w_2)} \quad , i = 1,2 \tag{3}$$

Layer (4): This layer is called the adaptive layer, and every node in this layers is called adaptive node. The node function in this layer is shown in Equation (4):

$$O_i^4 = \overline{w}_i(p_i x + q_i y + r_i) \tag{4}$$

Where $\overline{w}_i$ is the output resulted from layer 3, and $\{p_i, q_i, r_i\}$is the parameter set.

Layer (5): This is the last layer which is also called de-fuzzification layer and includes a single and stable node, labeled as $\sum$ which sums all the signals to determine the total output, shown in Equation (5):

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

It can be noticed that two adaptive layers exist in the structure of ANFIS mode, i.e., Layers first and fourth. In the first layer, three modifiable elements which are related to the input membership functions exist. These elements are the so-called premise elements. In addition, in the fourth layer, three modifiable factors which pertain to the first order polynomial exist. These factors are the so-called consequent factors (Boğa et al. 2013).

ANFIS is comprised of five layers. The first layer has elements that could control the position of fuzzy sets. The input factors are introduced to ANFIS model in this layer. In the second layer, the results are computed using the model nodes. In the third layer, the activity degree of all the rules would be normalized. In the fourth layer, the versatility of nodes happens. The fifth layer is the output layer [12,24,28,30,32–36].

4. Results and discussion

Concrete is one of the most important materials in civil engineering projects. Accordingly, many researchers [37–41] have been trying to enhance properties of concrete in different ways. To do so, researchers have conducted various investigations on different concrete properties in order to improve the mechanical properties. Besides, in order to reinforce the concrete, various material and methods were studied as well [42]. Here, the application of ANFIS model is used in determining the drift in reinforced concrete structure. The data in ANFIS model are divided into three groups of training, check, and test. In this research, the ANFIS modeling was performed in MATLAB software. The data were divided into three subsets of training (60% of data, i.e., 180 samples), validation (20% of the total data, i.e., 60 samples), and test (20% of data, i.e., 60 samples). This division is due to both increase the generalization capacity of the ANN model and overcomes over-fitting. The number and percentage of the data points assigned to each specific group are presented in Table 2.

Table 2.
Proportions of Data in Each Group.

	ANFIS model groups			
	Training	Check	Test	Total
Number of data points	180	60	60	300
Percentage of data points assigned	60%	20%	20%	100%

The coefficient of determination (R^2) is picked as the performance criterion for comparison of the results and sensitivity analysis as shown in Equation (6) [32]:

$$R^2 = \frac{[\sum_{i=1}^{n}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})]^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i-\bar{\hat{y}})^2} \quad (6)$$

Where y_i is the experimental values of the i^{th} specimen; $\bar{y}$ is the averaged experimental value; $\hat{y}_i$ is the calculated value of i^{th} specimen; and $\bar{\hat{y}}$ is the averaged calculated value.

Figures 2, 3, and 4 present the correlation between the target and output values for three different steps of training, validation, and test, respectively.

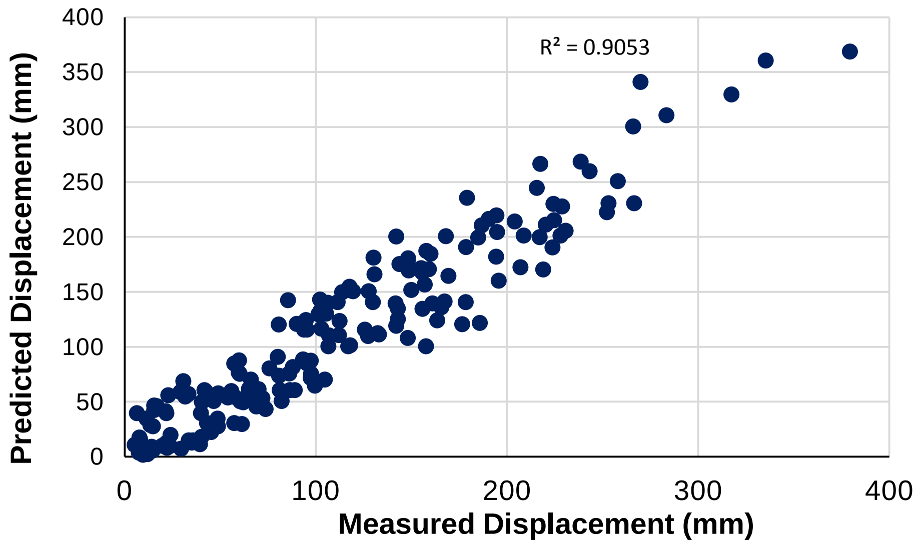

Fig. 2. Correlation between the output and target values for training data.

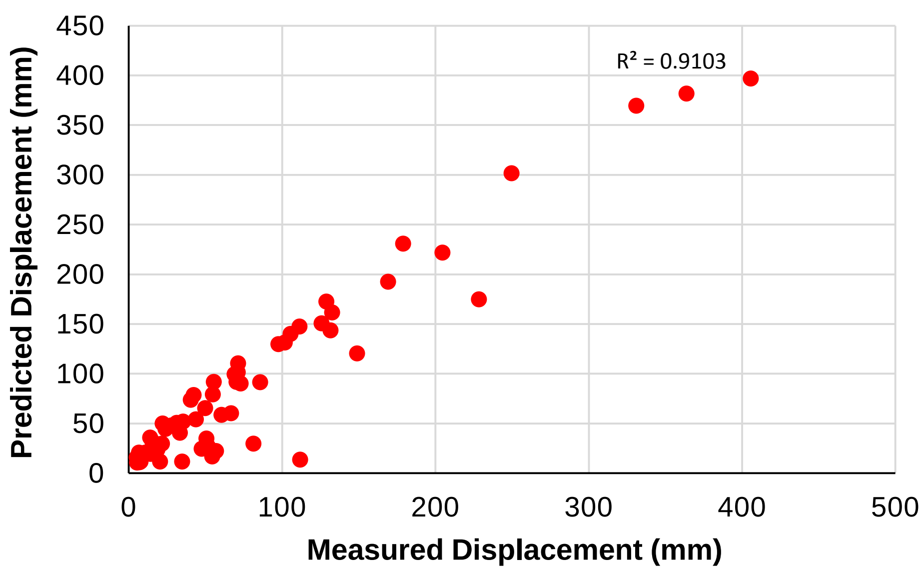

Fig. 3. Correlation between output and target values for Check data.

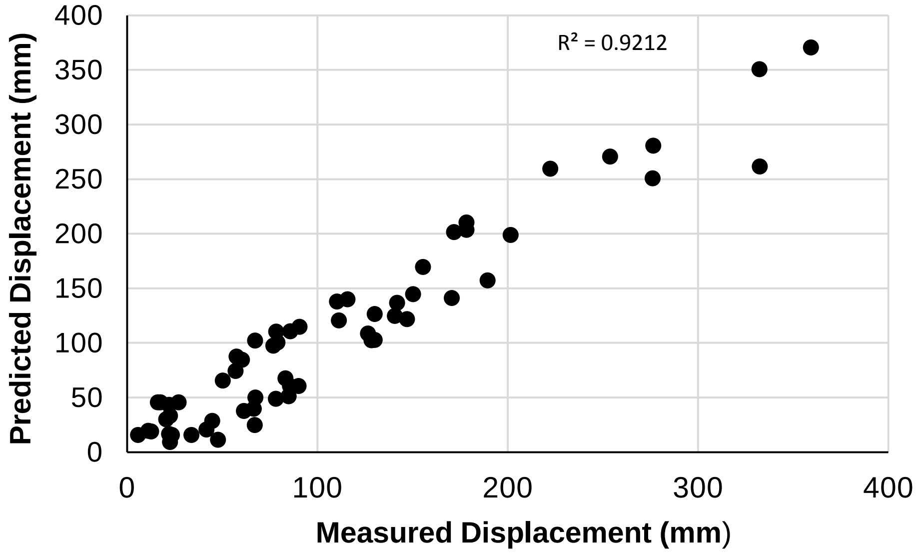

Fig. 4. Correlation between output and target values for test data.

Figure 5 compares the coefficient of determination of the training, check, and test groups together.

Fig. 5. The coefficient of determinations for training, check, and test steps.

As illustrated in Figure 5, the ANFIS model is a reliable model for predicting the drift in the reinforced concrete building with a shear wall, and it is clearly shown for all the three steps of training, check, and test.

Furthermore, a sensitivity analysis (SA) was performed on the data to investigate the impact of changes in the six input parameter values (i.e. frequency, magnitude, peak ground acceleration (PGA), and shear wave velocity (*Vs*) of the earthquake and the distance from the earthquake epicenter) on the accuracy of the results. Commonly, the Sensitivity Analysis is to study the influence of changes in the model input values on the outputs [13,30]. As an example, Khademi et al. have used the SA in the case of the efficiency of the number of input parameters on compressive strength of concrete [13]. In this research, the impacts of all the input parameters on the results are investigated individually, and the results are shown in Figure 6.

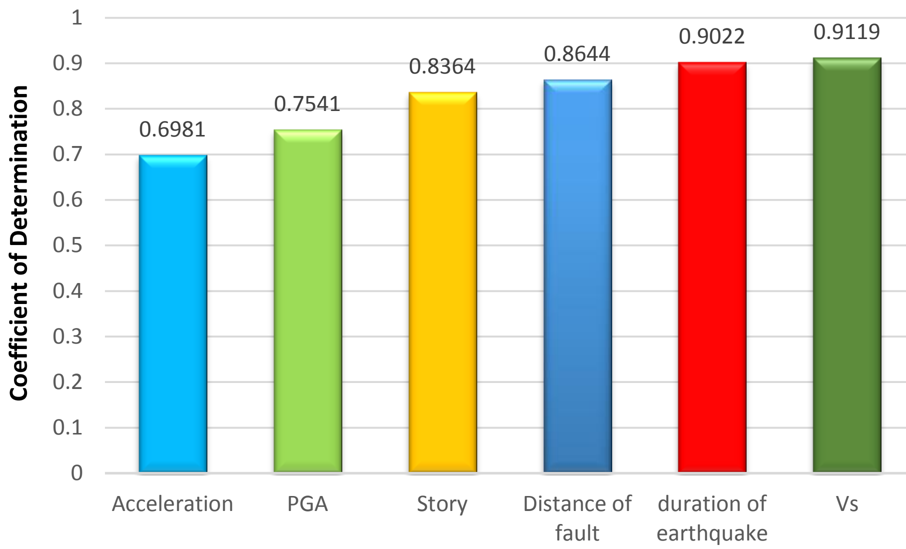

Fig. 6. The coefficient of determinations when each input parameter is removed in the ANFIS modeling**.**

As shown in Figure 6, different input parameters have different impacts on the results of the ANFIS modeling. According to this figure, acceleration is the most sensitive parameter, and Vs is the least sensitive parameter in ANFIS modeling of drift in the reinforced concrete building with the shear wall.

Acceleration with the coefficient of determination of equal to 0.6981 is the most sensitive parameter, and Vs with the coefficient of determination of equal to 0.9119 is the least sensitive parameter in ANFIS modeling of drift in the reinforced concrete building with the shear wall.

5. Conclusion

In this study, the capability of ANFIS model in estimating the displacement of the reinforced concrete structures during an earthquake was investigated. According to the results, the following outcomes were achieved:

a. The R^2 value of ANFIS model for the training step is determined as 0.9053, for the check step is determined as 0.9212, and for the test, the step is determined as 0.9103. Therefore, ANFIS model was shown to be an effective model for predicting the drift in the reinforced concrete building.

b. The sensitivity analysis was performed on the dataset. Results show various input parameter impacts on the coefficient of determination. Acceleration with the coefficient of determination of equal to 0.6981 is the most sensitive parameter, and Vs with the coefficient of determination of equal to 0.9119 is the least sensitive parameter in ANFIS modeling of drift in the reinforced concrete building with the shear wall.

c. According to the sensitivity analysis, acceleration has the most and shear wave velocity (*Vs*) has the lowest impacts on the coefficient of determination.

d. Several studies have already shown the capability of the ANFIS model in the predicting the behavior of various datasets. This study, once more, proves the capability of the ANFIS model for a new set of data.

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