Assessment of earthquake-induced slope deformation of earth dams using soft computing techniques

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Abstract

Evaluating behavior of earth dams under dynamic loads is one of the most important problems associated with the initial design of such massive structures. This study focuses on prediction of deformation of earth dams due to earthquake shaking. A total number of 103 real cases of deformation in earth dams due to earthquakes that has occurred over the past years were gathered and analyzed. Using soft computing methods, including feed-forward back-propagation and radial basis function based neural networks; two models were developed to predict slope deformations in earth dams under variant earthquake shaking. Earthquake magnitude (M_w), yield acceleration ratio (a_y/a_{max}), and fundamental period ratio (T_d/T_p) were considered as the most important factors contributing to the level of deformation in earth dams. Subsequently, a sensitivity analysis was conducted to assess the performance of proposed model under various conditions. Finally, the accuracy of the developed soft computing model was compared with the conventional relationships and models to estimate seismic deformations of earth dams. The results demonstrate that the developed neural model can provide accurate predictions in comparison to the available practical charts and recommendations.

Keywords: Earthquake; Earth dam; Slope deformation; ANN; RBF.

1. Introduction

It is highly crucial to study the behavior of dams under seismic loading. Inaccurate assessment of the behavior of dams under earthquake shaking could lead to catastrophic damages. Newmark (1965) proposed a sliding block model as the first technique to calculate permanent slope deformations. This simple technique was adopted to estimate the slope deformations under earthquake loading. In the sliding block method, the slide mass was assumed as a rigid block. Meanwhile, the input acceleration (e.g. caused by the earthquake) beyond the yield acceleration, moves the sliding block (Meehan and Vahedifard 2013; Jafarian and Lashgari 2016, 2017).

Some researchers have investigated and modified the sliding block model (Rathje and Bray 2000, Kramer and Smith 1997). In an earlier paper, Makdisi and Seed (1978) modified the sliding block model and included the acceleration of the slide mass response as input acceleration. Then, they adopted the input acceleration to calculate the extent of displacements. Strenk and Wartman (2011) examined the uncertainty of results obtained from the sliding block model in comparison to real cases. Furthermore, a few researchers explored the level of deformation in Earth slopes through numerical approaches such as finite difference (e.g., Kramer and Smith 1997) and finite element (Prevost et al. 1985) methods. In separate papers, Sarma (1975) and Yegian et al. (1991) included the parameters of strong ground motion to evaluate the slope deformation of Earth dams. Hynes-Griffin and Franklin (1984) did not include the vertical component of earthquake acceleration in their calculations. In fact, they estimated the level of deformation in earth dams based on the ratio of slope failure acceleration to maximum earthquake acceleration.

Earthquake-related problems are complex (Ishihara 1996; Jafarian et al. 2018a, b; Javdanian and Jafarian 2018). On the other hand, the behavior of large earth structures such as earth dams are affected by many factors such as fundamental period of dam, settlement characteristics and non-homogeneity (Rampello et al. 2009). Establishing accurate relationships between such factors poses a serious challenge for geotechnical engineers (Bray and Travasarou 2007; Siyahi and Arslan 2008; Javdanian et al. 2018a,b). These indicate that the advanced computational techniques should be employed to accurately assess the deformation in earth dams due to earthquake shaking. In recent years, soft computing methods (Javdanian et al. 2015b; Najafzadeh et al. 2013, Najafzadeh and Lim 2015) have been successfully used to solve complex problems and handle many geotechnical engineering analyses, such as seismic liquefaction potential of geomaterials (Javdanian 2017a; Hanna et al. 2007; Baziar and Jafarian 2007), dynamic behavior of soils (Javdanian 2017b; Javdanian et al. 2015a,b; Jafarian et al. 2014), lateral ground surface deformations (Javdanian and Mirkamali 2016), landslides analysis (Pradhan and Lee 2010a, b; Pham et al. 2016; Bui et al. 2016, 2017; Kalantar et al. 2018), soil stabilization (Javdanian et al. 2012; Javdanian 2017c; Javdanian and Lee 2018), shear wave velocity of soils (Ghorbani et al. 2012), and forecasting earthquake magnitude (Adeli and Panakkat 2009).

Review of the aforementioned published papers clearly indicates that the studies on earthquake-induced slope deformation of earth dam based on real cases are rarely found in the literature. This indicates that further studies are needed to address this important issue using robust computational intelligence methods. This study intended to predict the behavior of earth dams under earthquake-induced vibrations. Comprehensive database of slope deformations of earth dams due to earthquake shaking in various region of the world were collected and analyzed. Intelligent neural networks were employed to develop models evaluating the level of seismic deformation of earth dams. Then, sensitivity analysis was carried out on the models. Finally, the performance of the developed soft computing model was compared with the available recommendations for evaluating slope deformation of earth dams.

2. Earth dam: case studies

Wide-ranging database of slope deformations of embankments and earth dams due to past earthquake loading in different parts of the world were gathered. These results refer to homogeneous and non-homogeneous earth dams, embankment dams with concrete facing, rockfill dams and a few natural slopes. The collection covers dams whose behaviors were fully documented after well-recorded earthquakes (Abdel-Ghaffar and Scott 1979; Arrau et al. 1985; Choggang 1988; De Alba et al. 1988; Elgamal et al. 1990; Bardet and Davis 1996; Krinitzsky and Hynes 2002; EERI 2004). The collected data contain 103 real cases. Figs. 1(a-d) show the frequency distribution of earthquake magnitude (M_w), yield acceleration ratio (a_y/a_{max}), fundamental period ratio (T_d/T_p), and value of slope deformation (D_{ave}) for the collected results. The earthquake-induced slope deformation (D_{ave}) is the downward movement of the soil mass aligned along the inclination of the sliding surface. D_{avg} was computed by taking the dot product of the horizontal and vertical components of the observed deformations and a unit vector aligned along the average inclination of the base of the sliding surface. The base inclination angle was specified from the critical failure from the pseudo-static analyses. The parameters a_y, a_{max}, T_d and T_p represent yield acceleration, maximum horizontal earthquake acceleration, fundamental period of earth dam, and predominant earthquake period, respectively. The parameters M_w, a_{max} and T_p represent as characteristics of earthquake loading and the parameters a_y and T_d as geotechnical characteristics of earth dam were considered as most influential parameters. The yield acceleration (a_y) was estimated from pseudo-static slope stability analysis (Kaynia et al. 2011). The threshold acceleration above which the sliding mass is mobilized downslope called yield acceleration. The a_y was taken to be equal to the inertial acceleration that yields a factor of safety of one in a pseudo-static analysis of the slope. The fundamental period of earth dam was taken from the case history references, if available. Otherwise, is estimated as $T_d = 4H/V_s$ (Rathje and Bray, 1999); where H is the height of the earth dam and V_s is the shear wave velocity in the dam body.

Based on the analysis of gathered case histories and review of the previous studies (Saygili and Rathje 2008; Jafarian and Lashgari 2016) the parameters M_w, a_y/a_{max} and T_d/T_p were selected as input parameters in the model development. Subsequently, 75% of the collected data was employed in learning stage, whereas 25% was employed in validation stage. A trial selection procedure was performed for dividing the data to be used in learning and validation stages such that the statistical parameters of both categories remain as close as possible (Masters 1993). In order to accurately assess the model performance, different sets of data for learning and validation stages were selected with approximately equal statistical parameters. Subsequently, based on the error parameters, the best models were chosen for sensitivity analysis and comparisons. The statistical characteristics of inputs parameters (i.e., M_w, a_y/a_{max}, T_d/T_p) and output parameter (i.e., D_{ave}) for the learning and validation stages as well as the entire results are presented in Table 1. The detailed characteristics of database are presented in Table A1.

3. Model development

In this research, two soft computing-based models (i.e., feed forward back-propagation (FFBP) and radial basis function (RBF) neural networks) are developed to predict slope deformations of earth dams due to earthquake shaking.

3.1 FFBP model

One substantial benefit of the feed forward back-propagation (FFBP) networks in comparison to the other types of nonlinear methods is that they are universal predictors that can forecast many kinds of models with a high level of precision (Javdanian et al. 2015b). Initial assumption about the form of the model is not needed in the development process of model. The model is defined by three layers network of connected processing nodes (i.e., artificial neurons) (Fig. 2a).

The correlation between the inputs (x_1, ..., x_i) and the output (y_t) has the mathematical form according to Eq. (1):

$$y_t = w_0 + \sum_{j=1}^{S} w_j h\left(w_{0j} + \sum_{i=1}^{R} w_{i,j} x_i\right) + \varepsilon_t \tag{1}$$

where, $w_{i,j}$ (i = 0, 1, 2,…, R, j = 1, 2,…, S) and w_j (j = 0, 1, 2, ...,S) are connection weights (or model parameters); R and S are the number of input and hidden nodes, respectively; ε_t is the model's residual at the time t; and h is the transfer-function (e.g., tan-sigmoid and log-sigmoid). In fact, the feed forward based model (Eq. 1) carries out a nonlinear-functional capturing from the previous records to the future prediction y_t, as Eq. (2):

$$y_t = g(x_1, \dots, x_R, W) + \varepsilon_t \tag{2}$$

where, g is a function based on the connection weights and network structure, and W is a vector including all model parameters.

The structure of the best-developed FFBP-based model was produced with one hidden layer. Then, the input vector was linked to the hidden neurons using transfer function of tan-sigmoid and the hidden neurons layer was linked to the output layer with a linear function. Learning process was initiated by three hidden artificial neurons to obtain the optimum number of neurons and favorable accuracy (Schalkoff 1997). As a result, the model with best performance was built using 12 hidden artificial neurons. In addition, the number of epochs in which the learning and validation stages have the best outputs was obtained to be 400. In order to find a more efficient learning procedure, the inputs and output parameters were standardized to have unity standard deviation and zero mean.

3.2 RBF model

The radial basis function (RBF) network is commonly employed for approximation problem in multi-dimensional space (Jafarian et al. 2014). Broomhead and Lowe (1988) were pioneers in applying RBFs in design of neural networks. They showed that a nonlinear correlation could be developed by RBF based network and interpolation problems could be modeled. RBF networks are local artificial networks in comparison to the FFBP networks, which carry out global capturing. RBF network utilizes a single class of processing units, and any of these units is receptive to a local domain of the input vector (Demuth et al. 2014). As shown in Fig. 2b, the RBF network structure consists of three layers. Radially symmetric function is employed as activation functions of hidden nodes in the RBF network.

In spite of feed forward networks, the input layer values of RBF networks are forwarded to the hidden layer without multiplying by connection weight. Subsequently, the hidden layer units assess the spacing between an input vectors with the center of its radial basis function and generates an output value based on the space. Although, many radial basis functions have been used in hidden layer, Gaussian function is the most commonly utilized in various applications (Chen et al., 1991). The mathematical function of the hidden neurons characterized by the Gaussian function is represented in Eq. (3):

$$\rho_j = exp\left(-\frac{\left\|X - \delta_j\right\|^2}{2\mu_j^2}\right), j = 1, 2, \dots, N \qquad (3)$$

where, ρ_j is the output of the j^{th} node in hidden layer; X is the input vector, $\left\|X - \delta_j\right\|$ is Euclidian distance, δ_j is center of the j^{th} Gaussian function, μ_j is radius of the Gaussian function of the j^{th} node, and N is the number of nodes in hidden layer.

The neuron in the output layer generates a weighted sum by the output of hidden layer and the weights connecting the hidden layer to the output layer. The output value of neural network can be introduced as Eq. (4):

$$y_k = \sum_{j=1}^{N} \rho_j w_j + b_{0k} \tag{4}$$

where, w_j is the connection weight of hidden neuron j, and b_{0k} is the bias for final (output) layer neuron.

In the present research, radial basis function (RBF) network was utilized to predict slope deformation of earth dams under earthquake loading. The best-selected RBF network has 3 neurons in the input layer, 14 neurons in the hidden layer, and 1 neuron in the output layer, respectively. A spread of radial basis of one (1) was appropriate in this study.

3.3 Performance assessment

Correlation coefficient, R, mean absolute percentage of error (MAPE), root mean square error (RMSE), scatter index (SI), and Bias were utilized to assess accuracy of developed FFBP and RBF based models using Eqs. (5-9):

$$R = \frac{\sum_{i=1}^{N}[X_{i-measured} - \bar{X}_{measured}][X_{i-predicted} - \bar{X}_{predicted}]}{\sqrt{\sum_{i=1}^{N}[X_{i-measured} - \bar{X}_{measured}]^2 \cdot \sum_{i=1}^{N}[X_{i-predicted} - \bar{X}_{predicted}]^2}} \tag{5}$$

$$MAPE = \frac{1}{N}\left[\frac{\sum_{i=1}^{N}|X_{i-predicted} - X_{i-measured}|}{\sum_{i=1}^{N} X_{i-measured}} \times 100\right] \tag{6}$$

$$RMSE = \left[\frac{\sum_{i=1}^{N}[X_{i-predicted} - X_{i-measured}]^2}{N}\right]^{0.5} \tag{7}$$

$$SI = \frac{RMSE}{(1/N)\sum_{i=1}^{N} X_{i-measured}} \tag{8}$$

$$Bias = \frac{1}{N}\sum_{i=1}^{N}\left[X_{i-predicted} - X_{i-measured}\right] \tag{9}$$

where, $X_{i\text{-}measured}$ is the measured slope deformation (from case histories), $X_{i\text{-}predicted}$ is the predicted slope deformation (output of developed model), $\bar{X}_{measured}$ is the mean of measured values of dam deformations, $\bar{X}_{predicted}$ is the mean of predicted values of dam deformations, and N is the number of deformation results.

4. Results and discussions

This study covered several networks with different initial parameters. With respect to the calculated error parameters, the models with the highest accuracy were selected to predict the slope deformation of earth dams under earthquake loading. The accuracy of the developed feed forward back-propagation (FFBP) model and radial basis function (RBF) model were compared with the measured values and the predicted values of D_{ave} and are shown in Figs. 3 and 4, respectively. Also, the histogram of the residuals (i.e., predicted values minus measured values) and normalized D_{ave} (i.e., the ratio of the measured D_{ave} values to the predicted D_{ave} values) against predicted amounts of D_{ave} for both FFBP- and RBF-based models in the learning and validation stages are also superimposed in these figures.

Results indicated that, the values of R, RMSE, MAPE, SI and Bias of the developed FFBP model for assessing seismic slope deformations of earth dams (Fig. 3) were 0.912, 2.492, 1.101, 0.645 and 0.173 in the learning stage and 0.887, 2.824, 1.275, 0.897 and 0.223 in the validation stage, respectively. These parameters for the developed RBF model (Fig. 4) were 0.801, 2.648, 1.369, 0.685, and 0.471 in the learning stage and 0.725, 3.107, 1.683, 0.987, and 0.728 in the validation stage, respectively.

Table 2 provides the values of R, MAPE, RMSE, SI and Bias for FFBP and RBF models in the learning and validation stages as well as the entire results recorded from the behavior of earth dams under previous earthquakes. The FFBP model No. 1 and RBF model No. 1 are the most appropriate models to predict slope deformations of earth dams induced by earthquake shaking. The results (Table 2) indicate the reasonable accuracy of soft computing based models in estimating seismic deformation of earth dams. Moreover, the results suggest that FFBP offered a higher accuracy than RBF in estimation of deformations. Next, the performance of the developed FFBP-based model was investigated in different conditions and in comparison with available relationships for estimation of earthquake-induced slope deformation of earth dams.

4.1 Sensitivity analysis

A sensitivity analysis was conducted to investigate: 1) the effect of each parameter involved in slope deformation of earth dams due to earthquake loading; and 2) the extent of consistency between the proposed soft computing models (i.e., FFBP model No. 1 and RBF model No. 1) and the results of real cases under different conditions. To this end, the effect of variations in each input parameters (i.e., M_w, a_y/a_{max} and T_d/T_p) on the amount of seismic deformation of earth dams (D_{ave}) was examined. Meanwhile, other parameters assumed constant values equal to their mean values in the data set (Table 1).

The variation of seismic slope deformation of earth dams predicted by FFBP-based model versus the yield acceleration ratio (a_y/a_{max}) and fundamental period ratio (T_d/T_p) at different earthquake magnitudes are depicted in Figs. 5 and 6, respectively. These figures also show the real values of D_{ave} in earth dams caused by previous earthquakes along with the best-fitted curve for the purpose of comparison. As shown in Figs. 5 and 6, an increase in a_y/a_{max} and T_d/T_p led to lower earthquake induced slope deformation of earth dams (D_{ave}). Moreover, greater earthquake magnitudes led to higher D_{ave}. In general, the comparison of D_{ave} variations versus the most important parameters affecting the seismic deformation of earth dams with the results of real case histories demonstrated the appropriate performance of the developed FFBP model.

5. Comparison with the available recommendations

Fig. 7 illustrates the performance of the FFBP based model in comparison to the conventional relationships (Saygili and Rathje 2008; Jibson 2007; Ambraseys and Menu 1988; Hynes-Griffin and Franklin 1984; Makdisi and Seed 1978) for estimating the slope deformation of earth dams due to earthquake loading. The relationships for earthquake-induced deformations of soil slopes are based on analyses of ground motions records using the Newmark sliding block. Fig. 7 displays cumulative frequency of relative error for developed model and available equations (Table 3). The relative error was calculated using Eq. (10):

$$RE = \frac{D_{ave-p} - D_{ave-m}}{D_{ave-m}} \times 100 \tag{10}$$

where, the D_{ave-p} is the average slope deformation predicted by the proposed FFBP model and also available relationships and D_{ave-m} is the recorded slope deformations under previous earthquake shaking.

The relative error of available equations was calculated for the ranges presented in column 3 of Table 3. The values of relative error versus the measured values of seismic deformations are also added to the Figs. 7(a-f). As shown in Fig. 7, the developed FFBP model offers a reasonable accuracy compared to the available recommendations for assessment of slope deformation of earth dams due to earthquake shaking.

The behavioral complexity of earth structures under earthquake loading has prevented the conventional equations from accurately reflecting all factors contributing to the level of slope deformation. Nevertheless, the conventional equations and models (Table 3) are still extensively adopted in practical problems of geotechnical earthquake engineering. The adoption of advanced computing methods can definitely be an effective step towards mitigation of uncertainty concerning the estimation of deformation in earth dams under earthquake shaking.

6. Summary and conclusions

Accurate prediction of earthquake-induced slope deformations of earth dams is an important prerequisite for safe design. Therefore, it is critical to make an accurate assessment of how dams behave under earthquake shaking. This study attempts to predict the extent of slope deformation of earth dams under earthquake loads. To this end, a large set of real deformations found in different types of earth dams during past earthquakes were collected and analyzed. Then, the most important parameters contributing to slope displacement were determined. Earthquake magnitude (M_w), maximum horizontal earthquake acceleration (a_{max}), yield acceleration of earth dam slope (a_y), predominant earthquake period (T_P), and fundamental period of earth dam (T_d) are considered as most important parameters controlling the extent of seismic deformations in earth dams. Two artificial intelligence based models (including radial basis function, RBF, and feed forward back-propagation, FFBP, networks) were developed for prediction of earthquake induced slope deformations of earth dams (D_{ave}). Performance of these models is validated using some part of gathered case histories. The results demonstrate that neural models considering the M_w, a_{max} and T_P as strong ground motions parameters and a_y and T_d as geotechnical parameters are able to estimate the seismic slope deformations of earth dams with reasonable accuracy.

Comparing the predicted amounts of slope deformations with the recorded field data during past earthquakes showed reasonable accuracy of the FFBP (R=0.906, RMSE=2.543, MAPE=1.167, SI=0.690, Bias=0.186) and RBF (R=0.782, RMSE=2.814, MAPE=1.471, SI=0.764, Bias=0.584) based models. The error parameters indicated that the developed FFBP-based model has higher accuracy than the RBF-based model in assessment of seismic slope dam deformations.

A sensitivity analysis was performed to assess the influence of each input parameter on the amount of earthquake-induced slope deformations of earth dams and to better realize the performance of the proposed FFBP model. The variations trends of predicted D_{ave}-a_y/a_{max} and D_{ave}-T_d/T_p curves under different values of M_w were compared to the real case studies (historical events). The comparison results demonstrates reasonable performance of the developed FFBP-based model in the prediction of seismic slope deformations under various conditions. Finally, the performance of the proposed FFBP model was compared with the available relationships for evaluation of D_{ave}. The results clearly indicate that the proposed FFBP-based model has a higher precision in comparison to the previous recommendations.

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List of Tables

List of Figures