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The use of neural networks for the prediction of the critical factor of safety of an artificial slope subjected to earthquake forces

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Abstract This study deals with the development of Artificial Neural Network (ANN) and Multiple Regression (MR) models for estimating the critical factor of safety (F_s) value of a typical artificial slope subjected to earthquake forces. To achieve this, while the geometry of the slope and the properties of the man-made soil are kept constant, the natural subsoil properties, namely, cohesion, internal angle of friction, the bulk unit weight of the layer beneath the ground surface and the seismic coefficient, varied during slope stability analyses. Then, the F_s values of this slope were calculated using the simplified Bishop method, and the minimum (*critical*) F_s value for each case was determined and used in the development of the ANN and MR models. The results obtained from the models were compared with those obtained from the calculations. Moreover, several performance indices, such as determination coefficient, variance account for, mean absolute error and root mean square error, were calculated to check the prediction capacity of the models developed. The obtained indices make it clear that the ANN model has shown a higher prediction performance than the MR model.

1. Introduction

Slope stability is extremely important in the design and construction of highways, open pits, and earth dams [1]. Slope stability analysis is mostly performed under static loading [2]. However, in a seismically active region, earthquakes are an important force that can cause the failure of slopes [2]. Therefore, in these regions, it is also necessary to perform seismic slope stability analysis [2]. The Pseudo-Static (PS) approach is the most common procedure employed for seismic slope stability evaluation, even though more advanced and rigorous methods of analysis are currently available [3]. This approach has been implemented in various limit equilibrium methods in which earthquake effects are represented by an equivalent static force [4]. Limit equilibrium methods satisfy either some or all equilibrium conditions. Satisfied equilibrium conditions include:

(1) Some or all inter slice forces [5,6];
(2) Moment and/or some forces [7,8];
(3) Moment and all forces [9–11].

Fellenious [5], Taylor [7] and Bishop [8] methods can be used for circular slip surfaces, while others can be utilized for circular and non-circular slip surfaces. Janbu [6] and Sarma [1] methods are usually preferred in seismic slope stability analysis.

Artificial Neural Networks (ANNs) are very sophisticated modeling techniques, capable of modeling extremely complex functions [12]. ANNs currently attract many researchers studying slope instability, owing to their successful performance in modeling non-linear multivariate problems [12,13]. The main characteristics of ANNs, in dealing with quantitative and qualitative indexes, include large-scale parallel-distributed processing, continuously nonlinear dynamics, collective computation, high fault tolerance, self organization, self learning, and real time treatment [14]. In this study, an ANN model, with respect to the above advantages, and a Multiple Regression (MR) model

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were developed to predict the critical F_s value of a typical embankment slope subjected to earthquake forces. With this purpose in mind, a computer program was developed in the Matlab programming environment [15]. While the geometry of the slope and the properties of the soil involved in the slope are kept constant, the soil properties, namely, cohesion, c, internal angle of friction, ϕ, and bulk unit weight, γ, of the layer beneath the ground surface and seismic coefficient, k, varied during slope stability analyses. Then, the F_s values of the artificial slope were calculated by using the simplified Bishop method [8]. The minimum (critical) F_s value for each case was then determined and used in the development of the ANN and MR models. The ANN and MR results were compared with the results obtained from the simplified Bishop method [3] to examine the performance of the prediction capacity of the models developed in the study.

2. Artificial neural networks

Artificial Neural Networks (ANNs) are parallel connectionist structures constructed to simulate the working network of neurons in the human brain [16]. An ANN is made up of three or more layers: an input layer, one or more hidden layers, and one output layer [12]. The neurons in the input layer receive input from the external environment [12]. This layer does not perform any computations [12]. The hidden layer, which receives inputs from the input layer, performs computation and provides the outputs to the output layer [12]. The output layer consists of neurons that communicate the output of system to the user in the external environment [17]. This ANN architecture is commonly referred to as a fully interconnected feed-forward Multi-Layer Perceptron (MLP) [18].

The usage of a number of hidden layers in the ANN depends on the degree of complexity in the pattern recognition problem, and one or two hidden layers are found to be quite useful for most problems [19–21]. The number of neurons in the hidden layers also depends on the nature of the problem, and various methods have been employed by several researchers to determine them [22–27]. However, these methods present guidelines only for selection of an adequate number of neurons [28].

Learning in a MLP is an unconstrained optimization problem, which is subjected to the minimization of a global error function depending on the synaptic weights of the network [18]. For given training data, consisting of input–output vectors, values of synaptic weights in a MLP are iteratively updated by a learning algorithm to approximate the target behavior [18]. This update process is usually performed by backpropagating the error signal, layer by layer, and adapting synaptic weights, with respect to the magnitude of error signal [18]. Several learning algorithms have been developed. The back-propagation learning algorithm is the most commonly used neural network algorithm [29] and has been applied with great success to model many phenomena in the field of geotechnical engineering [30,31]. It has lower memory requirements than most algorithms and usually reaches an acceptable error level quite quickly, although it can then be very slow to converge properly on an error minimum [32]. It is most appropriate for training MLP [32]. Each hidden and output neuron processes its input(s) by multiplying each by its weight, summing the product, and then processing the sum using a non-linear transfer function, also called an activation function, to obtain the desired result [28]. The most common transfer function implemented in the literature is the sigmoid function. The neural network "learns" by modifying the weights of the neurons in response to the errors between the actual output and the target output values [28]. This is performed through a gradient descent on the sum of the squares of the errors for all training patterns [14,30]. The changes in the weights are proportional to the negative of the derivative of the error term [28]. One pass through the set of training patterns together with the associated updating of the weights is called a cycle or an epoch [28]. Training is carried out by repeatedly presenting the entire set of training patterns (updating the weights at the end of each epoch) until the average sum squared error over all the training patterns is minimal and within the tolerance specified for the problem [28].

At the end of the training phase, the neural network should correctly reproduce the target output values for training data; provided errors are minimal (i.e. convergence occurs) [28]. The associated trained weights of the neurons are then stored in the neural network memory [28]. In the next phase, the neural network is fed a separate set of data. In the testing phase, the neural network predictions using the trained weights are compared to the target output values [28]. The performance of the overall ANN model can be assessed by several criteria. These criteria contain coefficient of determination, r^2, root mean squared error, mean absolute error, minimal absolute error, maximum absolute error and variance account for. A well trained model should result in an r^2 value close to 1 and small values of error terms.

In this study, determination of the critical F_s value of a typical artificial slope subjected to earthquake forces has been modeled using the ANN in which network training was accomplished with the neural network toolbox written in a Matlab environment (Math Works 7.0 Inc. 2006). The Levenberg–Marquardt back-propagation learning algorithm [33] was used at the training stage. Details of the simplified Bishop method applied for estimating the critical F_s value of the slope, which have yielded the data for the ANN and MR models, are presented in the following section.

3. Calculation of factor of safety value of the widely-used artificial slope subjected to earthquake forces

A computer program was developed in the Matlab programming environment for estimating factor of safety, F_s, of a typical artificial slope subjected to earthquake forces [15]. Among the limit equilibrium methods [5–11], the simplified Bishop method [8] was selected in this study, due to its simplicity, which makes it easier for this application. In the simplified Bishop method [8], it is assumed that the failure surface is represented by a circular arch, which has a center represented by O and a radius represented by R [1]. The soil mass of the chosen failure surface is divided into n vertical slices, as depicted in Figure 1. For the ith slice, the width is b_i, the angle of base is α_i, the weight is W_i, the horizontal interslice forces are E_i and E_{i+1}, the vertical interslice forces are X_i and X_{i+1}, the normal force that affects the middle of the slice is N_i, and the tangential force that affects base of the slice is T_i [1]. Considering the vertical force equilibrium and the moment equilibrium, with respect to the centre, O, of the circular slip surface, the factor of safety, F_s, is determined using the following equation:

$$F_s = \frac{\sum_{i=1}^{n} \left[(W_i + X_{i+1} - X_i - u_i b_i)\tan\phi' + c_i' b_i\right]/m_{\alpha i}}{\sum_{i=1}^{n} W_i \sin\alpha_i}, \qquad (1)$$

where c is the cohesion, ϕ' is the angle of internal friction, u is the pore water pressure at the base and $m_{\alpha i}$ is given in the following equation:

$$m_{\alpha i} = \cos\alpha_i + \left(\frac{\sin\alpha_i \tan\phi_i}{F_s}\right). \tag{2}$$

The simplified Bishop method [8] assumes that the contribution of vertical interslice forces to the factor of safety is neglected. In this study, it was assumed that the ground water table is deep, and so the ground water does not have any influence on slope stability. Then, F_s values were determined using the following equation:

$$F_s = \frac{\sum_{i=1}^{n}\left[W_i \tan\phi' + c_i' b_i\right]/m_{\alpha i}}{\sum_{i=1}^{n} W_i \sin\alpha_i}. \tag{3}$$

The Pseudo-Static (PS) approach, apparently first introduced by Terzaghi [34], is still the most common procedure employed for standard, seismic slope stability evaluation [4]. Therefore, in this study, the PS approach was used for considering the effects of an earthquake. This approach is a generalization of common limit equilibrium slope stability analysis [4]. In this approach, the earthquake effects are represented by an equivalent static force, the magnitude of which is the product of a seismic coefficient, k, and the weight, W, of the sliding mass [4]. The PS approach has been implemented in the simplified Bishop method [8] (Eq. (3)), and the factor of safety, F_s, values were then determined.

$$F_s = \frac{\sum_{i=1}^{n}\left[W_i \tan\phi' + c_i' b_i\right]/m_{\alpha i}}{\sum_{i=1}^{n} W_i \sin\alpha_i + \sum_{i=1}^{n} kW_i}. \tag{4}$$

In this study, a typical man-made slope used in the highway embankments in Turkey was chosen (Figure 2). As shown in Figure 2, the horizontal to vertical ratio of the slope was 2/1, the height of the slope was 10 m (after which the slope angle must be flattened by cutting berms based on the Turkish State Highway Authorities), the soil properties of the fill material were chosen as $c = 0$, $\phi = 35°$ and $\gamma = 20$ kN/m^3, and the ground surface was assumed as horizontal. While the geometry and the soil properties (c, ϕ, and γ) of the man-made slope are kept constant, the soil properties (c, ϕ, and γ) of the sublayer beneath the ground surface, denoted as Layer 2 in Figure 2, and seismic coefficient, k, varied during the analyses, as follows. The ϕ value was allowed to vary from 15° to 40°, with a step of 5°. The c value for each ϕ value was varied from 5 to 50 kN/m^2, with a step of 5 kN/m^2. The γ value for each ϕ–c pair was varied as 16, 18, 20 and 22 kN/m^3. Terzaghi [34] suggested $k = 0.1$ for severe earthquakes, $k = 0.25$ for violent-destructive earthquakes, and $k = 0.5$ for catastrophic earthquakes. Therefore, in this study, the k value was allowed to vary from 0.1 to 0.5. with a step of 0.1. Then, the F_s values of the artificial slope were calculated using Eq. (4) for each trial failure surface and the minimum (critical) F_s value was then determined for each case by using the written program.

4. Artificial neural network model

An ANN model is designated to predict the critical factor of safety (F_s) value of the widely used artificial slope subjected to earthquake forces. Three soil parameters of layer 2 in Figure 2, namely, bulk unit weight, γ, cohesion, c, internal angle of friction, ϕ, and seismic coefficient, k, were used as the input parameters in the ANN model, while the calculated F_s value was the output parameter. The boundaries of the input and output parameters are given in Table 1. The input and output data were scaled to lie between 0 and 1, by using the normalizing expression:

$$x_{norm} = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})}, \tag{5}$$

where x_{norm} is the normalized value, x is the actual value, $x_{\max}$ is the maximum value and $x_{\min}$ is the minimum value of a generic parameter.

It is common practice to divide the available data into two subsets: a training set to construct the neural network model, and an independent validation set to estimate model performance in the deployed environment [35]. However, dividing the data into only two subsets may lead to model over-fitting [35]. Over-fitting makes Multi-Layer Perceptrons (MLPs) memorize training patterns in such a way that they cannot generalize well to new data [12]. As a result, the crossvalidation technique [36], considered to be the most effective method to ensure that over-fitting does not occur [37], was used as the stopping criterion in this study. In this technique, the database is divided into three subsets: training, validation and testing. The training set is used to adjust the connection weights [38]. The testing set is used to check the performance of the model at various stages of training, and to determine when to stop training to avoid over-fitting [38]. The validation set is used to estimate the performance of the trained network in the

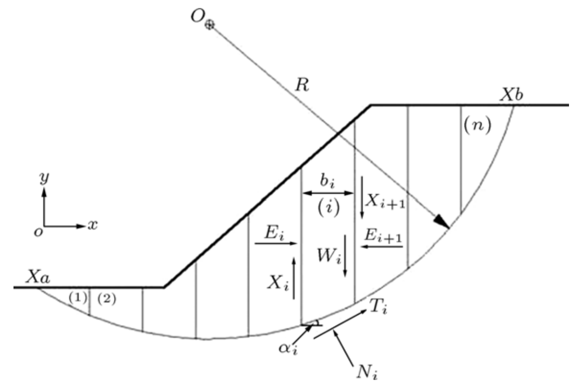

Figure 1: The forces acting on the slice [1].

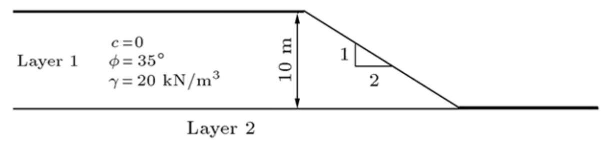

Figure 2: The geometry of the slope and the properties of the soil involved in the slope.

Table 1: Boundaries of the parameters used for the models developed.

Data type	Model parameters	Minimum value	Maximum value
Input	ϕ(°)	15	40
	c (kN/m^2)	5	50
	γ (kN/m^3)	16	22
	k	0.1	0.5
Output	F_s	0.37	3.8

deployed environment [38]. Usually, two-thirds of the data are suggested for model training (i.e. training and testing sets) and one-third for validation [39]. Shahin et al. [38] investigated the impact of the proportion of the data used in various subsets on the performance of the ANN model developed for estimating the settlement of shallow foundations, and found that there is no clear relationship between the proportion of data for training, testing and validation, and the model performance. However, they found that the optimal model performance was obtained when 20% of the data were used for validation and the remaining data were divided into 70% for training and 30% for testing. Therefore, in total, 56% of the data (i.e., 672 data sets) were randomly selected and used for training, 24% (i.e., 288 data sets) for testing, and 20% (i.e., 240 data sets) for validation in the ANN model developed in this study.

The neural network toolbox of MATLAB7.0, a popular numerical computation and visualization software [21], was used for the training, validation and testing of MLPs. Firstly, one hidden layer was chosen. Then, the optimum number of neurons in the hidden layer of the model was determined by varying the numbers, starting with a minimum of 1 then increasing the network size up to $(2I + 1)$ (I is the number of input variables) in steps, by adding 1 neuron each time. It should be noted that $(2I+1)$ is the upper limit for the number of hidden layer neurons needed to map any continuous function work with I inputs, as discussed by Caudill [40]. Different transfer functions (such as log-sigmoid [41] and tan-sigmoid [20]) were investigated to achieve the best performance in training, as well as in testing. Two momentum factors, μ (= 0.01 and 0.001), were selected for the training process to search for the most efficient ANN architecture. In this study, the coefficient of determination, r^2, was represented by:

$$r^2 = 1 - \frac{\sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}, \tag{6}$$

and the mean absolute error *MAE* was represented by:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} \left|y_i - \hat{y}_i\right|, \tag{7}$$

where y is the actual value, $\hat{y}$ is the predicted value, $\bar{y}$ is the mean of the y values, and N is the number of the sample. The above variables were used to evaluate the performance of the developed ANN model. If r^2 is 1.00 and MAE is 0, the model is treated as excellent.

The performance of the network during the training and testing processes was examined for each network size until no significant improvement occurred. The optimal ANNs performance was obtained, with the model having 5 neurons in the hidden layer, 145 epochs, a 0.001 momentum factor, and a log-sigmoid transfer (activation) function in the neurons of the hidden layer and in the neuron of the output layer.

5. Multiple regression model

Multiple Regression (MR) is a statistical technique that allows us to predict someone's score on one variable on the basis of their scores on several other variables [42]. MR is employed to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable [43]. The MR equation takes the form $y = b_1x_1 + b_2x_2 + \cdots\cdots + b_nx_n + c$, where $\{b_1, b_2, \ldots\ldots, b_n\}$ are the regression coefficients, y is now written as a function of n independent variables; $x_1, x_2, x_3, \ldots\ldots, x_n$, and c is y-intercept [44].

The critical factor of safety (F_s) of a slope strongly depends on a sliding resistance, which is physically and analytically linked to the soil parameters (γ, c, and ϕ) and seismic coefficient k. As mentioned earlier, in this study, while the geometry and soil properties (γ, c, and ϕ) of the typical embankment slope were kept constant, the subsoil properties and seismic coefficients varied during the slope stability analysis. Therefore, MR analysis was carried out by using a SPSS 10.0 package to correlate the determined F_s value to the three soil parameters (γ, c, and ϕ) of layer 2 given in Figure 2 and seismic coefficient k. The data used while developing the ANN model (i.e., 1200 data sets) were used in the development of the MR model. The MR model revealed the following correlations:

$$F_s = 0.667 - 2.430k + 0.024c + 0.031\phi,$$
$$r^2 = 0.878 \tag{8}$$
$$F_s = 0.800 - 2.430k + 0.024c + 1.324\tan\phi,$$
$$r^2 = 0.872 \tag{9}$$
$$F_s = 1.247 - 2.430k - 0.030\gamma + 0.024c + 0.031\phi,$$
$$r^2 = 0.892 \tag{10}$$
$$F_s = 1.380 - 2.430k - 0.030\gamma + 0.024c + 1.324\tan\phi,$$
$$r^2 = 0.885. \tag{11}$$

In Eqs. (8)–(11), c was in kN/m^2, γ was in kN/m^3, and ϕ was in degrees.

6. Results and discussion

A comparison of F_s values calculated from the simplified Bishop method [8], with the F_s values predicted from the ANN model, is depicted in Figures 3–5 for training, validation, and testing samples, respectively. It can be noted from the figures that predicted F_s values are quite close to the calculated F_s values, as their r^2 values are very close to unity. A paired t-test, a statistical test, uses the mean of the difference between the observations in one group and the matched observations in the other group. A paired t-test is performed to determine if there is a significant difference between two observations. A paired t-test result can be expressed in terms of a p-value, which represents the weight of evidence for rejecting the null hypothesis [45]. The null hypothesis is the equality of mean of difference between comparisons [46]. The null hypothesis can be rejected, that is, the mean of difference between comparisons are significantly different, if the p-value is less than the selected significance level [46]. A significance level of 0.05 is used for all paired t-tests [46]. Thus, $p > 0.05$ meant that there was not a meaningful difference and $p < 0.05$ meant that there was a meaningful difference [47]. In this study, a paired t-test was performed by using the SPSS 10.0 package to look for a statistically significant difference between calculated and predicted F_s values. The p-value was found as 0.428 indicating that no significant difference in F_s values was observed between calculated and predicted values. From here, it can be concluded that the F_s value of the artificial slope used in this study could be predicted from easily determined soil properties and the seismic coefficient, using trained ANNs values, with acceptable accuracy, at the preliminary stage of designing the artificial slope.

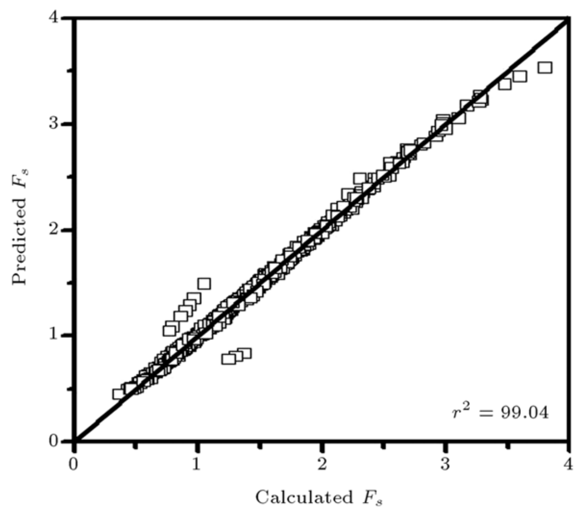

Figure 3: The comparison of the calculated F_s values with the predicted F_s values from the ANN model for training samples.

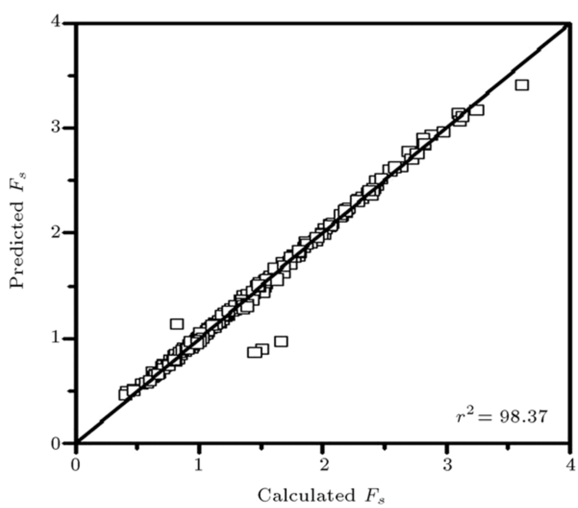

Figure 4: The comparison of the calculated F_s values with the predicted F_s values from the ANN model for validation samples.

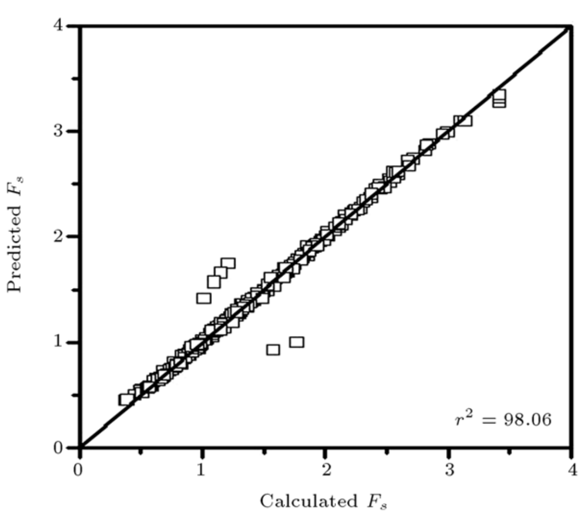

Figure 5: The comparison of the calculated F_s values with the predicted F_s values from the ANN model for testing samples.

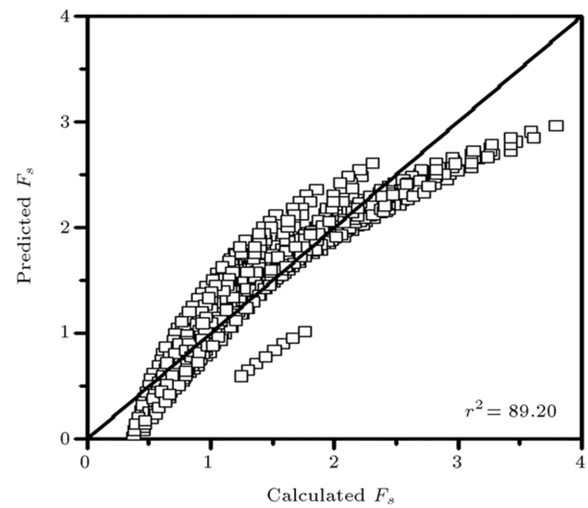

Figure 6: The comparison of the calculated F_s values with the predicted F_s values from the MR model for all samples.

It is noted from the results of the MR analysis (Eqs. (8)–(11)) that Eq. (10) has the highest r^2 value of 0.892. Therefore, in order to show the relationship between calculated and predicted F_s values, F_s values predicted from Eq. (10) were compared with the F_s values calculated from the simplified Bishop method [8], as shown in Figure 6 for all samples. It can be noticed from the ure that predicted F_s values from Eq. (10) are in good agreement with the calculated F_s values, as r^2 of 0.892. A paired-T test, using the SPSS 10.0 package, was also performed to determine whether there was a significant difference between calculated and predicted F_s values. The p-value was then found as 0.002 indicating that there was meaningful difference between the calculated and predicted F_s values. Therefore, the use of Eq. (10) is not recommended at the preliminary stage of designing the artificial slope.

In fact, the coefficient of correlation between the measured and predicted values is a good indicator to check the prediction performance of the model. In this study, the variance *VAF* was represented by:

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{var}\left(y - \hat{y}\right)}{\mathrm{var}\left(y\right)}\right] \times 100, \tag{12}$$

and the Root Mean Square Error, *RMSE,* was represented by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}, \tag{13}$$

where var denotes the variance, y is the measured value, $\hat{y}$ is the predicted value, and N is the number of the sample. The above variables were computed to control the performance of the predictive models developed in the study, as employed by Erzin et al. [28], Erzin [48], Erzin and Yukselen [49], Erzin et al. [50,51]. If VAF is 100 % and RMSE is 0, the model is treated as excellent.

The performance indices calculated for the ANN and MR models (i.e. Eq. (10)) developed in this study are given in Table 2. The ANN model has exhibited a higher prediction performance than the MR model, based on the performance indices in Table 2. As mentioned by Yılmaz and Yuksek [43], this higher performance of the ANN model was sourced from a greater degree of robustness and fault tolerance than the MR model, because there are many more processing neurons, each with primarily local connections.

Table 2: Performance indices (r^2, RMSE, MAE, and VAF) of the ANN and MR models developed.

Model	Data	r^2	MAE	RMSE	VAF (%)
ANN	Training set	99.04	0.02	0.06	99.04
	Validation set	98.37	0.03	0.08	98.36
	Testing set	98.06	0.03	0.09	98.06
MR	All set	89.20	0.14	0.19	89.20

7. Conclusions

In this study, efforts were made to develop Artificial Neural Network (ANN) and Multiple Regression (MR) models that can be employed for estimating the critical F_s value of a widely-used artificial slope subjected to earthquake forces. The purpose was to demonstrate that the ANN model can be useful for a preliminary stage of design of a typical embankment slope with constant properties developing along an area with variable subsoil conditions. For this purpose, a typical man-made slope used in the highway embankments in Turkey (Figure 2) was chosen. Then, while the geometry of the slope and the properties of the embankment soil are kept constant, the natural subsoil properties, namely, cohesion, c, internal angle of friction, ϕ, and bulk unit weight, γ, of the layer beneath the ground surface and seismic coefficient, k, varied during the slope stability analyses. Then, the F_s values of this slope were calculated by using the simplified Bishop method and the minimum (critical) F_s value for each case was determined and used in the development of the ANN and MR models. The input parameters used in the ANN and MR models are the three soil properties, namely, bulk unit weight (γ), cohesion (c), and angle of internal friction (ϕ) of the layer beneath the ground surface and seismic coefficient (k). The output parameter is the determined critical factor of safety (F_s). The results obtained from the ANN and MR models were compared vis-à-vis those obtained from the calculations. It is found that the ANN model exhibits more reliable predictions than the MR model, provided that a linear relationship, such as Eq. (10), is used. Therefore, the critical F_s value of the artificial slope considered in this study could be predicted using trained ANN structures, quite easily and efficiently.

To check the prediction performance of the ANN and MR models developed, several performance indices, such as r^2, VAF, MAE, and RMSE, were calculated. The ANN model has shown higher prediction performance than MR models, based on the performance indices, provided that a linear relationship, such as Eq. (10), is used. The performance level attained in the ANN model has shown that the ANN model developed can be useful for the preliminary stage of design of a typical man-made highway embankment slope, with constant geometry and soil properties, developed along an area with variable subsoil conditions. The performance of the ANN model has also shown that the neural network is a useful tool to minimize uncertainties encountered during soil engineering projects. For this reason, the use of a neural network may provide new approaches and methodologies, and minimize the potential inconsistency of correlations.

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