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Influence of Seismic Loading on Slope Instabilities

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ABSTRACT

Accurate estimation of seismic slope stability is a very challenging task in geotechnical earthquake engineering. It requires information about several parameters like geometrical parameters, shear strength parameters and seismic coefficient of the study region. Conventionally stability of a slope is assessed by using either limit equilibrium methods or stability charts. Limit equilibrium methods take time in modeling and design of slope. Whereas stability charts also take lot of time for carrying out iteration procedure to obtain stability factor. ANN (artificial neural network) a soft computing technic used to solve nonlinear behaviors of dynamic systems can be applied to slope stability problems. ANN can also be used to identify the relative contribution of training input parameters. ANN takes very less time for calculating stability factor of a slope. However, ANN initially requires huge data for its training. In this present paper, we calculated stability of large number of slopes under earthquake loading and then results are used in ANN training. Geo-studio's Slope/W software is used to calculate this data set. We have finally assessed the relative importance of various contributing parameters on slope stability. It is found that contribution of seismic coefficient on slope stability is very significant in the calculation of slope stability.

Introduction

Earthquakes often cause instability of various manmade structures such as road embankments, dams, landfills, earth dams, open pits etc. They also cause instabilities to natural slopes like mudslides, landslides, and avalanches on steeper hills or mountains. These slopes instabilities due to earthquakes are annually causing tremendous damages around the world to build environment as well as human lives. Hence, it is very important to accurately assess the seismic slope stability of these structures.

Seismic slope stability of an earth structure is not only influenced by characteristics of earthquake loading, but also influenced by number of other parameters such as shear strength parameters (cohesion C, angle of internal friction φ), geometrical parameters (slope angle β and height H), density of soil ϒ. Even though simple pseudo static slope stability analyses are commonly used for analyzing seismic slope stability, it is desirable to know relative significance of each of these factors on the stability. It is very difficult to assess relative importance of these parameters. In this study, we had made an attempt to assess the relative importance of seismic loading with respect to other parameters using Artificial Neural Network (ANN).

ANN is a powerful, statistical modeling technique (Shahin et al., 2001), and very useful in problems where the relationship between dependent and independent parameters is complex and

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complicated. ANN has been increasingly used in the field geotechnical engineering. The application of ANNs for solving complex slope stability problems has been recently applied by many researches (e.g. Lu and Rosenbaum, 2003; Sakellariou and Ferentinou, 2004; Erzin and Cetin, 2012; Erzin and Cetin, 2013).

In this study, for estimating importance of various parameters on seismic slope stability, ANN is initially trained with huge data set. Details of data set used are given in the following section. After satisfactory training of ANN, the residual interconnection weights are collected from the trained network. From these residual weights, relative contribution of various parameters has been calculated following the procedure developed by Garson (1991). Further details of training and calculation of the contribution factors are given in the corresponding sections.

Selection of Data

The accuracy of ANN depends not only on the quality but also the quantity of the data used for its training. Training of ANN with huge data, improves its accuracy particularly for complex problem like slope stability. Here we prepared huge data set for this purpose. We analyzed different slopes under different levels of seismic loading. We varied the strength parameters (C, φ),slope angle (β), unit weight of soil (ϒ) varied uniformly over possible parameter ranges. This helps the proper training of ANN. For this study, possible data ranges are considered from the study by (Erzin and Cetin, 2012).

Selected data ranges are presented below in Table 1. The φ value was varied from 12° to 40°, with an interval of 7°. The C value was varied from 5to 50 kN/m^2 , with an interval of 10 kN/m^2. γ values were also varied from 16 to 22 kN/m^3 with an interval of 2 kN/m3. Slope angle β was varied from 25^o to 45^o with an interval of 10^o. Seismic coefficient k was varied in the range of 0 to 0.3 with an interval of 0.1. With these ranges, total of 720 cases were consider for training and testing of ANN.

Table 1: Data ranges consider for calculating FoS and used for training ANN.

Parameter	Range	Interval	No. of Cases
Cohesion, C(kPa)	5-50	10kPa	5
Angle of Friction, Φ	12^0-40^0	7^0	4
Angle of Inclination, β	25^0-40^0	5^0	4
Unit Weight, ϒ(kN/m^3)	16-22	$3kN/m^3$	3
Seismic loading K_h	0	0.3	3
Total Number of Cases = 5*4*4*3*3 =			720

Seismic Slope Stability Analysis

For each of the case given in Table 1, seismic slope stability analysis is carried. For this purpose Slope/W module presented in Geo-studio (2012) software was used for calculating factor of safety. In Slope/W, pseudo static slope stability analysis had been carried out using simplified Bishop method, this method is being used widely in assessing stability of slopes and it is considered as the best method within the limit equilibrium methods for assessing the stability factor (Zhu, 2008). This method assumes tangential inter slice forces are equal and opposite, satisfies vertical force equilibrium for each slice and overall moment equilibrium about the center of the circular trial surface. In this study, total of 740 homogenous finite slopes having different shear strength parameters and slope parameters as given in Table 1 were analyzed. In this study, ground water table was considered deep in all the cases. And hence the ground water does not have any influence on seismically induced slope stability. Thus, the results are applicable only to the fully drained conditions, where the effects of pore pressures (PwP) can be neglected. Typical seismic stability factor calculation is shown in Figure 1.

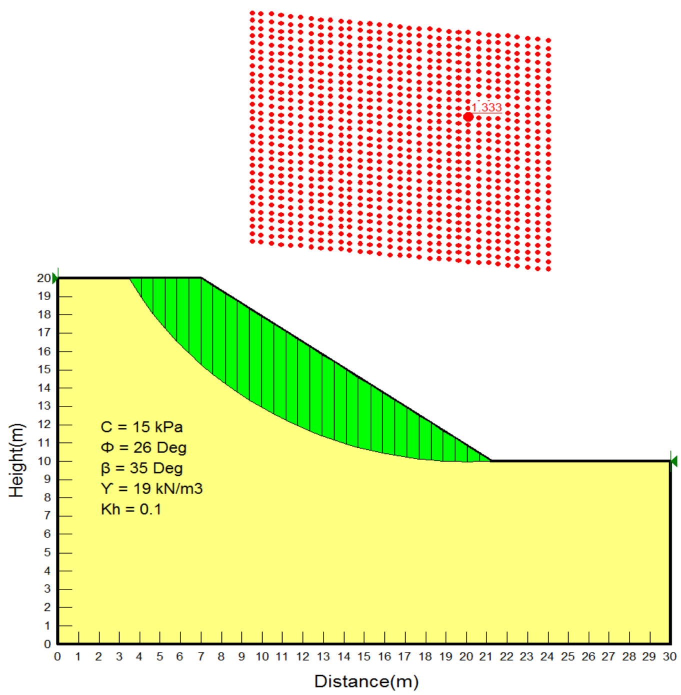


Figure 1. Typical slope considered for carrying out seismic slope stability analysis

Artificial Neural Network

Artificial Neural Networks (ANNs) simulates the working network of neurons in the human brain. An ANN consists of three layers: input layer, hidden layers, output layer. The main purpose of input layer is to receive information from the external environment; this layer does not execute any computational calculations. The hidden layer, which takes the information from the input layer, performs computations and supplies the modified information to the output layer. Hidden layers can be one or more, that depends upon the complexity and nonlinearity of the problem. The output layer neurons pass the output of ANN to the user in the external environment.

ANN used in this study, takes C, ϕ, β, Υ, K_h as inputs to input layer. Here in our study, we consider only one hidden layer. Output layer consists of FoS of the slope. ANN used in this study is shown in Figure 2.

Bayesian regulation [TRAINBR] network training function is used here. This training function updates the weights and bias values according to error optimization. It minimizes a combination of mean squared errors with respect to interconnection weights, and then finds the correct combination so as to produce a network that predicts well. Activation functions used in this study were 'tansig' and 'purlin'. Tansig was used between input layer and hidden layer, whereas purlin was used between hidden layer and output layer.

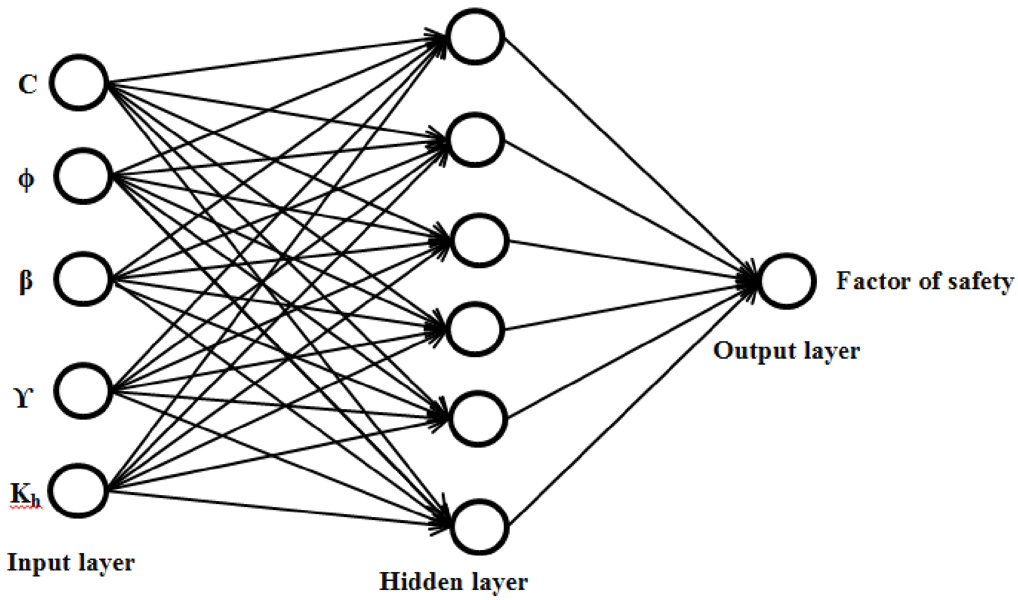


Figure 2: ANN Network considered in the study.

Training and testing of ANN

Total data set of 740 cases was divided into two different sets for the purpose of training and testing. The training set is the largest set and was used by neural network to learn patterns present in the data. In this work 80% of total data considered for training. The testing set was used to assess the capability ability of trained neural network. Remaining 20% of total data considered for testing. Testing a neural network to learn patterns in the data involves iteratively presenting it with examples of the correct known answers. The main aim of training ANN is to obtain the inter-connected weights between the neurons, which determine the global minimum of error function. This involves decision regarding the number of iterations i.e., when to stop training a neural network and the selection of learning rate.

Figure 3 shows the performance of neural networks during training and testing. X axis represents iterations whereas Y axis represents mean square error. Mean square error is reducing up to 50th iterations. it finally becomes a constant value i.e. is 0.0096. Figure 4 shows the regression plots. Subplots of the figure show regression performance of training, testing and over all data. Here X axis is factor of safety obtained from ANN whereas Y axis is calculated factor of safety using Bishop method. All the subplots show clearly that calculated factor of safety (targeted) and obtained ANN factor of safety is almost same. Equation on Y axis represents the straight line, which all figures having approximately ‘0’ coefficient and slope approximately ‘1’. From these figures, we can conclude that targeted factor of safety and calculated factor of safety is almost same.

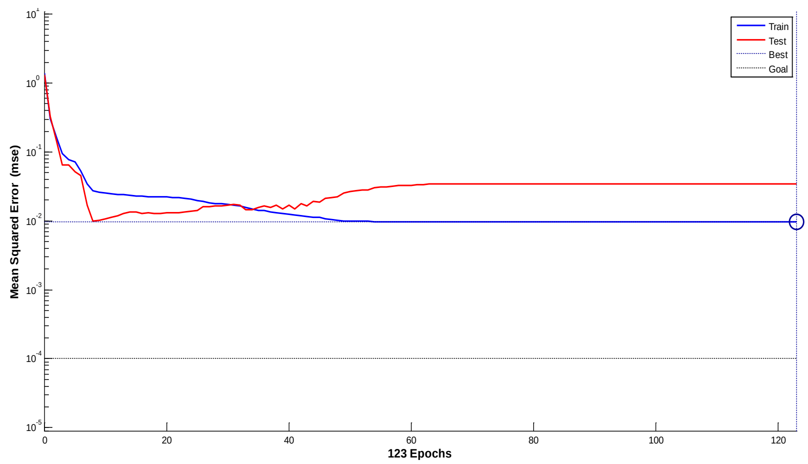
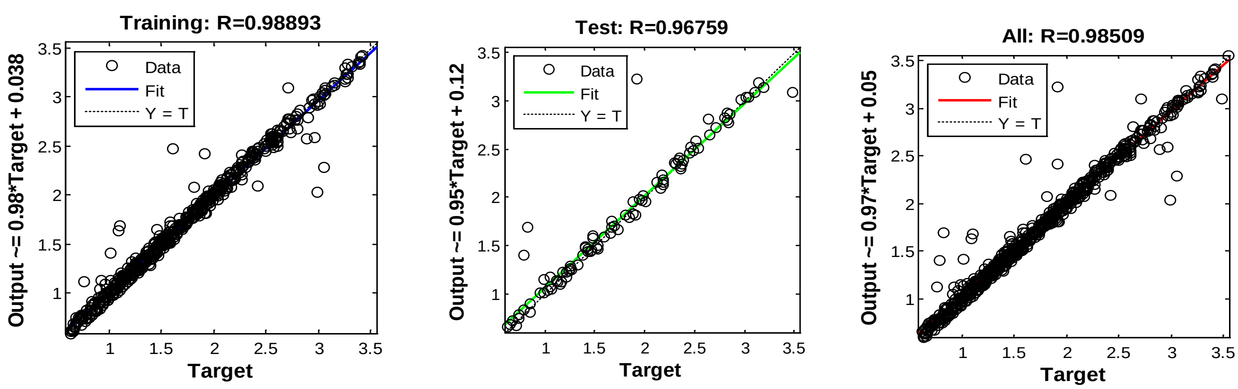


Figure 3: Performance of the ANN during training and testing.



(a) (b) (c)

Figure 4: Regression plots after training (a), testing (b) and overall (c).

Relative Importance of the Parameters

The main objective of this study is to obtain the relative importance of various parameters, which are used in the seismic slope stability assessment of slopes and to identify the relative contribution of seismic coefficient. During training process initial inter connection weights are assigned arbitrarily and then training process is initiated. These weights are continuously updating until an acceptable training accuracy is reached. The final weights obtained from the training are further used to process the testing data. After satisfactory training and testing of ANN the residual interconnection weights between neurons was collected and presented in Table 2. For calculating relative contributions of parameters, we had used a method developed by Garson (1991). This method has been successfully used in various problems (Goh, 1995a; Sakellariou and Ferentinou, 2005). By applying same procedure using residual interconnected weights obtained from trained ANN, we calculated the relative contribution of all the parameters.

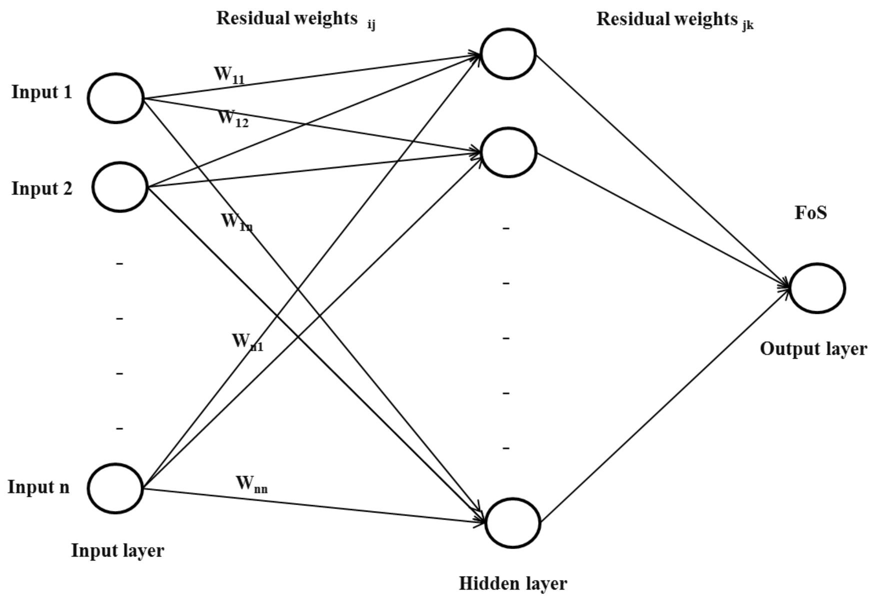


Figure 5: Residual weights of typical ANN architecture.

In the present work, considered neural network consists of five input neurons, six hidden neurons and only one output neuron. Their inter-connected weights are presented in the above Table 2. w_{ij} Figure 5 represents the weights from input to hidden layer. Whereas w_{jk} represents the weights from hidden to output layer. Based on these weights, related importance of the parameters is calculated using this method by (Garson, 1991) the calculated relative importance of the parameters are tabulated in Table 3.

Table 2: Weights obtained after training ANN.

Hidden neurons	**Inter connected residual weights**						
	β	**C**	**φ**	**ϒ**	**K_h**		**FoS**
1	-0.17147	0.42999	0.30902	-0.08291	0.19497		0.73809
2	0.56002	-0.19953	-0.38079	0.19647	0.75709		-0.64911
3	-0.05544	-0.0578	0.08266	0.020024	1.0105		-0.87551
4	0.16153	-0.67742	-0.10863	-0.01964	-0.45115		-0.90369
5	-0.32689	-0.3186	0.3594	0.40393	0.050963		-0.35478
6	-0.01921	-0.23851	0.29065	0.12944	0.2595		0.82166

Table 3: Final Relative importance of considered parameters.

Parameter	β	C	φ	ϒ	K_h
Relative Importance	13.58%	24.24%	19.03%	10.14%	32.99%

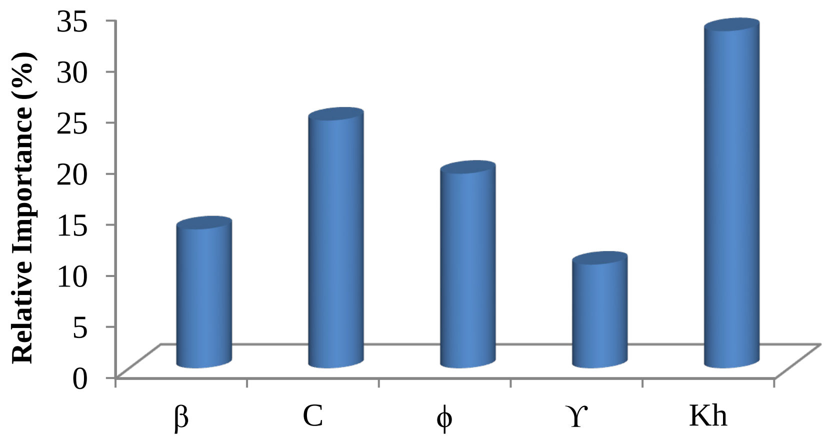


Figure 6: Relative contribution of all parameters.

Conclusions

The main objective of this study is to obtain the relative importance of various parameters and to identify the relative contribution of seismic loading on slope stability. If the parameters' relative contribution is more, its sensitiveness plays a major role in the calculations of factor of safety. Even if a small deviation in input value will result in maximum variation in the factor of safety calculations. Therefore it is very important to identify the relative contribution of various parameters in calculation of seismic factor of safety. From the results of the study, relative contribution of various parameters including seismic coefficient are shown in the Figure 6. From this figure, we can clearly understand that the importance of the seismic loading on the slope stability. Relative contribution of seismic loading in terms of seismic coefficient is 33%. Only after seismic coefficient, strength parameters are major contributing factors. Contribution of cohesion, C is of 25 % and φ is of 19%. Unit weight of the soil is affecting less compared to all other parameters (10%). So from the study, we can conclude that accurate estimation of seismic loading in terms of seismic coefficient is very important for the reliable assessment of stability of slopes under earthquake loading. Further, the estimated relative importance of various parameters can used to account the effects of uncertainties on the FOS estimated by reliability based methods. Relative importance of the parameters estimated here can also be used in the development of weights for the empirical methods used in landslide hazard zonation (LHZ). LHZ is carried most commonly by weighting different causative factors. However, the weights used in these studies are empirical. Based on the results of this study, one can obtained more reliable weights for various causative factors.

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