SENSITIVE ANALYSIS OF SOIL PARAMETERS ON STABILITY NUMBERS

Bimlesh Kumar

Research Scholar, Department of Civil Engineering, Indian Institute of Science, Bangalore - 560012,India
bimk@civil.iisc.ernet.in

Pijush Samui

Research Scholar, Department of Civil Engineering, Indian Institute of Science, Bangalore -560012,India.
pijush@civil.iisc.ernet.in

Abstract

In general, Stability number can be expressed as a function comprising of pore water pressures coefficient (r_u), horizontal earthquake coefficient (k_h), slope angle (β) and friction angle (ϕ) in associated flow rule. Then it is important to know how different parameters influence the stability number. These influences may be obtained through the sensitivity analysis of the parameters. Due its facility in solving non linear problems, Artificial Neural Networks (ANN) has been proposed, as a powerful tool, to represent the stability number. Neural Networks are typically thought of as black boxes trained to a specific task on a large number of data samples. In many applications it becomes necessary to "look inside" of these black boxes before they can be used in practice. Sensitivity analysis is one of best ways to look inside the neural model and ascertain that which parameters are having more effect on the output. Sensitivity analysis is a method for extracting the cause and effect relationship between the inputs and outputs of the network. The basic idea is that each input channel to the network is offset slightly and the corresponding change in the output(s) is reported. So, through differentiation of a previously trained net, the sensitivity factors of the main parameters of solar collectors is calculated and discussed. The sensitivity factors show how much the input variables influence the output variables. In this paper, the sensitivity analysis for stability number's main parameters is discussed. The result indicates that the r_u is having more influence on stability number than any other parameter followed byβ k_h and ϕ. The stability numbers have been found to decrease continuously with (i) increase in r_u, (ii) increase in k_h and (iii) increase in slope angle (β) (iv) decrease in ϕ.

Key words: slope stability, Artificial Neural Network, stability number.

INTRODUCTION

The stability of homogeneous slopes can be expressed in terms of a dimensionless group known as the stability number, N, which is defined as, $\gamma H_c/c$ where 'c' is the cohesion, γ is the bulk unit weight of the soil and H_c is critical height of the slope. The design of earthen embankments is quite often carried out with the use of stability numbers as originally introduced by Taylor (1948). Taylor provided the charts indicating the variation of Ns for homogeneous slope with changes in slope angle (β) for various soil friction angles (ϕ). Later on Bishop (1955) used the method of slices in obtaining the stability of slopes. In order to solve the problem, Bishop assumed that the resultant of inter slices forces acts in the horizontal direction. It is found that the method of slice do not satisfy all the conditions of statical equilibrium.Chen (1975) used the upper bound theorem of the limit analysis to obtain the critical heights for the homogeneous soil slopes. A rotational discontinuity mechanism was assumed in this analysis; it was indicated that in order that the rupture surface remains kinematically admissible, its shape should become an arc of the logarithmic spiral. However, Chen (1975) did not incorporate either the effect of pseudo-static earthquake body forces or the pore water pressure. Michalowski (2002) also used the upper bound theorem of limit analysis in order to obtain the stability numbers for homogeneous slopes in the presence of pore water pressures as well as pseudo-static earthquake forces and formulated the following expression;

$$N = f\left(r_u , \varphi, k_h , \beta \right) \qquad (1)$$

Where the definitions of H, ϕ and β are given in Figure 1. Where r_u is the pore water pressure coefficient and k_h is the horizontal earthquake coefficient.

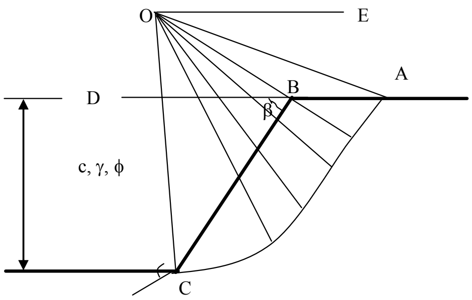

Figure 1. Slope geometry.

NEURAL NETWORK

Neural networks, as they are known today, originate from the work of Mcculloch and Pitts (1943), who demonstrated the ability of interconnected neurons to calculate some logical functions. Neural networks are made up of a great number of individual processing elements, the neurons, which perform simple tasks. A neuron is the basic building block of neural network technology which performs a nonlinear transformation of the weighted sum of the incoming inputs to produce the output of the neuron. The input to a neuron can come from other neurons or from outside the network. The nonlinear transfer function can be a threshold, a sigmoid, a sine or a hyperbolic tangent function**.** In this study, Levenberg-Marquardt Backpropagation algorithm has been. The theory and implementation of Levenberg-Marquardt Backpropagation has given by More (1977).

RESULTS OF NEURAL MODELING

In order to analyze the sensitiveness of the parameters affecting the stability number of the homogeneous slope, neural network has been optimized by generating the input and target vectors from the charts of Michalowski (2002). Total numbers of training patterns given in the neural network are 2000 and for testing 500. The critical step in building a robust ANN is to create an architecture, which should be as simple as possible and has a fast capacity for learning the data set. The robustness of the ANN will be the result of the complex interactions between its topology and the learning scheme. The choice of the input variables is the key to insure complete description of the systems, whereas the qualities as well as the number of the training observations have a tremendous impact on both the reliability and performance of the ANN. Determining the size of the layers is also an important issue. One of the most used approaches is the constructive method, which is used to determine the topology of the network during the training phase as an integral part of the learning algorithm. The common strategy of the constructive methods is to start with a small network, train the network until the performance criterion has been reached, add a new node and continue until a 'global' performance in terms of error criterion has reached an acceptable level. The final architecture of neural net used in the analysis is shown in Figure 2. The transfer function used in the hidden layer is tanh and at the output layer is purelin. The maximum epochs has been set to 10000. Entire modeling has been done by using MATLAB software. Results of neural modeling are shown in Figures 3, 4 and 5.

SENSITIVITY ANALYSIS

Sensitivity analysis is a method for extracting the cause and effect relationship between the inputs and outputs of the network. The basic idea is that each input channel to the network is offset slightly and the corresponding change in the output is reported. To ascertain the influence of the input variables on output variables, sensitivity analysis is also carried out. This testing process provides a measure of the relative importance among the inputs of the neural model and illustrates how the model output varies in response to variation of an input. The first input is varied between its mean ± standard deviations while all other inputs are fixed at their respective means. Similar exercises have been made for all others input parameters.

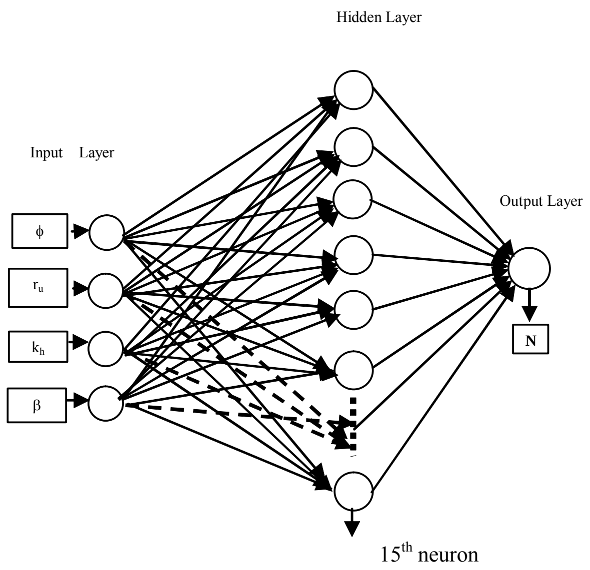

Figure 2. Neural net architecture used in the analysis.

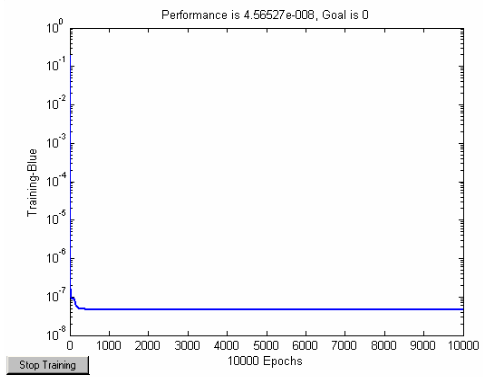

Figure3. MSE versus epochs.

As shown in Figure 6, pore water pressure coefficient is having more influence on stability number followed by the slope angle (β),k_h and ϕ. The stability number as a function of r_u by keeping the other parameters as constant, as predicted by the ANN model is shown in Figure 7. The stability numbers have been found to decrease with an increase in r_u. Figure 8 gives the stability numbers characteristics as a function of k_h. It has been found that the stability numbers is decreasing

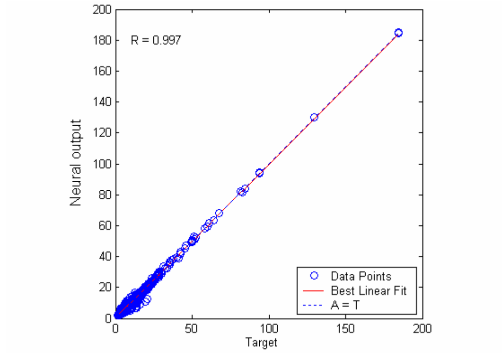

Figure 4. Results of training phase.

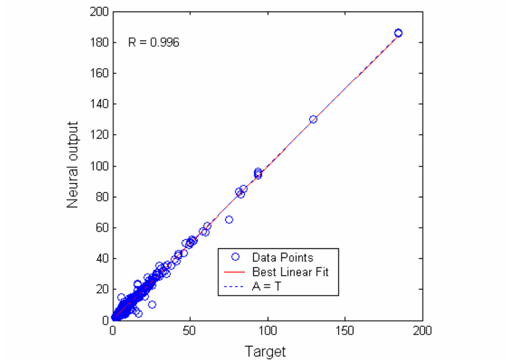

Figure 5.Results of testing phase.

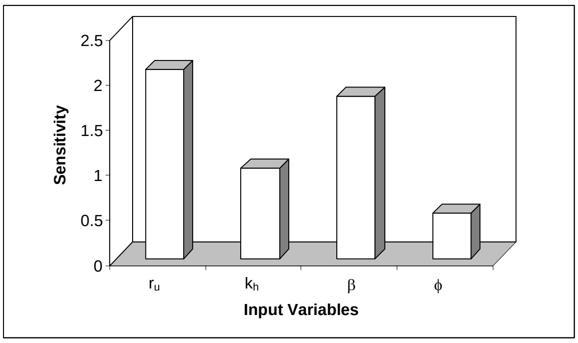

Figure 6. Sensitivity analysis of Stability numbers.

with an increase in k_h. Effect of slope angle is illustrated in Figure 9. It shows that the stability numbers have been found to decrease continuously with an increase in slope angle β. Effect of friction angle ϕ is depicted in Figure 10. It is seen clearly from Figure 10 that an increase in ϕ will increase the stability number.

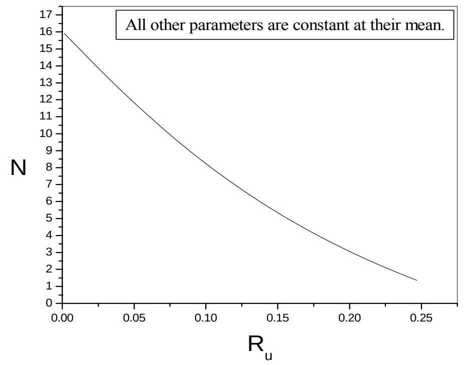

Figure 7. Effect of r_u on stability number.

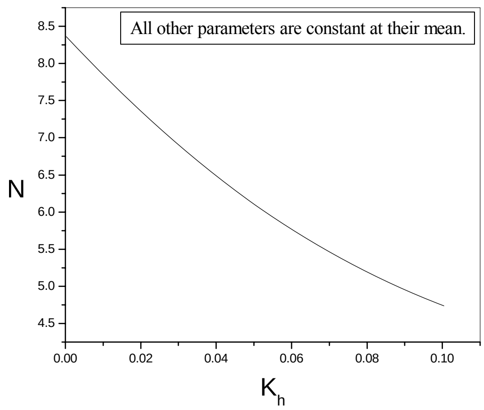

Figure 8. Effect of k_h on stability number.

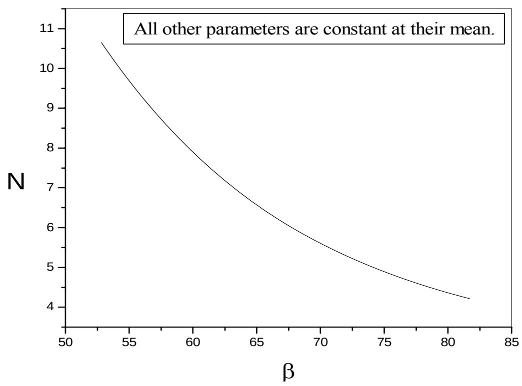

Figure 9 .Effect of β on stability number.

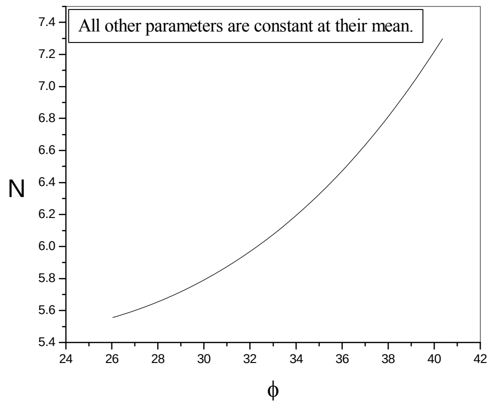

Figure 10. Effect of ϕ on stability number.

CONCLUSION

The results presented in this paper have clearly shown that the neural network methodology can be used efficiently to predict the stability numbers for non homogeneous soil slope. The main advantage of neural networks is to remove the burden of finding an appropriate model structure or to find a useful regression equation. The network showed excellent learning performance and achieved good generalization. Sensitivity analyses with the trained neural net or during training could provide valuable additional information on the relative influence of various parameters on the stability number. The r_u is having more influence on stability number than any other parameter. The stability numbers have been found to decrease continuously with (i) increase in r_u, (ii) increase in k_h and (iii) increase in slope angle (β).The stability number will increase with an increase in ϕ.

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