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Research Article

An Artificial Neural Network Method for Forecasting the Stability of Soil Slopes

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Abstract: Artificial neural network (ANN) methods, based on sophisticated models, have been developed recently that can predict slope stability. In this study, we have developed a genetic algorithm (GA) based on ANN to assess the stability of soil slope. Firstly, an ANN-based genetic algorithm was trained for nonlinear input-output mapping of the slope. A total of 190 soil slopes with unique values of shear strength properties (friction angle, cohesion, and unit weight), geometric parameters (slope angle and slope height) and corresponding factor of safety (FS) have been collected to give a neural network training dataset. Then, a three-layer neural network model is established based on GA. The prediction and performance ability of the established model is assessed using the correlation coefficient (R^2). By the outcomes, the trained ANN model with the R^2 value of 0.98 is reliable, valid and simple for evaluating the soil slope stability and estimating the FS. Additionally, the proposed neural network model is applied to a case of soil slope from prior studies. Findings show that the developed ANN model can be versatile in studying the stability of soil slopes.

Keywords: Soil Slope, Cohesion (c), Genetic Algorithm (GA), Internal Friction Angle (ϕ), Slop Angle (θ).

1. INTRODUCTION

Researchers usually determine the soil slope stability and failure process to exactly categorise critical slip surfaces [1]. Several analytical methods are also documented to estimate the factor of safety (FS) of different slopes [2]. Because soil strength properties and slope profile affect the stability of loose slopes [3]. Therefore, the analysis evaluation of slope stability is of great engineering significance in the geotechnical field [3, 4]. A variety of slope stability analyzing and forecasting methods have been proposed, which can be divided into two categories: the extreme balance method and the numerical analysis method. Janbu method, Swedish division method, Sarma method, Bishop method and residual thrust method are well-known methods today. The advantage of these methods is that they are strictly based on the theory of slope geology. For example, the Bishop method assumes that the forces between the blocks are horizontal, and the Swedish assumes that the combined forces between the slices are parallel [3, 5]. These assumptions are often far from the actual physical and technical behaviour of the rock and soil material, and therefore their accuracy is greatly

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reduced [6]. However, Finite element technique (FEM), distinct element approach (DEM), boundary element method (BEM) and particle flow method are much handy [2, 6]. The numerical analysis method is often based on some hypothesis about the physical properties of rock and soil material, and its accuracy is highly dependent on the slope model and input parameters (shear strength properties). Therefore, results from these numerical methods are often difficult to confirm the reality [7].

The method of judgment of the critical slip surface is directly connected to way of determining the minimum safety factor. Some scholars have used limit equilibrium techniques to evaluate FS and slip surface statically [8, 9], or numerically [10, 11]. To determine the minimum FS for a sliding surface, the limiting equilibrium technique may allow a precise and accurate evaluation method during large-scale stability investigations. Therefore, commonly used approaches are limiting equilibrium techniques; hence, cannot be used to locate CFS with general limit under composite conditions. On the other hand, optimisation techniques are considered as an effective tool to estimate FS for typical slip surfaces [12] and dynamic programming is used to allocate the non-circular slip surface [11]. Monte Carlo techniques can evaluate slope FS and critical slip surface [13]. Other researchers proposed a few conventional solutions for rock slope stability analyses [14, 15].

Many methods and techniques have been introduced previously to assess soil slope stability. Such as the Bishop method [8], Baker technique [16], extended Spencer method [17], and Morgenstern and Price approach [18] are well known today. The above techniques are not laborious [19], but numerical modelling techniques are time-saving and appropriate for slope stability investigation [20]. Some scholars presented key block [21] and fuzzy key-block [22] methods that can be used for slope failure analysis. Other used genetic algorithms [23] and optimization techniques [24] for non-circular sliding surface determination.

Recently, ANN based methods have emerged in the field of geotechnical engineering for slope stability prediction [25]. Previously, ANN models were established based on material strength properties ignoring slope profile.

In the present study, a high nonlinear artificial neural network (ANN) model is presented to predict soil slope stability. Firstly, a genetic optimization algorithm is established based on soil properties and slope profiles. The accuracy of the proposed model is judged through the correlation coefficient (R^2). Combined with case studies and the results from SLOPE/W software, the forecasting abality of the proposed ANN model is effective.

2. METHODOLOGY AND ANN METHOD

Studying soil slope stability is one of the most important kinds of research in the geology and geo-engineering fields. Many geotechnical researchers of the 20th century divided the sliding mass of the slope into several slices to calculate the accurate value of FS [8, 26, 27]. Furthermore, because of the rise of computer technology statistically more laborious equations can be solved easily to resolve soil and rock mechanics problems [28, 29]. Numerical models are not generally straightforward for operators and are considered supplementary means capable of delivering information helpful for stability analysis [28]. However, ANN-based models are powerful tools for tackling difficult stability issues [30].

ANN is an intelligence managing technique that can learn, generalise and recall from training records [31, 32]. ANN is a model established with the help of a set of several basic handling elements known as neurons. Neurons are rigorously interlinked computational components that can perform data representation and data processing using wide similar computation [31, 33]. The vigorous computational structure of ANN can be used to train a complex model [34, 35]. Numerous ANN designs have been previously used in civil and geotechnical engineering applications [34, 36] and soil slope stability prediction [33, 37].

ANN is a kind of nonlinear structure that has clear nonlinear planning capacity. ANN could also be used for nonlinear mapping without knowing the specific distribution of data [38]. Artificial neural networks are a self-learning technique that stores the outcomes in the upper limit of neurons by using the relation weight between nerve cells. After this, new engineering examples were entered, and the network used its nonlinear mapping capability to give heuristic inferences. To predict the slope status and FS, based on slope parameters, a new ANN model is shown in Fig. 1. Many engineering experiences show that the main factors affecting the stability of slope are the physical and mechanical properties, slope geometry, groundwater, and external loads. As well as the properties of soil slope materials are mostly controlled by the weight of the rock and soil body. Cohesion (c), geometry and internal friction (ϕ) of the soil slope are mostly controlled by the slope angle (θ) and height (H). So, the modelling of slope for stability estimation can be founded by mapping the relationship (G).

$$y = G(\gamma, E, c, \phi, H, h, w) \qquad (1)$$

In equation (1), the value of y (y is the safety value) ranges from 0-1, and if $y = 0$, then the slope will be thought-out unstable, and if $y = 1$, indicates that the slope is stable. G is highly nonlinear due to the complexity of the shear strength and geometric properties of the slope material. It is difficult to precisely describe G by mathematical equations. Given the high nonlinear mapping capability of neural networks, we have used neural networks to describe G, which can be affected by density (γ), Young's modulus (E), cohesion (c), angle of internal friction (ϕ), overall height (H), slope height (h), slope angle (θ) and weight of water (w =0). The prediction of slope stability by neural network can be divided into two stages: the first stage is the self-learning stage of the network. This stage was achieved by previous studies. The second stage is the prediction stage, which predicts the stability of the slope directly.

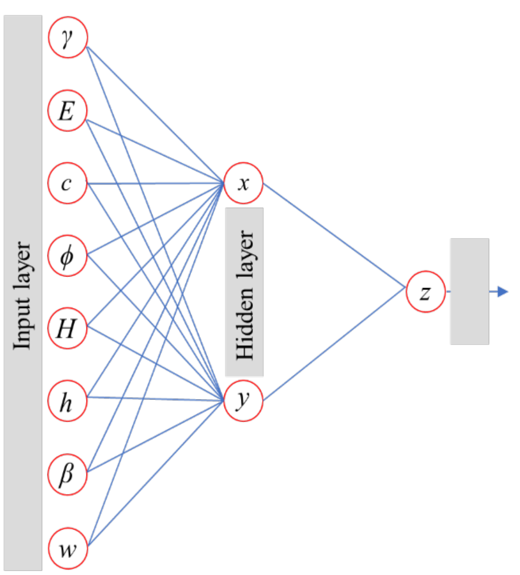

Fig. 1. Neural model for FS prediction.

3. STRUCTURE OF ANN

Because the slope stability problems are highly nonlinear, which requires the neural network to be used to map. The mapping relationship (G) can be as close to the objective reality as possible and ANN should have a strong enough generalization ability to get the correct results based on input parameters. The capacity and generalization ability of a neural network depends largely on the structure, of the structure of the neural network, including the connection mode of neurons in the network and the connection weight between neurons. The proper connection mode and optimized connection weight are important to neural networks' capacity and generalization ability.

The shortcomings of conventional neural network algorithms during the data optimization process are not obvious. The selection of connection mode and the weight of neural networks cannot be processed systematically. The conventional ANN technique determines the connection between neurons in the network according to the experience. Then the neural network samples rearrange the input data to make a proper connection between networks. Also, if the input data are not met, then all the optimization steps are repeated to find out optimal solution. Additionally, it is very difficult to find out the optimal network by using conventional method. So, the capacity of traditional ANN model is insufficient and the ability to generalize data is poor for solving large slope stability problems. In addition, the learning ability of the traditional ANN method is low, and it is not easy to fall into local extreme values.

Obviously, according to the characteristics of the problem, the number of neurons in the input layer are 6, corresponding to the 6 factors considered in this research, and the number of neurons in the output layer is 1, which corresponds to the final output result. The middle layer is set to m layer and each layer has n neurons. The connection of the neurons is a single-layer forward, i.e., the descending layer can only be connected to the neurons in the subsequent layer. For the convenience of calculation, the connection weights between neurons in each layer of the neural network and the thresholds of each neuron are deposited into a one-dimensional vector as:

$$X = (X_1, X_2, ..., X_N) = (W_1, W_2, ..., W_l, q_1, q_2, ..., q_k) \qquad (2)$$

Where, W_1, W_2 and W_N are the connection weight in the neural network and q_1, q_2 and q_k are the threshold for neurons in ANN. The genetic algorithm does not directly influence the input parameters. However, on a particular encrypting of the input parameters, the current study utilizes dual encrypting by adjusting the vector as:

$$\acute{\imath}_i = X_i \in [\varepsilon_{i\,\min} = \varepsilon_{i\,\max}] \quad (3)$$

While encrypting precision of a dual coding length (L_i) could be estimated through equation (4) as:

$$Li = int[log2\frac{x_{i\,max} - X_{i\,min}}{e} + 1] + 1 \quad (4)$$

To make the calculation simple, the undefined binary encoding length (L) of the variable is as:

$$L = max\ (L_i) \quad (5)$$

Total output error E of the network can be defined as:

$$E(\hat{\imath}) = \frac{1}{2}\sum_{s=1}^{s}\left(Y^{s*} - Y^{s}\right)^2 \quad (6)$$

Where, Y^{s*} and Y^s are the expected and actual layers of the neurons for S group samples. Accordingly, the adaptability function of the genetic algorithm, $F(\acute{\imath})$, can be defined as:

$$E(x) = C - E(x) \quad (7)$$

Where, C = const., and satisfied: C > $|E_{max}(\acute{\imath})|$, E_{max} ($\acute{\imath}$) is the maximum output error for the network. The selected population size is N_p. Cross probability is P_C. When the above steps are completed, the structure of the neural network is tuned as follows: if a weight is 0 or the absolute value is small, there is no connection between the corresponding two neurons. If the input weight of a neuron is 0 or the absolute value is less than 1, the neuron is considered redundant, and the neuron is removed. After adjusting the structure of the neural network, let the network re-learn the sample and further adjust the weight of the network, because at this time the structure of the network is close to optimal, and the learning process will be completed quickly.

4. RESULTS AND DISCUSSION

4.1. Numerical Example

Several examples of slopes were collected from the literature [8, 27]. An extreme probability function (*P*) is obtained from the arithmetic hypothesis test. The numbers of soil slope stability controlling factors are not similar in different cases. Furthermore, dissimilarity cannot be helpful to the analysis of the ANN model. The reason is that the input parameters involved during the training of the model required to be processed and standardised, which can be done as:

$$h_i^* = \frac{2(h_i - h_{min})}{h_{max} - h_{min}} - 1 \quad (8)$$

Where, h_i and h_i^* are equivalence variables before and after soil slope failure, respectively. h_{min} and h_{max} are the lower and upper bounds of the variables, respectively. The parameters in equation (8) were assessed from the engineering examples.

In this study, three intermediate layers were initially selected by twelve neurons. The population size for the genetic algorithm was selected as N_P = 100, copy probability P_S = 0.6. Cross probability $P_{C=}$ 0.4, probability of variation P_m = 0.05, interval of the network connection weigh is taken -10 and 10. The threshold interval of neurons is taken as a sample of standardized slope engineering data. After the end of the learning process, delete the connection right absolute value of less than 0.1. Let the neural network re-learn the samples to obtain the optimal network structure. To test the effectiveness of the established method, the stability of the 10 soil slopes is forecasted in Table 1.

Table 1. Slope examples and input data.

Slope	γ (kN/m³)	c (kPa)	ϕ (°)	θ (°)	H (m)	Status
1	19.6	0	25	18	6.9	Unstable
2	27.1	30	37	36	100	Stable
3	31.6	40	39	38	100	Stable
4	23.2	0	23	22	8	Unstable
5	18.1	14	30	36	25	Unstable
6	20.7	30	0	32	65	Unstable
7	29.2	8	35	35	77	Unstable
8	26.1	70	38	45	215	Unstable
9	23.1	45	35	50	285	Stable
10	28.8	35	35	48	355	Stable

Standardized data was used as inputs in the neural network and its stability was predicted. The actual situation of the slopes is shown in Table 2. From the results of Table 2, only the slope analysis results (stabilisation) of example six are inconsistent with

Table 2. Comparison in between current results and previous results of slopes.

Slope	Actual results	Studied results
1	Unstable	Unstable
2	Stable	Stable
3	Stable	Stable
4	Unstable	Unstable
5	Unstable	Unstable
6	Unstable	Stable
7	Unstable	Unstable
8	Unstable	Unstable
9	Stable	Stable
10	Stable	Stable

the actual situation (destruction). The accuracy of the proposed model is 97%, which shows that the forecast method proposed in the present study has a high forecast accuracy.

A comparison of FS values predicted from the ANN models and with that of the values obtained from the numerical analysis is depicted in Figure 2. The coefficient of correlation (R^2) between the simulated and predicted values reveals an outstanding forecast ability of the model. There is barely a meaningful contrast between the ability of the ANN training model. It can be understood that the ability of the training model did not change significantly when the amount of the input properties was decreased to 8. However, a significant change in R^2 value is observed during the testing phase (Figure 2).

4.2. Model Application

In this section, considering the key objective of the present research, the established artificial model is utilized for soil slope status and FS calculation challenges from the previous studies. These challenges are taken for soil slope.

4.2.1. Case 1

In the first text, the efficiency and applicability of the recommended model in automatically predicting stability and factor of safety are observed by adopting the homogeneous earth slope from the publication study of Nouri *et al*. [39]. In the current test, the slope status and FS predicted by the ANN model matched with those acquired by prior

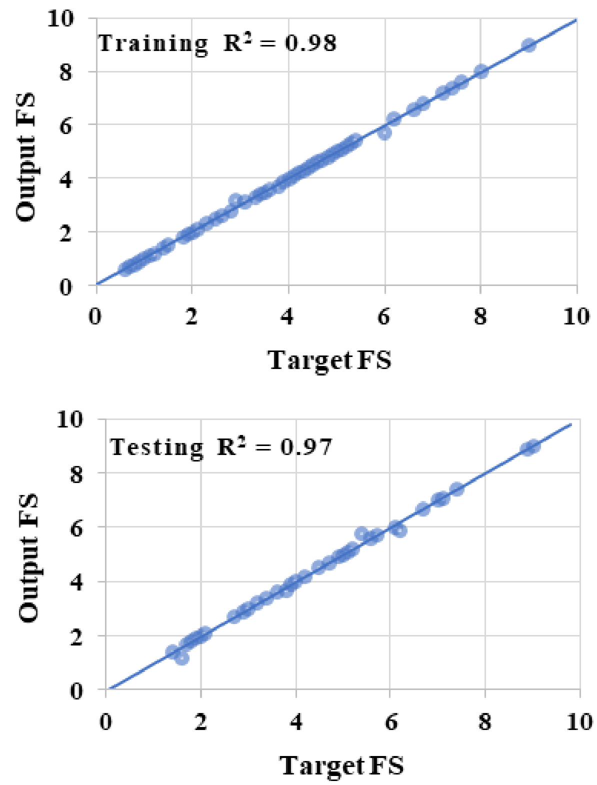

Fig. 2. Neutral model for FS prediction.

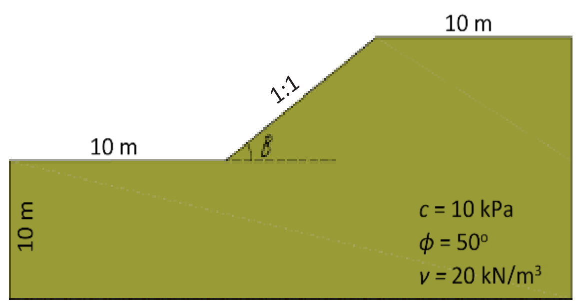

Fig. 3. Properties of soil slope, from Nouri *et al.* [39].

Table 3. Input parameters for case 2, from Sakellariou and Ferentinou [40].

Case No.	γ (kN/m³)	c (kPa)	ϕ (°)	θ (°)	H (m)
1	18.84	14.36	25	20	35.50
2	20.60	16.28	26.5	30	40.00
3	21.40	10.00	30.34	30	20.00
4	20.96	19.96	40.01	40.02	12.00

Table 4. Difference between the actual and forecasted FS.

Case No.	Slope/W	[40]	[25]	Current model
1	1.87	1.95	1.87	1.88
2	1.25	1.24	1.25	1.25
3	1.70	1.75	1.70	1.70
4	1.84	1.91	1.84	1.84

studies including those achieved by SLOPE/W. The strength and geometric input parameters of the soil slope are presented in Figure 3. Slope angle is 45^o and the height is 20 m. The minimum value of FS was generated from SLOPE/W and proposed ANN model. The actual FS of soil slope as reported by Nouri *et al*. [39] is 0.288. The FS of 0.294 and 0.289 were estimated by using SLOPE/W and proposed ANN model, respectively. These findings show that the new ANN model is more effective in forecasting the stability factor of soil slope.

4.2.2. Case 2

Here, 4 slope cases studied by Sakellariou and Ferentinou [40] are reanalyzed as test studies. These cases are totally dry soil slopes. The input data set of these cases is presented in Table 3.

The simulated value of FS of these studies is given in Table 4. Furthermore, the factor of safety forecasted by Sakellariou and Ferentinou [40] and Khajehzadeh *et al*. [25] are given, respectively, in the third and fourth columns of Table 5. The predicted FS from the ANN model is presented in the last column of Table 5. As the findings reveal, matched with SLOPE/W and the previous surveys, the forecasted safety factors utilising the anticipated ANN model are greatly closer to the actual safety factors.

5. CONCLUSIONS

In this study, a new genetic algorithm-based ANN model is proposed to predict the soil slope status and corresponding stability factor. A potential homogenous soil slope with different values of slope angle (θ), height (H), soil internal friction (ϕ), density (γ) and cohesion force (c), are considered as input data sets to train and develop artificial models. The accuracy of the proposed model is checked by SLOPE/W software and previous case studies. Based on the findings, the following conclusions can be drawn:

a) The comparison of the anticipated GA shows that the artificial neural network model is betters than Slope/W and the other techniques. The new GA can be effectively used for the case studies of homogeneous dry soil slopes to estimate FS with a coefficient of correlation R^2 almost equal to 0.98.
b) According to the numerical experiment, the GA outperforms the other methods and could provide a lower value of FS.
c) The engineering examples showed that the forecasting accuracy of the proposed method is high; it is generally difficult to find the optimal network structure by this method.

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7. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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