

A New Optimization-Based Intelligent Method For Evaluation Of Road Embankment Slope Stability

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ABSTRACT

The study of slope stability is a common issue for geotechnical and geological engineers. But, suitable computer codes are not frequently user friendly, and supplementary resources accomplished of providing facts for practicing engineers. This study established a genetic algorithm based on artificial neural network (ANN) to predict the stability of embankment soil slope. To provide a neural network training dataset, the total height (H), slope height (h), soil unit weight (γ), slope angle (β), soil friction angle (ϕ), soil cohesion (c), and soil Young's modulus (E) and their corresponding FS of more than 400 soil slopes were collected from previous publications. Root mean square error (RMSE) and correlation coefficient (R^2) were used to assess the generated model's performance and predictive ability. The optimization model with the RMSE value of 0.023 and the R^2 value of 0.984 is a dependable, straightforward, and valid computational model for estimating the FS of

slope, according to the obtained results. Furthermore, the created ANN model is applied to a soil slope case study, and the outcomes show that the suggested model may outperform current approaches and offer superior optimal solutions.

Keywords: ANN, Optimization Algorithm, Slope Stability, FS, Cohesion (c), Internal Friction Angle (ϕ)

INTRODUCTION

For geotechnical researchers, predicting the stability of road embankments and soil slopes is crucial since it provides the fundamental data needed to plan slope reinforcement. Slope stability determination has attracted the interest of numerous researchers due to its practical significance. Slope stability status has recently been investigated by numerous researchers using optimization strategies and artificial neural networks (ANN) [1-3]. ANN is a helpful method for developing a relationship between the different slope strength characteristics and predicting the stability of the soil slope [4]. Slope stability factor can be more accurately and conveniently estimated with ANN [5]. Advanced modeling techniques called Artificial Neural Networks (ANNs) are capable of simulating incredibly complex processes [6]. There has been a growing interest in using ANNs for geotechnical engineering problems since they have demonstrated a high level of effectiveness for function approximation in various fields [7, 8]. Researchers have provided a variety of ANN-based models in the field of slope stability analysis to forecast the factors of safety (FS) of earth slopes taking into account various elements. The ANN model was trained using a variety of soil strength characteristics, including unit weight, cohesion, and angle of internal friction, slope angle, height, and pore water pressure [1].

Optimization and artificial neural networks (ANNs) are sophisticated modeling techniques that can replicate incredibly complicated functions. There has been a growing interest in using optimization and artificial neural networks (ANNs) to solve geotechnical engineering problems since optimization has demonstrated a high degree of effectiveness for function approximation [6, 9, 10]. For the purpose of estimating slope stability under static load, Chakraborty and Goswami [11] created an ANN and multiple linear regression (MLR) model. An ANN system made up of multilayer perceptron networks was introduced by Suma'']

\\'';LGD

JNJUJ n et al. [12] to forecast slope stability in a given area. The slope stability condition was the output parameter, and a number of significant parameters were employed as input parameters, such as total stress, effective stress, angle of slope, coefficient of cohesion, internal friction angle, and horizontal coefficient of earthquake. Using several data sets of geometry and shear strength parameters, Nanehkaran et al. [13] employed a machine learning algorithm to forecast the minimum factor of safety under static load.

In order to train the neural network model for forecasting the factor of safety of an earth slope, Jellali and Frikha [14] used the particle swarm optimization method. Five

characteristics were used as model inputs in their investigation: slope gradient, height, cohesiveness, peak ground acceleration, and friction angle. To train the ANN model, Asteris et al. [15] used four metaheuristic algorithms: particle swarm optimization, imperialist competitive algorithm, genetic algorithm, and artificial bee colony. Their findings showed that particle swarm optimization performed better than alternative techniques for ANN and FS prediction training. In order to train a new ANN model, Moayedi et al. [16] created an ANN technique based on the imperialist competition algorithm for evaluating the dimensionless stability number of a two-layered cohesive slope. Slope angle, undrained shear strength ratio, and depth factor—that is, the ratio of soil stratum thickness to slope height—were the input properties used in their analysis.

The genetic ANN model combined with optimization technique has a straightforward structure and no complex mathematical functions as compared to other ANN models. The equations for informing the population in the genetic ANN model only depend on the quantity of input parameters used in the training phase. The genetic model is better suitable for solving optimization problems and is superior to other workable methods in determining optimal solutions [17–19]. Nevertheless, the genetic model is unable to converge to a satisfactory solution due to receiving deceit in native targets [13]. An optimization method based on soil strength and slope geometric profile is developed in conjunction with a genetic algorithm to overcome this disadvantage. The suggested coupled optimization-based ANN model makes use of the genetic algorithm's exploration and ANN's exploitation capabilities, which can enhance the outcomes.

In order to forecast the stability factor (FS) of road embankment soil slope, a novel optimization technique combined with a genetic algorithm based on artificial neural network (ANN) technique is presented in this research. Initially, this optimization technique is developed using geometric parameters such as slope and soil strength characteristics. The new forecasting method works well when combined with earlier research and a case study.

METHODOLOGY

Data set

A dataset of 390 soil slopes which were previously studied by Ray et al. [9] has been used to train ANN model. Also, some dataset of different soil slopes was collected to train ANN model in this research as presented in Table 1. Unit weight (γ), cohesiveness (c), Young's modulus of soil (E), angle of internal friction (ϕ), average slope angle (β), slope total height (H), slope height (h), and slope width (w) are the eight main influencing factors that have been taken into consideration. Table 1 presents an overview of the slope stability database about the characteristics of road embankments.

Table 1. Input parameters of soil slopes

Reference	γ (kN/m ³)	c (MPa)	ϕ (°)	E (MPa)	w/m	H/m	h/m	β (°)	FS
[20]	25.5	0.037	30	35000	85	61	38	43.0	1.49
[21]	24.0	0.950	40	20000	30	15	10	45.0	1.16

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[22]	20.0	0.012	20	200	30	15	10	45.0	1.00
[23]	20.0	0.012	20	200	30	15	10	45.0	1.06
[24]	18.5	0.010	0	1000	35	12.5	5	26.6	0.64
[25]	17.6	0.009	10	200	25	10	5	26.6	1.34
[26]	17.6	0.009	10	200	25	10	5	26.6	1.32
[27]	17.6	0.009	10	200	25	10	5	26.6	1.32
[28]	17.6	0.009	10	200	25	10	5	26.6	1.33
[29]	19.5	0.004	27	1000	60	35	10	63.4	1.36
[28]	19.0	0.015	20	200	35	12	8.5	63.4	1.11
[30]	19.0	0.020	19	1000	35	12	8.5	63.4	1.48

Neural network method

The current study's goal is to forecast FS using pertinent geotechnical and physical characteristics of residual soil slope. One type of nonlinear dynamic system with significant nonlinear mapping capabilities is the artificial neural network, which may be utilized for nonlinear mapping even in the absence of knowledge about the precise distribution of data and the constraint relationship between data [31]. Artificial neural networks are self-learning systems that use the connection weight between neurons to store learning outcomes in the threshold of neurons. The network will then use its nonlinear mapping capacity to provide heuristic judgments when new engineering examples are entered.

Information processing strategies that can select, remember, and simplify from training data sets are known as ANN-based techniques [32, 33]. ANNs are mathematical models made up of many neurons, which are basic processing units. The functional network of neurons in the human brain is modeled by an artificial neural network (ANN), a parallel connectionist structure. Neurons, which are incredibly complex mathematical processing units, make up ANNs [34]. Neurons are connected by weights and biases. An ANN network is composed of the input layer, hidden layer, and output layer [9]. Fig. 1 depicts a typical ANN model utilized in this investigation.

After receiving data, the neurons in the input layer pass it to the hidden layer, which performs calculations and transmits the outcomes to the final layer. Neurons that transmit the system's output to the user make up the output layer. The intricacy of the problem dictates how many hidden layers an ANN uses. A limited network structure prevents it from achieving a high degree of effectiveness. Additionally, if it is too large, it will result in needless complexity, loss of generalizability, and redundant internal connections. It has been discovered that one or two hidden layers are adequate, appropriate for the majority of circumstances, and capable of solving any complex function [9, 35]. In this work, the ANN architecture were generated by applying two hidden layers x, and y, as shown in Fig. 1.

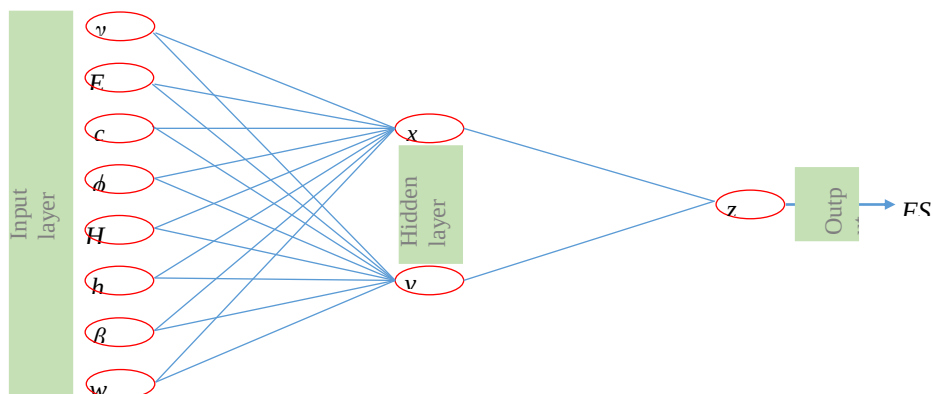


Fig. 1. Neural model for FS prediction

MATLAB software was used to create the optimization-based ANN model. The model is developed using a multi-layer forward network with two neurons in the hidden layer and sixteen neurons in the output layer (Fig. 1). The genetic model was developed using the entire data set, which was separated into training, testing, and validation sets. Eighty-five percent of the 370 slope examples in the data set were used for training, with the remaining data being used for model validation. Levenberg-Marquardt propagation was used to train the network until the training error was small enough, or until the training error changed very little or not at all. It is expected that the prediction equation achieves a tight association and the training phase ends when the value of R^2 of all three sets—training, testing, and validation—approaches near unity. In order to model slope for stability assessment, the mapping connection (M) must be found as,

$$FS = M(\gamma, c, \phi, E, \beta, H, h, w)$$

(1)

Slope is unstable if $FS = 0$ or $FS < 1$. The value of FS in Eq. 1 ranges from 0 to 3. The slope is steady if $FS > 1$. Because of the intricacy of the slope's strength and geometric characteristics, M is very nonlinear. It is challenging to use mathematical formulas to characterize M. This research describes M, which can be influenced by γ , c , ϕ , E , H , h , and w , using genetic-based optimization neural networks due to the strong nonlinear mapping capability of neural networks. Neural network slope stability prediction can be broken down into two phases: the first is the network's self-learning phase, in which the nonlinear mapping relationship M is generated near objective reality by analyzing current engineering instances.

Structure of ANN

Due to the extreme nonlinearity of the slope stability issues, mapping using a neural network is necessary. On the one hand, ANN should have a strong enough generalization ability to produce accurate results based on input parameters, and the mapping relationship (M) can be as close to the objective reality as possible. The structure of a neural network, particularly the connection method and connection weight between neurons, has a significant impact on its capacity and ability to generalize [2]. Neural networks' capacity and capacity to generalize depend heavily on the appropriate connection mechanism and optimized connection weight.

It is clear that the traditional neural network method has flaws when it comes to network structure optimization: Initially, the network connection mode and connection weight optimization are chosen in a methodical manner. The general approach is to use experience to identify the connections between neurons in the network. The neural network samples were then modified to create a link between networks. Repeat the previous steps if the conditions are not met. Finding the ideal network structure with this approach is typically challenging. Therefore, for tackling large slope stability problems, either the network capacity is insufficient or the ability to generalize is weak [4]. Furthermore, the network has a low learning efficiency and is prone to local extreme values. This approach makes it tough to manage the ANN's learning time, which makes it extremely challenging for the network to efficiently recall its prior engineering expertise.

The number of neurons in the input layer is sixteen, which corresponds to the sixteen factors taken into consideration in this study, and the number of neurons in the output layer is one (FS), which corresponds to the final output result, based on the features of the problem. Each of the two middle layers, x and y , has n neurons. Neurons are connected in a single layer forward, meaning that neurons in one layer can only be connected to neurons in another layer. The thresholds of each neuron and the connection weights between neurons in each layer of the neural network are deposited into a one-dimensional vector as follows for ease of computation:

$$u = (u_1, u_2, \dots, u_N) = (t_1, t_2, \dots, t_l, q_1, q_2, \dots, q_k)$$

(2)

where q_1, q_2 , and q_k are the ANN neuron thresholds and t_1, t_2 , and t_N are the neural network's connection weights. The reference variable is not directly impacted by the genetic method. But, on a certain coding of the reference variable, this paper uses binary coding by setting the vector $\hat{u}_i = X_i \in [\varepsilon_{i \min} = \varepsilon_{i \max}]$, and the coding accuracy of the binary encoding length (L_i) can be calculated by using the Eq. 3 as:

$$L_i = \text{int}[\log_2 \frac{u_{i \max} - u_{i \min}}{e} + 1] + 1$$

(3)

To simplify the computation, the variable's undefined binary encoding length (L) is as follows: $L = \max(L_i)$. The network's overall output error e can be expressed as,

$$e(\hat{i}) = \frac{1}{2} \sum_{n=1}^n (Y^{s*} - Y^s)^2$$

(4)

where Y^{s*} and Y^s represent the expected and actual neuronal layers for samples from n groups. Consequently, the genetic algorithm's adaptation function, $F(i)$, can be described as

$$F(x) = G - E(x)$$

(5)

where $G = \text{constant}$ ($G > |E_{\max}(i)|$, and $E_{\max}(i)$ is the absolute output error for the network. N_p is the population size. Fractious probability is P_c . There are some steps to design the algorithm;

Step 1: If the probability of variation is P_m and then the design algorithm is as follows:

$$x_i^p = x_{i \min} + (x_{i \max} - x_{i \min}) \sum_{j=1}^{L_i} g_{ij}^p 2^{j-1} (2^{L_i} - 1)$$

(6)

And ($P \in [1, N_p]$; $I \in [1, N]$)

where N_p is a system for a selected population having size N , which is a dimensionality of the vector. x_i^p is a vector, x^p is directional vector, g_{ij}^p is a first genetic factor on the i slope material and p is the individual space for genetic algorithms.

Step 2: N_p is decoding function, and t^p ($p = 1, \dots, N_p$) and correspond to the connection and thresholds of the neural networks, these weights and thresholds are assigned to the neural network, run the network, calculate the total error of the network by setting $E_p(t^p)$, ($p \in [1, N_p]$) and its adaptability is $F_p(t^p)$, ($p \in [1, N_p]$). Step 3: If $\min E_p > \hat{a}^*$ from total permissible output error of the network convergent, then the maximum adaptability (F_{pmax}) corresponds to individual, and the corresponding vector after decoding is the t^{opt} , which correspond thresholds, optimal values and thresholds of the desired network, and the calculation ends. Otherwise, go to step 4. Step 4: According to the selected replication probability P_s , the cross probability is P_c , the probability of variation is P_m , which needs to operate separately during ANN setting. Step 5: Use the method decoding in Eq. 6, and repeat step 2.

The neural network's structure is adjusted as follows when the aforementioned procedures are finished: if a weight is zero or the absolute value is extremely small, there is no link between the corresponding two neurons. A neuron is deemed redundant and eliminated if its input weight is zero or its absolute value is less than one. Once the neural network's structure has been adjusted, allow the network to re-learn the sample and make additional adjustments to the network's weight. Since the network's structure is now nearly ideal, the learning process will be finished quickly.

RESULTS AND DISCUSSIONS

Accuracy of new method

Determination coefficient R^2 , mean absolute error (MAE), and root mean squared error (RMSE) are widely utilized and well-known today to assess the correctness of the new approach. The R^2 number, which is an arithmetical metric for assessing a technique's accuracy in predicting actual data sets, specifies the goodness of method. The model's performance is also evaluated using the Root Mean Squared Error (RMSE) approach. A procedure is deemed exceptional if the RMSE is zero. The RMSE will be greater than zero if the measured and anticipated values differ.

The performance of the suggested reduction approach was assessed using the determination coefficient R^2 , mean absolute error (MAE), and root mean squared error (RMSE). The method's predicting precision is high when the R^2 is higher and the MAE and RMSE are smaller. These matrices made use of the following three equations (7-9):

$$R^2 = \sum_{i=1}^n (P_i - \bar{Q})^2 / \sum_{i=1}^n (Q_i - \bar{Q})^2 \quad (7)$$

$$MAE = 1/a |FS_0 - FS_P| \quad (8)$$

$$RMSE = \sqrt{1/a (\sum_{i=1}^a (FS_0 - FS_P)^2)} \quad (9)$$

where P and Q are the forecasted values and n is the total number of samples. FS_o and FS_p are observed and predicted factor of safety and a is total observations.

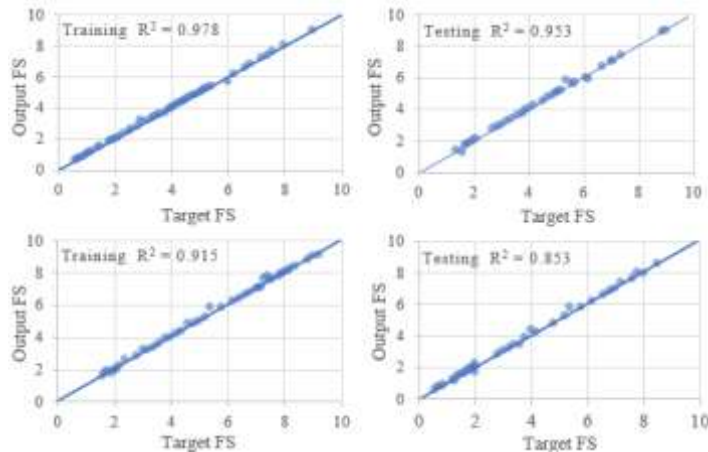


Fig. 2. Accuracy of new reduction factor technique.

A comparison of targeted and output FS is presented in Fig. 2, for the teaching and testing stage. The constant of determination (R^2) between the measured and predicted values shows a good forecasting capacity of the method. MAE = 0.0498 and RMSE = 0.0669. There is almost not any remarkable dissimilarity between the performances of new method and previous methods during the training and testing stage (Fig. 2). In addition, there is no noticeable difference in R^2 during training and testing stage (Fig. 2). Results showed that the developed reduction factor technique is good in forecasting precise maximum value of corresponding safety factor (FS).

Model Application

Case 1-4

The constructed artificial model is used for soil slope status and FS calculation difficulties from earlier studies in this part, taking into account the main goal of the current study. Soil slope is the subject of these issues. As shown in Table 2, four soil slope examples with associated FS were gathered from the literature. Additionally, the outcomes of the suggested optimization-based approach are contrasted with those of earlier research. Three intermediate layers with two neurons were first chosen for this investigation. $N_p = 100$ and copy probability $P_s = 0.7$ were chosen as the population sizes for the genetic algorithm. The interval of the network connection weight is selected as $[-10, 10]$, the cross probability $P_c = 0.5$, and the probability of variation $P_m = 0.04$.

Neuronal threshold intervals are used as a sample of standardized slope engineering data. Delete the connection right absolute value of less than 0.1 once the learning process is complete. To get the best network structure, let the neural network re-learn the samples.

The statistical hypothesis test yields the extreme probability value (P). The study of neural networks, where sample data used in learning must be standardized and handled in a standardized way, will not benefit from this discreteness.

$$K_i^* = \frac{2(K_i - K_{h_{\min}})}{K_{\max} - K_{\min}} - 1 \quad (10)$$

where K_i and K_i^* are standardization control variable values before and after soil slope slide, respectively; $K_{\max}$ and $K_{\min}$ are the upper and lower limits of the variables and these are determined according to the engineering experience.

In order to check the efficiency of the proposed technique, the stability of the four soil slopes is forecasted, as presented in Table 2. Standardized data was used as inputs to forecast the stability of soil slopes. Previous results of FS and current results of FS are shown in Table 2. Forecasted results were consistent with the previous results. The accuracy of the proposed optimization-based ANN was 96%, which shows the high predicting performance of the proposed method.

Table 2. Comparison of results of FS.

Reference	[36]	[37]	[38]	[39]
FS (previous study)	1.31	1.42	1.36	1.17
FS (current study)	1.34	1.39	1.36	1.20

Case 5

Using the homogeneous earth slope from the publication study of Nouri et al. [40], the effectiveness and applicability of the suggested model in automatically forecasting stability and factor of safety were examined in this subsection. The slope status and FS predicted by the ANN model in the current test matched those obtained by previous research, including those obtained by slope/W. Fig. 3 shows the slope geometry and soil strength characteristics. According to Fig. 3, the Slope/W software creates the same slope model and assigns material properties. Fig. 3 shows the soil slope's strength and geometric input parameters. The height is 20 meters, and the slope angle is 45 degrees. The safety factors contour map is presented (Fig. 4). Table 3 shows the results of simulating the potential value of FS using Slope/W and the suggested ANN at the same slope conditions. The FS value was 0.288 from the Nouri et al. [40] study, 0.298 from Slope/W, and 0.286 from optimization-based ANN. Less than 3% of the three outcomes differed, demonstrating the suggested method's strong predictive ability.

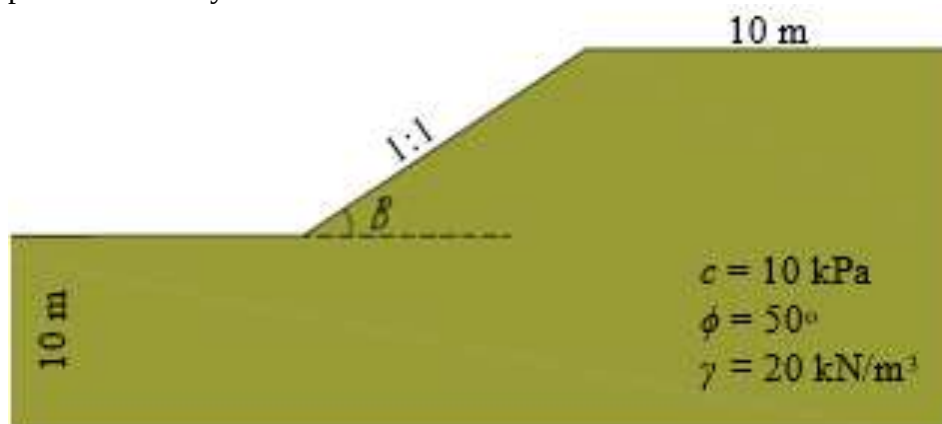


Fig. 3. Slope geometry and input parameters, from Nouri et al. [40].

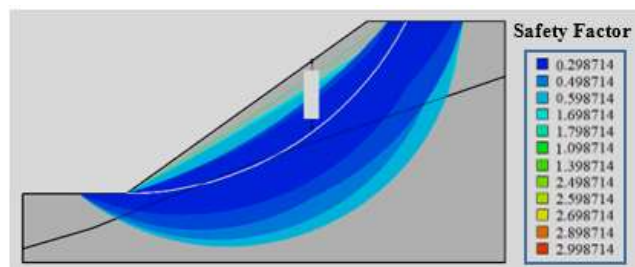


Fig. 4. Slope FS from SLOPW/W analysis.

Table 3 minimum value of safety factors for case.

Reference	Slope/W	Current model
[40]	0.298	0.286

CONCLUSIONS

In this particular research, a new optimization-based ANN method is developed to predict the stability factor (FS) of soil slope. Soil unit weight, cohesion, internal friction, young's modulus, total height, slope height, and slope angle were used as training data sets. The optimized network structure was obtained by using genetic algorithm and the forecasting accuracy of proposed ANN method was improved for soil slopes. The proposed ANN model can be applied for the estimation of FS for soil slope with MAE = 0.0498 and RMSE = 0.0669 and correlation coefficient $R^2 = 0.934$. The new optimization-based ANN was also successfully applied to determine the FS of five soil slopes from the literature and results were compared with Slope/W. According to the previous results and numerical results, the optimization-based ANN better than other methods and can predict an appropriate value of FS for soil slope. Also, it is usually problematic to search out the ideal ANN architecture by this method.

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