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Slope Stability Prediction of Road Embankment using Artificial Neural Network Combined with Genetic Algorithm

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ABSTRACT

The prediction of slope stability was performed using artificial neural networks (ANNs) in this work. The factor of safety determined by numerical analysis was used to develop ANN's data sets. The inputs to the network are slope height, applied surcharge and slope angle. Correlation coefficients between numerical data and ANNs outputs showed the feasibility of ANNs for successfully modelling and predicting safety issues. The ANNs training phase is improved using a genetic algorithm (GA), and the results are compared to those obtained without GA trained ANNs. A sensitivity analysis is conducted to ascertain the relative contribution of different factors on slope stability. The slope angle and applied surcharge have a significant effect on slope stability.

Keywords: Prediction; Road embankment; Slope stability; Safety factor; Artificial neural networks

INTRODUCTION

Landslides are one of the most serious environmental threats on the planet. Annually, landslides cause significant harm to a large number of private and public assets. Countries invest significant financial capital in mitigating this disruption. Slope stability analysis is the simplest and most popular method for identifying possible landslide parts. A number of parameters determine the stability of a slope. The most important parameters affecting slope stability are geometrical structure, shear strength, gravity and water content. The slope height, angle, unit weight, and soil shear strength characteristics, as well as the pore-pressure ratio, determine these parameters. These influencing criteria are fraught with uncertainty. This results in a statistically indeterminate and non-linear challenge for slope stability research. Numerous assumptions have been made to simplify this challenge, resulting in several methods for slope stability analysis.

The expression factor of safety (FOS) is often used to describe the stabilization of slopes. In general, when FOS is greater than one, a slope is called secure against failure. Numerous techniques have been devised in the past for determining the value of FOS. Slope stability research has traditionally relied on both Limit Equilibrium Methods (LEM) and Numerical Methods (NM). Each approach has several advantages and disadvantages. The traditional techniques for analyzing slope stability are dynamic, iterative, and impose a disproportionate burden on the computer system. This led the researchers to do further study into other techniques for determining slope stability. Researchers have recently focused their efforts on soft computing methods to solve such extremely complicated, non-linear, multivariate problems. Researchers have attempted to solve this form of issue using neural networks, vector machine algorithms, etc. In several areas, including geotechnical engineering, artificial neural networks (ANN) have shown a strong degree of performance in approximating functions. Numerous scholars have proposed various ANN-based models for resolving difficult problems. Numerous researchers have used ANN to investigate slope stability issues (Erzin & Cetin, 2012; Mamat et al., 2021).

The ANNs is a kind of network that uses machine learning to anticipate the connection between an input and its associated output for a particular data collection. ANNs are composed of intricately linked networks of processing units known as neurons. A neuron's relation to another neuron holds a certain weight. Certain biases are often linked to neurons. The relation weights and biases are calibrated to provide a minor possible error function depending on the input and corresponding target output values supplied. This technique is generally referred to as Back Propagation (BP). Typically, weights and prejudices values are optimized using optimization techniques such as Gradient Descent (GD), Stochastic Gradient Descent (SDM), Levenberg–Marquardt (LM), and the Adam optimizer. Shahin et al. (2002), noted that since these algorithms are initial point-based, the BP algorithm is vulnerable to initial weight. Additionally, many algorithms have disadvantages, such as a slow learning rate and a tendency to get trapped in local minima (Mamat et al., 2019). Numerous researches have shown ways to circumvent these constraints via the use of metaheuristic techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC).

GA is a highly effective metaheuristic optimization strategy focused on the social and mutual behaviour of several organisms. GA has been shown to increase efficiency when combined with ANN (Le et al., 2019; Li et al., 2021). The hybrid ANN-GA model has been applied to various complicated civil engineering issues, including predicting water quality parameters (Mulia et al., 2013) and drillability of rocks with strength properties (Khandelwal & Armaghani, 2016). Koopialipoor et al. (2019), examined the accuracy prediction of slope stability under static and dynamic conditions using an ANN-GA hybrid network. Using the numerical modelling, 699 homogenous slopes with soil density of 18 kN/m^3 data were produced for FOS. The slope stability findings were obtained by considering a wide range of input parameter values. The hybrid ANN-GA model was constructed using the database. The prediction effectiveness of the ANN-GA hybrid model is compared to that of ANN models.

This study aims to develop a feed-forward multi-layer perceptron (MLP) artificial neural network (ANN) trained to predict the FOS using backpropagation. The slope height, applied surcharge, and slope angle are input parameters to the network. The ANN training phase is optimized using a genetic algorithm (GA), and the results are compared to those achieved using a non-GA trained ANN. Additionally, a sensitivity analysis is conducted to ascertain the relative contribution of each input component to slope stability.

ESTABLISHED DATABASE

A database of 100 homogeneous slopes (with soil unit weight of 17kN/m^3) the most efficient factors on FOS is used in this study, along with their FOS values as device performance. According to previous research (e.g., Sakellariou & Ferentinou (2005); Choobbasti et al. (2009); Erzın & Cetin (2014)), the slope angle, slope height, and applied surcharge were chosen as inputs for ANN modelling. Additionally, slope or embankment heights of 1, 1.5, 2, 2.5, and 3 m were regarded. The slope angle was set between 15 and 45 degrees. Applied surcharges in the range of 0–15 kN/m^2 were considered and modelled.

Plaxis 2D software was used to model 100 homogeneous slopes to determine their FOS values. In order to ensure that the models behaved rigidly, they were all set on bedrock. Additionally, a crest width of 11m was allocated to each of the 100 models. Following the execution of each model, a FOS value representative of the particular state was obtained. Two models are built using the database as mentioned above to predict the FOS of slopes, and then the correct one is chosen and implemented.

ARTIFICIAL NEURAL NETWORKS

The neural network is an effort to mimic the brain learning process; to do so, it was necessary to determine the fundamental properties of human neurons and their connections and then program a device to imitate these properties. A neuron receives messages from neighbouring neurons through a network of fine structures called "dendrites" in the human brain (Mamat et al., 2020). Then, electrical impulses are sent down a narrow chain termed an "axon," which branches into thousands of branches. Each branch ends in a structure called a "synapse," which converts the signal from the axon to an electrical response that suppresses or stimulates the behaviour of the linked neurons. When excitatory feedback exceeds inhibitory input by a sufficient amount, the neuron sends an electrical signal down its axon. Learning occurs due to changes in the efficacy of synapses, which alters the impact of one neuron on the others.

The artificial neural network is made up of linked "modules" that function as model neurons. Each unit is linked to the next through a programmed "weight" similar to human brain synapses. Most of the ANNs ignore the intricate architecture of dendrites and axons instead of expressing the electrical output as a single integer indicating its firing rate—its activation.

MULTI-LAYER PERCEPTRON

The MLP is a multi-layer feed-forward network which is the most often used neural network model for various tasks, including function approximation, pattern recognition, and nonlinear device identification (Mamat et al., 2019). The data layer is the initial layer of MLP where it is composed of units that feed the neural network's remaining layers with input patterns. The last layer is the output layer, which consists of a collection of units representing the output characteristics of the neural network. These two levels are intermediate layers of units known as hidden layers due to their lack of visible interaction with the outer world.

These hidden units are in charge of extracting relevant characteristics from the input data and then estimating the values on the output units. Three layers of units constitute the network: an input layer, one or more hidden layers, and an output layer. The MLP architecture is shown in Figure 1. Each unit in a layer is connected to all units in the next layer through adjustable weights that reflect the strength of the relationship between this unit and the related unit in the succeeding layer.

Additionally, MLPs have a threshold unit and are connected to all units except the input layer. In order to build a neural network, the linked weights and thresholds are continuously adjusted until the network's error is as little as possible. The training technique is used to tune these weights and thresholds.

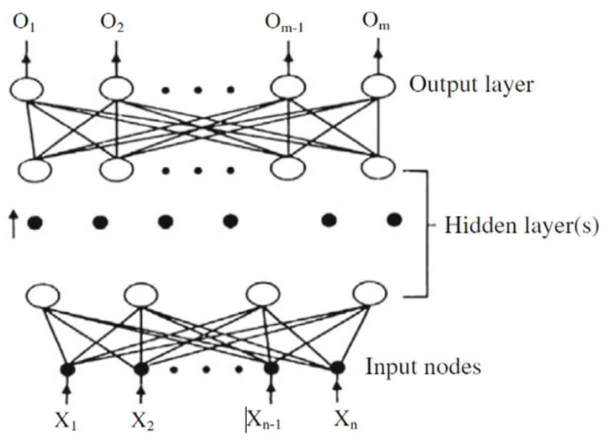

FIGURE 1. MLP architecture (Genel et al., 2003)

BACK-PROPAGATION ALGORITHM

A crucial element of most neural network modelling and classification work is the back-propagation training method, an iterative gradient descent approach used in supervised learning. The MLP's goal output error is decreased via a sequence of training input-output pairings to minimize the mean square error (MSE). The backpropagation method is implemented in two steps; the first step estimates the actual outputs of the net and the errors of both output nodes. The second is to reverse the error transmission, spreading these mistakes throughout the network layers, assigning each node a proportionate error share to its contribution and modifying the weights to minimize the error; this is commonly called the cost mechanism.

Due to an overwhelming amount of repetitions, back-propagation is particularly sluggish, and the issue of local minima additionally burdens it. Thus, several computed numerical methods have been conducted, and extensions and changes are considered to address these issues, for example, the use of the momentum concept. Each time the weight shifts, momentum is proportional to the weight change and must be remembered for future usage.

Recently, numerous researchers have suggested many variations of automating adjustments to the values as they develop. The standard approach is to check whether the particular weight update reduced the cost feature. Otherwise, phase overrun can be avoided. If such is not the case, then the phase error may be reduced. However, if several successive measurements reveal a decrease in cost, the overall cost estimate is certain to be optimistic. As training error is meant to be minimized, generalization error must be minimized as well. This is more difficult because there are no clear criteria for choosing when to stop network testing. Before there can be any advancement in the training process, however, some requirements must be fulfilled. There are two possible options for training sessions: pattern mode or batch mode. A training pattern is introduced into the input layer, and all weights are adjusted before the following design is presented. On the other hand, the second method uses adjusted weights until all the training patterns have been presented.

ANN-GA OPTIMIZATION

It is suggested that the developed network be trained using GA. The advantage of employing an ANN model in conjunction with GA is that it optimizes network weights during training to minimize MSE. Genetic algorithms are used in the genetic control section to optimize one or more parameters in the neural network. While input columns, the number of memory clicks, and the learning thresholds are often optimized, the number of hidden processing elements (PEs) and the input rows are the most frequently considered. Many more network settings may be adjusted. During the trial period, the cost of the various options is utilized to evaluate their effectiveness.

RESULTS AND DISCUSSION

PREDICTION WITH ANN

The developed ANNs model from this study used MLP, which was trained using the backpropagation gradient descent training method, and all were made using supervised learning. ANN training was aided by a momentum value of 0.7 and a learning rate beginning value of 1.0, as these allowed the ANN to converge on a solution quickly. The epoch limit was set to 50,000 for the batch weight update procedure. To enhance the ANN's generalization ability, a second data collection known as the cross-validation data set is utilized as testing stopping criteria. The MATLAB software was used to train, verify and test the previously constructed neural networks.

In order to stimulate the appropriate neural network development, data were randomly selected from all of the data sheets (100 in total) processed for mathematical analysis, as follows: the 70 training patterns specimens, 15 cross-validation pattern specimens, and 15 test pattern specimens are already on hand. When run, the validation sets gave the most favourable MSE, and epoch numbers were picked from the training sets. The smallest mean square gap between the intended and predicted values derived from the grid is applied to the test data sets to choose the best net.

TABLE 1. Trials of the ANN

No	Network	Training (MSE)	Validation (MSE)	Test (MSE)
1	3-4-1	$3.47x10^{-8}$	$8.73x10^{-9}$	$1.37x10^{-9}$
2	3-5-1	$3.13x10^{-8}$	$6.32x10^{-9}$	$3.56x10^{-9}$
3	3-6-1	$2.58x10^{-9}$	$4.89x10^{-9}$	$7.93x10^{-9}$
4	3-4-2-1	$8.95x10^{-9}$	$3.57x10^{-9}$	$2.54x10^{-10}$
5	*3-4-5-1*	$7.33x10^{-10}$	$1.21x10^{-9}$	$3.49x10^{-10}$
6	3-6-4-1	$5.14x10^{-10}$	$4.92x10^{-9}$	$5.92x10^{-10}$
7	3-6-6-1	$8.15x10^{-9}$	$7.74x10^{-9}$	$2.24x10^{-9}$
8	3-6-7-1	$6.44x10^{-9}$	$9.68x10^{-9}$	$4.52x10^{-9}$
9	3-6-8-1	$2.69x10^{-9}$	$8.47x10^{-9}$	$6.96x10^{-9}$
10	3-7-7-1	$1.74x10^{-9}$	$7.16x10^{-9}$	$8.48x10^{-9}$

TABLE 2. Correlation coefficients for slope stability prediction

Best network	Training	Validation	Test
3-4-5-1	0.996	0.993	0.989

The network was provided with three inputs (slope height, slope angle and surcharge application). Ten different neural networks were made with different hidden layers and hidden unit counts to find the best configuration. Table 1 presents the networks that have been used to calculate the FOS. According to this table, the best network design for predicting FOS is the 3-4-5-1 structure, with an MSE of 3.49x10-10.

Figure 2 shows the relationship between the actual and predicted optimum neural network design for predicting the FOS. The best-obtained network's efficiency was assessed by calculating correlation coefficients between the objectives and related network outputs. Since the correlation coefficient determines how much the targets can explain the difference in outputs, it can be said that the correlation between the ANN outputs and the targets is high if the coefficient equals one. The correlation coefficient table is provided in Table 2 to illustrate the correlations of the best-achieved neural network for each of the preparation, validation and test data sets. These correlation coefficients are nearing 1, as is clear from this table. The calculated numerical technique and anticipated FOS values in Figures 2, Tables 2 and 3 are almost identical, suggesting that the ANN produced may be effectively utilized to model and predict slope stability

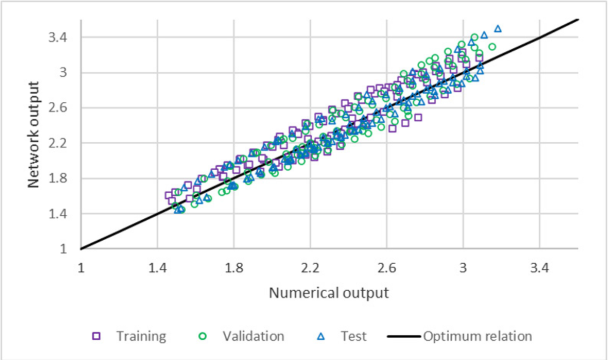

FIGURE 2. Relationship between numerical and predicted output values of the best network

The ANN with GA's input columns, learning speeds, momentum terms, secret PEs and network weights were all tuned using the identical data sets as the prior network. Table 4 describes the training parameters for the ANN with GA, with a population size of 10 and a maximum generation count of 15.

The GA was used in two instances to train the ANN: one with a hidden layer and two with hidden layers. Results from using GA for training the network are shown in Table 5. The best ANN produced in the trials of Table 1, which did not use GA, was qualified and tested on the test data set. In Table 6, the absolute relative error and mean square error (MSE) are presented. Despite the ANN being trained with the GA on the test data collection, as shown in Table 7, the absolute relative and mean square errors were still noticeable. As shown in Tables 6 and 7, the error variance of ANN training in FOS is decreased because of the GA optimization method used in the prediction process.

TABLE 3. Comparing numerical computed to each of the better observed ANN's predicted values

No	Slope height (m)	Applied surcharge (kN/m2)	Slope angle (degree)	Numerical method	ANN	Absolute relative error (%)
1	1	0	25	1.73	1.91	9.26
2	1	0	30	1.46	1.61	9.26
3	1	0	35	1.57	1.57	0.20
4	1	0	40	2.03	2.24	9.26
5	1	0	45	2.11	2.33	9.26
6	1	10	25	1.83	2.02	9.26
7	1	10	30	1.94	1.88	3.09
8	1	10	35	2.08	2.02	3.09
9	1	10	40	2.15	2.09	3.09
10	1	10	45	2.22	2.04	8.70
11	1	20	25	2.29	2.10	8.70
12	1	20	30	2.36	2.17	8.70
13	1	20	35	2.42	2.35	3.09
14	1	20	40	2.49	2.42	3.09
15	1	20	45	2.56	2.82	9.26
16	1	30	25	2.63	2.37	11.11
17	1	30	30	2.70	2.43	11.11
18	1	30	35	2.77	2.49	11.11
19	1	30	40	2.83	2.69	5.26
20	1	30	45	2.90	2.76	5.26
21	2	0	25	2.97	2.82	5.26
22	2	0	30	2.04	1.94	5.26
23	2	0	35	2.11	2.00	5.26
24	2	0	40	2.17	2.07	5.26
25	2	0	45	2.24	2.22	1.01
26	2	10	25	2.31	2.29	1.01
27	2	10	30	2.38	2.36	1.01
28	2	10	35	2.45	2.42	1.01
29	2	10	40	2.52	2.49	1.01
30	2	10	45	2.58	2.56	1.01
31	2	20	25	2.65	2.80	5.21
32	2	20	30	2.72	2.87	5.21
33	2	20	35	2.79	2.94	5.21
34	2	20	40	2.86	3.01	5.21
35	2	20	45	2.92	3.09	5.21
36	2	30	25	2.99	3.16	5.21
37	2	30	30	2.06	2.17	5.21
38	2	30	35	2.13	2.32	8.09
39	2	30	40	2.20	2.39	8.09
40	2	30	45	2.27	2.47	8.09
41	3	0	25	2.33	2.54	8.09
42	3	0	30	2.40	2.61	8.09
43	3	0	35	2.47	2.69	8.09
44	3	0	40	2.54	2.76	8.09
45	3	0	45	2.61	2.84	8.09

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46	3	10	25	2.68	2.91	8.09
47	3	10	30	2.74	2.98	8.09
48	3	10	35	2.81	2.89	2.63
49	3	10	40	2.88	2.96	2.63
50	3	10	45	2.95	3.03	2.63
51	3	20	25	3.02	3.10	2.63
52	3	20	30	3.08	3.17	2.63
53	3	20	35	2.65	2.72	2.63
54	3	20	40	2.42	2.49	2.63
55	3	20	45	2.19	2.25	2.63
56	3	30	25	1.96	2.01	2.63
57	3	30	30	1.73	1.90	9.26
58	3	30	35	1.49	1.65	9.26
59	3	30	40	1.56	1.72	9.26
60	3	30	45	1.63	1.80	9.26
61	4	0	25	1.70	1.87	9.26
62	4	0	30	1.77	1.95	9.26
63	4	0	35	1.83	2.02	9.26
64	4	0	40	1.90	2.10	9.26
65	4	0	45	1.97	2.17	9.26
66	4	10	25	2.04	2.27	10.31
67	4	10	30	2.11	2.35	10.31
68	4	10	35	2.18	2.43	10.31
69	4	10	40	2.24	2.50	10.31
70	4	10	45	2.31	2.58	10.31
71	4	20	25	2.38	2.65	10.31
72	4	20	30	2.45	2.73	10.31
73	4	20	35	2.52	2.81	10.31
74	4	20	40	2.58	2.79	7.24
75	4	20	45	2.65	2.86	7.24
76	4	30	25	2.72	2.93	7.24
77	4	30	30	2.79	3.01	7.24
78	4	30	35	2.86	3.08	7.24
79	4	30	40	2.93	3.15	7.24
80	4	30	45	2.99	3.23	7.24
81	5	0	25	2.76	2.98	7.24
82	5	0	30	2.63	2.84	7.24
83	5	0	35	2.40	2.59	7.24
84	5	0	40	2.27	2.44	7.24
85	5	0	45	2.14	2.30	7.24
86	5	10	25	2.00	2.16	7.24
87	5	10	30	1.87	1.95	4.21
88	5	10	35	1.74	1.82	4.21
89	5	10	40	1.61	1.68	4.21
90	5	10	45	1.48	1.54	4.21
91	5	20	25	1.74	1.82	4.21
92	5	20	30	1.81	1.89	4.21

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93	5	20	35	1.88	1.96	4.21
94	5	20	40	1.95	2.04	4.21
95	5	20	45	2.02	1.98	2.04
96	5	30	25	2.09	2.04	2.04
97	5	30	30	2.15	2.11	2.04
98	5	30	35	2.22	2.18	2.04
99	5	30	40	2.29	2.24	2.04
100	5	30	45	2.36	2.31	2.04
		Mean absolute relative error (%)				6.15

TABLE 4. Training conditions for the ANN with GA

	One hidden layer	Two hidden layers
Number of inputs PEs	3	3
Number of hidden PEs	8	6 for 1st hidden layer and 7 for 2nd hidden layers
Number of output PEs	1	1
Number of epochs	50,000	50,000
Population sizes	10	10
Maximum generations	15	15

TABLE 5. Fitness values obtained by training ANN with GA

Optimization	One hidden layer		Two hidden layers	
	Best fitness	Average fitness	Best fitness	Average fitness
Generation	10	6	8	9
Minimum MSE	$6.95\text{x}10^{-4}$	$2.11\text{x}10^{-3}$	$1.25\text{x}10^{-3}$	$2.23\text{x}10^{-3}$
Final MSE	$6.95\text{x}10^{-4}$	$3.38\text{x}10^{-3}$	$1.25\text{x}10^{-3}$	$2.97\text{x}10^{-3}$

TABLE 6. Absolute relative error of the best-achieved ANN trained without the use of GA

No	Slope height (m)	Applied surcharge (kN/m2)	Slope angle (degree)	Numerical method	ANN	Absolute relative error (%)
1	1	0	35	1.57	1.57	0.20
2	1	10	35	2.08	2.02	3.09
3	1	20	40	2.49	2.42	3.09
4	2	0	25	2.97	2.82	5.26
5	2	10	35	2.45	2.42	1.01
6	2	30	40	2.20	2.39	8.09
7	3	20	35	2.65	2.72	2.63
8	4	10	30	2.11	2.35	10.31
9	5	0	35	2.40	2.59	7.24
10	5	30	25	2.09	2.04	2.04
Mean absolute relative error (%)						4.23
MSE					1.96x10-10	

TABLE 7. Absolute relative error of the best-achieved ANN trained without the use of GA

No	Numerical method	One hidden layer		Two hidden layers	
		Prediction	Absolute relative error (%)	Prediction	Absolute relative error (%)
1	1.57	1.54	1.91	1.56	0.64
2	2.08	2.12	1.92	2.11	1.44
3	2.49	2.45	1.61	2.52	1.20
4	2.97	3.03	2.02	2.95	0.67
5	2.45	2.39	2.45	2.47	0.82
6	2.20	2.26	2.73	2.18	0.91
7	2.65	2.59	2.26	2.64	0.38
8	2.11	2.14	1.42	2.09	0.95
9	2.40	2.33	2.92	2.42	0.83
10	2.09	2.14	2.39	2.11	0.96
Mean absolute relative error (%)			2.16		0.88
MSE		$5.73x10^{-10}$		$12.67x10^{-10}$	

SENSITIVITY ANALYSIS

Sensitivity analysis is performed to determine the effect of varied input process parameters on the output response slope stability. Generally, FOS values that are smaller than one are unsafe. Based on Figure 3 and Table 8, the applied surcharge is most significant on stability, followed by slope angle and height. Besides, the slope height has a comparatively small effect on the slope stability.

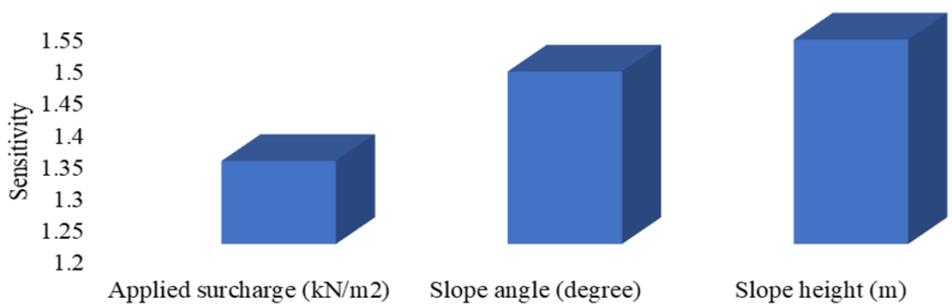

FIGURE 3. Sensitivity analysis for slope stability

TABLE 8. Absolute relative error of the best-achieved ANN trained with GA

Sensitivity	FOS
Applied surcharge (kN/m²)	1.33
Slope angle (degree)	1.47
Slope height (m)	1.52

CONCLUSIONS

The slope stability was predicted in this analysis using a feed-forward back propagation neural network technique. Numerous attempts were performed to achieve the optimal network configuration. The findings support the following conclusions:

- 3-4-5-1 was the best network configuration for predicting slope stability. The test data set has a mean-squared error of 3.49x10-10.
- Correlation coefficients for each of the training, validation and test data sets for the best obtained ANN method are all equal to one, indicating that the ANNs model can predict slope stability effectively.
- For the prediction of slope stability, ANN with GA is more accurate than ANN without GA.
- According to the sensitivity study results, the applied surcharge has the most significant effect on the slope stability, accompanied by the slope angle, and the slope height has a comparatively small effect on the slope stability.

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DECLARATION OF COMPETING INTEREST

None.

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