Chapter 6

Application of artificial intelligence in predicting slope stability in open-pit mines: A case study with a novel imperialist competitive algorithm-based radial basis function neural network

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1 Introduction

In open-pit mines, slope stability is considered a complicated problem that can affect the mining operations, economic loss, and even be fatal to humans if the failures occur. In effect, increasing the slope angle can decrease the stripping ratio and prove economic benefits; however, it can make the slope fail and damage the human/workers as well as equipment [1]. Therefore, computing the factor of safety (FOS) for slopes has been proposed, aiming to ensure the stability of the slope, safety for workers, and avoiding the disprove economic benefits [2–4]. To do this, several software has been introduced in recent years, such as Geostudio, Phase2, and Optum G2, to name a few. However, these packages are often costly and cannot use as a rapid method in situ.

To overcome this disadvantage, many scholars and researchers studied and proposed various artificial intelligence (AI)-based models to predict FOS based on the datasets analyzed by the above software in laboratories, such as artificial neural network (ANN) [5], GA (genetic algorithm)-ANN, ABC (artificial bee

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colony)-ANN, ICA (imperialist competitive algorithm)-ANN, and PSO (particle swarm optimization)-ANN [6]; HHO (Harris hawks' optimization)-ANN [7]; BSO (brainstorm optimization)-RBFNN (radial basis function neural network), to name a few. All of them demonstrated that AI-based models are very promising in predicting FOS with high accuracy, and they also recommended that can be used instead of the geotechnical software in in situ.

In this chapter, we introduce an application of AI for predicting FOS using the ICA-RBFNN model. It is worth mentioning that this model has not been used for predicting FOS before. Also, the PSO-RBFNN model was developed and compared to the ICA-RBFNN model in terms of modeling and performance.

2 Methodology

2.1 Radial basis function neural network (RBFNN)

RBFNN is an enhanced version of the MLP (multilayer perceptron neural network) that was introduced by Broomhead and Lowe [8]. It consists of three layers: Input, hidden, and output layers. Unlike MLP, the RBFNN uses unsupervised methods to train the network under linear weights. First, RBFNN uses the K-means clustering algorithm to select the weights randomly [9]. Second, matrix multiplication or gradient descent algorithms are used to calculate the weights between the hidden and output layers [10,11]. Remarkably, it does not use any activation functions during training the network like MLP, and unsupervised processes are used to model the nonlinear relationships of the datasets. The general architecture of RBFNN for predicting FOS is illustrated in Fig. 1.

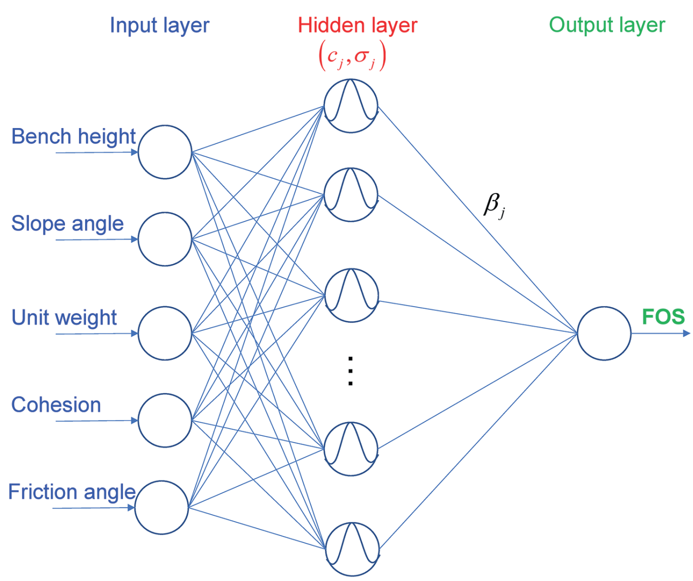

FIG. 1 General architecture of RBFNN for predicting FOS.

2.2 Imperialist competitive algorithm (ICA)

ICA is an evolutionary computing algorithm for optimization problems based on human societies that was proposed by Atashpaz-Gargari and Lucas [12]. This algorithm, similar to other optimization algorithms, requires an initial number of populations to make different solutions, and each solution is made by an individual, called a country. Among the generated countries, the best countries with the best fitness values are called imperialists, and the others are named colonies.

In ICA, each imperialist will dominate several colonies depending on its power. However, as is simulated in a war, the imperialists proceed in a competition to come over the colonies of each other. Stronger empires tend to conquer the colonies of weaker empires and become the strongest. If an empire could not preserve its power, it may be defeated by other empires, and any empires have a chance to become the strongest empire. The mathematical model of ICA can be read more in the following literature [13–17]. The framework of the ICA is introduced in Fig. 2.

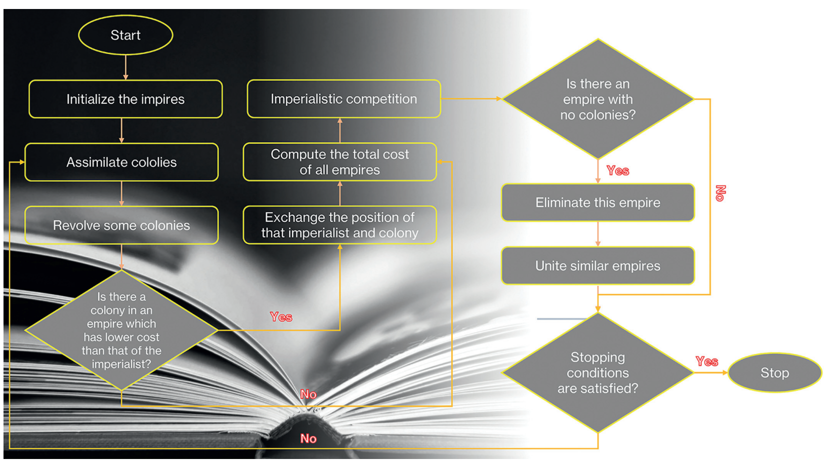

FIG. 2 Framework of the ICA.

2.3 Proposing the ICA-RBFNN model

In this chapter, the novel ICA-RBFNN model is proposed to predict FOS based on the combination of ICA and RBFNN. Accordingly, the ICA plays a role in optimizing the weights of the RBFNN model, aiming to improve the accuracy of the traditional RBFNN model. It generates several solutions corresponding to sets of weights. Subsequently, the generated weights are imported to the RBFNN model and optimized to predict the outcome predictions, that is, FOS values. Root Mean Squared Error (RMSE) is used to evaluate the performance of the optimization process, named the objective function, and it is described as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{i\_FOS} - \widehat{y}_{i\_FOS}\right)^2} \tag{1}$$

where n is the total number of FOS simulations, y_{i_FOS} stands for the i^{th} actual FOS, and $\widehat{y}_{i\_FOS}$ denotes the i^{th} predicted FOS.

The ICA-RBFNN framework is proposed in Fig. 3.

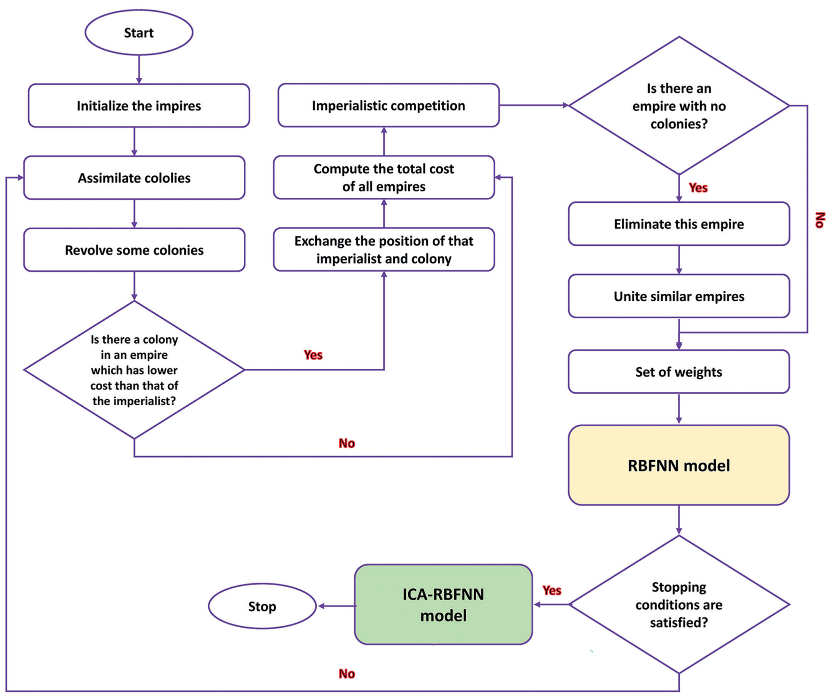

FIG. 3 Framework of the ICA-RBFNN model for predicting FOS.

2.4 Model assessment metrics

For assessment of the models' efficiency, five metrics, including mean absolute error (MAE), RMSE, determination coefficient (R^2), mean absolute percentage error (MAPE), and variance accounted for (VAF), were used as described in Eqs. (1)–(5).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{i\_\mathrm{FOS}} - \widehat{y}_{i\_FOS}\right|, \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_{i\_\mathrm{FOS}} - \widehat{y}_{i\_FOS}\right)^2}{\sum_{i=1}^{n} \left(y_{i\_\mathrm{FOS}} - \overline{y}_{i\_FOS}\right)^2}, \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{\left|y_{i\_FOS} - \widehat{y}_{i\_FOS}\right|}{y_{i\_FOS}}, \tag{4}$$

$$\mathrm{VAF} = \left(1 - \frac{\mathrm{var}\left(y_{i\_FOS} - \widehat{y}_{i\_FOS}\right)}{\mathrm{var}\left(y_{i\_FOS}\right)}\right) \times 100, \tag{5}$$

where n is the total number of FOS simulations, y_{i_FOS} stands for the i^{th} actual FOS, $\widehat{y}_{i\_FOS}$ denotes the i^{th} predicted FOS, and $\overline{y}_{FOS}$ represents the mean of actual FOS.

3 Application

3.1 Data preparation

To interpret the performance of the proposed ICA-RBFNN model in practice for predicting FOS, an open-pit coal mine in Vietnam was selected as a case study (Fig. 4). In this mine, the bench height was designed in a range of 5–15 m. However, some benches have been merged, in practice, with total heights of 30–40 m. This led to the significant slope height (H), that is, 66–249 m. The investigated locations for computing FOS in this mine have slope

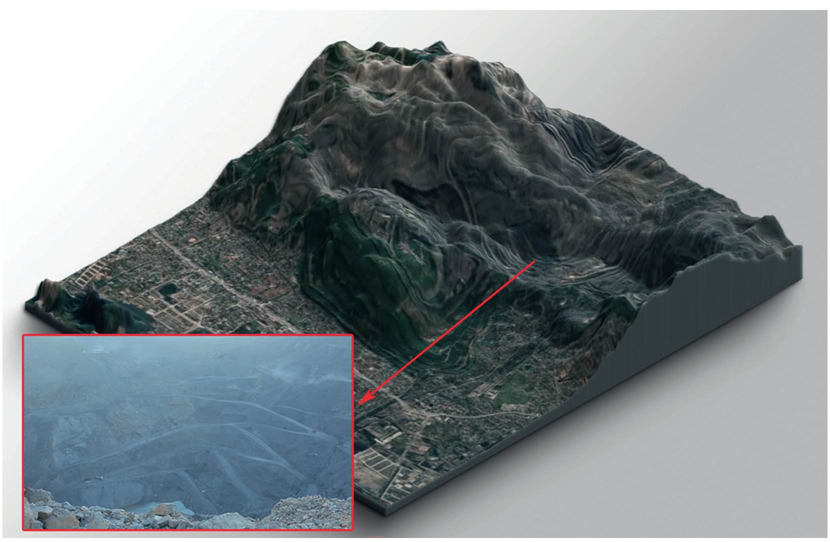

FIG. 4 Location of the study area.

TABLE 1 Summary of the inputs and FOS analyzed by the Geostudio software.

	Input parameters					Output parameter
Category	β	*H*	ϕ′	γ	c′	*FOS*
Min.	30.6	66	22.1	18.2	51.21	0.858
Mean	38.76	143.7	30.09	24.84	93.74	1.276
Max.	50.2	249	38	32.38	153.35	1.798

angles (β) in the range of 30°–50°. The other parameters, such as the unit weight (γ), cohesion (c'), and friction angle (ϕ'), are summarized in Table 1.

Before applying the proposed ICA-RBFNN model for predicting FOS, the FOS analysis was conducted under the Geostudio environment using the simplest Bishop method. Accordingly, 495 cases were analyzed using the limit equilibrium analysis with different values of the inputs to calculate the FOS, as shown in Fig. 5. A wide range of slip surfaces, as well as the critical slip surface, were investigated and defined (Fig. 5).

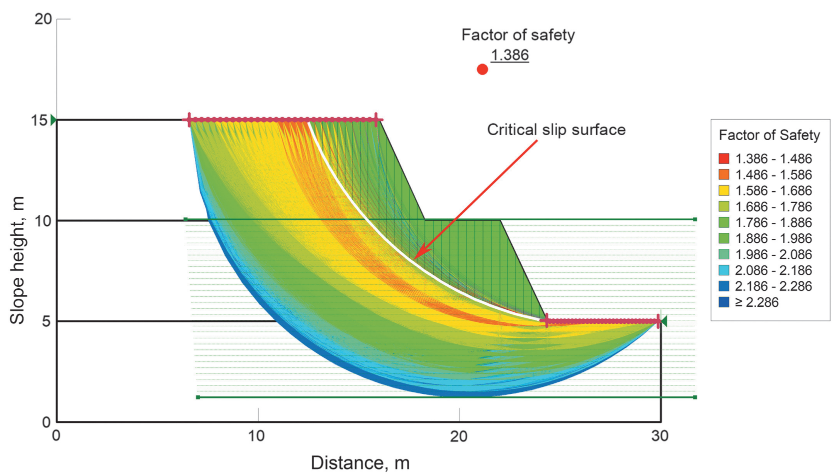

FIG. 5 Analyzing the FOS using Geostudio software.

3.2 Model development

To develop the ICA-RBFNN model for predicting FOS, the framework that was proposed in Fig. 3 was applied. Before applying this framework, the dataset was divided into two parts, 70% of the whole dataset was used for training, and the remaining 30% was used for testing. The ICA's parameters were setup before the optimization progress is processed, including the number of empires = 5, the selection pressure = 1, the assimilation coefficient = 1.5, the revolution probability = 0.05, the revolution rate = 0.1, the revolution step size = 0.1, the revolution step size damp rate = 0.99, and the colonies coefficient = 0.1. RMSE was used as the objective function to measure the performance of the optimization process while training the RBFNN model. Also, the different number of population sizes were considered in the range of 50–500. In addition, due to the stochastic mechanism of the metaheuristic algorithms, the ICA-RBFNN models were implemented in four runs to select the best one. The performance curves of the optimization process of the ICA-RBFNN model are shown in Fig. 6.

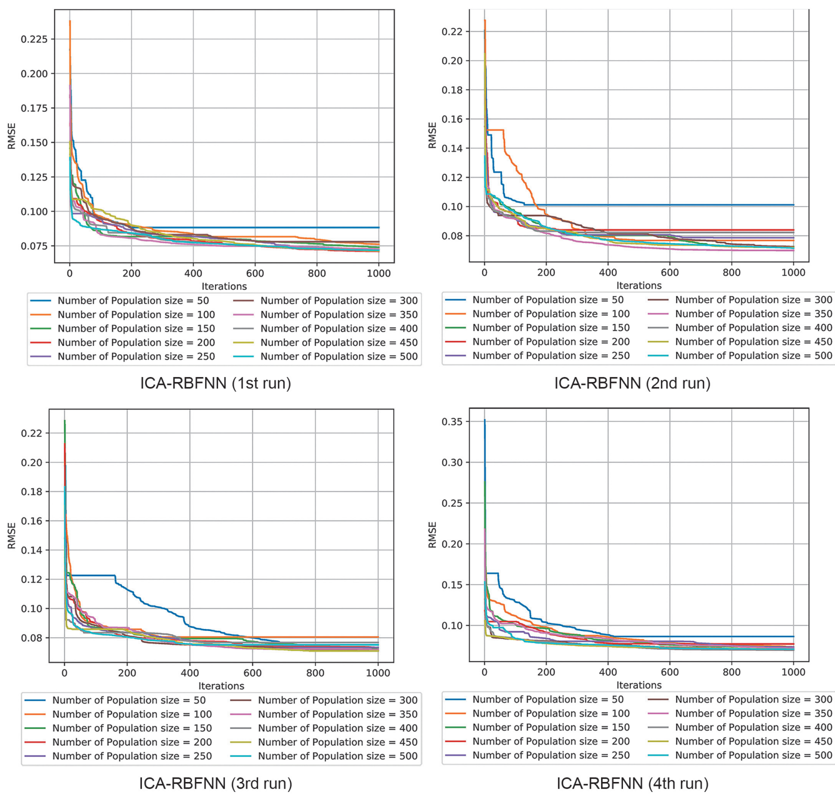

FIG. 6 Optimization performance of the ICA-RBFNN model for predicting FOS.

Furthermore, for an unbiased assessment, the PSO-RBFNN model was also developed to predict FOS based on the same dataset and approach. Please note that the PSO algorithm is well-known as one of the most common metaheuristic algorithms used in many optimization problems with promising results [18–24]. For the PSO's parameters, the following settings were established: The local coefficient = 1.2, the global coefficient = 1.2, the minimum weight of the bird = 0.4, and the maximum weight of the bird = 0.9. The optimization performance of the PSO-RBFNN model for predicting FOS is shown in Fig. 7.

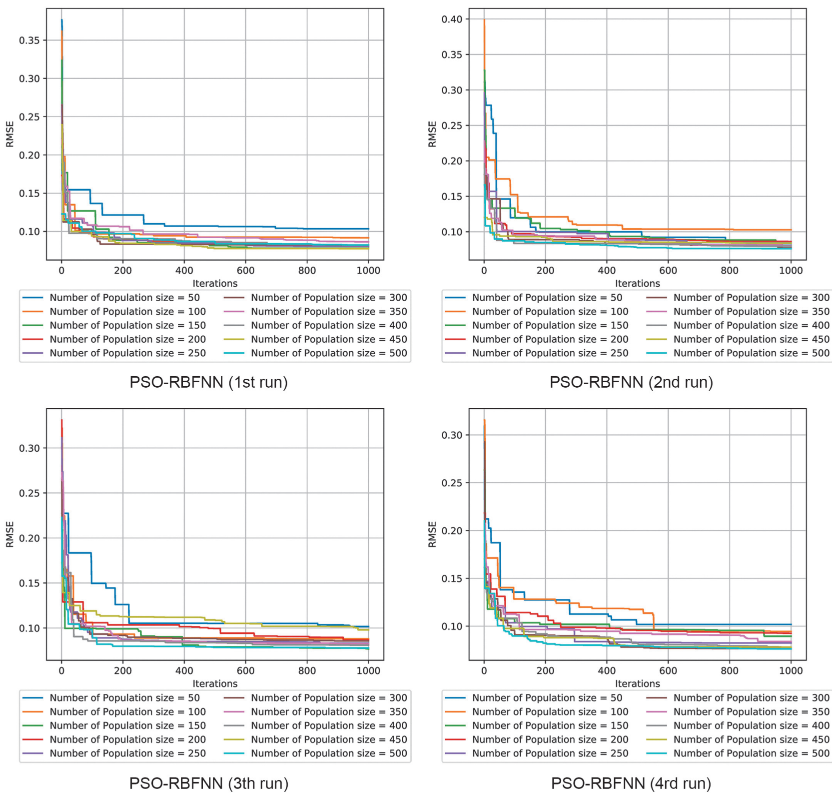

FIG. 7 Optimization performance of the PSO-RBFNN model for predicting FOS.

4 Results and discussion

After the ICA-RBFNN and PSO-RBFNN models were well-developed for predicting FOS, as described above, now it is time to evaluate their obtained results as well as the discussions about them. The performance metrics, that is, MAE, RMSE, R^2, MAPE, and VAF, were computed using Eqs. (1)–(5). The results are shown in Table 2.

TABLE 2 **Performance of the ICA-RBFNN and PSO-RBFNN model for predicting FOS.**

Model	Number of populations	Training				
		MAE	*RMSE*	R^2	*MAPE*	*VAF*
ICA-RBFNN	500	0.045	0.057	0.927	0.031	92.810
PSO-RBFNN	150	0.048	0.061	0.916	0.033	91.586
		Testing				
ICA-RBFNN	500	0.041	0.051	0.935	0.029	92.940
PSO-RBFNN	150	0.043	0.053	0.931	0.030	92.546

Based on the performance metrics computed in Table 2, conspicuously enough that the ICA-RBFNN and PSO-RBFNN models are robust soft computing models for predicting FOS with accuracies around ~93%. Remarkably, the ICA-RBFNN model provided slightly higher performance than the PSO-RBFNN model. It is noted that the best ICA-RBFNN model was determined with several populations of 500; meanwhile, the optimal number of populations for the PSO-RBFNN model is 150. Of course, this did not indicate that more significant populations had more excellent performance because the number of populations is equal to 500 for the PSO-RBFNN model, its performance is lower than the number of populations of 150, as shown in Fig. 7. This problem is due to the stochastic mechanism of the metaheuristic algorithms [25,26]. For further assessment of the obtained results, the outcome predictions of the ICA-RBFNN and PSO-RBFNN models on the testing dataset were exhaustively visualized and analyzed through the absolute comparison, correlation, and relative error (RE), as shown in Fig. 8.

As depicted in Fig. 8, it is tough to determine which model is superior because they are also dissimilar. The results showed that both the ICA-RBFNN and PSO-RBFNN models developed in this study are close to the actual model in predicting FOS values. Furthermore, we can see that the error margin of these models is ±7.5% only in terms of RE. In other words, they can be used instead of the Geo-studio software with an acceptable result in the case of rapid determination of FOS with a large computing capacity. However, as interpreted above, the ICA-RBFNN model is still better than the PSO-RBFNN model with superior performance.

To demonstrate the performance of these models; in practice, two cases of slopes were investigated and analyzed under the simple Bishop method of the

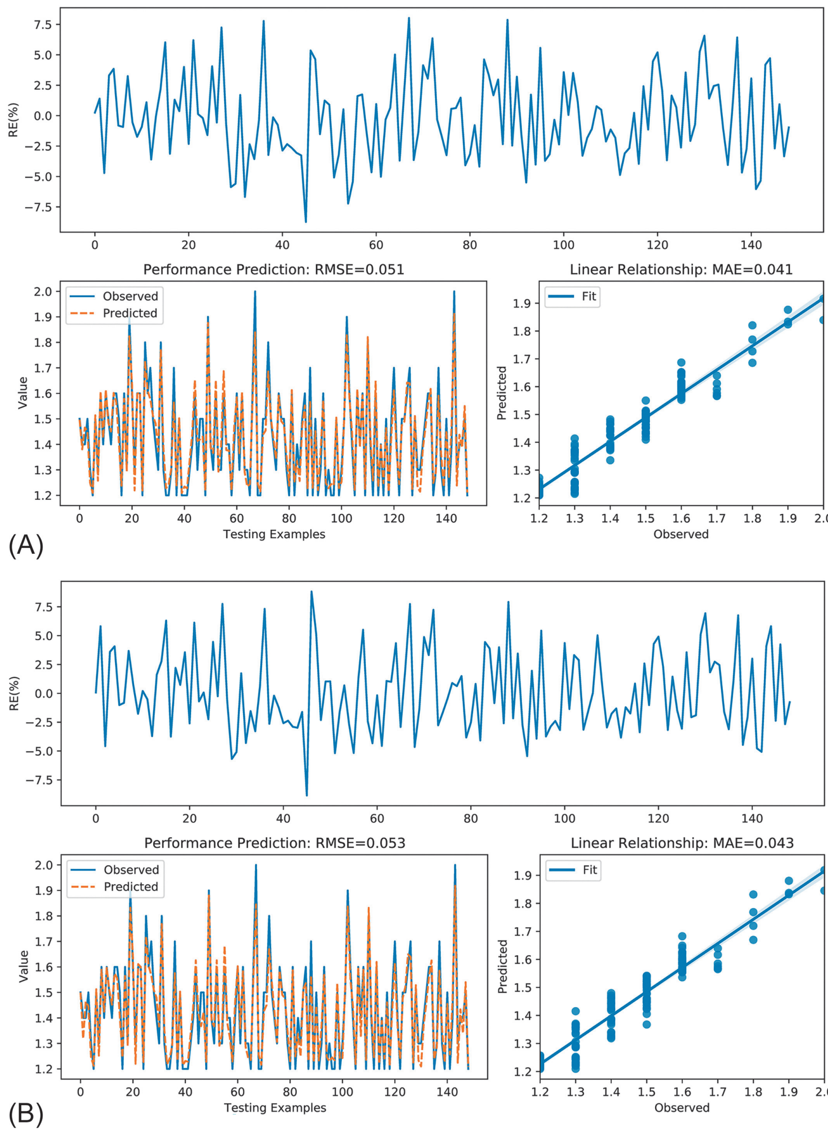

FIG. 8 Performance of (A) the ICA-RBFNN model vs. (B) the PSO-RBFNN model on the testing dataset.

Geostudio, as illustrated in Fig. 9. Different values of geotechnical parameters were also embedded in the tool to explore the FOS, and the analyzed results are summarized in Table 3. It is worth mentioning that in these three cases, some benches have been merged into one bench with a large bench height, for example, 20–30m. This may lead to hazards for the slopes, and they should be analyzed and predicted comprehensively.

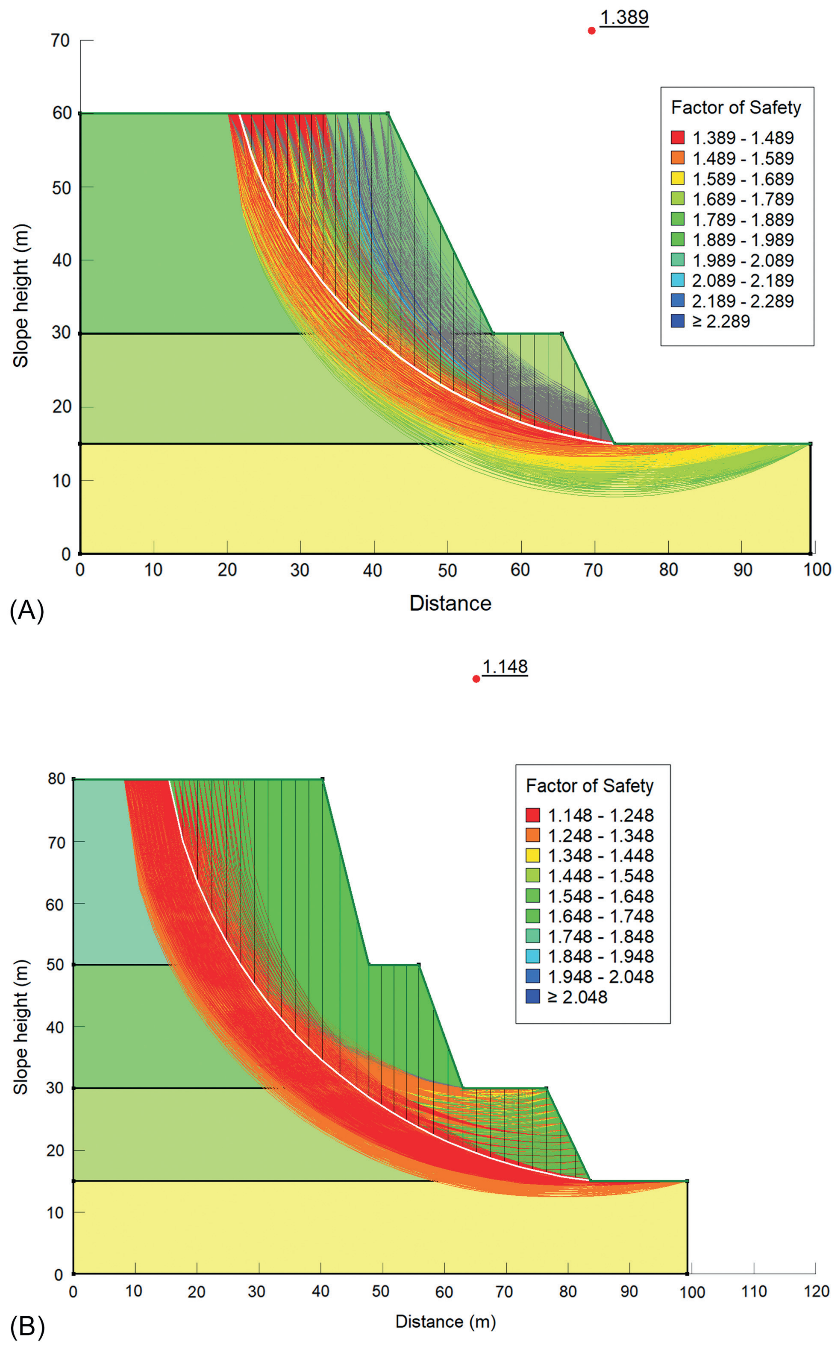

FIG. 9 Evaluation of slope stability with large bench height and slope height. (A) Case #1: The slope height is 60 m and the slope angle is 46 degree. (B) Case #2: The slope height is 80 m and the slope angle is 54 degree.

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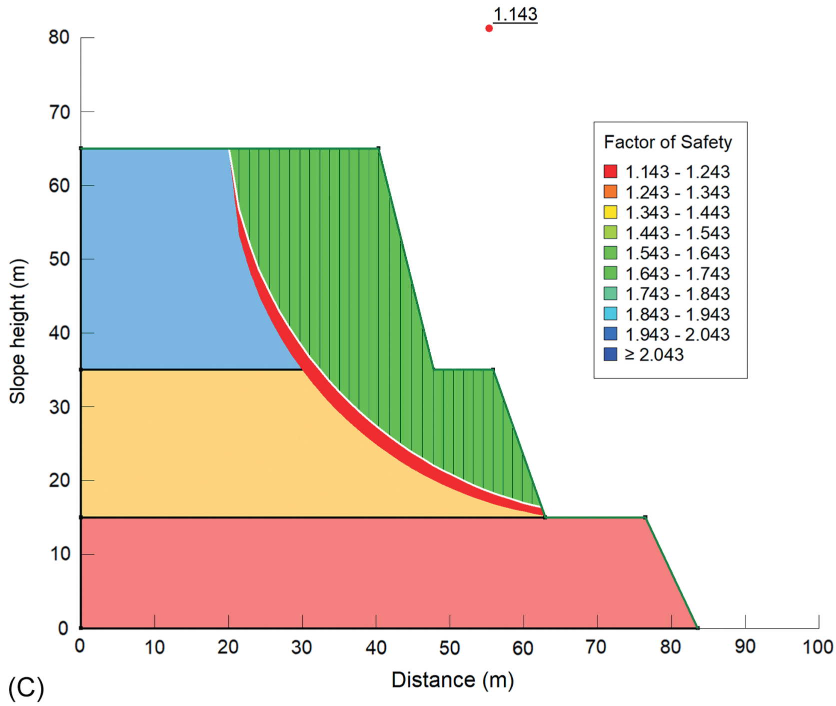

FIG. 9, CONT'D (C) Case #3: The slope height is 65 m and the slope angle is 56 degree.

TABLE 3 Summary of the validation dataset analyzed by the Geostudio software.

Case study	Slopes' parameters		Rock layers' properties			FOS
	H	β	γ	c'	ϕ'	
Case #1	60	46	22.5	121.7	27.5	1.389
			22.6	125.4	22.3	
			21.1	120.8	23.8	
Case #2	80	54	20.5	119.8	28.2	1.148
			24.7	121.5	24.5	
			23.9	120.2	25.6	
			23.7	116.2	26.3	
Case #3	65	56	24.7	121.5	24.5	1.143
			23.9	120.2	25.6	
			23.7	116.2	26.3	

Next, the input variables, including H, β, γ, c', and ϕ' were imported to the developed ICA-RBFNN and PSO-RBFNN models to predict FOS. The prediction results and actual FOS values are listed and compared in Table 4.

TABLE 4 Comparison of the predicted and analyzed FOS values in practice.

Case study	Analyzed FOS	ICA-RBFNN	PSO-RBFNN
Case #1	1.389	1.402	1.516
Case #2	1.148	1.207	1.025
Case #3	1.143	1.182	1.285

Based on the validation results shown in Table 4, the proposed ICA-RBFNN and PSO-RBFNN models predicted FOS with a very promising result. The obtained accuracies are very interesting, especially the obtained predictions by the ICA-RBFNN model. These results demonstrated that the ICA-RBFNN model is a potential tool that can be applied, in practice, to predict FOS under different conditions of geotechnical parameters to control the slope stability in open-pit mines.

5 Conclusion

Slope stability is a complex problem in open-pit mines due to the uncertain parameters of rock mass and uncontrollable parameters during exploitation. This chapter introduced an application of AI in predicting slope stability in open-pit mines (i.e., FOS) with high reliability through the robustness of the ICA-RBFNN model as a prime example. The results demonstrated that AI techniques/models could completely be applied to predict and evaluate the slope stability in open-pit mines properly.

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