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Performance Prediction Evaluation of Machine Learning Models for Slope Stability Analysis: A Comparison Between ANN, ANN-ICA and ANFIS

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Abstract: - Slope stability analysis is crucial in civil engineering for the design and maintenance of embankments, especially those constructed on soft soils. Traditional methods like the limit equilibrium method (LEM) and finite element method (FEM) are time-consuming and require significant expertise. This study explores the application of three machine learning models—Artificial Neural Network (ANN), ANN combined with Imperialist Competitive Algorithm (ANN-ICA), and Adaptive Neuro-Fuzzy Inference System (ANFIS)—to predict slope stability. A numerical analysis using PLAXIS 2D software generated a database encompassing various geometric characteristics such as slope height, surcharge, and slope angle. These features served as input parameters, while the factor of safety (FOS) values were used as target outputs. The performance of each model was evaluated using determination coefficients (R^2) and root mean square errors (RMSE). The ANN-ICA hybrid model demonstrated superior predictive accuracy, with R^2 and RMSE values of 0.998 and 0.041 for training datasets, respectively, outperforming the standalone ANN (R^2 = 0.724, RMSE = 0.124) and ANFIS (R^2 = 0.858, RMSE = 0.052) models. This study highlights the potential of hybrid machine learning approaches in enhancing the efficiency and accuracy of slope stability predictions, offering a promising alternative to traditional methods.

Keywords: Slope Stability, Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System, Optimization Algorithm, Imperialist Competitive Algorithm.

1 Introduction

Slope stability analysis is a fundamental aspect of civil engineering, particularly in designing and maintaining embankments constructed on soft soils [1]. Traditional methods such as the limit equilibrium method (LEM) and finite element method (FEM) have been extensively used for this purpose. However, these methods are time-consuming and require significant computational resources and expert knowledge for slope stability analysis due to considering stress-strain behaviour boundary conditions [2] and the need for precise modelling of parameters such as cohesion and internal friction angle [3], complex geological conditions [4], detailed material behaviour input [5], and accounting for factors like water pressure and seismic loads [6]. The increasing complexity of modern engineering projects necessitates more efficient and accurate predictive tools. This study addresses this need by exploring the application of advanced machine learning models to enhance the accuracy and efficiency of slope stability predictions.

In recent years, machine learning techniques have gained traction in various engineering disciplines due to their ability to model complex, nonlinear relationships. Among these techniques, Artificial Neural Networks (ANNs)

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have shown promising results, particularly when combined with optimization algorithms. Chakraborty and Goswami [7] use ANN to predict the slope factor of safety (FOS) value and compare the prediction accuracy with the output produced by FEM. In another study, Mamat et al. [8] found that the ANN model showed good potential for predicting slope stability improved with PVDs. Choobbasti et al. [9] Choobbasti et al. comparing the results of the multi-layer perceptron ANN model predictions with the LEM and found that the calculation results are quite similar between the two methods. Sari et al. [10] have predicted slope safety factors using ANFIS and found that the prediction performance generated is high with low error. Although comparative studies of these two models' performance in predicting slope stability are limited, most previous researchers in various fields such as fracture energy [11] and solar performance [12], have reported that ANFIS is superior to ANN because the ANFIS network is formed from a combination of ANN and fuzzy inference system (FIS). In order to address ANFIS predictive capabilities, several researchers have combined ANNs with optimization algorithms.

Recently, researchers have studied the effects of ANN with genetic algorithm (GA) [13], particle swarm optimization (PSO) [14], imperialist competitive algorithm (ICA) [15] and artificial bee colony (ABC) [16]. The optimization algorithm is reported to be capable of performing a global search to determine the weight and bias of the ANN network. Due to ANN has problems with slow learning rate [17] and trapped in local minima [18], the hybrid approach using optimization algorithms is able to adjust weight and bias to improve predictive performance.

This study investigates the performance of three machine learning models: a standalone ANN, an ANN combined with the Imperialist Competitive Algorithm (ANN-ICA), and an Adaptive Neuro-Fuzzy Inference System (ANFIS). By leveraging these models, we aim to overcome the limitations of traditional methods and provide a more robust predictive framework for slope stability analysis. In order to develop a comprehensive dataset, we conducted a numerical analysis using PLAXIS 2D software, which allowed us to simulate various geometric characteristics such as slope height, surcharge, and slope angle. These simulations generated a database of factor of safety (FOS) values used as target outputs for our models. The performance of each model was evaluated based on determination coefficients (R^2) and root mean square errors (RMSE). The findings of this study highlight the potential of hybrid machine learning approaches in advancing the field of slope stability analysis. By adopting these advanced predictive models, engineers can achieve more reliable and efficient slope stability assessments, ultimately enhancing the safety and sustainability of infrastructure development.

2 Machine Learnings

2.1 *Artificial Neural Network*

Artificial Neural Network (ANN) is an information processing technique designed to resemble the human brain [23]. These networks primarily comprise two types: recurrent networks (RN) and feed-forward (FF) networks. The application of ANN-FF is realistic when there is no time-dependent parameter [24]. One of the most widely used ANN-FF models is multi-layer perceptron neural networks. The network structure consists of three main elements: the input layer, the hidden layer and the output layer. All data from the input layer will be sent on each layer to the output layer via neurons. The neurons are linked through different weights. All artificial joints of the system receive a weighted total of arriving signals to pass a particular activation mechanism to provide more realistic performance. In approximating various functions in high-dimensional space, ANN-MLP works exceptionally efficiently. However, after the data is transmitted to ANN and before analysis of the results, ANN must be trained.

Backpropagation (BP) is most commonly used to develop ANN-MLP among various learning algorithms proposed in literature [25]. In these structure network, the data imported into the input layer begins to spread via connection weight to the hidden nodes. At any node, it calculates the sum of weighted input signals and then adds the output to the value threshold. The combined input is subsequently transferred through a nonlinear transfer function for the node's output. However, the subsequent neuron layer input normally comes from each neuron output. This process goes on until the output is produced. The generated output is checked for the desired output to determine the error. BP is primarily used to adjust the neuron's weight through iterative to minimise the mean square error (MSE).

2.2 *Imperialist Competitive Algorithm*

The imperialist competitive algorithm (ICA) is global search population-based algorithm that serves to optimise problems [26]. It starts with countries, a starting population that is unintended, similar to other GA and PSO optimising algorithms. After number of countries (N_c) are developed, several

of them are chosen for imperialism (N_i), such as root mean square error (RMSE). The other countries are then known as colonies (N_{col}). Following their intial control, all countries are distributed among empires. The best imperialist and the lowest RMSE will draw additional colonies. Three ICA algorithm operators are competitiveness, revolution and assimilation. Assimilation and revolutions will make a colony greater its imperialist state and empower a whole empire [27].

In rivalry, the imperialist operators strive to get more colonies and empires to control other empires. The empires can obtain at least the weakest empire of a colony, depending upon their competence. If whole empires, but the best, or user defined end principles such as the ideal RMSE are optimistically reached, the process comes to an end. It is worth noting that the number of decades (N_d) is in principle like the number of iterations of the PSO method. Many information is available on the mathematical formulation of ICA, and in previous relevant articles, it has been studied and discussed [27]–[29]. The ICA flowchart for greater comprehension of the method is shown in Figure 1.

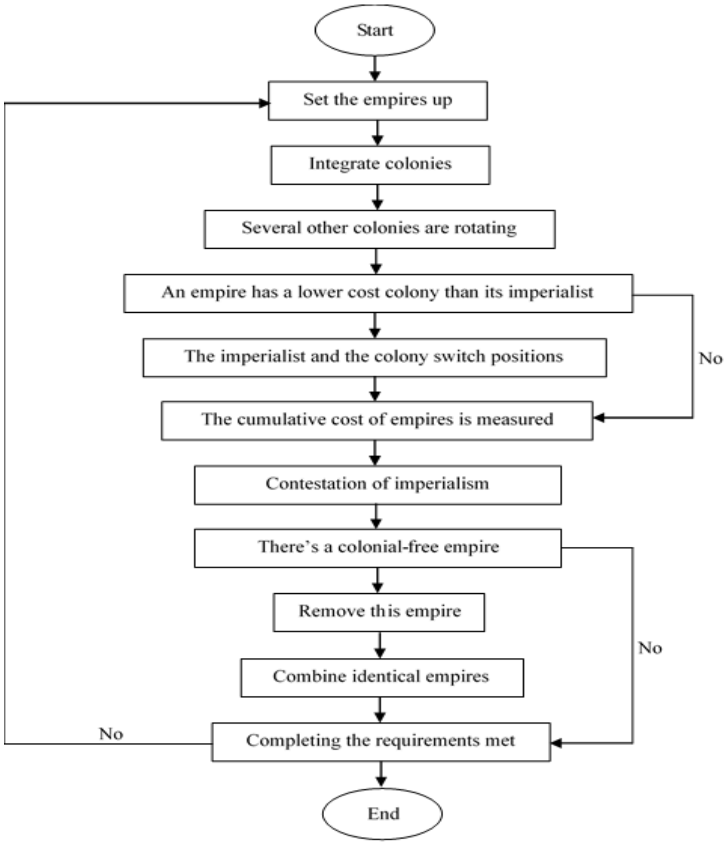

Figure 1 Flowchart of ICA algorithm

2.3 *Hybrid Model of ANN-ICA*

The optimal search process for the ANNs could fail, and weakness BP is an algorithm for the unsatisfied solution learning local search. Several efforts were made to boost the performance of ANNs by applying optimization algorithms such as PSO, GA and ICA. Optimization algorithms can be applied to change the ANN bias and weight in order to enhance its efficiency. As to the ANN's local minimum, the frequency of convergence is typically higher, whereas optimisation algorithms capable of detecting a global minimum. Thus, hybrid systems such as ANN-ICA benefit from search features of both ANN and ICA techniques. ICA searches for a global minimum for search space the ANN uses it to determine the best results for the network system. A brief overview is explained about the experimental system in the following section, and the further information is given about ANN-ICA.

2.4 *Adaptive Neuro-Fuzzy Inferece System*

The adaptive neuro-fuzzy inference system (ANFIS) model has been developed to mitigate the generalisation and complexity of ANN-BP and to enhance its ability to learn in fuzzy logic system (FIS) [30]. Several researchers have previously reviewed in detail on modelling and structure of ANFIS [31]–[33]. Basically, ANFIS incorporates the ANN's learning power with the fuzzy logic capacity. In memorising pattern, the ANN-BP is a successful technique. Still, it can be trapped in a local minimum, to obtain optimal results within the solution sapace such as global minimum solution. Thus, ANN-BP is able to prevent such deficiencies by the FIS. In particular, the Takagi-Sugeno (TS) of FIS offers a model upgrading knowledge platform enabling the system to more easily adjust itself to the studied phenomenon's realities by setting IF-THEN rules. Thus, this system optimises the linear or nonlinear parameters with the gradient descent and least square algorithm.

A fuzzy set theory in which the limits were not explicitly specified, but the boundries were incremental [34]. This system is defined by the spectrum of membership functions (MFs) grades, which assigns a membership rating from zero to one to each objective. Today, technique are combined with the soft computing in ANN, fuzzy set and fuzzy systems. It should be noted, combining the fuzzy logic with the neural network is an essential idea in overcoming both techniques' disadvantages. Even for complex systems, neural networks are used to adjust fuzzy systems' MF. The weight of the neural net utilising fuzzy rules give an in-depth perspective into the neural network and allow it to develop better neural networks. The neuro-fuzzy approach's non-linear membership feature decrease rule-based recall, thereby minimising implementation costs. Thus, combining the FIS with neural networks handles both techniques' shortcomings and provide an excellent opportunity for data processing to solve the essential and dynamic engineering issue.

In ANFIS architecture, there is five-layer structure typically includes the fuzzification layer, production layer, normalization layer, de-fuzzification layer and output layer. After training data for ANFIS identified, several MFs are calculated for each input, and the process continues until the training is complete, and the output of the prediction is satisfactory. In order to define linear parameters in a foward pass, the approach is based on ANFIS, which uses the least-squares approach. In contrast, the linear parameters are maintained continuously by the gradient desent method to update the nonlinear parameters.

3 Methods and Datasets Preparation

3.1 *Numerical Model*

Numerical analysis is conducted to establish a database for the development of machine learning models. Therefore, this study generated 100 man-made slopes designs through analysis with the FEM using PLAXIS 2D software version 8.2. Table 1 shows slope design with different geometry analyzed to generate FOS values used as database in development of machine learning models. As shown in the table, the range of values for slope height, surcharge and slope angle is 1 to 3 m, 0 to 15 kN/m^2 and 25^0 to 45^0. It should be noted that geometric characteristics will be used as input parameters, while FOS values are used as target values in the performance evaluation of machine learning models. Several recent studies have suggested that three geometric features can be considered as input parameters for predicting FOS [35], [36].

Table 1 Differential geometric characteristic of slope design

Design no.	Slope height (m)	Surcharge (kN/m^2)	Slope angle (^{0})
1 to 5	1	0	25,30,35,40,45
6 to 10	1	5	25,30,35,40,45
11 to 15	1	10	25,30,35,40,45
16 to 20	1	15	25,30,35,40,45
21 to 25	1.5	0	25,30,35,40,45
26 to 30	1.5	5	25,30,35,40,45

31 to 35	1.5	10	25,30,35,40,45
36 to 40	1.5	15	25,30,35,40,45
41 to 45	2	0	25,30,35,40,45
46 to 50	2	5	25,30,35,40,45
51 to 55	2	10	25,30,35,40,45
56 to 60	2	15	25,30,35,40,45
61 to 65	2.5	0	25,30,35,40,45
66 to 70	2.5	5	25,30,35,40,45
71 to 75	2.5	10	25,30,35,40,45
76 to 80	2.5	15	25,30,35,40,45
81 to 85	3	0	25,30,35,40,45
86 to 90	3	5	25,30,35,40,45
91 to 95	3	10	25,30,35,40,45
96 to 100	3	15	25,30,35,40,45

Due to the slope was built on soft ground and improved with prefabricated vertical drains (PVDs), the ground behaviour modelling performed based on equivalent plane strain. In this paper, the equivalent plane strain model of Indraratna and Redana [37] was applied. A triangular element of 15 nodes discretized the model. In 12,3485 elements and 24,252 nodes, the area studied was discrete. In order to reduce the boundary effect, the model width was chosen as 120 m and set the ground depth was to 40 m. The ground surface was preserved as drainage condition while the PVDs were modelled as equivalent plane strain vertical stripes. The mandrel radius is 0.045 m and the drainage stripes and smear zone are calculated half width of 0.028 and 0.157 m respectively.

The effective drainage zone has a half-width of 0.5 m, and drainage canals with high permeability were referred to as vertical drains. The discharge capacity has a significant effect on the finite element analysis results [38], [39]. According to the theoretical permeability, the PVDs are over 5.0 x 10^{-4} m/s, meaning the theoretical discharge capacity is over 980 m^3/year. However, the drainage stripe's equivalent permeability is 2.25 x 10^{-3} m/s. Thus, the discharge capacity effect is ignored in this study. The soft ground is assumed to adhere to the Cam-Clay model, and the slope filling is supposed to follow the model of Mohr Coulomb. Tables 2 and 3 for geotechnical parameters of soft ground and earth-slope fillings obtained via laboratory tests are presented. In this finite element analysis, FOS is estimated by reducing the shear strength parameters until the soil mass fails or it is better known by the phi-c reduction method.

Table 2 Summary of the soft ground parameters modelling

Soil types	γ (kN/m^3)	κ	λ	M	v	k_h (10^{-7} m/s)	k_v (10^{-7} m/s)
Silty clay	18.5	0.02	0.1	1.0	0.3	6.7	3.4
Clayey silt	18.0	0.03	0.09	1.0	0.3	4.5	2.3

Table 3 Summary of the earth-slope fillings parameters modelling

Soil types	γ (kN/m^3)	E (MPa)	c (kN/m^2)	ϕ (^{0})	ν	k_h (10^{-7} m/s)	k_v (10^{-7} m/s)

Sandy silt	16.5	14.5	10	20	0.30	3.0	2.0
Drainage sand	17.0	14.0	0	30	0.25	1.5	1.5

3.2 *ANN Modelling*

At an early stage in developing the ANN model, datasets should be normalized to achive better efficiency. The normalization process can prevent all the complexities encountered during the design process. Each datasets consists of training and testing compenents for enhanced performance. A total of 30% (30 datasets), and the remaining 70% (70 datasets) from all datasets have been selected randomly for training, and testing data, respectively in this study. The main geometric features of slope height, slope angle and surcharge are considered input parameters while safety factor as an output parameter in model development of all types of machine lessons used in the study.

A number of researchers have indicate that ANN with a single hidden layer can estimate any continuous function [40], [41]. Thus a hidden layer has been employed in this analysis, and the number of optimum nodes is determined by the trial and error method with a range of 1 to 20. A logsig tranfer function will be adopted for input function while will apply linear function for the output layer with learning rate of 0.01 and an iteration number of 1000 to achive the result. In developing ANN models Levenberg–Marquardt (LM) learning algorithm was used. As a result, the ANN model architecture with 3-6-1 was the best based on the determination coefficient (R^2), and the RMSE produced was 0.98 and 0.07, respectively.

3.3 *ANFIS Modelling*

In this study, the ANFIS model analysis was conducted with MATLAB R2019a. ANFIS builds FIS with an MFs tuned using a propagation algorithm. Due to the Sugeno type system's limitations that require a single output, the FIS needs to have three inputs and one output. The system has three inputs, nine MF inputs, 27 rules and 27 MF outputs to produce one output. Next, the grid partition method is used to generate the TS in the FIS structure. In this process, optimal MFs is essential to produce good results. By using the trial and error method, the MF of Gaussian is selected on the input layer while linear on the output layer.

A hybrid learning algorithm that uses a combination of the least-squares method and gradient descent BP method to identify Sugeno type FIS parameters is used while the number of epochs for learning is set to 100 and error tolerance to zero. The benefit of hybrid procedure is the use of BP for the input member parameter and the least-squares calculation for the output member parameters. In order to view the performances of the model, 85 model datasets used training and used 15 data for validation. This study extracted the FOS values for training and validation datasets in Excel file and input to the programme to implement ANFIS in MATLAB R2010b.

3.4 *ANN-ICA Modelling*

The essential parameters must be explored in order to achiebe the best ANN-ICA model. ANN design can be defined before ICA parameters are investigated. This was done in the sense of a trial and error method, and a 3-6-1 architecture has been found to be stronger. The most prominent parameters on ICA include N_c, N_d and N_i. Various N_c value have been used in prior studies to overcome engineering issues. A total of eight ANN-ICA hybrid models were designed in this analysis with different N_cs, as shown in Table 4. In order to determine the optimum N_c, N_d and N_i values were used 300 and 100, respectively. N_c with a value of 400 was found to show better performance for the ANN-ICA model than other N_c. Thus, in the ANN-ICA modelling, the value of 450, namely model 8, was chosen as N_c optimum.

Table 4 Performance with different N_c

Model	N_c	Train		Test	
		R^2	RMSE	R^2	RMSE
1	50	0.833	0.104	0.685	0.079
2	100	0.829	0.112	0.678	0.082
3	150	0.792	0.126	0.697	0.094
4	200	0.833	0.106	0.701	0.075

5	250	0.814	0.121	0.695	0.083
6	300	0.848	0.098	0.712	0.071
7	350	0.827	0.103	0.676	0.078
8	400	0.859	0.092	0.728	0.069

The next ANN-ICA modelling is to evaluate N_d. The outcome of a study of various N_d is realistic means of deciding the N_d optimum. Another parametric analysis to assess N_d's effect on network efficiency has been conducted. A fixed N_d with 1000 has been used in this study. Such analyses were carried out for each decade to track cost feature or RMSE changes. Figure 2 shows N_d for N_c parametric study findings from 50 to 500. At beginning of decades, this figure showed significant changes, whereas N_d = 500 were moderate. No significant change have occurred in RMSE results for all N_c after mentioned N_d. The optimum N_d in ANN-ICA modelling was set to be 500. It should be noted that other ICA parameters from previous steps have been used in determining N_d.

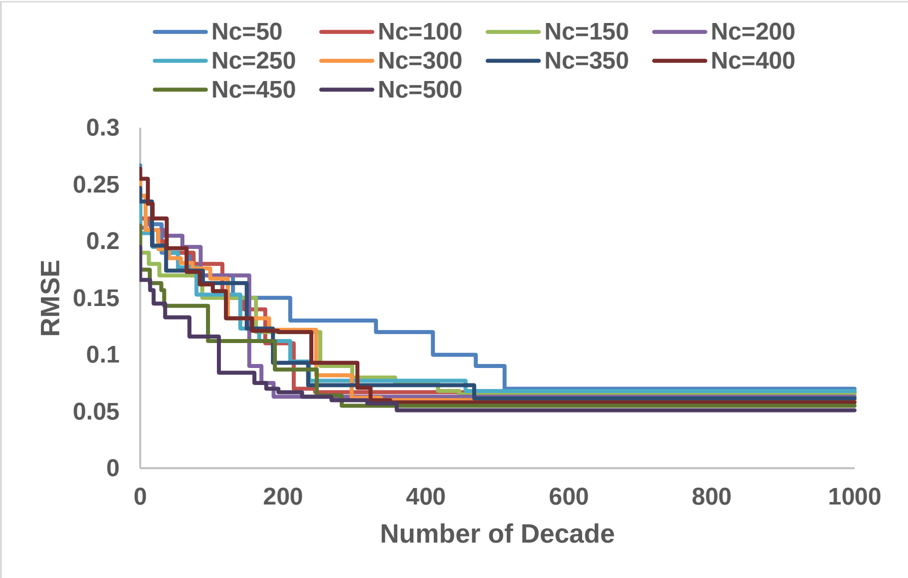

Figure 2 The influence of N_d on ANN-ICA performance

Another sensitivity analysis is required to determine the optimum N_i. In order to decide the appropriate N_i, N_i with values of 10 to 50 have been used. The parameters of the previous steps have been used in this phase. Table 5 demonstrates the performance indexes of various N_i, i.e., R^2 and RMSE, for the training and testing of datasets. Table 4 indicates N_i with 30 or model 3 is the best performance compared to others. Thus, the value 30 was selected to be the optimum N_i for ANN-ICA modelling to slope stability prediction.

Table 5 Performance with different N_i

Model	N_i	Train		Test	
		R^2	RMSE	R^2	RMSE
1	10	0.788	0.083	0.671	0.126
2	20	0.802	0.076	0.724	0.113
3	30	0.796	0.087	0.667	0.135
4	40	0.817	0.075	0.733	0.109
5	50	0.853	0.071	0.754	0.102

4 Results and Discussion

Three machine learning methods have been developed in this study to predict the slope stability built on the soft ground treated with PVDs, namely ANN, ANN-ICA and ANFIS. A total of 100 datasets have been randomly chosen to developed machine learning models, utilising two various datasets: training and testing. The R^2 and RMSE values were used to evaluate the three model's predictive performance. Theoretically, if the values of R^2 is one and RMSE is zero, the model would be excellent.

Table 6 summarises the models's performances indices on the randomly selected training and testing datasets. It should be noted; high training datasets performance suggest that the predictive model's training processes are accurate if the testing datasets prove that these model's generalisation potential is satisfactory. As shown in Table 5, R^2 values of (0.724, 0.858 and 0.998) and (0.737, 0.879 and 0.996) were obtained for training and testing of ANN, ANFIS and ANN-ICA models, respectively. In addition, the RMSE value is close to zero found on the ANFIS and ANN-ICA models for training and testing with values of 0.052 and 0.041 and 0.061 and 0.047, respectively. However, the hybrid model ANN-ICA was found to produce the lowest error than the general machine learning model. These results indicate that can achieve minimum system errors by combining machine learning models with optimization algorithms can provide superior predictive performance.

Table 6 Performance Indices of Each Machine Learning Model

Model	Training		Testing	
	R^2	RMSE	R^2	RMSE
ANN	0.724	0.124	0.737	0.103
ANFIS	0.858	0.052	0.879	0.061
ANN-ICA	0.998	0.041	0.996	0.047

Figures 3, 4 and 5 show the relationship between the values of estimated and predicted. As shown, the ANN model developed with ICA provides higher capability in slope stability predictions. Moreover, this study's results are better than several other related studies, such as Choobbasti et al. [9] with R^2=0.92, Mamat et al. [39] with R^2=0.95 and Fattahi [42] with R^2=0.95. Thus, the prediction model developed with ICA is proposed for similar situations in the future.

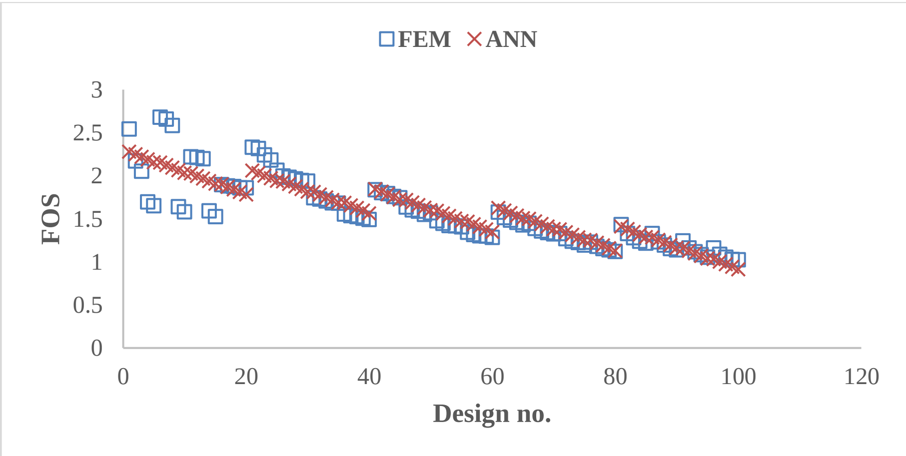

Figure 3 FOS relationship between ANN and FEM

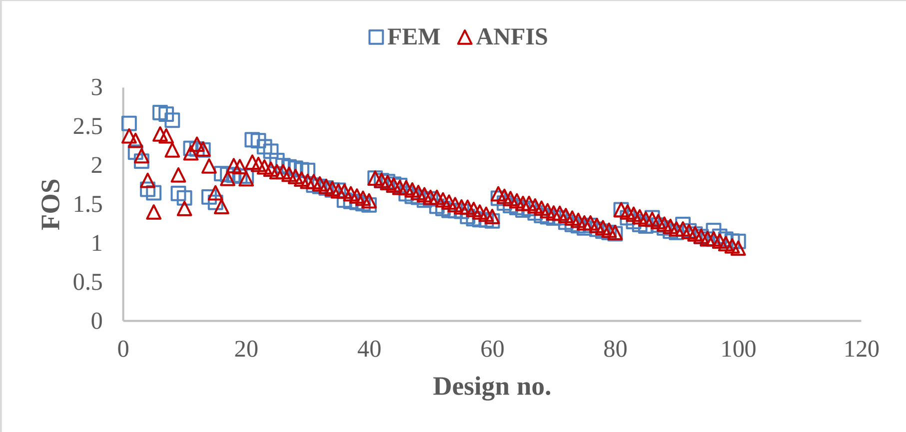

Figure 4 FOS relationship between ANFIS and FEM

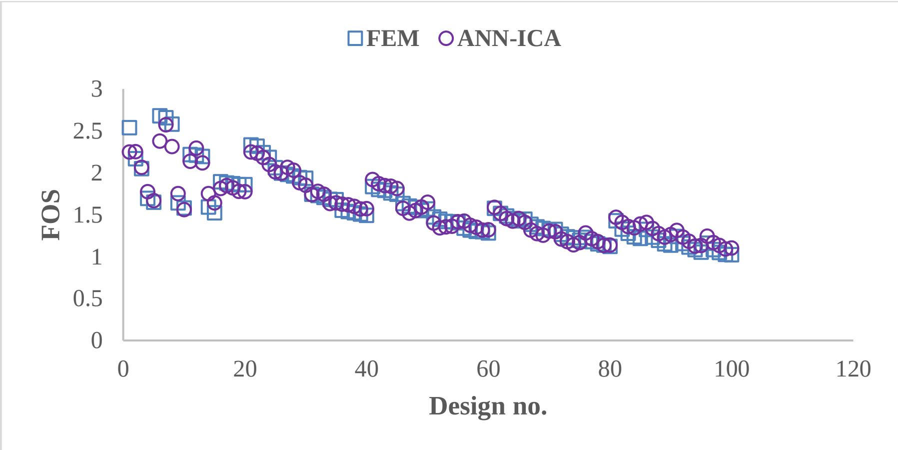

Figure 5 FOS relationship between ANN-ICA and FEM

5 Conclusions

Input parameters were considered to provide a good database to predict slope stability, geometric characteristics, e.g, slope height, surcharge and slope angle. Then three machine learning models were developed to predict FOS, namely ANN, ANFIS and ANN-ICA. The optimum parameter of ANN, ANFIS and ICA were indentified and determined in the present study. Several models of ANN, ANFIS and ANN-ICA were used to predict FOS and the best models were chosen to be introduced in this study. In terms of the most common performance indices, carefully assess all of the models presented. After the assessment, it was found that the ANN-ICA model obtains better results in both the train and the testing to solving the FOS problem. As a result, the R^2 values for training and testing of ANN-ICA, ANFIS and ANN models obtained were (0.998, 0.858 and 0.724) and (0.996, 0.879 and 0.737), respectively. These results show that machine learning models with a combination of optimization algorithms can produce better predictions.

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