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Slope stability prediction using the Artificial Neural Network (ANN)

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SLOPE STABILITY PREDICTION USING THE ARTIFICIAL NEURAL NETWORK (ANN)

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ABSTRACT: Slope failure is a significant risk in both civil and mining operations. This failure phenomenon is more likely to occur during the high rainfall season, areas with a high probability of seismic activity and in cold countries due to freezing-thawing. Further, a poor understanding of hydrogeology and geotechnical factors can contribute to erroneous engineering designs. Several Limit Equilibrium Methods (LEMs) and numerical modelling tools have been developed over the years. However, the highlighted success of the Artificial Neural Networks (ANNs) in other disciplines/sectors has motivated researchers to implement ANNs to forecast the Factor Of Safety (FOS). This paper aims to develop ANNs to predict the value of the FOS for slopes formed by (i) uniform one soil/rock material and (ii) formed by two soil/rock materials. Each of these slopes contains three sub-models with 6, 7 and 8 input material parameters. Thousands of FOS values were generated for each sub-model using LEMs by randomly generating material input parameters. Over 80% of generated FOS values were used to train ANNs and the remaining 20% were used to for validation. The one-material models performed better than the two-material models overall. The first sub-model from the one-material models and the third sub-model from the two-material models exhibited the best performance compared to the other sub-models, achieving Mean Square Error (MSE) of 8.35E-04 and 5.10E-3, respectively. The third sub-model from the one-material models and the first sub-model from the two-material models have a MSE of 2.00E-3 and 9.80E-3, respectively. The second sub-models have shown the lowest performance compared to the other models. The minimal errors between LEMs and ANNs have led to the conclusion that ANN can be used as a tool for a quick and first-pass analysis by design engineers without undertaking rigours, complex, time-consuming and tedious computation of FOS using LEMs. An actual field-tested database can be usedto predict real-world slope failures.

INTRODUCTION

Slope failures and landslides can cause a severe negative impact on the economy as well as causing human fatalities in critical areas. Several factors can play a significant role in the stability of slopes. Therefore, analysing the stability of a slope is a significant task for geotechnical engineers to predict the stability of the slopes. The failure of slopes can occur via various mechanisms, such as circular failure, planar failure, wedge failure and toppling failure. In addition, the stability of slopes can be identified after calculating the Factor of Safety (FOS). The researchers introduced multiple methods to analyse the stability of inclinations and predict the FOS. Limit Equilibrium Methods (LEMs) such as the Ordinary (Fellenius), Bishop, Spencer, Janbu, Morgenstern-Price and Sarma are well-known methods among geotechnical engineers. Geotechnical engineers have used LEMs to predict a slope's stability for many years. The slope stability problem is classified as a nonlinear problem and analysing the slope using the LEMs is complex and time-consuming. Not only, but also, each method has its own individual assumptions as well. Therefore, researchers endeavour to find an efficient way to calculate the FOS rapidly with a high accuracy level. Artificial Neural Networks (ANNs) have attracted geotechnical attention following the outstanding success that ANNs have achieved in the prediction process.

LITERATURE REVIEW

The ANN follows a similar method of processing the information in the human brain. It requires a database, and through the information provided in the database, it will begin to process the data and develop an ANN. Therefore, after the ANN has been created, it will predict the targeted outcomes the users want. However, a large dataset will be required to construct an ANN model with a high accuracy level. Furthermore, due to the continued success of the ANN in the prediction process, it has attracted researchers in this field to apply slope stability estimations. Consequently, several studies have been

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conducted to investigate the effectiveness of ANNs in forecasting the safety factor for several types of slopes.

The branch of ANNs was invented in the 1980s to simulate the information process in the human brain (Lawal and Kwon 2021, p. 249). The objective of ANN is to solve complex problems and forecast the desirable outcome that the users want to achieve for a specific problem. **Figure 1** shows that ANN architecture consists of three main layers: input layer, hidden layers, and output layer (Lawal and Kwon 2021, p. 249). The neurons in each layer are the channels that link all the layers together, and the information is transferred based on the weight and bias associated with each neuron (Lawal and Kwon 2021, p. 249).

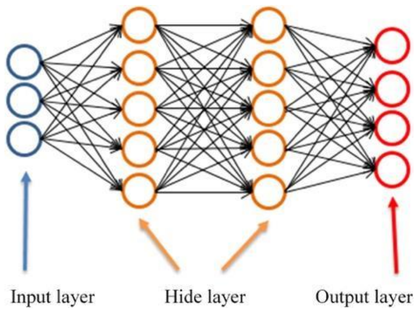

Figure 1: ANN architecture (Liao & Liao 2020)

Mahmoodzadeh, et al. (2021) studied various hybrid machine-learning techniques that were established to predict the stability of the ground inclination. This study has implemented machine learning techniques, including deep neural networks, decision trees, K-nearest neighbours, Gaussian Process Regression (GPR), long short-term memory and support vector regression. Three hundred and forty-four ground inclination cases were considered and analysed with PLAXIS software using finite element analysis methods. Soil unit weight, cohesion, friction angle, pore pressure coefficient, slope height and angle. All the machine learning used in this study achieved logical and acceptable results; however, among all the techniques used in this study, the GPR technique achieved the best R^2=0.8139 RMSE=0.160893 and MAPE=7.209772%. In addition, Abdalla, Attom and Hawileh (2014) investigated the stability of clayey soil slopes by developing two multilayer perceptron (MLP) ANN models. One hundred and sixty slope cases were considered to train the network. The database was prepared using the limit equilibrium method, Fellenius (Ordinary), Bishop, Janbu, and Spencer. The first model has considered different parameters to those from the second model, stability number (c/γH), angle of internal friction and slope angle. In contrast, the second model considered slope angle and height, friction angle, cohesion, and soil unit weight. The first model performed better than the second model, especially Bishop's method, which achieved a value of 0.0073, 1.52 %, and 0.997 for the Normalized Mean Square Error (NMSE), Mean Absolute Percent Error (MAPE) and correlation coefficient.

Khajehzadeh et al. (2022) developed an ANN to calculate the safety factor under static and dynamic conditions for homogenous slopes that include two layers. The study has used slope height and angle, friction angle, cohesion, soil unit weight and acceleration coefficient as input parameters for the ANN for 189 slope cases. The Adaptive Sine Cosine Pattern Search (ASCPS) algorithm and Morgenstern and Price method were used side by side to train the ANN. As a result, the study produced an acceptable ANN model, as the Root Mean Square Error (RMSE) and correlation coefficient (R) equals 0.023 and 0.984, respectively. Likewise, Goswami and Chakraborty (2022) have used the ANN to predict the safety factor of two-layer slopes. However, Goswami and Chakraborty (2022) have used slightly different input parameters for the 620 slope cases. They have used the slope's Inclination angle, the slope's height, slope height to layer thickness ratio (d/H), cohesion layer 1 the cohesion layer 2, the friction of angle and unit weight. In addition, they have implemented Multiple Linear Regression (MLR) and Multiple Nonlinear Regression (MNLR) methods to train the network. The study has achieved a value of 0.92 for the correlation coefficient (R). Furthermore, the MLR and ANN methods were also used by Chakraborty and Goswami (2017) to forecast the slope stability and verify the constructed models with several case studies that have been developed as well. However, Chakraborty and Goswami (2017), used the slope elevation, cohesion, internal friction angle, slope angle, soil unit weight and pore water pressure as the parameters for200 slope cases used to train the network. The safety factor for the trained dataset was calculated based on LEMs such as the Fellenius method, Bishop's method, Morgenstern-Price method, and Janbu method. The study found that the similarity between Bishop's model and the ANN and MLR is 99.63% and 96.14%, respectively. In addition, Bishop's model in ANN has achieved a Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) of 0.04 and 0.03, respectively.

Gordan et al. (2015) Generated two different intelligent models' ANN (back-propagation) and Particle Swarm Optimisation (PSO) to evaluate the slope FOS. Thedataset used in this study contains 699 slopes with the following slope geometry, slope angle and height, and the soil properties, cohesion and friction angle. The study also considered the peak ground acceleration to be one of the inputs to illustrate the stability under seismic or dynamic conditions. The ANN model was trained with 80% of the database, and the remaining 20% was used for testing and validations. PSO intelligent model provides a higher accuracy compared to the ANN model system. The R^2 value for ANN and PSO equals 0.915 and 0.986, respectively, and RMSE for ANN and PSO are 0.057 and 0.022, respectively. Koopialipoor et al, (2018) have extended the Gordan et al. (2015) study and utilised the ANN to assess the FOS for homogenous slopes under two different conditions, static and dynamic. In addition, a combination of intelligent systems was implemented to modify the weights and biases of the ANN; Imperialist Competitive Algorithm (ICA), Genetic Algorithm (GA), PSO and Artificial Bee Colony (ABC). The dataset used in this study contains 699 slopes with the following slope geometry, slope angle and height, and the soil properties cohesion and friction angle. The study also considered the peak ground acceleration to be one of the inputs to illustrate the stability under seismic or dynamic conditions. The ANN model was trained with 80% of the database, and the remaining 20% was used for testing and validations. The study found that all the ANN systems provide a high level of accuracy in the slope FOS prediction. However, PSO provides a slightly higher accuracy than the other used intelligence systems. In addition, Rukhaiyar, Alam and Samadhiya (2018) established a study to compare the accuracy between numerical limit equilibrium models and the constructed PSO-ANN model. The database consists of 83 natural inclinations exposed to circular failure mechanisms gathered from many different studies. The considered ground inclination geometry and soil properties parameters in this study are a unit weight of slope material, cohesion and angle of internal friction, average angle of slope, height of slope and pore water pressure coefficient. PSO-ANN produced more accurate FOS values than the numerical and Limit equilibrium analysis.

Wang, Moayedi, and Kok Foong (2020) developed an ANN combined with the most effective algorithms GA to predict the slope FOS for pure cohesive slopes. The database used in this study consists of 630 slopes, and finite element limit equilibrium analysis was applied to all the databases. Four hundred and forty one slopes from the datasets were used to train both models, and the remaining 30% were used for testing. The input for both of the intelligent models consists of the following parameters, slope angle, setback distance ratio (b/B), applied stresses on the slope (Fy) and undrained shear strength of the cohesive soil (Cu). The MLP and GA- MLP models produce a reliable slope FOS estimation. However, GA-MLP provides more accurate results compared to MLP. R^2 values for both the training and testing model in GA-MLP equal (0.975 and 0.097) and (0.969 and 0.107), respectively. The higher the number for R^2 and lower the number of RMSE emphasises that GA-MLP provides more accurate results than the other suggested models in this study.

Marrapu, Kukunuri and Jakka (2021) conducted a study that aims to train many synthetic databases using the ANN and use the real field slope information to improve the efficiency of the ANN model. The database used in this study consists of 15,000 slopes with the following slope geometry and soil properties: slope inclination and height, soil unit weight, internal friction angle, cohesion and pore pressure. The actual field-tested database consists of 27 cases. In addition, Slope elevation, internal friction angle and slope angle are the most sensitive parameters compared to the other parameters of the FOS (Marrapu, Kukunuri and Jakka, 2021). In addition, Verma et al. (2016) Investigated the stability of road cuts infield that are highly exposed to landslide hazards by applying finite element methods and ANNs. One hundred slope cases were analysed using the finite element method and PLAXIS software. 90% of the slopes were trained via a feed-forward back-propagation neural network. The ANN model has achieved 1.04 and 0.973, Mean Absolute Percentage Error (MAPE) and a correlation coefficient (R), respectively. Khandelwal, Rai and Shrivastva (2015) conducted a study to forecast the stability of the dragline dump slope in the coal mine by creating an ANN model and Multiple Regression Analysis (MRA). Khandelwal, Rai and Shrivastva (2015) considered 216 dragline dump slope cases to train the

ANN models. They also used the following parameters as inputs for the ANN models, dragline dump slope, height dragline dump slope angle and coal-rib height. Both models achieved RMSE values of 0.020894 and 0.003784 for MRA and ANN. Whereas Variance Accounted For (VAF) reached 97.67 and 99.92 for MRA and ANN models, respectively. Based on the different performance indicators used in this study, it is evident that the ANN model achieved more reliable accuracy than MRA. None of the ANN models considers the groundwater table for the slope stability analysis and seismic acceleration. This paper considers these additional factors in the ANN model and aims to utilize Levenberg-Marquardt and Bayesian Regularization for forecasting FOS and the computed mean errors are used to estimate the performance of ANN.

METHODOLOGY

Dataset Generation

Ten inputs were considered in this paper. Slope height (H), slope angle (β), cohesion (c), soil or rock unit weight (γ), friction angle (φ) and pore water pressure coefficient (r_u). Likewise, the research utilised further inputs as well, depth of the slope (D), water table level horizontal seismic acceleration (kh), and thickness of the layers (t) for the two-material models. The function of "RANDDARRAY", available in Microsoft Excel, was used to generate random values of the inputs after considering the reasonable ranges of every input from the extensive literature review. **Tables 1 and 2** illustrate the statistics of the inputs which are used to train the dataset. Following the generating of the inputs, the FOS (FOS) was calculated by implementing the LEMs Bishop, Spencer, Janbu and Morgenstern-Price methods using HYRACAN software. In addition, because the HYRCAN software has the feature of running Python code, a Python code has been generated to read the inputs from the excel file. However, it also must be noted that the Python library in HYRCAN doesn't have "pandas" and "numpy" functions which are necessary to run the code. As a result, they have been added to the python library by installing both functions in the Python library linked to the software.

Developing Artificial Neural Networks (ANNs)

Two main models are considered, one-material and two-material models (**Figure 2**), and each contains three sub-models. The following inputs are fixed in all the models unit weight, cohesion, friction angle, slope angle and height. However, five inputs are either replaced or added to the sub-models, such as pore water pressure coefficient, depth, water table level, horizontal seismic acceleration, and layer thickness.

Table 1: Geometry Statistics

	Slope angle (β°)	*Height of slope, (H) m*	*Depth, (D) m*	*Upper Layer Thickness (t_1) m*	*Lower Layer Thickness (t_2) m*
Maximum value	60.0	100.0	196.6	99.0	293.0
Minimum value	10.0	5.0	8.3	1.0	9.0
Mean value	35.3	52.4	102.2	26.4	128.2
Standard deviation	14.5	27.5	55.1	21.8	71.5
Median	35.7	52.6	102.8	20.1	126.7

Table 2: Materials statistics

	Unit weight, Υ (kN/m³)	*Cohesion, c (kPa)*	*Internal friction angle (ϕ°)*	*Pore pressure, r_u*	*Water table level (m)*	*Horizontal seismic acceleration, Kh, (g)*
Maximum value	30	69.94	44.93	0.5	295	0.299
Minimum value	10	0	0	0	8.9	0.1
Mean value	20	36	22	0.2	127.2	0.2
Standard deviation	6	20	13	0.1	70.8	0.1
Median	20	37	22	0.2	125.9	0.2

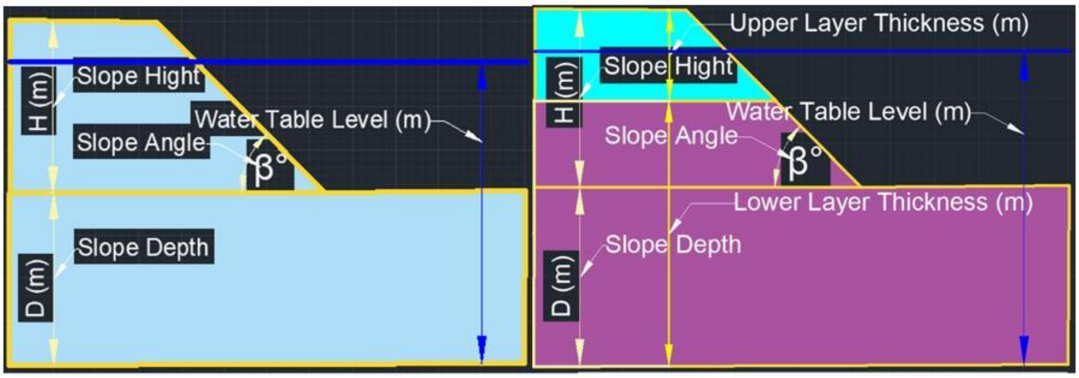

Figure 2: Configuration of one-material soil/rock layer (left figure) and two-material models along with various parameters used in ANN.

ONE-MATERIAL ANN MODELS

A simple feed-forward neural backpropagation was elected to train the datasets through the MATLAB R2022 neural network fitting toolbox. After multiple training sessions, it was highlighted that two training algorithms, Levenberg-Marquardt and Bayesian Regularization, are appropriate for the main two models as they provided a better MSE compared to the Scaled Conjugate Gradient (SCG). In addition, it was noted that applying the Bayesian Regularisation with two hidden layers provides a better MSE. However, using Levenberg-Marquardt algorithms with one hidden layer also gave a reasonable MSE value, especially for the one material slope. Therefore, it must be noted that Levenberg-Marquardt backpropagation is used as a training algorithm for the one-material models.

The first sub-model consisting of six inputs Slope height (H), slope angle (β), cohesion (c), soil or rock unit weight (γ), friction angle (φ), and pore water pressure coefficient (r_u) was trained three times until achieving the best possible performance at 12 nodes. The MSE for training, validation and testing was 8.54E-04, 6.32E-04 and 8.91E-04, respectively. In addition, **Figure 3** illustrates that the best validation performance reached 6.32E-4 at 99 epochs. **Table 3** shows the FOS of four samples using the established ANN and HYRCAN software.

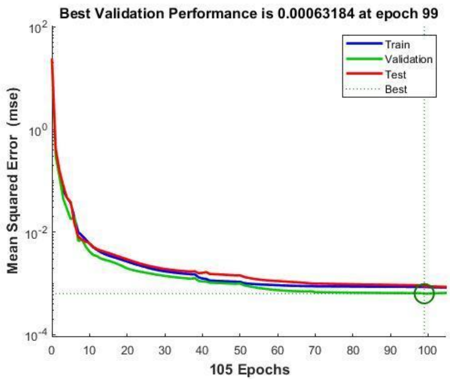

Figure 3: First sub-model performance

Table 3: First sub-model evaluation

FOS (HYRCAN)				FOS (ANN)			
Bishop	M-P	Janbu	Spencer	Bishop	M-P	Janbu	Spencer
0.54	0.54	0.52	0.54	0.52	0.52	0.49	0.52
0.58	0.58	0.55	0.58	0.58	0.57	0.54	0.57
0.33	0.35	0.31	0.35	0.36	0.38	0.28	0.38
1.84	1.84	1.71	1.84	1.83	1.82	1.71	1.82

The second sub-model consists of 7 inputs. Slope height (H), slope angle (β), cohesion (c), soil or rock unit weight (γ), friction angle (φ), depth of the slope and groundwater level. The dataset was trained 20 times until the best performance was achieved at 17 nodes. The MSE for training, validation and testing was 6.60E-3, 9.30E-3 and 7.10E-3, respectively. In addition, **Figure 4** illustrates that the best validation performance reached 9.31E-3 at 89 epochs.

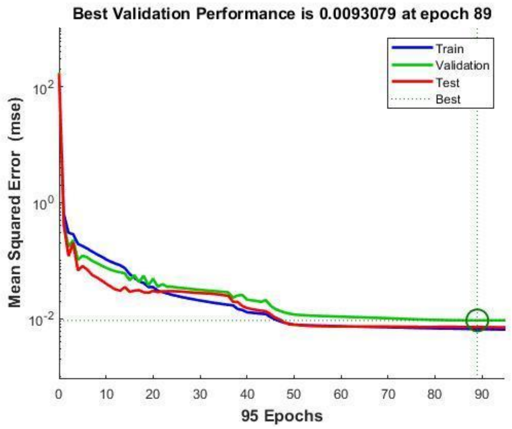

Figure 4: Second sub-model performance

Table 4: Second sub-model evaluation

FOS (HYRCAN)				FOS (ANN)			
Bishop	M-P	Janbu	Spencer	Bishop	M-P	Janbu	Spencer
0.76	0.76	0.71	0.76	0.79	0.79	0.72	0.78
0.74	0.74	0.68	0.74	0.77	0.77	0.72	0.76
1.22	1.22	1.19	1.22	1.32	1.32	1.26	1.3
2.07	2.08	1.83	2.08	2.04	2.04	1.81	2.05

The third sub-model consists of 8 inputs. Slope inclination (H), slope angle (β), cohesion (c), soil or rock unit weight (γ), friction angle (φ), depth of the slope, groundwater level and horizontal seismic acceleration (kh) as shown in figure 34. The dataset was trained 20 times until the best performance was achieved at 14 nodes. The MSE for training, validation and testing was 2.10E-3, 2.10E-3 and 2.50E-3, respectively. In addition, **Figure 5** illustrates that the best validation performance reached 2.64E-3 at 61 epochs.

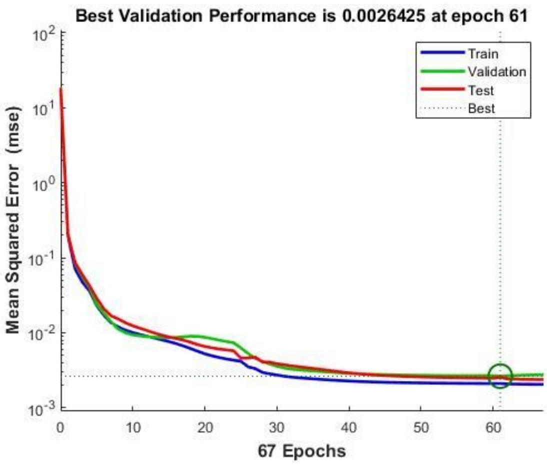

Figure 5: Third sub-model performance

Table 1: Third sub-model evaluation

FOS (HYRCAN)				FOS (ANN)			
Bishop	M-P	Janbu	Spencer	Bishop	M-P	Janbu	Spencer
0.49	0.5	0.42	0.5	0.47	0.48	0.41	0.46
0.32	0.33	0.28	0.33	0.33	0.34	0.3	0.34
0.72	0.72	0.7	0.72	0.69	0.7	0.62	0.71
0.94	0.95	0.82	0.96	0.94	0.96	0.84	0.97

TWO-MATERIAL ANN MODELS

On the other hand, Bayesian Regularization with two hidden layers provides better accuracy for the two-materials model than for the one hidden layer. The expected reason behind that is there is a large number of samples in the two-material models compared to the one-material models. Therefore, the numbers of the samples have been increased to achieve better MSE values.

In the first t sub-model, 13 inputs were considered. The slope geometry slope height (H), slope angle (β), depth of the slope and the properties of the two materials cohesion (c), soil or rock unit weight (γ), friction angle (φ), pore water pressure coefficient (r_u) as well as each layer thickness as shown in figure 38. The dataset was trained 40 times until the best performance was at 20 nodes with two hidden layers. The MSE for training and testing was 8.90E-3 and 1.84E-2, respectively. In addition, **Figure 6** illustrates that the best training performance reached 8.87E-3 at 806 epochs.

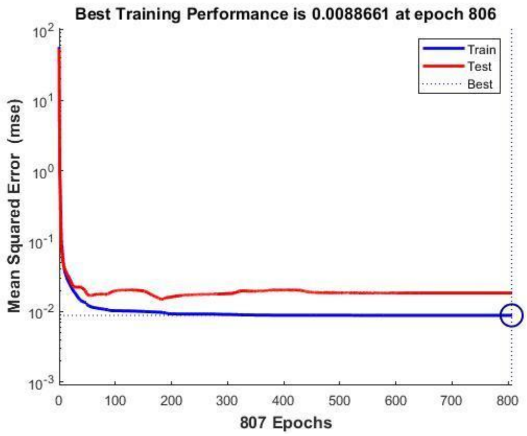

Figure 6: First sub-model performance

Table 6: First sub-model evaluation

FOS (HYRCAN)				FOS (ANN)			
Bishop	M-P	Janbu	Spencer	Bishop	M-P	Janbu	Spencer
0.94	0.94	0.89	0.94	0.91	0.91	0.86	0.91
0.46	0.46	0.41	0.46	0.42	0.42	0.38	0.41
0.84	0.75	0.72	0.78	0.86	0.86	0.78	0.86
1.29	1.29	1.24	1.29	1.25	1.25	1.16	1.25

In the second sub-model, the following 12 inputs were considered. The slope geometry, slope inclination (H), slope angle (β), depth of the slope and the properties of two materials cohesion (c), soil or rock unit weight (γ), friction angle (φ), groundwater level as well as each layer thickness as shown in figure 42. The dataset was trained 40 times until the best performance was achieved at 17 nodes with two hidden layers. The MSE for training and testing was 3.82E-2 and 7.00E-2, respectively. In addition, **Figure 7** illustrates that the best training performance reached 3.47E-2 at 165 epochs.

Figure 7: Second sub-model performance

Table 7: Second sub-model evaluation

FOS (HYRCAN)				FOS (ANN)			
Bishop	M-P	Janbu	Spencer	Bishop	M-P	Janbu	Spencer
1.14	1.14	1.06	1.14	1.27	1.27	1.18	1.27
0.8	0.8	0.74	0.8	0.69	0.68	0.65	0.66
1.18	1.16	1.06	1.16	1.21	1.21	1.1	1.23
2.17	2.17	2.1	2.17	2.37	2.37	2.2	2.38

In the third two-material sub-model, the following 13 inputs were considered. The slope geometry, slope inclination (H), slope angle (β), depth of the slope and the properties of the two materials cohesion (c), soil or rock unit weight (γ), friction angle (φ), groundwater table level as well as each layer thickness and horizontal seismic acceleration as shown in figure 46. The dataset was trained 30 times until the best performance was reached at 23 nodes with two hidden layers. The MSE for training and testing was 4.80E-3 and 7.80E- 3, respectively. In addition, **Figure 8** illustrates the training's best performance, reaching 4.75E-3 at 1000 epochs.

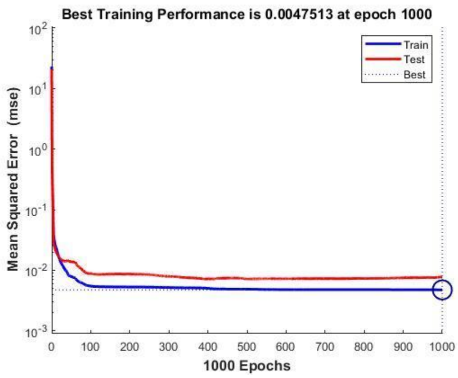

Figure 8: Third sub-model performance

Table 8: Third sub-model evaluation

FOS (HYRCAN)				FOS (ANN)			
Bishop	M-P	Janbu	Spencer	Bishop	M-P	Janbu	Spencer
0.80	0.80	0.73	0.80	0.78	0.80	0.74	0.80
0.43	0.43	0.38	0.43	0.39	0.40	0.35	0.40
0.77	0.76	0.67	0.76	0.79	0.80	0.69	0.81
1.13	1.14	1.08	1.14	1.15	1.16	1.08	1.16

DISCUSSION

Figure 9 below represents the performances of each model based on the mean squared error. It is evident from **Figure 9** that the one-material model performed better overall compared to the two-material model. The first sub-model of the one-material model and the third sub-model of the two-material models have the best performance compared to the rest as they achieved MSE of 8.35E-4 and 5.10E-3, respectively. The third sub-model from the one-material models and the first sub-model from the two-material models have MSE of 2.00E-3 and 9.80E-3, respectively. The second sub-models have shown the lowest performance compared to the other models. The expected variant for the decreased accuracy could be due to the increase in the sample quantity compared to the number of inputs. The number of inputs in the second sub-models for the main two models is 7 and 12 inputs, respectively. In contrast, the number of samples was 1000 and 2800, respectively. Many attempts have been made to detect if there is a clear relationship between the number of inputs, the number of neurons and hidden layers to the MSE. However, all the attempts could not detect a clear correlation between the mentioned variables. It has been found that the trial-and-error process is the optimum way to determine the appropriate number of neurons and hidden layers.

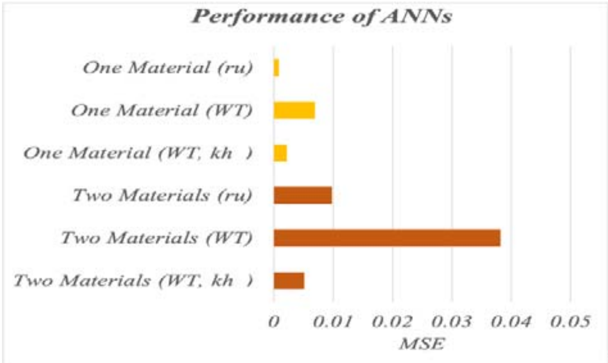

Figure 9: One-material and two-material models' performance

In addition, as the first sub-model in the one-material models achieved the minimum mean squared error, it was necessary to compare it with another published neural network. Two datasets were considered to evaluate the established neural network in this research, the first data set is from Chakraborty and Goswami 2017 study, and the second data set is from Marrapu, Kukunuri and Jakka (2021) study, which is an actual field. The results of the comparisons are shown in **Tables 9 and 10.**

Table 9 and 10: Chakraborty and Goswami 2017 ANN and Marrapu, Kukunuri and Jakka 2021ANN VS Al Muhalab ANN

ANN model result (Chakraborty & Goswami 2017)			*ANN model result Al-Muhalab*		
Bishop	M-P	Janbu	Bishop	M-P	Janbu
1.11	1.45	1.42	1.1	1.1	1.06
1.16	1.32	1.22	1.14	1.14	1.1
1.25	1.48	1.38	1.13	1.13	1.1
1.28	1.52	1.35	1.1	1.11	1.06

ANN model result (Marrapu, Kukunuri & Jakka 2021)			*ANN model result Al-Muhalab*		
Bishop	M-P	Janbu	Bishop	M-P	Janbu
2.00	*1.99*	*1.89*	*1.98*	*1.98*	*1.87*
1.53	*1.53*	*1.53*	*1.55*	*1.55*	*1.48*
1.48	*1.47*	*1.36*	*1.44*	*1.44*	*1.32*
1.40	*1.40*	*1.32*	*1.30*	*1.31*	*1.20*

CONCLUSIONS

In conclusion, the phenomenon of slope failures is a significant risk encountered by geotechnical engineers in both civil and mining industries. Therefore, mitigating and controlling this phenomenon, is important to save lives and billions of dollars and reduce the environmental impact associated with this phenomenon.

This paper aimed to develop an ANN that can predict the value of the safety factor for slopes using (LEMs), including Bishop's, Spencer Janbu's, and Morgenstern-Price's. This paper considers two main models of slopes: one-material and two-material models; each of the models includes three sub-models. Ten inputs were considered for the ANN. Slope inclination (H), slope angle (β), cohesion (c), soil or rock unit weight (γ), friction angle (φ) and pore water pressure coefficient (r_u), depth of the slope (D), water level table, horizontal seismic acceleration (kh), and thickness of the layers (t) for the two materials models.

Multiple attempts have been made to examine the correlation between the number of neurons and hidden layers and their influences on MSE. After all attempts, it has been found that the best process to elect the optimum neuron numbers and hidden layers numbers is the trial-and-error method. Levenberg-Marquardt and Bayesian Regularization, are appropriate for the main two models as they provided a better MSE compared to the Scaled Conjugate Gradient. In addition, it was noted that applying the Bayesian Regularisation with two hidden layers provides a better MSE. However, using Levenberg-Marquardt algorithms with one hidden layer also gave a reasonable MSE value, especially for the one material slope.

The one-material models overall performed better than the two-material models. The first sub-model of the one-material models and the third sub-model of the two-material models have the best performance compared to the others as they achieved MSE of 8.35E- 4 and 5.10E-3, respectively. The third sub-model of the one-material models and the first sub-model of the two-material models have a MSE of 2.00E-3 and 9.80E-3, respectively. The second two sub-models have shown the lowest performance compared to the other models.

These minimal errors between LEMs and ANNs have led to conclude that ANN can be used as a tool for a quick and first-pass analysis by the design engineers without undertaking rigours, complex, time-consuming and tedious computation of FOS using LEMs. Actual field-tested database can be included to predict real-world slope failures.

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