

Slope stability prediction of road embankment on soft ground treated with prefabricated vertical drains using artificial neural network

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Article Info

Article history:

Received Jan 15, 2020

Revised Apr 18, 2020

Accepted Apr 26, 2020

Keywords:

Artificial neural network

Numerical simulation

Prefabricated vertical drains

Slope stability

Soft ground

ABSTRACT

This paper presents the slope stability for road embankment constructed on the soft ground treated with prefabricated vertical drains (PVDs). The slope stability was evaluated based on the factor of safety (FOS) through numerical analysis and modeled with an artificial neural network (ANN). The permeability ratio of the smear effect was verified based on a comparative analysis between field data and numerical simulation to develop the datasets used in ANN model training. A total of 75 datasets generated from numerical simulations were randomly selected into three groups for training, testing, and validation. The coefficient of determination (R^2) and root mean square error (RMSE) were considered to evaluate the performance ANN model. It was found that the developed ANN model showed strong potential for predicting slope stability within the accepted range.

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1. INTRODUCTION

Construction of road embankment on the soft ground often leads to problems in the design stages. Soft soil is characterized as weak soil due to its high compressibility and low shear strength. For this reason, the soft ground should be treated to enhance the embankment stability. Various soft ground improvement methods can be used, such as the installation of piles, prefabricated vertical drains (PVDs) and stone columns. Installation of PVDs is a popular method at present due to its effectiveness to accelerate consolidation and time-saving construction.

Slope stability is the main factor contributing to the workability of road embankment [1]. Traditionally, the method of limit equilibrium [2] and finite element [3] are used to estimate slope stability. Recent trends, artificial intelligence approaches have been well received by researchers in various fields of study. The application of the artificial intelligence approach is crucial in solving complex tasks to save time, energy and improve service quality [4]. It also has great potential in automating repetitive operations and work.

The artificial intelligence technology is one of the branches of science in making objects as intelligent as humans [5]. The important part of artificial intelligence is machine learning, which is the ability of the machine to learn to be smart. Conceptually, the machines that human will need to learn must be equipped with a lot of information or data to make them smarter than other machines [6]. In other words, this machine will be equipped with thousands of attempts to complete a task. During this process, the machine will understand and learn concepts to solve the task.

There are several approaches to artificial intelligence approaches such as artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and support vector machine (SVM). However, ANN is often used in engineering applications. ANN is a network designed to resemble the human brain intended to perform a specific task [7]. One of the important features of ANN model analysis is the number of neurons in the hidden layer. Inconsistencies in the number of neurons in the hidden layer cause the network to respond that diverges to the target [8].

A key aspect for producing an ANN prediction model with relatively high accuracy is optimized based on the number of neurons [9]. There are various numbers of neurons reported from the results of previous studies. Due to the number of neurons in the hidden layer has been reported to be inconsistent, there is increasing concern among researchers [10-12]. The issue of the number of neurons has been a controversial subject and widely debated in the field of artificial intelligence. Most previous studies have only focus on optimizing the learning algorithm approach. Until recently, there was no reliable evidence that the number of neurons was determined to be used in the ANN prediction model for all engineering cases.

This paper seeks to present an appropriate ANN model for predicting slope stability with high accuracy. The optimum number of neurons in the hidden layer contributing to the prediction accuracy was determined based on the trial and error method. In order to improve numerical simulation results, validation of the smear effect parameter was performed by comparing the field data. This study provides an exciting opportunity to advance our knowledge in improving the prediction accuracy of ANN models.

2. NUMERICAL SIMULATION PROCEDURE

A road embankment built on the soft ground treated with PVDs, as shown in Figure 1, is used as a case study. The embankment is built to a height of 2m while the slope is 1V: 1.5H. A geotextile is placed on the soft ground surface as reinforcement to enhance embankment stability. The sand cushion was built on the soil surface to the height of 0.5m. The soft soil beneath the embankment consists of three layers, namely soft silty clay, silty clay, and clayey silt. The location of the groundwater level (GWL) is 2.3m from the soft ground surface. The PVDs were installed in soft ground to a depth of 14m with a distance between each other is 1m. Two settlement gauges (SG1 and SG2) were installed in the middle and toe of embankment on the soft ground surface to obtain measured data. Field measured data is observed for 177 days and collected weekly.

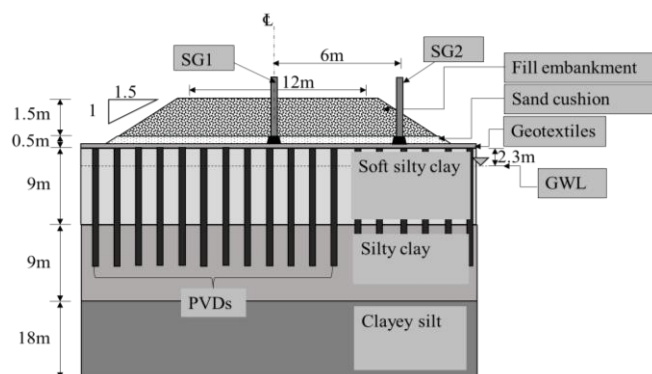


Figure 1. Cross-section of soil profile and instruments installation location

A series of laboratory tests were performed to determine the physical and engineering properties of the soft soil. The material parameters used in the numerical simulation are presented in Table 1. Numerical simulations were performed with software Plaxis 2D (version 8) by a plane strain model. The medium-mesh density consisting of 15-node triangular elements was used for numerical method analysis. The smearing effect was considered in the consolidation analysis of soft ground with PVDs. The equivalent horizontal permeability (k_{hpl}) proposed by Hird et al. [13] was used to develop the plane strain model. According to the

literature, the smear effect of permeability ratio of 3.4 and 5 are used to verify k_{hpl} values that produce accurate numerical simulation output. The material models of the embankment and soft ground are Mohr-Coulomb (MC) and Soft Soil (SS), respectively. In addition, PVDs is modelled with drains function while geotextiles is a geogrid function.

Table 1. The numerical parameters of the embankment and soft ground.

Parameters	Symbol	Unit	Fill	Sand	Geotextile	Soft silty clay	Silty clay	Clayey silt
Material model	-	-	MC	MC	-	SS	SS	SS
Types of model	-	-	Drained	Drained	Elastic	Undrained	Undrained	Undrained
Unit weight	γ	kN/m ³	18	19	-	14.2	13.8	13.6
Permeability	k	m/day	1	1	-	1.9×10^{-4}	1.5×10^{-4}	1.1×10^{-4}
Young's modulus	E	kN/m ²	5000	20000	-	-	-	-
Poisson's ratio	ν	-	0.3	0.3	-	-	-	-
Cohesion	c	kN/m ²	15	0	-	11	16	13.5
Friction angle	ϕ	0	20	30	-	0	0	0
Modified compression index	λ^*	-	-	-	-	0.123	0.108	0.097
Modified swelling index	κ^*	-	-	-	-	0.051	0.049	0.04
Normal elasticity	EA	kN/m	-	-	2000	-	-	-

3. NUMERICAL RESULTS AND DISCUSSION

In order to provide the ANN dataset, validation of the smear effect parameter was performed by comparing the results of the numerical simulation and measured. Correlation accuracy performance was assessed with the coefficient of determination (R^2) based on the soil settlement data. The settlement curves produced at SG1 and SG 2 has been illustrated in Figure 2a and b for 177 days. On the whole, the simulation results with $\eta = 3$ have shown considerably higher settlement than the other series. This may be because the pattern of permeability distribution in the soft soil is not consistent. Soft soil is characterized as high soil water content, and when forced to flow out through the PVDs, it will create an imbalance in the flow rate. This has been confirmed by several researchers who have investigated and discussed this issue [14-16].

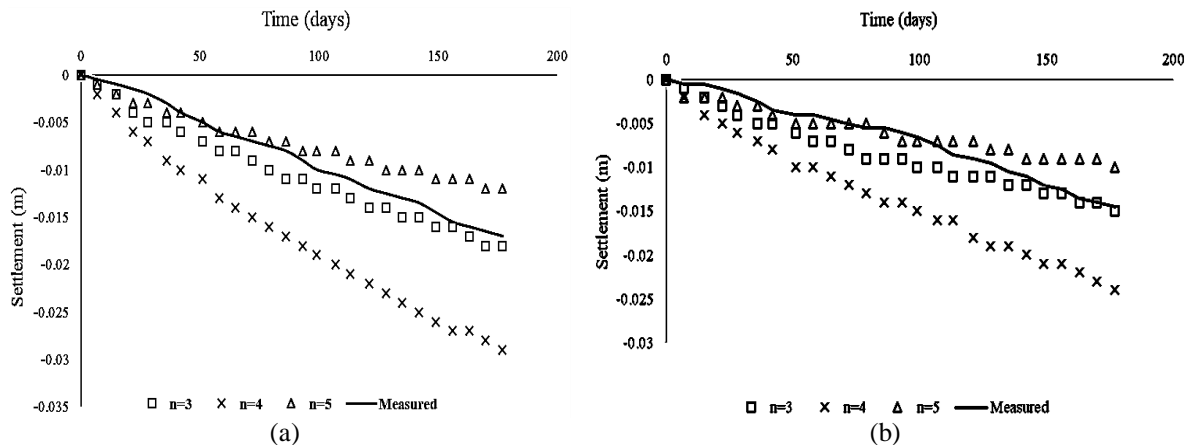


Figure 2. The relationship of soil settlement and time, (a) SG1, (b) SG2

Table 2 presents the R^2 of settlement from numerical simulation and measured. From the data in this table, it is clear that showing the accuracy of the numerical simulation model of settlement with $\eta=4$ yields the highest R^2 values in SG1 and SG2, respectively, 0.9858 and 0.9614. This result is in agreement with the findings of [17]. Interestingly, the output generated from the numerical method of ground settlement is considered good due to the values of R^2 exceeds 0.9. This indicates that the findings support the literature where the permeability ratio of smear effect with values of 3, 4 and 5 can be used for the consolidation analysis for soft ground treated with PVDs.

Table 2. The R^2 values obtained for numerical simulation.

$\eta = k_n/k_s$	SG1	SG2
3	0.9820	0.9409
4	0.9858	0.9614
5	0.9772	0.9264

4. ARTIFICIAL NEURAL NETWORK

Artificial neural network is a system that can acquire, store, and apply knowledge gained from experience. It can be used to organize and categorize information in ways that have proven effective in solving complex problems, difficult to understand or require additional information when solving with traditional computational methods [18]. Basically, ANN is composed of several processing units. Neural networks are developed based on the relationships between units that will respond in parallel to each input signal provided. To develop a neural network, the number of processing units must be determined at the input and output levels as well as the type of node that corresponds to the form of network to be used.

Generally, nodes have three layers: the input node, the hidden node, and the result node. Each node receives input signals via weighted and responds to the line weighted as output [19]. On the other hand, every relationship has its weight value. The weighted will be continuously updated when the learning process is performed on the network. Besides, it will always be adjusted so that the input and output behavior of the network is closer to the infrastructure that provides the input value [20]. ANNs can be presented in a more complex form where they contain a number of neurons that connect in which the output signal of one neuron will be the input signal to one or more neurons [21].

As in the biological nervous system, the relationship between the elements determines the function of the network. It can be trained to perform specific tasks by modifying the value of the connector or weighting between elements. Typically, the neural network was trained or modified to produce a specific input or output target specific. The modified neural network based on a comparison between the output and the target value so that the output value equals the value of the target network.

4.1. Optimum number determination of neurons in a hidden layer

More recent attention has focused on the optimum number of neurons in the hidden layer [22-24]. The small number of neurons will cause the network is not able to learn the relevance of the data. On the other hand, excessive numbers of neurons in the hidden layer interfere with network capability and cause the network to overfitting. Determining the number of neurons in a hidden layer is complicated to perform [25]. To date, there is no mathematical method that can be used to obtain the optimum number of neurons. The number of neurons in the hidden layer can be obtained after trying various network structures because there is still no theory that can be used to determine neurons number required in the hidden layer.

Generally, the number of neurons in the hidden layer is determined using a trial-and-error method. In this study, the optimum number of neurons in the hidden layer was determined by the trial-and-error method. The number of neurons in the hidden layer was evaluated ranging from one to 10 neurons. The number of neurons in the hidden layer is best to give the lowest error. Thus, the optimum number of neurons was determined based on two performance indices, namely, the values of root mean square error (RMSE) and the correlation coefficient.

4.2. ANN models development

MATLAB Neural Networks Toolbox version R2010b was used to analyze input and output data for ANN models. Table 3 shows the input and output parameters used for ANN prediction. The output parameter is used as the target value to evaluate the performance of the prediction.

Table 3. The input and output parameters for predictions

Data	Parameters	Unit
Input	Slope angle	degree
	Surcharge	kN/m ²
	Height of slope	m
Output	Factor of safety (FOS)	-

The ANN model structure used in this study is three inputs and one output. The network structure used is a multi-layer network consisting of input layers, hidden layers, and output layers. The network used is feed-forward with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer.

In ANN model analysis, data sets are randomly and automatically divided into three stages, namely training, validation and testing. The input and output vectors were divided into 70% (53 samples) for training, 15% (11 samples) for validation and another 15% (11 samples) for network testing. The flow chart for predicting slope stability in the study using the ANN model is shown in Figure 3. Training on the network was performed using a Levenberg-Marquardt backpropagation algorithm. The Levenberg-Marquardt backpropagation learning algorithm is designed specifically for squared error functions. It is more likely to be used because of its faster implementation than other types of backpropagation, such as the conjugate gradient and resilient.

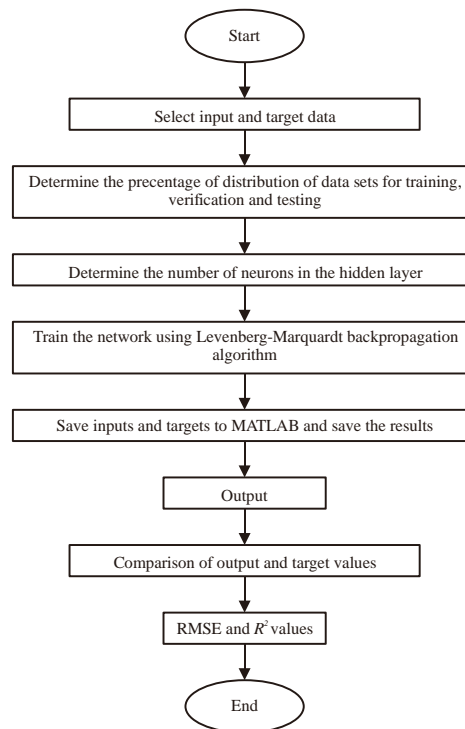


Figure 3. Flowchart slope stability prediction using the ANN model

4.3. Performance index

The prediction performance of the ANN model was evaluated by comparing the predicted output values with the target values using the coefficient of determination (R^2), and the root means square error (RMSE). If the value of R^2 is one, it means that the output value is equal to the target value and are considered a good model prediction. The smaller RMSE values are closer to the target values, and if its values are zero, it means no error and indicates the accuracy of the prediction model is good. The definitions of the statistical parameters used in this study to evaluate the ANN models are presented in (1) and (2).

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_{prd,i} - y_{exp,i})^2}{\sum_{i=1}^N (y_{prd,i} - y_m)^2} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=0}^N (y_{prd,i} - y_{exp,i})^2}{N}} \quad (2)$$

where y_m is the mean values, $y_{exp,i}$ is the measured values, $y_{prd,i}$ is the predicted values, and N is the data number.

The performance index used is capable of ensuring that the proposed model can provide a consistent level of accuracy in all periods. The advantages of using this statistical index are as performance indicators for the proposed model and ensuring that the results of errors when assessing model performance are small and acceptable errors. Besides, the use of these performance indices can guarantee a consistent level of

error that potentially provides the same level of error as the model is examined for invisible data during the test period.

5. PREDICTED RESULTS AND DISCUSSION

In order to assess the errors that arise during training, validating and testing in the ANN model, R^2 and RMSE were used. Trial and error method to determine the best number of neurons in the ANN network has been performed. Figure 4a and b show the relationship between the number of neurons with RMSE and R^2 , respectively. What is interesting in this graph is that the change in the number of neurons clearly affects the prediction performance. It can be seen that prediction performance changes significantly from the number of neurons 1 to 10. However, the subsequent increase in the number of neurons from 11 to 20 caused the prediction performance to decline, where the RMSE and R^2 values were relatively consistent. The use of a large number of neurons in the hidden layer can lead to overfitting.

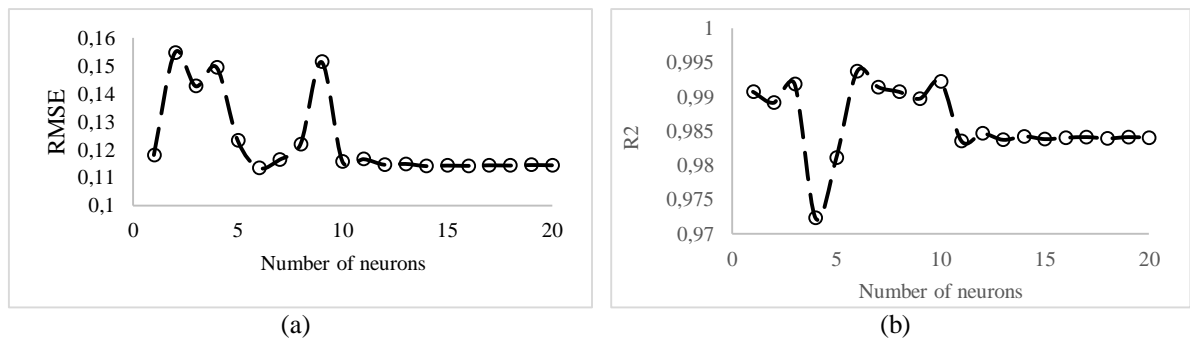


Figure 4. Relationship between statistical index and number of neurons, (a) RMSE, (b) R^2

Overfitting is a major issue when designing neural networks because the actual data obtained is small, relatively. If the number of parameters used in a network is significantly larger relative to the data size used, the neural network will tend to memorize rather than generalize the data properly. As a result, network performance during testing and applications will decline. The results show that the RMSE values are close to zero, and the R^2 values are close to one for predicting factor of safety (FOS) found in neurons of 6. Thus, the number of neurons six was chosen for use in the ANN network to predict slope stability.

A comparative analysis between target and output was performed to predict the safety factor of the embankment slope. Figure 5 shows the relationship between target and output. It can be seen that the target and output data seem to overlap with each other. On the other hand, the resulting error between these data is illustrated in Figure 6, where the error range is -0.05 to 0.05. These results suggest that a large amount of data is required while training the network to produce good predictions. This is due to the neural network needs to learn the whole pattern. The total data used will affect the performance of the network, especially in the testing and application stages.

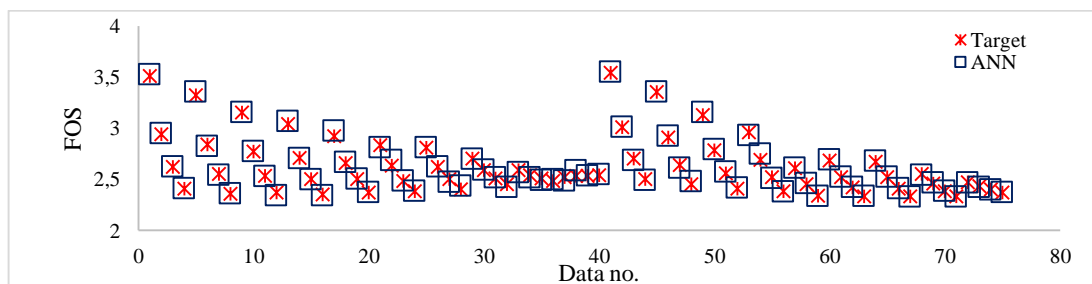


Figure 5. The relationship between FOS values calculated and ANN

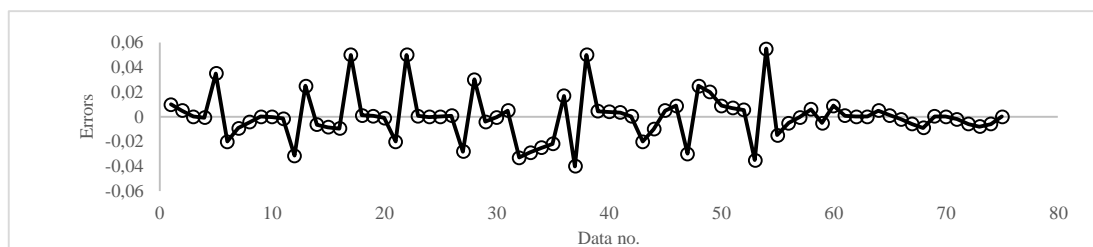


Figure 6. The error values between calculated and ANN

6. CONCLUSION

The main goal of the current study was to predict the slope stability for embankment built on the soft ground treated by PVDs. This study shows that the neurons number in the hidden layer contributes to the prediction accuracy. These findings suggest that the optimum neuron number can be achieved by the trial and error method for ANN training. The second major finding was that the permeability ratio of the smear effect is useful by applying a comparative analysis method between numerical simulation results and measured. The present study makes several noteworthy contributions to the ANN model prediction for improving the accuracy and method of estimating the permeability ratio of smear effect in consolidation analysis. The major limitation of this study is that the sample size used in ANN training is small at 75. What is now needed is a comparative study involving variations in the number of samples to investigate its influence on the prediction accuracy of ANN models.

ACKNOWLEDGEMENTS

This work was funded by a Fundamental Research Grant Scheme [Ref: FRGS/1/2018/TK06/UITM /01/1] based on collaboration between Universiti Teknologi MARA (UiTM), Politeknik Ungku Omar (PUO) and Universiti Kebangsaan Malaysia (UKM). The cooperation provided by UiTM Research Management Centre (UiTM-RMC) is also appreciated.

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