Artificial Neural Network Modelling for Slope Stability Analysis of Slopes Stabilized with Piles Using Levenberg-Marquardt Algorithm

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Abstract. Slope stability is critical in geotechnical engineering, particularly in landslides regions. Conventional methods like Limit Equilibrium Methods (LEM) and Finite Element Methods (FEM) need enhancement through advanced computational technologies. This study explores the use of Artificial Neural Networks (ANN) to predict the stability of slopes reinforced with continuous bored piles. A total of 112 reinforced slope designs were evaluated using 2D FEM to determine the Factor of Safety (FOS), which served as the target for the ANN model. The ANN model was trained using Levenberg-Marquardt algorithm and evaluated for its accuracy using the coefficient of determination (R^2) and Root Mean Square Error (RMSE). Results indicate that the ANN model demonstrates high accuracy in predicting FOS values, closely matching FEM calculations. The model offers a reliable and efficient tool for geotechnical engineers, providing faster and simpler alternatives for evaluating slope stability.

Keywords: ANN, Factor of Safety, Levenberg-Marquardt.

1 Introduction

Slope stability is critical in geotechnical engineering, particularly in regions prone to landslides. Failures can lead to economic losses, environmental damage, and safety risks. With rapid infrastructure development, real-time analysis is essential. Conventional methods like LEM and FEM are enhanced by AI, which excels at predicting soil and rock behavior due to its computational power and ability to process large datasets quickly [1], [2] and [3].

ANNs, inspired by the brain's neural structure, are effective for predictive modeling in engineering. They have been used to predict soil properties, evaluate foundations, and assess slope stability [1] and [4]. This study focuses on slopes reinforced with continuous bored piles. Slope with complex geomorphology and history of landslides, requires effective long-term stabilization methods. Bored piles, typically used for deep foundations, offer promising stability due to their deep penetration and load-

N. A. S. Abdullah et al. (eds.), *Proceedings of the International Conference on Innovation & Entrepreneurship in Computing, Engineering & Science Education (InvENT 2024)*, Advances in Computer Science Research 117,
https://doi.org/10.2991/978-94-6463-589-8_10

bearing capacity [5]. This research evaluates the slope stability stabilized with bored piles by considering single-row and double row piles.

Slope stability is measured based on the factor of safety (FOS), which considers soil parameters such as physical and engineering characteristics. The study employs 2D FEM to analyze the FOS of slopes before and after stabilization with bored. Mohamed et al. [6] further explain that 2D FEM calculations involve discretizing the slope into finite elements and applying appropriate constitutive models to depict soil or rock behavior. An ANN model, trained with the Levenberg-Marquardt algorithm was used to predicts the FOS. This algorithm is a widely used optimisation technique in neural networks due to its ability to converge quickly and accurately, even with small to medium-sized datasets [7]. Studies by [8], [9] and [10] have demonstrated its effectiveness in various engineering applications, including slope stability analysis.

The performance of the ANN model is evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE). By comparing the prediction of ANN model with the FOS values obtained from FEM analysis, the study aims to validate the effectiveness of ANN model and its potential as a predictive tool for slope stability. The integration of FEM and ANN presents a robust approach to slope stability analysis. By leveraging the capabilities of FEM for detailed analysis and ANN for rapid prediction, this methodology can serve as a valuable asset in engineering practices, contributing to efficient and effective slope stabilisation strategies.

2 Methodology

2.1 FOS analysis using FEM

Analysis of Existing Slope Stability.

An analysis of the existing slope stability was conducted to determine the FOS. According to the slope design guidelines by the Public Works Department Malaysia, the minimum allowable FOS for existing slopes without reinforcement is 1.30, as stated in [11]. Fig. 1 shows the critical slip surface and the FOS value for the existing slope without reinforcement. Numerical calculations using the 2D FEM method were performed to obtain the FOS values. This was done using the PLAXIS 2020 software, which is renowned for its ability to optimize engineering tasks [12]. The analysis confirmed that the current FOS was below 1.30, indicating a potential risk of slope failure.

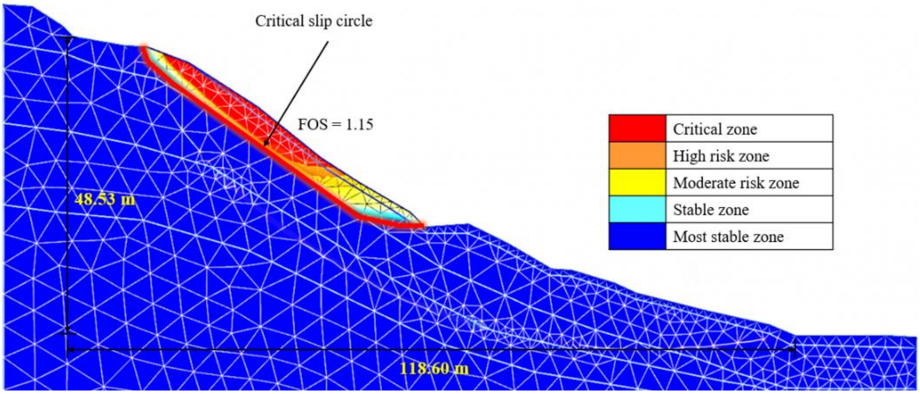

Fig. 1. The critical slip surface and the FOS value for the existing slope

Analysis of Reinforced Slope Stability

The stability analysis of slopes reinforced with bored piles was conducted using 2D FEM. Table 1 presents the parameters used in this study. A total of 112 reinforced slope designs were evaluated, considering parameters such as the number of pile rows, pile diameter, pile length, and pile position. Meanwhile, Fig. 2 illustrates a schematic example of pile positioning. The pile length was determined based on the L/H ratio, and the pile position was referred to as the (Xp/Lx) ratio.

Table 1. Input parameters, definition and value

Input	Unit	Value
Number of piles row	No.	1 - 2
Pile diameter	mm	800, 900, 1000, 1200, 1400 & 1500
Pile length (Row 1), L_1	m	Ratio L_1/H = 0.30 – 0.75
Position of the pile (Row 1) (from the toe of slope), Xp_1	m	Ratio Xp_1/Lx = 0.00 – 1.00
Pile length (Row 2), L_2	m	Ratio L_2/H = 0.30 – 0.75
Position of the pile (Row 2), Xp_2 (from the toe of slope)	m	Ratio Xp_2/Lx = 0.00 – 1.00

2.2 Development of the ANN Prediction Model.

The ANN prediction model was developed using MATLAB software to analyse the input and output data. The prediction model includes six input parameters to produce a single output: the FOS. The input data is shown in Table 1, while the target values for comparison were the FOS values obtained from the 2D FEM analysis.

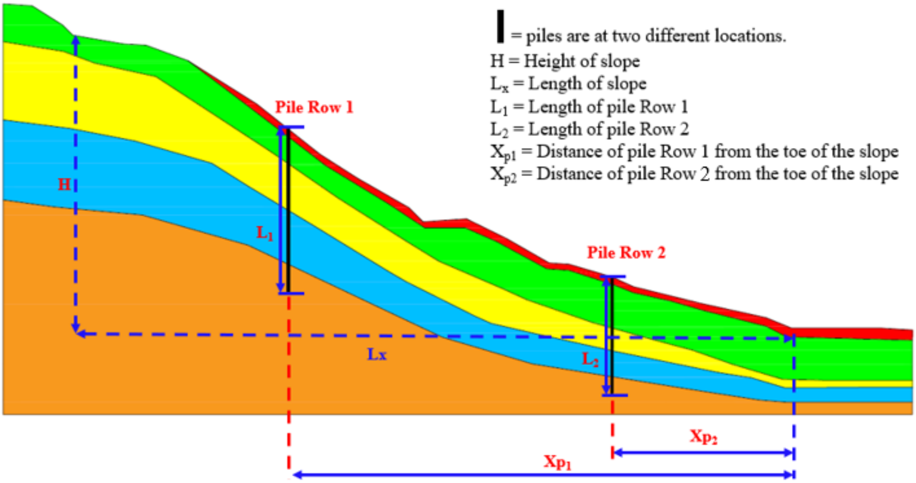

Fig. 2. A schematic example of the pile positions in Row 1 and Row 2.

In the analysis of the ANN model, the dataset of 112 samples was divided as follows: 70% (80 samples) for training, 15% (16 samples) for validation, and 15% (16 samples) for testing. Such a division is sufficient for the model to learn patterns and relationships within the data according to [13] and [14].

The optimal number of neurons in the hidden layer of an ANN plays a crucial role in determining the performance of the analysis [15]. Determining the optimal number of neurons ensures that the ANN has enough capacity to understand the data while maintaining computational efficiency and avoiding over-interpretation. This study determined the optimal number of neurons in the hidden layer using the equation stated in [16].

Fig. 3 illustrates the structure of the Artificial Neural Network (ANN) model developed for the study with the number of neurons as 14 in the hidden layer. The ANN model was trained using the Levenberg-Marquardt (LM) backpropagation learning algorithm. The LM algorithm was selected for its suitability, efficiency and speed in analysing datasets. It is particularly effective for problems involving non-linear model parameters and excels at minimising mean squared error [17]. By minimising the error function, the LM algorithm optimises the performance of the ANN prediction model [18].

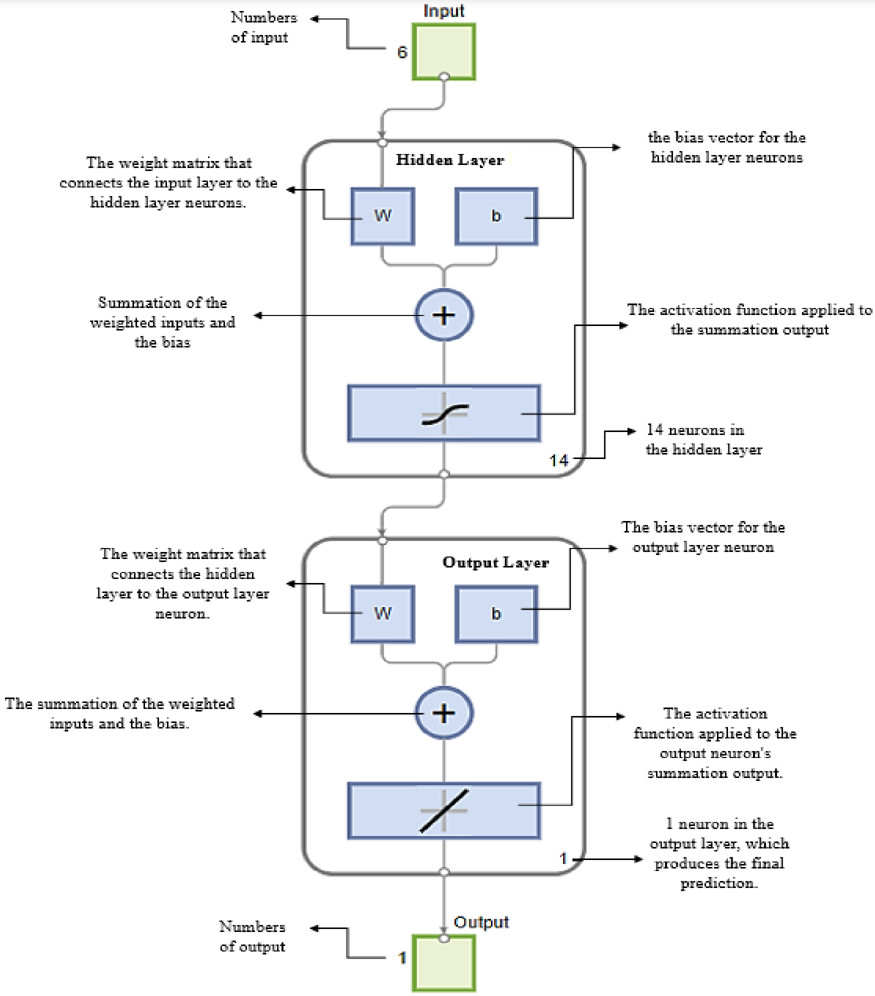

Fig. 3. The structure of the ANN prediction model

2.3 Evaluation of the ANN Prediction Model Performance

The performance of the ANN prediction model was evaluated by comparing its predicted FOS values with those from 2D FEM analysis, using the coefficient of determination (R^2) and Root Mean Square Error (RMSE) as metrics. An R^2 value of 1.0 indicates perfect alignment between predictions and targets, while a low RMSE value signifies minimal error and high accuracy. An RMSE approaching 0.00 suggests the prediction model closely matches the actual data, demonstrating the accuracy of the model and its reliability as stated in [19] and [20].

3 Result and Discussion

3.1 ANN Prediction Model

The ANN model was trained to predict the FOS of reinforced slopes using 112 data from the slope stability analysis generated by 2D numerical calculations. The development of these models is expected to provide an accurate and effective tool for geotechnical engineers to predict the stability of reinforced slopes, thereby aiding in the more efficient planning and execution of slope reinforcement projects.

Fig. 4 shows four linear regression plots comparing the target values (Target) with the Output values produced by the ANN model. These plots illustrate the performance of the ANN model across different stages: training, validation, testing, and the entire dataset. The Y=T line indicates that every point on the plot has the exact coordinates (Target, Output), meaning that the output values predicted by the ANN model are precisely equal to the actual target values. This line serves as a reference to assess the accuracy of the model. The closer the data points are to the Y=T line, the more accurate the ANN model is in predicting the target values. Moreover, the high prediction accuracy of the model is further supported by the high R values, which approach 1.0, indicating a strong and nearly perfect linear relationship between the output and the target values [21]. The consistent performance across the training, validations and testing phases indicates that the ANN model is robust and reliable for predicting the stability of slopes reinforced with bored piles.

Once the developed ANN prediction model achieved a high level of accuracy, the output and target values were compared to assess its performance. Fig. 5 shows the comparison between the FOS output predicted by the ANN model and the target FOS from the 2D FEM numerical calculations, arranged sequentially according to the data. The comparison indicates a good alignment between the ANN output and target values. This is evident from the proximity of the blue cross markers (ANN output) to the red square markers (targets) for most data points on the graph. There is also a substantial overlap between the ANN outputs and the targets, indicating high similarity.

Fig. 6 displays the error between the ANN model predictions (ANN output) and the target FOS data for various data sequences. Generally, the error for each data point falls within a small range, approximately -0.02 to 0.02. This indicates that the ANN model is highly accurate in predicting the target values, with minimal differences between the predicted and target values [19]. Most data points show very low errors, close to zero, demonstrating that the ANN model successfully predicts the FOS values with high precision for most of the data.

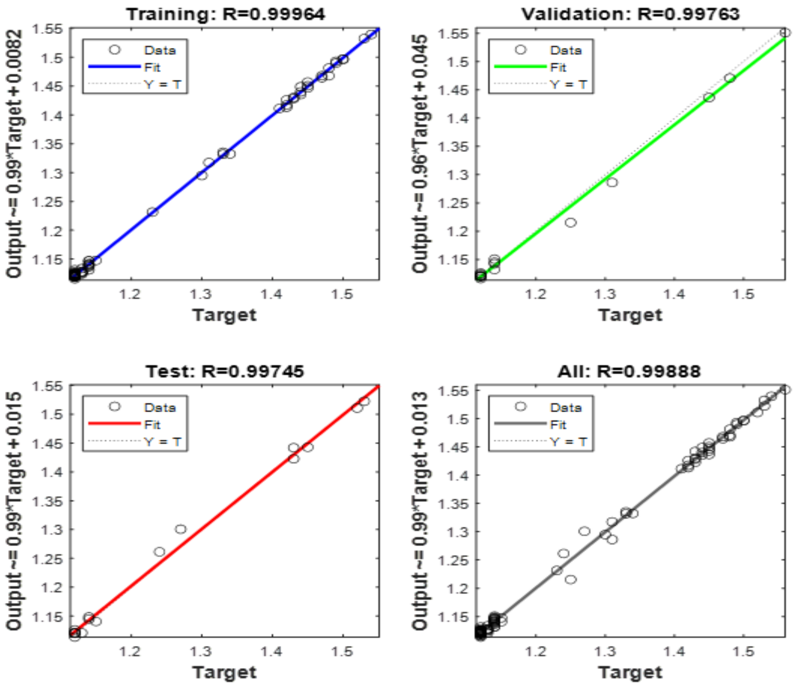

Fig. 4. Linear Regression of ANN training model, testing model, validation model and all data models.

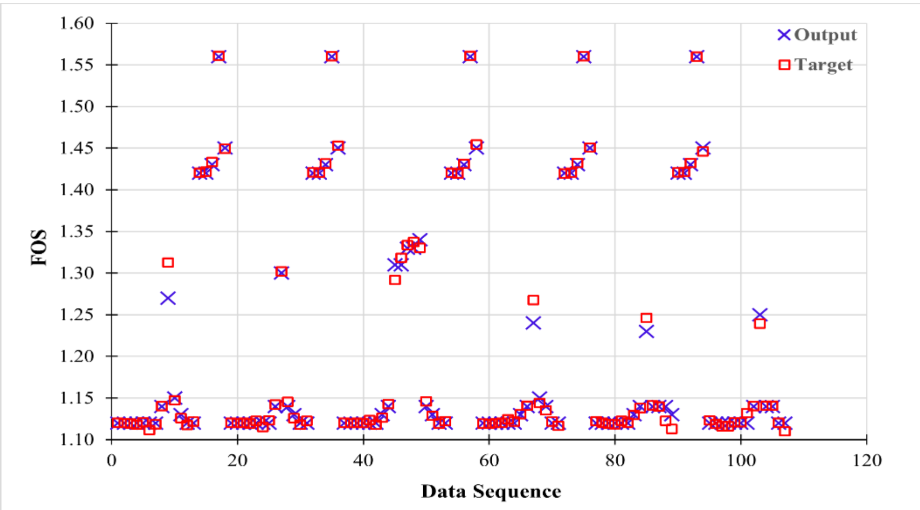

Fig. 5. Comparison of FOS by ANN Model Predictions (Output) with FOS by 2D FEM (Targets)

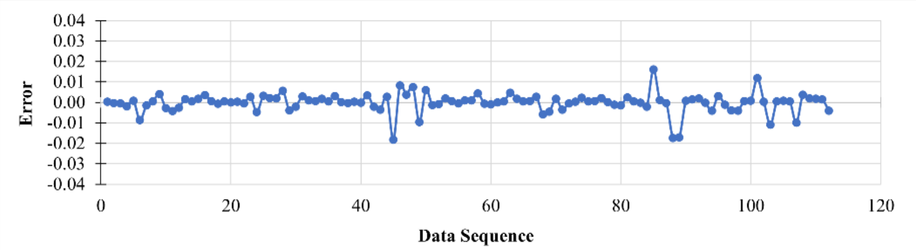

Fig. 6. The error according to the comparison between the prediction of ANN model (output) and the target values from the 2D FEM calculations.

Fig. 7 display the coefficient of determination (R^2) values as a performance validation for the ANN model predictions. The R^2 values range from 0 to 1.0, with an R^2 value of 1.0 indicating that the model explains all the variation in the data [22]. The figure shows the R^2 value for the comparison between the ANN output and the 2D FEM calculation targets. The obtained R^2 value of 0.9978 indicates that the ANN model has a very high capability to predict FOS values based on the data used in the 2D FEM analysis shows a solid relationship between the ANN output and the 2D FEM targets [23].

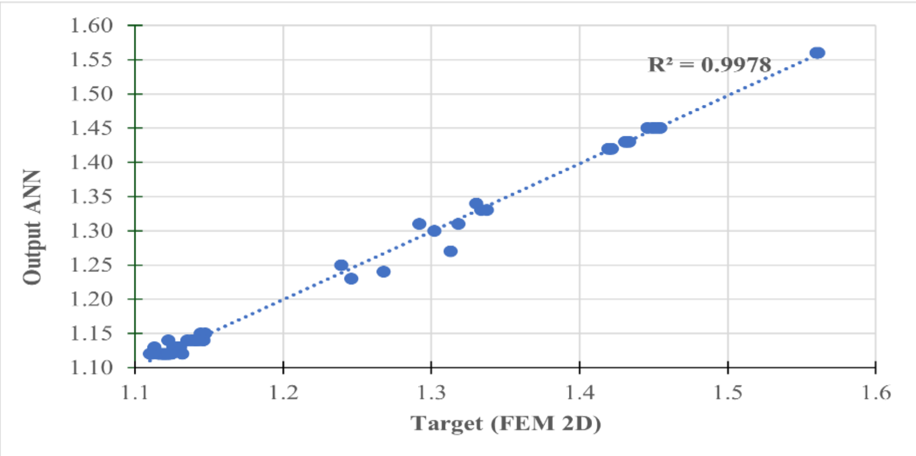

Fig. 7. The coefficient of determination (R^2) for the FOS comparison between the ANN model's predicted output and the 2D FEM (targets).

4 Conclusion

This study demonstrates the effective use of ANN in predicting the FOS for slopes stabilised with continuous bored piles. The ANN model, trained using the Levenberg-

Marquardt algorithm and data from 2D FEM analysis, shows high accuracy with R^2 values close to 1.0 and minimal RMSE proving its robustness and reliability. The research highlights the potential of ANN models as powerful tools in geotechnical engineering, particularly for real-time slope stability analysis. This can significantly aid in planning and executing slope reinforcement projects, enhancing safety and sustainability in landslide-prone areas.

In conclusion, the ANN model developed here is a valuable tool for geotechnical engineers, ensuring accurate and reliable slope stability assessments. Future research could explore other types of slope reinforcement and varied geological conditions, further broadening the applicability of ANN models in geotechnical engineering.

Acknowledgments. The authors sincerely thank the School of Civil Engineering, College of Engineering, Universiti Teknologi MARA (UiTM) and Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM).

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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