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A MACHINE LEARNING APPROACH TO FACILITATE STABILITY ANALYSIS IN SPATIALLY VARIABLE SOIL DEPOSITS USING RS2

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Slope stability analysis is a fundamental aspect of geotechnical engineering, primarily because it addresses the common issue of mobilized static shear stress in sloped grounds. Various methods are utilized in the literature to estimate the stability of infrastructures on sloped grounds, including the limit equilibrium method (LEM), finite element method (FEM), finite difference method (FDM), distinct element method (DEM), and finite element limit analysis (FELA). These numerical approaches are widely recognized in both research and practice. Each method has its own advantages and disadvantages, but more complex and versatile methods like FEM become essential for problems involving factors such as water presence, seismic loading, or the integration of structural elements like nailed walls and geogrid-reinforced slopes. The complexity further increases when considering the inherent variability of natural soil deposits. Addressing this variability involves numerous analyses through stochastic soil modeling, where the uncertainty of soil strength and stiffness parameters is accounted for. Random field theory combined with FEM can generate stability numbers for spatially variable slopes, with or without structural elements.

To accurately estimate the probability of failure or the reliability index for variable sloped grounds, important for addressing the uncertainty and risks associated with soil parameter variability, numerous numerical analyses are required. However, extensive FEM analyses are both demanding and costly, making the process less attractive. A compromise is to conduct a limited number of analyses to train a machine learning-based artificial neural network (ANN), which can then perform additional analyses within the same statistical parameter family. This article utilizes the FEM program RS2 to obtain results on the stochastic stability of a spatially variable slope. These results are integrated with a Radial Basis Function (RBF) algorithm to train and execute subsequent large-scale numerical analyses, ensuring accuracy throughout the process.

Keywords: Artificial Neural Network (ANN); Radial Basis Function (RBF); Inherent Variability; Reliability-Based Design; Slope Stability; RS2.

1. Introduction

The inherent variability of soil shear strength parameters is a fundamental characteristic of natural deposits. Its impact on the stability of geo-structures and the associated uncertainties has been a subject of debate in recent years. Slope stability is among the most critical types of instability in geotechnical engineering, often characterized by the formation of a continuous slip surface through the weakest points within the study domain. Several researchers, including Jamshidi Chenari and Alaie (2015), Sasanian *et al.* (2019), Javankhoshdel *et al.* (2021), and Mafi *et al.* (2021), have explored the influence of shear strength variability on slope stability. A notable challenge in probabilistic slope stability analysis is the large number of realizations required to reliably estimate the probability of failure (P_f) or the reliability index, particularly for high-consequence failures. Standards such as the Canadian Foundation Engineering Manual (CFEM, 2023) and the Canadian Highway Bridge Design Code (CHBDC, CSA, 2019) provide guidelines for the global stability design of embankments and slopes. These standards stipulate that for slope stability problems, the soil load has a load factor of 1.0, and the factor of safety derived from a limit equilibrium analysis should not be less than $1/\psi\phi_{gu}$, where ψ represents the consequence of failure factor and φ_{gu} is the strength reduction factor specified for "global stability" in CFEM (2023). The chosen consequence level determines the target P_f, which in turn dictates the minimum number of realizations required for accurate P_f estimations. Jamshidi Chenari *et al.* (2024) provide detailed insights into how the minimum number of simulations for probabilistic analyses is influenced by the target P_f. They emphasize the importance of soft computing methods, such as artificial neural networks (ANN), in scenarios where performing a large number of numerical analysis is computationally infeasible. Fathipour *et al.* (2023) and Jamshidi Chenari *et al.* (2023) demonstrated that response surface modeling (RSM) can generate accurate predictions even when trained on a limited dataset. However, their studies were confined to homogeneous random fields, lacking the broader scope of spatially variable random fields addressed in the current article. In this study, a radial-basis function (RBF) algorithm is employed to predict factors of safety (FoS) for a slope stability problem using data generated from the finite element program RS2. This approach bridges the gap between traditional probabilistic analyses and more computationally efficient surrogate modeling techniques.

2. Stochastic Slope Stability Analysis

A slope stability model, originally proposed by Huang *et al.* (2010), was selected for use in stochastic stability analyses (Figure 1). The spatial variability parameters defined by them were employed to perform numerical slope stability analyses in the finite element program RS2. Table 1 provides details on the deterministic and stochastic parameters used in this study, including the mean and coefficient of variation (CoV) for the stochastic parameters. For simplicity, no cross-correlation was assumed between the cohesion and internal friction angle random fields, a conservative assumption supported by Ranjbar Pouya *et al.* (2014). Log-normally distributed random fields for cohesion and internal friction angle were generated in the limit equilibrium-based program Slide2 using a Markovian autocorrelation function and local average subdivision (LAS) theory, with a scale of fluctuation (ô) of *5 m*. A library of 2,000 realizations was then imported into RS2 to perform slope stability analyses for each realization. The strength reduction method (SRM), an iterative bracketing technique, was implemented in RS2 to estimate the FoS for each realization. This approach provides reliable FoS values, capturing the impact of spatial variability in the stochastic parameters.

Table 1. Deterministic and stochastic parameters utilized in this study

Parameter	Type	Mean	CoV (%)
Mean cohesion, c (kPa)	Stochastic	7	30
Mean friction angle, Æ(p)	Stochastic	20	30
Deformation modulus, E (MPa)	Deterministic	50	-
Poisson’s ratio, ½	Deterministic	0.4	-
Unit weight, ³ (kN/m^3)	Deterministic	20	-

A ten-meter slope (*H*=10m), as illustrated in Figure 1, was used to perform stability analyses in RS2. A sample cohesion realization is shown in Figure 1(a) with the output for the SRM analysis shown in Figure 1(b). The mean FoSfor 2.000 realizations is 1.16, closely matching the deterministic FoS reported by Huang *et al.* (2010), with a CoV of 0.09. The P_f estimated from the RS2 results is 0.045. Similar calculations using the same realizations in Slide2 produced an identical $P_f$value.For 2,000 realizations, the total computation time using the domain shown in Figure 1(a) is 192 hours (8 days) on a Laptop computer equipped with an 11th Gen Intel(R) Core(TM) i7-11850H @ 2.50GHz, 2.50 GHz, running RS2 version 2024.

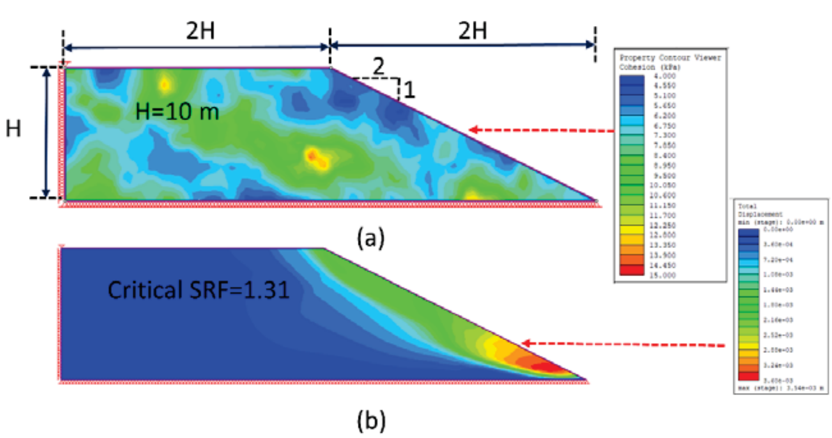
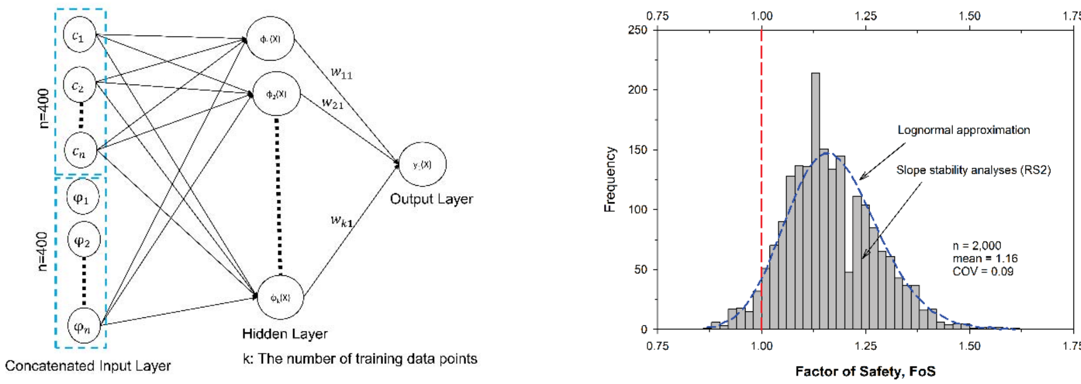


Fig. 1.Slope stability analysis in the finite element program RS2; a) sample cohesion realization; b) sampleSRM output.

3. ANN algorithm

An RBF algorithm, as introduced in Ghiassian *et al.*(2006) and Jamshidi Chenari *et al.*(2024), was employed to represent the machine learning approach adopted in this study. Figure 2(a) depicts the architecture of the adopted ANN algorithm. In this study, data preparation involved concatenating two 400×1 column vectors representing the random fields for cohesion and internal friction angle in the domain of study. The output vector, corresponding to the FoS of the slope, is retrieved from a log-normally distributed population, as illustrated in Figure 2(b). A total of 500 realizations, randomly sampled from the pool of 2,000 data points, were utilized during the training phase of the RBF algorithm. The remaining 1,500 data points from the RS2 results were reserved for testing, where the trained algorithm was used to predict data for the unexposed points.Additionally, another scenario was tested, wherein only 100 data points were used for the training phase, while the remaining 1,900 data points were reserved for testing. This alternative scenario aimed to evaluate time efficiency while maintaining robust performance.

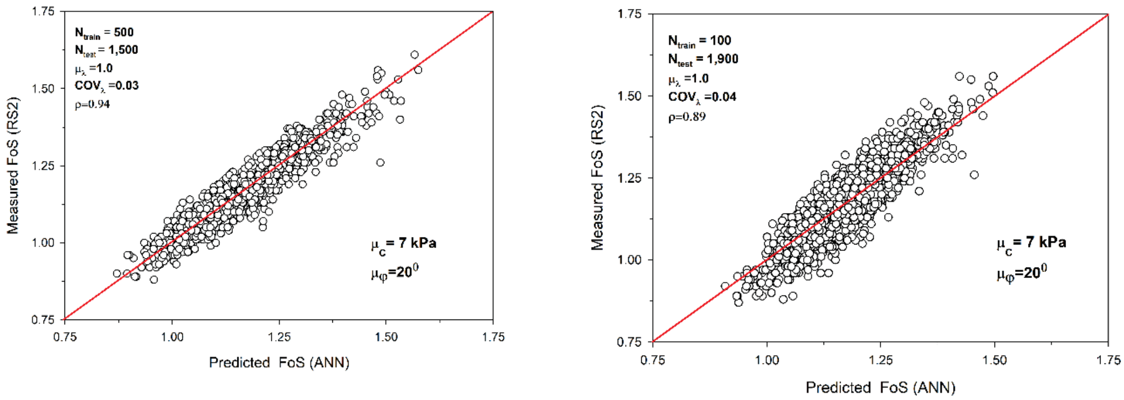


(a) (b)

Fig. 2.RBF algorithm in the current machine learning study; a) architecture of the ANN algorithm; b)frequency plot of the FoS utilized in the output layer.

4. Results and Discussion

The proposed RBF algorithm was trained using 500 data points randomly sampled from the entire dataset, followed by testing the trained network with the remaining 1,500 data points. Figure 3(a) presents the measured versus predicted FoS values, along with the associated bias statistics.The model bias (λ), defined as the ratio of measured to predicted FoS values, averages at 1.0, with a very small coefficient of variation (COV$_\lambda$) of approximately 3%. The P_f, defined as the likelihood of FoS<1, is calculated as 0.044 and 0.045 using the measured and predicted outcomes, respectively.Overall, the comparison demonstrates the robustness of the designed RBF algorithm in accurately predicting the FoS against slope failure using data generated from the finite element analysis program RS2.



(a) (b)

Fig. 3.Predicted versus measured plots for μ_c=7 kPa and $\mu_{Æ}$=20 psing the RBF algorithm; a) NoR=500; b) NoR=100.

The designed RBF algorithm was further evaluated by training the ANN network using only 100 data points. The objective was to enhance computational efficiency by reducing the time required to generate input data using the finite element program RS2. Each SRM-based FoS calculation in RS2 takes approximately 6 minutes to complete, highlighting the benefit of minimizing the number of training data points.Figure 3(b) illustrates the measured versus predicted FoS values, along with the corresponding bias statistics. The model bias (λ) averages at 1.0, with a coefficient of variation (COV_λ) of approximately 4% and a Pearson correlation coefficient of 0.89 between the measured and predicted FoS values. The probability of failure (P_f) is calculated as 0.044 and 0.02 based on the measured and predicted outcomes, respectively.Although the ANN model trained with 500 data points outperforms the one trained with only 100 data points, the latter still demonstrates satisfactory performance. Simplicity and efficiency of the proposed RBF-based ANN algorithm makes it a viable candidate for integration into existing commercial stability analysis software.

5. Conclusion

This study employed an efficient ANN model, specifically the RBF algorithm, to predict the FoS of a typical spatially variable slope. The spatial variability of the sloped ground was incorporated to estimate the $P_f$of the slope. In reliability-based design, a large number of stochastic slope stability analyses are typically required to achieve reliable P_f estimates. However, SRM-based software packages are often time-intensive, requiring substantial computational effort to complete a sufficient number of analyses.To address this challenge, the study implemented an effective RBF algorithm, combined with a limited number of numerical simulations, to accurately generate outcomes for forward prediction purposes.

The main conclusions from this set of analyses can be summarized as follows:

1. The training and testing process demonstrated the high efficiency and robustness of the proposed ANN algorithm, making it suitable for integration into commercially available slope stability analysis software.
2. Even a minimal number of slope stability analyses, as low as 100, is sufficient to produce highly accurate forward-looking predictions, further confirming the robustness of the employed algorithm.

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