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ANN-Based Prediction of Slope Stability Using a Dimensionless Formulation for Homogeneous Dry Slopes

Pablo Gondim de Oliveira
Civil Engineer, Prefeitura Municipal de Joinville, Joinville, Brazil, pablo.gondim.oliveira@gmail.com

Naloan Coutinho Sampa
Professor, Federal University of Santa Catarina, Florianópolis, Brazil, naloan.sampa@ufsc.br

Maria Eduarda Vieira
Student of Civil Engineer, Federal University of Santa Catarina, Florianópolis, Brazil, maria.eduarda.v@grad.ufsc.br

ABSTRACT: This study presents the development of an artificial neural network (ANN) model as a surrogate tool for predicting the factor of safety (FS) of homogeneous dry slopes with circular failure surfaces. A dataset of 455 samples was generated through parametric analyses using the Morgenstern–Price limit equilibrium method implemented in Slope/W. The problem was formulated using dimensionless and geometric parameters, namely the stability number (N_s), slope angle (β), and soil friction angle (ϕ). A systematic evaluation of ANN architectures was conducted, considering variations in the number of hidden layers, neurons, activation functions, and optimization algorithms. The optimal configuration consisted of four hidden layers with a total of 95 neurons, ReLU activation functions, and the Adam optimizer. Model training incorporated data normalization and cross-validation to improve generalization. The selected model achieved high predictive accuracy within the training domain, with a coefficient of determination (R^2) of 0.999 and a mean absolute error (MAE) of 0.0344 for the test dataset. Comparisons with limit equilibrium methods and strength reduction analyses indicated strong agreement. Consistent trends were also observed in relation to empirical stability equations. However, larger discrepancies were identified when compared with stability charts, particularly for conditions outside the training range, indicating limitations in extrapolation. The results demonstrate that ANN-based models can provide efficient and accurate predictions of slope stability for homogeneous dry conditions, serving as a practical alternative for preliminary analyses. The results highlight both the efficiency of ANN-based surrogate models and the importance of representative datasets for reliable application.

KEYWORDS: artificial neural networks; slope stability; factor of safety; stability number; surrogate modeling.

1 INTRODUCTION

Slope stability analysis is a fundamental problem in geotechnical engineering, involving the estimation of the factor of safety (FS) and the identification of potential failure mechanisms. Among the available approaches, limit equilibrium methods (LEM) are widely used in engineering practice due to their simplicity, robustness and ability to incorporate different loading and soil conditions (Duncan, 2005; Abramson et al., 2002). However, these methods typically require iterative procedures with varying slip surfaces to determine the critical condition, which can be computationally demanding and time-consuming (Mamat et al., 2022; Ray et al., 2020).

Numerical approaches based on the method (SRM) provide more rigorous solutions by incorporating stress-strain relationships and failure mechanisms without predefining the slip surface (Dawson et al., 1999; Cheng et al., 2007). Despite their advantages, these methods involve high computational cost and require careful modeling assumptions, including mesh discretization, constitutive models, and convergence criteria (Duncan, 1996; Kolbadi et al., 2019). On the other hand, simplified tools such as stability charts and empirical equations allow rapid estimation of FS, but their applicability is generally limited to specific conditions (Taylor, 1937; Barnes, 1991; Sampa and Schorr, 2024).

Given these limitations, there is an increasing demand for methods that combine accuracy with computational efficiency. In recent years, artificial intelligence techniques, particularly artificial neural

networks (ANNs), have been increasingly applied to geotechnical problems due to their ability to model complex and nonlinear relationships between input parameters and system responses (Shahin et al., 2002; Haykin, 2001; Bui et al., 2019). Several studies have demonstrated the effectiveness of ANNs in predicting slope stability and related geotechnical phenomena (Abdalla et al., 2014; Gelisli et al., 2015; Rukhaiyar et al., 2017; Mamat et al., 2022; Ray et al., 2020). However, the predictive performance and generalization capability of these models depend strongly on the representativeness and range of the training dataset.

For homogeneous slopes, the use of dimensionless parameters, such as the stability number (N_s), provides a consistent framework to relate soil strength and slope geometry, reducing problem dimensionality and facilitating generalization (Taylor, 1937; Duncan, 1996; Sampa and Schorr, 2024). This approach has been widely adopted in stability charts and analytical formulations for preliminary design and analysis.

In this context, this study proposes the development of an ANN-based model to predict the factor of safety of homogeneous dry slopes with circular failure surfaces. The model is formulated using the stability number (N_s), slope angle (β), and soil friction angle (ϕ) as input variables. A dataset comprising 455 samples was generated through parametric analyses using the Morgenstern–Price method (Morgenstern and Price, 1965) implemented in Slope/W (GeoStudio, 2021).

A systematic evaluation of ANN architectures is conducted to identify the optimal configuration. The performance of the proposed model is assessed through comparisons with limit equilibrium methods, strength reduction analyses, stability charts, and empirical equations reported in the literature. Additionally, the generalization capability of the model is evaluated, particularly for conditions outside the training domain.

Despite the increasing application of artificial neural networks in slope stability analysis, there remains a lack of studies that integrate dimensionless formulations, such as the stability number (NS), with systematic comparisons across different classes of methods, including limit equilibrium, numerical methods, stability charts, and stability equations. In addition, the generalization capability of ANN models under controlled parametric conditions is still not fully understood.

The main contribution of this study lies in the development of a computationally efficient ANN model and a comprehensive comparison with established methods.

2 METHODOLOGY

The proposed methodology aims to develop a predictive artificial neural network (ANN) model for estimating the factor of safety (FS) of homogeneous dry slopes. The approach is structured into four main stages (Figure 1): (i) problem definition and dataset generation, (ii) data preprocessing, (iii) ANN model development, and (iv) model evaluation and comparison.

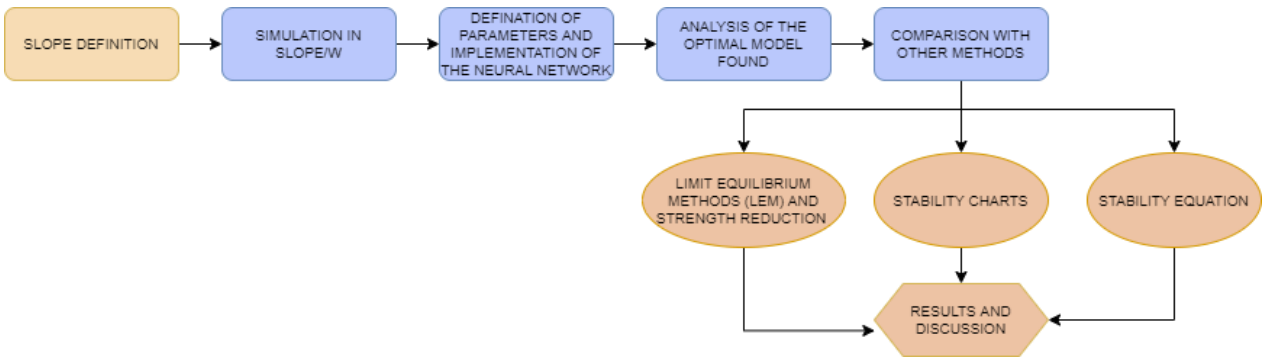


Figure 1. The methodology structure.

2.1 Problem Definition and Dataset Generation

The study focuses on homogeneous dry slopes subjected to circular failure mechanisms. The factor of safety (FS) is computed using the Morgenstern-Price method (Morgenstern and Price, 1965), a rigorous limit equilibrium formulation that satisfies both force and moment equilibrium. All analyses were performed using the Slope/W module of GeoStudio (GeoStudio, 2021).

A parametric analysis was conducted to generate a consistent and controlled dataset. The following variables were considered: slope angle (β): 15º to 85º; friction angle (ϕ): 10º to 40º; cohesion (c): 0 to 16 kPa; soil unit weight (γ): 10 to 25 kN/m³; and foundation depth (d) of 10 m.

The slope height (H) was kept constant at 3.5 m, and the foundation width was fixed at 30 m to ensure consistency across simulations (Figure 2). A total of 455 slope configurations were analyzed. For each case, the critical FS was determined through an automatic search of potential slip surfaces, based on multiple trial circles.

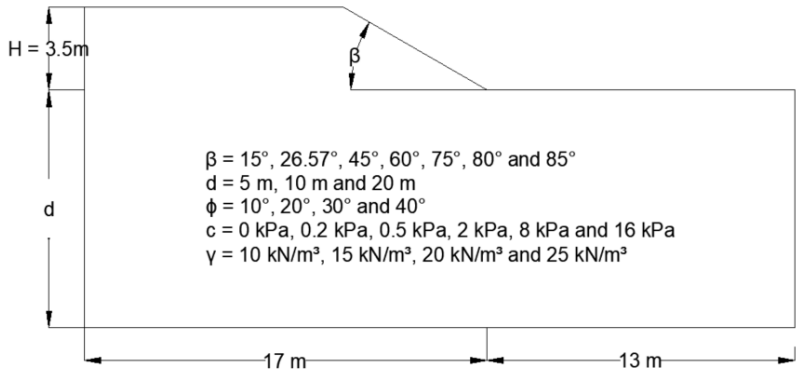


Figure 2. Representation of the theoretical slope and parameters.

To reduce the dimensionality of the problem and improve generalization, the results were reformulated using the stability number ($N_s = c/(\gamma\, H)$), which relates soil strength parameters and slope geometry in a dimensionless form. This approach is consistent with classical stability charts and enables a more compact representation of the problem. The final dataset was defined as stability number (N_s), slope angle (β), and friction angle (ϕ) for input variables, and as factor of safety (FS) for output variable.

Figure 3 illustrates the range of variation for N_s, β, ϕ and FS, as well as the frequency of values within each range

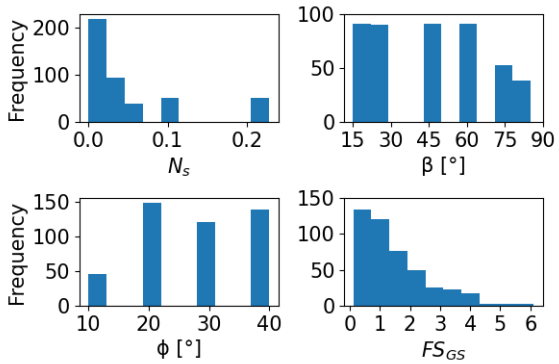


Figura 2. Intervalo de dados dos parâmetros do modelo.

Although the dataset size is relatively limited, the use of a controlled parametric study ensures a structured and consistent coverage of the input space. This approach reduces noise and variability typically associated with field data and allows the ANN model to learn the underlying relationships more effectively.

2.2 Data Preprocessing and Partitioning

Prior to training, all input variables were normalized using standardization (zero mean and unit variance), which improves numerical stability and convergence of gradient-based optimization algorithms (Haykin, 2001; Géron, 2021). The normalization parameters were computed exclusively from the training dataset to prevent information leakage.

The dataset was randomly divided into three subsets: training set: 68% (309 samples), validation set: 12% (55 samples), and testing set: 20% (91 samples).

The validation set was used to monitor model performance during training and to define the stopping criterion, aiming to mitigate overfitting. This strategy is consistent with best practices in machine learning applications for geotechnical problems.

2.3 ANN model development

A feedforward multilayer perceptron (MLP) architecture was adopted due to its proven capability to approximate nonlinear relationships in geotechnical systems (Shahin et al., 2002; Haykin, 2001). The model maps the input variables (N_s, β, ϕ) to the output variable (FS).

Given the absence of a universal procedure for defining the optimal ANN architecture, a systematic parametric analysis of hyperparameters was conducted. The following aspects were investigated: number of hidden layers: 1 to 4; number of neurons per layer: 2 to 45; activation functions: hyperbolic tangent (tanh) and rectified linear unit (ReLU); and optimization algorithms: Adam and RMSprop.

Weight initialization followed established practices to improve training stability. He initialization was adopted for ReLU-based networks (He et al., 2015), while Glorot initialization was used for tanh-based models (Glorot and Bengio, 2010).

The loss function used during training was the mean squared error (MSE), due to its sensitivity to large deviations and suitability for regression problems. Model performance was also evaluated using the mean absolute error (MAE) and the correlation coefficient (r).

It is noted that the relatively small dataset size, combined with a multi-layer architecture, may introduce a risk of overfitting. This issue was mitigated through cross-validation, dataset partitioning, and consistency checks between training, validation, and testing errors.

2.4 Training Strategy and Model Selection

The training process employed mini-batch gradient descent, with batch sizes ranging from 32 to 128. The optimal performance was achieved with a batch size of 32.

Cross-validation was used as a stopping criterion, based on the performance of the validation dataset. This approach prevents excessive fitting to the training data and improves the generalization capability of the model.

Batch normalization was also evaluated as a regularization strategy. However, it did not lead to significant improvements in predictive accuracy and increased computational cost; therefore, it was not included in the final model.

The optimal ANN architecture consisted of four hidden layers with 35, 30, 20, and 10 neurons, respectively, using ReLU activation functions and the Adam optimizer. This configuration provided the best balance between accuracy and generalization.

2.5 Model Evaluation and Comparison

The predictive performance of the selected model was evaluated using the independent testing dataset. The predicted FS values were compared with those obtained from Slope/W analyses, which served as reference solutions.

To further assess the robustness of the proposed model, comparisons were performed with different classes of methods: (i) limit equilibrium methods (e.g., Fellenius, Janbu); (ii) strength reduction method using finite elements (Plaxis); (iii) stability charts (e.g., Barnes, Bishop and Morgenstern), and (iv) stability equations (e.g., Sah et al., Yang et al., Huang, Chien and Tsai, Sampa and Schorr).

Finally, the generalization capability of the ANN model was evaluated by analyzing its predictive performance across the range of input parameters and identifying deviations for conditions outside the training domain.

3 RESULTS AND DISCUSSION

This section presents a detailed evaluation of the predictive performance of the proposed artificial neural network (ANN) model, followed by a comparative analysis with conventional methods and an assessment of its generalization capability.

3.1 ANN predictive performance

The performance of the ANN model was evaluated using training, validation, and testing datasets. A strong correlation was observed between the predicted factor of safety (FS_{ANN}) and the reference values obtained from Slope/W analyses (FS_{GS}), with a correlation coefficient (r) equal to 0.999 (Figure 4).

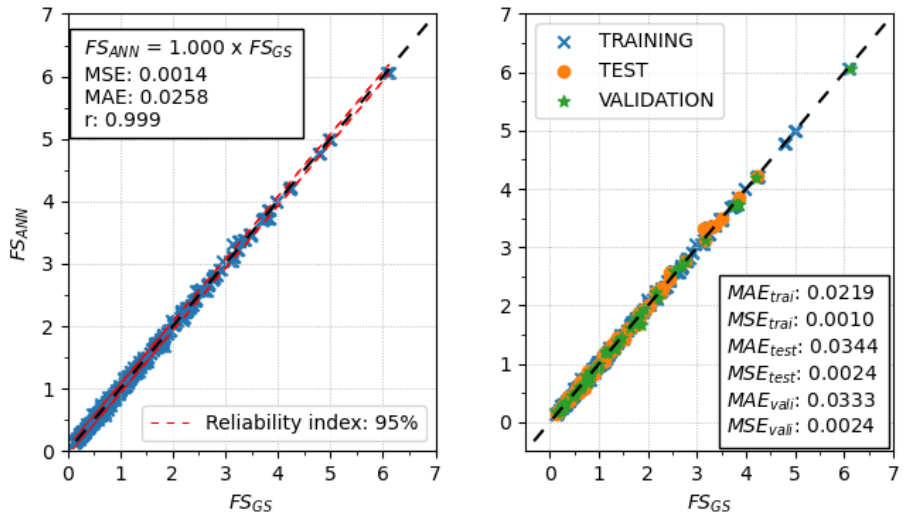


Figure 4. Comparison of ANN model predictions with Factor of Safety (FS) values obtained from GeoStudio (GS).

The error metrics indicate high predictive accuracy, with mean absolute error (MAE) values of 0.0219, 0.0333, and 0.0344 for the training, validation, and testing datasets, respectively. The low dispersion of results and the consistency between datasets suggest that the model achieved an adequate balance between fitting capability and generalization.

The slightly higher error observed in the testing dataset, compared to training and validation, is expected and indicates that the model is not overfitted to the training data. This behavior is consistent with the use of cross-validation as a stopping criterion.

From a functional perspective, the ANN successfully captured the nonlinear relationship between the input variables (N_s, β, ϕ) and the factor of safety. The high accuracy obtained suggests that the model effectively approximates the solution space defined by the limit equilibrium analyses.

3.2 Influence of Input Parameters

The results indicate that the factor of safety is strongly influenced by the stability number (N_s), which governs the relationship between shear strength and slope geometry. Higher values of N_s generally correspond to more stable conditions, as expected from classical formulations (Taylor, 1937).

The slope angle (β) also plays a critical role, with steeper slopes leading to lower FS values due to increased driving forces. Similarly, the friction angle (ϕ) contributes positively to stability, as higher values increase the shear strength along the potential failure surface.

The ANN model was able to capture these trends consistently, as evidenced by the smooth variation of predicted FS values across the input parameter space. This indicates that the model learned physically meaningful relationships rather than merely interpolating the dataset.

3.3 Comparison with Conventional Methods

The ANN predictions were compared with results obtained from different classes of methods (Figure 5), including limit equilibrium methods (LEM), strength reduction method (SRM), stability charts, and empirical equations.

In comparison with LEM results (e.g., Fellenius, Janbu, and generalized Janbu), the ANN model showed very close agreement, with minimal dispersion and no significant bias. This is expected, as the ANN was trained on data generated using a rigorous LEM formulation (Morgenstern–Price).

Similarly, comparisons with SRM results obtained from finite element analyses (Plaxis) showed consistent trends, indicating that the ANN model is capable of reproducing solutions obtained from more advanced numerical methods.

For empirical stability equations (e.g., Huang, Chien and Tsai, and Sampa and Schorr), the ANN predictions exhibited good agreement in most cases, although some deviations were observed in Sah et al., Yang et al.. These differences can be attributed to the simplifying assumptions inherent in regression-based formulations, which may not fully capture the nonlinear interactions between parameters.

In contrast, larger discrepancies were observed in comparisons with stability charts (e.g., Barnes, Bishop and Morgenstern, O'Connor and Mitchell). These methods showed greater variability and occasional outliers. This behavior is associated with the inherent limitations of stability charts, including interpolation errors, discretization of parameter space, and simplified assumptions regarding geometry and boundary conditions.

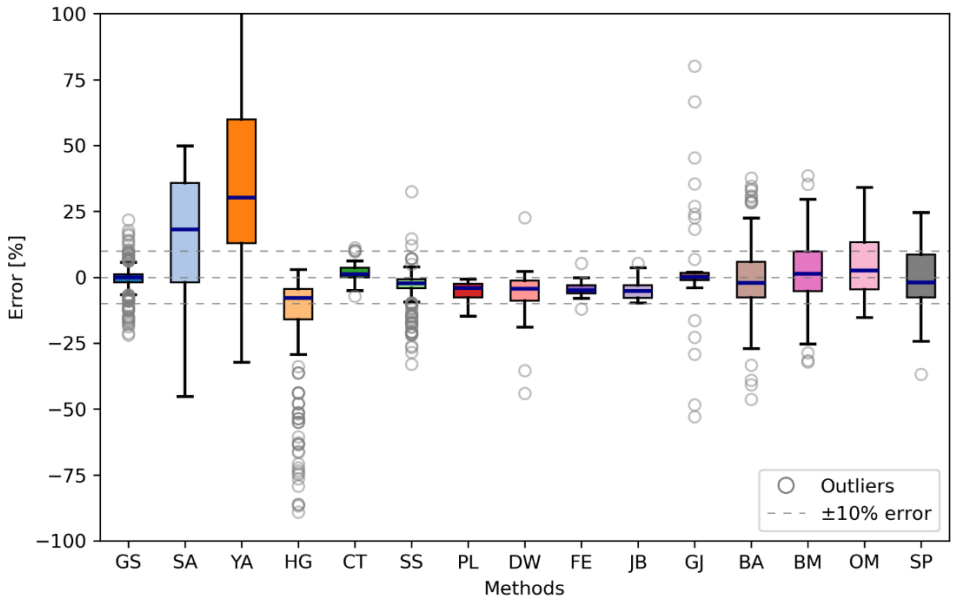


Figure 5. Boxplot chart comparing the prediction results of the developed artificial neural network model and the methods of GS, SA, YA, HG, CT, SS, PL, DW, FE, JB, JG, BA, BM, OM, and SP.

Note: Slope/w (GS), Chien and Tsai (CT), Huang (HG), Sampa and Schorr (SS), Plaxis (PL), Fellenius (FE), Janbu (1968), Janbu Generalizado (JG), Barnes (BA), Bishop and Morgenstern (BM), O'Connor and Mitchell (OM), Spencer (SP).

Quantitatively, most of the ANN predictions remained within a deviation range of approximately ±10% when compared to the reference solutions, which is consistent with acceptable variability observed among traditional methods. This further supports the reliability of the proposed model as an alternative predictive tool. Overall, the ANN model demonstrated a level of accuracy comparable to rigorous methods, while providing significantly faster predictions.

3.4 Generalization capability

The generalization capability of the ANN model was evaluated by analyzing its performance across different regions of the input space.

Within the range of the training data, the model exhibited stable and accurate predictions, with low error and consistent trends. However, deviations were observed when comparing ANN predictions with methods based on conditions that extend beyond the training domain, particularly in the case of stability charts.

These discrepancies indicate that the ANN model has limited extrapolation capability, as it approximates the solution space defined by the training data rather than the governing physical equations explicitly. Consequently, predictions outside the trained parameter range may not follow the expected mechanical behavior, particularly in regions where nonlinear interactions between variables become more pronounced.

Additionally, variations in parameters such as foundation depth (d), which are not explicitly included in the ANN input variables but influence the calculation of N_s, may contribute to differences observed in comparisons with external methods.

These findings highlight the importance of ensuring that the training dataset adequately represents the range of conditions for which the model is intended to be applied.

4 CONCLUSIONS

An artificial neural network (ANN) model was developed to predict the factor of safety (FS) of homogeneous dry slopes using a dimensionless formulation based on the stability number (N_s), slope angle (β), and friction angle (ϕ). The model demonstrated high predictive accuracy and was able to consistently reproduce results obtained from rigorous limit equilibrium analyses.

Comparisons with conventional methods showed strong agreement with limit equilibrium and strength reduction approaches, as well as with stability equations, while larger discrepancies were observed for stability equations proposed by Sah et al. and Yang et al.. and stability charts due to their simplified assumptions and discretization.

The use of N_s proved effective in reducing problem dimensionality and contributed to consistent predictions across different slope configurations. However, the model is limited to the range of the training dataset and to simplified conditions, not accounting for pore pressure, soil heterogeneity, or external loading.

From a practical perspective, the ANN can be used as a fast surrogate tool for preliminary analyses and parametric studies. Future work should focus on expanding the dataset and incorporating more complex conditions to improve generalization.

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