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Finite Element Limit Analysis (FELA) and Machine Learning Modelling for 2D Slope Stability Analysis

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Background

Slope stability analysis is a fundamental aspect of geotechnical engineering, as it directly impacts the safety of both infrastructure and human life. With the growing integration of data-driven techniques across various engineering fields, machine learning, particularly Artificial Neural Networks (ANNs) has shown promising potential in enhancing predictive capabilities. This study serves as a preliminary investigation into the application of data-driven ANN models for 2D dry translational slope stability analysis. The proposed ANN model demonstrates excellent predictive performance, achieving a coefficient of determination (R^2) of 0.990 and a root mean square error (RMSE) of 0.311 in estimating the factor of safety (FOS) of translational slopes for a given set of input parameters. This approach highlights the potential of ANNs as efficient and accurate tools for slope stability assessment.

Methodology

1. Data generation

- A total of 126 translational slope configurations were modelled by varying soil parameters and slope geometries.
- Finite Element Limit Analysis (FELA) approach was used in model generation using Optum G2 software (Optum CE,2024), incorporating a strength reduction process.
- Each model was meshed with 5,000 elements, 3 mesh iterations and mesh refinement along the failure plane to ensure accuracy.
- For each configuration, both upper and lower bound solutions were obtained. The average of these bounds was taken as the representative Factor of Safety (FOS), as the true FOS lies between these two limits.
- The primary input parameters considered in the modelling included slope angle (β), unit weight (γ), friction angle (ϕ'), cohesion (c'), slope height (H), and depth of the failure surface (z).
- To streamline the data generation process by reducing the number of distinct cases, the stability number ($c'/\gamma H \tan\phi'$) was used, by fixing H= 5 m, ϕ'= 30˚ and γ = 18 kNm^{-3}, to vary c' from 1 kPa to 60 kPa.
- Table 1 presents the parameters used in FELA, Figure 1 illustrates the meshing and input parameters used in the modelling and Figure 2 (a) and (b) shows the UB and LB failure mechanism for c' = 10.4kPa, β = 20˚, z =1m and $c'/\gamma H \tan\phi'$ = 0.2

Table 1 Input parameters used in FELA

Input Parameter	Description	Values
z/H	Relative depth of the failure plane	0.1, 0.2, 0.3
β	Slope angle	10˚, 20˚,30˚, 40˚,50˚, 60˚,70˚
$\frac{c'}{\gamma H \tan\phi'}$	Stability number	0.02, 0.05, 0.1,0.2,0.5,1

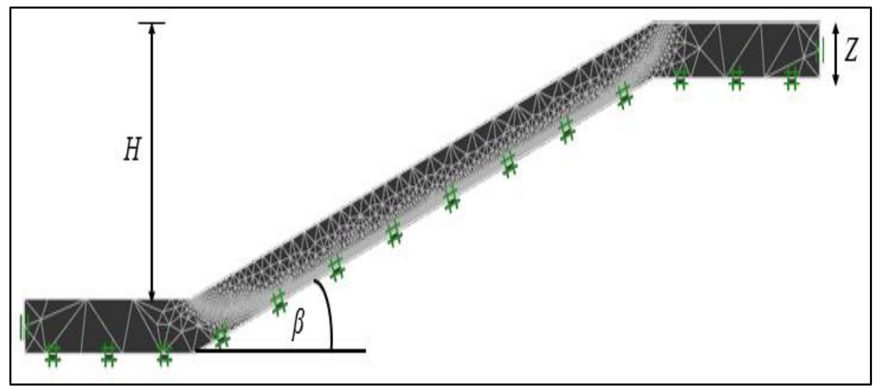

Fig 1 Mesh and boundary conditions of the FE model (β = 20˚)

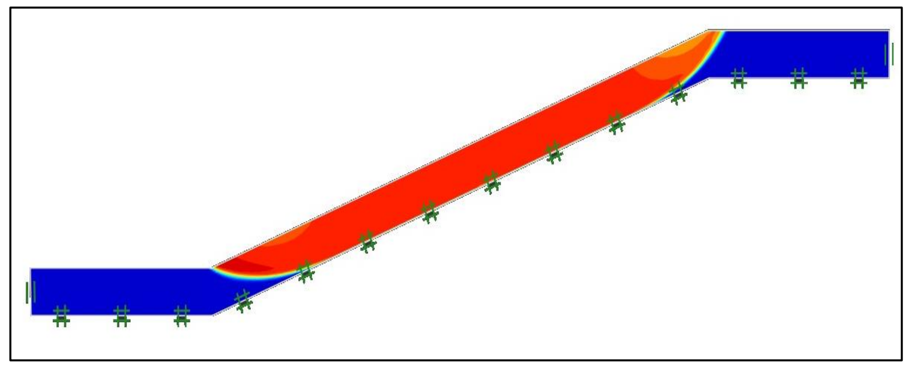

Fig 2 Upper bound limit analysis failure mechanism of the FE model (c' = 10.4kPa, β = 20˚, z = 1m and $c'/\gamma H \tan\phi'$ = 0.2)

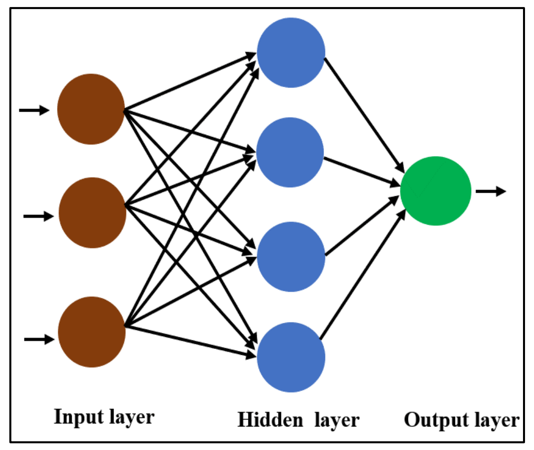

Fig 4 Schematic diagram of an ANN architecture of 3-4-1

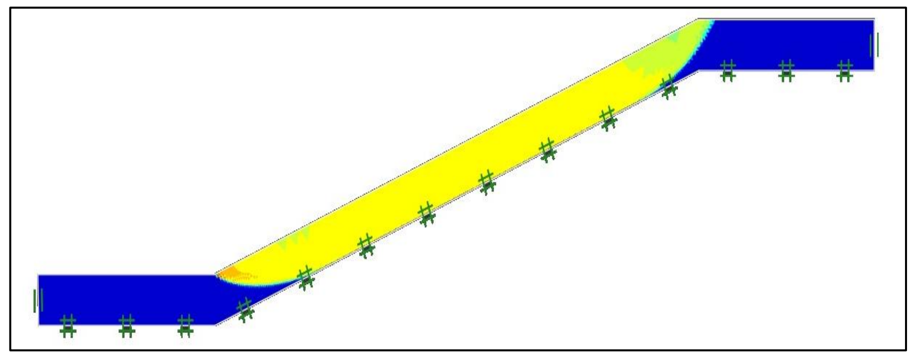

Fig 3 Lower bound limit analysis failure mechanism of the FE model (c' = 10.4kPa, β = 20˚, z = 1m and $c'/\gamma H \tan\phi'$ = 0.2)

2. Development of the ANN model

- An Artificial Neural Network (ANN) typically consists of three layers: an input layer, one or more hidden layers, and an output layer.
- The number of neurons in each layer, along with the number of hidden layers, can be adjusted and optimized to enhance predictive performance.
- For example, an ANN configuration described as 3-4-1 includes three input neurons, four neurons in a single hidden layer, and one output neuron, as illustrated in Figure 4.
- ANN models are often referred to as black-box predictive models due to their ability to model complex, nonlinear relationships without requiring explicit formulation.
- In this study, Python programming language was used to build, train, test, and validate the ANN model with 70% data used for training and 30% data used for testing.
- Six input parameters were used: slope angle (β), unit weight (γ), friction angle (ϕ'), depth of the failure surface (z), slope height (H), and cohesion (c'), with the factor of safety (FOS) as the output.
- After evaluating multiple architectures, the optimal ANN structure was identified as 6-35-1, consisting of 6 input neurons, 35 neurons in one hidden layer, and 1 output neuron based on the complexity of the dataset and overall model accuracy.

Research approach

Define slope geometries and soil parameters

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Perform slope stability analysis using FELA

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Develop 2D translational slope database

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Design and train the ANN model

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Validate model performance

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Predict FOS for given input parameters using the model

Aim

To develop a predictive model for 2D translational slope stability assessment using Artificial Neural Networks

Objectives

- To perform a parametric study and compile a comprehensive database of 2D translational slopes.
- To train an ANN model using the developed dataset for predicting the Factor of Safety (FOS) of dry translational slopes based on key input parameters.

Results and Discussion

The proposed ANN model demonstrated strong predictive performance on both training and testing datasets. For the training dataset, the model achieved a Mean Squared Error (MSE) of 0.241 and an R^2 (Coefficient of Determination) of 0.9929, indicating an excellent fit. On the testing dataset, the model maintained good accuracy with an MSE of 0.472 and an R^2 of 0.9833.

The overall performance of the final ANN model, combining both training and testing results, yielded an R^2 of 0.9906 and an MSE of 0.311, confirming the model's reliability. Figures 5, 6, and 7 illustrate the model's performance for the training data, testing data, and combined dataset, respectively.

Further validation was conducted by comparing the predicted Factor of Safety (FOS) values from the ANN model against those obtained using the Finite Element Limit Analysis (FELA) method for various slope angles (β) as illustrated in Figure 8. This comparison was made for the case where $c'/\gamma H \tan\phi'$ = 0.05 and z = 1 m. The results showed that the ANN model's predictions closely aligned with the FELA outputs, demonstrating the model's effectiveness and accuracy in predicting slope stability.

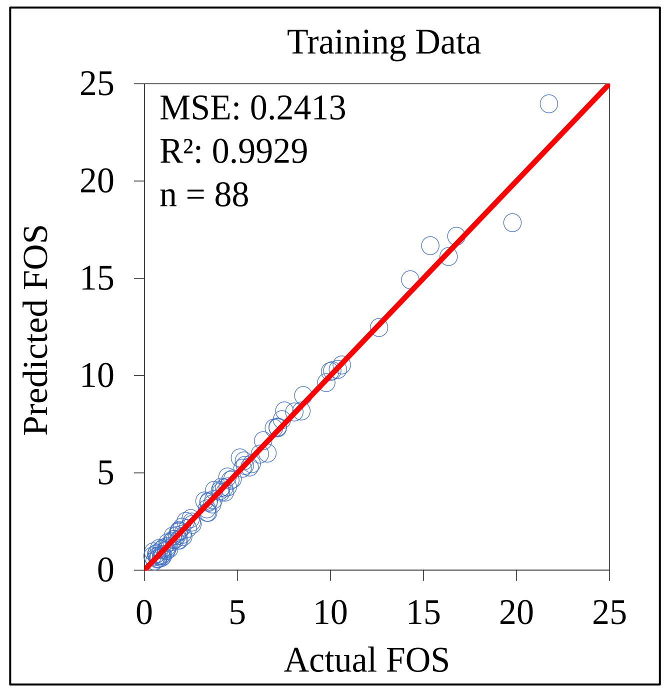

Fig 5 Performance of the training dataset

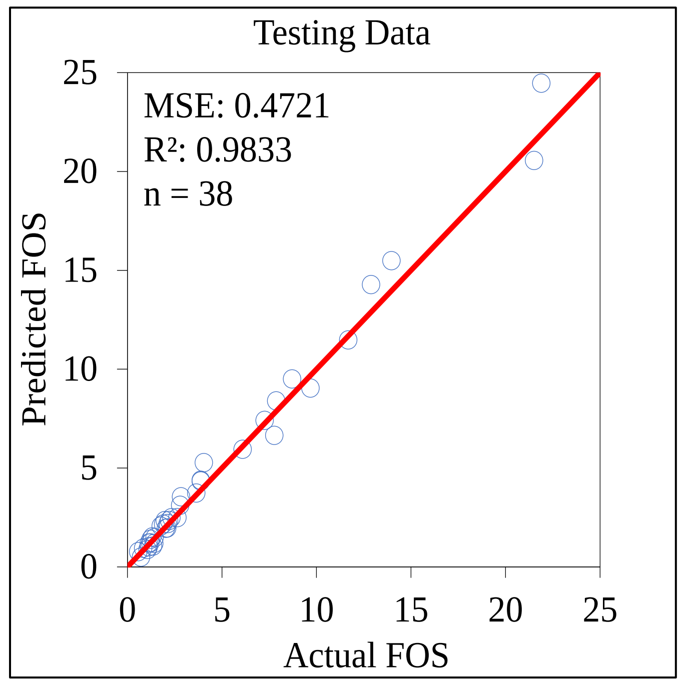

Fig 6 Performance of the testing dataset

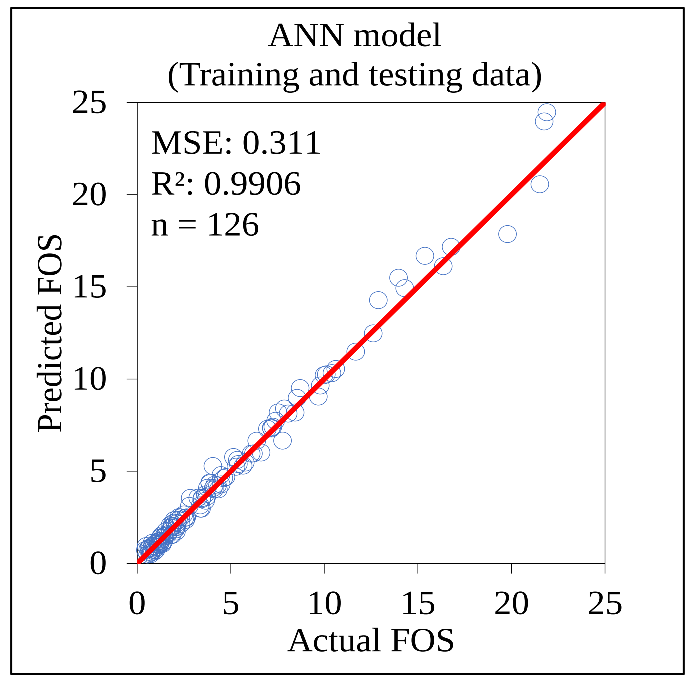

Fig 7 Performance of the ANN model

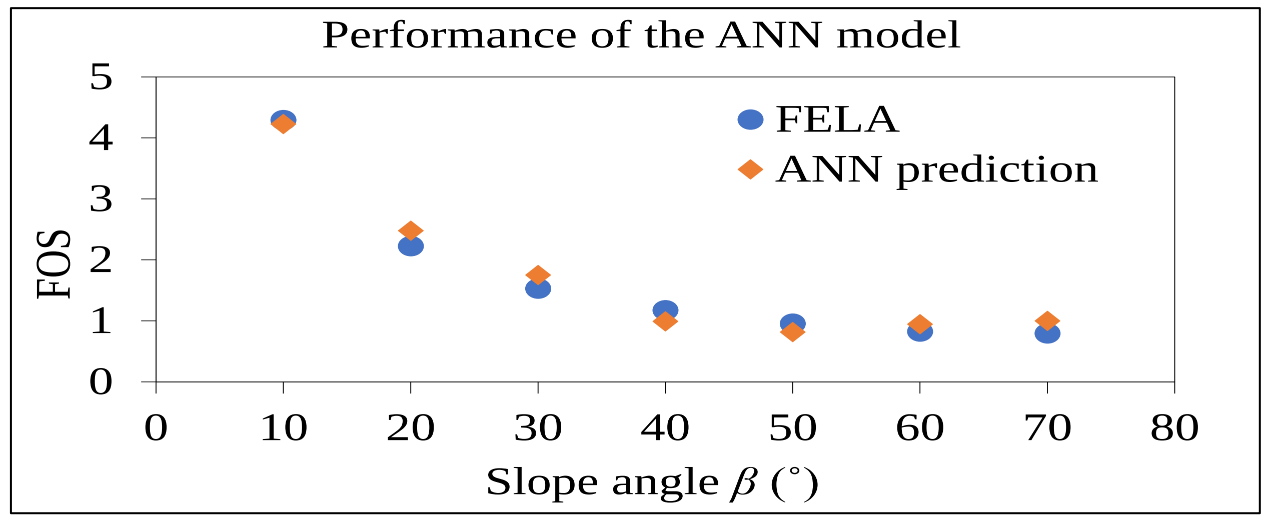

Fig 8 FELA vs ANN predictions for different β for the case $c'/\gamma H \tan\phi'$ = 0.05 and z = 1 m

Conclusion

- The proposed Artificial Neural Network (ANN) model showed excellent predictive performance of R^2 = 0.990 and RMSE = 0.311.
- The predicted Factor of Safety (FOS) values closely matched those obtained from Finite Element Limit Analysis (FELA).
- Results demonstrate a high accuracy and reliability of the ANN model in estimating FOS for translational slopes.
- The study confirms the potential of ANN as a fast and effective tool for slope stability assessment.

Future work

- This study serves as a preliminary investigation into the application of data-driven ANN models for 2D dry translational slope stability analysis.
- Future research will explore the applicability of ANN models under varying pore pressure conditions, including both saturated and unsaturated slopes.
- The dataset will be expanded to include a wider range of soil properties and slope geometries, enhancing the model's learning capacity and generalizability.
- Integration of physics-based equations will be considered to develop Physics-Informed Machine Learning (PIML) models, combining data-driven methods with fundamental geotechnical principles.

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