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A Novel Multi-Objective Particle Swarm Optimized RF-SVR Model for Reinforced Soil Slope Stability Analysis

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Abstract: In geotechnical engineering, the stability analysis of reinforced soil slopes is important to ensure the safety and longevity of infrastructures. In this study, a novel multi-objective particle swarm optimized RF-SVR (random forest and support vector regression) model aimed to evaluate the stability of reinforced soil slopes. The proposed Hybrid RF-SVR-MOPSOA model combines the advantages of both machine learning techniques and optimization algorithms and offers enhanced predictive accuracy and efficiency. Assessing the model's effectiveness involves proposed model was compared with three traditional regression models: Elastic net regression (ENR), ridge regression (RR), and lasso regression (LR). Various performance assessment parameters and ROC curve plots were employed to determine the most suitable model for reinforced soil slope stability analysis. The findings indicate that the proposed hybrid RF-SVR-MOPSOA model demonstrates superior performance compared to other traditional regression models. This innovative approach significantly expands the possibilities for enhancing the assessment of slope stability and ensuring safer and more resilient infrastructural development.

Keywords: Soil stability analysis, Factor of safety, Multi-objective particle swarm optimization, Support vector regression, Random forest regression.

1. Introduction

In the field of civil engineering, reinforced soil slopes are common usage for stabilizing steep ground and mitigating soil erosion [1, 2]. The analysis of slope stability is of utmost importance to prevent potential failures and maintain long-term performance [3-5]. The assessment of safety and performance for slope structures has become an essential focus in geotechnical engineering, leading to increased attention on reinforced soil slope stability analysis. Structures such as retaining walls, embankments, and natural slopes frequently experience issues like soil erosion, groundwater infiltration, and instability [6]. Limit equilibrium and finite element methods are conventional approaches used to analyze slope stability, but they often have limitations. These methods may not adequately address the complex and interconnected factors influencing slope stability [7]. To address these limitations, this study has investigated the integration of optimization techniques with machine learning algorithms, aiming to develop more precise and efficient models for slope stability analysis.

This study introduces a novel approach for reinforced soil slope stability analysis, combining the power of multi-objective particle swarm optimization (PSO) with the robustness of random forest support vector regression (RF-SVR). The proposed model aims to simultaneously optimize multiple objectives related to slope stability, such as the factor of safety, taking into account the influence of reinforcement parameters. The effectiveness of addressing multi-objective optimization problems is demonstrated by the particle swarm optimization algorithm, which draws inspiration from the collective actions of bird flocks or fish schools. [8-10]. This enables those in charge of making decisions to choose the most fitting solution according to their particular needs. The random forest support vector regression technique models the complex relationships between input variables and slope stability indicators. RF-SVR combines the ensemble learning capabilities of random forest with the robustness of support vector regression, enabling accurate predictions even with noisy and high-dimensional data. The following represents the literature review based on this study.

Many researchers have traditionally determined soil slope stability using conventional methods [11-14]. Typically, conventional methods are constrained to specific failure surface shapes, such as circular or non-circular surfaces. As a result, their capacity to analyze slopes with irregular shapes or intricate geometries is restricted. Traditional methods may struggle to handle complex loadings or dynamic forces that can influence slope stability, such as seismic or cyclic loading. Sharma et al. [15] employed the FEM to examine the stability of steep slopes reinforced with soil. Also, the impact of altering soil parameters, precisely the impact of cohesion and angle of internal friction on embankments with steep slopes was investigated with varying heights (6m-30m). The study found that using a tiered structure or adding a berm slightly improved the safety factor concerning the overall stability and significantly decreased forces.

Karthik et al. [16] performed a sensitivity analysis on slope stability utilizing the FEM. They focused on a homogeneous slope with c-ϕ soil analyzing to evaluate the influence of different parameters on stability of slope. Additionally, the research investigated how various constitutive models affect the slope's FoS. The results showed that the slope FoS was influenced by slope height, slope angle, soil friction angle, basis weight and cohesion. Halder et al. [17] conducted a comprehensive analysis of slope stability using the FEM. Also analyzed the stability of slopes with four different non-homogeneous soil types and assessed the safety factors for varying heights of slope. Afterwards, the researchers performed a similar analysis on the slopes using homogeneous soil and compared the outcomes. The result found that, with an increase in the height of the slopes, the factor of safety decreased. Various authors have conducted soil slope analyses based on different parameters and reported improved results [18-24].

In this work by Świtała et al. [18], a coupled hydro-mechanical model for root-reinforced soils was developed. The study focuses on the implementation of a numerical model that considers the influence of plant roots on the mechanical and hydrological behavior of soil. The constitutive model is based on a Cam-clay model for unsaturated soils, incorporating the expansion of the yield surface dependent on soil suction and plant root reinforcement. The model was successfully implemented in a finite element code, and its performance was demonstrated through various numerical examples. Sungkar et al. [19] conducted a slope stability analysis using both Bishop and FEM. The study evaluates the safety factor of a landslide-prone area on a national road. The existing conditions were assessed using the Bishop method and validated with FEM. The study also proposes reinforcement strategies using sheet piles, analyzing their impact on the safety factor. The results indicate the need for reinforcement to prevent landslides, with variations in sheet pile placement affecting the safety factor after reinforcement.

Sui et al. [20] investigated the stability of ecological slopes using a 3D FEM. Focusing on the Longlang Expressway construction project, the study analyzed the effects of grass and shrub plant roots on slope stability under different rainfall events. Results demonstrated the varying contributions of herbaceous and shrub plants to slope safety factor under different rainfall intensities and durations. The findings provide a theoretical basis for ecological slope protection technology. Villalobos and Villalobos [21] explored the effect of nail spacing on the global stability of soil-nailed walls. The study utilized both limit equilibrium and FEM to assess soil-nailed wall stability. The research highlighted that nail spacing can influence the global factor of safety under certain conditions, emphasizing the importance of careful assessment, especially for steep walls and close nail spacing. The FEM was recommended for soil nailing designs for its improved reliability. Lin et al. [22] investigated the effects of dilatancy angle on slope stability using the 3D FEM strength reduction technique. The study constructed a 3D slope model using PLAXIS software, considering the impact of dilatancy angle on convergence and failure mechanisms. The research revealed that dilatancy angles have a significant effect on slope stability, emphasizing the need for engineers to consider these angles in stability analyses.

Pandey et al. [23] conducted numerical studies on the behavior of slopes reinforced with soil nails. Using FEM, the study analyzed the response of soil slopes with and without soil nails under static and dynamic loading, considering factors such as slope angle and seismic conditions. The investigation provided insights into failure patterns and internal reactions in soil nails, contributing to the understanding of reinforced soil slope behavior. Mohamed et al. [24] presented a FEM of the soil-

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nailing process in nailed-soil slopes. The study simulated various stages of the soil-nailing process using PLAXIS software, considering different soil parameters. The research investigated the performance of the soil-nailing process during construction and under varying overburden pressure and soil density, demonstrating the potential of the FEM to simulate field scenarios and guide construction and maintenance practices.

Based on the literature survey conducted, several research gaps have been identified within the analyzing the stability of reinforced soil slopes. The majority of existing studies have focused on analysis of soil slope stability employing both traditional and FEM, while there is a lack of research specifically dedicated to reinforced soil slope stability analysis. Studies about individual or hybrid regression models for reinforced soil slope stability analysis are still rare. As reinforced soil stability analysis involves multiple influencing factors and parameters, the utilization of novel optimization algorithms can enhance the accuracy and efficiency of the models. The literature review suggests a lack of studies incorporating such algorithms to optimize the regression models. RF and SVR models have been widely used due to their ability to handle non-linear relationships and capture complex patterns in the data. Particle swarm optimization (PSO) has also been successfully applied in optimizing various engineering problems. However, the integration of multi-objective optimization with RF and SVR for reinforced soil slope stability analysis is relatively unexplored in the literature.

To address these research gaps, the present study aims to develop a reinforced soil slope stability analysis using a hybrid regression model with a novel optimization algorithm. By combining regression modeling techniques and advanced optimization methods, this study seeks to improve the accuracy and efficiency of analyzing reinforced soil slopes. Integrating RF and SVR techniques can enhance the predictive capability and provide a more comprehensive analysis of reinforced soil slope stability. Additionally, the proposed model can address the limitations of traditional methods by considering multiple interacting factors. Therefore, the research gap lies in the development and evaluation of a novel multi-objective particle swarm optimized RF-SVR model for reinforced soil slope stability analysis, which can contribute to the advancement of geotechnical engineering practices.

1.1 Problem statement and motivation:

The stability analysis of reinforced soil slopes involves determining the critical factors that affect slope failure, such as soil properties, external loading conditions, and the effectiveness of the reinforcement system. Traditional methods for slope stability analysis often rely on simplified assumptions or empirical equations, which may lead to inaccuracies and conservative designs. Furthermore, the complex nature of the problem, involving multiple interacting variables, poses a significant challenge in accurately modeling and predicting the behavior of reinforced soil slopes.

Therefore, there is a need for an innovative approach that can address these challenges and provide a more reliable and accurate slope stability analysis. This research aims to improve the accuracy and efficiency of reinforced soil slope stability analysis. By integrating multi-objective PSO with RF-SVR aims to overcome the limitations of traditional methods and provide a comprehensive and robust analysis of slope stability. The proposed model integrates RF and SVR, leveraging machine learning capabilities to capture complex relationships and patterns in the data. The model employs MOPSOA to optimize the parameters, enhancing the accuracy and efficiency of the stability predictions. Unlike conventional methods that often assume linear relationships, the hybrid model can handle non-linear relationships between various factors affecting slope stability. The proposed model is data-driven, allowing it to adapt to diverse soil conditions and failure mechanisms without relying on simplifying assumptions. The developed model can assist engineers and designers in making informed decisions regarding the design and reinforcement of slopes, ultimately leading to safer and more cost-effective slope structures. The developed model improves prediction accuracy by capturing the non-linear relationships between input variables and slope stability indicators. Finally, it allows for optimizing reinforcement parameters to enhance slope stability performance. Overall while conventional methods have their limitations, the proposed hybrid RF-SVR-MOPSOA model addresses some of these drawbacks by incorporating machine learning and optimization techniques, providing a more versatile and accurate approach to assessing reinforced soil slope stability. The data-driven nature and the ability to handle non-linear relationships make it a promising tool for enhancing slope stability analysis in geotechnical engineering. Table 1 provides a list of acronyms.

The research objectives of this study are as follows:

Table 1. List of acronyms

MOPSOA	Multi-Objective Particle Swarm Optimization Algorithm
RF	Random Forest
SVR	Support Vector Regression
ENR	Elastic Net Regression
RR	Ridge Regression
LR	Lasso Regression
PSO	particle swarm optimization
FEM	finite element methods
GPI	Global Performance Indicator
NS	Nash-Sutcliffe efficiency
LMI	Legate and McCabe's Index
VAF	Variance Account Factor
RMSE	Root Mean Square Error
WI	Willmott's Index for agreement
MAPE	Mean Absolute Percentage Error
PI	Performance Index
RSR	Root Sum of Squares of the Residuals
MBE	Mean Bias Error
NMBE	Normalized Mean Bias Error
RPD	Relative Percentage Difference
MAE	Mean Absolute Error
RBF	Radial Basis Function

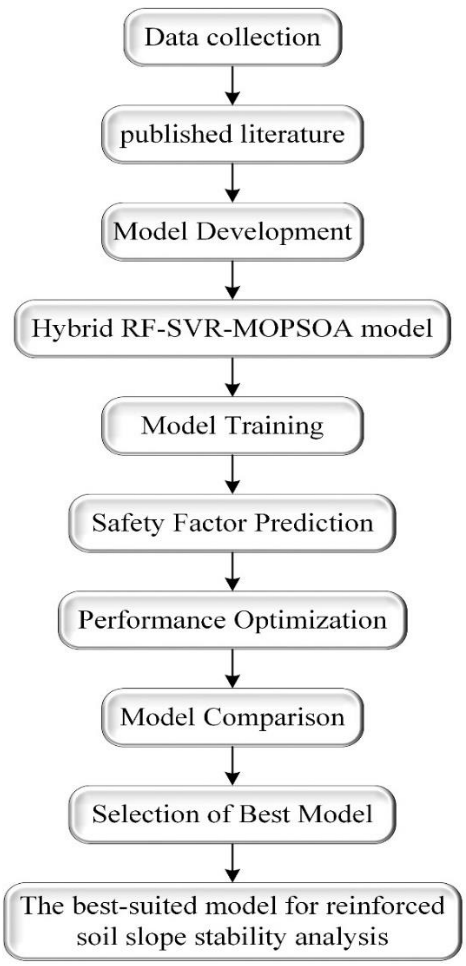

Figure. 1 Layout of the proposed methodology

- To develop a hybrid RF-SVR-MOPSOA model for analyzing the stability of reinforced soil slope.
- To predict the safety factor of reinforced soil slopes by utilizing the trained hybrid RF-SVR-MOPSOA model based on the given input data.
- To assess and contrast the performance of the proposed model in comparison to alternative regression models such as ENR, RR and LR.
- To assess various performance evaluation parameters for comparing and determining the most appropriate model.
- To consider ROC curve performance for the most effective and accurate in predicting reinforced soil slope stability.

The study is organized into the following sections: section 2 describes the process of data collection, including the selection of input variables and data sources and the methodology of the proposed model. Section 3 presents the findings obtained from applying the models. Section 4 summarizes the key findings of the study, highlights the limitations of the study and suggests areas for future research to improve further and expand the modeling approach.

2. Data collection and methodology

2.1 Proposed methodology:

The proposed study aims to assess the reinforced soil slope stability using a novel multi-objective particle swarm optimized RF-SVR model. The methodology involves several steps as follows: Data was gathered from previous studies using a method called data acquisition from literature, specifically focusing on relevant input parameters such as slope ratio (1:1 and 2:1), cohesion (C) ranging from 5 to 30 kPa, friction angle (φ) ranging from 10° to 20°, slope angle (45° to 54°), bar inclination (0° to 25°) and some reinforced layers (10 to 18). A Hybrid RF-SVR-MOPSOA model was developed by integrating the RF and SVR techniques with the MOPSOA. The collected input and output data were then utilized to train the model. The trained Hybrid RF-SVR-MOPSOA model was used to predict the safety factor based on the input data. Additionally, the MOPSOA algorithm was employed to optimize the predicted output performance.

The output performance obtained from the proposed model was compared with the performance achieved through the traditional

Table 2. Selected parameters and its ranges

Input parameters and its ranges		Output parameter
Slope (ratio)	1:1 and 2:1	Safety factor
Cohesion, C (kPa)	5 to 30	
Friction angle, φ (°)	10 to 20	
Slope angle, (°)	45 to 54	
Bar inclination,(°)	0 to 25	
Number of reinforce layers	10 to 18	

method. Various performance assessment parameters were evaluated, such as global performance indicator (GPI), nash-sutcliffe efficiency (NS), expanded uncertainty (U_{95}), legate and McCabe's index (LMI), variance account factor (VAF), root mean square error (RMSE), Willmott's index for agreement (WI), R^2 (determination coefficient), t-statistic, Adj. R^2 (adjusted coefficient of determination), MAPE (mean absolute percentage error), bias factor, performance index (PI), RSR (root sum of squares of the residuals), mean bias error (MBE), normalized mean bias error (NMBE), relative percentage difference (RPD), mean absolute error (MAE) and reliability index (β).

The performance assessment parameters were utilized to compare and determine the most appropriate model. The proposed hybrid RF-SVR-MOPSOA model performance was evaluated in comparison with alternative regression models such as the ENR, RR and LR, serving as a statistical summary to illustrate the best-suited model for reinforced soil slope stability analysis. Fig. 1 illustrates the layout of the proposed methodology, outlining the step-by-step approach to be followed throughout the study.

2.2 Data collection

The proposed study collected input and output data from existing studies. The criteria for selecting input and output data from the literature were as follows: Data related to slope stability analysis and reinforced soil slopes were considered, focusing on the specific problem being addressed in the study. Data from reputable sources were chosen to ensure the accuracy and reliability of the information. The selected parameters were chosen based on their significance in the analysis of reinforced soil slope stability, and their potential impact on the safety factor was considered. To capture a comprehensive view of the problem, a reasonable range of variation for each input parameter was selected. The selected input and output data were consistent with the objectives of this study and the methodology used to develop the proposed multi-objective particle swarm optimized RF-SVR model. By adhering to these criteria, this study ensured that the input and output data collected from the literature were appropriate for conducting a robust analysis of reinforced soil slope stability. Table 2 presents the selected parameters and their respective ranges used in the study. Table 3 presents the collected input and output data for this study.

2.3 Proposed models for reinforced soil slope stability analysis

2.3.1. Random forest model

Random forest, an expansion of decision tree framework, constitutes a component of the bagging family of algorithms, serving for classification and regression tasks. During the training phase, random forest constructs multiple decision trees and combines their predictions to enhance accuracy and robustness in making predictions. To initiate random forest, it generates multiple subsets of the training data using bootstrap sampling, involving random sampling of the training data with replacement. A separate decision tree is built for each subset of the data, differing slightly from the conventional decision tree construction process. In every tree node, the random forest algorithm evaluates just a random subset of features to divide the data, instead of analyzing all the features. The diversity among the trees is a result of this randomization. In the prediction phase, the new data point is processed through each decision tree, and each tree offers its prediction. In the case of regression tasks, the final prediction is calculated by averaging the predictions of all trees.

The random forest model comprises multiple decision trees, each having its unique set of rules, making it challenging to represent the entire model with a single equation. However, when dealing with regression tasks, the prediction for a new data point (X_{new}) was determined by computing the mean of forecasts generated by each individual tree (Y_{pred_i}) among the "n" decision trees present in the random forest, as shown in Eq. (1).

$$RandomForest(X_{new}) = \frac{1}{n}\sum_{i=1}^{n} Y_{pred_i} \qquad (1)$$

2.3.2. Support vector regressions model

SVR, an algorithm for regression tasks, falls

Table 3. Collected input and output data for this study

References	Input data						Output data
	Slope (ratio)	Cohesion, C (kPa)	Friction angle, φ (°)	Slope angle (°)	Bar inclination (°)	Number of reinforce layers	Safety factor
Qiu and Wang [25]	1:1	25	20	0	0	0	1.68
	1:1	20	20	0	0	0	1.46
	1:1	15	20	0	0	0	1.24
	1:1	10	20	0	0	0	1.00
	1:1	30	15	0	0	0	1.73
	1:1	25	15	0	0	0	1.52
	1:1	20	15	0	0	0	1.30
	1:1	15	15	0	0	0	1.09
	1:1	25	10	0	0	0	1.35
	1:1	20	10	0	0	0	1.15
	2:1	20	20	0	0	0	1.96
	2:1	15	20	0	0	0	1.71
	2:1	10	20	0	0	0	1.44
	2:1	5	20	0	0	0	1.15
	2:1	25	15	0	0	0	1.78
	2:1	20	15	0	0	0	1.55
	2:1	15	15	0	0	0	1.31
	2:1	10	15	0	0	0	1.06
	2:1	15	10	0	0	0	1.21
Sazzad and Rahat [26]	0	0	0	45	0	0	1.59
	0	0	0	45	5	0	1.82
	0	0	0	45	10	0	1.76
	0	0	0	45	15	0	1.74
	0	0	0	45	20	0	1.61
	0	0	0	45	25	0	1.47
	0	0	0	49	0	0	1.17
	0	0	0	49	5	0	1.43
	0	0	0	49	10	0	1.72
	0	0	0	49	15	0	1.63
	0	0	0	49	20	0	1.45
	0	0	0	49	25	0	1.11
	0	0	0	54	0	0	1.20
	0	0	0	54	5	0	1.59
	0	0	0	54	10	0	1.73
	0	0	0	54	15	0	1.68
	0	0	0	54	20	0	1.44
	0	0	0	54	25	0	1.17
	0	0	0	0	0	10	1.18
	0	0	0	0	0	11	1.31
	0	0	0	0	0	12	1.44
	0	0	0	0	0	13	1.77
	0	0	0	0	0	14	1.74
	0	0	0	0	0	15	1.68
	0	0	0	0	0	16	1.59
	0	0	0	0	0	17	1.54
	0	0	0	0	0	18	1.46

under the category of support vector machines (SVM). Its objective is to locate a hyperplane that effectively accommodates the data points within a defined margin while allowing room for errors within a given tolerance (epsilon). By employing kernel functions, SVR is adept at capturing intricate connections between features and target variables, even those that exhibit non-linear patterns. Through the use of kernel functions, SVR maps the initial feature space into a higher-dimensional one, with typical examples of kernel functions comprising linear, polynomial, radial basis function (RBF), and sigmoid.

SVR identifies the optimal hyperplane in the transformed space by minimizing errors and defining it through a weight vector (w) and bias term (b). The SVR method excludes data points within a certain margin from being treated as errors, resulting in their loss function contribution being zero. SVR endeavors to minimize errors beyond the margin and those surpassing epsilon by incorporating them into the loss function. The objective of SVR is to determine the regression function $f(X_i)$ that minimizes the loss function while adhering to the constraints set by the margin and epsilon. The fundamental expression for the SVR model can be stated as following Eqs. (2)-(5):

$$Giventrainingdata: (X\_i, y\_i) for i = 1,2, \ldots n \quad (2)$$

$$Minimize: \frac{1}{2}\left||w|\right|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (3)$$

Subject to:

$$y_i - f(X_i) \leq \varepsilon + \xi_i \quad (4)$$

$$f(X_i) - y_i \leq \varepsilon + \xi_i^* \quad (5)$$

Where, $f(X_i)$ is the predicted value for the data point X_i, ε is the margin or tube width, ξ_i and ξ_i^* are variables that represent the prediction error, C is the regularization parameter that balances the trade-off between maximizing margin and minimizing errors.

2.3.3. Multi-objective particle swarm optimization algorithm

Multi-objective particle swarm optimization (MOPSO) is a distinctive variant of the particle swarm optimization (PSO) algorithm that is tailored for addressing multiple objectives simultaneously created specifically for tackling multi-objective optimization problems. MOPSO consists of several essential elements: particle representation, objective functions, pareto dominance, personal best (pBest) and global best (gBest).

The MOPSO algorithm employs particles to represent potential solutions to the multi-objective problem. Each particle is represented as a vector of decision variables. The objective functions assess the fitness of each particle on the basis of its performance concerning each objective. Pareto dominance is a way to figure out if one solution, “A” is better than another solution “B”. A solution that is not dominated by any other solution is deemed Pareto-optimal. Every particle maintains its personal best position by considering its historical best performance during optimization. The best solution found among all the particles in the entire group is known as the global best position. The MOPSO algorithm can be summarized as follows steps:

Step 1: Initialization

Begin by setting up the particle population with randomly assigned positions and velocities. Set pBest and gBest for each particle.

Step 2: Fitness evaluation

Evaluate the fitness of each particle by computing its objective function values.

Step 3: Pareto domination

Identify the non-dominated solutions in the current population to form the pareto-optimal front.

Step 4: Update pBest and gBest

Update the personal best and global best positions based on the current pareto-optimal front.

Step 5: Velocity update

Update each particle’s velocity to move towards pBest and gBest positions.

Step 6: Position update

Adjust the particle's position according to the updated velocity.

Step 7: Termination criterion

Iterate through steps 2 to 6 until the termination condition is satisfied, such as reaching the maximum iteration limit. Eqs. (6) and (7) expressed the particle position update and velocity update in the MOPSO algorithm.

$$Newparticleposition = currentposition + velocity \quad (6)$$

$$Newvelocity = \omega \times currentvelocity + c_1 \times random() \times (pBestposition - currentposition) + c_2 \times random() \times (gBestposition - currentposition) \quad (7)$$

Where, ω is inertial weight, c_1 and c_2 are the acceleration constants $random()$ is a random number ranging from 0 to 1, respectively.

Let X and Y be two particles, X dominates Y as expressed in Eq. (8);

$$\forall i: f_i(X) \leq f_i(Y) \wedge \exists j: f_j(X) \langle f_j(Y) \quad (8)$$

Where, $f_i(X)$ and $f_i(Y)$ are the objective function values of X and Y for the i-th objective, respectively. The current particle's fitness was assessed in relation to its highest individual fitness achievement. Should the current level of fitness be greater, proceed to modify the pBest position and fitness accordingly. The non-dominated solutions within the current population were identified to create the pareto-optimal front. Select the best solution from this front to establish the new gBest position.

2.3.4. Hybrid RF-SVR-MOPSOA model

The hybrid RF-SVR-MOPSOA model is a combination of the random forest (RF), support vector regression (SVR), and multi-objective particle swarm optimization algorithm (MOPSOA) to analyze the reinforced soil slope stability. The hybrid RF-SVR-MOPSOA model offers a powerful and innovative approach for analyzing reinforced soil slope stability, combining the strengths of multiple techniques to provide accurate, robust, and efficient solutions, thereby assisting in enhancing the safety and cost-effectiveness of slope stabilization projects.

The combination of RF and SVR allows the model to exploit the strengths of both techniques. By combining these methods, the model can achieve higher accuracy in predicting slope stability. The hybrid model benefits from the robustness of ensemble learning provided by random forest; also leads to improved generalization and reduced risk of overfitting. Incorporating the MOPSOA enables the model to consider multiple objectives simultaneously, such as maximizing slope stability while minimizing material usage or construction cost. The hybrid approach aims to overcome limitations and weaknesses present in individual models. The hybrid RF-SVR-MOPSOA model is designed to predict the safety factor of a reinforced soil slope based on various input parameters. The safety factor is a critical measure in geotechnical engineering that represents the steadiness of a slope; an increased safety factor suggests a slope with greater stability.

The input data and output data for the model include the following parameters; slope ratio, cohesion, friction angle, slope angle, bar inclination and number of reinforced layers and safety factor. The slope ratio represents the ratio of the vertical rise to the horizontal run of the slope. Cohesion is a measure of the soil's internal strength. The friction angle represents the angle of internal friction between soil particles. The slope angle is determined as the angle between a horizontal plane at a specific point on the land's surface. Bar inclination is the inclination angle of the reinforcement bars used in the slope. The model aims to predict the safety factor of the reinforced soil slope. The safety factor is a dimensionless value that quantifies the stability of the slope. A safety factor above 1 signifies a secure slope, whereas a safety factor below 1 indicates an insecure slope.

2.3.4.1. Model training and optimization

The training and optimization process of the hybrid RF-SVR-MOPSOA model for reinforced soil slope stability analysis involves the following steps:

Data pre-processing: The first step is to collect and pre-process the data related to the reinforced soil slopes. This data should include factors influencing slope stability, such as soil properties, reinforcement characteristics, and external loading conditions. This study collected slope ratio, cohesion, friction angle, slope angle, bar inclination, and the number of reinforced layers and safety factors. Clean the data by handling any missing values, outliers, or noise that may affect the model's performance. The dataset was divided into input features (independent variables) and the corresponding slope stability values (dependent variable).

Data splitting: Before training the model, the data is split into two groups: one for training and the other for testing purposes. The training set was utilized for constructing the model, while its performance and capability were assessed through the testing set. This investigation partitioned the data, allocating 70% for the training set and 30% for the testing set.

Random forest (RF) training: Start training the random forest model using the training set.

Support vector regression (SVR) training: After training the RF model, proceed with training the SVR model using the same training set.

Hybrid model integration: The RF and SVR models were combined to create the Hybrid RF-SVR model. This was done using the weighted average of their predictions or feeding their outputs as input to another model.

Multi-objective particle swarm optimization algorithm (MOPSOA): The multi-objective particle swarm optimization algorithm was implemented to optimize the hybrid RF-SVR model. The position of the particles representing the best solutions from the MOPSOA was used to get the corresponding weights for combining the predictions from the RF and SVR models. The final prediction of the safety factor was determined through the utilization of weighted combination of the RF and SVR model outputs.

Evaluation and validation: Once the hybrid RF-SVR-MOPSOA model is trained and optimized, the testing set is utilized to assess its performance. Various evaluation metrics were calculated to assess how well the model predicts the slope stability values on unseen data. The parameters and hyperparameters of the individual algorithms were fine-tuned and achieved optimal performance by MOPSOA.

Testing and deployment: Once the model is validated and tuned, which is used to predict the safety factors (F) of reinforced soil slopes using Eq. (9).

$$F_{predicted} = \frac{F_{actual} - F_{min}}{Fmin_{max}} \tag{9}$$

2.3.5. Model evaluation

A wide array of statistical parameters supports the model's fitness and sufficiency. These parameters include NS, GPI, LMI, U_{95}, RMSE, VAF, R^2, WI, t-statistic, MAPE, Adj. R^2, PI, Bias Factor, RSR, NMBE, MBE, MAE, RPD and β [27]. These statistical parameters collectively provide a comprehensive evaluation of the hybrid RF-SVR-MOPSOA model's performance and suitability for reinforced soil slope stability analysis. Eqs. (10) to (28) were utilized for the computation of the above mentioned statistical parameters. Table 4 shows the notation list that explains the meaning of functions and variables used in these mathematical formulas.

2.3.5.1. Global performance indicator (GPI):

GPI is a comprehensive metric that combines multiple performance indicators to provide an overall assessment of a model. GPI is a single value that evaluates how accurate a model is by looking at multiple factors. A higher GPI means the model is more accurate.

Table 4. Notation list

n	Total number of data points
N	Total number of data points
i	Index for actual and predicted values
d_i	i^{th} actual value
y_i	i^{th} predicted value
p	Number of predicting variables
d_{mean}	Mean of actual values
SD	Standard deviation of actual values
μ_F	Safety factor mean value
σ_F	Safety factor standard deviation value

$$GPI = MBE \times RMSE \times U_{95} \times t_{stat} \times (1 - R^2) \tag{10}$$

2.3.5.2. Nash-sutcliffe efficiency (NS):

NS is a statistical measure commonly used to assess the accuracy of model predictions. It compares the simulated values to the observed values, providing a single metric for model performance with values ranging from negative (poor fit) to 1 (perfect fit). A higher NS, close to 1, means the model and the data match well.

$$NS = 1 - \frac{\sum_{i=1}^{n}(d_i - y_i)^2}{\sum_{i=1}^{n}(d_i - d_{mean})^2} \tag{11}$$

2.3.5.3. Expanded uncertainty (U_{95}):

U_{95} shows how good a model is at short-term predictions, with a 95% confidence interval. It accounts for various sources of uncertainty, providing a more realistic and conservative estimate of measurement reliability.

$$U_{95} = 1.96 \times (SD^2 + RMSE^2)^{1/2} \tag{12}$$

2.3.5.4. Legate and McCabe's index (LMI):

LMI is a hydrological metric used to evaluate the accuracy of simulations. It considers both the timing and magnitude of simulated and observed values, providing a comprehensive assessment of model performance. LMI measures the difference between a model's predictions. A lower LMI value indicates a better performance of the model.

$$LMI = 1 - \left[\frac{\sum_{i=1}^{N}|d_i - y_i|}{\sum_{i=1}^{N}|d_i - d_{mean}|}\right] \tag{13}$$

2.3.5.5. Variance account factor (VAF):

VAF is a metric used to assess the effectiveness of the model. It compares the variance of the estimated effort to the total variance, offering insights into the accuracy of model. VAF shows how well a model is performing, with a value closer to 100% indicating better performance.

$$VAF = \left[1 - \frac{var(d_i - y_i)}{var(d_i)}\right] \times 100 \tag{14}$$

2.3.5.6. Root mean square error (RMSE):

RMSE widely used in various fields, such as statistics and geosciences, providing a measure of the model's predictive accuracy. RMSE calculates the average difference between predicted and actual values. Lower RMSE values mean better model performance.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i - y_i)^2} \quad (15)$$

2.3.5.7. Willmott's index for agreement (WI):

WI assesses the agreement between observed and simulated data, considering both the systematic and random errors. WI estimates prediction errors in a model, with 1 meaning perfect agreement, 0 meaning no agreement, and -1 meaning total disagreement.

$$WI = 1 - \left[\frac{\sum_{i=1}^{N}(d_i - y_i)^2}{\sum_{i=1}^{N}(|y_i - d_{mean}| + |d_i - d_{mean}|)^2}\right] \quad (16)$$

2.3.5.8. Determination coefficient (R^2):

The R^2 represents the proportion of the variance in the dependent variable that is predictable from the independent variable(s). R^2 shows how well the predicted data aligns with the regression line. It ranges from 0 to 1, with higher values indicating a better fit of the model to the data.

$$R^2 = \frac{\sum_{i=1}^{n}(d_i - d_{mean})^2 - \sum_{i=1}^{n}(d_i - y_i)^2}{\sum_{i=1}^{n}(d_i - d_{mean})^2} \quad (17)$$

2.3.5.9. T-statistic:

The t-statistic assesses the significance of the difference between the sample mean and the hypothesized population mean. It is widely used in hypothesis testing to determine whether an observed effect is statistically significant. Lower t-statistic values indicating better predictive capability.

$$\text{t-statistic} = \sqrt{\frac{(N-1)MBE^2}{RMSE^2 - MBE^2}} \quad (18)$$

2.3.5.10. Adjusted coefficient of determination (Adj. R^2):

The adjusted R^2 considers the number of predictors in a model, providing a more accurate representation of the model's goodness of fit. It evaluates the suitability of a regression model's fit, adjusting for the number of predictors.

$$Adj.R^2 = 1 - \frac{(n-1)}{(n-p-1)}(1 - R^2) \quad (19)$$

2.3.5.11. Mean absolute percentage error (MAPE):

MAPE measures the accuracy of a forecasting method by calculating the percentage difference between predicted and observed values. It provides a clear indication of the average magnitude of errors in percentage terms.

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{d_i - y_i}{d_i}\right| \quad (20)$$

2.3.5.12. Bias factor:

Bias factor quantifies the systematic error in a model. Bias Factor measures the variance between average predicted and observed values. It helps identify whether the model tends to consistently overestimate or underestimate the true values. A value close to zero means unbiased predictions.

$$Biasfactor = \frac{1}{N}\sum_{i=1}^{n}\frac{y_i}{d_i} \quad (21)$$

2.3.5.13. Performance index (PI):

PI is commonly used to assess schedule performance. It calculates the accuracy of the model predictions around the observed values. A smaller value of PI indicates that the model predictions are accurate.

$$PI = Adj.R^2 - RMSE + 0.01VAF \quad (22)$$

2.3.5.14 Root Sum of Squares of the Residuals (RSR):

RSR is a hydrological metric used to evaluate the goodness of fit in simulations. It considers the squared differences between simulated and observed values, providing a measure of model accuracy. RSR's lower values indicate improved model performance.

$$RSR = \frac{RMSE}{\sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i - d_{mean})^2}} \quad (23)$$

2.3.5.15. Mean bias error (MBE):

MBE quantifies the average difference between predicted and observed values, indicating the overall bias in a model. Positive values suggest overestimation, while negative values indicate underestimation.

$$MAE = \frac{1}{N}\sum_{i=1}^{n}(y_i - d_i) \quad (24)$$

2.3.5.16. Normalized mean bias error (NMBE):

NMBE is a normalized version of MBE, expressed as a percentage of the observed mean. It provides a standardized measure of bias, allowing for comparisons between different datasets or models. NMBE compares MBE results by adjusting them, considering the average of measured values.

$$NMBE(\%) = \frac{\frac{1}{N}\sum_{i=1}^{n}(y_i - d_i)}{\frac{1}{N}\sum_{i=1}^{n}(d_i)} \times 100 \quad (25)$$

2.3.5.17. Relative percentage difference (RPD):

RPD is a metric used to assess the agreement between two sets of values, considering both magnitude and direction. RPD shows the relationship between observed values' standard deviation and the model's RMSE.

$$RPD = \frac{SD}{RMSE} \quad (26)$$

2.3.5.18. Mean absolute error (MAE):

MAE quantifies the average absolute difference between predicted and observed values. It provides a straightforward measure of accuracy, with lower values indicating better model performance.

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|(y_i - d_i)| \quad (27)$$

2.3.5.19. Reliability index (β):

The reliability index is commonly used in geotechnical engineering to assess the safety of structures or slopes. It is calculated based on the ratio of the available strength to the applied loads, providing a safety margin. It indicates the smallest separation between the origin in the reduced variable space and the surface representing failure, with higher values indicating better reliability.

$$\beta = \frac{\mu_F - 1}{\sigma_F} \quad (28)$$

3. Result and discussion

3.1 Safety factor prediction

Fig. 2 shows the predicted safety factors for the proposed hybrid RF-SVR-MOPSOA model and three other regression models: Elastic net regression (ENR), ridge regression (RR), and lasso regression (LR). The analysis was conducted using the MATLAB programming language. The predicted safety factors by the proposed model are very close to the actual safety factors. This suggests that the proposed model is an excellent fit for the data and can capture the underlying patterns effectively. The predicted safety factors by ENR are reasonably close to the actual values. However, compared to the proposed model, it exhibits a lower level of accuracy. Both RR and LR indicate a lesser ability to predict the variability in the data compared to ENR. As a result, the predicted safety factors by these models deviate from the actual values compared to the proposed and ENR models.

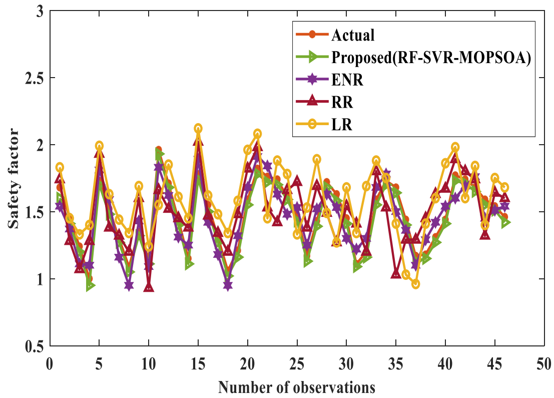

Figure. 2 Performances of predicted safety factor

The proposed model combines the strengths of the RF-SVR model and MOPSOA optimization, allowing it to handle both linear and non-linear relationships in the data. This adaptability enables the model to make accurate predictions of safety factors, leading to minimal deviations between the predicted and actual values. In contrast, the other regression models (ENR, RR, and LR) have limitations in handling non-linearity. They may suffer underfitting or overfitting issues, leading to larger deviations between the predicted and actual safety factors. Overall, the proposed hybrid RF-SVR-MOPSOA model demonstrates superior performance in predicting safety factors compared to traditional regression models such as ENR, RR, and LR. It achieves almost perfect accuracy, indicating its effectiveness in predicting the data. This suggests that the proposed model could be a promising approach for predicting safety factors in the reinforced soil slope stability.

Additionally, Figs. 3-6 demonstrate the R^2 (coefficient of determination) values for the training and testing datasets, which indicate the goodness-of-fit of each model. The R^2 values for the training dataset indicate how well each model fits the training data. A value of 1 indicates a perfect fit, while values closer to 0 indicate a poorer fit. The proposed Hybrid RF-SVR-MOPSOA model has an exceptionally high R^2 value of 0.9995, suggesting an excellent fit to the training data. It outperforms the other models significantly in this aspect. ENR also shows a reasonably high R^2 value of 0.9872, indicating a good fit, while RR and LR have lower R^2 values, suggesting weaker fits to the training data.

The R^2 values for the testing dataset are slightly

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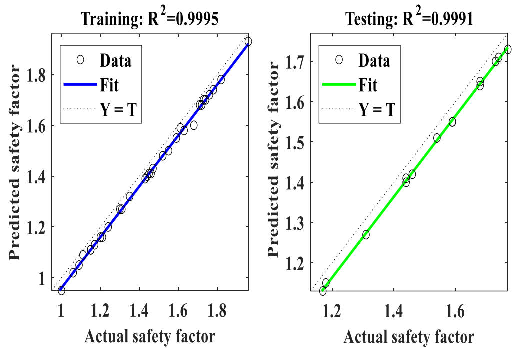

Figure. 3 Regression plots for proposed model

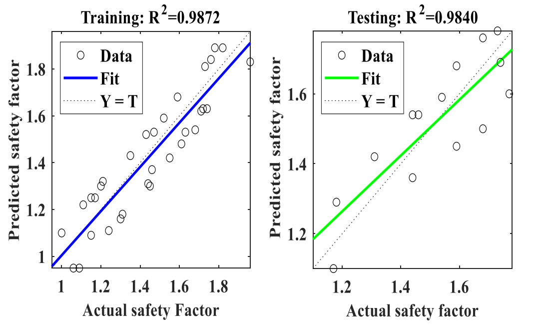

Figure. 4 Regression plots for elastic net regression model

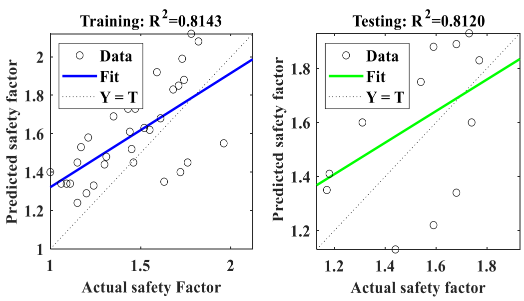

Figure. 5 Regression plots for ridge regression model

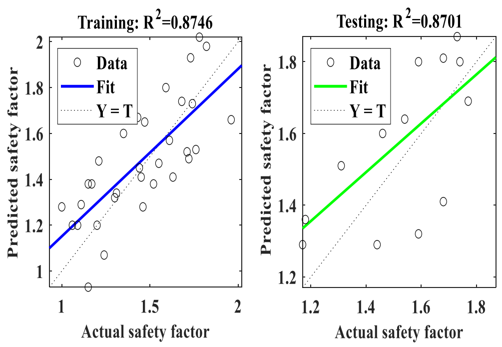

Figure. 6 Regression plots for the lasso regression model

lower than the training R^2 values for all models, which is expected. The proposed model maintains a high R^2 value of 0.9991, indicating strong generalization to new data. ENR demonstrates good generalization with an R^2 value of 0.9840, while RR and LR also show acceptable generalization but with a lower R^2 value of 0.8120 0.8701 compared to the proposed model and ENR. Based on the R^2 values, the proposed hybrid RF-SVR-MOPSOA model significantly outperforms all the other regression models in training and testing data. It achieves near-perfect accuracy, with R^2 values close to 1 for training and testing datasets. The proposed model combines multiple techniques (RF and SVR with the MOPSO algorithm) to create a hybrid model that is more powerful in capturing complex relationships in the data, which leads to achieving a near-perfect fit and accurately predicting the safety factors. On the other hand, the other regression models (ENR, RR, and LR) show progressively lower R^2 values, indicating a lower ability to explain the variance in the data because these regression models use single algorithms and are less effective at capturing complex patterns present in the data, resulting in lower R^2 values.

3.2 Performance metrics

Table 5 provides a thorough evaluation of performance metrics, drawing a comparison between the newly introduced Hybrid RF-SVR-MOPSOA model and several traditional regression models, including ENR, RR, and LR, for predicting safety factors. The evaluation metrics utilized in the comparison offer valuable comprehensions into the effectiveness of each model and make precise predictions. Additionally, the metrics employed to evaluate the performance of the models encompass various statistical indicators commonly employed in regression analysis. The proposed hybrid model shows promising performance across various metrics. It outperforms all traditional regression models in terms of most of the evaluation metrics, including GPI, NS, U_{95}, LMI, VAF, RMSE, WI, R^2, t-statistic, Adj. R^2, MAPE, Bias Factor, PI, RSR, MBE, NMBE, RPD, MAE, and β. These results indicate that the hybrid model is superior and has more accurate prediction performances than others.

The traditional regression models also demonstrate acceptable performance but generally fall short compared to the proposed hybrid model. The proposed model achieves an impressive VAF of 99.98%, indicating high accuracy. This high accuracy is further supported by the low RMSE, which indicates small prediction errors. The proposed model has the lowest t-statistic value (0.1523), suggesting that its coefficients are statistically significant compared to the traditional regression models.

Table 5. Performance comparison of the proposed hybrid RF-SVR-MOPSOA model and traditional regression models for safety factor prediction

Evaluation metrics	Proposed model (Hybrid RF-SVR-MOPSOA)	Elastic Net Regression	Ridge Regression	Lasso Regression
GPI	1.53	1.50	1.48	1.47
NS	0.9956	0.9653	0.8451	0.8249
U_{95}	0.00453	0.0654	0.0754	0.0755
LMI	0.9851	0.9752	0.9625	0.9425
VAF	99.98%	95.85%	92.72%	90.98%
RMSE	0.0031	0.057	0.0184	0.0256
WI	0.9997	0.9754	0.9121	0.8942
R^2	0.9995	0.9872	0.8746	0.8143
t-statistic	0.1523	0.4265	0.4523	0.5124
Adj. R^2	0.9998	0.9974	0.8142	0.8003
MAPE	0.0038	0.0375	0.0452	0.0478
Bias Factor	0.99984	0.9821	0.9725	0.9642
PI	1.9975	1.5246	1.2541	1.0025
RSR	0.00214	0.0142	0.0158	0.0163
MBE	0.00147	0.0125	0.0142	0.0168
NMBE	0.00135	0.0254	0.0275	0.0298
RPD	2.857	2.694	2.634	2.599
MAE	0.00129	0.0152	0.0254	0.0325
β	1.0084	1.0052	1.0026	0.9852

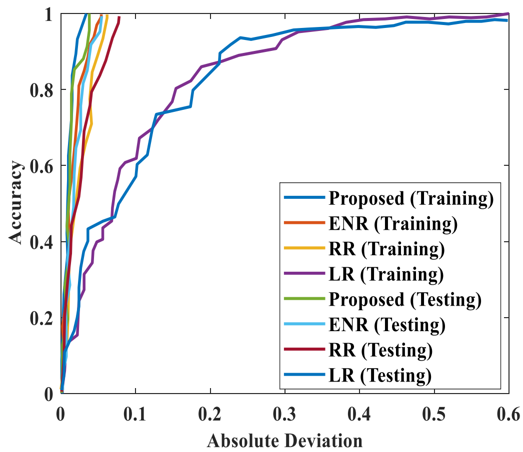

Figure. 7 ROC curve plot for proposed with traditional models

The proposed model exhibits a low RSR, MBE, NMBE, and MAE, which indicates that it is less sensitive to outliers and performs well in predicting safety factors than other models. The RPD value for the proposed model is significantly higher than the traditional regression models, indicating better generalization capabilities and less over fitting. The β value represents the slope of the regression line. The proposed model has a β value close to 1, indicating that it provides an accurate linear fit to the data. These findings further suggest that the hybrid model is a promising approach for safety factor prediction.

Fig. 7 displays the ROC curve plot for the proposed model (Hybrid RF-SVR-MOPSOA), ENR, RR, and LR. The ROC curve analysis suggests that the suggested model surpasses the other regression models when considering the balance between sensitivity and specificity. This suggests that the proposed model is a more promising approach for predicting the safety factor than elastic ENR, RR, and LR.

3.2 Comparative analysis of slope stability evaluation studies

Table 6 shows the comparison of proposed and existing studies on slope stability. The proposed study employs a hybrid model (RF-SVR-MOPSOA) on reinforced soil slope data, demonstrating superior accuracy in comparison to traditional regression models. Notably, it exhibits exceptional adaptability to both linear and non-linear relationships, achieving an outstanding R^2 value of 0.9995 on training data. It achieves exceptional accuracy metrics, confirmed by ROC curve analysis, making it promising for slope stability prediction.

GA-ANFIS, RFC, and GMDH techniques were applied to shear strength parameters. The GA-ANFIS model outperformed RFC and GMDH, exhibiting high accuracy metrics such as NS, VAF, RMSE, bias factor, R^2, PI, GPI, -stat, U95, tand β. This study highlights GA-ANFIS as a reliable soft computing technique for slope stability analysis [27]. Extreme learning machine (ELM) was utilized on worldwide slope cases, demonstrating its advantages over GRNN and genetic algorithm models. The ELM model exhibited good predictability for slope stability analysis, along with lower mean absolute percentage errors compared to other models [28]. A multi-layer perceptron neural network (MLPNN) optimized by evolutionary optimization (EO) and variable screening algorithm (VSA) was applied to finite element simulation data. The hybrid models showed improved performance, with lower training and testing RMSE. EO outperformed VSA in optimizing MLPNN [29]. An artificial neural network (ANN) was employed on numerical analysis data, showcasing the strong potential of ANN for predicting slope stability. The model's performance was evaluated using R^2 and RMSE metrics [30]. An extreme learning neural network was applied to finite element upper and lower bound limit analysis, generating stability charts. The ANN-based tool provides a quick first assessment of three-layered soil slope stability, maintaining good accuracy and convenience [31]. Existing studies employ various techniques, each showcasing reliability in slope stability analysis. The proposed study's novelty lies in the integration of RF, SVR, and MOPSOA, providing superior accuracy and adaptability.

4. Conclusions and future scope

The proposed study aims to evaluate the reinforced soil slopes stability using a novel multi-objective particle swarm optimized RF-SVR model. The following are the summary of this study:

- The proposed hybrid RF-SVR-MOPSOA model demonstrates superior accuracy in predicting safety factors compared to traditional regression models (ENR, RR, and LR).
- ENR shows reasonably close predictions to actual values but exhibits lower accuracy than the proposed model, while both RR and LR display lesser ability to predict variability, resulting in larger deviations.
- The hybrid RF-SVR-MOPSOA model combines the strengths of RF-SVR and MOPSOA optimization, enabling it to handle both linear and non-linear relationships effectively.
- This adaptability leads to almost perfect accuracy, minimal deviations between predicted and actual values, and suggests the proposed model's potential as a promising approach for predicting safety factors in reinforced soil slope stability.
- The proposed hybrid RF-SVR-MOPSOA model exhibits an exceptional R^2 value of 0.9995 on the training dataset, indicating an outstanding fit and outperforming other models significantly. ENR also shows a reasonably high R^2 value of 0.9872, suggesting a good fit, while RR and LR have lower R^2 values, indicating weaker fits to the training data.
- Key metrics, such as GPI, NS, U_{95}, LMI, VAF, RMSE, WI, R^2, t-statistic, Adj. R^2, MAPE, bias factor, PI, RSR, MBE, NMBE, RPD, MAE, and β, consistently show that the hybrid model outperforms, indicating more accurate and reliable predictions for safety factors.
- The proposed hybrid model achieves an impressive VAF of 99.98%, highlighting its high accuracy in predicting safety factors.
- The model's low RMSE and the lowest t-statistic value (0.1523) signify small prediction errors and statistically significant coefficients, respectively.
- The hybrid model exhibits low values for RSR, MBE, NMBE, and MAE, indicating robustness against outliers and superior predictive performance compared to traditional regression models.
- The higher RPD value for the hybrid model suggests better generalization capabilities and less overfitting, while the β value close to 1 indicates an accurate linear fit to the data, reinforcing the model's promise for safety factor prediction.
- The ROC curve analysis also confirms the superiority of the proposed model over the traditional regression models in terms of sensitivity and specificity trade-offs. Based on the findings, it can be concluded that the proposed hybrid RF-SVR-MOPSOA model is a highly effective and accurate approach for predicting safety factors in reinforced soil slope stability.
- Based on the findings, this study makes a substantial scientific contribution by introducing a novel hybrid RF-SVR-MOPSOA model that not only outperforms traditional regression models but also demonstrates adaptability, robustness, and potential for further improvements in predicting safety factors in reinforced soil slope stability.
- Engineers and researchers can influence the Hybrid RF-SVR-MOPSOA model to make more reliable predictions, contributing to improved slope design and risk assessment in civil engineering projects.

The results of this study suggest multiple possible avenues for further research: Investigating the importance of different features and employing advanced feature engineering techniques could improve the model's performance and interpretability. Exploring the combination of multiple predictive models through ensemble techniques could lead to even better predictive performance.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization: Ippili Saikrishnamacharyulu and Balendra Mouli Marrapu; methodology: Ippili Saikrishnamacharyulu; Software: Ippili

Saikrishnamacharyulu; Validation: Ippili Saikrishnamacharyulu, Balendra Mouli Marrapu, and Vasala Madhavarao; formal analysis: Ippili Saikrishnamacharyulu; Vasala Madhavarao; investigation: Ippili Saikrishnamacharyulu; resources: Ippili Saikrishnamacharyulu; data curation: Ippili Saikrishnamacharyulu; writing—original draft preparation: Ippili Saikrishnamacharyulu; writing—review and editing: Vasala Madhavarao; visualization: Ippili Saikrishnamacharyulu; supervision: Balendra Mouli Marrapu; project administration: Balendra Mouli Marrapu; funding acquisition: Balendra Mouli Marrapu".

References

[1] I. P. Damians, Y. Miyata, P. Rimoldi, N. Touze, and J. Kraus, "Sustainability of geosynthetics-based landslide stabilization solutions", *In Progress in Landslide Research and Technology*, Vol. 1, No. 1, pp. 197-205, 2023.

[2] T. L. Gouw, "Case histories on the application of vacuum preloading and geosynthetic-reinforced soil structures in Indonesia", *Indian Geotechnical Journal*, Vol. 50, pp. 37-213, 2020.

[3] M. T. Löbmann, C. Geitner, C. Wellstein, and S. Zerbe, "The influence of herbaceous vegetation on slope stability–A review", *Earth-Science Reviews*, Vol. 209, p. 103328, 2020.

[4] C. Li, Z. Fu, Y. Wang, H. Tang, J. Yan, W. Gong, W. Yao, and R. E. Criss, "Susceptibility of reservoir-induced landslides and strategies for increasing the slope stability in the Three Gorges Reservoir Area: Zigui Basin as an example", *Engineering Geology*, Vol. 261, p. 105279, 2019.

[5] O. Ghorbanzadeh, S. R. Meena, T. Blaschke, and J. Aryal, "UAV-based slope failure detection using deep-learning convolutional neural networks", *Remote Sensing*, Vol. 11, No. 17, p. 2046, 2019.

[6] S. Kumar, and L. B. Roy, "Rainfall induced geotextile reinforced model slope embankment subjected to surcharge loading: a review study", *Archives of Computational Methods in Engineering*, Vol. 1, pp. 1-9, 2022.

[7] X. Diao, K. Wu, D. Zhou, J. Wang, Z. Duan, and Z. Yu, "Combining subsidence theory and slope stability analysis method for building damage assessment in mountainous mining subsidence regions", *PLoS One*. Vol. 14, No. 2, p. e0210021, 2019.

[8] A. G. Gad, "Particle swarm optimization algorithm and its applications: a systematic review", *Archives of Computational Methods in Engineering*, Vol. 29, No. 5, pp. 61-2531, 2022.

[9] J. Nayak, H. Swapnarekha, B. Naik, G. Dhiman, and S. Vimal, "25 years of particle swarm optimization: Flourishing voyage of two decades", *Archives of Computational Methods in Engineering*, Vol. 30, No. 3, pp. 725-1663, 2023.

[10] U. A. Salaria, M. I. Menhas, and S. Manzoor, "Quasi oppositional population based global particle swarm optimizer with inertial weights (qpgpso-w) for solving economic load dispatch problem", *IEEE Access*. Vol. 9, pp. 95-134081, 2021.

[11] P. Dastpak, R. J. Chenari, B. Cami, and S. Javankhoshdel, "Noncircular deterministic and stochastic slope stability analyses and design of simple geosynthetic-reinforced soil slopes", *International Journal of Geomechanics*, Vol. 21, No. 9, p. 04021155, 2021.

[12] H. Djeffal and S. Belkacemi, "A New Approach for Evaluating the Soil Slope Reinforcement Tensile Forces Using Limit Equilibrium Methods", *Geotechnical and Geological Engineering*, Vol. 39, pp. 27-2313, 2021.

[13] H. Djeffal and S. Belkacemi, "Effect of soil-reinforcement interaction coefficient on reinforcement tension distribution of reinforced slopes", *Geotextiles and Geomembranes*, Vol. 48, No. 4, pp. 80-572, 2020.

[14] G. Pokharel, A. Fujii, and H. Miki, "Centrifuge model testing of reinforced soil slopes in the perspective of Kanto Loam", *InSlope Stability Engineering: Proceedings of the International Symposium, IS-Shikoku'99 Routledge*, p. 985, 2021.

[15] A. Sharma, P. T. Raju, V. Sreedhar, and H. Mahiyar, "Slope stability analysis of steep-reinforced soil slopes using finite element method", *In Geotechnical Applications: IGC 2016*, Vol. 4, pp. 163-171, 2019.

[16] A. V. Karthik, R. Manideep, and J. T. Chavda, "Sensitivity analysis of slope stability using finite element method", *Innovative Infrastructure Solutions*, Vol. 7, No. 2, p. 184, 2022.

[17] S. Halder, M. O. Imam, and M. S. Basir, "A detailed analysis of slope stability using finite element method (FEM)", *In: Proc. of 3rd International Conference on Advances in Civil Engineering* pp. 21-23, 2016.

[18] B. M. Świtała, W. Wu, and S. Wang, "Implementation of a coupled hydro-

Received: October 30, 2023. Revised: December 2, 2023.

mechanical model for root-reinforced soils in finite element code", *Computers and Geotechnics*, Vol. 112, pp. 197-203, 2019.

[19] M. Sungkar, M. Munirwansyah, R. P. Munirwan, and D. Safrina, "Slope stability analysis using Bishop and finite element methods. In IOP conference series: materials science and engineering", *IOP Publishing*, Vol. 933, No. 1, p. 012035, 2020.

[20] Z. Sui, W. Yuan, W. Yi, and W. Yang, "Stability analysis of ecological slopes based on a 3D finite element model", *Advances in Materials Science and Engineering*, Vol. 2021, p. 1, 2021.

[21] S. A. Villalobos and F. A. Villalobos, "Effect of nail spacing on the global stability of soil nailed walls using limit equilibrium and finite element methods", *Transportation Geotechnics*, Vol. 26, p. 100454, 2021.

[22] H. D. Lin, W. C. Wang, and A. J. Li, "Investigation of dilatancy angle effects on slope stability using the 3D finite element method strength reduction technique", *Computers and Geotechnics*, Vol. 118, p. 103295, 2020.

[23] A. Pandey, S. Jaiswal, and V. B. Chauhan, "Numerical studies on the behavior of slope reinforced with soil nails", In: *Local Site Effects and Ground Failures: Select Proceedings of 7th ICRAGEE 2020 Singapore: Springer Singapore*, pp. 217-228, 2021.

[24] M. H. Mohamed, M. Ahmed, J. Mallick, and S. A. Qadhi, "Finite Element Modeling of the Soil-Nailing Process in Nailed-Soil Slopes", *Applied Sciences*, Vol. 13, No. 4, p. 2139, 2023.

[25] C. Qiu and P. A. Wang, "Analytical Calculation for slope stability based on the Combination of Horizontal Slice Method and Oblique Slice Method", *In IOP Conference Series: Materials Science and Engineering. IOP Publishing*, Vol. 307, No. 1, p. 012059, 2018.

[26] M. M. Sazzad and T. Rahat, "Numerical analysis of reinforced slope using Limit Equilibrium Method", In: *Proc. of 4th International Conference on Civil Engineering for Sustainable Development, Bangladesh*, 2018.

[27] R. Ray, S. S. Choudhary, L. B. Roy, M. R. Kaloop, P. Samui, P. U. Kurup, J. Ahn, and J. W. Hu, "Reliability analysis of reinforced soil slope stability using GA-ANFIS, RFC, and GMDH soft computing techniques", *Case Studies in Construction Materials*, p. 18, 2023.

[28] Z. Liu, J. Shao, W. Xu, H. Chen, and Y. Zhang, "An extreme learning machine approach for slope stability evaluation and prediction", *Natural Hazards*, Vol. 73, pp.787-804, 2014.

[29] L. K. Foong and H. Moayedi, "Slope stability evaluation using neural network optimized by equilibrium optimization and vortex search algorithm", *Engineering with Computers*, pp. 1-15, 2021.

[30] R. C. Mamat, A. Kasa, S. F. M. Razali, A. Ramli, and M. B. H. C. Omar, "Slope stability prediction of road embankment on soft ground treated with prefabricated vertical drains using artificial neural network", *IAES International Journal of Artificial Intelligence*, Vol. 9, No. 2, p. 236, 2020.

[31] A. J. Li, K. Lim, and A. Fatty, "Stability evaluations of three-layered soil slopes based on extreme learning neural network", *Journal of the Chinese Institute of Engineers*, Vol. 43, No. 7, pp. 628-637, 2020.