

An investigation on anisotropic soil slope stability by LS-SVM and LEM approaches

Ali Doostvandi

Department of Civil and Environmental Engineering, Texas A&M University, College Station, Texas, USA

Mohammad HajiAzizi

Department of Civil Engineering, Razi University, Kermanshah, Iran, and

Fatemeh Pariafsai

Department of Construction Management, Bowling Green State University, Bowling Green, Ohio, USA

Abstract

Purpose – This study aims to use regression Least-Square Support Vector Machine (LS-SVM) as a probabilistic model to determine the factor of safety (FS) and probability of failure (PF) of anisotropic soil slopes.

Design/methodology/approach – This research uses machine learning (ML) techniques to predict soil slope failure. Due to the lack of analytical solutions for measuring FS and PF, it is more convenient to use surrogate models like probabilistic modeling, which is suitable for performing repetitive calculations to compute the effect of uncertainty on the anisotropic soil slope stability. The study first uses the Limit Equilibrium Method (LEM) based on a probabilistic evaluation over the Latin Hypercube Sampling (LHS) technique for two anisotropic soil slope profiles to assess FS and PF. Then, using one of the supervised methods of ML named LS-SVM, the outcomes (FS and PF) were compared to evaluate the efficiency of the LS-SVM method in predicting the stability of such complex soil slope profiles.

Findings – This method increases the computational performance of low-probability analysis significantly. The compared results by FS-PF plots show that the proposed method is valuable for analyzing complex slopes under different probabilistic distributions. Accordingly, to obtain a precise estimate of slope stability, all layers must be included in the probabilistic modeling in the LS-SVM method.

Originality/value – Combining LS-SVM and LEM offers a unique and innovative approach to address the anisotropic behavior of soil slope stability analysis. The initiative part of this paper is to evaluate the stability of an anisotropic soil slope based on one ML method, the Least-Square Support Vector Machine (LS-SVM). The soil slope is defined as complex because there are uncertainties in the slope profile characteristics transformed to LS-SVM. Consequently, several input parameters are effective in finding FS and PF as output parameters.

Keywords LS-SVM, Probabilistic modeling, Uncertainty, Anisotropic soil slope, Machine learning

Paper type Research paper

1. Introduction

Traditional assessments such as limit analysis have become a prevalent practice for calculating factors of safety (FS). The value of FS must meet a minimum requirement defined by previous experience and professional judgment (Cheung, 2012). Furthermore, calculating FS of slope can be satisfied through numerical codes such as finite element method (FEM) and finite difference method (FDM) and analytical solutions (Duncan, 1996). It is crucial to consider uncertainties in soil parameters, level of site exploration and laboratory research efforts as random variables and perform probabilistic analysis to calculate the probability of failure (PF) for each soil slope. In probabilistic modeling, slope safety is assessed through the reliability index or failure probability. Thus, operating by a probabilistic framework has the advantage of logically considering the system's reliability (Griffiths *et al.*, 2007; El-

Ramly *et al.*, 2002). PF can be determined by analyzing the percentage of FS lower than one in the overall number of FS calculations. However, one critical problem was that different slopes with identical FS presented diverse PF. However, due to variations in standard deviation, these differences in PF with identical FS were not surprising (Kang *et al.*, 2015). On the other hand, PF could be determined by looking at the failure statistics of a wide range of similar slopes. This method could have been more efficient because the slopes varied widely between locations, making it difficult to find many similar slopes that had failed. When combining all slopes for statistical analysis, the predicted probability value could not differentiate between a well and a poorly constructed slope profile or between slopes with various degrees of uncertainty (Cheung,

The current issue and full text archive of this journal is available on Emerald Insight at: <https://www.emerald.com/insight/1708-5284.htm>



World Journal of Engineering
22/6 (2025) 1187–1201
Emerald Publishing Limited [ISSN 1708-5284]
[DOI 10.1108/WJE-12-2023-0536]

© Ali Doostvandi, Mohammad HajiAzizi and Fatemeh Pariafsai. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licences/by/4.0/legalcode>

Received 30 December 2023

Revised 4 August 2024

Accepted 24 August 2024

2012). Also, because multi-surface slopes may have several possible failure surfaces, more than one PF must be considered in the calculation. It should be noted that the PF of the sample surface can be lower than the PF of the global system containing all critical surfaces (Oka and Wu, 1990; Cho, 2013). Some approaches, such as Monte Carlo simulation (MC), were presented to calculate a more accurate PF for the entire system. Moreover, the Subset Simulation method (SS) and Importance Sampling technique (IS) is a development of MC (Fenton and Griffiths, 2008; Wang *et al.*, 2010; Griffiths *et al.*, 2009). It was mentioned that system evaluation is an efficient tool for slope assessment (Zhang *et al.*, 2012). The anisotropic characteristics of geostructures are one of the major causes of enhancing the PF. Lai *et al.* (2022) proposed an ML method named Multivariate Adaptive Regression Splines to generate failure mechanisms of the bearing capacity of ring foundations over anisotropic and heterogeneous clays and compare to finite element (FE) and NGI-ADP model that is an elastoplastic constitutive model that simulates the behavior of clay and accounts for the anisotropy of undrained shear strength and stiffness. A wide range of research has gone into using reliability methods. The reliability-bounds theory was used to calculate the upper and lower bounds of the slope profile (Ji and Low, 2012; Oka and Wu, 1990; Low *et al.*, 2011; Cho, 2013). Besides, methods for assessing system reliability based on a collection of representative surfaces were also investigated (Cho, 2013; Zhang *et al.*, 2012; Li and Dong, 2012); however, it was inefficient at low probability degrees (Jiang *et al.*, 2015). As a result of stratification caused by sedimentation, erosion, compaction and particle orientation, some soil masses have different degrees of anisotropy (Assouline and Or, 2006). Theoretical solutions to geotechnical problems usually simplify assumptions concerning soil homogeneity and isotropy (Bozorgpour *et al.*, 2021). Researchers have addressed the impact of spatial variability of soils based on probabilistic modeling and stated that spatial variability should be considered when modeling anisotropic soil masses (Wang *et al.*, 2020c; Cho, 2010). Such complicated analysis is time-consuming, and machine learning (ML) techniques can improve this. There are several functions of ML used in geotechnical engineering. Researchers used the Neural Network method (NN) to predict slope reliability (Wang *et al.*, 2005; Zhou and Chen, 2009). Besides, the Relevance Vector Machine method (RVM) was applied to examine a connection between the stability of the slope profile and influence factors (Zhao *et al.*, 2012; Hoang and Tien, 2016; Phoon and Zhang, 2023) recommended novel ML algorithms called data-centric geotechnics to develop new solutions such as Data-driven site characterization and satisfy new needs from digital transformation within the stability of geotechnics. Zhang *et al.* (2023a, 2023b), provided a systematic analysis of the application of ML within geostructures such as slopes, tunneling and excavations and indicated major challenges considering reliability analysis such as the selection of ML models and the optimization, and time-variant reliability analysis. In another study, Bozorgzadeh and Feng (2024) emphasized the significance of data-centricity, transparency and appropriateness for geotechnical data, termed “data-centric geotechnics.” They concluded that stricter guidelines are necessary for evaluating training in ML models to ensure

their acceptance and practical application. Furthermore, researchers used SVM to predict the stability of slope systems (Li and Dong, 2012; Li and Wang, 2010; Samui, 2008). Least-Square Support Vector Machine (LS-SVM), a derived model from SVM and Evolutionary Polynomial Regression methods were also applied to create a mapping function between input and output data (Suykens *et al.*, 2002; Ahangar-Asr *et al.*, 2010; Samui and Kothari, 2010). Another approach based on the Gaussian method was developed to analyze slopes among mountain roads (Ching *et al.*, 2011). In another study, a slope classification model that combined LS-SVM and the firefly algorithm (FA) was used (Hoang and Pham, 2016). Another study introduced a Bayesian framework-based probabilistic slope assessment model (Cheng and Hoang, 2016). A Bayes Discriminant approach was developed for evaluating open-pit slopes (Yan and Bayes, 2011). Due to the forecasting breakdowns on mountainous roads, a swarm-optimized fuzzy model was used (Cheng and Hoang, 2015).

2. Literature review

Design complexities in soil slope stability made researchers come up with more sophisticated solutions in which as many uncertainties in soil behavior have been satisfied. Nowadays, using ML techniques has been more prevalent in this way, although each approach has its benefits and limitations. LS-SVM was used to compute the reliability of a soft clay foundation settlement (Wang *et al.*, 2013). They adopted the Decimal Ant Colony Algorithm to optimize training data. Training data was created based on a probabilistic distribution. The crucial point is how to make a relationship between input and output in training data because the better the accuracy; however, avoiding overestimation is vital. In another study, a Relevance Vector Machine Classifier (RVMC) was used to identify and anticipate potential landslides in mountain areas (Hoang and Tien, 2016). The benefit of using a classifier method is that results are split into two categories: landslide and non-landslide modes. The Cuckoo Search Optimization (CSO) was considered as another optimization function on Kernel radius basis function (RBF) known as hyper-parameters (explained in the following) as a critical point. Because the performance of RVMC directly depends on the quality of the Kernel RBF parameters. As discussed above, uncertainty plays a critical role in soil slope stability and RVMC, showing a probabilistic outcome captured this issue, unlike NN. Hoang and Pham (2016) discovered that using Metaheuristic-Optimized Least-Square Support Vector Classification enables them to improve the failure predictability of soil slopes in contrast to traditional methods. The term classification allowed them to separate the results into unstable and stable modes. They required input data such as water pressure, cohesion, frictional angle, unit weight and slope height to obtain FS as the output data. Similar to previous studies, they considered an optimization method called Firefly Algorithm to generate hyperparameters and remove potential errors. They used 168 case study data sets to validate the results, resulting in a 4% progress in prediction accuracy. A flexible structure is one of the advantages of ML algorithms, which allows it to change the relation between parameters based on the existing data. On the other hand, one of the drawbacks of the classification method

compared to regression is that the output data set could only be split into two predetermined groups. At the same time, it may be deceptive in some cases. Another problem is that more variables, such as climate changes, vegetation diversity and seismic risks, should be considered when evaluating input data to reach a more reliable output data set (Wang *et al.*, 2013; Hoang and Tien, 2016; Hoang and Pham, 2016). In this way, another research was conducted including 12 variables as input data sets, such as lithology, profile and plan curvature, utilization of land and location of faults to address this issue (Youssef and Pourghasemi, 2021). Moreover, they compared seven ML algorithms' results, such as NN, Random Forest (RF) and Linear Discriminant Analysis, to assess the ability of these algorithms to identify potential landslides. A total of 243 landslides in Saudi Arabia were analyzed for this study. The results showed that slope length, angle, distance from the road and faults are the most practical terms for identifying potential landslides. Moreover, using 70% of data for training is a reasonable estimate to arrive at an acceptable accuracy. In another study, a Convolutional Neural Network along with the optimization algorithm Grey Wolf Optimizer (GWO) and Imperialist Competitive Algorithm (ICA) was used to address landslide potential in Incheon, South Korea (Hakim *et al.*, 2022). They factored 18 valuable items such as valley death, forest type and density, drainage, wetness index, height and angle of the slope. Seventy percent of the randomly prepared data set was considered for the training data set, and the remaining 30% went for the testing data set. The outcomes showed that using optimization algorithms, specifically those with the ML method GWO, significantly impacts anticipating and identifying more susceptible landslides. Notably, they realized that forest age and diameter are the most influential factors used in the study. In a systematic review paper, some of the shortcomings of applying ML algorithms in geo-structure reliability evaluations was mentioned (Zhang *et al.*, 2023a, 2023b). In a new study, Tran *et al.* (2024) used a combination of Finite Element Limit Analysis (FELA) and Artificial Neural Network (ANN) to develop failure envelopes in strip footing created on anisotropic clays subjected to general loads. They stated that there are reasonable connections between input data (obtained from FELA) and output data (trained by ANN) compared to output data from FELA. Despite fascinating advances concerning using ML in geotechnical reliability analysis, they declared significant drawbacks. For instance, the analysis should consider the effect of available factors during the time, while most of the study is conducted at a specific time. Moreover, evaluations should use a three-dimensional analysis to obtain exact results. Finally, it is necessary to develop new updates in ML techniques that require fewer training data sets to increase computational efficiency because conducting suitable training data sets with the current approaches requires time-consuming reliability analysis. These studies show that ML is a helpful tool for creating a standardized presentation of the slope profile and allows for accurate slope reliability examinations. Among these methods, ANN, SVM, LS-SVM, and GP are more popular (Sakellariou and Ferentinou, 2005; Pal and Deswal, 2010; Samui *et al.*, 2013; Goh and Kulhaw, 2003; Alidadi and Pezeshk, 2024). The literature describes the benefits and drawbacks of each method mentioned. Many of these general conclusions are listed below:

- ANN uses many hidden layers and nodes, and acquiring an optimal compound becomes complicated, while LS-SVM includes two hyper-parameters (Samui *et al.*, 2013).
- If the training data sets are chosen incorrectly, results of GP and NN methods culminate in incorrect interpretations of local minimums, while these obstacles are covered by SVM and LS-SVM methods (Gunn, 1998; Suykens and Vandewalle, 1999; Rasmussen and Williams, 2006; Gori and Tesi, 1992).
- Using kernel functions in regression GP act appropriately, like SVM and regression LS-SVM, and inappropriately for the NN process (Bennett and Campbell, 2000).

LS-SVM involves the benefits of SVM, such as providing strong normalization capabilities and supplementary superiorities. The loss function in LS-SVM relies on the least-square errors rather than nonnegative errors. Hence, LS-SVM manifests the training model as a linear function that reduces computational time rather than a quadratic programming function. LS-SVM's hyperparameters are regularization and kernel functions that enhance their efficiency. This study primarily assesses the application of regression LS-SVM for two soil slopes created on a linear anisotropic model to examine the accuracy of this machine-learning technique compared to the limit equilibrium method (LEM)-based MCS method. In this study, LS-SVM predicts FS and PF for both anisotropic soil slopes based on input data sets. The work is structured as follows. The principles of LS-SVM regression are mentioned in Section 2. The considered anisotropic criterion is introduced in Section 3 and variables used in the model for each layer are also defined in Section 3.1. In Section 4, two examples of applying the proposed method are introduced. Section 5 proposes techniques for data scattering. Section 6 discusses the assessment of PF and FS, and Section 7 provides conclusions.

3. Basics of the least-square support vector machine regression

This research aims to survey the power of regression LS-SVM in the prediction of FS and PF. The training and testing data sets, RBF kernel and generalization approach have been employed using MATLAB. Consider a training data set included N points, $\{\mathbf{x}_i, y_i\}_{i=1}^N$, while input data sets are $\mathbf{x}_i \in \mathbf{R}^n$, and output data sets are $y_i \in \mathbf{R}$. $\mathbf{R}^n$ and $\mathbf{R}$ form n -dimensional and one-dimensional vector spaces, respectively. In the feature space, the LS-SVM model is defined as:

$$y_{(i)} = \mathbf{w}^T \varphi(\mathbf{x}_i) + b + e_i \quad i = 1, \dots, N \quad (1)$$

In explaining LS-SVM's performance, the optimization subject is constructed in a primal weight space:

Minimization Function:

$$\mathcal{J}(\mathbf{w}, \mathbf{e}) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \gamma \sum_{i=1}^N e_i^2 \quad (2)$$

In the above formula, $\mathcal{J}$ = cost function including fitting errors e_i (Sum Squared Error); γ = positive constant indicating the effect of regularization term; $\mathbf{w}$ = tuneable weight vector ($\mathbf{w} \in \mathbf{R}^n$); eventually b = reflect the bias phrase ($b \in \mathbf{R}$). Particularly, $\varphi(\cdot)$ as a nonlinear function transmits the primitive

input data set $\mathbf{x}_i$ to a feature space with a higher dimension. Then it turns a nonlinear objective function into a linear function to consider a regression analysis. This act culminates in a simplified cost function. See Equation (2) and Figure 1 (Samui and Kothari, 2010).

The LS-SVM in primal weight space computes the following formula:

$$y(\mathbf{x}) = \mathbf{w}^T \varphi(\mathbf{x}) + b \quad (3)$$

As the weight vector is made of high dimensions, it is unfeasible to solve $\mathbf{w}$ from equation (2) directly. So, LS-SVM model is fabricated in a dual-space. The Lagrangian mechanism is defined as:

$$\mathcal{L}(\mathbf{w}, b, \mathbf{e}; \boldsymbol{\alpha}) = \mathcal{J}(\mathbf{w}, \mathbf{e}) - \sum_{i=1}^N \alpha_i \left\{ \left[\mathbf{w}^T \varphi(\mathbf{x}_i) + b + e_i \right] - y_i \right\} \quad (4)$$

The values of α_i create the “support” vectors $\boldsymbol{\alpha}$. ($\alpha_i \in \mathbf{R}$) The optimal solution for this equation is specified in equation (5):

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial \mathbf{w}} = 0; & \mathbf{w} = \boldsymbol{\alpha}^T \varphi(\mathbf{x}_i) \\ \frac{\partial \mathcal{L}}{\partial b} = 0; & \sum_{i=1}^N \alpha_i = 0 \\ \frac{\partial \mathcal{L}}{\partial e_i} = 0; & \alpha_i = \gamma e_i \\ \frac{\partial \mathcal{L}}{\partial \alpha_i} = 0; & \mathbf{w}^T \varphi(\mathbf{x}_i) + e_i - y_i = 0 \end{cases} \quad (5)$$

$i = 1, \dots, N$

According to equation (5), the solutions are the support vector ($\boldsymbol{\alpha}$) and the bias term (b):

$$\begin{bmatrix} 0 & \mathbf{1}_v^T \\ \mathbf{1}_v & \Omega + \frac{1}{\gamma} \mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \quad (6)$$

where $\mathbf{1}_v = [1, \dots, 1]$; $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_N]$; $\mathbf{y} = [y_1, \dots, y_N]$; and Ω = a matrix including the inputs of $\Omega_{ij} = \varphi(\mathbf{x}_i)^T \varphi(\mathbf{x}_j)$ for $i, j = 1$ to N . Furthermore, according to Mercer's clause the

mapping function $\varphi(\cdot)$, is distinguished through a kernel function:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i)^T \varphi(\mathbf{x}_j), i, j = 1, \dots, N \quad (7)$$

For RBF, the following equation applies:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp \left\{ - \left| \mathbf{x}_i - \mathbf{x}_j \right|^2 / \sigma^2 \right\} \quad (8)$$

Considering σ as a predefined constant of the RBF equation. Eventually, the LS-SVM mechanism for function anticipation is acquired as follows:

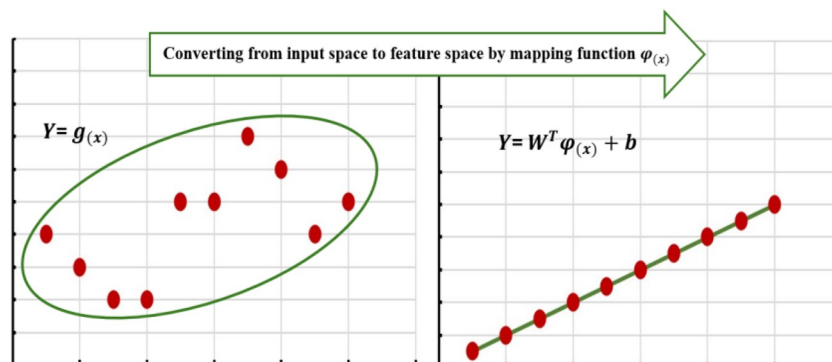
$$y(\mathbf{x}) = \sum_{i=1}^N \alpha_i K(\mathbf{x}, \mathbf{x}_i) + b \quad (9)$$

The results of LS-SVM depend on σ and γ . These coefficients are characterized (or trained) through trial and error to arrive at an optimal solution. Determining these parameters enables the developed LS-SVM to create a relationship between input (training data) and output data (testing data). Then, the developed LS-SVM is used to define the estimated data sets. The Toolbox of LS-SVMlab implemented LS-SVM, and the authors performed coding.

3.1 The utilization of least-square support vector machine in slope stability modeling

Factor of Safety: Due to various uncertainties in geotechnical assessments, slope stability is one of the issues that should be modeled probabilistically. Moreover, FS is a function of geotechnical parameters that define the state of stability involving unit weight, soil strength parameters and geometries. As previously mentioned, the FS function is presented explicitly for most geotechnical issues. As a result, the most common numerical simulation methods used are LEM, FEM and FDM. In this study, the following variables were used in the linear anisotropic model of soil slope. These variables were cohesion C , frictional angle Φ , anisotropic angle β , unit weight γ and parameters that define linear transition A and B, which will be defined in

Figure 1 Conversion from input space to feature space



Source: (After Ji et al., 2017)

section 3. They are shown as a vector $\mathbf{x} = [x_1, x_2, \dots, x_n]$. Thus, FS is defined considering every slope variable as follows:

$$FS = LS - SVM(x) = LS - SVM(x_1, \dots, x_n) \quad (10)$$

Probability of Failure: PF for n test number is set by Latin Hypercube Sampling (LHS) as follows:

$$PF = \frac{n' [LSSVM(x_1, \dots, x_N) < 1]}{n} \quad (11)$$

where $n' [LSSVM(x_1, \dots, x_N) < 1]$ indicates the number of LHS outputs that are less than one (Ji *et al.*, 2017). PF is measured by the number of safety factors that are less than 1.0 divided by the whole number of converged Latin Hypercube trials. LHS enables researchers to design experiments with as many points as required or expected. Moreover, for computer analyses, it is an appealing sampling technique that is flexible enough to provide data and not only is suitable for modeling under a variety of assumptions but can cover small and large design areas (Viana, 2013).

4. Failure criterion

Geotechnical engineering is afflicted by complexity and variability. Measurement and model uncertainties and spatial variability are potential sources of uncertainties (Phoon and Kulhawy, 1999; Tatsuoka *et al.*, 1990) concentrated on the influence of inherent anisotropic on the air pluvial Toyoura and Shirasu sands, accounting for most of the overall uncertainty. He found that the soil mass's friction and dilation angles decreased as the bedding plane angle increased. For example, in Toyoura sand, as the direction of the maximum stress obliquity plane approached that of the bedding plane direction, the angle of internal friction decreased. Another study investigated the effect of anisotropy on shear strength parameters experimentally to validate their numerical modeling (Tong *et al.*, 2014). However, only a few studies have simultaneously looked at a frictional angle, cohesion and unit weight anisotropy and compared findings to the LS-SVM process. In this study, an anisotropic model of a cohesive frictional body is presented, where the anisotropy is introduced by weak planes and different characteristics than the soil "matrix." In this way, frictional angle, cohesion, unit weight, anisotropic angle and the slope profile's linear transformations from bedding plane to soil mass were all considered.

4.1 Anisotropic linear modeling

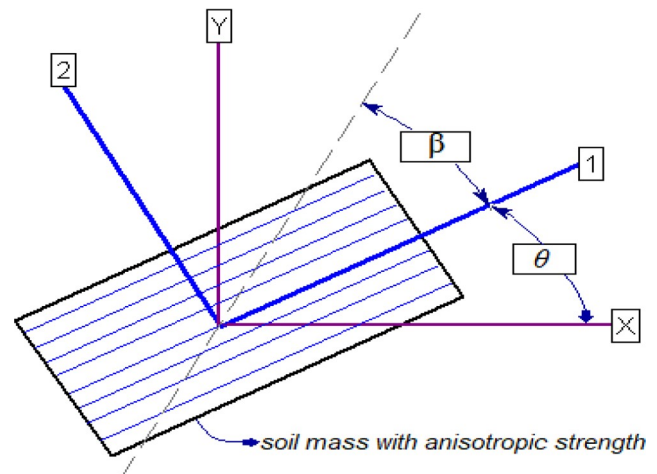
The Linear Anisotropic approach was suggested by Snowden (2007). He specified variables that included the anisotropy characteristics of the slope model as follows:

- Minimum shear strength C_1, Φ_1 for bedding plane.
- Maximum shear strength C_2, Φ_2 for soil mass.
- Anisotropic angle β for an arbitrary plane.
- Bedding plane direction angle θ from horizontal.
- Linear transformation parameters A, B from bedding plane strength to soil mass strength.

The Anisotropic Linear approach is according to the Mohr-Coulomb model. This method assumes minimum shear

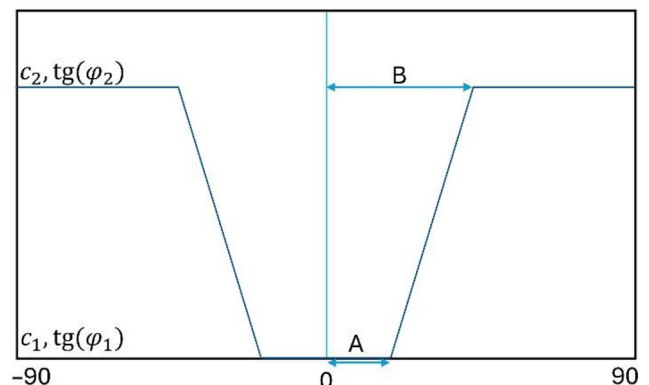
strength happens in the bedding plane's orientation. In the following Figure 2, a two-direction plot shows the bedding plane characterized by parameters C_1, Φ_1 and an arbitrary plane characterized by C_2, Φ_2 but has the parameters according to Figure 3, which is taken by β angle from the direction 1. Consider an arbitrary plane that makes an β angle concerning the 1-direction, as shown in the following Figure 2. This represents the orientation of a respective slice base. The relation between shear strength parameters and β angle is represented as follows. Based on the anisotropic input variables ($C_1, \Phi_1, C_2, \Phi_2, A, B, \beta$), the cohesion and the tangent of a frictional angle are calculated for any plane orientation in Figure 3. Parameter A represents half of an angular range for the bedding planes for which the shearing strength parameters are C_1, Φ_1 . It should be noted that $B > A$. Between two ranges (for $A < \beta < B$) parameters C_2, Φ_2 are assumed based on the linear transition. In cases β beyond B , parameters C_2, Φ_2 are assumed for soil mass (Figure 3) (Snowden, 2007).

Figure 2 The direction of an individual plane



Source: (After Snowden, 2007)

Figure 3 Anisotropy angle (β)



Source: (After Snowden, 2007)

According to the proposed method, the computing of shear strength parameters is calculated based on the t variable defined as:

$$t = \frac{|\beta| - A}{B - A} \quad (12)$$

The cohesion and friction angle are then calculated using the following equations:

$$\begin{cases} t \leq 0 & C = C_1 \\ 0 < t < 1 & C = C_1(1 - t) + C_2(t) \\ t \geq 1 & C = C_2 \end{cases} \quad (13a)$$

$$\begin{cases} t \leq 0 & \tan\Phi = \tan\Phi_1 \\ 0 < t < 1 & \tan\Phi = \tan\Phi_1(1 - t) + \tan\Phi_2(t) \\ t \geq 1 & \tan\Phi = \tan\Phi_2 \end{cases} \quad (13b)$$

5. Illustrative examples

Two typical soil slopes based on the linear anisotropic model are evaluated to demonstrate the validity of LS-SVM. The first example is a slope profile from the Association for Computer-Aided Design (Giam and Donald, 1989). As shown in Tables 1 and 2, LS-SVM – a surrogate model for analyzing

this anisotropic soil slope-consists of 20 attributes of soil variables, including 19 attributes for input variables as soil properties according to disparate levels of variation and one for output data or FS. The slope profile is shown in Figure 4. LS-SVM's objective is to measure FS and PF based on training data sets. First, the FS of the slope profile is calculated using LEM-based LHS and the non-circular slip surfaces method. The critical FS was 1.315, with a PF of 2.628%. The most critical surface of the slope passes across all three layers. The modeling result of the anisotropic soil slope is also presented in Figure 4, while the Spencer approach with 35 slices was chosen. For the second and third layers, cohesion and frictional angle are modeled with uniform distributions, and the other variables, such as γ , A , B and β , are distributed normally, as shown in Table 2. In contrast, the results for the same slope profile but with normal cohesion and frictional angle distributions differ. FS is 1.308, with a PF of 0.056%. The strategy for creating LS-SVM parameters is argued subsequently.

6. The influence of data scattering in space-filling by Latin hypercube sampling approach

Since the validity of LS-SVM is heavily dependent on training data, their quality and quantity play crucial roles in predicting FS and PF. Producing enough training data should agree with

Table 1 Soil properties of the first layer

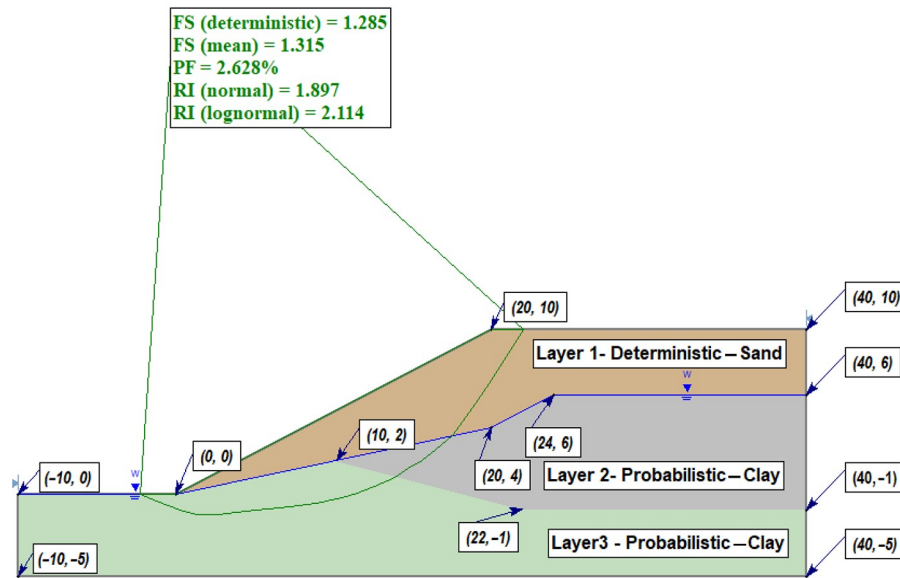
Statement	Strength Type	Cohesion (kPa)		Frictional angle (°)		Unit Weight (kN/m ³)	Statistical distribution
		Mean	COV	Mean	COV		
Sand layer 1	Mohr-Coulomb	0	—	38	—	19.5	NA

Source: Table by authors

Table 2 Soil properties of the second and third layers

Statement	Attribute	Distribution	Mean	Std. dev	Rel. min	Rel. max
Clay Layer 2	Cohesion ₁ (kPa)	Uniform	7.8	—	1	3
Clay Layer 2	Φ_1 (°)	Uniform	34	—	9	9
Clay Layer 2	Cohesion ₂ (kPa)	Uniform	5.3	—	1	3
Clay Layer 2	Φ_2 (°)	Uniform	23	—	9	9
Clay Layer 2	Unit Weight (kN/m ³)	Normal	19.5	9	1.5	1.5
Clay Layer 2	A angle (°)	Normal	27	1	2	2
Clay Layer 2	B angle (°)	Normal	10	1	2	2
Clay Layer 2	Anisotropic Angle β (°)	Normal	28	3	9	9
Clay Layer 3	Cohesion ₁ (kPa)	Uniform	9.6	—	1	3
Clay Layer 3	Φ_1 (°)	Uniform	33	—	9	9
Clay Layer 3	Cohesion ₂ (kPa)	Uniform	7.2	—	1	3
Clay Layer 3	Φ_2 (°)	Uniform	20	—	9	9
Clay Layer 3	Unit Weight (kN/m ³)	Normal	19.5	9	1.5	1.5
Clay Layer 3	A angle (°)	Normal	25	1	2	2
Clay Layer 3	B angle (°)	Normal	12	1	2	2
Clay Layer 3	Anisotropic Angle β (°)	Normal	18	3	9	9

Source: Table by authors

Figure 4 Slope profile of example one

Source: (After Ji *et al.*, 2017)

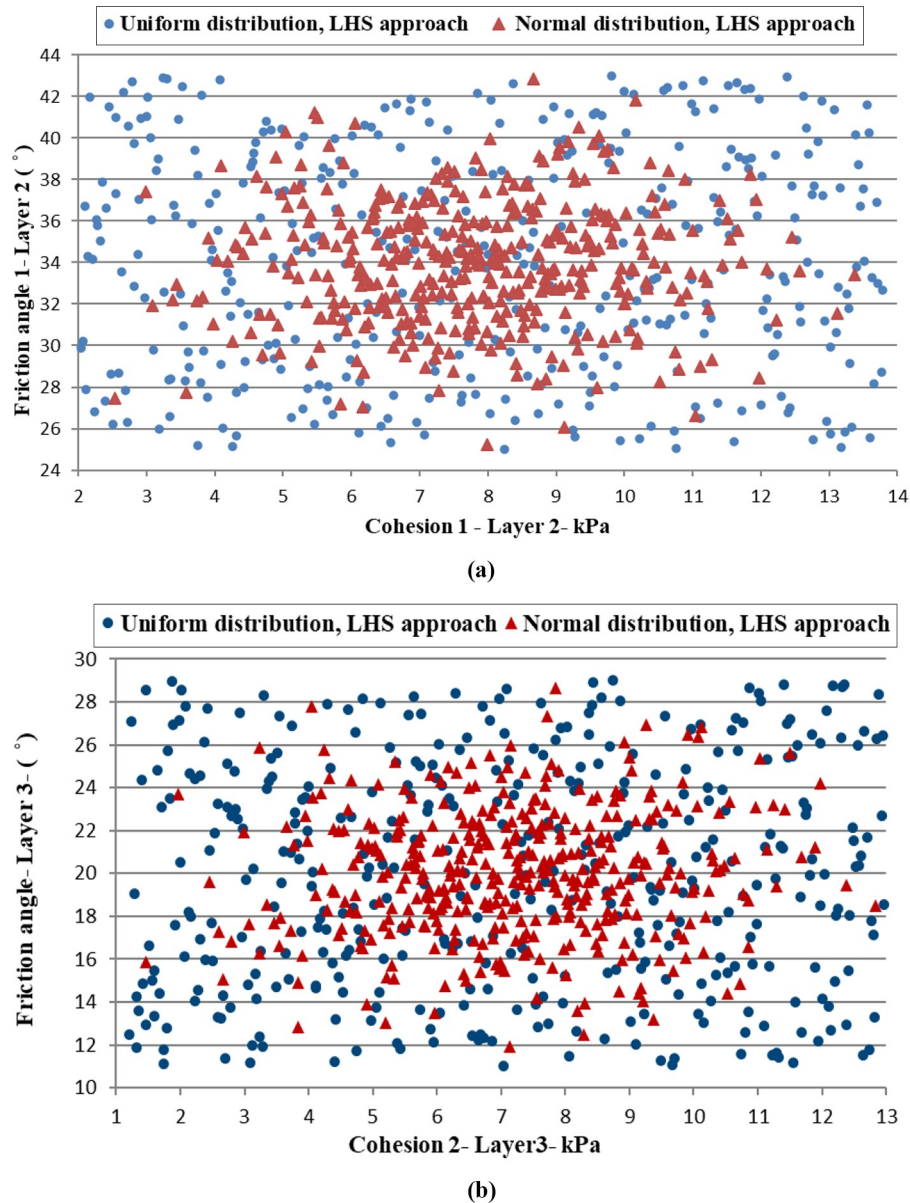
specific criteria. While generating a small size of training data sets culminates in missing out on the “support” elements, a superfluous size will result in surplus computations. That is an obstructive issue as it leads to a decrease in LS-SVM accuracy. Consequently, using less than 650 training data sets in this study (Figure 8) was considered a reasonable choice. Furthermore, to capture a global characteristic of the slope profile, two of the trained variables (in both examples, C and Φ) were distributed uniformly, reflecting not only a local-in the vicinity of mean value-but a general characteristic of the variables compared to a normal distribution. Although various techniques for using uniform sampling exist, LHS is a flexible method (Pronzato and Muller, 2012). LHS was implemented for multivariate statistical distributions of various types (Palisade Corporation, 2009). As a result of poor space-filling, there are many inefficiencies in using LS-SVM. For example, some areas can occur in the profile in which sufficient information is not obtained. This study distributed variables C and Φ for each clay layer uniformly based on the LHS technique. The effect of LHS performance in space-filling for 400 data sets of the anisotropic soil slope parameters is shown in Figure 5.

One hundred and fifty training and 1,850 testing data sets were generated based on normal and uniform distributions using the LHS technique, as shown in Figures 6 and 7, respectively. The model predicted reasonably well for $FS > 1.15$ for the uniformly trained data set, as depicted in Figure 6, but its proficiency worsens sharply when FS becomes less than $FS = 1.0$. In the normal distribution (Figure 6), owing to the high probability of occurrence near the mean value of FS , more samples are chosen and fewer in other areas. In this situation, the success of global prediction is not guaranteed. In contrast, the operation of trained LS-SVM under uniform distributions is shown in Figure 7. The difference in the scattering of FS is noticeable. The combination of LHS and

imposed uniform design balances FS distribution. That is one of the most important results of space-filling with different distributions of training data sets. Although using a uniform distribution and changing data set size is desirable, the tabularized uniform design sampling data significantly requires additional computational effort as the data dimension rises. The rule of thumb says that a size of 10 to 15 times training data sets of the dimension of the random variables could be eligible (Kang *et al.*, 2015), and as a result, the execution of LS-SVM depends on the size of the training data, which ranges between 100 and 200 in this study. The execution of LS-SVM becomes optimized when the numbers of training data sets obtain a particular number (using minimum data). While, increasing training data set should not lead to overfitting.

7. The application of least-square support vector machine in modeling factor of safety and probability of failure

To cover all possible failure modes, the analysis of PF requires a large number of FS estimations on slope surfaces. It has been proven that the multiple response surfaces method is acceptable for assessing multilayered slopes. The controversial aspect is determining the size and type of the multiple response surfaces, as they require a substantial amount of additional effort. These kinds of complex slopes could easily be analyzed using LS-SVM as an alternative method (Ji *et al.*, 2017). A comparison between FS computed by LEM-based MCS and estimated FS by LS-SVM for 51 output data sets and 99 training data sets is shown in Figure 9. The LS-SVM model reflects an acceptable connection between 19 input variables and FS as the only output variable. It can be seen that the FS estimated by LS-SVM is in an acceptable agreement with FS measured by LEM-based MCS for more than 94% while the LS-SVM was trained only with 99 training data sets. The

Figure 5 Space-filling performance with LHS for 400 data sets

Notes: (a) layer two (C_1, Φ_1); (b) layer three (C_2, Φ_2)

Source: Figure by authors

robustness of the LS-SVM method is validated through Figure 9 with converging 19 input variables, resulting in an FS as a final output using only 99 training data sets. For both Spencer and Bishop's simplified methods, LHS results according to LS-SVM and Direct MCS demonstrating the effectiveness of the proposed approach are depicted in Table 3. As can be seen, the FS and PF computed by MCS and LS-SVM under the Spencer model are close to each other, while MCS uses 25,000 simulations and LS-SVM uses only 150 training data sets (the additional 400 data sets are considered for testing data sets). The same procedure applies to the two different methods under the Bishop Simplified model.

However, more discrepancy is observed in comparing PFs to FSs. To compare the efficiency of two models of ML, the accuracy of LS-SVM and SVM with two kinds of Kernel functions (RBF and Linear) for the same amount of data (150 training data against 400 testing data) is shown in Table 4. The results show that the combination of LS-SVM and RBF Kernel outperforms SVM and Linear Kernel, due to fewer errors and higher correlation. Linear LS-SVM and linear SVM were ranked, respectively. This outperforming proves that using the right ML model (LS-SVM or SVM) is prioritized over choosing the suitable Kernel function. PF calculated using the LS-SVM method agrees with that measured using direct MCS

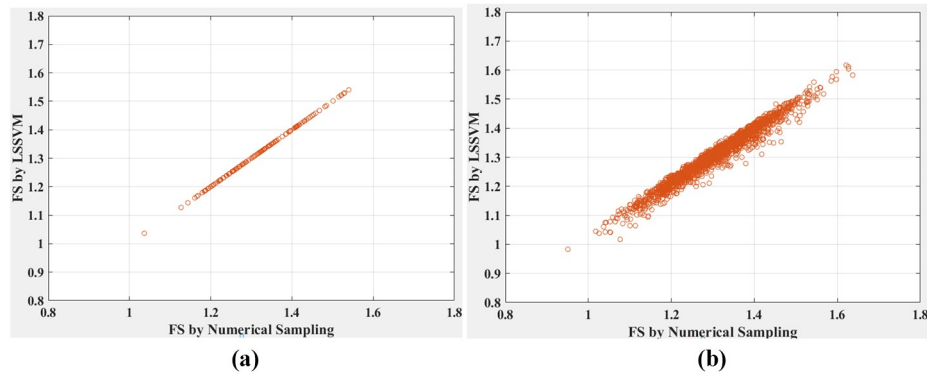
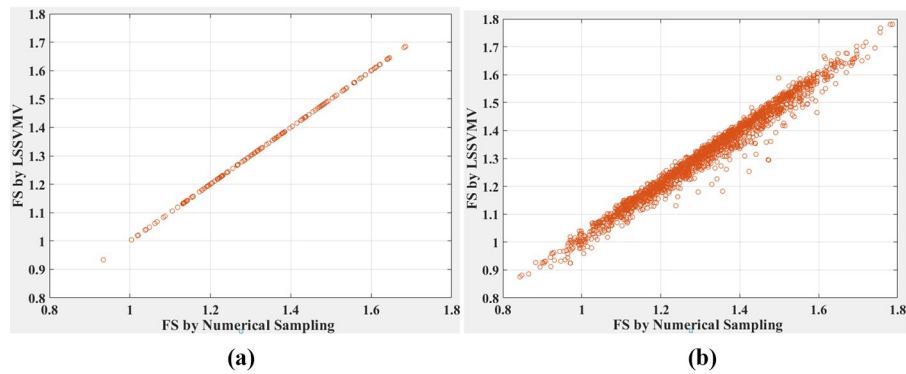
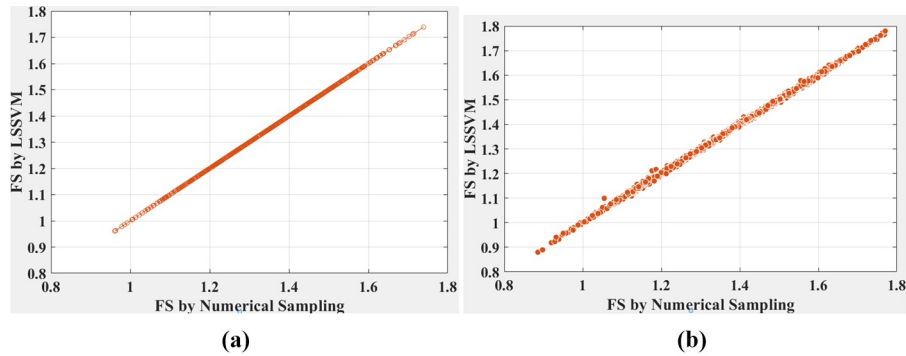
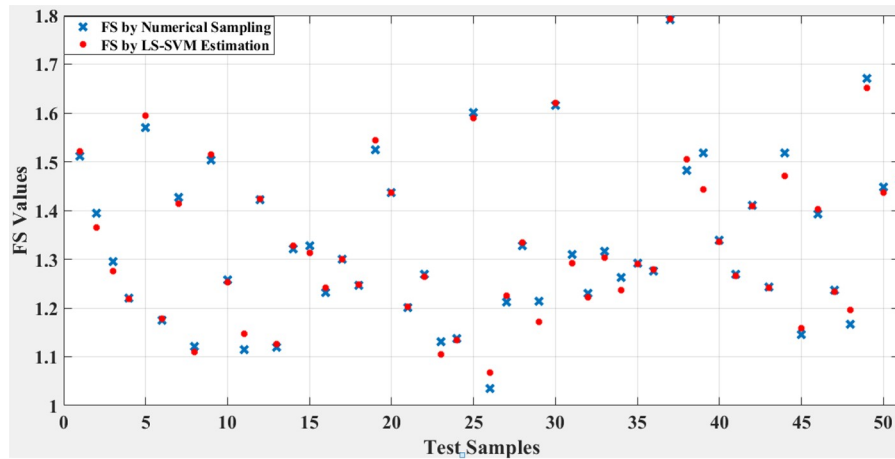
Figure 6 LHS subjected to normal distributions**Notes:** (a) 150 training data; (b) 1850 testing data**Source:** Figure by authors**Figure 7** LHS subjected to uniform distributions**Notes:** (a) 150 training data; (b) 1850 testing data**Source:** Figure by authors**Figure 8** LHS subjected to uniform distributions for overfitting modeling**Notes:** (a) 650 training data; (b) 2200 testing data**Source:** Figure by authors

Figure 9 Comparison of FS results for example 1

Source: Figure by authors

Table 3 Comparison of failure probabilities

Probabilistic Model	FS Model	Probability of Failure (%)	FS
Direct MCS, 25000	Spencer	2.5	1.316
LHS, LSSVM, 550	Spencer	2.73	1.312
Direct MCS, 25000	Bishop Simplified	6.604	1.242
LHS, LSSVM, 550	Bishop Simplified	5.97	1.24

Source: Table by authors

Table 4 Comparison of model accuracy

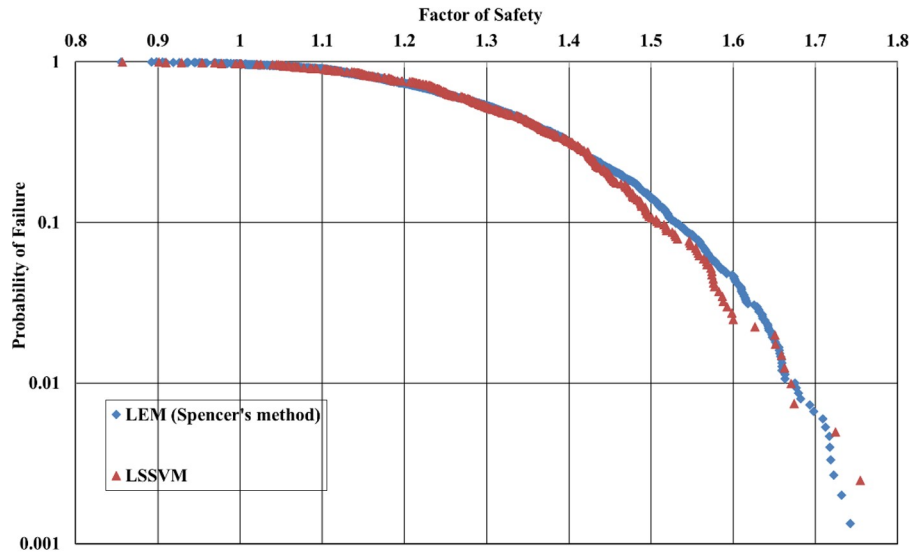
Kernel Function	Model	MSE	MAE	Correlation
RBF	LSSVM	0.0004	0.0152	0.9927
RBF	SVM	0.0025	0.0353	0.9662
Linear	LSSVM	0.0007	0.0195	0.9877
Linear	SVM	0.0007	0.0182	0.9871

Source: Table by authors

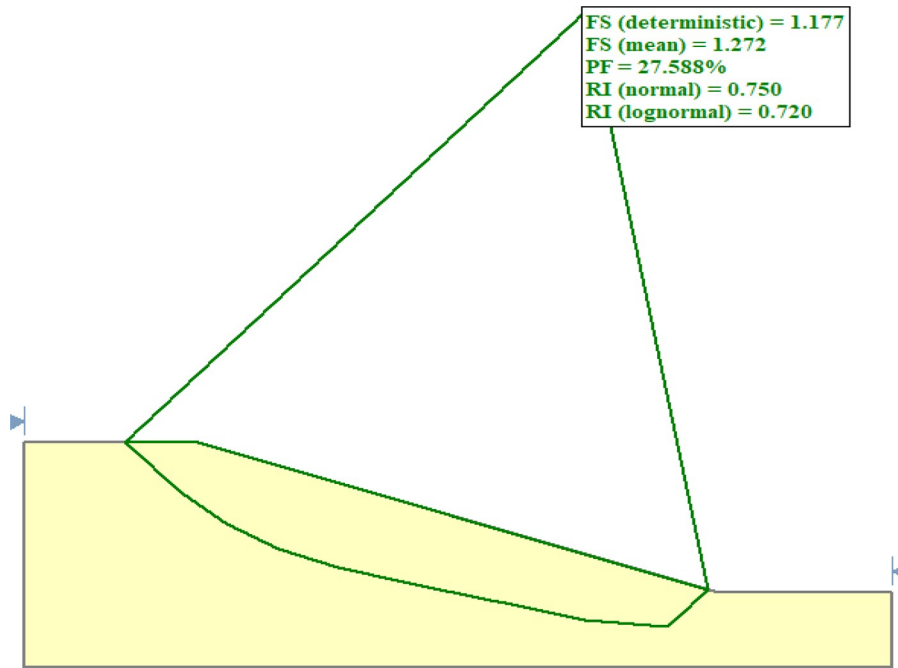
specially for $FS < 1.423$, as depicted in Figure 10, while the LS-SVM method needed merely 150 runs of FS (training data), and the direct MCS required 25,000 runs. The performance of the LS-SVM model in Figure 10 shows several incorrect estimations for $FS > 1.423$ that are mostly attributed to deterministic values of the first layer (sand) that had yet to be modeled probabilistically. Initially, the LS-SVM was modeled with 150 data sets, including probabilistic distributions for variables of layers two and three (clay layers) and deterministic values for layer one (sand layer) since cohesion = 0 kPa and friction angle = 38° , respectively, and without any probabilistic distributions. As a consequence, the LS-SVM was unable to consider the changes of the cohesion parameter probabilistically in layer one for this complex slope, and

LS-SVM did not prosper to learn the failure mechanisms entirely in this layer due to a lack of diversity in cohesion and friction angle values in sand layer. In other words, only if all layers participate in the stability analysis with their probabilistic distributions it is possible to generate accurate training data and, consequently, accurate prediction of PF and FS of soil slope by the LS-SVM method. Increasing the number of training data sets and considering the variability of the sand layer is one way to boost the prediction. However, the increased computational effort has no discernible effect on the accuracy of system failure prediction. Another significant issue that should be considered is perceiving overfitting risk in training data. The authors performed another analysis on the soil slope profile of example one with 650 training data sets (Figure 8). The results show approximately a 4% difference between PF obtained by testing data sets in LS-SVM compared to the LEM-based MCS on slide software. While this accuracy is impressive, the crucial point is that when preparing training data sets, we must avoid overproduction, which leads to overfitting. Overfitting jeopardizes computational efficiency, and researchers should refrain from using the results of training data sets overproduction in other studies. Although overfitting may result in a highly reliable relationship between training and testing data specified in one slope profile, expecting such accuracy in other problems is not guaranteed and leads to poor, and high-error predictions. As a result, achieving excessive accuracy may not be always desired and efficient.

In the second example, an anisotropic one-layer clay slope exemplifies the other prosperous usage of LS-SVM for slope reliability (Zhao, 2008). The soil slope profile for the 25,000 simulations under the LHS and non-circular slip surfaces method is depicted in Figure 11 with the associated mean FS and PF. The assumed properties of the soil are listed in Table 5. As discussed in Section 4, two types of cohesions and friction angles should be defined, and notably only cohesion values are distributed uniformly. One hundred and fifty training data sets and 400 testing data sets are used here. Moreover, eight input variables as vector x that includes $[\gamma, c_1, c_2, \phi_1, \phi_2, \beta, A, B]$ representing anisotropic clay characteristics are used. These

Figure 10 Comparison of PF-FS for anisotropic slope-example 1

Source: Figure by authors

Figure 11 Slope profile of example two

Source: (After Zhao, 2008)

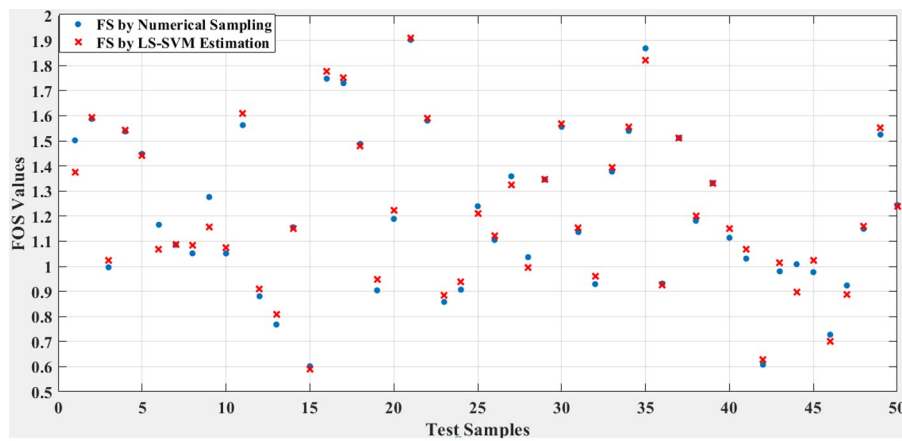
input data have been created based on the LEM-based LHS technique. A comparison of the LS-SVM method's predicted FS with that of an LEM-based LHS model is shown in Figure 12 for 99 training and 51 testing data sets. Although few discrepancies are observed between estimated and measured data in Figure 12 such as test samples number 1, 6, 9 and 44, the overall trend indicates a reliable agreement. A comparison of FS and PF from Direct MCS and LS-SVM in Spencer and

Bishop's Simplified methods is also depicted in Table 6. For only 150 training data sets, the LS-SVM model performs with high similarity to the LEM-based MCS method in both Spencer and Bishop Simplified methods, expectedly. To clarify, FS obtained from MCS and LS-SVM under the Spencer method are 1.335 and 1.31 while the first method needed 25,000 runs and the second method needed only 150 runs. Please note that the 550 mentioned in Table 6 is the

Table 5 Soil properties of example two

Statement	Attribute	Distribution	Mean	SD	Rel. min	Rel. max
Clay Layer 1	Cohesion 1 (kPa)	Uniform	15	—	1	3
Clay Layer 1	Φ 1 (°)	Uniform	18	—	9	9
Clay Layer 1	Cohesion 2 (kPa)	Uniform	9	—	1	3
Clay Layer 1	Φ 2 (°)	Uniform	9	—	9	9
Clay Layer 1	Unit Weight (kN/m ³)	Normal	20	9	1.5	1.5
Clay Layer 1	A angle (°)	Normal	10	1	2	2
Clay Layer 1	B angle (°)	Normal	30	1	2	2
Clay Layer 1	Anisotropic Angle β (°)	Normal	16	3	9	9

Source: Table by authors

Figure 12 Comparison of FS results for example 2

Source: Figure by authors

Table 6 Comparison of failure probabilities

Probabilistic Model	FS Model	Probability of failure (%)	FS
Direct MCS, 25000	Spencer	12.824	1.335
LHS, LSSVM, 550	Spencer	13.47	1.31
Direct MCS, 25000	Bishop simplified	15.104	1.319
LHS, LSSVM, 550	Bishop simplified	16.2	1.328

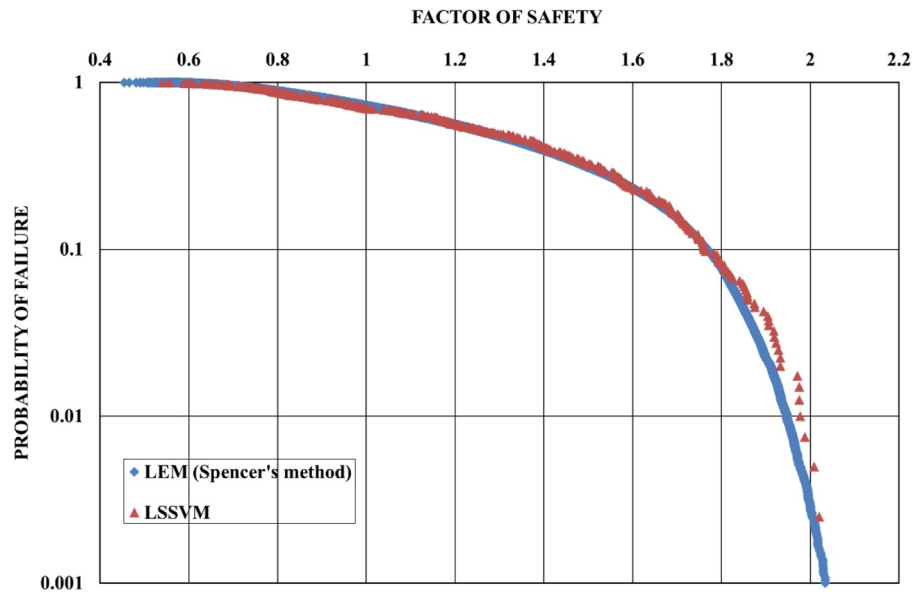
Source: Table by authors

entire number of training (150) and testing (400) data sets. One of the most important reasons is that the entire layer has been subjected to probabilistic analysis, and the attributes mentioned in Table 5 have been trained with their probabilistic distributions LS-SVM. Even though both methods can analyze PF, a combination of LS-SVM with LEM-based LHS has advantages mentioned in the following: (1) this technique considers data scattering completely in producing data. (2) Since LEM-based LHS strengthens the general prediction of FS, it allows the surrogate model to be used in various situations regarding soil slope (Ji *et al.*, 2017). PF-FS plot of the second example is shown in Figure 13. The improvement of estimated FSs and PFs in the LS-SVM method is remarkable in

the entire trend in Figure 13, compared to Figure 10. One of the main reasons is all attributes of soil slope were trained probabilistically during the progression of the LS-SVM model. Consequently, a superior application of LS-SVM performance for this One-layer clay slope has resulted as expected.

8. Conclusions

This study applied LS-SVM combined with LEM-based LHS as a surrogate model for stability analysis of anisotropic slopes based on two typical soil slope examples. At first, 25,000 LHS was used to analyze two soil slope profiles. Nineteen and eight variables were used as input data in two examples, respectively. The generated data sets with uniform distributions were then used in LS-SVM. The minority of these data sets were used as training data, and the remainder were used as testing data. Next, based on input training data sets, the LS-SVM method produced estimated FSs. Estimated FSs were then compared with FSs obtained from LEM-based MCS to indicate the efficiency of LS-SVM in estimating FS and PF with lower data computationally (see Figures 9 and 12). Furthermore, another comparison between PFs obtained from LS-SVM and direct MCS methods was performed. (Table 6). Significantly, the proposed approach demonstrated adequate efficiency in slope system reliability.

Figure 13 Comparison of PF-FS for anisotropic slope-example 2

Source: Figure by authors

The following is a conclusion of the paper's results:

- LS-SVM used uniform distributions for cohesion and frictional angle parameters in clay layers to develop more reasonable outputs (FS) based on input data sets (Figures 5 and 7). Consequently, even for multi-failure slopes, the LS-SVM model can predict PF and FS with high degree of accuracy, provided that all soil layers are incorporated with their probabilistic distributions.
- We must use probabilistic distributions in designing every layer to obtain the best-fitted results for FS and PF in the LS-SVM method. In this situation, LS-SVM and training data can learn much better about each layer's engineering attribute, such as cohesion, frictional angle and FS. In the first example and considering Table 3, there was about a 9% difference between the PF of LEM-based MCS and LS-SVM methods. This error was significantly due to the deterministic value of the cohesion in layer one (sand layer) that was not considered probabilistically in modeling. However, this difference dropped into 5% in the second example, according to Table 6.
- LS-SVM method's high power and capacity was demonstrated by its ability to produce estimated FSs with high accuracy compared to FS computed by LEM-based MCS. In the first example, nineteen variables and in the second example, eight variables of soil characteristics-under different distributions-were included in the modeling, and it is observed that the accuracy of estimated FSs benefited from high accuracy, while a lower amount of data (150 training data sets) was used in training LS-SVM model.
- While more training data sets lead to greater precision, one of the critical responsibilities of the LS-SVM method is analyzing the problem within an optimal size of training data sets. Tables 3 and 6, Figures 10 and 13 present the numerical proficiency of the model by comparing the results of generating 150 training data against 25000 data. Because

of this, smaller training data sizes are recommended for slope stability analyses with less complexity (less than 50).

- Using an optimization algorithm on the LS-SVM method is recommended to obtain more fitted hyperparameters, resulting in fewer errors. Also, more studies are needed to consider the effect of added uncertainty caused by non-cohesive layers in the training data.

References

- Ahangar-Asr, A., Faramarzi, A. and Javadi, A.A. (2010), "A new approach for prediction of the stability of soil and rock slopes", *Engineering Computations*, Vol. 27 No. 7, pp. 878-893.
- Alidadi, N. and Pezeshk, S. (2024), "Ground-Motion model for small-to-moderate potentially induced earthquakes using an ensemble machine learning approach for CENA", *Bulletin of the Seismological Society of America*, Vol. 114 No. 4, pp. 2202-2215.
- Assouline, S. and Or, D. (2006), "Anisotropy factor of saturated and unsaturated soils", *Water Resources Research*, Vol. 42 No. 12, p. W12403.
- Bennett, K.P. and Campbell, C. (2000), "Support vector machines: hype or hallelujah?", *ACM SIGKDD Explorations Newsletter*, Vol. 2 No. 2, pp. 1-13.
- Bozorgpour, M.H., Binesh, S.M. and Rahmani, R. (2021), "Probabilistic stability analysis of geo-structures in anisotropic clayey soils with spatial variability", *Computers and Geotechnics*, Vol. 133, p. 104044.
- Bozorgzadeh, N. and Feng, Y. (2024), "Evaluation structures for machine learning models in geotechnical engineering", *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, Vol. 18 No. 1, pp. 52-59.
- Cheng, M.Y. and Hoang, N.D. (2016), "Slope collapse prediction using Bayesian framework with k-nearest neighbor

- density estimation: case study in Taiwan”, *Journal of Computing in Civil Engineering*, Vol. 30 No. 1, p. 4014116.
- Cheng, N.-D. and Hoang, A. (2015), “Swarm-optimized fuzzy instance-based learning approach for predicting slope collapses in Mountain roads”, *Knowledge-Based Systems*, Vol. 76 No. 11, pp. 256–263.
- Cheung, T. (2012), “Bayesian calibration of slope failure probability”, *Int J Geotech Geoenviron Eng, ASCE*.
- Ching, J., Liao, H.J. and Lee, J.Y. (2011), “Predicting rainfall-induced landslide potential along a Mountain road in Taiwan”, *Géotechnique*, Vol. 61 No. 2, pp. 153–166.
- Cho, S.E. (2010), “Probabilistic assessment of slope stability that considers the spatial variability of soil properties”, *Journal of Geotechnical and Geoenvironmental Engineering*, Vol. 136 No. 7, pp. 975–984.
- Cho, S.E. (2013), “First-order reliability analysis of slope considering multiple failure modes”, *Engineering Geology*, Vol. 154, pp. 98–105.
- Duncan, J.M. (1996), “State of the art: limit equilibrium and finite element analysis of slopes”, *Journal of Geotechnical Engineering*, Vol. 122 No. 7, 577–596, doi: [10.1061/\(ASCE\)0733-9410\(1996\)122:7\(577\)](https://doi.org/10.1061/(ASCE)0733-9410(1996)122:7(577)).
- El-Ramly, H., Morgenstern, N.R. and Cruden, D.M. (2002), “Probabilistic slope stability analysis for practice”, *Canadian Geotechnical Journal*, Vol. 39 No. 3, pp. 665–683, doi: [10.1139/t02-034](https://doi.org/10.1139/t02-034).
- Fenton, G.A. and Griffiths, D.V. (2008), *Risk Assessment in Geotechnical Engineering*, John Wiley & Sons, New York, NY.
- Giam, P.S.K. and Donald, I.B. (1989), “Example problems for testing soil slope stability programs”, *Civil Engineering Research Rep*, No. 8/1989, Monash Univ, Clayton, VIC, Australia.
- Goh, A.T.C. and Kulhawy, F.H. (2003), “Neural network approach to model the limit state surface for reliability analysis”, *Canadian Geotechnical Journal*, Vol. 40 No. 6, pp. 1235–1244.
- Gori, M. and Tesi, A. (1992), “On the problem of local minima in backpropagation”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 14 No. 1, pp. 76–86.
- Griffiths, D.V., Fenton, G.A. and Denavit, M.D. (2007), “Traditional and advanced probabilistic slope stability analysis”, *Probabilistic Applications in Geotechnical Engineering. Geotechnical Special Publication No. 170. Proceedings of the Geo-Denver Symposium, Denver, CO, February 18–21 [Sponsored by the Geo-Institute of ASCE]*.
- Griffiths, D.V., Huang, J. and Fenton, G.A. (2009), “Influence of spatial variability on slope reliability using 2-D random fields”, *Journal of Geotechnical and Geoenvironmental Engineering*, Vol. 135 No. 10, pp. 1367–1378.
- Gunn, S.R. (1998), “Support vector machines for classification and regression”, *ISIS Technical Rep*, No. 14, Univ. of Southampton, Southampton, UK.
- Hakim, W.L., Rezaie, F., Nur, A.S., Panahi, M., Khosravi, K., Lee, C.W. and Lee, S. (2022), “Convolutional neural network (CNN) with metaheuristic optimization algorithms for landslide susceptibility mapping in Icheon, South Korea”, *Journal of Environmental Management*, Vol. 305, p. 114367.
- Hoang, N.D. and Tien, B.D. (2016), “A novel relevance vector machine classifier with cuckoo search optimization for spatial prediction of landslides”, *Journal of Computing in Civil Engineering*, Vol. 30 No. 5, p. 4016001.
- Hoang, N.D. and Pham, A.D. (2016), “Hybrid artificial intelligence approach based on metaheuristic and machine learning for slope stability assessment: a multinational data analysis”, *Expert Systems with Applications*, Vol. 46, pp. 60–68.
- Ji, J. and Low, B.K. (2012), “Stratified response surfaces for system probabilistic evaluation of slopes”, *Journal of Geotechnical and Geoenvironmental Engineering*, Vol. 138 No. 11, pp. 1398–1406.
- Ji, J., Zhang, C., Gui, Y., Lü, Q. and Kodikara, J. (2017), “New observations on the application of LS-SVM in slope system reliability analysis”, *Journal of Computing in Civil Engineering*, Vol. 31 No. 2.
- Jiang, S.H., Li, D.Q., Cao, Z.J., Zhou, C.B. and Phoon, K.K. (2015), “Efficient system reliability analysis of slope stability in spatially variable soils using Monte Carlo simulation”, *Journal of Geotechnical and Geoenvironmental Engineering*, Vol. 141 No. 2, p. 4014096.
- Kang, F., Han, S., Salgado, R. and Li, J. (2015), “System probabilistic stability analysis of soil slopes using Gaussian process regression with Latin hypercube sampling”, *Computers and Geotechnics*, Vol. 63, pp. 13–25.
- Lai, V.Q., Shiau, J., Keawsawasvong, S. and Tran, D.T. (2022), “Bearing capacity of ring foundations on anisotropic and heterogenous clays: FEA, NGI-ADP, and MARS”, *Geotechnical and Geological Engineering*, Vol. 40 No. 7, pp. 3913–3928.
- Li, J. and Dong, M. (2012), “Method to predict slope safety factor using SVM”, *Proc. of the Earth and Space: Engineering, Science, Construction, and Operations in Challenging Environments, Pasadena, CA, United States, ASCE*, pp. 888–899.
- Li, J. and Wang, F. (2010), “Study on the forecasting models of slope stability under data mining”, *Proc. of the Earth and Space: Engineering, Science, Construction, and Operations in Challenging Environments, Honolulu, HI, United States, ASCE*, pp. 765–776.
- Low, B.K., Zhang, J. and Tang, W.H. (2011), “Efficient system reliability analysis illustrated for a retaining wall and a soil slope”, *Computers and Geotechnics*, Vol. 38 No. 2, pp. 196–204.
- Oka, Y. and Wu, T.H. (1990), “System reliability of slope stability”, *Journal of Geotechnical Engineering*, Vol. 116 No. 8, pp. 1185–1189.
- Pal, M. and Deswal, S. (2010), “Modelling pile capacity using Gaussian process regression”, *Computers and Geotechnics*, Vol. 37 Nos 7/8, pp. 942–947.
- Palisade Corporation (2009), “@RISK: risk analysis and simulation add-in for microsoft excel (version 5.5)”, *Palisade Corporation*.
- Phoon, K.K. and Zhang, W. (2023), “Future of machine learning in geotechnics”, *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, Vol. 17 No. 1, pp. 7–22.
- Phoon, K. and Kulhawy, F.H. (1999), “Characterization of geotechnical variability”, *Canadian Geotechnical Journal*, Vol. 36 No. 4, pp. 612–624, doi: [10.1139/t99-038](https://doi.org/10.1139/t99-038).

- Pronzato, L. and Muller, W.G. (2012), "Design of computer experiments: space filling and beyond", *Statistics and Computing*, Vol. 22 No. 3, pp. 681-701.
- Rasmussen, C.E. and Williams, C.K.I. (2006), *Gaussian Processes for Machine Learning*, MIT Press, Cambridge, MA.
- Sakellariou, M. and Ferentinou, M. (2005), "A study of slope stability prediction using neural networks", *Geotechnical and Geological Engineering*, Vol. 23 No. 4, pp. 419-445.
- Samui, P. (2008), "Slope stability analysis: a support vector machine approach. Environ", *Environmental Geology*, Vol. 56 No. 2, pp. 255-267.
- Samui, P. and Kothari, D.P. (2010), "Utilization of a least square support vector machine (LSSVM) for slope stability analysis", *Scientia Iranica*, Vol. 18 No. 1, pp. 53-58.
- Samui, P., Lansivaara, T. and Bhatt, M. (2013), "Least square support vector machine applied to slope reliability analysis", *Geotechnical and Geological Engineering*, Vol. 31 No. 4, pp. 1329-1334.
- Snowden (2007), "Proposal for additional features in Slide2 and SWEDGE", *Unpublished Memorandum to Rockscience*.
- Suykens, J.A.K. and Vandewalle, J. (1999), "Least squares support vector machine classifiers", *Neural Process. Lett.*, Vol. 9 No. 3, pp. 293-300.
- Suykens, J.A.K., Gestel, T., Brabanter, J., Moor, B. and Vandewalle, J. (2002), *Least Squares Support Vector Machines*, World Scientific, Singapore.
- Tatsuoka, F., Nakamura, S., Huang, C. and Tani, K. (1990), "Strength anisotropy and shear band direction in plane strain tests of sand", *Soils and Foundations*, Vol. 30 No. 1, pp. 35-54.
- Tong, Z., Fu, P., Zhou, S. and Dafalias, Y.F. (2014), "Experimental investigation of shear strength of sands with inherent fabric anisotropy", *Acta Geotechnica*, Vol. 9 No. 2, pp. 257-275.
- Tran, D.T., Tran, M.N., Lai, V.Q. and Keawsawasvong, S. (2024), "Advanced FELA-ANN framework for developing 3D failure envelopes for strip foundations on anisotropic clays", *Modeling Earth Systems and Environment*, Vol. 10 No. 2, pp. 2375-2392.
- Viana, F.A.C. (2013), "Things you wanted to know about the Latin hypercube design and were afraid to ask", *10th World Congress on Structural and Multidisciplinary Optimization*, Orlando, FL, pp. 19-24.
- Wang, H.B., Xu, W.Y. and Xu, R.C. (2005), "Slope stability evaluation using back propagation neural networks", *Engineering Geology*, Vol. 80 Nos 3/4, pp. 302-315.
- Wang, Y., Cao, Z. and Au, S.K. (2010), "Efficient Monte Carlo simulation of parameter sensitivity in probabilistic slope stability analysis", *Computers and Geotechnics*, Vol. 37 Nos 7/8, pp. 1015-1022.
- Wang, Y., Zhao, X. and Wang, B. (2013), "LS-SVM and Monte Carlo methods-based reliability analysis for settlement of soft clayey foundation", *Journal of Rock Mechanics and Geotechnical Engineering*, Vol. 5 No. 4, pp. 213-317.
- Wang, M.Y., Liu, Y., Ding, Y.N. and Yi, B.L. (2020c), "Probabilistic stability analyses of multi-stage soil slopes by bivariate random fields and finite element methods", *Computers and Geotechnics*, Vol. 122, p. 103529.
- Yan, X. and Bayes, L. (2011), "Discriminant analysis method for predicting the stability of open pit slope", *Proc. of the International Conference on Electric Technology and Civil Engineering, ICETCE, 22-24, Lushan, China*, pp. 147-150.
- Youssef, A.M. and Pourghasemi, H.R. (2021), "Landslide susceptibility mapping using machine learning algorithms and comparison of their performance at Abha basin, Asir region, Saudi Arabia." *Journal of Geoscience Frontiers*, Vol. 12 No. 2, pp. 639-655.
- Zhang, J., Huang, H.W. and Phoon, K.K. (2012), "Application of the Kriging-based response surface method to the system reliability of soil slopes", *Journal of Geotechnical and Geoenvironmental Engineering*, Vol. 139 No. 4, pp. 651-655.
- Zhang, W., Gu, X., Han, L. and Wang, L. (2023a), "Comprehensive review of machine learning in geotechnical reliability analysis: algorithms, applications and further challenges." *journal of*, *Applied Soft Computing*, Vol. 136, p. 110066.
- Zhang, W., Gu, X., Hong, L., Han, L. and Wang, L. (2023b), "Comprehensive review of machine learning in geotechnical reliability analysis: algorithms, applications and further challenges", *Applied Soft Computing*, Vol. 136, p. 110066.
- Zhao, H. (2008), "Slope reliability analysis using a support vector machine", *Computers and Geotechnics*, Vol. 35 No. 3, pp. 459-467.
- Zhao, H., Yin, S. and Ru, Z. (2012), "Relevance vector machine applied to slope stability analysis", *International Journal for Numerical and Analytical Methods in Geomechanics*, Vol. 36 No. 5, pp. 643-652.
- Zhou, K. and Chen, Z.Q. (2009), "Stability prediction of tailing dam slope based on neural network pattern recognition", *Proc. Of the Second International Conference on Environmental and Computer Science, ICECS '09, 28-30. Dubai, the United Arab Emirates*, pp. 380-383.

Further reading

- Fomenko, I.K., Pendin, V.V. and Gorobtsov, D.N. (2016), "Evaluation of stability of pit in rocky soil", *Mining Science and Technology*, No. 3, pp. 10-21, doi: [10.17073/2500-0632-2016-3-10-19](https://doi.org/10.17073/2500-0632-2016-3-10-19).
- Fomenko, I. and Zerkal, O. (2017), "The application of anisotropy of soil properties in the probabilistic analysis of landslides activity", *Procedia Engineering*, Vol. 189, pp. 886-892.
- Zerkal, O.V. and Fomenko, I.K. (2017), "The application of anisotropy of soil properties in the probabilistic analysis of landslides activity", *Enginernaja Geologia*, Vol. 4, pp. 4-21.

Corresponding author

Ali Doostvandi can be contacted at: ali.doostvandi@gmail.com

For instructions on how to order reprints of this article, please visit our website:

www.emeraldgroupublishing.com/licensing/reprints.htm

Or contact us for further details: permissions@emeraldinsight.com