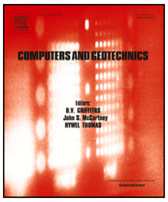
Computers and Geotechnics 161 (2023) 105577

Contents lists available at ScienceDirect

Computers and Geotechnics

journal homepage: www.elsevier.com/locate/compgeo



Research paper

Adaptation of traditional risk-based methodology for slopes to probabilistic-based approach integrating surrogate models[☆]

Carlos Mendoza Cabanzo [*], Joaquim Tinoco, Hélder S. Sousa, Mário Coelho, José C. Matos

University of Minho, ISISE, ARISE, Department of Civil Engineering, Alameda da Universidade, Guimarães 4800 058, Portugal

ARTICLE INFO

Keywords:
Risk analysis
Seismic fragility curves
Parametric analysis
Railway systems
Surrogate models

ABSTRACT

Due to the economic importance that railways systems have in Europe, it is pertinent to ensure good performance and long-term safety. Failure of earth structures (e.g., slopes) often results in major economic consequences, and it is a result of the uncertainties associated with these structures and their failure modes due to a given hazard. Nowadays, different methodologies can be used to assess slopes during operational phases, but often the required information to achieve a reliable assessment may provide the methodologies inapplicable, especially when assessing multiple assets. This research uses methodologies that have been implemented in the industry and adapts them to a probabilistic approach toward risk assessment, supported by the implementation of kriging surrogate model, thus improving its reliability while maintaining the same level of information and computational cost required for its application. A soil cutting located in the Lisbon (Portugal) was selected as case study. Seismic fragility curves are obtained, and a moderate risk level is obtained. The derived fragility curves are based on peak ground acceleration and were developed for different combinations of geometric and geotechnical parameters. The methodology provides useful information for prioritizing assets and taking preventive actions to maintain the desired performance of the railway system.

1. Introduction

Railway systems are significant, and thus the effects due to failures of its assets are of utmost relevance. Asset management is key to maintaining the desired performance level. One of the many ways used in the industry is to prioritize interventions, to reduce risk related to failure according to a risk assessment due to a specific failure mode of a given asset under an expected hazard (Papathanasiou and Adey, 2020, 2021). Failure of earthwork often results in significant damage to the railway system. Thus, management for maintaining the desired performance is of utmost importance (Power et al., 2016).

Currently, there is a wide range of techniques for the assessment of slope stability during the construction phase, but there are not enough methodologies that can be applied during the operational phase. Moreover, it is important that these methodologies work using information that can be easily obtained from inspections, monitoring, or indirect sources (Pinheiro et al., 2015).

Nowadays, the available methodologies for the assessment of slope stability can be organized into different categories, which the most common are either semi-quantitative (Pinheiro et al., 2015; Ersöz and Topal, 2018; Zhang et al., 2018) or quantitative (Cheng et al., 2018; Li et al., 2017; Tang et al., 2018), which the latter usually require more detailed information about the case study and specialized professionals. Likewise, these methodologies can have a deterministic (Pinheiro et al., 2015; Ersöz and Topal, 2018; Zhang et al., 2018) or probabilistic approach (Cheng et al., 2018; Li et al., 2017; Tang et al., 2018; Dyson and Tolooiyan, 2019; Liu et al., 2020; da Silva, 2015; Wang et al., 2020). In the deterministic approach, while useful for faster assessment of a given asset, do not provide a full description of the behavior of the case study because the failure probability is heavily affected by the uncertainties (e.g., parameter, model) and the quality of the data used as inputs (da Silva, 2015).

The following methodologies are used for the assessment of slope stability and are based on empirical methods (Pinheiro et al., 2015; Ersöz and Topal, 2018; Zhang et al., 2018), analytical methods (Li et al., 2017; Tang et al., 2018; Liu et al., 2020) or numerical methods (Cheng et al., 2018; Dyson and Tolooiyan, 2019; Wang et al., 2020). Each one of them has its own advantage in terms of the reliability of the output and the quality and amount of information needed to perform it. Additionally, it may also depend on the type of slope that is going to be studied, e.g., rock (Pinheiro et al., 2015; Ersöz and Topal, 2018;

[☆] This document is the results of the research project funded by the European Regional Development Fund.

[*] Corresponding author.

E-mail addresses: id10427@alunos.uminho.pt (C. Mendoza Cabanzo), jtinoco@civil.uminho.pt (J. Tinoco), hssousa@civil.uminho.pt (H.S. Sousa), mcoelho@civil.uminho.pt (M. Coelho), jmatos@civil.uminho.pt (J.C. Matos).

https://doi.org/10.1016/j.compgeo.2023.105577
Received 20 March 2023; Received in revised form 2 June 2023; Accepted 6 June 2023

Cheng et al., 2018) or soil (Zhang et al., 2018; Tang et al., 2018; Dyson and Tolooiyan, 2019; Liu et al., 2020; Wang et al., 2020). That, in combination with a given hazard, such as rainfall (Zhang et al., 2018; Tang et al., 2018) will allow identifying the failure mechanism, like slip surface (Li et al., 2017; Dyson and Tolooiyan, 2019; Liu et al., 2020; Wang et al., 2020) or planar failure (Ersöz and Topal, 2018).

Different methodologies have their own advantages, and it is commonly agreed that semi-quantitative methodologies based on empirical knowledge are faster and more widely used for maintaining a constant assessment of assets. In Portugal, The Slope Quality Index (SQI) was developed and implemented to aid the asset management of roadway systems, particularly to assess the stability of rock slopes (Pinheiro et al., 2015). Later, some modifications to this methodology were implemented to consider the uncertainty of the input by assuming parameters as random variables (da Silva, 2015).

Representing the spatial variability of properties in soil slopes is complex and requires high computational time and effort. Several approaches have been implemented for stability analyses using 2D and 3D numerical models (Dyson and Tolooiyan, 2019; Wang et al., 2020; Bardhan and Samui, 2022; Liu et al., 2018; Li et al., 2019). However, these approaches achieve an accurate representation of the spatial variability problem at the cost of high computational demand which when applied to a network with multiple assets would not be practical (Jiang et al., 2022).

Surrogate modeling techniques have been employed to address slope stability problems involving various failure modes. In Ji et al. (2017) a surrogate model based on the least-squares support vector machine was introduced for probabilistic analysis, emphasizing the importance of experimental design in enhancing the predictive capabilities of the surrogate model.

Recently, there have been advancements in the field of reliability analysis for slope stability. Ji et al. (2019) proposed an inverse first-order reliability method, which utilizes a limited number of finite element models to achieve convergence and attain a desired performance considering material uncertainties. Study focused on rotational displacement of slopes subjected to seismic hazards have been considered for reliability analysis (Ji et al., 2020, 2021).

Fragility analysis considering uncertainties of mechanical and geometric properties have been applied to the study of fragility of slopes considering different hazard scenarios (Rossi et al., 2021; Tsompanakis et al., 2010; Wu, 2015). Seismic fragility has been performed using different approaches that require great computational cost like incremental dynamic analysis (Hu et al., 2019). However, methods using analytical solutions based on circular sliding surfaces have been applied with satisfactory reliability and less computational demand (Wu, 2015).

Likewise, risk-based methodologies that offer more precise information about the failure probability and risk level are usually more demanding in terms of computational power, specialized human resources, and quality of information (Cheng et al., 2018; Tang et al., 2018). Regardless of the different probabilistic methods used for risk analyses of slopes. Monte Carlo-based methods are still widely used due to the reduced computational cost of simulation methods like surrogate models (Bardhan and Samui, 2022; Jiang et al., 2022).

The present case study aims to a simplified approach to the probabilistic analysis of slope stability while using surrogate modeling techniques, that could be used to ease the computational process of more detailed analyses of critical structures within the network. The present paper is structures as follows. Section 2 contains an overview of the general methodology for risk assessment. Sections 3 and 4 explain the characteristics of the selected case study and the application of the methodology. Finally, conclusions drawn during the research are presented.

2. Methodology

Risk-based methodologies for the analysis of railway structures have been implemented before. In which the risk is computed using different strategies where first the occurrence of an event is computed (e.g., failure) and then assessed against the consequences associated with the event (da Silva et al., 2017; Pardo, 2009). Therefore, risk can be defined as a measurement of uncertainties that can harm a specific asset. Thus, a probabilistic approach was selected, allowing the consideration of parameter uncertainties in the assessment of the asset.

Generally, during a risk assessment, three parameters are used to describe risk, which usually are hazards, vulnerability, and consequences, where they are related to the probability of a given hazard to occur, the susceptibility of a system to be affected by a given hazard, and to the quantification of the effects, respectively (Pardo, 2009).

2.1. *The Slope Quality Index (SQI)*

The slope quality index was developed as an empirical system to obtain a quality index of rock slopes in road infrastructures, which varies between 1 and 5, corresponding to slopes in very good and very bad condition states. Finally, a qualitative classification of a risk level can be inferred based on the final value of the index (Pinheiro et al., 2015).

For the computation of the index, factors related to slope stability are assessed. Each of these factors is estimated using a combination of several parameters evaluated in the same SQI range. The weight of each factor and parameter, which represents the importance and influence on slope stability, was defined based on a survey performed on a group of professionals actively working in the field of slope stability. These factors and parameters were defined based on extensive research, and intervals for each parameter were defined based on existing references and experts' experiences (Pinheiro et al., 2015).

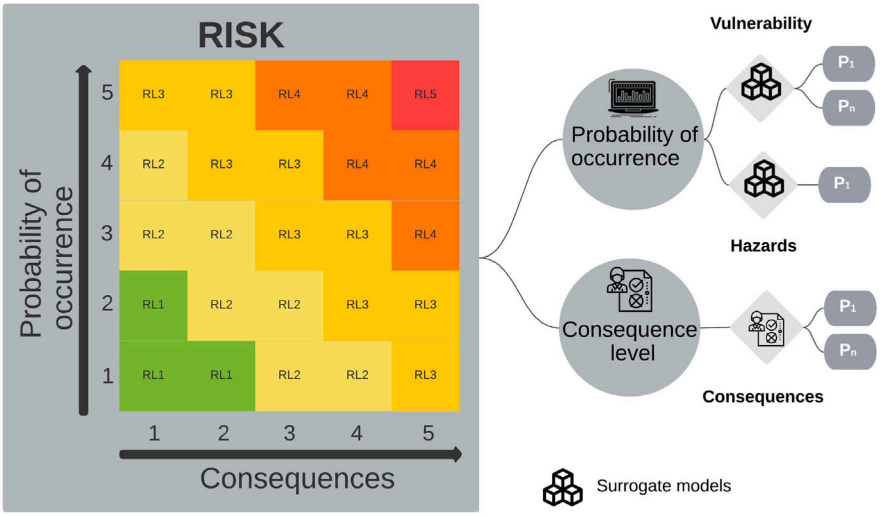
The SQI uses a deterministic approach, to reduce the uncertainty in the input, a modification of the base methodology where triangular probabilistic distributions were considered for some parameters, this approach showed that even by including some limited probabilistic framework the risk assessment would be greatly improved thus allowing for a better representation of the slope (da Silva, 2015).

The present study aims to improve the methodology but includes a more accurate representation of parameter uncertainties while maintaining a suitable level of complexity so it can be easily applied for the assessment of the slope structures within the Portuguese railway network.

2.2. *Adapting to a risk framework*

The SQI provides a qualitative risk assessment, nevertheless, there are some limitations on its assessment because of it deterministic approach. To better represent the uncertainties associated to the asset, some of the parameters used in the SQI methodology are selected and will be employed for the probabilistic analysis in different categories of the risk assessment as presented in Table 1. Moreover, parameters not included in the SQI methodology might be added to better represent the asset conditions. Parameters related to the geometry, materials, and state of the slopes are used in the first category related to the vulnerability of the slope. Three main hazards are considered: earthquakes, saturation, and loading, which can be related to parameters inside the SQI methodology and more hazards. For the assessment of the consequences, parameters that can be related to the importance of the railway in proximity to the slope are selected and will be assessed within the same range defined by the SQI methodology (from 1 to 5, where 5 is the most unfavorable scenario).

Some parameters from the SQI parameters are adapted to better fit the necessities of the case study. The main difference can be associated with the SQI being developed for rock slopes. Thus, information



Probability of occurrence	1	2	3	4	5
5	RL3	RL3	RL4	RL4	RL5
4	RL2	RL3	RL3	RL4	RL4
3	RL2	RL2	RL3	RL3	RL4
2	RL1	RL2	RL2	RL3	RL3
1	RL1	RL1	RL2	RL2	RL3

Fig. 1. The proposed risk matrix for the probabilistic assessment of slopes based on the SQI methodology.

Table 1
Adapted parameters from the SQI methodology to a risk-based approach.

SQI range	Risk-based		
Factors/Parameters	Hazard	Vulnerability	Consequences
Slope height		Slope height	
Slope angle		Slope angle	
Distance to railroad			Distance to railroad
Geological		Soil-type Soil-unit weight Soil-cohesion Soil-friction angle	
Drainage systems	Water table depth		
Seismic zones	Seismic zones		
Traffic-maximum speed			Traffic-maximum speed
Traffic-average daily traffic			Traffic-average daily traffic
Overload	Overload		

describing the rock formation was modified to parameters that better describe soil slopes (e.g., Soil type and mechanical properties) which are also present in other methodologies designed for soil slopes (Remédio, 2014). Moreover, the main source for stability assessment in the SQI is empirical classification systems, such as Rock Mass Rating, Q, or SMR (Todd, 2014) which are replaced by the 2D limit equilibrium model, an analytical approach that assesses the stability of the slope using a security factor obtained by resolving acting forces on the slope (Bishop, 1955).

Risk is often defined by the probability of failure times the mean value of the consequences associated with a particular failure mode (Jiang et al., 2022), in this study this approach was represented by a risk matrix that was based on the consequences and probability of occurrence indexes (Fig. 1), these approach has been widely used in different methodologies for the assessment of railway systems (da Silva et al., 2017; Pardo, 2009).

The probability of occurrence is related to the frequency at that events occur, and it relates to the failure of the slope due to a given hazard and its probability of occurrence, i.e., hazard and vulnerability. The level of probability of occurrence was assessed in a 1 to 5 range (Table 2) based on the results from the probabilistic stability analysis and hazards assessed. The latter is related to the consequences resulting from the effects that the failure of the structure has on the railway, and this is why consequences are considered mainly with parameters of the railway. Some of these parameters are the maximum speed, number, and width of the detour routes, and the importance of the route. Table 3 shows an example of the classifications used to qualitatively assess consequences in the example.

Table 2
Occurrence probability classification.
Source: Obtained from Pardo (2009).

Occurrence level	Probability [%]
1	<0.01%
2	[0.01%-0.10%]
3	[0.10%-1.00%]
4	[1.00%-10.00%]
5	>10.00%

The final goal of the risk assessment is to aid the asset management decision-making process for the mitigation or avoidance of the consequences associated with a failure event. For the planning of interventions, a complete analysis of the impacts associated with an asset state should be conducted. Nevertheless, the requirements and costs, e.g., detailed data, complex methods, and time, associated with a detailed risk analysis, may be inadequate for its implementation in the full length of the railway network (Papathanasiou et al., 2020). Therefore, an easy-to-implement risk-based methodology may allow identifying the assets that may require more detailed analysis, thus optimizing the available resources. To achieve this risk levels were implemented based on a review of commonly used methodologies (da Silva, 2015; da Silva et al., 2017; Pardo, 2009), and five different levels of risk are defined and represented in a risk matrix depicted in Fig. 1:

- RL1 (the lowest risk level) represents an acceptable risk where an accident may occur with little to no consequences and no immediate interventions are required.

Table 3

Example of the level of consequences, classification, loading and importance of the railway.

Source: Adapted from Infraestruturas de Portugal (2021), Sventekova et al. (2021).

Level of consequences	Classification	Load/axis	Importance
1	A	until 16T	Single-track railways for passenger transport
2	B1, B2	until 18T	Secondary lines with simplified traffic
3	C2, C3, C4	until 20T	Secondary lines of regional importance
4	D2, D3	until 22,5T	Other main lines with trans-regional transport
5	D4	above 22,5T	Main lines of great economic and social importance

Table 4

Probabilistic distribution used to represent variability in geotechnical and geometrical parameters.

ID	Symbol	Description	Category	Units	COV (%)	Type	Reference
1	SA	Slope angle	Geometry	°	6	Gaussian	Martinović et al. (2016)
2	SH	Slope height	Geometry	m	14	Gaussian	Martinović et al. (2016)
3	γ	Unit weight	Soil parameter	kN/m^3	5	Lognormal	Vrouwenvelder (1997)
4	c	Cohesion	Soil parameter	kPa	10	Lognormal	Vrouwenvelder (1997)
5	Φ	Friction angle	Soil parameter	°	10	Lognormal	Vrouwenvelder (1997)

- RL2 represents a tolerable risk where an accident may occur with a moderate impact which may be controlled by the current level of maintenance, and monitoring is advised.
- RL3 represents a state where moderate impacts may evolve to severe consequences if no actions are employed to maintain the desired performance of the asset.
- RL4 represents a high-risk scenario where the frequency or the severity of accidents may develop critical impacts on the normal performance of the asset. Immediate actions and more detailed analyses are advised to go return to a lower risk level.
- RL5 represents the highest risk scenario and immediate action, and detailed analyses are required due to the high cost related to the possible consequences of an accident.

3. Probability analysis

Deterministic approaches have limitations when assessing the contributions of the uncertainties when assessing risk in assets (Papathanasiou and Adey, 2020). The first step in the risk-based analysis is to perform a probabilistic analysis to estimate the failure probability.

3.1. Case study

The case study selected under the Ferrovia 4.0 project is in Concordância de Xabregas (Fig. 2), a segment of the Portuguese railway system, located in Lisbon. The slope is located on the right side between PK 8614 and PK 8720. The selection of the case study was based on the importance that the track segment has since it is used by freight trains within the Linha da Matinha (Port of Lisbon) coming from the various locations on the Linha do Oeste (Martingança, Ramalhal, etc.), and by CP (Comboios Portugal) Regional for transit from the terminal in Santa Apolónia destined for the Linha do Oeste. On this single line, different trains transit for the transport of goods and passengers, reaching up to 400 per month, where the CP series 592, 0450, 2300, 3500, and 2240 stand out, which constitute the largest number of trips, have a maximum circulation speed up to 120 km/h and is aimed at transporting passengers on interregional and urban trips. This segment of the railway network has a classification of D2, with a load capacity of 22.5T/axis and a transit velocity under 50 km/h according to the National Railway Plan (Infraestruturas de Portugal, 2021).

The slope geometry is defined by an inclination between 45° and 60°, a maximum height of 8 m, and 2 meters from the lower rail. The slope material consists of layers of marly limestone and limestone sandstone (calcários margosos e grés calcários, in Portuguese), and its resistance parameters were obtained from de Sousa (2017). The rectangular drainage system can be found on the track deck. Furthermore, in the last 5 years, there have been no records of geotechnical anomalies on the slope.

3.2. Stability model

An analytical approach based on limit state equations was used to assess the stability of the slope. The Bishop simplified method (BSM (Bishop, 1955)) was selected and implemented using a MATLAB script to achieve a faster integration with the probabilistic analysis. Moreover, it has been determined that the results obtained from the BSM do not differ from the ones obtained from methods that satisfy more equilibrium conditions (Malkawi et al., 2000; Habibagahi and Shahghotian, 2002).

BSM computes the stability of the slope by dividing it into slices following a circular slip surface, which can be assumed without compromising the accuracy of the results unless geological conditions affect the shape of the surface (Habibagahi and Shahghotian, 2002; Kim and Salgado, 2009). Moreover, the Swedish circle method was used as a backup method to verify and to validate the results obtained from the BSM (Kim and Salgado, 2009; Knappett and Craig, 2012). A safety factor (FS), the ratio between the ultimate resistance and the total load applied, was used to quantify the stability of the slope.

Since the Lisbon region is among the most critical regarding seismic hazard, it was selected as the focus of this research. Thus, to represent the seismic action in the probabilistic analysis, pseudo-static coefficients, based on the seismic zones within the Eurocode (British Standards Institution, 1996), were implemented. Moreover, the water level was considered to better represent saturated materials. Finally, in the script it is possible to include overloads applied on the crown of the slope.

3.3. Variable definition

The composition of slopes is always changing, and some of their properties may be altered with time. Moreover, these are structures with heterogeneous behavior. It has been determined that uncertainties related to mechanical properties and pore pressure are the most influential when assessing the stability of a slope (Habibagahi and Shahghotian, 2002). Thus, parameter uncertainties were considered. The relevance of considering uncertainties and their correlations related to soil mechanical properties has been studied for different assets when performing reliability analyses (Cheng et al., 2018; Aladejare and Wang, 2018). Different values of the correlation coefficient for different combinations of soil parameters (e.g., unit weight, cohesion, and angle of friction) have been identified (Wu, 2013). The Gaussian copula was used to represent the dependence of soil random variables. In Table 4, the distributions used for the geometrical and geotechnical parameters can be found.

(a) Location (b) Elevation view

Fig. 2. Case study.

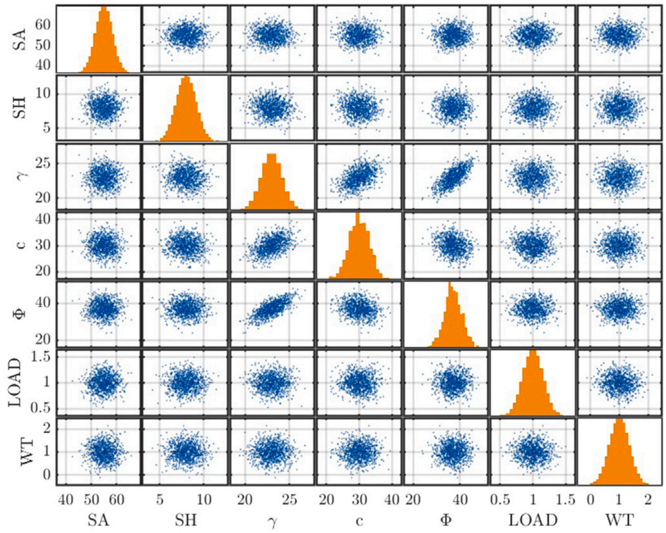


Fig. 3. LHS sampling for the random variables used for the probabilistic analysis.

3.4. *Hazard scenarios*

Determining the water table level in slopes, in most cases, is challenging. To consider the influence of this uncertainty in the methodology, the water table level was included as a random variable with a normal distribution (Shadabfar et al., 2020). To represent the loading of the railroad, the model LM71 was proposed by the Eurocode (British Standards Institution, 1996), and a normal distribution with COV of 15% was assumed, as recommended by Matos et al. (2019).

Seismic hazard was described in the analysis by using the peak ground acceleration (PGA) as the intensity measure. When assessing the stability of the slope values of PGA are used to compute the pseudo-static coefficients, according to the Eurocode (British Standards Institution, 1996). The values used for the fragility analysis are within a range from 0 to 1 g in increments of 0.05 g

Therefore, for the analysis of the case study, the saturation of the soil and loading of the slope were considered as random variables. The hazards considered are based on the project conditions according to the description of the case study. Thus, a set of random variables is defined using UQlab, a general-purpose Uncertainty Quantification framework running on MATLAB (Marelli and Sudret, 2014), then by using the Latin Hypercube Sampling method (LHS), a sample of the random variables is obtained (Fig. 3).

3.5. *Surrogate modeling*

Surrogate modeling techniques, applied to limit state analysis, have been used for the assessment of assets in railway networks (Cabanzo et al., 2022). A combination between kriging surrogate models and subset simulation (AK-SS) has been proven to be efficient in describing non-linear limit state functions (Guimarães et al., 2018). Therefore, a Kriging surrogate model using UQlab, by Marelli and Sudret (2014), was created and validated based on the random variables previously defined. The surrogate model uses a universal trend type, an anisotropic ellipsoidal Matérn 5/2 correlation function, used to define the Gaussian process and cross-validation estimation method. For the validation of the surrogate model, the leave-one-out method was used (Hastie et al., 2009).

The surrogate model is used to assess the stability of the slope in terms of FS. A sampling is generated, to obtain the probabilistic distribution of the FS using the MC sampling method. In Eq. (1), the stopping criterion for the LHS is shown and states that the standard error of the mean (SEM) should be less than 1% of the mean (Schuyler, 1998).

Equation 1. *Monte Carlo stopping criteria. Obtained from Schuyler (1998).*

$$SEM = \frac{s}{\sqrt{n}} < 1\%\mu \tag{1}$$

Where s is the standard deviation, n is the number of trials of the sample, and μ is the mean value. Convergence with negligible fluctuation was obtained by employing around 3000 experiments. Fig. 4 shows the range of critical slip surfaces, toe failure and the minimum and the maximum FS, obtained for each experiment within the sample are presented.

Finally, the probabilistic distribution is fitted to the histogram of minimum safety factors obtained for each value of PGA (Fig. 5). A Gumbel distribution was selected based on the Anderson–Darling test (Anon, 2008).

3.6. *Failure probability*

To evaluate the reliability of the structure, the limit state function (Eq. (2)) G was introduced to UQlab, using the capacity curve, R obtained from the probabilistic distribution of the FS and the Eurocode loading curve S defined by a Gaussian distribution of mean 1 and COV 15% (British Standards Institution, 1996)

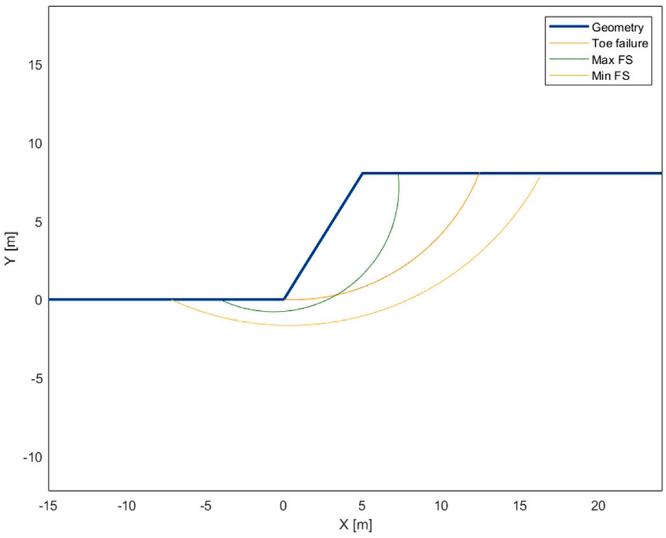


Fig. 4. Critical slip surfaces obtained in the probabilistic analysis.

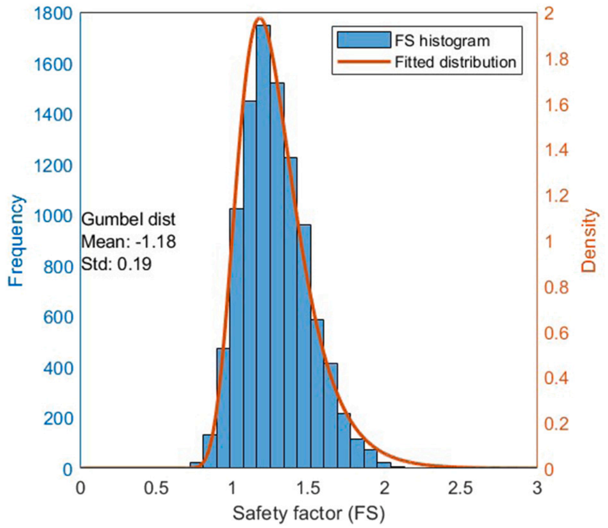


Fig. 5. FS histogram and fitted Gumbel distribution obtained in the probabilistic analysis.

Equation 2. *Limit state function.*

$$G = R - S \tag{2}$$

The failure probability was obtained by employing subset simulation (Au and Beck, 2001). As can be observed in Fig. 6, three subsets are defined to achieve convergence for the failure probability for the case study.

4. Fragility analysis

4.1. Sensitivity analysis

To better comprehend the impact of each random variable on the FS, a sensitivity analysis was performed and since some present correlation, the analysis of covariance (ANCOVA) was used (Xu and Gertner, 2008). Fig. 7 shows the results obtained from the sensitivity analysis for the case study considering the seismic coefficients for pseudo-static analysis defined in the Eurocodes (British Standards Institution, 1996). As expected, the parameters with the most influence over the FS are the slope height and the resistant properties of the soil material.

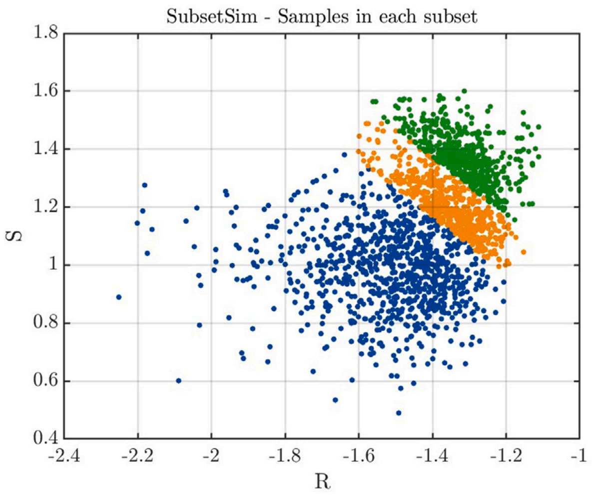


Fig. 6. Graphical representation of the subset simulation, where R is the resistance curve and S represents the loading curve.

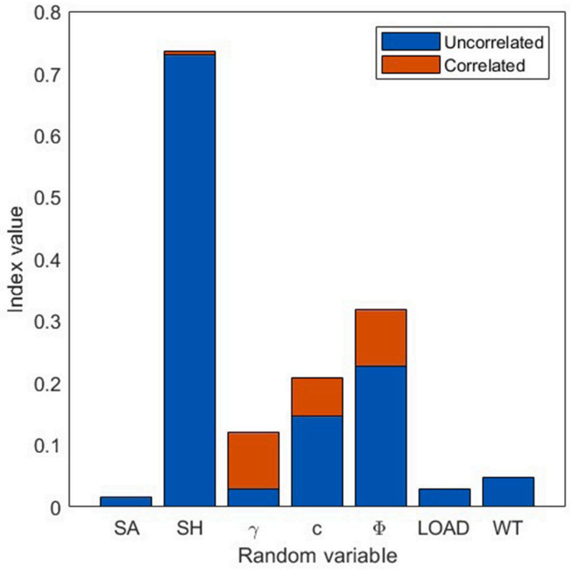


Fig. 7. Input variables sensitivity analysis and ANCOVA correlated and uncorrelated indexes.

The sensitivity analysis divides the uncertainty contribution of each parameter between uncorrelated and correlated contributions. As expected, the soil properties are more heavily influenced by the correlation (i.e., the magnitude of the correlated indices is higher than the uncorrelated ones). For the other parameters, it can be concluded that the correlation among input variables has only a weak effect on the response of the sensitivity analysis. Consequently, the parameter with higher contributions (above 0.2) to the stability of the slope are selected for a parametric analysis.

4.2. Fragility curves

Fragility curves are often obtained to correlate an intensity measure from a given hazard, with expected damage of the structure, e.g., collapse, by using exceedance probability and it is often characterized by a lognormal distribution. Where $\Phi(\cdot)$ represents the standard Gaussian cumulative distribution function, α is the median and β is the log-standard deviation represented by two coefficients, as seen in Eq. (3).

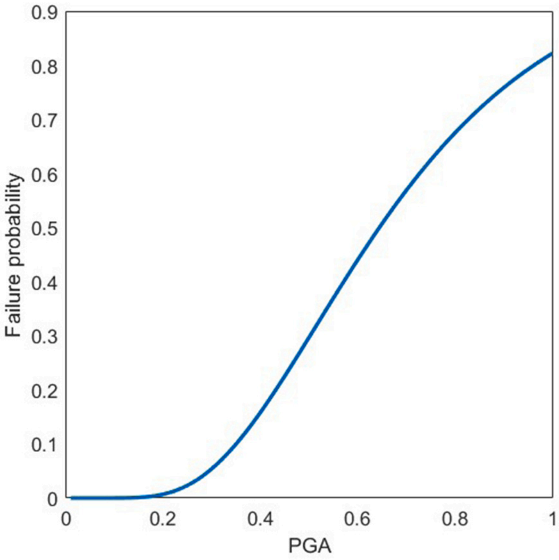


Fig. 8. Fragility curve of the soil cutting selected as case study.

Equation 3. *lognormal distribution used for the fragility curves.*

$$F_x(x) = \Phi\left(\frac{ln(x-\alpha)}{\beta}\right) \tag{3}$$

Fig. 8 shows the fragility curve obtained for the soil cutting selected as case study, considering PGA values between 0 g and 1 g. Failure probability increased with the peak ground acceleration due to its direct impact on the pseudo-static coefficients used in the stability analysis. It can be observed that the slope has a low probability of collapsing for values of PGA less than 0.2 g, which represents the maximum value in most Portuguese areas according to the Eurocode. Analyzing different seismic intensities may provide useful information for the decision-making process involved in asset management.

4.3. Parametric analysis

4.3.1. Slope height SH

Height was the parameter with highest influence on the FS of the slope, and as expected variation in height can have a drastically effect on the probability of failure of the slope. Fig. 9 presents the failure surface in which it can be observed an increase in the probability of failure with the height of the slope. It was found that for values above 30 m there is no influence in the fragility curves due to its high probability of failure for lower values of PGA (less than 0.2 g). It can be concluded that the failure probability is heavily affected by changes in height specially between the range of 8 and 15 m, thus making the proper characterization of the geometry of the slope key for a good assessment.

4.3.2. Soil mechanical properties

Soil resistance parameters are also relevant for the stability of the slope and as expected, they present a similar behavior, with increases in either the cohesion c or the friction angle Φ the failure probability decreases considerably. Figs. 10 and 11 show that at difference with the geometrical parameters the relation proportional to the failure probability.

5. Risk analysis

5.1. Probability of occurrence index

The case study is located within the Lisbon area which presents a seismic area 1.4 and 2.3 for types I and II actions, accordingly, which translates to a maximum PGA of approximately 0.17 g (British Standards Institution, 1996). Thus, the probability of failure can be determined from the fragility curve obtained for the case study. To obtain the index related to the probability of occurrence, the failure probability is computed with the likelihood of the seismic event, from the Eurocode, and then is categorized accordingly in Table 2, given an index of 3.

5.2. Consequences

There are many consequences associated with an event, failure of an asset may lead to accidents, delays and over costs associated with intervention processes. When there is an event, there are consequences to the owner of the railway system related to the interventions needed to ensure the desired performance level. Moreover, users may also be affected in the form of accidents, delays, and discomfort, among others (Papathanasiou and Adey, 2020).

In assessing the consequences, the parameters of the railway were considered as well as the operating conditions of the trains. The parameters considered are namely, the number of train tracks, the maximum speed of the train, the number of alternate routes and added distance, and the importance of the railway, giving an index of 4.

5.3. Risk assessment

The risk level that each slope presents is determined by the combination of its occurrence probability and consequences after failure and is therefore represented by the position of the slope on the risk matrix. Because fundamentally, risk assessment is used to aid the decision-making process based on the consequence of a potential failure as well as its likelihood (Power et al., 2016). In this scenario, an RL3 is obtained for the case study, see Fig. 12, based on the level of consequences (4) and the level of probability (3), representing a state where moderate impacts can evolve into serious consequences if no action is taken to maintain the desired performance of the asset.

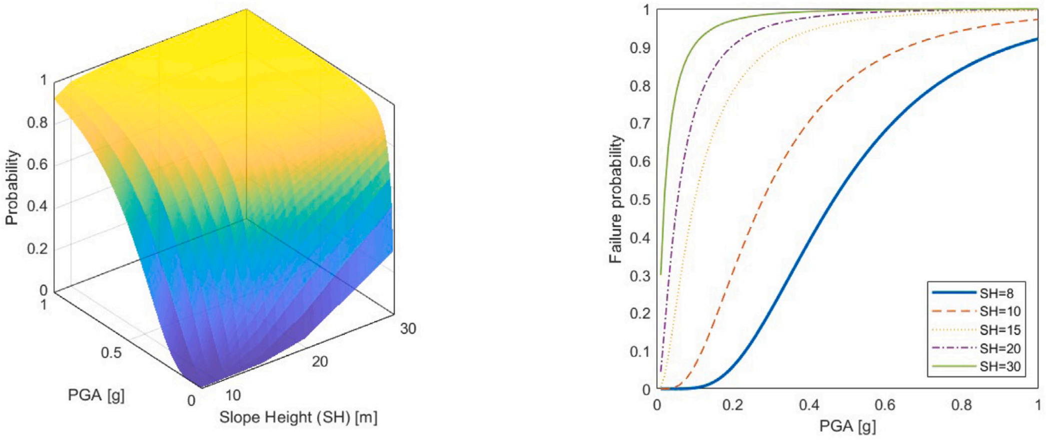
This methodology provides an alternative to assess the risk of assets while maintaining the same information required for the ones that have been implemented in the industry, which allows identifying the assets that could benefit from a more detailed assessment to improve the estimates of risks, costs, and consequences while providing an adequate representation of the hazards in terms of intensity and likelihood. Furthermore, it may provide the tools for prioritization of assets that need to be intervened, which may be achieved by comparing the reduction in risk after an intervention is implemented.

6. Conclusions

The proposed methodology has significant interest for the management of slopes in the scope of transportation infrastructures by providing a realistic evaluation of slopes not only to identify the slopes with high risk but also to allow monitoring of the overall condition of the slopes network. Moreover, this new modification to a system that is already being used in the industry, like the SQI index, may provide an alternative providing an assessment based on risk analysis without increasing the amount of information needed.

The example investigated in this paper show that considering uncertainties in different levels of the risk assessment can significantly increase the probability of failure of slopes that may have different geometries and geological conditions. The proposed method can effectively consider the effects of the above factors on the risk assessment of slopes.

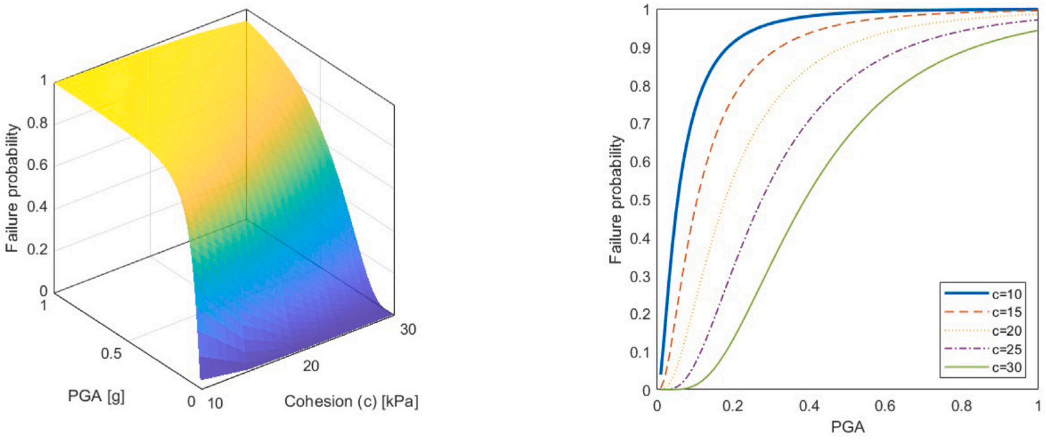
The probability of failure associated with a critical slip surface (e.g., no parameter uncertainties) as expected, is smaller than the one obtained by a system that contains multiple slip surfaces, resulting from the considered parameter uncertainties, which may provide a



(a) Fragility surface

(b) Fragility curves

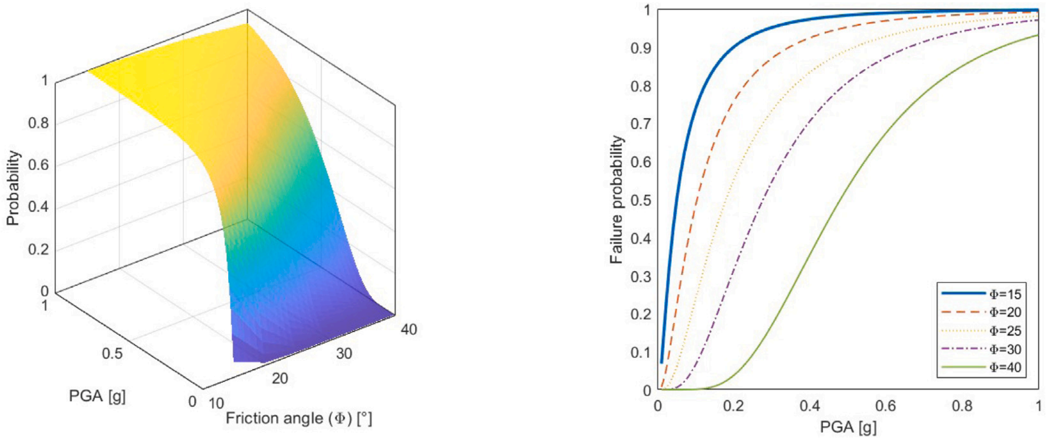
Fig. 9. Fragility analysis for height variation.



(a) Fragility surface

(b) Fragility curves

Fig. 10. Fragility analysis for soil cohesion variation.



(a) Fragility surface

(b) Fragility curves

Fig. 11. Fragility analysis for soil friction angle variation.

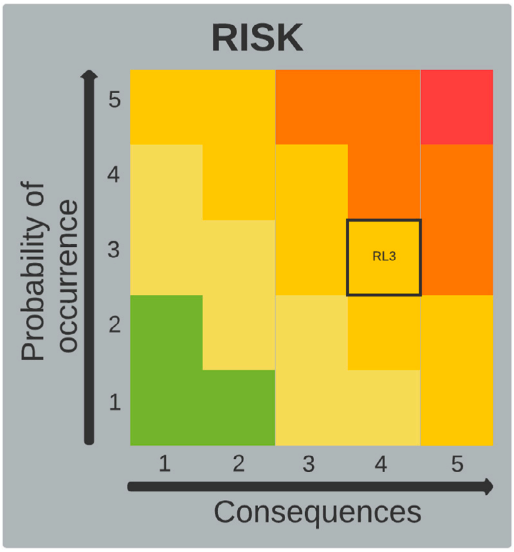


Fig. 12. The risk matrix was assessed on levels obtained for the case study.

more reliable result where an absolute sliding surface may be hard to define (Habibagahi and Shahghotian, 2002).

Information from the case study could be integrated with data collected from monitoring, thus allowing constant assessment, and supporting asset management in the decision-making process. Moreover, if enough information is available the probabilistic distributions for a given parameter can be better represented in the analysis thus greatly improving the quality of the analysis.

CRediT authorship contribution statement

Carlos Mendoza Cabanzo: Conceptualization, Formal analysis, Methodology, Writing – original draft. **Joaquim Tinoco:** Funding acquisition, Project administration, Supervision, Review and editing. **Hélder S. Sousa:** Validation, Review and editing. **Mário Coelho:** Software, Validation, Review and editing. **José C. Matos:** Resources, Supervision, Review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

This research was conducted under the project “Ferrovia 4.0” (POCI-01-0247-FEDER-046111; Lisboa-01-0247-FEDER-046111), by “Ferrovia” Consortium, and financed by European Regional Development Fund (ERDF), through the Incentive System to Research and Technological development, within the Portugal2020 Competitiveness and Internationalization Operational Program.

This work was partly financed by FCT/MCTES through national funds (PIDDAC) under the R&D Unit Institute for Sustainability and Innovation in Structural Engineering (ISISE), under reference UIDB/04029/2020, and under the Associate Laboratory Advanced Production and Intelligent Systems ARISE under reference LA/P/0112/2020.

This work is financed by national funds through FCT - Foundation for Science and Technology, under grant agreement 2022.09751.BD attributed to the 1st author.

References

Aladejare, A.E., Wang, Y., 2018. Influence of rock property correlation on reliability analysis of rock slope stability: From property characterization to reliability analysis. Geosci. Frontiers 9, 1639–1648.

Anon, 2008. Anderson–darling test. In: The Concise Encyclopedia of Statistics. Springer New York, New York, NY, pp. 12–14.

Au, S.K., Beck, J.L., 2001. Estimation of small failure probabilities in high dimensions by subset simulation. Probab. Eng. Mech. 16, 263–277.

Bardhan, A., Samui, P., 2022. Probabilistic slope stability analysis of Heavy-haul freight corridor using a hybrid machine learning paradigm. Transp. Geotech. 37.

Bishop, A.W., 1955. The use of the slip circle in the stability analysis of slopes. Géotechnique 5, 7–17.

British Standards Institution, 1996. Eurocode 8: Design Provisions for Earthquake Resistance of Structures : Part. 1-3 : General Rules, Specific Rules for Various Materials and Element. BSI, London, URL: https://cds.cern.ch/record/848046. Merged with DD-ENV-1998-1-1 and DD-ENV-1998-1-2 into prEN-1998-1.

Cabanzo, C.M., Santamaría, M., Sousa, H.S., Matos, J.C., 2022. In-plane fragility and parametric analyses of masonry arch bridges exposed to flood hazard using surrogate modeling techniques. Appl. Sci. 12, 1886.

Cheng, H., Chen, J., Chen, R., Chen, G., Zhong, Y., 2018. Risk assessment of slope failure considering the variability in soil properties. Comput. Geotech. 103, 61–72.

Dyson, A.P., Tolooiyan, A., 2019. Prediction and classification for finite element slope stability analysis by random field comparison. Comput. Geotech. 109, 117–129.

Ersöz, T., Topal, T., 2018. Assessment of rock slope stability with the effects of weathering and excavation by comparing deterministic methods and slope stability probability classification (SSPC). Environ. Earth Sci. 77.

Guimarães, H., Matos, J.C., Henriques, A.A., 2018. An innovative adaptive sparse response surface method for structural reliability analysis. Struct. Saf. 73, 12–28.

Habibagahi, G., Shahghotian, R., 2002. Reliability analysis of rock slopes using theory of fuzzy sets. In: Numerical Models in Geomechanics - 8th Proceedings of the International Symposium on Numerical Models in Geomechanics, NUMOG 2002. 27, pp. 547–551.

Hastie, T., Tibshirani, R., Friedman, J., 2009. The elements of Statistical Learning. In: Springer Series in Statistics.

Hu, H., Huang, Y., Chen, Z., 2019. Seismic fragility functions for slope stability analysis with multiple vulnerability states. Environ. Earth Sci. 78.

Infraestruturas de Portugal, 2021. 1ª Adenda do diretório da rede 2022. URL: https://servicos.infraestruturasdeportugal.pt/sites/default/files/inline-files/1ª20Adenda20Diretório20da20Rede202022.pdf.

Ji, J., Wang, C.-W., Gao, Y., Zhang, L., 2021. Probabilistic investigation of the seismic displacement of earth slopes under stochastic ground motion: a rotational sliding block analysis. Can. Geotech. J. 58 (7), 952–968.

Ji, J., Zhang, C., Gao, Y., Kodikara, J., 2019. Reliability-based design for geotechnical engineering: An inverse FORM approach for practice. Comput. Geotech. 111, 22–29.

Ji, J., Zhang, C., Gui, Y., Lü, Q., Kodikara, J., 2017. New observations on the application of LS-SVM in slope system reliability analysis. J. Comput. Civ. Eng. 31.

Ji, J., Zhang, W., Zhang, F., Gao, Y., Lü, Q., 2020. Reliability analysis on permanent displacement of earth slopes using the simplified bishop method. Comput. Geotech. 117.

Jiang, S.H., Huang, J., Griffiths, D.V., Deng, Z.P., 2022. Advances in reliability and risk analyses of slopes in spatially variable soils: A state-of-the-art review. Comput. Geotech. 141.

Kim, D., Salgado, R., 2009. Limit states and load resistance design of slopes and retaining structures. URL: https://docs.lib.purdue.edu/cgi/viewcontent.cgi?article=2674&context=jtrp.

Knappett, J., Craig, R., 2012. Craig's Soil Mechanics. CRC Press, URL: https://books.google.pt/books?id=oRhxDwAAQBAJ.

Li, D.Q., Wang, L., Cao, Z.J., Qi, X.H., 2019. Reliability analysis of unsaturated slope stability considering SWCC model selection and parameter uncertainties. Eng. Geol. 260, 105207.

Li, D.Q., Yang, Z.Y., Cao, Z.J., Au, S.K., Phoon, K.K., 2017. System reliability analysis of slope stability using generalized Subset Simulation. Appl. Math. Model. 46, 650–664.

Liu, X., Li, D.Q., Cao, Z.J., Wang, Y., 2020. Adaptive Monte Carlo simulation method for system reliability analysis of slope stability based on limit equilibrium methods. Eng. Geol. 264, 105384.

Liu, Y., Zhang, W., Zhang, L., Zhu, Z., Hu, J., Wei, H., 2018. Probabilistic stability analyses of undrained slopes by 3D random fields and finite element methods. Geosci. Front. 9, 1657–1664.

Malkawi, A.I.H., Hassan, W.F., Abdulla, F.A., 2000. Uncertainty and reliability analysis applied to slope stability. Struct. Saf. 22, 161–187.

Marelli, S., Sudret, B., 2014. UQLab: a framework for uncertainty quantification in MATLAB. The 2nd International Conference on Vulnerability and Risk Analysis and Management (ICVRAM 2014), pp. 2554–2563.

Martinović, K., Gavin, K., Reale, C., 2016. Assessing the vulnerability of Irish rail network earthworks. Transp. Res. Procedia 14, 1904–1913.

Matos, J.C., Moreira, V.N., Valente, I.B., Cruz, P.J., Neves, L.C., Galvão, N., 2019. Probabilistic-based assessment of existing steel-concrete composite bridges – Application to Sousa River Bridge. Eng. Struct. 181, 95–110.

Papathanasiou, N., Adey, B.T., 2020. Identifying the input uncertainties to quantify when prioritizing railway assets for risk-reducing interventions. Civ. Eng. 1, 106–131.

Papathanasiou, N., Adey, B.T., 2021. Making comparable risk estimates for railway assets of different types. Infrastructure Asset Manag. 8, 53–74.

Papathanasiou, N., Adey, B.T., Burkhalter, M., 2020. Defining and quantifying railway service to plan infrastructure interventions. Infrastructure Asset Manag. 7, 146–166.

Pardo, J.A.R., 2009. Metodologia para análise e gestão de riscos em projetos de pavimentos ferroviários. p. 187.

Pinheiro, M., Sanches, S., Miranda, T., Neves, A., Tinoco, J., Ferreira, A., Correia, A.G., 2015. A new empirical system for rock slope stability analysis in exploitation stage. Int. J. Rock Mech. Min. Sci. 76, 182–191.

Power, C., Mian, J., Spink, T., Abbott, S., Edwards, M., 2016. Development of an evidence-based geotechnical asset management policy for network rail, Great Britain. 143, Elsevier Ltd, pp. 726–733,

Remédio, F.H., 2014. Análise de estabilidade de taludes de aterro de resíduos urbanos utilizando parâmetros geotécnicos de propostas bibliográficas e correlações com nspt. Universidade Estadual Paulista 131.

Rossi, N., Bačić, M., Kovačević, M.S., Librić, L., 2021. Development of fragility curves for piping and slope stability of river levees. Water (Switzerland) 13.

Schuyler, J., 1998. #29: Monte Carlo simulation stopping rule with Latin hypercube sampling. URL: http://www.maxvalue.com/tip029.htm.

Shadabfar, M., Huang, H., Kordestani, H., Muho, E.V., 2020. Reliability analysis of slope stability considering uncertainty in water table level. ASCE-ASME J. Risk Uncertain. Eng. Syst. A 6, 1–8.

da Silva, S.A.E.S., 2015. Software with probabilistic approach of the Slope Quality Index (SQI). URL: https://hdl.handle.net/1822/40643.

da Silva, K.C., Carvalho, D., Mesquita, J., 2017. Método de gestão de risco em ferrovia. In: XII Conferencia Brasileira Sobre Estabilidade de Encostas. ABMS, Florianópolis.

de Sousa, M., 2017. Estabilidade de taludes em infra-estruturas rodoviárias Engenharia Civil.

Sventekova, E., Urbancova, Z., Holla, K., 2021. Assessment of the vulnerability of selected key elements of rail transport. Slovak case study. Appl. Sci. 11 (13).

Tang, G., Huang, J., Sheng, D., Sloan, S.W., 2018. Stability analysis of unsaturated soil slopes under random rainfall patterns. Eng. Geol. 245, 322–332.

Todd, M.K., 2014. Rock mass classification systems. In: Handbook of Geotechnical Investigation and Design Tables. pp. 287–304.

Tsompanakis, Y., Lagaros, N.D., Psarropoulos, P.N., Georgopoulos, E.C., 2010. Probabilistic seismic slope stability assessment of geostructures. Struct. Infrastructure Eng. 6, 179–191.

Vrouwenvelder, T., 1997. The JCSS probabilistic model code. Struct. Saf. 19, 245–251.

Wang, L., Wu, C., Tang, L., Zhang, W., Lacasse, S., Liu, H., Gao, L., 2020. Efficient reliability analysis of earth dam slope stability using extreme gradient boosting method. Acta Geotech. 15, 3135–3150.

Wu, X.Z., 2013. Trivariate analysis of soil ranking-correlated characteristics and its application to probabilistic stability assessments in geotechnical engineering problems. Soils Found. 53, 540–556.

Wu, X.Z., 2015. Development of fragility functions for slope instability analysis: Fragility functions for slope instability analysis. Landslides 12, 165–175.

Xu, C., Gertner, G.Z., 2008. Uncertainty and sensitivity analysis for models with correlated parameters. Reliab. Eng. Syst. Saf. 93, 1563–1573.

Zhang, J., He, P., Xiao, J., Xu, F., 2018. Risk assessment model of expansive soil slope stability based on Fuzzy-AHP method and its engineering application. Geomatics, Natural Hazards and Risk 9, 389–402.