Multi-modal risk assessment of slopes

Reale, Cormac; Gavin, Kenneth; Martinović, Karlo

Publication date
2016

Document Version
Final published version

Published in
Proceedings of the 4th International Conference on Road and Rail Infrastructure

MULTI-MODAL RISK ASSESSMENT OF SLOPES

Cormac Reale[1], Kenneth Gavin[2], Karlo Martinović[1]
[1] *University College Dublin, School of Civil Engineering, Ireland*
[2] *TU Delft, School of Civil Engineering, Netherlands*

Abstract

A significant proportion of European rail networks are built upon earthworks that are over one hundred years old. These earthworks are under increased pressure as they have to contend with heavier and more frequent traffic, far outside the scope of their design. To compound this problem further, recent years have seen unpredictable weather patterns develop with prolonged intense rainstorms commonplace. This has led to increased incidence of slope failures along rail networks, as many aged earthworks struggle to withstand such drastic changes in loading. Marginal engineered slopes fail depending on the triggering mechanism which presents itself first. Therefore the failure surface is intrinsically linked to the applied load i.e. surcharge loading will instigate a different type of landslide than prolonged rainfall. Therefore this paper proposes to analyse marginal slopes probabilistically as a system, where multiple slip circles are considered. A multi-modal optimisation algorithm LIPS (locally informed particle swarm optimisation) is used to locate all significant slip circles. In a slope with multiple potential failure surfaces the consequence of failure is not necessarily the same across the different slip surfaces. This paper addresses this deficit by examining the consequence of the different landslides should they occur. When combined with previously calculated probabilities of failure this will entail amount to a full geotechnical risk assessment of engineered slopes.

Keywords: reliability analysis, risk assessment, slope stability, engineered slopes, multi-modal

1 introduction

Slope instability is a major problem faced by all transport networks. This problem has increased in prevalence over recent years as a result of the increased rainfall levels brought about by climate change. This has led to a sharp increase in the number of shallow planar failures occurring annually. These failures are the result of infiltrating rainwater percolating downward through the soil. Saturating soil pore space, thereby temporarily removing the stability generated by soil suctions and consequently lowering the shear strength of the near surface soils [1, 2]. This is particularly concerning for aged transport networks such as the rail networks across both Ireland and the UK which weren't designed to modern exacting standards but were instead constructed by tipping methods in the mid-19th century. As a result many of these slopes are inclined at very steep angles, which would not be permitted by modern design guidelines [3]. This places them at an increased risk of failure. However given the scale of the networks involved and current economic circumstances, it is infeasible to replace all substandard slopes. Therefore it is imperative that we are able to identify and rank the slopes which represent the most risk to end users in order to determine which slopes to prioritise for remediation.

While significant research has been carried out on the field of landslide risk assessment it is typically carried out over a large study area using proxy measurements. This paper uses reliability theory to determine the probability of slope failure (hazard assessment). Thereby allowing for a more realistic estimate of slope capacity than traditional methods and hence a more accurate estimation of the failure probability. Furthermore, recognising that slopes are susceptible to many different failure mechanisms this paper analyses slope stability multi-modally using a particle swarm based algorithm (LIPS) which is able to detect all viable slip surfaces simultaneously. This optimisation process is used in conjunction with Bishops simplified slip circle and FORM (first order reliability method) to perform a hazard analysis in this paper.
Risk is typically defined as the product of a hazard (probability of failure) and its consequence. Naturally if a slope is subject to many different failure modes each will carry a different consequence. For example if a failure with a large volume of displaced soil occurs it will likely have greater consequence than a failure with negligible volume. This complicates slope risk assessment as the actual consequence is dependent on the particular failure event which occurs. However if all viable slip surfaces are used to perform the risk assessment the risk will more than likely be overestimated as many of the slip surfaces will be correlated. Therefore this paper performs consequence analysis and subsequent risk analysis on the slip surfaces determined to be representative by the LIPS optimisation process. Consequence is determined based on volume of soil displaced [4]. A hypothetical embankment case study is used to demonstrate the methodology.

2 Methodology

Risk is defined in this paper as the product of hazard and consequence. The following sections describe how hazard and consequence is obtained in this paper.

2.1 Probabilistic hazard assessment

Probabilistic methods have become increasingly common in Geotechnical Engineering over recent years. Slope stability in particular has received significant attention [5-8]. This is due to researchers recognizing that slope stability has significant uncertainties associated with it such as site investigation, slip surface location, climate and of course spatial variation. Reliability theory allows designers to assign statistical distributions to each variable thereby allowing for uncertainties to be accounted for within stability calculations. The performance function g(X) of a slope can be expressed as the difference between capacity (C) and demand (D), see Eqn 1.

$$g(X) = (C - D) \begin{cases} > 0, \text{ safe state} \\ = 0, \text{ limit state} \\ < 0, \text{ failure state} \end{cases} \tag{1}$$

$$g(X) = g(x_1, x_2, \ldots, x_n) \text{ for } i = 1 \text{ to } n$$

Where X is a vector of the different random variables (x_i) represented in the slope. Safety in a reliability analysis is typically expressed in terms of a reliability index, β, and a probability of failure, p_f. The probability of failure (p_f) can be defined as the probability at which the performance function is less than zero, see Eqn 2.

$$P_f = P[g(X) \leq 0] \tag{2}$$

In a normal space, the reliability index (β) is defined as the distance in standard deviations from the mean of the performance function to the design point, Eqn 3. This can be seen graphically in Fig 2.

$$\beta = \frac{E[g(X)]}{\sigma[g(X)]} \tag{3}$$

Where E[g(X)] is the mean of the performance function and σ[g(X)] is its standard deviation. When analysing slope stability the performance function of the slope is typically expressed as in Eqn (4).

$$g(X) = FOS - 1.0 \tag{4}$$

Where FOS is the factor of safety as defined by a relevant limit state Eqn. In this case Bishops simplified slip circle is used, see Eqn (5)

$$FOS = \frac{\sum_{i=1}^{n}[c_i \Delta x_i + (W_i - u_i \Delta x_i)\tan\phi_i]\frac{\sec\alpha_i}{1+\tan\phi_i \tan\alpha_i / FOS}}{\sum_{i=1}^{n} W_i \sin\alpha_i} \tag{5}$$

Where W_i is the weight of the ith slice, α_i is the tangential angle of the base of the ith slice, Δx_i is the ith slice width, ci is the cohesion of the soil on the base of the ith slice, ui is the pore water pressure at the base of the ith slice, and ϕ_I is the friction angle of the soil at the base of the ith slice. To obtain the minimum FOS of a slope, either a trial and error or an optimization technique must be implemented. Similarly to obtain the maximum probability of failure an optimisation needs to be implemented to find the design points of the random variables involved as well as the critical slip circle.

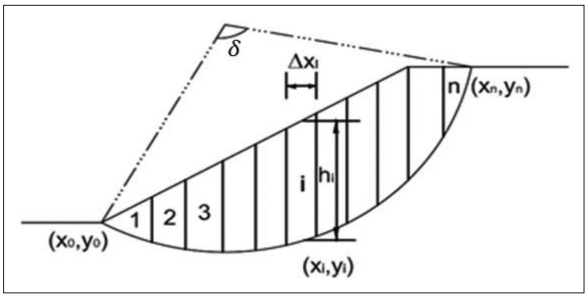

Figure 1 Terms used to describe slip surface geometry

2.1.1 First Order Reliability Methods Hasofer Lind

Hasofer & Lind (1974) proposed a method which assumes a first order tangent to the limit state function at the design point (i.e. when g(X) = 0) giving an exact solution for linear performance functions and a close approximation for nonlinear functions. This method known as the Hasofer Lind reliability index requires all computation to be carried out in the standard normal space. Therefore the vector of random variables (X) needs to be transformed into a vector of standardised normal uncorrelated variables ($\overline{X}$) prior to minimisation. Eqn (6) can be used to transform random variables into the standard normal space.

$$\overline{X}_i = \frac{x_i - \mu_{x_i}}{\sigma_{x_i}} \text{ for } i = [1,2,\ldots,n] \tag{6}$$

In this space the reliability index can be calculated by Eqn 7.

$$\beta = \min_{\bar{X} / \psi} \left\{ \overline{X}\overline{X}^{T} \right\}^{1/2} \tag{7}$$

Where the limit state surface Ψ is defined by $g(\overline{X})=0$.

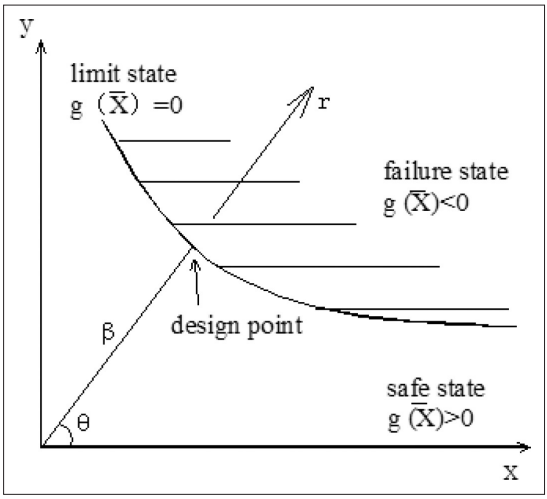

Figure 2 Hasofer Lind reliability index shown graphically as the minimum distance from the origin to the limit state surface in a reduced normal space.

2.1.2 Optimisation method- Locally Informed Particle Swarm Optimisation (LIPS)

In a multimodal problem, many extrema need to be located simultaneously, these optima can be located in vastly different areas of the search space. This paper uses a multi modal optimisation algorithm termed LIPS (locally informed particle swarm) to locate all significant minima. LIPS is a modified form of particle swarm optimisation (PSO) adapted to solve multi-modal problems. PSO optimises based on how we think swarm animals such as birds find food as a group. The general principle being that each particle in the swarm represents a solution (collection of design points) to an optimisation problem. These particles iteratively move about the search space or performance function surface with a velocity. Every iteration each particle updates its velocity and its position based on that particles best solution (lowest β or FOS) so far (termed pbest) and the swarms best solution so far (global optima termed gbest). When a particle is near an optima its velocity decreases. Each particle is aware of the current global best solution and if the program runs for long enough all particles should move towards this point.

LIPS differs from standard PSO in that not every particle is aware of the location of the global minimum, instead each particle is aware only of its personal best solution and that of its neighbourhood. Where a particles neighbourhood, is the m closest particles to that particle measured in Euclidean distance. This allows particles to learn from those particles immediately surrounding it, while also ensuring that particles on the opposite side of the search space have no influence. This allows LIPS to develop a number of stable niches in separate areas of the search space thereby allowing the algorithm to optimise simultaneously to multiple different local optima.

The velocities (V) and positions (U) of the particles are updated using Eqns (8 – 10). Further details on the optimisation process can be found in Reale et al. [9, 10].

$$U_{i,d}^{t+1} = U_{i,d}^{t} + V_{i,d}^{t} \tag{8}$$

$$V_{i,d}^{t+1} = \vartheta \cdot \left(V_{i,d}^{t} + \varphi \left(P_{i,d}^{t} - U_{i,d}^{t} \right) \right) \tag{9}$$

$$P_{i,d}^{t} = \frac{\sum_{j=1}^{nsize} \left(\varphi_j \cdot nbest_j \right) / nsize}{\varphi} \tag{10}$$

Where φ_j is a randomly distributed number in the range of [0, (4.1)/nsize] and φ is equal to the summation of φ_j . $nbest_j$ is the jth nearest neighbourhood to i^{th} particle's personal best (pbest), nsize is the neighbourhood size and ϑ is the inertia weight which balances the search between global and local performance.

2.2 Consequence analysis

Depending on the failure mode which occurs the consequence will be different. This paper assumes that the consequence is dependent on the volume of soil mobilised, or the cross sectional area of the displaced mass in two dimensions. However, some other term could easily be used to measure consequence where appropriate. In line with the methodology proposed by Zhang and Huang [4] this paper assumes that consequence is equal to the area displaced if failure occurs or 0 if failure does not occur, see Eqn 11.

$$C = \begin{cases} A_m & \text{if failure occurs} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

3 Case study

A hypothetical embankment is used to demonstrate the risk methodology. The embankment is approximately 10 m tall and is inclined at an angle of 38° to the horizontal, ground level is further inclined at an angle of 2° to the horizontal, see Fig 3. The embankment is founded upon a soft clay layer immediately overlying a stiff clay deposit. Gravel is found at depth. The geotechnical parameters used can be found in Table 1.

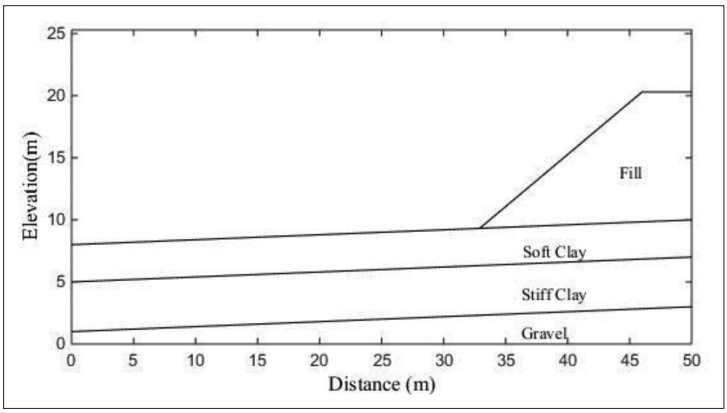

Figure 3 Slope profile

Table 1 Geotechnical parameters used in analysis

Property	Mean	Coefficient of Variation
Cohesion (embankment) (kPa)	7	0.2
Friction angle (embankment) (°)	34	0.05
Undrained Shear Strength (Soft Clay) (kPa)	35	0.1
Friction angle (Soft Clay) (°)	0	0
Undrained Shear Strength (Stiff Clay) (kPa)	70	0.1
Friction angle (Stiff Clay) (°)	0	0
Cohesion (Gravel) (kPa)	0	0
Friction angle (Gravel) (°)	38	0.05

LIPS detected three representative slip surfaces which can be seen in Fig 4. One shallow seated failure mode was detected which was entirely contained within the embankment fill, while two deeper seated failure modes were also observed. While the critical failure mode in this case is the largest failure mode (m3), failure mode m1 may in reality be more likely to failure if climate effects are taken into account as shallow landslides are preferentially deteriorated by rainfall. Therefore it is important to analyse critical slopes multi-modally in order to get a true picture of safety.

The reliability indices, corresponding probabilities of failure and areas are given in Table 2. Failure mode m3 represents the most risk as it has both the highest probability of failure and the largest area of potential soil displacement. Similarly failure mode m1 contributes significantly to the overall risk profile as it has also covers a large area. Failure mode m2 is not considered high risk, as although its probability of failure is not much less than the other two failure modes negligible soil will be displaced if failure occurs. Hence it is less likely to have a catastrophic impact. To obtain the total risk profile of the slope the risk of the individual failure modes is simply added together. In this case the total risk of a landslide on the slope is 1, see Table 2. It is important to note that this number is not a probability and is merely a dimensionless number which can be used to compare the relative risk of different slopes.

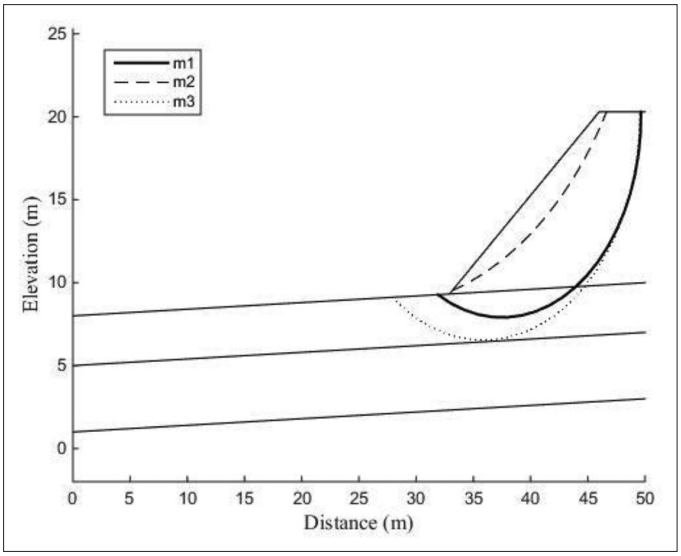

Figure 4 Representative Slip Surfaces detected by LIPS

Table 2 Hazard and risk results for critical slip surfaces.

Mode No:	Entry Pt	Exit Pt	β	P_f	Area (m^2)	Risk
m1	31.8935	49.6451	3.0669	0.0011	122.6397	0.135
m2	33.1429	46.6414	3.2403	0.0006	27.80363	0.017
m3	27.8879	49.5705	2.5036	0.0062	137.2494	0.851
					Total risk:	**1.00**

4 Conclusion

Across Europe Infrastructure managers are facing challenges in managing aged cutting and embankment assets with reduced budgets. Climate change is likely to cause an increase in the number of failures in these assets annually. This paper has shown the benefits of combining multi-modal optimisation algorithms with probabilistic methods for analysing existing railway slopes. The case study shows that shallow and deep seated failures, with similar probabilities of failure, can exist in the same slope. In which case, the actual critical slip surface is dependent on the triggering mechanism which presents itself first as opposed to the slip surface with the lowest reliability index. By using a multi-modal optimisation algorithm, LIPS, to calculate the probability of failure all viable slip circles are checked simultaneously, thereby eliminating the chance of a missing a key slip surface, thus removing subjectivity from the designer. However depending on the volume of soil displaced a shallow landslide may not represent that much of a risk to end users. To address this deficit this paper considers the volume of displaced soil as the consequence of a landslide occurring. Therefore by multiplying the probability of failure of each representative slip circle by the volume of soil displaced by said slip circle a risk profile can be obtained. This profile can then be used to gauge the relative risk of each failure mode and to compare the risk of slopes across an entire transport network. Thereby providing a methodology for prioritising expenditure on remediation works.

References

[1] Ridley, A., McGinnity, B., Vaughan, P.: Role of pore water pressures in embankment stability, Proc. Inst. Civ. Eng. Eng., vol. 157, no. 4, pp. 193–198, 2004.

[2] Xue, J., Gavin, K.: Effect of Rainfall Intensity on Infiltration into Partly Saturated Slopes, Geotech. Geol. Eng., vol. 26, no. 2, pp. 199–209, Oct. 2007.

[3] Jennings, P.J., Muldoon, P.: Assessment of Stability of Man-Made Slopes in Glacial Till: Case Study of Railway Slopes, Southwest Ireland, Proc. Semin. 'earthworks Transp. held in, Dublin, Ireland, 12th December 2001, 2001.

[4] Zhang, J., Huang, H.W.: Risk assessment of slope failure considering multiple slip surfaces, Comput. Geotech., vol. 74, pp. 188–195, Apr. 2016.

[5] Xu, B., Low, B.: Probabilistic stability analyses of embankments based on finite-element method, J. Geotech. Geoenvironmental ..., 2006.

[6] Gavin, K., Xue, J.: Design Charts for the Stability Analysis of Unsaturated Soil Slopes, Geotech. Geol. Eng., vol. 28, no. 1, pp. 79–90, Jan. 2010.

[7] Cheng, Y.M., Li, L., Liu, L.L.: Simplified approach for locating the critical probabilistic slip surface in limit equilibrium analysis, Nat. Hazards Earth Syst. Sci. Discuss., vol. 3, no. 2, pp. 1061–1112, Feb. 2015.

[8] Reale, C., Xue, J., Gavin, K.: Using reliability theory to assess the stability and prolong the design life of existing engineered slopes., in Risk Assessment and Management in Geotechnical Engineering: from Theory to Practice, ASCE Geotechnical Special Publication in Memory of the Late Professor Wilson H. Tang, 2016, p. Accepted.

[9] Reale, C., Xue, J., Pan, Z., Gavin, K.: Deterministic and probabilistic multi-modal analysis of slope stability, Comput. Geotech., vol. 66, no. (5), pp. 172–179, May 2015.

[10] Reale, C., Xue, J., Gavin, K.: System reliability of slopes using multimodal optimisation, Géotechnique, vol. 66, no. 5, pp. 413–423, Jan. 2016.