A Surrogate Model for Automating Slope Stability Analysis

Amichai Mitelman
Ariel University, Ariel, Israel

Beverly Yang
University of British Columbia, Vancouver, Canada

Davide Elmo
University of British Columbia, Vancouver, Canada

ABSTRACT: Owing to the advancements in the field of machine-learning (ML), the prospects of coupling ML with engineering analyses are currently being realized for various applications. Such applications can be particularly useful for geological engineering, where the ground properties are heterogeneous and hard to estimate accurately. In this regard, surrogate models are being increasingly used as tools to accelerate learning for both research and practical applications. In this paper, we describe the application of a surrogate model for the analysis of a slope stability problem using the limit equilibrium slice method. For setting up the surrogate model, two primary stages are required: 1) artificial data generation, where numerous results are computed, and: 2) data learning, where ML is used for building the correlation between the problem inputs and results of interest. Through this relatively simple example, we demonstrate how routine engineering tasks can be readily automated.

Keywords: Surrogate models, Machine-learning, Slope stability, Probability of failure.

1 INTRODUCTION

Given the state of current knowledge in rock engineering, most problems do not allow for accurate predictions of rock mass response to excavations (Elmo et al., 2022). In rock and soil engineering projects, owing to the heterogeneous nature of the geological materials, it is generally advised to examine a range of input parameters, even after rigorous site investigations (Lees, 2013). For this reason, probabilistic tools have been coupled with geotechnical analysis (Abdulai & Sharifzadeh, 2021). For some problems, it is advantageous to use approximated closed-from solutions for rigorous probabilistic analysis that consider the range of inputs and results, rather than invest in a small number of highly complicated numerical models (Mitelman & Elmo, 2019). Indeed, commercial codes that rely on simpler solutions offer built-in probabilistic analysis capabilities. Examples include commercial codes such as RocSupport, for tunnel support design, and Slide, for slope stability problems (Rocscience, 2004). Due to the rapid advancements in computing power, it has become more reachable to couple probabilistic analysis with numerical modeling codes. An example for this is the Monte Carlo analysis feature available in the elastoplastic numerical code RS2 (Rocscience, 2007). Probabilistic analysis allows the engineers to extract valuable insights for the investigated problem, primarily, by allowing for the assessment of the range of anticipated outcomes. In addition, probabilistic analysis can be used for computing the probability of failure (PoF), which provides a better means for determining the reliability of a system compared to the traditional factor of safety (FoS) (Phoon et al., 2022).

With the immense increase of computing power and digital data generation, ML algorithms have emerged as powerful computational tools for applications that require the analysis of large sets of data. ML has been recognized as a potential tool for revolutionizing the field of rock mechanics by collecting extensive field data via digital instrumentation and correlating it to various measurable rock mass responses (Morgenroth et al., 2019). The main obstacles of actualizing many potential applications of ML for such research projects is related to the acquisition of data. The cost of monitoring device installation is great, and in many projects, limited reliable data is generated. Moreover, the data that is generated often requires extensive efforts for preparing the data for ML.

Another potential of ML involves coupling it with artificial data generated by numerical modeling. This type of coupling is often referred to as surrogate models. An excellent review of the concept of surrogate models is given by Furtney et al. (2022). Surrogate models allow for fast and efficient analysis of various problems (Tao et al. 2022; Salazar and Hariri-Ardebili, 2022). Compared to field data, artificial data is relatively easy to generate and prepare. Particularly, when probabilistic tools allow for the user to export data as an Excel table, or any other form of text file. Using open-source packages, this data can be readily "learned" by ML models.

In this paper, we present an example of a surrogate model trained on artificial data generated via the program Slide2, by RocScience. This program is based on the limit equilibrium method of slices. Currently, there are many excellent textbooks that provide both theoretical background, as well as practical exercises and code examples for the application of ML (e.g. Géron, 2022). Rather than focusing on technical aspects of ML implementation, we focus here on the general framework and application of the surrogate model.

2 SLOPE STABILITY PROBLEM BACKGROUND AND DEFINITION

Historically, numerous limit equilibrium methods have been developed for slope stability analysis (Hoek & Bray, 1981). Within these methods, the FoS is calculated as the ratio of rock or soil shear strength to the shear strength on the verge of failure. For a rock mass that behaves as an equivalent continuum, the method of slices can be used for FoS calculation. Several researchers have developed different limit equilibrium methods. In particular, the slice method allows for solving slope problems using an iterative solving scheme, where the plane with minimal shear resistance is searched for. A number of solutions have been derived for the method of slices according to different underlying assumptions. A review of this method, as well as the popular approaches, is given by (Budhu, 2020).

Following the advent of numerical codes, Zienkiewicz et al. (1975) developed the shear reduction method (SRM), where the FE code gradually reduces the shear strength, until failure initiates. Compared to limit equilibrium methods, there are different advantages of solving slope stability problems with FE codes. This has been realized by commercial codes that have included SRM as a built-in feature (Rocscience, 2007). However, implementation of SRM requires an iterative solving scheme, where a single slope model is re-computed with a diminishing set of values for the strength parameters. Hence, checking for different slope angles with different ranges of input parameters would require the user to build several models, where each model would require a lengthy solving time. In addition, this process would be limited to a uniform diminishing of the strength properties. For example, if using the Mohr-Coulomb failure criterion, the pre-defined cohesion and friction angle are reduced simultaneously, and other possible combinations.

For the current example, the following scenario is analyzed: the stability of a rock slope made of sandstone material is investigated. The sandstone strength varies considerably, from soil-like material up to weak rock. The slope height is fixed, and the slope angle varies from 60^{o} to 90^{0}. At the top level of the slope is a distributed load of 100 kPa is in order to account for loading from future structures. Figure 1 shows the problem geometry.

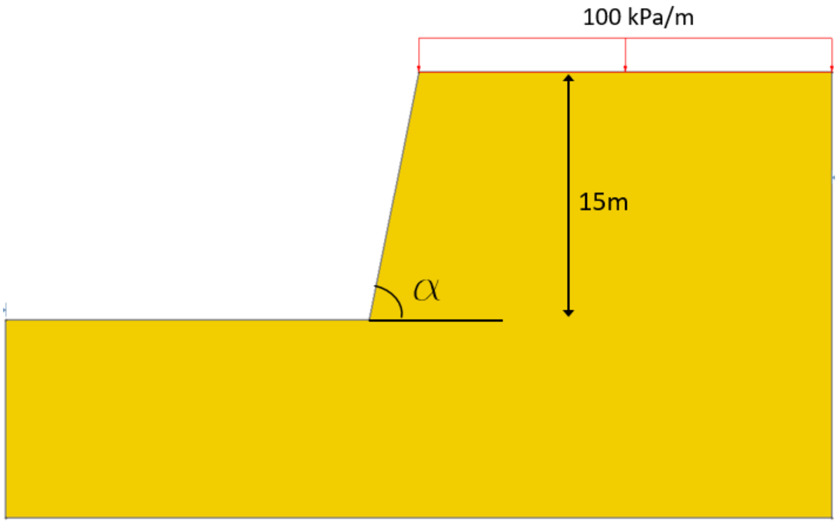

Figure 1. FE model for verification. The slope angle α is varied from 60º to 90º.

The rock mass is generally massive, and therefore an equivalent continuum behavior using the Mohr-Coulomb failure criterion is deemed as a sufficient approximation of reality. Accordingly, three input parameters are varied: the friction angle, cohesion, and unit weight of the rock mass. The minimum, mean and maximum values of each input parameter are listed in Table 1. The slope is divided into 50 slices, and the Morgenstern & Price slice method is used for the analysis (Morgenstern & Price, 1967).

Table 1. Input parameters and their variation.

Rock mass inputs	Units	Minimum	Mean	Maximum
Cohesion	[kPa]	50	100	150
Friction angle	[°]	20	40	60
Unit weight	[kN/m^3]	20	22	24

Figure 2 shows the results of the Monte Carlo analysis according to the input parameters listed in Table 1, as well as the variation of slope angle. The histogram shows the distribution of FoS, where for instances of failure (i.e. FoS<1) the bars are marked in red. The PoF is equal to the number of failure instances divided by the total instances. For this example, PoF=5.4%.

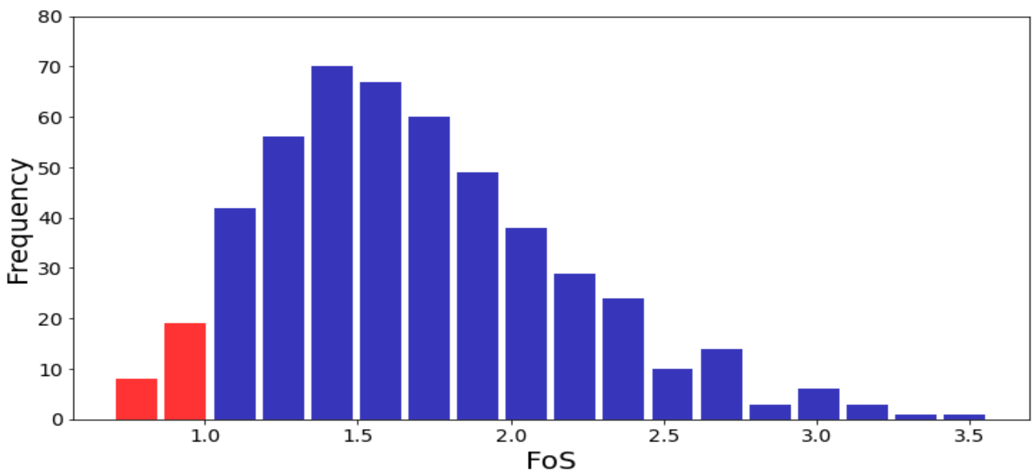

Figure 2. Monte Carlo results for FoS and PoF.

3 SLOPE STABILITY SURROGATE MODEL

In order to build a surrogate model, the user needs to define their desired learning process. The straightforward operation of surrogate models is for forward analysis, i.e. the input parameters are defined as inputs, and the results of interest are defined as target outputs. This type of surrogate model allows for instantaneous predictions given any set of input parameters within the defined range used for training the ML model. During project construction, it is frequent that decisions must be made rapidly, rendering the surrogate model a highly useful tool. Some applications require solving for the inverse problems, i.e. results are defined as inputs and input parameters are defined as target outputs, which are more difficult to solve accurately, and in some cases may be unsolvable. For both forward and inverse problems, the standard ML approach involves applying supervised learning models. For this paper, ML is used for developing a forward analysis surrogate model.

It is standard practice to compare a number of ML models, and to select the one that is most accurate. For this problem, a simple multiple linear regression model is found to perform well on a data set of 500 models (the coefficient of determination R^2=0.96, and root mean square error RMSE=0.1). This high accuracy is found satisfactory, and therefore the ML model can be used as a surrogate model for making further predictions. Hence, in given combination of input parameters and slope angle can be fed as input into the model, and the corresponding FoS can be computed instantaneously.

Other operations that are not as straight-forward could be undertaken as well. For example, let us consider the automation of the computation of the PoF for any narrow range of input parameters. This capability is particularly useful for geotechnical applications, where in the beginning of a project a wide range of parameters must be estimated, as the available field data is limited. As the project progresses, the estimated data is narrowed. In order to do so, a Monte Carlo algorithm can be used to generate new data within the defined narrow range. The surrogate model can then make predictions of the FoS. Finally, the PoF can be computed. The proposed scheme is shown in Figure 3.

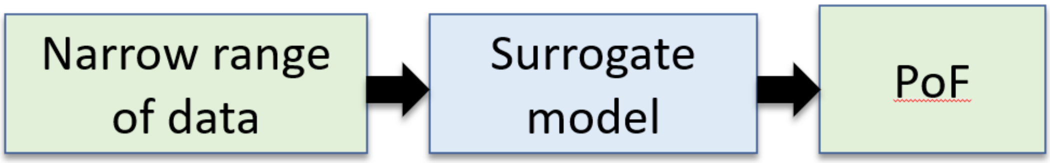

Figure 3. Proposed scheme for automating PoF for narrow range of data.

The problem presented here assumes many simplifying conditions. Depending on the complexity of the problem, the ML process may require more intensive programming. As stated, the program Slide2 consists of a built-in Monte Carlo model generator for varying input parameters, as well as other inputs (e.g. groundwater level, ground support, and more). However, it is currently not possible to include the variation of geometry within the automated solving process in Slide2. Thus, in order to obtain results of a different slope angles, the modeling process was repeated manually varying slope angles. The authors encourage managers and developers of engineering software programs to allow for users to readily implement ML tools for automation and enhanced analysis capabilities. Specifically, probabilistic analysis are an ideal starting point for such applications. With slight modifications, built-in probabilistic tools could provide users with the ability to generate datasets that consist of varying input parameters, as well as varying slope geometry.

REFERENCES

Abdulai, M. & Sharifzadeh, M. (2021). Probability Methods for Stability Design of Open Pit Rock Slopes: An Overview. Geosciences, 11(8), 319.

Budhu, M. (2020). Soil mechanics and foundations (Issue 1). Wiley.

Elmo, D., Mitelman, A. & Yang, B. (2022). Examining Rock Engineering Knowledge through a Philosophical Lens. Geosciences, 12(4), 174.

Furtney, J. K., Thielsen, C., Fu, W. & le Goc, R. (2022). Surrogate Models in Rock and Soil Mechanics: Integrating Numerical Modeling and Machine Learning. Rock Mechanics and Rock Engineering, 55(5), 2845–2859.

Géron, A. (2022). Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. ‘ O’Reilly Media, Inc.’

Hoek, E. & Bray, J. D. (1981). Rock slope engineering. CRC Press.

Lees, A. (2013). Geotechnical finite element analysis. ICE publishing.

Mitelman, A. & Elmo, D. (2019). Analysis of tunnel-support interaction using an equivalent boundary beam. Tunnelling and Underground Space Technology, 84. https://doi.org/10.1016/j.tust.2018.11.021

Morgenroth, J., Khan, U. T. & Perras, M. A. (2019). An overview of opportunities for machine learning methods in underground rock engineering design. Geosciences, 9(12), 504.

Morgenstern, N. R. & Price, V. E. (1967). A numerical method for solving the equations of stability of general slip surfaces. The Computer Journal, 9(4), 388–393.

Phoon, K.-K., Cao, Z.-J., Ji, J., Leung, Y. F., Najjar, S., Shuku, T., Tang, C., Yin, Z.-Y., Ikumasa, Y. & Ching, J. (2022). Geotechnical uncertainty, modeling, and decision making. Soils and Foundations, 62(5), 101189.

Rocscience. (2004). Rocscience software products: Dips, Slide, Phase2. Rocscience Toronto.

Rocscience. (2007). Phase2 version 6.020. Rocscience Inc. Toronto.

Salazar, F. & Hariri-Ardebili, M. A. (2022). Coupling machine learning and stochastic finite element to evaluate heterogeneous concrete infrastructure. Engineering Structures, 260, 114190.

Tao, Y., He, W., Sun, H., Cai, Y. & Chen, J. (2022). Multi-objective optimization-based prediction of excavation-induced tunnel displacement. Underground Space.

Zienkiewicz, O. C., Humpheson, C. & Lewis, R. W. (1975). Associated and non-associated visco-plasticity and plasticity in soil mechanics. Geotechnique, 25(4), 671–689.