

Research Paper

Three-dimensional slope reliability and risk assessment using auxiliary random finite element method



Te Xiao^a, Dian-Qing Li^{a,*}, Zi-Jun Cao^a, Siu-Kui Au^b, Kok-Kwang Phoon^c

^aState Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, 8 Donghu South Road, Wuhan 430072, PR China

^bInstitute for Risk and Uncertainty, University of Liverpool, Harrison Hughes Building, Brownlow Hill, Liverpool L69 3GH, United Kingdom

^cDepartment of Civil and Environmental Engineering, National University of Singapore, Blk E1A, #07-03, 1 Engineering Drive 2, Singapore 117576, Singapore

ARTICLE INFO

Article history:

Received 18 February 2016

Received in revised form 10 May 2016

Accepted 29 May 2016

Keywords:

Slope stability

Reliability analysis

Risk assessment

Spatial variability

Random finite element method

Response conditioning method

ABSTRACT

This paper aims to propose an auxiliary random finite element method (ARFEM) for efficient three-dimensional (3-D) slope reliability analysis and risk assessment considering spatial variability of soil properties. The ARFEM mainly consists of two steps: (1) preliminary analysis using a relatively coarse finite-element model and Subset Simulation, and (2) target analysis using a detailed finite-element model and response conditioning method. The 3-D spatial variability of soil properties is explicitly modeled using the expansion optimal linear estimation approach. A 3-D soil slope example is presented to demonstrate the validity of ARFEM. Finally, a sensitivity study is carried out to explore the effect of horizontal spatial variability. The results indicate that the proposed ARFEM not only provides reasonably accurate estimates of slope failure probability and risk, but also significantly reduces the computational effort at small probability levels. 3-D slope probabilistic analysis (including both 3-D slope stability analysis and 3-D spatial variability modeling) can reflect slope failure mechanism more realistically in terms of the shape, location and length of slip surface. Horizontal spatial variability can significantly influence the failure mode, reliability and risk of 3-D slopes, especially for long slopes with relatively strong horizontal spatial variability. These effects can be properly incorporated into 3-D slope reliability analysis and risk assessment using ARFEM.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Slope failure (e.g., landslides) is one of the major natural hazards in the world. The occurrence probability and risk of slope failure are related to various geotechnical uncertainties (e.g., [7,23–25,27,30,34,39,44,45]), among which spatial variability of soil properties is one of the most significant uncertainties affecting slope reliability and risk. Previous studies on slope reliability analysis and risk assessment that account for spatial variability mainly focus on two-dimensional (2-D) analysis, such as Griffiths and Fenton [11], Santoso et al. [41], Wang et al. [51], Huang et al. [17], Zhu et al. [54], Li et al. [28,29,33,35], Jamshidi Chenari and Alaie [18]. As shown in Fig. 1, 2-D analysis implicitly assumes infinite length of slope and perfect correlation of soil properties (i.e., infinite spatial autocorrelation distance) in the axial direction. Based on these assumptions, slopes fail along columnar slip surface with infinite length in three-dimensional (3-D) space. This is inconsistent with

the actual failure surfaces observed in slope engineering, where slope may fail at any locations of the slope with an irregular and finite slip surface. Thus, it is necessary to investigate 3-D slope reliability analysis and risk assessment, particularly with both 3-D slope stability analysis and 3-D spatial variability modeling of soil properties.

Several studies (e.g., [14,15,20,21,46,47]) have made attempts to assess 3-D slope reliability. These studies can be classified into three categories according to the adopted reliability methods: first-order second-moment method (FOSM), first-order reliability method (FORM), and Monte Carlo Simulation (MCS). Vanmarcke [46,47] pioneered analytical 3-D slope reliability analysis using FOSM and considered the problem as an extension of 2-D slope reliability analysis based on local average and first-passage theories. This work is elegant and valuable. However, it assumed that slope fails along several prescribed cylindrical slip surfaces, which may lead to an overestimated slope reliability since many other potential slip surfaces (e.g., non-cylindrical ones) are ignored. By only accounting for the axial spatial variability, FORM was also applied to 3-D slope reliability analysis [20,21]. If 3-D spatial variability in axial, lateral and vertical directions as shown in Fig. 1 are

* Corresponding author.

E-mail address: dianqing@whu.edu.cn (D.-Q. Li).

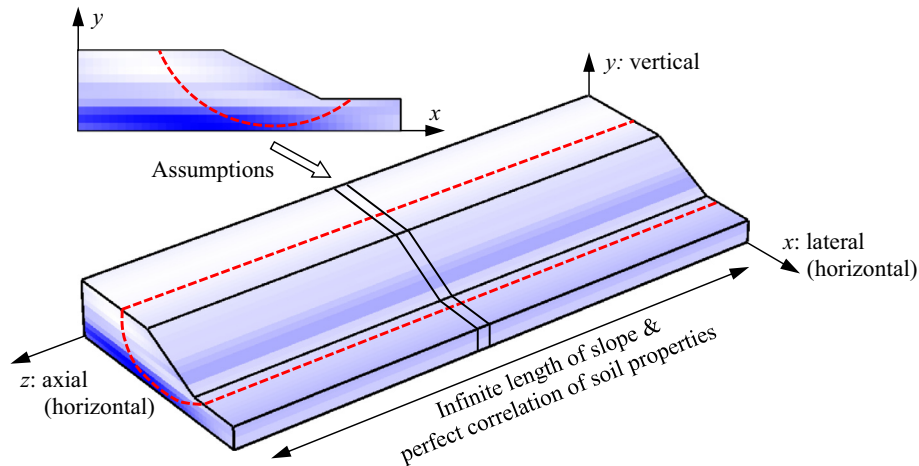


Fig. 1. Assumptions made in 2-D slope reliability analysis.

completely taken into consideration, FORM may encounter computational difficulties, such as high-dimensional problem [43].

Compared with FOSM and FORM, MCS is the most widely-used reliability method for 3-D slope reliability analysis, thanks to the development of random finite element method (RFEM) [11]. The original RFEM, also referred as MCS-based RFEM, incorporates the spatial variability of soil properties into slope reliability analysis using finite-element (FE) analysis and MCS. There are several successful applications of RFEM in reliability analysis of 3-D slope (e.g., [14–16,36]) and slope risk assessment (e.g., [17,31]). RFEM is a rigorous approach since the FE analysis of slope stability can automatically locate the critical slip surface without assumptions on the shape and location. Nevertheless, MCS-based RFEM usually requires intensive computational efforts [19], particularly for detailed 3-D FE models and small probability levels (e.g., slope failure probability $P_f < 10^{-3}$). One simple strategy to address this problem is to adopt a relatively coarse FE model (e.g., the model with coarse FE mesh) in RFEM to improve the computational efficiency of deterministic slope stability analysis. However, coarse FE model may not produce accurate results compared to detailed FE model (e.g., the model with fine FE mesh). For this reason, another RFEM run with detailed FE model is still requisite if more accurate results are required, for example, at later design stages. The computational effort paid for the coarse FE model-based RFEM is thus wasted, and it cannot facilitate the detailed FE model-based RFEM neither, because of no interaction between the two RFEM runs.

In addition, previous studies based on 2-D analysis indicated that the horizontal spatial variability (i.e., lateral spatial variability in the 3-D perspective, see Fig. 1) has minimal influence on slope reliability (e.g., [22,53]). One possible reason is that the lateral scale of slopes is almost in the same order of magnitude as the horizontal autocorrelation distance, namely 20–40 m [38]. In this case, the effect of horizontal spatial variability cannot be captured in 2-D slope reliability analysis. For 3-D slopes, the axial scale can be much larger than the horizontal autocorrelation distance. The effect of horizontal spatial variability on 3-D slope reliability and risk has not been explored systematically.

This paper aims to propose an auxiliary random finite element method (ARFEM) for efficient 3-D slope reliability analysis and risk assessment, and to explore the effect of horizontal spatial variability on 3-D slopes. To achieve these goals, the paper is organized as below. In Section 2, the ARFEM is developed. In Section 3, the modeling of 3-D spatially variable soil properties is presented. The computational effort of ARFEM is discussed in Section 4 and the implementation procedure of ARFEM is summarized in Section 5.

A 3-D soil slope example is then presented in Section 6 to demonstrate the validity of ARFEM. Finally, a sensitivity study is carried out to explore the effect of horizontal spatial variability on 3-D slope reliability and risk in Section 7.

2. Auxiliary random finite element method

In slope reliability analysis and risk assessment, the probability of slope failure, P_f , is defined as the probability that the safety factor of slope stability, FS , is smaller than a given threshold fs (e.g., $fs = 1$), namely $P_f = P(FS < fs)$, and the slope failure risk, R , can be defined as the product of P_f and the average failure consequence \bar{C} [17,31]. The computational efficiency and accuracy of P_f and R depend on the deterministic analysis model of slope stability, such as the FE models with coarse and fine FE meshes (referred as coarse and fine FE models, respectively). Both of these two FE models are adopted in ARFEM, which, in turn, constitute two major steps of ARFEM: (1) preliminary analysis using a relatively coarse FE model and Subset Simulation (SS) [3], and (2) target analysis using a fine FE model and response conditioning method (RCM) [2]. They are provided in the following two subsections. To facilitate understanding, subscripts “ p ” and “ t ” shall denote the estimates obtained from preliminary and target analyses of ARFEM, respectively.

2.1. Preliminary analysis using coarse FE model and SS

Preliminary analysis aims to efficiently assess slope reliability and risk. For this purpose, coarse FE model and SS are adopted to perform deterministic slope stability analysis and slope reliability analysis at small probability levels, respectively. SS [3,4] stems from the idea that a small failure probability can be expressed as a product of larger conditional failure probabilities for some intermediate failure events, thereby converting a rare event simulation problem into a sequence of more frequent ones. Let $fs_1 > fs_2 > \dots > fs_{m-1} > fs > fs_m$ be a decreasing sequence of intermediate threshold values, and $F_{p,k} = \{FS_p < fs_k, k = 1, 2, \dots, m\}$ be the intermediate failure events. In implementation, fs_k ($k = 1, 2, \dots, m$) are determined adaptively so that the estimates of $P(F_{p,1})$ and $P(F_{p,k}|F_{p,k-1})$, $k = 2, 3, \dots, m$, always correspond to a common specified value of conditional probability p_0 . An SS run with m simulation levels (including one direct MCS level and $m - 1$ levels of Markov Chain MCS) and N samples in each level results in $mN(1 - p_0) + Np_0$ samples in total.

Download English Version:

<https://daneshyari.com/en/article/254513>

Download Persian Version:

<https://daneshyari.com/article/254513>

[Daneshyari.com](https://daneshyari.com)