Computers and Geotechnics 92 (2017) 121–131

Contents lists available at ScienceDirect

Computers and Geotechnics

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

Reliability evaluation of slope considering geological uncertainty and inherent variability of soil parameters

Zhi-Ping Deng [a], Dian-Qing Li [a,*], Xiao-Hui Qi [a], Zi-Jun Cao [a], Kok-Kwang Phoon [b]

[a] State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, 8 Donghu South Road, Wuhan 430072, PR China
[b] Department 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 13 November 2016
Received in revised form 21 July 2017
Accepted 23 July 2017

Keywords:
Slope stability
Geological uncertainty
Inherent variability
Reliability analysis

ABSTRACT

Geological uncertainty is often ignored in slope reliability analysis, even though the inherent variability of soil parameters is considered. This paper aims to propose a method for slope reliability analysis by considering both the inherent variability of soil parameters and geological uncertainty. A coupled Markov chain (CMC) model is used to simulate the geological uncertainty. An implementation procedure for slope reliability considering the aforementioned two types of uncertainty is provided. A slope reliability problem is analyzed to validate the proposed method with the borehole data from Perth, Australia. Different borehole layout schemes are designed to reflect the effect of both number and location of boreholes on slope reliability. Moreover, which type of uncertainty mentioned above has a greater impact on slope reliability is explored. The results indicate that the proposed method can effectively evaluate the slope reliability considering these two types of uncertainty. If only the inherent variability is considered, the accuracy of reliability analysis mainly depends on the used geological profiles. Borehole layout scheme has a significant effect on slope reliability. Both probability of failure (P_f) and mean of factor of safety (*FS*) of slope do not monotonously vary with an increasing number of boreholes. The boreholes designed in the critical influence zone can provide more information to improve the accuracy of slope reliability. The coefficients of variation (COVs) of shear strength parameters and the discrepancy among the means of shear strengths for different soils play different and major role between the two types of uncertainty in the reliability analysis of soil slope.

1. Introduction

Soil heterogeneity has a considerable effect on the deformation and stability of geotechnical structures, such as slopes and foundations (e.g., [11,8,36,24,21,23,20]). Such heterogeneity of soil properties is mainly twofold: inherent variability and geological uncertainty [8]. The former one implies that soil parameters are different from one point to another in space, and is mainly due to different deposition conditions and loading histories of soils [30]. The later geological uncertainty appears in the form of one soil layer embedded in another or inclusion of pockets of a different soil type within a more uniform soil mass. This non-stationary and discrete heterogeneity widely exists in real landslide cases (e.g., [9,14]). In the literature (e.g., [10,3,2,41,38,16,24,15,17,40]), most studies focused on the role of inherent variability only and ignored the impact of geological uncertainty on the geotechnical reliability.

A few studies have been conducted to investigate the effect of geological uncertainty (e.g., [5,34,13,19,7,31]). For example, Tang et al. [34] proposed a renewal process to describe the probabilistic characteristics of a soil stratum consisting of two distinct material types. Halim [13] evaluated the reliability of geotechnical systems considering the uncertainty of geological anomaly. Kohno et al. [19] studied the system reliability of a tunnel running through two types of rock. Note that only two types of soils are considered in these work. However, in geotechnical practice, geological uncertainty typically involves more than two types of soils in a layered profile (e.g., [9,14]). To rationally characterize this kind of soil heterogeneity, a coupled Markov chain (CMC) model was proposed by Elfeki and Dekking [7]. To facilitate its application in geotechnical practice, Qi et al. [31] proposed a practical method to estimate one key input of the CMC model, i.e., horizontal transition probability matrix (HTPM). On the basis of Qi et al.'s [31] study, Li et al. [21] further proposed a probabilistic approach for slope reliability evaluation with the consideration of geological uncertainty. However, the inherent variability of soil parameters is not considered in Li et al.'s [21] study. In summary, the previous work

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

http://dx.doi.org/10.1016/j.compgeo.2017.07.020
0266-352X/

indicates that both inherent variability of soil parameters and geological uncertainty are key elements in slope reliability analysis, but only one type of them is considered. It is herein necessary to incorporate these two types of uncertainties consistently into the probabilistic analysis of slope stability.

This paper aims to propose a method for slope reliability evaluation by considering both inherent variability of soil parameters and geological uncertainty. To achieve this aim, this paper is organized as follows. In Section 2, the theory behind the modeling of geological uncertainty by the CMC model is introduced. In Section 3, the midpoint method based on a Cholesky decomposition technique is adopted to discretize random fields within different geological units. Taking the realizations of random fields as input data, the factor of safety (*FS*) of a slope is calculated using the finite element-strength reduction method. The implementation procedure for slope reliability evaluation considering both inherent variability of soil parameters and geological uncertainty is given in Section 4. In Section 5, the proposed method is illustrated and validated with a soil slope and real borehole data from the Central Business District in Perth, Australia. Some conclusions are drawn in Section 6.

2. Simulation of geological uncertainty using the Coupled Markov chain model

Following Qi et al. [31], here the CMC model is used to simulate the geological uncertainty. The reasons for choosing the CMC model are threefold: (1) it is theoretically simple and can handle any number of soil types, (2) borehole data (which fixed the stratigraphy in known locations) can be incorporated directly using a conditional simulation scheme, and (3) this model has high efficiency and explicitness. One-dimensional (1-D) Markov chain is a probabilistic model based on the idea that the state of a system in a current step depends only on the state in the previous step. Given a sequence of random variables $Z_1, Z_2, \ldots, Z_n$ taking values in the state space $\{S_1, S_2, \ldots, S_m\}$ (m is the total number of states), this sequence is a 1-D Markov chain if

$$P(Z_k = S_j | Z_{k-1} = S_i, Z_{k-2} = S_l, Z_{k-3} = S_q, \ldots, Z_1 = S_p) = P(Z_k = S_j | Z_{k-1} = S_i) \tag{1}$$

where $P(Z_k = S_j | Z_{k-1} = S_i, Z_{k-2} = S_l, Z_{k-3} = S_q, \ldots, Z_1 = S_p)$ is the probability of $Z_k = S_j$, given that $Z_{k-1} = S_i, Z_{k-2} = S_l, Z_{k-3} = S_q, \ldots, Z_1 = S_p$, and $P(Z_k = S_j | Z_{k-1} = S_i)$ is the probability of $Z_k = S_j$, given that $Z_{k-1} = S_i$. For the soil system possessing the Markovian property, the Markov chain state S_i $(i = 1, \ldots, m)$ can be viewed as the soil types, e.g., S_1 = clay, S_2 = sand, S_3 = silt; the Markov chain step can be deemed as distance in space, e.g., step 1 = interval between 0 and 0.5 m, step 2 = interval between 0.5 and 1.0 m. For homogeneous Markov chain, the one-step probability of transition is independent of the step, i.e., $P(Z_k = S_j | Z_{k-1} = S_i) = P(Z_{k-1} = S_j | Z_{k-2} = S_i)$. Therefore, a simple symbol p_{ij} is introduced to represent the one-step probability of transition, i.e., Eq. (1). The characters i and j in the symbol denote the soil states of the previous and current steps, respectively. The one-step probability for all the transitions can be denoted as a matrix $\boldsymbol{P}$ (also called transition probability matrix, TPM), whose elements are $p_{ij}(i = 1, \ldots, m; j = 1, \ldots, m)$.

It is natural to model the soil transition with two different 1-D Markov chains. One describes the variations in the horizontal direction, and the other describes the variations in the vertical direction. The two chains have two transition probability matrices, i.e., HTPM ($\boldsymbol{P^h}$) and vertical transition probability matrix (VTPM, $\boldsymbol{P^v}$). Elfeki [6] developed a methodology to efficiently couple the two chains, which is called the CMC model. However, the initial model cannot condition on more than one borehole. To overcome this limitation, Elfeki and Dekking [7] developed a conditional simulation methodology by using the borehole stratigraphy at the left, upper, and right boundaries (the shaded area in Fig. 1). As shown in Fig. 1, the domain to be modeled is discretized into a number of cells of the same size. The state of a cell (i, j) ($i > 1$, i = column number; $j > 1$, j = row number) depends on the states of the cells on the top [cell $(i, j-1)$], left [cell $(i-1, j)$] of the current cell, and rightmost (N_x, j). Soil states on dark blue[1] cells are fixed. States on the leftmost and rightmost columns are revealed by two boreholes, while states on the top row can be directly obtained by observing from the ground surface. They can be used as conditional starting states for simulating the states of the other cells inside the domain. The dependence of the cell states is described in terms of transition probabilities as Elfeki and Dekking [7]

$$p_{lr,k|q} = P(Z_{i,j} = S_k | Z_{i-1,j} = S_l, Z_{i,j-1} = S_r, Z_{N_x,j} = S_q) = \frac{p^h_{lk} p^{h(N_x-i)}_{kq} p^v_{rk}}{\sum_{f=1}^{m} p^h_{lf} p^{h(N_x-i)}_{fq} p^v_{rf}} \tag{2}$$

where $p_{lr,k|q}$ is the probability that cell (i, j) is in state S_k, given that cells $(i-1, j)$, $(i, j-1)$, and (N_x, j) are in states S_l, S_r, and S_q, respectively; $Z_{i,j}$, $Z_{i-1,j}$, $Z_{i,j-1}$, and $Z_{N_x,j}$ are the states in cells (i, j), $(i-1, j)$, $(i, j-1)$, and (N_x, j), respectively; p^h_{lk} and p^v_{rk} are the corresponding elements of the horizontal and vertical transition probability matrices, $\boldsymbol{P^h}$ and $\boldsymbol{P^v}$, respectively; and $p^{h(N_x-i)}_{kq}$ [$p^{h(N_x-i)}_{fq}$] is the probability of transition from S_k (S_f) to S_q in (N_x-i) steps in the horizontal direction. It is the corresponding element of $(\boldsymbol{P^h})^{(N_x-i)}$, i.e., the matrix obtained by multiplying HTPM itself by (N_x-i) times.

3. Simulation of inherent variability of soil parameters using random field theory

After characterizing the geological uncertainty, the resulting stratification of soil profile can be obtained. For a specified geological unit (or soil layer), the inherent variability of soil parameters can be characterized by random fields [35]. In this study, the overall random fields are non-stationary because of various types of soils within different sub-layers. The method in Lu and Zhang [27] can be adopted to model the inherent variability of soil parameters. For a given soil profile underlying a slope, the simulation domain can be portioned into multiple non-overlapping subdomains. The soil properties are assumed to be statistically stationary within each subdomain. Furthermore, the covariance between any two points in different layers is assumed to be zero. For illustration, an exponential two-dimensional (2-D) autocorrelation function with different autocorrelation distances in horizontal and vertical directions is adopted to characterize the autocorrelations between different points in each soil layer as follows:

$$\rho(\tau_x, \tau_y) = \exp\left[-2\left(\frac{\tau_x}{\delta_h} + \frac{\tau_y}{\delta_v}\right)\right] \tag{3}$$

where $\rho(\tau_x, \tau_y)$ is the correlation coefficient between two arbitrary points in a soil layer; τ_x and τ_y are the horizontal and vertical distances between two points in space, respectively; and δ_h and δ_v are the horizontal and vertical scale of fluctuations (SOFs) of soil parameters, respectively.

This paper mainly focuses on the effect of inherent spatial variability of shear strength (e.g., cohesion c and friction angle ϕ) on slope reliability. To avoid negative values of the shear strength parameters, following Jiang et al. [16], a 2-D stationary

[1] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.