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Probabilistic analysis of ultimate seismic bearing capacity of strip foundations

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ABSTRACT

This paper presents a reliability analysis of the pseudo-static seismic bearing capacity of a strip foundation using the limit equilibrium theory. The first-order reliability method (FORM) is employed to calculate the reliability index. The response surface methodology (RSM) is used to assess the Hasofer–Lind reliability index and then it is optimized using a genetic algorithm (GA). The random variables used are the soil shear strength parameters and the seismic coefficients (k_h and k_v). Two assumptions (normal and non-normal distribution) are used for the random variables. The assumption of uncorrelated variables was found to be conservative in comparison to that of negatively correlated soil shear strength parameters. The assumption of non-normal distribution for the random variables can induce a negative effect on the reliability index of the practical range of the seismic bearing capacity.

1. Introduction

Uncertainty is an important issue in engineering design as geotechnical engineers can basically introduce uncertainty in the design when using a global safety factor. Reliability methods have therefore become promising when assessing the effect of uncertainty on geotechnical structure design. The designs using reliability assessment were applied to many geotechnical engineering projects (e.g. Mollon et al., 2009a,b, 2011, 2013; Griffiths and Fenton, 2001; Griffiths et al., 2002; Kulhawy and Phoon, 2002).

Many theories have also been used to study the seismic bearing capacity of a strip foundation (e.g. Budhu and AlKarni, 1993; Dormieux and Pecker, 1995; Soubra, 1997). Their results indicated that the value of the bearing capacity decreased with the increase of the seismic acceleration coefficient. Inertia forces in the soil mass decrease the bearing capacity of the soil and, as a result, the bearing capacity of the foundation decreases. In recent years, some researchers such as Zeng and Steedman (1998), Garnier and Pecker (1999), Askari and Farzaneh (2003), Gajan et al. (2005), Knappett et al. (2006), and Merlos and Romo (2006) have drawn the same conclusions by using the dynamic centrifuge tests. Using the characteristics method, Cascone and Casablanca (2016) evaluated the static and seismic bearing capacity factors for a shallow strip foundation by the pseudo-static approach. Other researchers such as Pane et al. (2016) numerically obtained the bearing capacity of soils under dynamic conditions. Shafiee and Jahanandish (2010) employed the finite element method to determine the seismic bearing capacity of strip foundations with various seismic coefficients and friction angles. They also presented curves relating the seismic bearing capacity factors to the seismic acceleration coefficient.

In this context, the homogeneous soils and seismic properties are used to analyze the seismic bearing capacity of strip foundations. The bearing capacity is calculated using a single deterministic set of parameters. Reliability analysis is then used to assess the combined effects of uncertainties and provide a logical framework for selecting the bearing capacity that is appropriate for a degree of uncertainty and the failure consequences. Thus, the reliability assessment useful for providing better engineering decisions is performed as an alternative to the deterministic assessment.

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Over the last fifteen years, the reliability analysis of shallow foundations subjected to a centered static vertical load has been studied by Fenton and Griffiths (2002, 2003), Sivakumar Babu et al. (2006), and Youssef Abdel Massih et al. (2008). However, the reliability analyses of shallow foundations subjected to inclined, eccentric or complex loads are rarely investigated (Ahmed and Soubra, 2014). Probabilistic approaches for seismic bearing capacity of shallow foundation are seldom elaborated in the literature (Youssef Abdel Massih et al., 2008; Baroth et al., 2011). Johari et al. (2017) used the slip lines method coupled with the random field theory to estimate the seismic bearing capacity of strip foundations. The bearing capacity factors N_i (N_c, N_q and N_γ) are assessed stochastically, with the values depending on friction angle.

In previous researches, different types of simulation approaches were used to assess the reliability of geotechnical systems, in which the response surface methodology (RSM) is basically used. Monte Carlo simulation (MCS) (Wang et al., 2010) and importance sampling (IS) (Mollon et al., 2009a) offered the implied estimates of the system failure probability (P_f). However, they are rather time-consuming (e.g. finite element method or finite difference method). Different types of RSMs such as classic RSM, artificial neural network (ANN) based RSM (Cho, 2009) and Kriging-based RSM (Zhang et al., 2013) have been proposed to overcome this disadvantage. However, they are all approximate methods which cannot provide precise estimates.

This paper presents a reliability analysis of the seismic bearing capacity of a strip foundation under pseudo-static seismic loading. The uncertain parameters are modeled by random variables. These variables are the soil shear strength parameters and the seismic coefficients (k_h and k_v). Only the punching failure mode of the ultimate limit states is studied. The deterministic model is based on the limit equilibrium theory (Budhu and Al-Karni, 1993). The Hasofer–Lind reliability index (β_{HL}) was adopted to calculate the reliability of the seismic bearing capacity. The RSM optimized by the genetic algorithm (GA) have been used to find the approximate performance function and derive β_{HL}. The RSM optimized by GA saves computation time compared with the conventional RSM methods (Hamrouni et al., 2017a,b, 2018). The influence of normal and non-normal parameters distribution as well as the correlation between soil shear strength parameters on the failure probability is studied.

2. Ellipsoid approach in reliability theory

The safety of geotechnical structures can be represented by its β_{HL} value which takes the inherent uncertainties as input parameters. The β_{HL} (Hasofer and Lind, 1974) is the most widely used indicator in the literature. Its matrix formulation is (Ditlevsen, 1981)

$$\beta_{HL} = \min_{\boldsymbol{G}(\boldsymbol{x})=\boldsymbol{0}} \sqrt{(\boldsymbol{x}-\boldsymbol{\mu})^{T}\boldsymbol{C}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})} \tag{1}$$

where $\boldsymbol{\mu}$ is a vector of mean values, $\boldsymbol{x}$ is a vector representing the n random variables and $\boldsymbol{C}$ is a matrix covariance.

The minimization of Eq. (1) is performed using the constraint $\boldsymbol{G}(\boldsymbol{x}) \le \boldsymbol{0}$ where the n-dimensional domain of the random variables is separated by the limit state performance ($\boldsymbol{G}(\boldsymbol{x}) = \boldsymbol{0}$) into two regions: an unsafe region F represented by $\boldsymbol{G}(\boldsymbol{x}) \le \boldsymbol{0}$ and a safe region given by $\boldsymbol{G}(\boldsymbol{x}) > \boldsymbol{0}$. Eq. (1) is used in a form of the classical method to calculate β_{HL}, which is based on the transformation of the performance limit state initially defined in the space of the physical variables. This state must be shown in the space of the normal random variables, centered, reduced and uncorrelated, which is also called standard space. The β_{HL} is the shortest distance between the origin of the space and the state boundary surface.

Low and Tang (2004) proposed an interpretation of β_{HL}. The concept of iso-probability ellipsoid leads to a simpler calculation method for β_{HL} in the original physical variables (see Fig. 1). Low and Tang (2004), Mollon et al. (2009b), Lü et al. (2011), Low (2014) and Hamrouni et al. (2017a,b, 2018) demonstrated that the ellipticity (ratio between the axes) of the critical dispersion ellipsoid corresponds to the value of β_{HL}, which is the smallest ellipsoid dispersion that just touches the limit state surface to the unit dispersion ellipsoid, i.e. the one obtained for $\beta_{HL} = 1$ in Eq. (1) without minimization.

They also stated that the intersection point between the critical dispersion ellipsoid and the equivalent performance limit state surface is called the design point (see Fig. 1). In the case of non-normal random variables, the Hasofer–Lind method can be extended. A transformation of each non-normal random variable into an equivalent normal random variable with an average $\boldsymbol{\mu}^N$ and a standard deviation $\boldsymbol{\sigma}^N$ was proposed by Rackwitz and Flessler (1978). Using the above-mentioned procedure, the transformation makes it possible to estimate a solution in a reduced space. The equivalent parameters evaluated at the design point $\boldsymbol{X}_i^*$ are given by

$$\boldsymbol{\mu}_i^N = -\boldsymbol{\sigma}_i^N \boldsymbol{\Phi}^{-1}\left[\boldsymbol{F}_{\boldsymbol{X}_i}\left(\boldsymbol{X}_i^*\right)\right] + \boldsymbol{X}_i^* \tag{2}$$

$$\boldsymbol{\sigma}_i^N = \frac{\boldsymbol{\phi}\left\{\boldsymbol{\Phi}^{-1}\left[\boldsymbol{F}_{\boldsymbol{X}_i}\left(\boldsymbol{X}_i^*\right)\right]\right\}}{\boldsymbol{f}_{\boldsymbol{X}_i}\left(\boldsymbol{X}_i^*\right)} \tag{3}$$

where $\boldsymbol{\Phi}$ and $\boldsymbol{\phi}$ are the cumulative density function (CDF) and the probability density function (PDF) of the standard variables, respectively; $\boldsymbol{F}_{\boldsymbol{X}_i}$ and $\boldsymbol{f}_{\boldsymbol{X}_i}$ are the CDF and PDF of the original non-normal random variables, respectively. The CDFs and PDFs of the real variables and the equivalent normal variables identified at the design point on the performance state surface are assimilated after derivation of Eqs. (2) and (3).

Low and Tang (1997, 2004) implemented an inclined ellipsoid and an optimization algorithm to minimize the dispersion ellipsoid. Eq. (1) can then be rewritten as

$$\beta_{HL} = \min_{x \in F} \sqrt{\left[\frac{\boldsymbol{x}-\boldsymbol{\mu}_{\boldsymbol{x}}^N}{\boldsymbol{\sigma}_{\boldsymbol{x}}^N}\right]^{T} [\boldsymbol{R}]^{-1} \left[\frac{\boldsymbol{x}-\boldsymbol{\mu}_{\boldsymbol{x}}^N}{\boldsymbol{\sigma}_{\boldsymbol{x}}^N}\right]} \tag{4}$$

where $[\boldsymbol{R}]^{-1}$ is the inverse of the correlation matrix $[\boldsymbol{R}]$. The configuration of the ellipsoid can be presented by this equation.

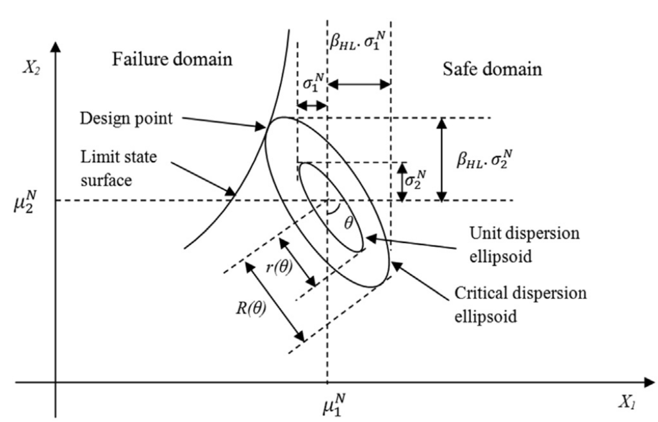

Fig. 1. Design point and equivalent normal dispersion ellipses in the space of two random variables.

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