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Research Paper

An efficient probabilistic back-analysis method for braced excavations using wall deflection data at multiple points

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ABSTRACT

This paper presents an efficient Bayesian back-analysis procedure for braced excavations using wall deflection data at multiple points. Response surfaces obtained from finite element analyses are adopted to efficiently evaluate the wall responses. Deflection data for 49 wall sections from 11 case histories are collected to characterize the model error of the finite element method for evaluating the deflections at various points. A braced excavation project in Hang Zhou, China is chosen to illustrate the effectiveness of the proposed procedure. The results indicate that the soil parameters could be updated more significantly for the updating that uses the deflection data at multiple points than that only uses the maximum deflection data. The predicted deflections from the updated parameters agree fairly well with the field observations. The main significance of the proposed procedure is that it improves the updating efficiency of the soil parameters without adding monitoring effort compared with the traditional method that uses the maximum deflection data.

1. Introduction

Accurate estimation of soil parameters is vital to prediction of the wall and ground responses in a braced excavation project. Due to the inherent uncertainty and measurement error, soil parameters measured in laboratory testing normally suffer from errors [28,18,43]. Additionally, the soil samples tested in a laboratory might not be representative of the soil mass in the field [33]. Direct use of the soil parameters from laboratory tests in reliability analysis of a braced excavation problem might lead to an unrealistic evaluation of the safety of the excavation system. Hence, it is desirable to reduce the uncertainty in the soil parameter for more rational reliability-based design of the excavation system. Methods used to reduce the uncertainty in soil parameters can be generally classified into two categories. The first category adopts certain empirical relations or statistical correlations between the soil parameters (such as undrained shear strength and friction angle) and selected field or laboratory test results (such as overconsolidation ratio, cone tip resistance in the cone penetration test and standard penetration test value). The field or laboratory test results are used as conditional information to update the soil parameter distributions. Examples of this category can be found in the work of Cao and Wang [3], Ching et al. [4], Ching et al. [5] and Wang et al. [36]. The second category adopts selected field observations to reduce the uncertainty in the soil parameters via back analysis. This category of methods has been widely applied (e.g., [9,11,14]) due to several attractive advantages. One remarkable merit is that back analysis using field observations partially reflects field conditions such as the effective normal stress and shear displacement rate of the soil mass [33]. These conditions cannot be reproduced in the laboratory. In addition, the back analysis incorporates certain important factors that might not be well represented by the laboratory samples, such as the structural fabric of the soil and pre-existing shear planes [33].

Many methods are available for back analysis of soil parameters, such as the least squares method (e.g., [9]), artificial neural networks (e.g., [10]), genetic algorithm (e.g., [11]), maximum likelihood method (e.g., [38]) and Bayesian method (e.g., [13,37]). Most of the methods (e.g., least squares method, artificial neural networks) treat the soil parameters as constants rather than random variables. The results for these back-analysis methods are a set of fixed values, but these fixed values are not necessarily the true values of the soil parameters because uncertainties usually exist in both the field observations and the calculation models [14,41]. Recently, the Bayesian method has gained wide application in a variety of geotechnical problems, such as slope stability [41], pile

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capacity [27] and braced excavations [14,37]. The Bayesian method is superior to the aforementioned back-analysis methods in several aspects. First, uncertainty in the soil parameters can be adequately considered in this method. In addition, the Bayesian method can logically incorporate other sources of information, such as prior knowledge or expert judgement on the soil parameters [42].

For application of Bayesian updating in the problem of braced excavation, Wang et al. [37] updated the model factor of a semi-empirical KJHH model for prediction of the maximum ground settlement using centrifuge data. The updated model was further used to predict the maximum ground settlement and calculate the reliability of the braced excavation problem. The KJHH model consists of three polynomial functions which are used to predict the maximum wall deflection (MWD), maximum ground settlement (MGS) and surface settlement profile (SSP). The functions are obtained by fitting the inputs (i.e. soil and structure parameters) and outputs (i.e. MWD, MGS and SSP) of some artificial finite element analyses of braced excavations. The finite element analyses used in the KJHH model merely consider one typical case of the braced excavation, i.e. the case with a flat ground surface underlain by certain soft to medium clays. In addition, only the parameters of the softest soil and supporting structures are selected as the inputs of the KJHH model. Details of the model could be found in Kung et al. [15]. Juang et al. [14] proposed a Bayesian framework for updating of soil parameters using field observations in multistage braced excavations. The framework provides a reasonable method for adjustment of a possibly unsafe or uneconomical design scheme as determined prior to excavation. However, certain drawbacks exist in the framework that limit its applicability and updating efficiency. First, similar to Wang et al. [37], the semi-empirical KJHH model was adopted to evaluate the maximum wall deflection and maximum ground settlement. The model is only applicable to specific conditions, i.e., excavations with a flat ground surface underlain by certain soft to medium clays. Excavation problems with complex boundary conditions (e.g. rotation fixity of the wall) or irregular geometries (e.g., excavation in an inclined slope) cannot be handled by this model. This limitation restricts the applicability of the framework. Second, the framework only uses the maximum wall deflection and maximum ground settlement data in the Bayesian updating because the outputs of the KJHH model are limited to the MWD and MGS. This amount of data might not be sufficient to update the soil parameter efficiently, as demonstrated later in the paper. Third, the framework could only update the parameters of the softest clay layer because the inputs of the KJHH model only contain these soil parameters. In reality, the MWD may be sensitive to the soil parameters of other soil layers. The importance of the soil parameters for layers other than the softest clay is neglected in the framework. Finally, measurement errors of the observation data are not considered and model errors are viewed as random variables with fixed probability distributions. These treatments are not realistic because any observation inevitably suffers from certain measurement errors. In addition, the distribution of the model error may not be accurate due to limited database and the model uncertainty needs to be updated when more observation information are available.

In practice, the deflection data for multiple points on the wall are always available. Acquisition of these data generally requires the same monitoring efforts as the maximum wall deflection. It is of interest to examine whether the efficiency of Bayesian updating improves if additional wall deflection data are used. Hence, this paper proposes a more versatile and efficient Bayesian back-analysis framework using the wall deflection data at multiple points. In the framework, model errors are also considered as random variables and are updated together with the soil parameters for various soil layers. To overcome the applicability problem mentioned previously, a response surface method is adopted to rapidly calculate the wall response. The response surface acts as a surrogate for any numerical method (such as the finite element method or finite difference method). It appears in the form of polynomial functions, and can be readily constructed using the results of several trial analyses with the numerical method. With the help of response surface method, the proposed framework could deal with any complicated problem and thus is more versatile than Juang et al. [14]. Similar to Juang et al. [14], Bayesian updating is conducted in a stage-by-stage manner. The updated soil parameter and model errors in the current excavation stage is used to predict the maximum wall deflection of the subsequent excavation stages. The efficiency of the Bayesian updating is evaluated by comparing the predicted maximum wall deflection with the observed maximum wall deflection. The model uncertainty of finite element method is characterized using wall deflection data for 49 wall sections from 11 case histories to obtain the prior distribution and correlation structure of the model errors. A multi-layer excavation problem in Hang Zhou, China is chosen to illustrate the effectiveness of the proposed framework. The spatial variability of the soil parameters are not considered in this paper. The effects of the prior coefficient of variance (COV) of the soil parameters on Bayesian updating are also discussed.

2. Method for updating the soil parameters

This section describes the method used in updating the soil parameters and model errors. First, the framework for Bayesian updating is briefly reviewed. Note that numerical analyses of geotechnical problems customarily require inputs of multiple soil parameters, such as cohesion (c), friction angle (ϕ) and elastic modulus (E). The number of input parameters might increase if multiple soil layers exist in a soil profile (each soil layer possesses one set of soil parameters). Hence, the information to be updated in the Bayesian framework is a joint probability density function (PDF) of multiple soil parameters. For each parameter, calculation of the marginal distribution or the statistics (such as the mean and standard deviation) always involves a high-dimensional integral. This task is quite difficult or even impossible to accomplish. Although analytical solutions or approximate solutions have been proposed in the past [42], those solutions apply only to limited cases. Specifically, the solutions are effective only if the prior distribution of the soil parameter is a normal distribution and the geotechnical responses [such as the factor of safety (FOS) or displacement of geotechnical structures] vary linearly with the input parameters. Hence, a highly efficient sampling technique is adopted in this paper, namely, the Markov chain Monte Carlo (MCMC) simulation method. Another difficulty frequently encountered in the Bayesian updating framework is repeated evaluation of the geotechnical response. It is costly and time-consuming to calculate the geotechnical response hundreds of thousands of times using traditional numerical methods such as the finite element method (FEM) or finite difference method (FDM). To cope with this problem, a response surface method is adopted to ease the computational burden.

2.1. Framework for Bayesian updating

The framework begins with the uncertainty of the geotechnical models. It is well recognized that model error exists in any geotechnical model due to oversimplification of the real conditions of geotechnical structures, such as boundary conditions and constitutive models of the soils [40]. Due to the model error, the responses of one geotechnical structure evaluated from any model generally do not agree with the observed performances of the structure. The model error is usually represented by a model bias