



Updating performance of high rock slopes by combining incremental time-series monitoring data and three-dimensional numerical analysis



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ABSTRACT

Predicted performance of a complex geotechnical system is subject to errors due to the uncertainties associated with both the prediction model and the system parameters. This paper aims to develop a multi-step updating method to reduce the uncertainties of the prediction model and system parameters using incremental time-series monitoring data, and to enhance the prediction of the future performance of the complex geotechnical system. The multi-step updating method considers inherent uncertainty of the system, model uncertainty and measurement uncertainty. The prediction is updated and improved step by step with new monitoring information using Bayes' theorem. Two realistic geotechnical cases including a basement excavation and a multi-stage excavation of a high rock slope are presented for illustration. The multi-step updating method integrates the theoretical computational model with observational evidence. With more monitoring information being incorporated, the prediction becomes closer to the actual performance of the system, and the distributions of the system parameters become closer to the reality.

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1. Introduction

To accurately predict the performance and safety of a complex geotechnical system is important. However, the predicted performance from a theoretical model is subject to errors. Sources of errors include the uncertainties associated with both the prediction model and the system parameters. The former are often caused by simplification of the problem at hand physically and geometrically. The latter are caused by spatial variability of soils and rocks, measurement errors and transformation errors.

As an additional safety measure, field monitoring is routinely conducted in many geotechnical systems to evaluate their safety, provide basis for safety control measures, warn of impending failures and mitigate risks of system failures [1]. Monitoring data can be used as a complement in the prediction of the future performance of the geotechnical system by reducing the uncertainties in the prediction model and the input parameters.

Researchers have conducted regression analysis on monitoring data, used the data to calibrate the parameters of some empirical models, and then made predictions using the calibrated empirical models [2–4]. Artificial intelligence has also been used to give

predictions [5,6]. These methods may yield satisfactory results. However, several important issues are not fully considered and require further investigations.

One difficulty is how to incorporate different sources of uncertainty into the predictions. Three primary sources of uncertainties have been identified by Phoon and Kulhawy [7,8]; namely the uncertainties associated with the geotechnical system (inherent variability), the field measurements (measurement uncertainty), and the prediction model (model uncertainty). They should be rationally considered in the analysis since geotechnical variability is inevitable. A sophisticated theoretical model is essential to capture the physical aspects of a complex system; but the uncertainties associated with the model and its parameters should be considered.

The second issue is how to update theoretical predictions using new monitoring information. Very often, the quantities of interest are monitored and time-series monitoring data is obtained. As time goes by, new monitoring information will be available. Previous theoretical predictions can then be updated with the new monitoring information.

The third difficulty when dealing with monitoring data is the late mobilization of the monitoring program. Monitoring instruments are often installed at a certain time of construction. The system performance before the installation of the instruments is not known. For example, the displacements of a particular system

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are monitored only after doubt about the safety of the system becomes a concern. The monitoring data obtained is not the actual total displacement. Instead, what can be obtained are the incremental displacements with respect to the start of a process of interest, such as an excavation process, or a rainfall process. Therefore, one has to rely on incremental monitoring data rather than cumulative data.

The objective of this paper is to propose a method to predict the future performance of a geotechnical system using incremental time-series monitoring data. This method is expected to incorporate various sources of uncertainty, and update theoretical predictions step by step with new monitoring information. The structure of this paper is as follows. First, the proposed method for multi-step updating of the predictions of system performance using incremental time-series monitoring data is introduced. Thereafter, two realistic geotechnical cases, namely a multi-stage basement excavation in Taipei [9,10] and a multi-stage excavation of an extremely high rock slope in Southwest China, are presented to illustrate the proposed method.

2. Proposed method for multi-step updating of the prediction of system performance

2.1. Prior prediction of system performance

Let vector $\theta = [\theta_1, \theta_2, \dots, \theta_n]$ denote the geotechnical system parameters. All the elements of θ are random variables that characterize the variability of the geotechnical system. Let Y denote the monitored quantity of the system, and Y_i ($i=0, 1, \dots, m$) denote the value of Y at time T_i ($T_0 < T_1 < \dots < T_m$), where T_0 is the starting time of a geotechnical process of interest. Let $Y_0=0$. In this way, Y_i denotes the increment of Y by time T_i with respect to the start of the process. For consistency, throughout this paper, the phrase “value of Y ” means the increment of Y with respect to the start of the process.

In practical applications, one can always use some theoretical models to analyze the performance of the geotechnical system. These models can be either explicit or implicit. Let $g_i(\theta)$ denote the model prediction of Y_i . Since any model is only an approximation or simplification of the real world, model uncertainty always exists [11,12]. Let ε denote the model bias factor, which is used to characterize the model uncertainty and relate model prediction $g_i(\theta)$ to monitored quantity Y_i as:

$$Y_i = \varepsilon g_i(\theta) = h_i(\mathbf{X}) \quad (i=1, 2, \dots, m) \quad (1)$$

where $\mathbf{X} = \{\theta, \varepsilon\}$. Let $f_X(\mathbf{X})$ denote the prior probability density function representing one's knowledge about \mathbf{X} . At the beginning of the process, a prior prediction of the evolution of Y with time can be made by calculating the mean value of Y_i as:

$$E(Y_i) = \int_{-\infty}^{+\infty} h_i(\mathbf{x}) f_X(\mathbf{x}) d\mathbf{x} \quad (i=1, 2, \dots, m) \quad (2)$$

2.2. Updating theoretical prediction with a single piece of monitoring information

The prior prediction given by Eq. (2) is usually not very reliable, because the prior knowledge about \mathbf{X} is usually limited in most cases, especially the knowledge about the model bias factor ε . This leads to the objective of this study, which is to reduce the uncertainties of the model and the system parameters with new monitoring information, and to update the prediction of Y to make it more reliable.

Suppose, at time T_1 , the monitoring result about Y_1 is $Y_1=y_1$. With this monitoring information, the prediction of Y in the future,

namely the predicted value about Y_2, Y_3, \dots, Y_m , can be updated. The measurement uncertainty, which is induced by imperfect measurement techniques, instruments or procedural control, is also included here. Let ζ denote the measurement uncertainty. The monitoring result can be related to ζ as follows:

$$y_1 = \varepsilon g_1(\theta) + \zeta = h_1(\mathbf{X}) + \zeta \quad (3)$$

According to Bayes' theorem, the distribution of \mathbf{X} can be updated, referred to as the posterior distribution as:

$$f_{X|y_1}(\mathbf{X}) = \frac{f_X(\mathbf{X})L(\mathbf{X})}{\int_{-\infty}^{+\infty} f_X(\mathbf{x})L(\mathbf{x})d\mathbf{x}} \quad (4)$$

where $L(\mathbf{X})$ is the likelihood function of the monitoring result.

Bayesian updating with equality-type information (i.e. the information is expressed as an equality equation) has been discussed by Straub [13]. In that method, the equality information is transformed into inequality information by transforming the likelihood function. In this paper, the likelihood function is transformed in a similar way as:

$$\begin{aligned} L(\mathbf{x}) &= \Pr[(y_1 = h_1(\mathbf{X}) + \zeta) | X = \mathbf{x}] = \Pr[y_1 = h_1(\mathbf{x}) + \zeta] \\ &= \Pr[\zeta = y_1 - h_1(\mathbf{x})] = c\varphi_\zeta[y_1 - h_1(\mathbf{x})] \end{aligned} \quad (5)$$

where $\varphi_\zeta(\bullet)$ is the probability density function of ζ , and c is a proportionality coefficient. Eq. (5) is valid only when \mathbf{X} and ζ are independent. This condition holds, according to the definitions of \mathbf{X} and ζ .

Substituting Eq. (5) into Eq. (4) yields

$$f_{X|y_1}(\mathbf{X}) = \frac{f_X(\mathbf{X})\varphi_\zeta[y_1 - h_1(\mathbf{x})]}{\int_{-\infty}^{+\infty} f_X(\mathbf{x})\varphi_\zeta[y_1 - h_1(\mathbf{x})]d\mathbf{x}} \quad (6)$$

Coefficient c drops out, because it is the same in both the numerator and the denominator in Eq. (6). Note that the denominator in Eq. (6) is a constant, which makes the probability density function valid.

The updated prediction of Y in the future step can then be made by calculating the mean value of Y_i ($i=2, 3, \dots, m$) with respect to the posterior distribution of \mathbf{X} as:

$$\begin{aligned} E(Y_i) &= \int_{-\infty}^{+\infty} h_i(\mathbf{x}) f_{X|y_1}(\mathbf{x}) d\mathbf{x} \\ &= \frac{\int_{-\infty}^{+\infty} h_i(\mathbf{x}) f_X(\mathbf{x}) \varphi_\zeta[y_1 - h_1(\mathbf{x})] d\mathbf{x}}{\int_{-\infty}^{+\infty} f_X(\mathbf{x}) \varphi_\zeta[y_1 - h_1(\mathbf{x})] d\mathbf{x}} \quad (i=2, 3, \dots, m) \end{aligned} \quad (7)$$

Eq. (7) can be calculated by adapting a structural reliability method such as Monte Carlo simulation, importance sampling, and subset simulation.

2.3. Updating theoretical prediction with multiple pieces of monitoring information

At the next moment T_2 , when the second piece of monitoring information $Y_2=y_2$ is available, it can be used to conduct the second updating of the prediction about Y_3, Y_4, \dots, Y_m . The updated predictions should be closer to the actual performance of the system as more monitoring information is incorporated.

When the j th piece of monitoring information $Y_j=y_j$ is available at T_j ($1 < j < m$), the j th updating of the prediction about Y_k ($j < k < m$) can be conducted. When multiple pieces of monitoring information are available, such information can be considered either as a whole, or one by one, which will be introduced separately in the following sections.

2.3.1. Considering multiple pieces of information as a whole

The multiple pieces of monitoring information ($Y_1=y_1, \dots, Y_j=y_j$) can be considered as one piece of integrated information.

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