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Calibrating cross-site variability for reliability-based design of pile foundations

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ABSTRACT

The cross-site variability (i.e., variability from site to site) makes the statistics of the bias factor of a design model vary from site to site. How to characterize the cross-site variability of the model bias factor is important for design of pile foundations based on site-specific load test data. In this study, a probabilistic model that allows for explicit modeling of the cross-site variability is suggested. An equation is derived based on Bayes' theorem to calibrate the suggested model with load test data from different sites, which is applicable even when the number of load tests at each site is small. A procedure based on hybrid Markov Chain Monte Carlo simulation is employed to solve the Bayesian equation. How to update the statistics of the model bias factor, when applied to a future site, with site-specific load test data is also described. As an illustration, the probabilistic model is applied to the design of bored piles in Shanghai, China. It is found that, given a certain number of site-specific pile load tests, the effect of updating depends on the mean and the COV of the measured model bias factor. With the assistance of regional experience, a small number of load tests can significantly reduce the uncertainty associated with the design model, and further increase in the number of load tests may not change the site-specific statistics of the bias factor and hence the resistance factor substantially.

1. Introduction

In the design of pile foundations, a model bias factor R is often used to consider the uncertainties associated with a bearing capacity prediction equation. Mathematically, the model bias factor R is defined as follows

$$R = \frac{\text{Measured bearing capacity}}{\text{Predicted bearing capacity}} \tag{1}$$

The uncertainties in R may come from spatial variability of the ground, soil-testing errors, transformation errors when obtaining design parameters, and deficiency of the design equation. The mean and the coefficient of variation (COV) of the model bias factor, which are denoted as λ_R and δ_R in this study, are often calculated based on a statistical analysis of the measured and calculated capacities of load test piles installed at different sites in the same region. It is implicitly assumed that the model bias factors for piles from different sites follow a common probability distribution, i.e., the statistics of the model bias factor at different sites are the same. Let x_{ij} denote the jth measured model bias factor at site i. Fig. 1 shows the relationship between model bias factors measured from load tests at different sites and the statistics of the model bias factor assumed in many studies.

Static load test is an effective means to reduce the uncertainty in pile design. In practice, it is commonly accepted that a few load tests could significantly reduce the required design factor of safety (FOS) at a site. For instance, the required FOS can be reduced from 3.0 if based on empirical pile design equations to 2.0 if further verified by a sufficient number of proof load tests [1]. If the statistics of the model bias factor from different sites are assumed the same, however, the phenomenon that the design FOS is sensitive to the site-specific load test results may not be modeled correctly. Based on such an assumption, the regional and site-specific statistics of the model bias factor are the same, and the load test data from different sites will have the same impact on the statistics of the model bias factor. In such a case, a limited number of additional load tests at a site can hardly change the statistics of the model bias factor calibrated based on a regional database with a much larger number of load tests. For instance, if the regional statistics of the model bias factor are determined based on 30 measurements of model bias factor, additional three or four measurements of model bias factor may not change the statistics of the model bias factor significantly.

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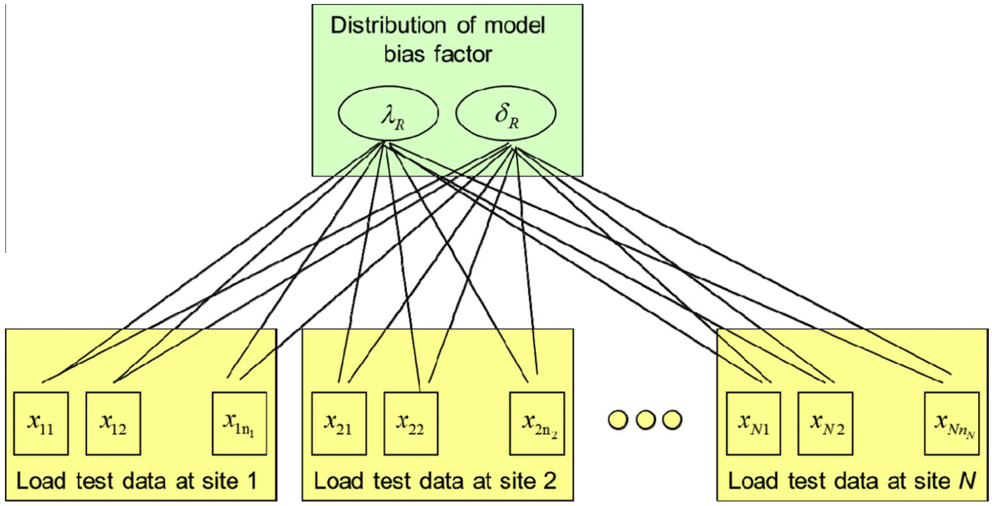

Fig. 1. Relationship between site-specific load test data and model bias factor ignoring cross-site variability.

Consequently, the design FOS will also not be affected significantly by the load test data at the site. Thus, assuming the statistics of model bias factor from different sites are the same contradicts with the current use of site-specific load test data for pile design.

The assumption that the model bias factors for different sites in a region have the same statistics, however, may not always be true. The variation in factors such as soil properties and workmanship from site to site may make the statistics of model bias factor differ from one site to another even in the same region [2]. The importance of the cross-site variability (i.e., variability from site to site) in designing piles based on load tests has also been noticed in several studies [2–5]. They found that the variability of the model bias factor within a site is generally smaller than that in a region. If the cross-site variability is known, a few site-specific load tests can update the statistics of the model bias factor substantially. As such, a limited number of site-specific load tests can indeed alter the design FOS at a site significantly. Thus, the key of designing piles based on site-specific load test data hinges on the characterization of cross-site variability of the model bias factor. In principle, one can estimate the statistics of the model bias factor at each site in a region, and then analyze the variability of such statistics to estimate the cross-site variability. In practice, however, the number of load test data conducted at a site is typically small, which are not sufficient to estimate the statistics of the model bias factor at a site accurately. As such, how to estimate the cross-site variability is difficult [3,5].

The objective of this paper is to suggest a method to (1) model and calibrate the cross-site variability associated with the model bias factor for design of pile foundations; (2) update the statistics of the bias factor with the site-specific load test data; and (3) determine resistance factor for design based on site-specific load test data. This paper is organized as follows. First, the probabilistic model for the bias factor is described. Then, how to calibrate the suggested model based on regional load test data from different sites is suggested. Thereafter, how the probabilistic model can be updated with site-specific load test data is described, followed by the method for reliability-based design of pile foundations using site-specific load test data. Finally, the proposed method for pile design is illustrated with an example and how different factors affect the pile design based on load tests is discussed.

2. Probabilistic modeling of model bias considering cross-site variability

As mentioned previously, due to the presence of cross-site variability, the mean and COV of the model bias factor, R, at each site may not be the same. Let λ_i and δ_i denote the mean and the COV of the model bias factor at the ith site. As the model bias factor is commonly modeled as a lognormal random variable (e.g., [5–9]), the probability density function (PDF) of the model bias factor at site i can be written as follows (e.g., [10])

$$f(r|\lambda_i, \delta_i) = \frac{1}{\sqrt{2\pi}\zeta_i r} \exp\left[-\frac{(\ln r - \mu_i)^2}{2\zeta_i^2}\right] \tag{2}$$

where μ_i and ζ_i are the mean and standard deviation of $\ln R$ which can be calculated as follows (e.g., [10])

$$\zeta_i = \sqrt{\ln(1 + \delta_i^2)} \tag{3}$$

$$\mu_i = \ln \lambda_i - \frac{1}{2}\zeta_i^2 \tag{4}$$

While the value of λ_i is site specific, it might be reasonable to expect that λ_i values at different sites from a region follow a certain probability distribution. As λ_i is non-negative, it is convenient to assume that λ_i follow a lognormal distribution with a mean of μ_λ and a COV of δ_λ. Similarly, it can also be assumed that δ_i of different sites in a region follow a lognormal distribution with a mean of μ_δ and a COV of δ_δ. Fig. 2 shows the relationship between the model bias factors at different sites and the statistics of the model bias factor considered in this study. In this figure, the value of the model bias factor varies within a site, reflecting the effect of within-site variability. The statistics of the model bias factor vary from site to site, reflecting the effect of cross-site variability. While the measured model bias factors from different sites are statistically independent given that the site-specific statistics of the model bias factors are known, these observations are correlated because the statistics of the site-specific model bias factors from different sites follow the common probability distributions. In the model described here, δ_λ characterizes the cross-site variability of the mean of the model bias factor (λ_i). If $\delta_\lambda = 0$, there is no cross-site variability about λ_i. Similarly, δ_δ characterizes the cross-site variability of the COV of the model bias factor (δ_i). As such, both the cross-site variability about the mean and the COV of the model bias factor are considered. When $\delta_\lambda = 0$ and $\delta_\delta = 0$, there is no cross-site variability in both λ_i and δ_i. Thus, the conventional model for the bias factor can be viewed as a special case of the model suggested in the present study.

Application of the above probabilistic model requires calibration of the following model parameters: μ_λ, δ_λ, μ_δ, and δ_δ. In theory, one can first calculate the values of λ_i based on the site-specific load test data, and then estimate the values of μ_λ and δ_λ based