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Research Paper

Calibration of resistance factor for design of pile foundations considering feasibility robustness

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ABSTRACT

The resistance factor for pile foundations in load and resistance factor design (LRFD) is traditionally calibrated considering target reliability index (β_T) and statistics of load and resistance bias factors. However, the resistance bias factor is hard to quantify statistically. Consequently, the design obtained using the calibrated resistance factor can still miss β_T if the variation in resistance bias factor has been underestimated. In this paper, we propose a new resistance factor calibration approach to address this dilemma by considering "feasibility robustness" of design in the calibration process. Herein, the feasibility robustness is defined as a probability that the β_T requirement can still be satisfied even in the presence of uncertainty or variation in the computed bearing capacity. For illustration, LRFD approach for pile foundations commonly used in Shanghai, China is examined. Emphasis is placed on re-calibration of resistance factors at various feasibility robustness levels, with due consideration of the variation in the resistance bias factor. A case study is presented to illustrate the use of the re-calibrated resistance factors. The results show that the feasibility robustness is gained at the expense of cost efficiency; in other words, the two objectives are conflicting. To aid in the design decision-making, an optimal feasibility robustness level and corresponding resistance factors are suggested in the absence of a designer's preference.

1. Introduction

Foundations have traditionally been designed based on the allowable stress design (ASD) approach, which normally employs a single global factor of safety (*FS*) to cope with all uncertainties associated with load and resistance (e.g., [5,28,3,13]). However, the nominal *FS* obtained from a deterministic method cannot accurately reflect the true level of safety [10,22]. Currently, the load and resistance factor design (LRFD) approach, which is a simpler variant of the reliability-based design method, has been gaining acceptance. Compared with ASD approach, the LRFD approach that is based on reliability theory can reasonably consider load and resistance uncertainties in the design [28,21]. The LRFD approach generally uses load factors and resistance factor to account for the uncertainty in load and resistance, respectively. In recent years, extensive research (e.g., [34,26,1,19,36,22]) was conducted to calibrate resistance factor for the design of pile foundation for a given set of load factors. Generally, the resistance factor is calibrated to a prescribed target reliability index β_T considering the statistics of load and resistance bias factors [38,35].

In LRFD, the resistance bias factor is defined as the ratio of the measured bearing capacity from a load test to the predicted (or computed) bearing capacity by a static bearing capacity model, and is modeled as a random variable reflecting mainly the uncertainty in the model that is used to compute the capacity. A proper statistical characterization of resistance bias factor requires collection of reliable static load test data, which is the most important task for LRFD calibration [19]. In practice, however, the resistance bias factor statistics are hard to ascertain, particularly when the data are limited in quality and/or quantity [2]. Thus, uncertainty is inherent in the derived statistical parameters of the resistance bias factor. Unfortunately, the resistance factor calibrated for LRFD is very sensitive to the uncertainty in the resistance bias factor. Consequently, a design obtained using the calibrated resistance factor may not achieve β_T (i.e., the design is not feasible) if the variation in the resistance bias factor is underestimated.

To address this dilemma, the authors propose a new approach for resistance factor calibration that considers explicitly the feasibility robustness of design [25]. Emphasis of this paper is placed

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on re-calibration of resistance factor with due consideration of variation in the resistance bias factor. By considering the feasibility robustness, design using the re-calibrated resistance factor will always satisfy the β_T requirement to the extent defined by engineer even if uncertainty exists in the computed capacity.

It should be noted that the robustness design concept is not new; in fact, it was introduced by Taguchi [30] and has been used widely in various engineering fields (e.g., [31,6,9,24,4,20,18,27]). Furthermore, examples of geotechnical design with LRFD approach considering design robustness have been reported [16,11]. However, this paper represents the first attempt at introducing the robustness concept into the LRFD calibration. The novelty of this paper is evidenced in the results presented.

This paper is outlined as follows. First, the traditional approach of resistance factor calibration and its possible drawback are presented through a LRFD calibration practice of pile foundations in Shanghai, China. Next, the feasibility robustness concept is introduced, followed by the development of the new resistance factor calibration approach considering feasibility robustness. Then, the resistance factors are re-calibrated at various predefined levels of feasibility robustness and illustrated through a bored pile design example. Finally, a most preferred feasibility robustness level and the corresponding resistance factors are suggested in the absence of a designer's preference.

2. Traditional approach for resistance factor calibration

In this section, the traditional resistance factor calibration process is reviewed using an example reported by Li et al. [22] that describes Shanghai, China experience. In Li et al. [22], resistance factors for total load-carrying capacity are calibrated for driven piles and bored piles designed by three commonly used methods in Shanghai, i.e., the static load test-based method (LT method), the design table method (DT method), and the cone penetration test-based method (CPT method). The details of these methods are summarized in Appendix A. Let R, Q_D, and Q_L denote total capacity, dead load, and live load, respectively. The design equation in Shanghai can be expressed as:

$$\frac{R_n}{\gamma_R} = \gamma_D Q_{Dn} + \gamma_L Q_{Ln} \tag{1}$$

where R_n, Q_{Dn}, and Q_{Ln} are the nominal values for R, Q_D, and Q_L, respectively; and γ_R, γ_D, and γ_L are the partial factors for R, Q_D, and Q_L, respectively. Note that in some codes, such as AASHTO [1], a partial factor ϕ is applied to resistance in a form such that $\gamma_R = 1/\phi$.

According to AASHTO [1], using an assumption of lognormal distribution function for resistance and loads, reliability index β can be calculated using first order second moment method as (after [33,37]):

$$\beta \approx \frac{\ln\left(\frac{\lambda_R \gamma_R (\gamma_D + \gamma_L \rho)}{\lambda_D + \lambda_L \rho}\sqrt{\frac{1+\mathrm{COV}_Q^2}{1+\mathrm{COV}_R^2}}\right)}{\sqrt{\ln\left[\left(1+\mathrm{COV}_R^2\right)\left(1+\mathrm{COV}_Q^2\right)\right]}} \tag{2}$$

where λ_R, λ_D, and λ_L are mean bias factors of resistance, dead load, and live load, respectively; ρ is the live load to dead load ratio; Q is the total load (i.e., $Q = Q_D + Q_L$); COV_R and COV_Q are the coefficients of variation of the resistance bias factor and load bias factor, respectively. According to Li et al. [22], COV_Q can be calculated as:

$$\mathrm{COV}_Q = \frac{1}{1+\rho}\sqrt{\mathrm{COV}_D^2 + \rho^2 \mathrm{COV}_L^2} \tag{3}$$

where COV_D and COV_L are COVs of dead load bias factor and live load bias factor, respectively. As noted in Zhang et al. [39], when an empirical relationship is used to compute the bearing capacity, the computed capacity is subjected to two types of uncertainties, i.e., the within-site variability and the cross-site variability. The within-site variability is mainly caused by the inherent variability of soil properties in the zone influencing each pile and by the construction errors associated with the site-specific workmanship. The cross-site variability is mainly caused by the regional variation in soil properties and by the construction errors associated with the workmanship in a region. In Li et al. [22], both the within-site variability and the cross-site variability of the pile capacity are considered; thus λ_R and COV_R can be further written as:

$$\lambda_R = \lambda_{R1}\lambda_{R2} \tag{4}$$

$$\mathrm{COV}_R = \sqrt{\mathrm{COV}_{R1}^2 + \mathrm{COV}_{R2}^2} \tag{5}$$

where λ_{R1} and COV_{R1} are the mean and COV of the bias factor accounting for within-site variability, respectively; and λ_{R2} and COV_{R2} are the mean and COV of the bias factor accounting for cross-site variability, respectively.

In resistance factor calibration, a target reliability index β_T is pre-defined. Based on Eq. (2), the value of γ_R required to achieve β_T can be obtained as:

$$\gamma_R = \frac{\lambda_D + \lambda_L \rho}{\lambda_R(\gamma_D + \gamma_L \rho)}\sqrt{\frac{1+\mathrm{COV}_R^2}{1+\mathrm{COV}_Q^2}} \times \exp\left(\beta_T\sqrt{\ln\left[\left(1+\mathrm{COV}_R^2\right)\left(1+\mathrm{COV}_Q^2\right)\right]}\right) \tag{6}$$

Eq. (6) shows that γ_R is a function of β_T, load bias factor statistics, and resistance bias factor statistics. The load bias factor statistics employed by Li et al. [22] are those used in the national code for foundation design in China [23]: $\lambda_D = 1.0$, $\lambda_L = 1.0$, $\mathrm{COV}_D = 0.07$, and $\mathrm{COV}_L = 0.29$. Based on MOC [23], load partial factors $\gamma_D = 1.0$ and $\gamma_L = 1.0$ are adopted; additionally, a live load to dead load ratio of $\rho = 0.2$ is used [22]. The resistance bias factor statistics (i.e., λ_R and COV_R) can be obtained by conducting statistical analysis on cases with both static load test and prediction results.

The within-site variability can be characterized by comparing capacities of piles within a site. In Li et al. [22], a load test database consisting of 146 piles from 32 sites and another database comprising 37 piles from 10 sites were used to characterize the within-site variability for driven piles and bored piles, respectively. In these load tests, piles with identical geometry at each site were loaded until failure occurred. The ultimate bearing capacity was determined with a comprehensive analysis on the load-displacement (Q-s) curve and the corresponding displacement-logarithm of time (s-lg$t$) curve. The load at the start point of a steep drop on the Q-s curve and the load beyond which the settlement will not converge on the s-lg$t$ curve was taken as the ultimate bearing capacity [29,37]. Details on these piles are summarized in Tables 1 and 2.

According to Zhang et al. [39], the within-site variability refers to the variability in the pile capacity values within a site and thus, the mean of these values is truly reflected by the mean of the measured capacity values, which is based on the proven theory that the sample mean is an unbiased estimate of the population mean. Therefore, the within-site variability of the pile capacity prediction is unbiased [39,22], i.e., $\lambda_{R1} = 1$. On the other hand, the value of COV_{R1} is determined by calculating the COV of the measured capacities of the piles within a site. Note that values of COV_{R1} vary from site to site. The values of COV_{R1} of driven piles are in the range of 0.031–0.155 with a mean of 0.087 and a COV of 0.36. The values of COV_{R1} of bored piles are in the range of 0.049–0.179 with a mean of 0.093 and a COV of 0.44. In Li et al. [22], as in other traditional LRFD calibration studies (e.g., [26]), the means of those COV_{R1}