1   **Calibration of Resistance Factor for Design of Pile Foundations**
2   **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.

Keywords: Pile foundations; Load and resistance factor design; Uncertainty; Target reliability index; Feasibility robustness; Calibration.

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., Bathurst et al. 2011; Reddy and Stuedlein 2013; Bach and van Gelder 2014; Huang et al. 2016). However, the nominal FS obtained from a deterministic method cannot accurately reflect the true level of safety (Fenton et al. 2015; Li et al. 2015). Currently, the load and resistance factor design (LRFD) approach, which is a simpler variant of the reliability-based design (RBD) 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 (Reddy and Stuedlein 2013; Li et al. 2016). 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., Yoon and O'Neill 1997; Paikowsky 2004; AASHTO 2007; Kwak et al. 2010; Yu et al. 2012; Li et al. 2015) 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 (Zhang et al. 2006; Yoon et al. 2008).

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 (Kwak et al. 2010). In practice, however, the resistance bias factor statistics are hard to ascertain, particularly when the data are limited in quality and/or quantity (Allen 2005). 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 (Parkinson et al. 1993). Emphasis of this paper is placed 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 (1986) and has been used widely in various engineering fields (e.g., Tsui 1992; Chen et al. 1996; Doltsinis et al. 2005; Park et al. 2006; Beyer and Sendhoff 2007; Lee et al. 2010; Khoshnevisan et al. 2016; Peng et al. 2016). Furthermore, examples of geotechnical design with LRFD approach considering design robustness have been reported (Juang et al. 2013; Gong et al. 2016a). 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. (2015) that describes Shanghai, China experience. In Li et al. (2015), 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 I. 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:

$$\frac{R_n}{\gamma_R} = \gamma_D Q_{Dn} + \gamma_L Q_{Ln} \quad (1)$$

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 (2007), a partial factor ϕ is applied to resistance in a form such that $\gamma_R = 1/\phi$.

According to AASHTO (2007), 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 Withiam et al., 2001; Zhang et al. 2005):

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

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. (2015), COV_Q can be calculated as:

$$COV_Q = \frac{1}{1+\rho} \sqrt{COV_D^2 + \rho^2 COV_L^2} \quad (3)$$

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. (2004), 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. (2015), 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:

$$\lambda_R = \lambda_{R1} \lambda_{R2} \quad (4)$$

$$COV_R = \sqrt{COV_{R1}^2 + COV_{R2}^2} \quad (5)$$

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:

$$\gamma_R = \frac{\lambda_D + \lambda_L \rho}{\lambda_R (\gamma_D + \gamma_L \rho)} \sqrt{\frac{1 + COV_R^2}{1 + COV_Q^2}} \exp\left(\beta_T \sqrt{\ln\left[\left(1 + COV_R^2\right)\left(1 + COV_Q^2\right)\right]}\right) \quad (6)$$

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. (2015) are those used in the national code for foundation design in China (MOC, 2002): $\lambda_D = 1.0$, $\lambda_L = 1.0$, $COV_D =$

0.07, and $COV_L = 0.29$. Based on MOC (2002), 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 (Li et al. 2015). 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. (2015), 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 (SUCCC 2010; Zhang et al. 2005). Details on these piles are summarized in Table 1 and Table 2.

According to Zhang et al. (2004), 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 (Zhang et al. 2004; Li et al. 2015), 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. (2015), as in other traditional LRFD calibration studies (e.g., Paikowsky 2004), the means of those COV_{R1} values for driven piles and bored piles are adopted

in calibration, as listed in Table 3, and the uncertainties in those COV_{R1} values are ignored.

The cross-site variability can be characterized by comparing the measured and predicted bearing capacities of piles from different sites. A bearing capacity ratio is first obtained for each site by dividing the mean of measured bearing capacities at this site by the computed bearing capacity (e.g., predicted capacity using DT method for bored piles listed in Table 2). The mean and the COV of the bearing capacity ratios are regarded as the estimates of λ_{R2} and COV_{R2} . For the piles designed using LT method, the computed capacity is taken as the mean of measured capacities, thus the values of bearing capacity ratio for all sites are taken as 1 which lead to $\lambda_{R2} = 1$ and $COV_{R2} = 0$. For the bored piles designed using DT method, the bearing capacity ratios for 10 sites in Table 2 are calculated (e.g., a ratio of 0.808 for site 1). The mean and COV of the 10 ratios are computed and taken as λ_{R2} and COV_{R2} , respectively, i.e., $\lambda_{R2} = 0.996$ and $COV_{R2} = 0.184$, for the DT method for bored piles. Note that the driven piles in Table 1 are not used for characterizing the cross-site variability using DT method and CPT method. In Li et al. (2015), for driven piles designed using DT method and CPT method, the values of λ_{R2} and COV_{R2} based on the previous design code are reviewed and adopted. The characterization of cross-site variability for different design methods and different piles are also summarized in Table 3.

The statistics of resistance bias factor (i.e., λ_R and COV_R) are then obtained using Eqs. (4) and (5) based on the characterized within-site variability and cross-site variability. Among the design methods, the LT method has the smallest COV, as it is free from cross-site variability. On the other hand, the DT method has the largest uncertainty. Having obtained the statistics of load bias factor and resistance bias factor, the required γ_R corresponding to a specified target reliability index, say, $\beta_T = 3.7$ (Li et al. 2015), can be calculated using Eq. (6). The calibrated values of γ_R for different design methods and different piles obtained by Li et al. (2015) are listed in Table 3.

In the aforementioned resistance factor calibration process, $COV_{R1} = 0.087$ and $COV_{R1} = 0.093$, the mean values of the respective COVs, are adopted for the analysis of driven piles and bored piles, respectively. However, COV_{R1} actually varies from site to site as seen in Tables 1 and 2. This variation in COV_{R1} is not reflected in the traditional resistance factor calibration; and as such, uncertainty in the computed capacity is not fully accounted for when the calibrated γ_R is applied to a future case. To characterize the distribution of COV_{R1} , Fig. 1 (a) and (b) illustrates the cumulative frequency of observed COV_{R1} from the adopted database (see Tables 1 and 2) for driven piles and bored piles, respectively. Lognormal cumulative distribution function (CDF) curve is also plotted in Fig. 1 to fit the data set. Approximations are superimposed on the CDF curve using the computed values of the mean and COV. Visually, the lognormal CDF matches the cumulative frequency of COV_{R1} well. Therefore, COV_{R1} is treated as a lognormal random variable in this paper.

To investigate the effect of variation in COV_{R1} on the β of design using the calibrated resistance factors in Li et al. (2015), Monte Carlo Simulation (MCS) (Jiang et al. 2015) is performed to generate 5000 random samples of COV_{R1} and the corresponding values of β are computed using Eq. (2) for different types of piles and different design methods. Fig. 2 shows histograms of relative frequency of β for different types of piles and different design methods. It is observed that β values distribute in wide ranges and many of the designs cannot achieve $\beta_T = 3.7$ (i.e., $\beta < \beta_T$). Furthermore, Fig. 2 also shows the cumulative frequency curves of β . With the aid of these cumulative curves, the probability of ($\beta < \beta_T$) can be readily obtained. The values of this probability for driven piles designed with the LT method, DT method, and CPT method are 0.466, 0.511, and 0.485, respectively. For bored piles using LT method and DT method, the values are 0.442 and 0.500, respectively. The implication is that when γ_R obtained from the traditional LRFD calibration that does not consider the variation in COV_{R1} is used, there is a high chance that the safety requirement (i.e., $\beta \geq \beta_T$) will not be satisfied (i.e., the

design is not feasible). In other words, the design using this γ_R may not meet the safety requirement due to the uncertainty in the computed capacity. This is a drawback of the traditional resistance factor calibration. To reduce the chance for the violation of safety requirement, or to improve the feasibility robustness of the design using partial factors, a new resistance factor calibration approach considering robustness is proposed.

3. Resistance Factor Calibration Considering Robustness

3.1. Feasibility robustness

In this paper, “feasibility robustness” (Parkinson et al. 1993) is adopted to measure the robustness of partial-factor design with respect to uncertain parameters (i.e., COV_{R1}) in the calibration process. Herein, the feasibility robustness is the robustness against the uncertainty in the assessed safety level, and is defined as the probability that β_T can still be satisfied even with the variation in COV_{R1} . Symbolically, feasibility robustness is formulated as (Juang and Wang 2013; Juang et al. 2013):

$$P[(\beta - \beta_T) \geq 0] \geq P_0 \quad (7)$$

where $P[(\beta - \beta_T) \geq 0]$ is the probability that β_T is satisfied; and P_0 is a pre-defined acceptable level of this probability (i.e., feasibility robustness).

Determining $P[(\beta - \beta_T) \geq 0]$ of a design given γ_R requires knowledge of the distribution of the corresponding β . As shown in Fig. 2, the values of $P[(\beta - \beta_T) \geq 0]$ of those piles designed with the calibrated γ_R can be evaluated based on the corresponding cumulative frequency curves obtained from MCS. The results are summarized in Table 4. For example, for driven piles designed using LT method with $\gamma_R = 1.53$, the value of $P[(\beta - 3.7) \geq 0]$ is 0.534. If the feasibility robustness level is pre-selected as $P_0 = 0.6$, the design using $\gamma_R = 1.53$ cannot meet the feasibility robustness requirement (since 0.534 is less than the prescribed level of 0.6). Although MCS provides a rigorous way to determine the feasibility robustness $P[(\beta - \beta_T) \geq 0]$,

it is time consuming. Simulations show that the resulting histogram of β can be approximated well with a normal distribution, as depicted in Fig. 2. Thus, if the mean and standard deviation of β , denoted as μ_β and σ_β , can be determined, the feasibility robustness of design can readily be computed with the assumption of normal distribution as (Juang et al., 2013; Wang et al. 2013):

$$P[(\beta - \beta_T) \geq 0] = \Phi\left(\frac{\mu_\beta - \beta_T}{\sigma_\beta}\right) \geq P_0 \quad (8)$$

where Φ is cumulative standard normal distribution function.

Therefore, the evaluation of feasibility robustness is reduced to a task of determining μ_β and σ_β . In this paper, seven point estimate method (PEM) developed by Zhao and Ono (2000) is adopted to estimate μ_β and σ_β . Since β is the function of single random variable COV_{R1} in this problem, the seven-point PEM first assigns the values of COV_{R1} at each estimating point; then β_i ($i = 1, 2, \dots, 7$) is evaluated at each point using Eq. (2). The resulting seven β_i values are then used to compute the μ_β and σ_β , as (Zhao and Ono 2000):

$$\mu_\beta = \sum_{i=1}^7 P_i \beta_i \quad (9)$$

$$\sigma_\beta^2 = \sum_{i=1}^7 P_i (\beta_i - \mu_\beta)^2 \quad (10)$$

where P_i ($i = 1, 2, \dots, 7$) are the weights corresponding to estimating points as per Zhao and Ono (2000). The readers are referred to Zhao and Ono (2000) for details on PEM.

Using PEM, the feasibility robustness of the design using the calibrated γ_R reported by Li et al. (2015) are calculated and displayed in Table 4. Comparing with the results computed with MCS, it shows that the two approaches are quite consistent and the PEM-based approach for feasibility robustness (Eqs. 8-10) is judged adequate in terms of accuracy.

3.2 Calibration of resistance factor with robustness consideration

The aforementioned procedure to evaluate feasibility robustness of a design using the

existing γ_R actually is the inverse of the task of resistance factor calibration considering robustness. Here, the resistance factor calibration considering robustness is a process of determining the value of γ_R such that the resulting design can achieve the pre-defined feasibility robustness level, i.e., $P[(\beta - \beta_T) \geq 0] = P_0$.

The resistance factor calibration process considering feasibility robustness proposed herein can be implemented using a trial-and-error approach, in which a trial γ_R is assumed and then checked against feasibility robustness requirement using MCS or PEM, followed by revision of the γ_R , if necessary. Alternatively, it is noted that the feasibility robustness can be expressed as a function of γ_R , e.g., in a form of $P[(\beta - \beta_T)] = G(\gamma_R)$, by combining Eqs. (2), (8), (9), and (10). Thus, once the target P_0 is defined, the corresponding γ_R can be readily determined by solving the equation $G(\gamma_R) = P_0$, in lieu of the trial-and-error process.

In the present study, six feasibility robustness levels (i.e., $P_0 = 0.5, 0.6, \dots, 0.9, 0.99$), are selected for illustration purpose. Among these pre-defined target levels, the lower bound $P_0 = 0.5$ is selected to ensure an average level that $\mu_\beta \geq \beta_T$ as per Eq. (8); the upper bound $P_0 = 0.99$ represents an extreme design scenario. To be consistent with Li et al. (2015), $\beta_T = 3.7$ is adopted in the calibration. Using the proposed calibration procedure (i.e., solving $G(\gamma_R) = P_0$), the values of γ_R compatible with $\gamma_L = 1.0$ and $\gamma_D = 1.0$ to achieve pre-defined target robustness levels for different types of piles and different design methods are determined and the results are given in Table 5. For example, when the feasibility robustness level is set as $P_0 = 0.5$, the values of γ_R for driven piles designed with LT method, DT method, and CPT method are 1.52, 1.95, and 1.72, respectively; for bored piles designed using LT method and DT method, the values are 1.53 and 2.30, respectively. **Noted that the somewhat unusual load factors of 1.0 adopted from Chinese and Shanghai codes should only be used in conjunction with the resistance factors calibrated to the target reliability index under this setting of load factors. As the values of load factors are set to 1.0, the values of γ_R are essentially the same as the nominal**

FS (see Eq. (1)). Note that the required γ_R increases with increasing P_0 , as expected. To achieve the same P_0 , DT method requires larger γ_R , as it is associated with greater uncertainties while the required γ_R for LT method is smaller due to the lower uncertainties involved with LT method. Thus, although a smaller nominal *FS* is required in LT method, the reliability level and robustness level are indeed same as those using DT method that yield a larger nominal *FS*. This further illustrates the limitation of the ASD approach, i.e., the nominal *FS* cannot accurately reflect the true level of safety. Using Table 5, the designer can first select the P_0 for a given project and then use the corresponding γ_R to perform the design of piles. Such design is guaranteed to have a level of feasibility robustness of P_0 (meaning that the chance for the design to remain feasible regardless of the variation of COV_{R1} is P_0).

Furthermore, the values of μ_β and σ_β at various feasibility robustness levels corresponding to the resistance factors listed in Table 5 are calculated using Eqs. (9) and (10), and the results are summarized in Table 6. Note that for the same P_0 , piles designed with LT method have the largest μ_β , e.g., 4.38 for driven piles and 4.54 for bored piles when P_0 is 0.8. This is consistent with the view that LT method is the most reliable. On the other hand, piles designed with DT method have the smallest μ_β , e.g., 3.98 for both driven piles and bored piles when P_0 is 0.8. It should also be noted that both the values of μ_β and σ_β increase with increasing P_0 . The implication is that feasibility robustness is primarily affected by μ_β as per Eq. (8).

4. Design Example Using the Re-calibrated Resistance Factors

To illustrate use of the calibrated resistance factors considering feasibility robustness listed in Table 5, a bored pile is designed using DT method for a sand profile. The bored pile with diameter $D = 0.85$ m shown in Fig. 3 is embedded at a depth of L , (i.e., the pile length is L). The soil layer surrounding bored pile is divided into 5 sub-layers, as shown in Fig. 3. The suggested values of unit toe resistance q_t and unit side resistance f_{si} for each soil layer are also

given in Fig. 3. The bored pile in this problem is intended to carry axial compressive loads of 2500 kN dead load (Q_{Dn}) and 500 kN live load (Q_{Ln}). Using live load and dead load factors of 1.0 and 1.0, respectively, the design load is 3000 kN.

Using the corresponding γ_R in Table 5, the values of required pile length L at various feasibility robustness levels can be determined by Eqs. (1) and (A1) using DT method, and the design results are illustrated in Fig. 4. For example, the required depths for $P_0 = 0.5$ and $P_0 = 0.99$ are $L = 45.9$ m and $L = 53.6$ m, respectively. It can be seen that the value of L increases with increasing P_0 . That is to say, larger pile length is required to achieve higher feasibility robustness levels (i.e. larger P_0 values). Note that the L (at a given D) can be treated as an index of construction cost. The implication is that design with high robustness against variation in the computed capacity can always be achieved at the expense of cost efficiency. However, this may not be desired and a tradeoff between cost efficiency and design robustness must be made. The discussion in the section that follows focuses on this tradeoff issue.

5. Further Discussion

Table 5 provides the resistance factors calibrated to $\beta_T = 3.7$ and various target levels of feasibility robustness P_0 . Designers can select γ_R corresponding to the desired P_0 for a given project. Generally, a design with higher feasibility robustness and relatively lower cost is desired. However, as shown in the above bored pile design example, feasibility robustness and cost efficiency are conflicting to each other. When there is no strong preference by the designer, a tradeoff decision may be based on an optimization of γ_R performed with respect to two objectives, design robustness and cost efficiency.

Note that according to Eq. (1), for a given loading, use of a higher γ_R implies the need for a higher nominal bearing capacity, which in turn, points to the need for a larger L and thus, a greater cost. Thus, the cost can be effectively reflected in γ_R . In this study, a discrete design

space is considered for the optimization of γ_R , in which P_0 will be selected from the range of 0.5 to 0.99 with an increment of 0.01. The multi-objective optimization is set up as follows:

Find: An optimal γ_R compatible with $\gamma_L = 1.0$ and $\gamma_D = 1.0$

Subject to: $G(\gamma_R) = P_0 \in \{0.5, 0.51, 0.52, \dots, 0.99\}$

Objectives: Maximizing the feasibility robustness (in terms of P_0)

Minimizing the construction cost (in terms of γ_R)

The values of γ_R corresponding to the 50 potential feasibility robustness levels are determined by solving $G(\gamma_R) = P_0$, respectively. Fig. 5 shows the variation of calibrated γ_R as a function of P_0 , for different combinations of pile types and design methods. As shown in Fig. 5, γ_R increases as P_0 increases, and the curves have the similar trend with the relationship between L and P_0 shown in Fig. 4, as expected. Thus, a tradeoff exists between design robustness and cost efficiency; the tradeoff relationship is presented here as a Pareto front (Cheng and Li 1997; Khoshnevisan et al. 2014; Gong et al. 2016b). The knee point (Deb and Gupta 2011) on the Pareto front conceptually yields the best compromise among conflicting objectives. In other words, the knee point may be taken as the most preferred choice. In this study, the minimum distance approach (Khoshnevisan et al. 2014; Gong et al. 2016a) is used to determine the knee point, in which a point that has the minimum distance from the “utopia point” in a normalized space of the objective functions is taken as the knee point. Interested readers are referred to Khoshnevisan et al. (2014) and Gong et al. (2016a) for additional details on the minimum distance approach.

With the minimum distance approach, knee points for different types of piles designed using different methods are readily identified, as also shown in Fig. 5. Consider, for example, driven piles designed using LT method, the knee point identified in Fig. 5(a) has the following

parameters $P_0 = 0.86$ and $\gamma_R = 1.68$. As can be observed in Fig. 5(a), on the left side of knee point, the curve is relatively flat, indicating a slight reduction in γ_R (i.e., cost) would lead to a large decrease in design robustness (as reflected by a markedly decrease in P_0), which is undesirable. On the other side of the knee point, the slope is relatively sharp, indicating a slight gain in P_0 (i.e., a slight improvement of feasibility robustness) requires a large increase in γ_R , rendering it cost inefficient. Therefore, the knee point on the Pareto front represents the best compromise between design robustness and cost efficiency.

The values of P_0 and γ_R corresponding to those knee points shown in Fig. 5 are summarized in Table 7. Note that the values of P_0 vary from 0.84 to 0.88. For consistency and simplicity, in all scenarios, P_0 is set at 0.85 and the γ_R values are adjusted slightly, and the final results are listed in Table 7, which are recommended for typical geotechnical practice. The previous bored pile example is redesigned herein using $\gamma_R = 2.47$ selected from Table 7 compatible with $\gamma_L = 1.0$ and $\gamma_D = 1.0$. To meet $P_0 = 0.85$, the final L is determined to be 48.75 m and is shown in Fig. 4.

6. Concluding Remarks

This paper presents a new resistance factor (γ_R) calibration approach considering feasibility robustness. The new approach is demonstrated with a pile design calibration example that describes Shanghai, China experience. Herein, the feasibility robustness is defined as a probability that the safety requirement can still be satisfied even if the capacity of the designed system is uncertain (i.e., exhibiting significant variation) due to the uncertainty in resistance bias factors. With due consideration of the variation in the resistance bias factor, the proposed calibration approach aims to obtain γ_R so that the resulting design is robust against uncertainty in the computed bearing capacity.

The presented results show that without considering design robustness, the design using

calibrated γ_R obtained from the traditional LRFD calibration process can still miss the target reliability index (β_T) because of the underestimation of the variation in resistance bias factor. By considering feasibility robustness in the calibration process, γ_R is re-calibrated in this study, which can be selected for future applications based on the desired feasibility robustness level. A case study is performed using the re-calibrated γ_R . It shows that feasibility robustness and cost efficiency are two conflicting objectives. To aid in decision-making in the design process, a feasibility robustness level of 0.85 and corresponding values of γ_R , which are obtained through a multi-objective optimization, are suggested in the absence of a designer's preference.

It should be noted that the calibrated resistance factors are obtained specifically for design of piles in Shanghai, as assumptions based on local practice are made. Further studies are warranted to confirm the general applicability of the proposed calibration approach.

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507

508 **Appendix I. Pile design methods used in Shanghai, China**

509 **Load Test-Based (LT) Method**

510 LT method is considered as the most reliable approach for pile design. When the static
511 load test is used to determine the design capacity, at least 3 piles or 1% of the total number of
512 production piles should be tested. However, if the number of production piles is smaller than
513 50, the number of piles to be tested can be reduced to a minimum of 2. The ultimate pile
514 capacity at the site is chosen as the mean of the measured bearing capacities. For each pile, the
515 ultimate bearing capacity was determined by examining the load-displacement (Q - s) curve and
516 the corresponding displacement-logarithm of time (s - $\lg t$) curve. The load at the start point of a
517 steep drop on the Q - s curve and the load beyond which the settlement will not converge on the
518 s - $\lg t$ curve was taken as the ultimate bearing capacity (SUCCC 2010; Zhang et al. 2005).

519 In LT method, the piles are initially designed based on the design table (DT) method or
520 the cone penetration test-based (CPT) method. If static load tests show that the bearing capacity
521 of the initially designed piles is not adequate and the design needs to be revised, the bearing
522 capacity of the revised piles should also be measured by static load tests. LT method is often
523 used for important projects, or when the site condition is complex, new construction methods
524 are employed, or new types of piles are used.

525 **Design Table (DT) Method**

526 In DT method, the nominal bearing capacity of a pile is determined empirically based
527 on the soil profile as:

$$528 \quad R_n = R_t + R_s = q_t A_t + U_p \sum_{i=1}^n f_{si} z_i \quad (\text{A1})$$

529 where R_t is side resistance; R_s is toe resistance; q_t is unit toe resistance; A_t is cross-section area
530 of pile end; U_p is perimeter of pile; f_{si} is unit side resistance of the i^{th} soil layer, z_i = thickness
531 of pile interfacing with the i^{th} soil layer; and n is the number of soil layers surrounding the pile.

532 **Cone Penetration Test-based (CPT) Method**

533 In CPT method, the bearing capacity of a pile is calculated using the following equation:

534
$$R_c = R_t + R_s = \alpha_b q_{ct} A_t + U_p \sum_{i=1}^n f_{si} z_i \quad (\text{A2})$$

535 where α_b is correction factor; and q_{ct} is cone tip resistance measured at the pile toe.

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Table 1. Summary of driven piles for code calibration (modified after Li et al. 2015)

Site No.	Site Name	Dimension (mm)	No. of piles	Measured ultimate bearing capacity (kN)	Statistics of measured bearing capacity	
					Mean (kN)	COV
1	Shanghai Jiangping High School	250×250	6	558; 496; 558; 558; 558; 550	546	0.046
2	Tangzhen Commodity Housing	250×250	3	765; 720; 810	765	0.083
3	Shanghai F1 Speedway	250×250	3	980; 900; 1000	960	0.055
4	Yueda Residential Building	300×300	3	462; 594; 600	552	0.141
5	Shenyuan Construction Site #1	200×200	3	500; 450; 425	458	0.083
6	Shenyuan Construction Site #2	250×250	4	750; 780; 720; 636	722	0.086
7	Kangtai Residential Building	200×200	4	460; 440; 396; 480	444	0.081
8	Shanghai Haide Apartment	250×250	3	240; 270; 210	240	0.125
9	Donglan Xincun	250×250	8	700; 770; 840; 770; 700; 770; 840; 630	753	0.096
10	Xincheng Residential Building	250×250	5	540; 540; 600; 540; 540	552	0.049
11	Rongnanyuan Extension	250×250	11	403; 403; 403; 403; 403; 403; 403; 403; 403; 403; 358	399	0.034
12	Qingchi Project Phase I	250×250	3	567; 491; 567	542	0.081
13	Shanghai Dekui Plant	250×250	8	461; 461; 461; 461; 461; 461; 461; 403	454	0.045
14	2205 Gonghexin Rd	250×250	3	736; 736; 644	705	0.075
15	Shanghai Tennis Club	300×300	3	720; 600; 720		0.102
16	Jinda Residential Building	300×300	14	786; 672; 784; 896; 672; 896; 672; 784; 784; 1008; 1008; 1008; 1008	840	0.155
17	Runjiang Project Phase I	300×300	3	448; 538; 538	508	0.102
18	Wenhuayuan Phase V	350×350	3	1550; 1639; 1806	1665	0.078
19	Shanghai Dingxin Apartment	350×350	8	1280; 1440; 1280; 1280; 1280; 1280; 1600; 1600	1380	0.106
20	ECNU Middle School	350×350	3	630; 720; 717	689	0.074
21	ECNU Science Park	350×350	6	1079; 960; 960; 960; 969; 969	983	0.048
22	Feilipu Plant	400×400	3	1425; 1425; 1350	1440	0.031
23	Site #2	—	3	1250; 1200; 1500	1317	0.122
24	Site #4	—	3	2700; 2300; 2600	2533	0.082

25	Site #7	–	4	470; 560; 440; 420	473	0.131
26	Site #9	–	3	890; 1050; 1100	1013	0.108
27	Site #14	–	3	1300; 1520; 1550	1457	0.094
28	Site #19	–	4	–	–	0.060
29	Site #24	–	3	–	–	0.080
30	Site #30	–	4	–	–	0.103
31	Site #31	–	4	–	–	0.122
32	Site #32	–	4	–	–	0.097

Table 2. Summary of bored piles for code calibration (modified after Li et al. 2015)

Site No.	Site Name	Diameter (mm)	No. of piles	Measured ultimate bearing capacity (kN)	Statistics of measured bearing capacity		Predicted bearing capacity using DT method (kN)
					Mean (kN)	COV	
1	Zhongjian Mansion	850	3	8192; 8192; 7168	7850	0.075	9717
2	Metro Line 10 Parking Lot 1	600	3	4008; 5025; 3685	4239	0.131	3900
3	Metro Line 10 Parking Lot 2	600	4	3900; 3600; 3600; 3300	3600	0.068	2965
4	Yuyuan Community	550	6	2420; 2420; 2240; 1960; 2240; 2800	2347	0.119	2140
5	Gaofufang	700	3	8840; 8840; 7480	8387	0.094	7572
6	Shanghai Quality Inspection	650	3	1860; 1780; 1670	1770	0.054	2218
7	Taihongxinyuan	600	5	2700; 2700; 3000; 2700; 2700	2760	0.049	2830
8	Yueyang Plaza	850	3	10000; 8000; 11500	9833	0.179	11,529
9	Zhongsheng Commercial Center	900	3	5460; 5460; 4550	5157	0.102	4078
10	Chunguang Garment Factory	600	4	2400; 2400; 2400; 2700	2475	0.061	3273

Table 3. Summary of resistance bias factor statistics used in calibration and resulting calibrated partial factors (modified after Li et al. 2015)

	Driven piles			Bored piles	
	LT method	DT method	CPT method	LT method	LT method
λ_{R1}	1	1	1	1	1
COV_{R1}	0.087	0.087	0.087	0.093	0.093
λ_{R2}	1	1.025	1.006	1	0.996
COV_{R2}	0	0.144	0.093	0	0.184
λ_R	1	1.025	1.006	1	0.996
COV_R	0.087	0.168	0.127	0.093	0.206
γ_R	1.53	1.93	1.72	1.56	2.26

Table 4. Feasibility robustness of calibrated partial factors in Li et al. (2015) obtained from MCS and PEM

Approach	Driven piles			Bored piles	
	LT method	DT method	CPT method	LT method	DT method
MCS	0.534	0.489	0.515	0.558	0.500
PEM	0.541	0.479	0.506	0.578	0.464

* The numerical entries in this table are feasibility robustness, $P[(\beta - \beta_T) \geq 0]$.

Table 5. Calibrated resistance factors (γ_R) for load-carrying capacity at different feasibility robustness levels

P_0	Driven piles			Bored piles	
	LT method	DT method	CPT method	LT method	DT method
0.5	1.52	1.95	1.72	1.53	2.30
0.6	1.55	1.98	1.75	1.57	2.34
0.7	1.59	2.01	1.79	1.62	2.38
0.8	1.64	2.05	1.83	1.69	2.44
0.9	1.72	2.11	1.90	1.81	2.52
0.99	2.04	2.27	2.10	2.39	2.76

* Load factors used in this calibration are: $\gamma_L = 1.0$ and $\gamma_D = 1.0$ (Shanghai code)

Table 6. Values of μ_β and σ_β at various feasibility robustness levels

P_0	Driven piles						Bored piles			
	LT method		DT method		CPT method		LT method		DT method	
	μ_β	σ_β	μ_β	σ_β	μ_β	σ_β	μ_β	σ_β	μ_β	σ_β
0.5	3.70	0.67	3.70	0.30	3.70	0.43	3.70	0.83	3.70	0.30
0.6	3.88	0.70	3.79	0.30	3.80	0.44	3.90	0.89	3.79	0.31
0.7	4.11	0.74	3.87	0.31	3.95	0.46	4.18	0.93	3.86	0.31
0.8	4.38	0.79	3.98	0.32	4.10	0.47	4.54	1.01	3.98	0.32
0.9	4.81	0.87	4.13	0.33	4.36	0.50	5.14	1.13	4.12	0.33
0.99	6.32	1.13	4.53	0.36	5.04	0.56	7.56	1.65	4.54	0.36

Table 7. Calibrated partial factors obtained from knee point of Pareto front

Piles	Design method	Knee point		Suggested	
		P_0	γ_R	P_0	γ_R
Driven piles	LT method	0.86	1.68	0.85	1.67
	DT method	0.84	2.07	0.85	2.08
	CPT method	0.85	1.86	0.85	1.86
Bored piles	LT method	0.88	1.78	0.85	1.74
	DT method	0.84	2.46	0.85	2.47

* Partial factors for loads used in this calibration are: $\gamma_L = 1.0$ and $\gamma_D = 1.0$ (Shanghai code)

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Fig. 4. Design results at various feasibility robustness levels

Fig. 5. Pareto front showing tradeoff between feasibility robustness P_0 and resistance factors γ_R for different types of piles and different design methods

(a) Driven piles

(b) Bored piles

Fig. 1. Cumulative frequency of the observed COV_{R1} with fitted lognormal CDF for different types of piles

(a) Driven piles designed using LT method

(b) Driven piles designed using DT method

(c) Driven piles designed using CPT method

(d) Bored piles designed using LT method

(e) Bored piles designed using DT method

Fig. 2. Relative and cumulative frequency of β associated with calibrated γ_R for different types of piles and different design methods
(Note: $\beta_T = 3.7$)

Fig. 3. A bored pile design example

Fig. 4. Design results at various feasibility robustness levels

(a) Driven piles designed using LT method

(b) Driven piles designed using DT method

(c) Driven piles designed using CPT method

(d) Bored piles designed using LT method

(e) Bored piles designed using DT method

Fig. 5. Pareto front showing tradeoff between feasibility robustness and resistance factors for different types of piles and different design methods