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Research Paper

Probabilistic vs Deterministic Foundation Design: Impact of PDA and SLT Data on Required Safety Factor in an Indonesian Project Case Study

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Abstract

Foundation design using the Allowable Stress Design (ASD) method is characterized by less consistent reliability that is difficult to quantify, leading to overly conservative or optimistic design. Therefore, this study aimed to implement the Reliability-Based Design (RBD) method in foundation design to achieve consistent reliability levels and evaluate the equivalent safety factor generated. The design process was initially conducted based on API method and updated using field test data, namely the Pile Driving Analyzer (PDA) and Static Load Test (SLT). Statistical parameter updating was performed using a statistical analysis through the Bayesian updating method. The results showed that RBD method was capable of explicitly quantifying uncertainties. Furthermore, the availability of more and higher-quality data contributed to a more accurate representation of uncertainty, causing a greater reduction in the required equivalent factor of safety. This showed that the probabilistic method enabled the application of a lower safety factor compared to the conservative value of approximately 2.5 commonly adopted in ASD, without compromising the target reliability. Through the addition of data from PDA and SLT testing, this study showed that the RBD method could significantly reduce the required safety factor to a value of 1.68.

Keywords: *bayesian updating; equivalent factor of safety; PDA; reliability-based design; SLT.*

Introduction

Foundation design is still commonly relying on the Allowable Stress Design (ASD) method, which does not explicitly account for the variability of soil parameters and loads, resulting in less consistent reliability. In some cases, ASD can be overly conservative, leading to material and cost inefficiencies without a proportional increase in safety. Under certain conditions, ASD may produce overly optimistic design due to the inability to quantify real uncertainties encountered in the field, according to Tao et al. (2021), Phoon et al. (2024), and Jong & Ong (2024).

In the context of Indonesian soil conditions, the study conducted by Roniar et al. (2023) showed that the capacities obtained from 104 pile test data measurements differed from estimated values using commonly adopted empirical methods, which are often relied by practicing engineers. This inconsistency hinders balanced safety and efficiency, underscoring the need for approaches that can explicitly quantify the uncertainty associated with soil parameters and foundation resistance.

One design framework that attempts to quantify such uncertainties is the Load and Resistance Factor Design (LRFD) method. The LRFD method was developed using probabilistic principles and global data to calibrate load and resistance factors, but it still struggles to capture local soil conditions and data quality. Reliability-Based Design (RBD) addresses this limitation by allowing direct calibration with site-specific data, producing a more consistent and efficient design. Recent studies have further extended reliability-based approaches to geotechnical systems through reliability-based design optimization (RBDO), demonstrating improved reliability and cost efficiency in various applications such as soil slopes, excavation pits, strip footings, and retaining walls Liu et al. (2023). These findings indicate that reliability-based frameworks have been increasingly adopted in different geotechnical contexts beyond conventional deterministic design. Similar reliability-based studies have been reported in various regions, including Asia, Europe, and North America, highlighting the global interest in probabilistic foundation design approaches. This global trend is also reflected in design standards such as Eurocode 7, which permits the use of probabilistic methods in geotechnical design.

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However, despite the increasing adoption of probabilistic approaches in geotechnical engineering, important gaps remain. Limited studies have explicitly integrated Bayesian updating with site-specific pile load test data to recalibrate resistance parameters within a reliability-based framework. Most reliability analyses still rely on assumed statistical parameters or generalized databases without formally incorporating local field measurements. In addition, direct comparisons between Reliability-Based Design (RBD) and conventional Allowable Stress Design (ASD) using actual site data remain limited. Such comparisons are important to demonstrate the practical implications of adopting reliability-based approaches and to evaluate whether foundation design practices should gradually transition toward RBD, particularly in regions where ASD is still widely used.

To address these limitations, the initial pile capacity prediction in this study is first estimated using the American Petroleum Institute (API) method based on local N-SPT data obtained from the project site. This prediction serves as the prior resistance model within a reliability-based framework. Subsequently, site-specific field measurements obtained from Pile Driving Analyzer (PDA) and Static Load Test (SLT) are incorporated through Bayesian updating to recalibrate the resistance parameters. The updated resistance parameters are then used to evaluate reliability indices and corresponding safety factors, and the results are directly compared with those obtained from conventional Allowable Stress Design (ASD). By explicitly quantifying the impact of incorporating site-specific field data on design reliability, this study aims to provide practical insights for achieving more consistent and cost-efficient foundation designs without compromising safety.

Methodology

Site Condition and Available Data

This study used geotechnical data obtained from a wharf project in Indonesia, based on five nearby soil investigation points. Initially, subsurface conditions at the site were characterized using Standard Penetration Test (SPT) data obtained from the site investigation program. The resulting N-SPT profiles provide an initial understanding of the soil stratigraphy and are presented in Figure 1. Subsequently, during the pile driving process, the Pile Driving Record (PDR) was documented to monitor the hammer performance and pile penetration behavior in the field. The recorded PDR data are presented in Figure 2.

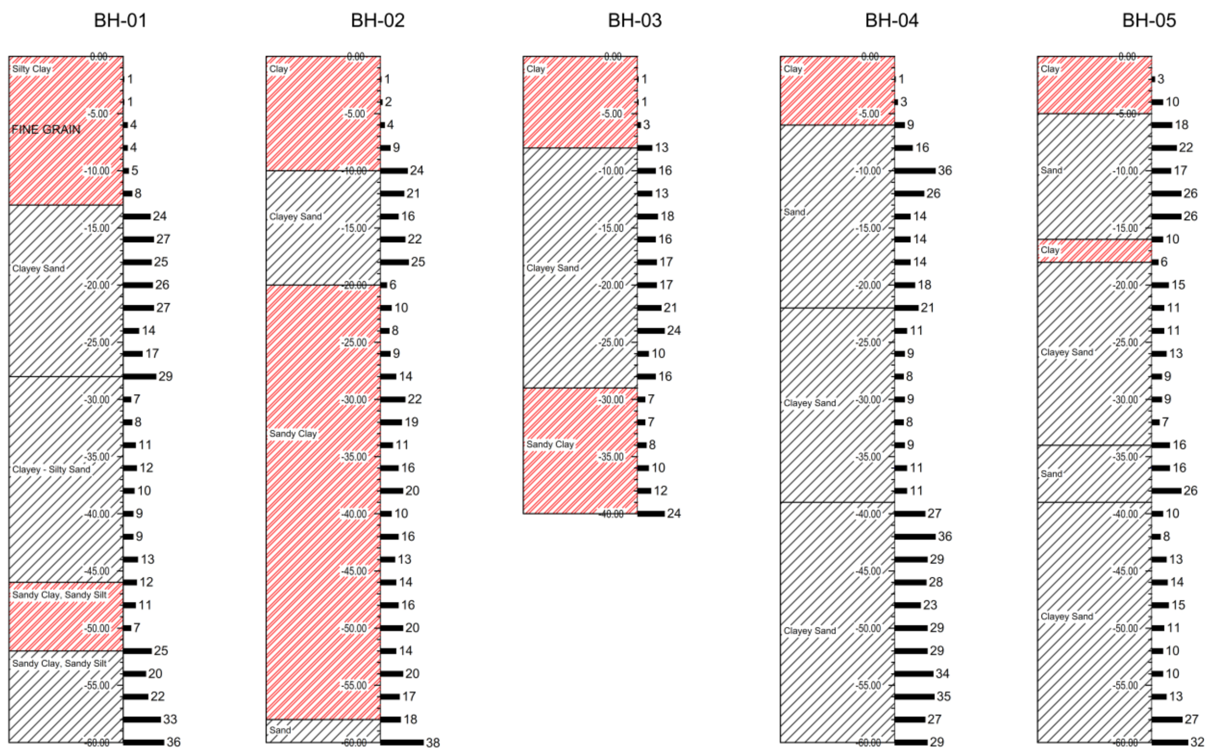

Figure 1 Standard penetration test result.

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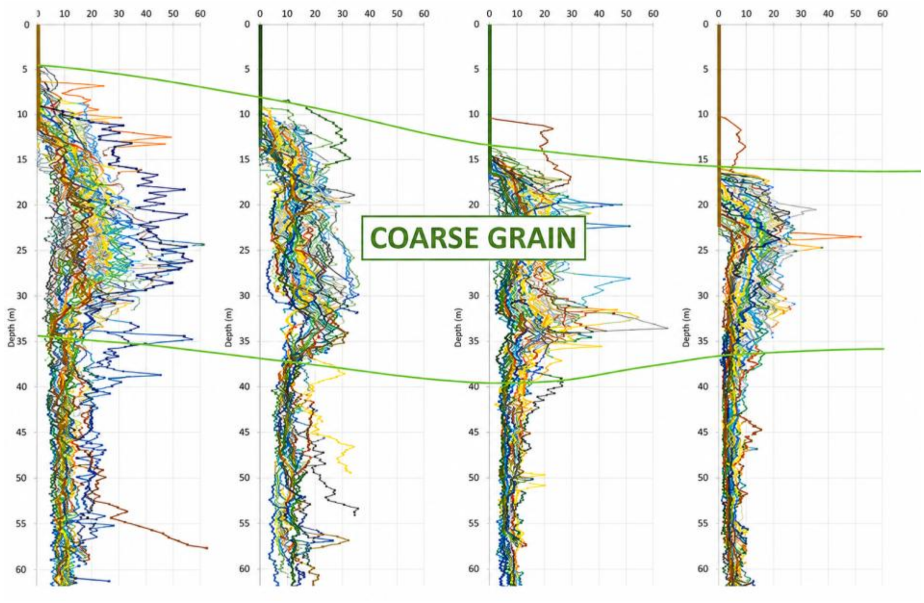

Figure 2 Pile driving record results.

Field investigation showed relatively uniform stratification with identifiable horizontal and vertical variability, alongside clear alternation of clay and sand layers. Additionally, N-SPT values within each layer were consistent, with only 15 blows of variation.

Based on the available data, a total of 117 PDA test results were collected, only 46 were used after applying the filtering criteria from What Constitutes a Good PDA Test Goble et al. (2008) to ensure data quality. For static load tests (SLT), five results were available, with three reaching failure based on the Mazurkiewicz criterion, while two did not. The use of this criterion follows recommendations from Lastiasih & Sidi (2014) and Lastiasih et al. (2013), who emphasized the need for correction factors to obtain more accurate pile capacities. Before these data can be incorporated into the reliability framework, their statistical characteristics must first be examined to determine an appropriate probabilistic model.

Shapiro-wilk Normality Test

From the site conditions that were conducted using field investigation, geotechnical data varied from one location to another. Therefore, normality test is essential to determine the type of data distribution. Some examples of normality test include Kolmogorov-Smirnov, Anderson-Darling, Lilliefors, and Shapiro-Wilk. In geotechnical practice, field test data such as PDA and SLT results are limited in number due to constraints in time, cost, and field conditions. This study applies the Shapiro-Wilk test due to high sensitivity and reliability for small to medium sample sizes (fewer than 50 data points) by Shapiro & Wilk (1965). Specifically, Shapiro-Wilk test compares actual data with a theoretical normal distribution and produces a p-value with a certain level of confidence.

In this study, a p-value threshold less than 0.05 shows that the data do not follow a normal distribution when the result is statistically insignificant. This testing is essential to determine whether the data follow a normal or log-normal distribution. Lumb (1966) found that geotechnical parameters tended to follow normal or log-normal distribution, as verified by Shapiro-Wilk. This test will be conducted on the data from PDA and SLT results. After establishing the statistical distribution of the resistance data, the next step is to relate these observations to the selected design prediction method.

Design Method and Tested Data Variability

Various design methods can be used for deep foundation. According to Zhang & Tang (2001), significant variation exists among different design methods due to uncertainties shown in the bias factor (λ_R) and coefficient of variation (COV_R). The bias factor (λ_R) represents the ratio of predicted bearing capacity to the actual capacity measured in the field. McVay et al. (2000) reported that a more accurate design method was shown by a lower COV_R value. To quantify the predictive performance of the selected design approach, the American Petroleum Institute (API) method was adopted as the baseline deterministic model.

The API method, originally developed for offshore pile foundation design, estimates pile bearing capacity based on static analysis of shaft resistance and end bearing using empirical soil parameters. The calculation of bearing capacity is essential for assessing the reliability of deep foundation design. In this study, the initial capacity from the API method was updated using statistical parameters derived from PDA, SLT, and their combined data. The parameters were then used to determine the reliability index and the corresponding safety factors.

To estimate the statistical parameters for both the API method and the test data, linear regression was performed to correlate predicted and measured capacities. Following Hannigan et al. (1997), the predicted–actual relationship was assumed linear, allowing calibration through regression. A regression through the origin was applied, showing a proportional relationship between predicted and actual capacities. This provided the bias factor (λ_R) and COV_R used in the Bayesian Updating process. These calibrated statistical parameters serve as prior information for the subsequent updating stage.

Field Load Variability

In reliability analysis, the variability of both load and capacity is essential to determining the reliability of a foundation system. Based on the analysis, capacity variability was represented using statistical parameters from the API method and refined as more field data were incorporated. In addition to resistance uncertainty, load variability must also be defined to complete the reliability formulation. However, load variability was defined deterministically in this study, according to the maximum expected field load and the spatial constraints of the wharf. This method ensured that the load input showed actual site conditions while keeping the reliability evaluation consistent.

Site Variability

In geotechnical engineering, pile capacity often varies even at sites with seemingly uniform soil. Evangelista et al. (1977) observed that the variability could originate from differences in soil behavior around the pile, geometry, concrete quality, construction methods, and set-up effects. Furthermore, Reese & O'Neill (1988) found that improper handling of bentonite slurry significantly reduced the shaft resistance factor (β). Chow et al. (1998) observed that pile capacity in sandy soils increased by more than 200% due to set-up effects occurring sometime after installation. Therefore, this inherent variability represented the minimum level of uncertainty (aleatory uncertainty) that could not be reduced at the site. To reduce epistemic uncertainty associated with model prediction, Bayesian updating is subsequently applied using the available field test data.

Pile Capacity Update with Field Test Data

One effective method for updating data when new field observations become available is Bayesian updating Pan et al. (2024). Bayesian updating is grounded in Bayes' Theorem, which expresses the posterior probability density function of a parameter μgiven observed data as:

$$f''(\mu) = \frac{L(\mu)f'(\mu)}{\int L(\mu)f'(\mu)d\mu} \tag{1}$$

where $f'(\mu)$represents the prior distribution describing the initial estimate of the parameter, $L(\mu)$is the likelihood function derived from observed field data, and $f''(\mu)$is the posterior distribution after incorporating new evidence. A previous study by Sidi (2017) analyzed probabilistic modeling framework with a single failure test result, showing that probability method could be used to update safety factor in design procedure. This method combines a prior distribution (initial knowledge) with a likelihood distribution based on observed data to produce a posterior distribution by Tao et al. (2021) and Ang & Tang (2007). Through this updating process, the uncertainty associated with the initial parameter estimates can be progressively reduced as additional field information becomes available. As a result, the updated parameters provide a more realistic representation of the actual system behavior, which improves the reliability and precision of subsequent reliability analyses and design evaluations.

In geotechnical reliability analysis, the relationship between predicted and measured pile capacity is commonly expressed using the bearing capacity ratio, defined as

$$x = \frac{Q_{measured}}{Q_{predicted}} \tag{2}$$

where $Q_{measured}$is the pile capacity obtained from field testing and $Q_{predicted}$is the capacity estimated using empirical design methods. At a given site, Whitman (1984) observed that the bearing capacity ratio $x$can reasonably be represented by a lognormal distribution. Based on the formulation presented by Ang & Tang (2007), the probability that the bearing capacity ratio exceeds a threshold value $x_T$can be expressed as shown in Eq. (3):

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$$p(x \geq x_T) = \int_{x_T}^{\infty} \frac{1}{\sqrt{2\pi}\xi x} exp\left(-\frac{1}{2}\left(\frac{ln(x)-\eta}{\xi}\right)^2\right) dx \tag{3}$$

which can be written in cumulative distribution form as shown in Eq. (4):

$$p(x \geq x_T) = \Phi\left(-\frac{ln(x_T)-\eta}{\xi}\right) \tag{4}$$

where η and ξ denote the mean and standard deviation of the natural logarithm of x, respectively, and Φrepresents the standard normal cumulative distribution function.

For a set of n independent pile test observations, the likelihood function describing the probability of observing the data given a parameter value μcan be written as shown in Eq. (5):

$$L(\mu) = \prod_{i=1}^{n} p(x \geq x_T|\mu) = \Phi^n\left(-\frac{ln(x_T)-\eta}{\xi}\right) \tag{5}$$

This likelihood function represents the contribution of the observed field data to the updating process. By combining the likelihood function with the prior distribution according to Bayes' theorem, the posterior distribution of the parameter can be expressed as shown in Eq. (6):

$$f''(\mu) = k\Phi^n\left(-\frac{ln(x_T)-\eta}{\xi}\right) f'(\mu) \tag{6}$$

where k is a normalization constant ensuring that the posterior probability density function integrates to unity.

In this study, the prior distribution represents the predicted pile capacity obtained using the American Petroleum Institute (API) method based on local N-SPT data collected from the project site. The prior model is characterized by its mean value and coefficient of variation (COV), which describe the initial uncertainty associated with the empirical pile capacity prediction. Field measurements obtained from Pile Driving Analyzer (PDA) and Static Load Test (SLT) are treated as observational data and used to construct the likelihood function following Eq. (5). Through Bayes' theorem, the prior distribution is updated using likelihood information derived from the PDA and SLT measurements, resulting in a posterior distribution as expressed in Eq. (6). The posterior distribution therefore reflects both the empirical prediction obtained from the API method and the actual performance of the piles observed in the field. Consequently, the updated posterior parameters provide a statistically refined estimate of pile resistance that incorporates both prior empirical knowledge and site-specific field evidence, leading to more reliable input parameters for the subsequent reliability analysis.

Reliability Target and the Corresponding Equation

The updated resistance parameters obtained from the Bayesian updating process provide statistically calibrated estimates of pile capacity that incorporate both empirical predictions and field measurements. To evaluate the safety level of the foundation system based on these updated parameters, a reliability analysis is subsequently performed. This analysis quantifies the probability of failure by considering the statistical variability of resistance and load effects within a probabilistic design framework.

Reliability analysis in geotechnical design is generally formulated using a limit state function, as defined in Eq. (7):

$$g(R,Q) = R - Q \tag{7}$$

where R denotes the resistance and Q represents the load effect. Failure occurs when $g(R,Q) \leq 0$. Accordingly, the probability of failure is expressed as shown in Eq. (8):

$$P_f = P[g(R,Q) \leq 0] \tag{8}$$

The level of safety of a structural or geotechnical system is commonly represented by the reliability index β', which is related to the probability of failure through the standard normal distribution function. In engineering practice, the First Order Reliability Method (FORM) is widely used to approximate the reliability index by linearizing the limit state function at the design point.

For cases where load and resistance follow log-normal distributions, the reliability index can be defined using a specified equation described by Whitman (1984) in Eq. (9):

$$\beta' = \frac{\ln\left(\frac{\bar{R}}{\bar{Q}}\sqrt{\frac{1+COV_Q^2}{1+COV_R^2}}\right)}{\sqrt{\ln\left[\left(1+COV_R^2\right)\left(1+COV_Q^2\right)\right]}} \tag{9}$$

When the load includes live and dead load components, the coefficient of variation of the total load can be calculated using the formulation proposed by Becker (1996), as shown in Eqs. (10) and (11):

$$\frac{\bar{R}}{\bar{Q}} = \frac{\lambda_R\, FOS\left(\frac{Q_D}{Q_L}+1\right)}{\lambda_{QD}\frac{Q_D}{Q_L}+\lambda_{QL}} \tag{10}$$

$$COV_Q^2 = COV_{QD}^2 + COV_{QL}^2 \tag{11}$$

In the design of pile group foundation, the phenomena of group and system effects are essential considerations in determining the overall reliability of the foundation system. Group effects (ζ) describe the collective performance of piles, expressed through an efficiency factor. Zhang et al. (2001) found that the average efficiency factor (μ_ζ) was higher in non-cohesive soils, with ground-contact pile caps improving load redistribution. These effects enhance load sharing and add redundancy. System effects (χ) represent system overall redundancy and the capacity to sustain loads despite partial element failure. Bea (1983) defined system effect as the ratio of the load causing total system failure to the load that triggers failure in the most critical component. A higher value of system effects implies a greater degree of redundancy and resilience within the structure.

Within the RBD framework, the safety of a pile was expressed through a reliability index (β’). According to AASHTO and the National Building Code of Canada (NRC), reliability levels are typically calculated using the First Order Reliability Method (FORM). The target reliability index (β’) depends on the structure risk category and the types of effects considered. For single pile system, Barker et al. (1991) and Withiam et al. (1997) calibrated current ASD methods and found that a typical target reliability index (β’) ranged from 2.0 to 2.5. For offshore structures, Bea (1983) suggested a broader range of 2.0 to 3.0 based on the desired level of reliability. Because infrastructure responses to loads vary significantly, the target reliability must be project-specific. Therefore, numerical simulations are commonly used to evaluate both group and system effects.

In this study, the target reliability index was adopted from the American Society of Civil Engineers (2017), without considering the effects of the superstructure. Since wharf structure was analyzed, it was under Risk Category IV, classified as an essential facility crucial for logistics and transportation. Compared to typical building structures (Risk Category II or III), which commonly correspond to reliability indices around 3.0–3.5, Risk Category IV structures require a higher level of safety due to their critical post-event functionality and socio-economic importance.

According to ASCE (2017), a target reliability index of β’ = 4.0 is recommended for essential facilities to limit the probability of failure to 7×10^{-7}/year, particularly when failure could disrupt strategic infrastructure operations. Although pile foundation failure may not always lead to progressive collapse of the entire superstructure, the potential operational interruption and economic consequences justify adopting the higher reliability target. Therefore, β’ = 4.0 was selected to represent a conservative yet code-consistent reliability level for the analyzed wharf foundation system.

Results

Data Distribution Check using the Shapiro-wilk Test

In this study, the reliability equations and Bayesian updating method assumed that the bearing capacity variable followed a log-normal distribution. Therefore, it is essential to perform a preliminary assessment of the field bearing capacity data distribution through normality testing. The Shapiro-Wilk test was selected for this purpose because of the accuracy, particularly with relatively small sample sizes. The study evaluated bearing capacity ratios based on actual pile capacity compared with PDA and SLT measurements. Subsequently, these bearing capacity ratios were visualized through histograms and corresponding plots, as shown in Figure 3.

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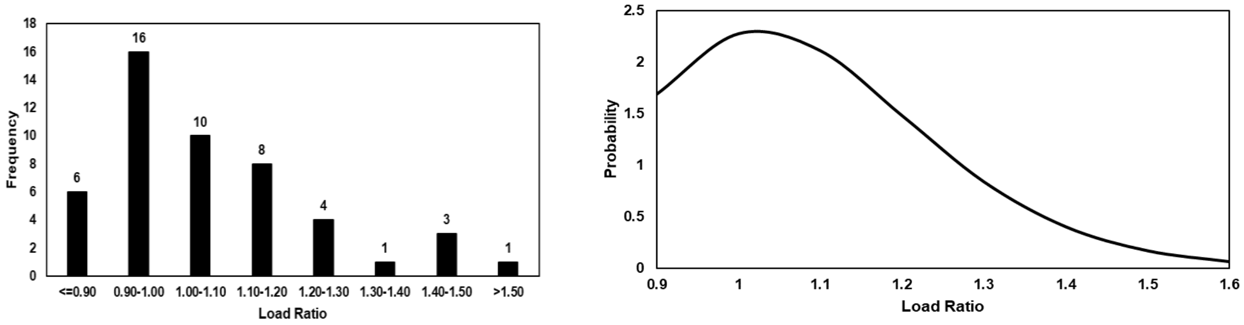


(a) (b)

Figure 3 Bearing Capacity Distribution (a) Histogram, (b) Graph.

Saphiro-Wilk test results showed an exceeded probability (z-value) of 5.18, corresponding to a p-value of 1.1 x 10^{-7}. In comparison, this value is significantly lower than the commonly accepted significance level of 0.05, leading to the conclusion that the data do not follow a normal distribution.

Minimum Field Variability

Field variability is attributed to aleatory uncertainties on soil stratigraphy and geotechnical parameters, representing a minimum level of variation that cannot be reduced, despite having an increased amount of data. Evangelista et al. (1977) reported that the extent of field variability was significantly influenced by type of foundation response, including elastic or rigid. Generally, rigid foundation is assessed based on changes in relative load to average settlement obtained by comparing responses at 1.0 and 1.5 times the design load.

In this study, the minimum field variability was determined by using data from static loading test to evaluate foundation capacity. The results showed that the coefficient of variance (COV_R) in the field was approximately 8%. This value was adopted to represent the inherent, estimated variability in site condition based on the available data, which could not be eliminated through improved data collection or more advanced testing.

Achieved Reliability Level and Equivalent Safety Factor

The results obtained from Shapiro-Wilk test indicates that the field test data followed a log-normal distribution. Therefore, the statistical parameters for the API method, PDA, and SLT datasets were determined using linear regression and subsequently refined through Bayesian updating. The reliability equation was applied to calculate the achieved reliability level for the design based on API method only, as well as with the addition of PDA, SLT, and their combination. The reliability level achieved was highly dependent on the statistical parameters derived from each method and the influence of incorporating additional data.

In addition to the statistical parameters of capacity (bearing resistance), the load statistics for the wharf are analyzed. These parameters was determined deterministically, leading to bias factor (λ_Q) of 1.04, a standard deviation (σ_Q) of 0.04, and a coefficient of variation (COV_Q) of 0.04. By targeting a reliability index (β') of 4.0, the designed infrastructure maintained a consistent probability of failure of 7×10^{-7}/year by adjusting the value of the required safety factor (SF). This value was compared with the initially used safety factor of 2.0 for the design with API method. When the calibrated value was below 2.0, the original design using SF = 2.0 could be considered acceptable.

The addition of PDA and SLT data to the initial API based design showed different effects on the statistical parameters. Calculation results showed that incorporating PDA data alone obtained a bias factor (λ_R) of 1.1 and a standard deviation (σ_R) of 0.23. The distribution of prior (API method), likelihood (PDA), and posterior distribution is shown in Figure 4.

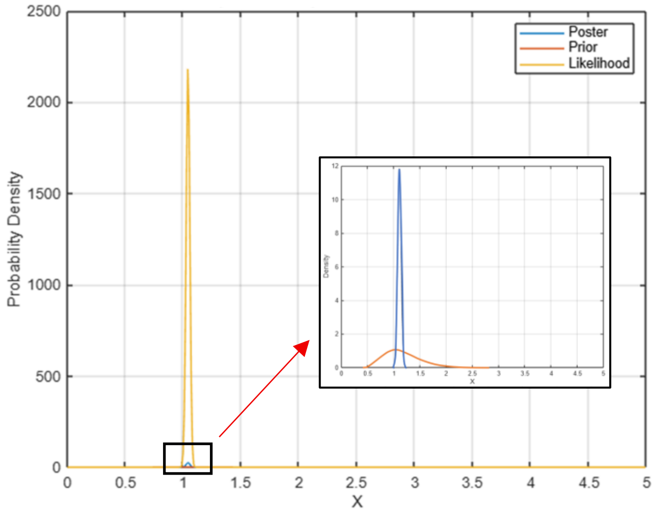
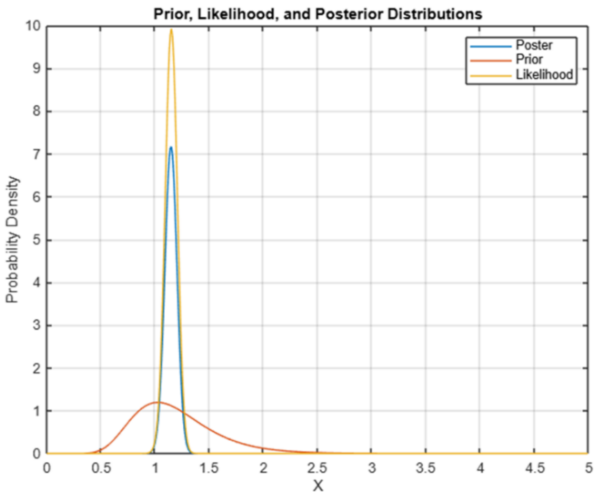
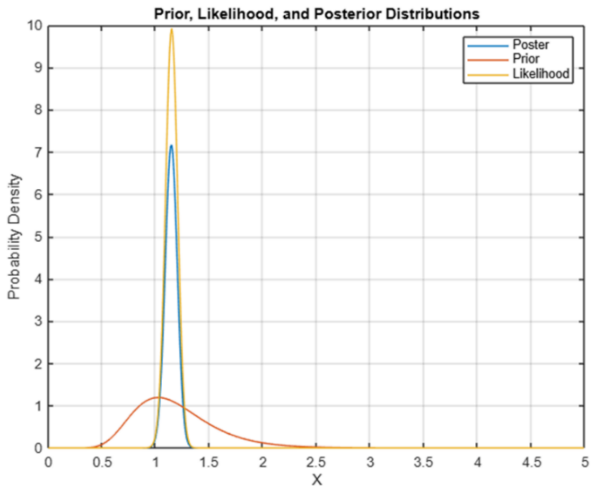


Figure 4 Bayesian updating API method with additional PDA test.

Following the evaluation of PDA data, the analysis is extended by incorporating SLT data to assess its influence on the statistical parameters. The inclusion of SLT (Static Load Test) data, which is conducted up to or near failure, provides a significant contribution in reducing uncertainty. This is because SLT tests that are carried out to failure yield a definitive value of actual bearing capacity in the field. With this level of certainty, the standard deviation becomes very small, reaching the minimum inherent uncertainty observed in the field. The statistical parameters were updated based on the API method, causing a standard deviation reduction (σ_R) to 0.11, which closely correlates with the observed field variation. In addition, the bias factor (λ_R) slightly decreases to 1.15. Below are the distribution of prior (API method), likelihood (SLT), and posterior distribution as shown in Figure 5.



(a)



(b)

Figure 5 Bayesian Updating API Method With Additional SLT Test.

When the PDA and SLT data are used together, the updated results show a bias factor (λ_R) of 1.14 and a standard deviation (σ_R) of 0.11. The combination still provides favorable statistical parameters, but the bias factor (λ_R) is slightly reduced compared to using only SLT data. The distribution of prior (API method), likelihood (SLT and PDA), and posterior distribution is shown in Figure 6.

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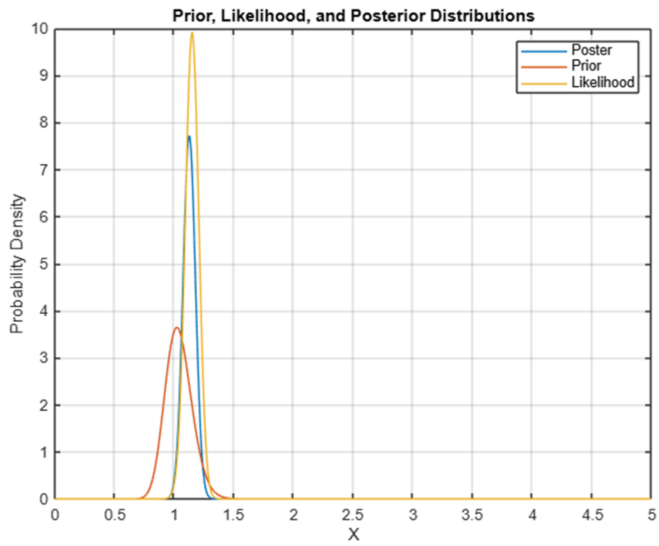

Figure 6 Bayesian updating API method with additional SLT and PDA Test.

Discussions

The Shapiro–Wilk test results indicate that the bearing capacity ratio data deviate from a normal distribution. This behavior is consistent with the observation by Lumb (1966), which states that geotechnical data generally follow either a normal or log-normal distribution. Given the non-normal nature of the dataset, the log-normal distribution is considered more representative of the underlying variability The determination of the data distribution is essential to ensure consistency with the assumptions adopted in the subsequent reliability equations and Bayesian updating framework. Accordingly, the adoption of a log-normal distribution in this study is justified and forms the basis for the reliability analysis and Bayesian updating procedure.

The observed field variability reflects aleatory uncertainty associated with natural variations in soil stratigraphy and geotechnical parameters. In this study, the coefficient of variation obtained from the SLT dataset is approximately 8%, which indicates a relatively low level of variability. This suggests that the observed variation is close to the inherent minimum variability governed by site conditions. Based on this observation, the analysis is further extended to evaluate how different datasets influence the reliability performance of the design.

Based on the results obtained from the PDA dataset, the PDA test contributed a substantial quantity of data. However, it exhibited higher variability and relatively lower bearing capacity values. This condition results in only marginal improvement of the statistical parameters compared to the API method alone. When the reliability was calibrated to the target β' = 4, safety factor was reduced to 2.68. This value is above the allowable threshold. Therefore, the design using only this dataset is not considered acceptable.

In contrast, the SLT dataset provides more consistent statistical characteristics with low variability. Based on these parameters, the calibrated safety factor (SF) is calculated to be 1.67, which is lower than the originally used SF of 2.0. Accordingly, the design is considered acceptable based on the target reliability index (β = 4.0).

When both PDA and SLT datasets are combined, the results reflect the influence of each dataset. PDA data increases the amount of available information. This leads to a slight reduction in the overall bias factor (λ_R). However, it also tends to produce lower bearing capacity values. Despite this, the resulting safety factor remains below 2.0, indicating that the design is still acceptable with respect to the target reliability.

Although PDA data do not statistically reduce uncertainty compared to SLT, it still plays an important role as a more economical and practical testing alternative, particularly for large-scale implementation. The large quantity of PDA data does not automatically lead to a significant reduction in the required safety factor, as the high variability in the results maintains a relatively large standard deviation (σ_R). In comparison, SLT data are more limited in quantity, but the higher quality in lower standard deviation effectively reduces the updated σ_R. This has a direct impact on lowering the required safety factor to meet the desired reliability level. Therefore, data quality plays a more critical role than quantity in managing uncertainty and enhancing design efficiency. A summary of the statistical parameters, reliability levels, and safety factors obtained from each Bayesian updating process is presented in Table 1. The corresponding safety factors and reliability levels for each data updating process are also illustrated in Figures 7 and 8, respectively.

Table 1 Statistic, Reliability, and Safety Factor Result of Each Bayesian Updating Data.

Parameter	API	API & PDA	API & SLT	API & PDA & SLT
λ_R	1.19	1.10	1.15	1.14
σ_R	0.32	0.23	0.11	0.11
β'	2.35	2.85	5.18	5.15
SF	3.44	2.68	1.67	1.68

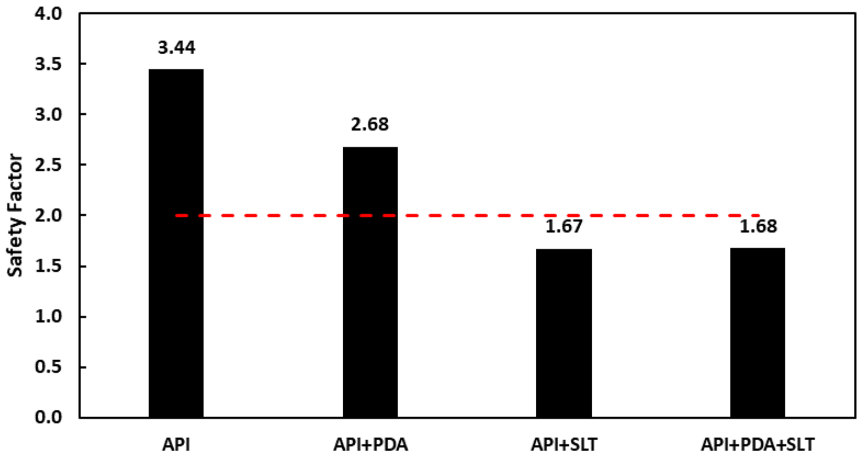

Figure 7 Reached safety factor of each data updating process.

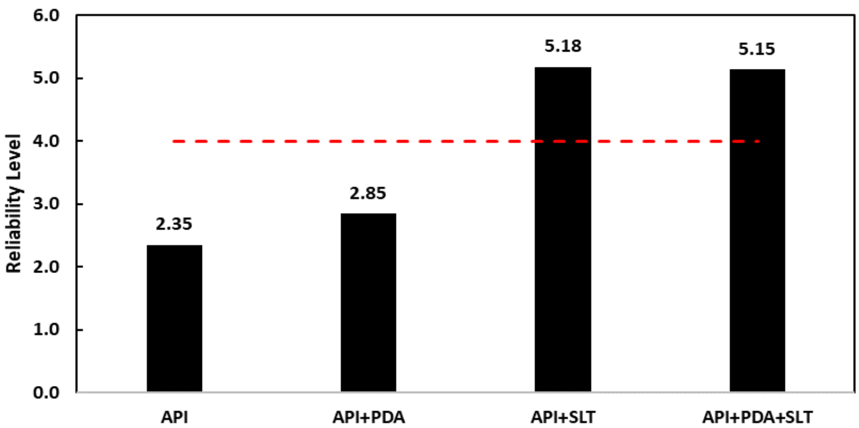

Figure 8 Reached Reliability Level for Each Data Updating Process.

Despite the encouraging results obtained from the Bayesian updating approach, several limitations should be acknowledged. First, the number of SLT samples used in this study was relatively small (n = 5), which may limit the statistical robustness of the posterior parameter estimation, particularly for extreme-value behavior. Second, the load effect was treated deterministically with fixed bias factor and variability parameters, which may underestimate the true uncertainty associated with operational and environmental loading conditions. A fully probabilistic treatment of load components could potentially influence the computed reliability index. Third, the findings are site-specific and derived from Indonesian wharf foundation data; therefore, the calibrated safety factors and reliability levels may not be directly generalizable to different soil conditions, pile types, or structural systems without further validation.

Conclusion

In conclusion, this study implemented a Reliability-Based Design (RBD) framework combined with Bayesian updating to evaluate the reliability performance of a wharf pile foundation system using site-specific field data. The primary objective was to incorporate Pile Driving Analyzer (PDA) and Static Load Test (SLT) measurements into the probabilistic framework and to assess their influence on the resulting reliability level and equivalent safety factor.

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The analysis provided a direct comparison of the effects of PDA data, SLT data, and their combined use within the Bayesian-updated reliability framework. When calibrated to a target reliability index of β'=4.0, updating the resistance model using PDA data alone yields a safety factor of 2.68, which does not satisfy the specified reliability requirement. Under the same reliability target, the conventional Allowable Stress Design (ASD) safety factor of 2.5 can be rationally reduced to 1.67 using SLT data, while the combination of PDA and SLT data results in a safety factor of 1.68. These values are compared with the safety factor of 2.0 adopted in the design, indicating that the SLT-only and combined PDA+SLT cases can be accepted, whereas the PDA-only case does not meet the acceptance criteria. These findings demonstrate that the incorporation of high-quality SLT measurements significantly improves the reliability calibration and enables a substantial reduction in safety factor while still maintaining the prescribed reliability level.

This study provides a practical demonstration of Bayesian-updated reliability-based design using site-specific data from a wharf project in Indonesia. The results highlight that reducing statistical uncertainty through reliable field testing plays a more critical role in achieving efficient and reliable foundation design than simply increasing the number of observations. Furthermore, the direct comparison between PDA and SLT data within a reliability-based framework provides valuable insight for practitioners in regions where deterministic ASD approaches are still commonly adopted.

For future research, incorporating spatial variability into the reliability analysis would enhance the robustness of the findings. The current study relied on selected datasets that were relatively close in location and had been filtered for quality, particularly for PDA data, and therefore did not fully capture spatial effects in an objective manner. Future studies could integrate spatial variability explicitly into the probabilistic framework so that the resulting reliability assessment is based purely on analytical representation of field conditions, minimizing subjective influence in data selection.

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Compliance with ethics guidelines

The authors declare they have no conflict of interest or financial conflicts to disclose.

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