A Bayesian Framework for Optimizing Proof Load Test Programs for Driven Piles

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Abstract: There is currently an inconsistency in the recommendations that are available in pile design codes and practices regarding the required number of proof-load tests and the level of the proof loads for piles. Najjar et al. (2017) proposed a pre-posterior decision-making framework to allow for selecting the optimal pile load test program that would result in the maximum expected benefit to a project while maintaining a target level of reliability in the pile design at the site. The proposed methodology was based on a robust Bayesian approach that allows for updating the capacity distribution of piles at a site given the results of the proof-load test program. The objectives of this paper are to (1) extend the statistical model that is proposed by Najjar et al. (2017) for the pile capacity by modeling the uncertainty in the pile capacity at the site (coefficient of variation due to spatial variability) as an uncertain variable that is updated with pile load test results, (2) investigate the effect using different probability distributions to represent the within-site variability on the updated reliability indices, and (3) apply the pre-posterior decision making framework to a practical design example.

Keywords: Proof load tests; reliability; decision analysis; spatial variability.

1 Introduction

Proof-load tests play an important role in verifying the validity of design methods and construction procedures. In current design and construction practices for deep foundations, designers are allowed to utilize reduced factors of safety provided that a pile load testing program is implemented on a number of foundations at the site. Many international design codes allow for the use of reduced factors of safety of different magnitudes depending on the number and type of pile load tests that are conducted. Some common recommendations from international pile design codes are presented in Matsumoto et al. (2008). These recommendations indicate variability in the correlation between the type and number of the specified pile load tests and the recommended reduced design factor of safety. Several researches such as Zhang and Tang (2002), Zhang (2004), Su (2006), Najjar and Gilbert (2009a), Kwak et al. (2010), Park et al. (2011, 2012), Abdallah et al. (2015a, 2015b), Huang et al. (2016), and Najjar et al. (2017) have targeted analyzing the impact of proof-load tests on the design of foundations in the framework of a reliability analysis. In these studies, results of proof load tests are used to update the main statistical descriptors of the pile capacity distribution, and the updated distribution is used to calculate an updated estimate of the proof-tested reliability index or probability of failure. These studies show the need for systematic and rational approaches that would allow for choosing the number of proof-load tests and the magnitude of the proof load that would maximize the value of any pile load test program.

Bayesian techniques can be used to update the probability distribution of the foundation capacity at the site given the result of a pile load test program. This analysis is referred to as a "posterior" analysis. Najjar et al. (2017) proposed a rational decision framework that is aimed at selecting the optimal pile load test program. The decision analysis is based on a "pre-posterior" decision making methodology that allows for selecting the pile load test program (number and level of proof load tests) that would result in the maximum expected benefit while maintaining a target level of reliability in the pile design at the site. The main decision alternatives were (1) the proof load level r_{proof} and (2) the number of proof load tests to be conducted, n. This methodology is original, practical, and is based on site-specific information that is unique to any given project.

In their proposed methodology, Najjar et al. (2017) adopted a statistical model for the pile capacity that is based on the model proposed by Zhang (2004) which considers that uncertainty in the pile capacity originates from two sources: (1) the uncertainty due to the model used to predict the capacity, and (2) the uncertainty due to inherent variability in the capacity within the site (within-site variability). The methodology assumes that model uncertainty due to bias in the predictions of available empirical models leads to uncertainty in the mean pile capacity at the site. This source of uncertainty is reflected in the probability distribution of the mean pile capacity, r_{mean}. The main limitation in the model that was proposed by Najjar et al. (2017) is that it assumes that the within-site variability could be represented by a constant coefficient of variation ($\delta r = 0.2$) that cannot be

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reduced by conducting pile load tests. The adoption of a constant COV of 0.2 that is not updated in the Bayesian exercise is a limitation that will be addressed in this study.

Another feature of the statistical pile capacity model adopted by Najjar et al. (2017) is the incorporation of an uncertain lower-bound capacity in the probability distribution of the mean pile capacity. Gilbert et al. (2005) and Najjar and Gilbert (2009b) hypothesized that there is a physical limit to the smallest possible capacity for a pile foundation, and that this limit is greater than zero. The basis for this hypothesis is that the strength of soil, even when substantially disturbed, is greater than zero. Gilbert et al. (2005) presented simple models for predicting lower-bound capacities for driven piles in sand and clay. In the Bayesian approach presented in Najjar et al. (2017), the lower-bound capacity was updated using pile load tests. However, results showed that the prior lower-bound distribution was not affected by the updating process, with the focus being on the distribution of the mean capacity. As a result, the revised probabilistic model that is presented in the paper for the pile capacity will assume that the lower-bound capacity is uncertain, but will not be updated given results of pile load tests.

The objectives of this paper are to (1) extend the statistical model that is proposed by Najjar et al. (2017) for the pile capacity by modeling the uncertainty in the pile capacity at the site (coefficient of variation due to spatial variability) as an uncertain variable that is updated with pile load test results, (2) investigate the effect of using different probability distributions to represent the within-site variability on the updated reliability indices, and (3) apply the pre-posterior decision making framework to a practical design example.

2 Revised Probabilistic Model for Pile Capacity

The revised probabilistic model for capacity that is presented in Figure 1 is proposed in this study to model the uncertainty in the pile capacity at a given site. The revised model considers that uncertainty in the pile capacity originates from two sources: (1) the mean pile capacity r_{mean} which reflects the model uncertainty in the pile capacity predictions and (2) the within-site variability as reflected through an uncertain coefficient of variation for the pile capacity r_{COV}. The concept of within-site variability of pile capacity originates from the work of Zhang and Tang (2002) who illustrated that piles constructed using the same design method may yield different capacities within one site as a result of spatial variability in the soil properties across the site. By analyzing results from nine different sites where multiple pile load tests that are conducted on identical piles were reported, Zhang and Tang (2002) showed that the COV representing within-site variability in pile capacities varied among sites and ranged from 0.1 to 0.3. In addition, the concept of a lower-bound capacity is incorporated in the model by truncating the distribution of the mean pile capacity using an uncertain lower-bound capacity. The mean pile capacity and the lower bound capacity will be modeled as truncated lognormal and conventional lognormal distributions, respectively. Whereas, for the coefficient of variation of the pile capacity, three potential probability distributions (uniform, truncated normal, and truncated lognormal) will be studied to investigate the sensitivity of the choice of the probability distribution of r_{COV} on the results. All three distributions assume that the mean of the r_{COV} is 0.3 and that the lower-bound and upper bound values of r_{COV} are 0.1 and 0.3 as per the data presented in Zhang and Tang (2002).

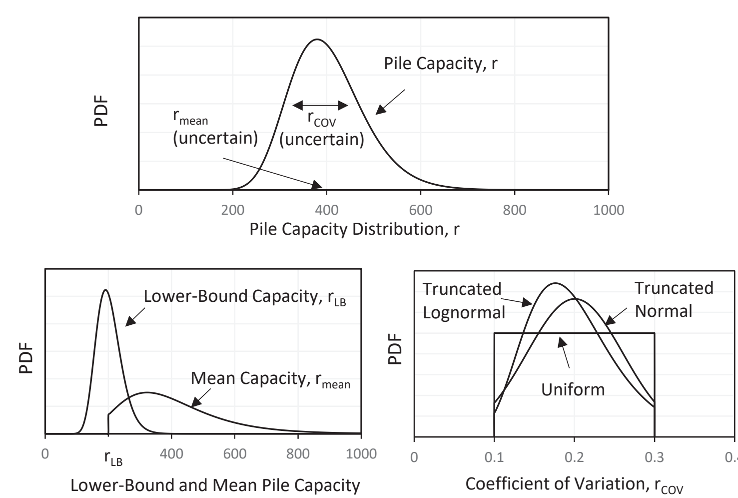

Figure 1. Revised probabilistic pile capacity model.

The probabilistic pile capacity model will be updated using Bayes' theorem given results of proof load tests. The mathematical expressions needed for updating the prior capacity model are presented in Malaeb

(2018). The effect of the updating process on the marginal PMFs of r_{mean} and r_{COV} is illustrated in Fig. 2a. The analysis pertains to the case where 5 successful proof load tests are conducted on piles designed with a factor of safety of 2.0 and tested at a proof load level of 2 times the design load. In the analysis, the load is assumed to be lognormally distributed with a COV of 0.15, whereas the lower-bound capacity is characterized by a mean that is equal to 0.5 times the mean of r_{mean} and a COV that is equal to 0.2. Finally, the COV of r_{mean} was assumed to be equal to 0.4. Results on Figure 2 are presented for the case where a truncated lognormal distribution is used to model the uncertainty in within site variability (r_{COV}). Results indicate that the effect of conducting proof load tests is concentrated on the distribution of the mean pile capacity r_{mean} compared to the distribution of r_{COV}. The distribution of r_{mean} is shifted significantly to the right as a result of the successful proof load test results. With regards to the effect of the updating process on r_{COV}, results show that the probability of smaller values of r_{COV} increased after updating whereas the probability masses for the higher values of r_{COV} were reduced. This observation was valid, irrespective of the type of distribution used to model r_{COV} (not shown graphically for length limitations). This is expected to have a positive impact on the updated reliability index for the proof-loaded design.

The effect of the updating process on the reliability index of the design is studied in Figure 3 which shows the variation of the reliability index with the number of positive load tests. Results are shown for different proof load levels (1.5 to 3 times the design load) and for the three candidate probability distributions of r_{COV}. Also shown on Figure 3 are results pertaining to the case where r_{COV} is assumed to be a deterministic value that is equal to the mean of r_{COV} for the other three distributions. Results on Figure 3 indicate that the effect of the choice of the probability distribution on the reliability index is relatively small and can be considered negligible. Since the updated reliability indices were found to be insensitive to the choice of the probability distribution describing r_{COV}, it could be concluded that the prior capacity distribution which represents within-site variability of identical piles could be represented by a coefficient of variation r_{COV} that follows a truncated lognormal distribution bounded between 0.1 and 0.3, with a mean of 0.2 and a COV of 0.31. Although the updated reliability indices were insensitive to the distribution of r_{COV}, results show that the assumption of a deterministic r_{COV} that is not updated in the Bayesian exercise results in reliability indices that are larger than the cases involving an uncertain r_{COV}. This indicates that the assumption of a deterministic r_{COV} (Najjar et al. 2017) may lead to unconservative results which incorrectly magnify the impact of proof-load tests on the updated reliability index.

3 Decision Making Framework

Najjar et al. (2017) presented a rational decision making framework that would facilitate the choice of a load test program that has the maximum expected benefit to the project. The main decision alternatives are (1) the proof load level r_{proof} and (2) the number of proof load tests, n. For each of the potential test outcomes that are associated with a decision alternative, the updated reliability index could be evaluated using Bayesian techniques. Outcomes where the updated reliability index is below the target indicate that the allowable capacity per pile (design load per pile) will have to be reduced in light of the load test results. The opposite is true for cases where the updated reliability index is above the target.

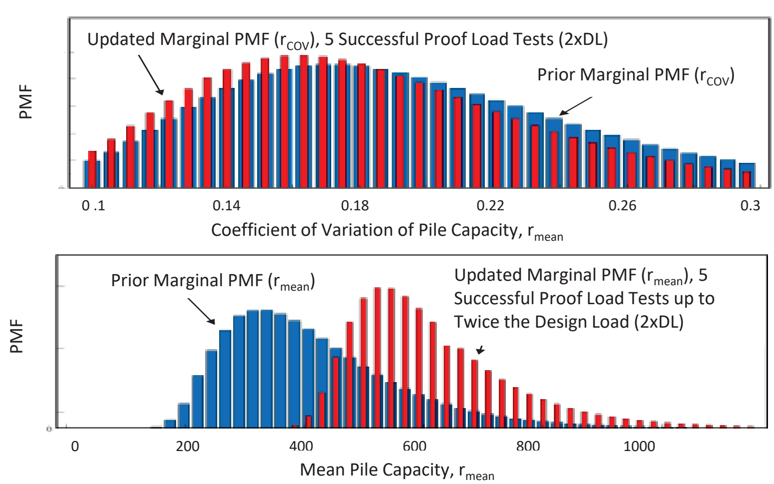

Figure 1. The prior and updated distributions of r_{mean} and r_{COV} for truncated Lognormal r_{COV}.

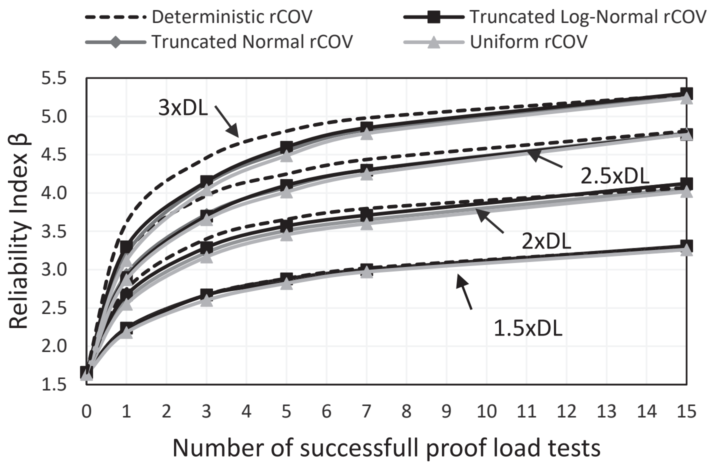

Figure 3. Effect of proof load test levels on the reliability index for different r_{COV} distributions (FS =2).

The allowable pile capacity could be calculated by utilizing the updated capacity distribution for that particular outcome. Any increase or decrease in the allowable capacity per pile as a result of conducting the proof load tests can be translated to a reduction/increase in the total number of piles required to support the superstructure loads without changing the geometry of the piles. Based on the above, the consequences of any potential test outcome will be reflected in the benefits/costs associated with reducing/increasing the required number of piles to support the superstructure load without changing the geometry of the piles under consideration. The financial benefit is reflected in the cost savings associated with this reduction in the number of piles. On the other hand, there is a negative financial cost that is associated with the cost of conducting the load test program alternatives and the cost of replacing failed piles when relevant. The net benefit of any test outcome can be calculated by subtracting the benefits due to reducing (or cost due to increasing) the number of piles in the site from the costs associated with conducting the proof load tests including the cost of replacing failed piles. Once the net benefit of all the test alternatives and their associated potential outcomes are calculated, the "expected" benefit of each alterative load test program can be calculated. The alternative pile testing program that has the highest expected benefit could then be selected as the test alternative that has the highest value.

To test the applicability of the decision making framework, four published case histories with representative soil profiles were selected. Two of the case histories (Nevels and Snethen 1994; Paik et al. 2003) involve sites that were predominantly sand (loose to medium dense for the Cimarron River site and dense sand for the Pigeon Creek site). The other two case histories (Hutchinson and Jensen 1968; Darragh and Bell 1969) involve slightly overconsolidated clay sites (Port of Khorramshahr site and Louisiana site). The pile is taken as precast circular concrete with a length of 7m and a diameter of 35.6 cm. The pile's geometry is taken the same in the four sites in order to show the effect of the soil type on the optimal proof load test program. The pile cost was taken as 116$/m and the cost of the test was taken as 10$/kN. The pre-posterior analysis is conducted for alternative proof-load test programs consisting of proof load tests at levels of 1.5xDL, 1.75xDL, 2xDL, 2.25xDL, and 2.5xDL. In each site, the optimal number of proof load tests is calculated for different prior number of piles in the site ranging from 50 to 1000 pile (small and larger superstructure loads, respectively). To make the analysis as realistic as possible, model uncertainty parameters that are consistent with the SPT-based API design method were used in the analysis. The model uncertainty parameters where taken from Lehane et al. (2017) and involve a bias factor of 1.66 and a COV of 0.56 (for piles in sand) and a bias factor of 1.54 and a COV of 0.33 (for piles in clay). These model statistics are needed to define the distribution of the mean pile capacity r_{mean}.

Figure 4 shows the results of the decision making exercise as reflected in the optimal number of tests and the optimal percentage of tests in the four sites considered. Results are given for cases involving an increasing number of piles in the site. The results for the four sites point to similarities in some aspects of the response and to differences in other aspects. For example, results indicate that the optimum proof load level is 2.25xDL in sandy sites compared to 2.5xDL in clayey sites. With regards to the optimal number of tests, as expected, results indicate that the optimal number of tests increases with the total number of piles in the site. For cases involving clay sites, the optimal number of tests increases from 2 to 3 tests for sites with around 50 to 100 piles to a maximum number of 12 to 13 tests for sites with 1000 piles. The optimal number of tests for sand sites was lower with values ranging from 1 to 2 tests for sites with 100 piles to a maximum of 7 pile load tests for sites with 1000 piles.

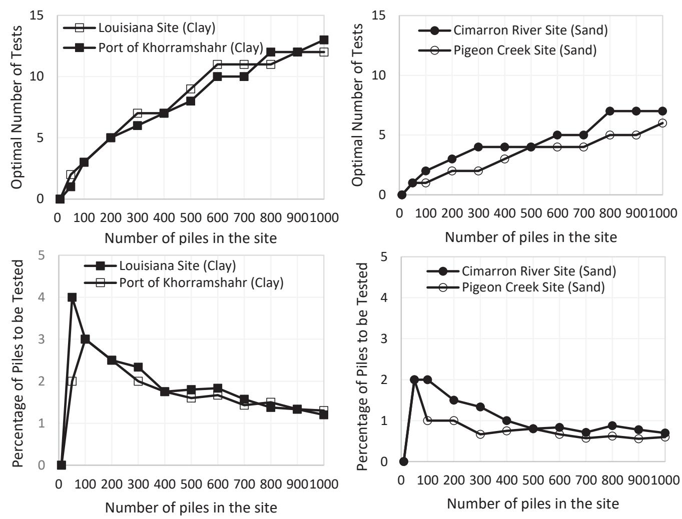

Figure 4. Optimal number of tests and optimal percentage of test piles in the four sites.

The fact that the required optimal number of static load tests for clay sites is higher than the number in sandy sites could be attributed to the differences in the bias factor statistics for the pile prediction models used to predict the pile's capacity in sand and clay. Piles in sand are expected to have a mean capacity distribution that is more uncertain (COV = 0.56) than piles in clay (COV= 0.33). This makes piles in sand more susceptible to updating using Bayesian techniques given results from successful proof load tests. As a result, a smaller number of positive tests is needed for piles in sand to shift the prior distribution of r_{mean} to the right.

If the optimal number of proof load tests in each site is expressed as a percentage of the total number of piles in the project, results on Figure 4 indicate that the percentage is high (reaching 4% for clayey sites and 2% for sandy sites) for sites with a small number of piles and decreases as the number of piles increases in the site, reaching values as low as 1% and 0.5% for clayey and sandy sites with 1000 piles, respectively. The high percentage of tests for the low number of piles can be explained by the fact that the optimal number of static proof load tests when the site consists of 50 piles is 1 to 2 tests which reflects the percentage of 2 and 4% respectively due to the small number of piles.

It is worth noting that the results of the decision making framework for the sites with clay resulted in more-or-less similar optimal proof load test programs. For the case of sand, slight differences were clearly visible between the two sites. This could be attributed to the difference in sand density between the two sites, leading to predicted capacities (design loads) that differed significantly. Since the test cost is a function of the design load, the optimal number of tests in the decision framework was affected by the densities of the two sites. The differences between the two sites were reduced however for sites with a larger number of piles, where the cost savings that were associated with reducing the number of piles in the site outweighed the effect of the test cost.

4 Conclusions

In this paper, the statistical model that was proposed by Najjar et al. (2017) to be a basis for a decision making framework that would optimize proof load test programs was updated to take into consideration an uncertain r_{COV} for the within-site variability in pile capacity. This uncertain r_{COV} was incorporated in the pile capacity model and updated given results from proof load tests. A decision making framework was then adopted to determine the optimum number and percentage of proof load tests for two sites with clays and two sites with sands.

Results indicated that the choice of the distribution (uniform, truncated normal, or truncated lognormal) of r_{COV} does not affect the reliability index of the pile design significantly. However, assuming that r_{COV} is deterministic results in reliability indices that are higher than the case where r_{COV} is assumed to be uncertain. Based on these observations, it was concluded that r_{COV} should be assumed to be a random variable in the statistical pile capacity model. Results also indicated that the clay sites require higher number of static proof load tests than sand sites for the same prior number of piles in the site. Moreover, the optimal level of the proof load was found to be 2.25xDL in sandy sites compared to 2.50xDL in clayey sites. These results were obtained when the API method was used to predict the pile capacity. These results are important since they indicate that the optimal number of proof load tests and the optimal proof load level in any given site could depend on the type of soil in the site (sand or clay), the density of the sand in the site (loose or dense), and on the number of piles in the site (magnitude of the superstructure loads). The decision making framework that is presented in Najjar et al. (2017) and which was slightly amended in this paper is the only rational approach that allows for taking all these factors into consideration when attempting to optimize the proof load test program for driven piles in sand and clay. Sensitivity analyses should be conducted in the future to check the sensitivity of the results to factors related to the cost of the pile load test and the cost of the piles in different areas of the world.

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