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Model selection issue in calibrating reliability-based resistance factors based on geotechnical in-situ test data

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ABSTRACT

This paper addresses the model selection issue often encountered in the process of calibrating reliability-based geotechnical resistance factors. A predictive model must be assumed for the purpose of calibrating resistance factors based on geotechnical in-situ test data. A question is raised by this research: which predictive model should we choose? What type of probability distribution model should we pick to model the model uncertainties? Those may be important questions to ask because the calibration results depend on the assumed predictive and probabilistic models. A full probabilistic framework is proposed in this research to resolve the model selection issue as well as to calibrate the geotechnical resistance factors. Two examples of geotechnical real dataset are used to illustrate the model selection issue and to demonstrate the use of the proposed methods. The proposed methods may contribute to code calibration based on geotechnical in-situ test data.

1. Introduction

Traditionally, geotechnical designs are usually achieved by the safety factor approach, which accounts for uncertainties with an empirical basis. Safety factor alone is not a consistent measure of uncertainties: it does not rigorously address how reliable the designed system is. As a simple example, two different geotechnical designs with the same factor of safety are usually not equally safe. Mathematically, safety factor is not a consistent indicator of safety status: the safety factor of the same limit state may change depending on the mathematical expression of the limit state function [1].

More recently, reliability-based design approaches have emerged as a new geotechnical design paradigm because reliability is a consistent measure of uncertainties. For reliability-based designs, one designs a geotechnical system so that its reliability is in an acceptable range. Moreover, a single factor, called the resistance factor, is often used to quantify resistance uncertainties to facilitate reliability-based designs.

A common way of calibrating resistance factors based on geotechnical in-situ load test data is described as follows. Given the observed resistances of m independent in-situ load tests $\{C_i : i = 1,\ldots,m\}$ and the corresponding predicted resistances $\{R_i : i = 1,\ldots,m\}$, the m resistance ratios $\{C_i/R_i : i = 1,\ldots,m\}$ are computed, and their mean value and coefficient of variation (c.o.v.) are estimated. By assuming lognormality or Gaussianity for the ratio, resistance factors can be calibrated with a simple probability analysis. This process of calibrating resistance factors have been implemented in [2–5].

A necessary step for the above procedure is to select a deterministic predictive resistance model, denoted by $r(Z)$, where Z contains all parameters necessary to compute the resistance, e.g.: soil properties, model parameters, etc. The predictive models reflect our belief on the behavior of the target geotechnical system. For instance, when a resistance factor for vertical bearing capacity of a pile is calibrated, a model capable of predicting the vertical capacity of the pile, e.g.: a SPT-N-based model, should be chosen a priori.

1.1. Selection of predictive model – a real database of pile proof load tests

Due to the uncertainties in geotechnical engineering, the chosen geotechnical predictive model is critical for calibrating resistance factors. However, the common procedure of calibrating resistance factors usually does not address the model selection issue: how do we know the chosen predictive model is plausible? A heuristic argument to resolve this issue is to compare the variability of the resistance ratios of various predictive models, and the model with the lowest variability is considered to be the best model. However, this heuristic argument causes counter-intuitive conclusions when we studied a real database of pile proof load tests, described as follows.

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A real database containing the proof load tests of 33 reinforced concrete driven piles in the west-coast region in Taiwan was studied. Each load test dataset contains the following information: (a) the actual ultimate vertical resistance of the pile determined by the Davisson's method, (b) the configuration of the pile, including the diameter and length, and (c) the soil profile and measured soil properties nearby the pile location, e.g.: measured unit weight, measured SPT-N value, measured undrained shear strength, etc. Based on the pile configurations, soil profile, and measured soil properties for the 33 test piles, the ultimate vertical resistances of the piles are predicted using three predictive models, listed in Table 1 [6].

The axial capacity of the pile (pile resistance) can be calculated as

$$Q_u = Q_s + Q_b = \sum f_s A_s + q_b A_b \quad (1)$$

where Q_u = ultimate pile resistance, Q_s = skin resistance of the pile shaft, Q_b = point resistance at pile tip, f_s = unit skin resistance stress, q_b = unit point resistance stress, A_s = surface area of pile shaft, A_b = cross-section area of pile tip. There are two common methods of calculating f_s and q_b: the static method and the SPT-N value method. These three models listed in Table 1 are developed primarily based on the Taiwan's foundation design code for building [7]. The first two models are the recommended practice in the current design code. The third model adopts a combination of design values recommended by the American Petroleum Institute [8], Kulhawy et al. [9], and Meyerhof [10].

Notice that in common practice, the predicted resistances $\{R_i : i = 1, \ldots, m\}$ are computed based on the ***measured*** soil properties. Compared with the actual resistances $\{C_i : i = 1, \ldots, m\}$, the m resistance ratios $\{C_i/R_i : i = 1, \ldots, m\}$ are computed, and their mean value and c.o.v. are listed in Table 1. It is seen that the SPT-N model results in the smallest resistance ratio variability, which is rather counter-intuitive. However, should the SPT-N model be the best model among the three models? Later, it will be clear that when a more rigorous treatment is taken, the concluded best model will change. The key argument is in the following issue: the predicted resistances $\{R_i : i = 1, \ldots, m\}$ should have been computed based on the ***actual*** soil properties rather than the ***measured*** ones.

1.2. Selection of probabilistic model of resistance ratios

Another issue regarding model selection happens as we choose the probabilistic model for the resistance ratios. As it will be seen in the examples, the choice of the type of the probability density function (PDF) of the resistance ratios has a certain effect on the calibrated resistance factors. In most literature, the lognormal distribution is often chosen as the PDF of the resistance ratios. Without verification, the adequacy of this choice might be questionable.

1.3. Focus of this paper

The focus of this paper is to provide a consistent and rigorous framework of selecting models for the purpose of calibrating resistance factors based on in-situ test data. The proposed full probabilistic framework is able to resolve the model selection issue for both the deterministic predictive models and probabilistic models. Moreover, the proposed framework can not only select the best model but also estimate the relation between the target reliability index and required resistance factor, i.e. accomplish the calibration of resistance factor at the same time. Our goal is to provide technical guidelines for geotechnical code calibration based on in-situ test data.

The structure of the paper is as follows: First the main idea of model selection will be discussed. An indicator called "model likelihood" will be proposed to quantify the plausibility of a chosen model. At the same time, a method of estimating the relation between the target reliability index and resistance factor will be presented. Finally, two examples of resistance factor calibration will be used to demonstrate the model selection issues.

1.4. Notations

In the forthcoming discussions, the following notations will be used: a capitalized letter denotes an uncertain variable; the lower case letter denotes a fixed value; the same lower case letter with a hat denotes a sampled or observed value of the uncertain variable. For instance, R denotes the uncertain resistance; r denotes a fixed value for the resistance; $\hat{r}$ denotes a sampled or observed value of R.

There are however some exceptions: the capitalized letter M is reserved to denote a chosen model; N is reserved to denote size (e.g., sample size); P denotes probability; H denotes entropy, etc: they are not uncertain variables. Furthermore, we will constantly use the notation $R_{1:m}$ to denote the dataset $\{R_i : i = 1, \ldots, m\}$, and similar notations will be taken for other variables. Some Greek letters, including $\{\mu, \delta, \theta\}$, means either uncertain variables or their fixed values depending on the context of the presentation.

2. Model selection based on in-situ test data

Let the in-situ test data be $\{\hat{c}_i : i = 1, \ldots, m\}$, where $\hat{c}_i \in \mathrm{R}$ is the observed resistance of the i-th test, and let $\hat{z}_i \in \mathrm{R}^{n_i}$ be the measured soil parameters at the i-th test site (n_i is the number of soil parameters). Let $\{M_n : n = 1, \ldots, N_M\}$ be the N_M chosen models for the dataset.

2.1. Model likelihood as model plausibility

One can quantify the relative plausibility of each model with $P(M_n|\hat{c}_{1:m})$, the probability that M_n is true conditioning on the data

Table 1
The three deterministic predictive models adopted for the pile load test dataset.

Model	Skin friction	End bearing	Resistance ratio statistics	
			Average	Coefficient of variation
SPT-N	Clay: $f_s = \alpha S_u$ [a]; Sand: $f_s = N/3 \leqslant 15T/m^2$	Clay: $q_b = 9S_u$; Sand: $q_b = 30\overline{N} \leqslant 1500T/m^2$	0.99	0.19
Static #1	Clay: $f_s = \alpha S_u$ [a]; Sand: $f_s = k\sigma'_v \tan\delta \leqslant f_{\max}$ [b]	Clay: $q_b = 9S_u$; Sand: $q_b = \sigma'_v N_q^* \leqslant q_{\max}$ [c]	1.16	0.23
Static #2	Clay: $f_s = \alpha S_u$ [d]; Sand: $f_s = k\sigma'_v \tan\delta \leqslant f_{\max}$ [e]	Clay: $q_b = 9S_u$; Sand: $q_b = \sigma'_v N_q^* \leqslant q_{\max}$ [f]	0.85	0.23

Remarks: S_u is the undrained shear strength of clay, N is the SPT-N value of sand, and $\overline{N}$ is the modified SPT-N value.
[a] α suggested by Tomlinson [11].
[b] $f_{\max}$ suggested by DM7-2 [12]; k and $\delta = 0.67\phi'$ suggested by Taiwan code [7].
[c] N_q^* and $q_{\max}$ suggested by DM7-2 [12].
[d] α suggested by API [8].
[e] $f_{\max}$ and k suggested by API [8]; $\delta = 0.9\phi'$ suggested by Kulhawy et al. [9].
[f] N_q^* suggested by Meyerhof [10]; $q_{\max}$ suggested by API [8].