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HIERARCHICAL BAYESIAN INFERENCE OF SOIL RESISTANCE TO OFFSHORE MONOPILE DRIVING

THOMAS A. VERGOTE[1] and SYLVIE RAYMACKERS[2]

[1] *Engineering, Design and Technology, DEME Group, Belgium.*
E-mail: vergote.thomas@deme-group.com
[2] *Engineering, Design and Technology, DEME Group, Belgium.*
E-mail: raymackers.sylvie@deme-group.com

CPT-based pile drivability predictions have been widely applied in recent years for offshore monopiles. These predictions rely on well-established empirical relations for the (semi-static) shaft- and end-bearing resistance of the monopile. However, significant uncertainties remain, which originate from geospatial and operational uncertainties and limitations of the empirical relations and the pile-soil interface. Some effects are clustered: differences in pile geometry, shape or material could affect predictions, such as microstructure, geological history, rate-effects and transitional soils. A hierarchical Bayesian approach is proposed for parameter inference for groups of installed monopiles, while also inferring a global probability distribution.

Keywords: Pile drivability; Bayesian; Hierarchical; CPT.

1. Introduction

For practical applications, pile drivability is typically predicted using a CPT-based prediction of the Soil Resistance to Driving (SRD), to predict the shaft resistance and end bearing of the pile during installation. The results are then used in a wave equation solver to model the dynamic effects of impact hammering, which finally result in a prediction of the amount of blows required to drive a pile to target depth. Perikleous and Stergiou (2020) show that the accuracy of SRD predictions is often low and require more (global) calibration.

These predictions need to be done at scale, for a large variety of soil conditions. Given the underlying uncertainties, model calibration is a critical part of the work, both to make better predictions in future projects and to quickly adapt operations during the execution of a project. A probabilistic, hierarchical process is proposed.

2. CPT-based drivability using a surrogate approach for the wave equation

The adopted drivability model consists of a (semi-)static component and a dynamic component. The wave equation can be solved numerically to simulate the impact waves through the pile explicitly, or it can be approximated by a surrogate model, using a collection of bearing graphs which express the relation between blow count and SRD. A single wave equation solution is only valid for a large number of conditions, such as the pile and hammer characteristics, damping etc. A surrogate is adopted by interpolating between the selected dimensions such as the pile diameter, damping parameters, energy of the hammer, shaft resistance ratio, etc. This surrogate model f enables fast predictions of the blow count n_{blows}, expressed as:

$$n_{blows} = f(F_{SRD}, D_{pile}, F_{shaft}/F_{SRD}, L_{pile}, d_{skin}, ...) \quad (1)$$

with F_{SRD}, the SRD, D_{pile} the diameter of the pile, F_{shaft}, the shaft resistance, L_{pile}, the length of the pile and d_{skin} the skin damping. The inverse surrogate, $F_{SRD} = g(n_{blows}, ...)$ is applied to get the expected soil resistance, given a number of blows.

This wave equation approximator takes F_{SRD} as an input, which is derived from the CPT data and pile size. Multiple CPT-based SRD models have been developed over the years to improve pile drivability predictions, Alm and Hamre (2001); Lehane *et al.* (2020); Stergiou *et al.* (2023). These models are used to predict the relevant resistance during pile driving from the cone resistance q_c and sleeve friction f_s, usually with different relations for sand and clay. The models rely on correlations and contain unavoidable uncertainties due to 3D effects such as radial expansion of the pile, rate effects, scale effects, especially with increasing size of monopiles, friction fatigue and uncertainties in the pile-soil interface, to name just a few. Next to these model uncertainties, there are also uncertainties in the soil itself for which (geospatial) probabilistic methods are recommended, Vergote and Raymackers (2022). A last set of uncertainties originate from the dynamic process, especially the energy losses and efficiency of the hammer.

3. Hierarchical approach to SRD calibration

Given the inherent uncertainties and required simplifications of an SRD model, calibration and validation of the model is essential. This can be done through a learning mechanism that relies on (local or global) numerical optimization to minimize a prediction error of the blow counts or required energy. With this approach, the model can be improved and the most important parameters can be identified. On the other hand, the optimization algorithm provides an optimum point, but no information on the certainty of each parameter and of the final prediction. Through Bayesian inference, the posterior distribution of model parameters can be derived. This provides a quantification of the model uncertainties which can be used for decision making as proposed in Vergote and Raymackers (2022). Markov Chain Monte Carlo sampling is used to update the SRD model for a given dataset. This is a ”fully pooled” approach, assuming the full dataset can be described by one distribution of parameters.

However, depending on the adopted dataset, the derived parameters can be quite

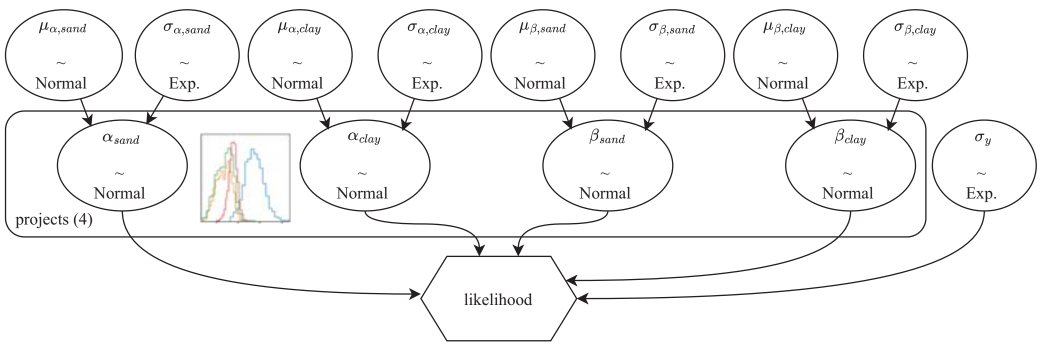

Fig. 1. Example of a hierarchical model approach for four parameters.

error of the SRD is reduced 14.35% from the pooled to partially pooled model. More importantly, deviations from the global parameter distribution can point us towards local variations in the soil response. The parameter distribution reveals signficant deviations in the shaft resistance, while the end bearing model parameters borrow from the same distribution across all projects.

5. Conclusions

A hierarchical Bayesian approach is adopted to model pile drivability. A Baysian approach allows to incorporate prior information in the model and identify uncertainties of model parameters. By adopting a hierarchical model, the parameter distribution per cluster can deviate. This was adopted for calibration of pile drivability of monopiles. The model enables higher accuracy and less uncertain predictions for piles within the same project. Model deviations can be attributed to differences in the shaft resistance in both sand and clay, while end bearing predictions followed the same distribution. The results can be used for further model improvements and identification of latent variables causing the differences in the clusters.

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