Imperial College London

15 June 2023

Data-driven approach to modelling bearing behaviors of OWT foundations

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Background

- Uncertainties of soil parameters have great effects on the behaviors of OWT foundations
- Sources of uncertainties: Lack of uniformity between in-situ test and laboratory experiment; spatial variability of soil profile, rationality of the constitutive model...
- Traditional statistical analysis is based on Monte Carlo, which is time-consuming and laborious.

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Background-Uncertainties

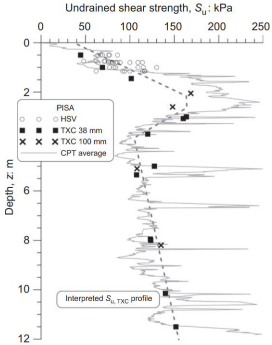

Figure 1: Untrained strength profile at Cowden[1]

In this soil profile, we can see that:

- Fluctuating curve indicates the spatial variability
- Non-uniformity between in-situ test and laboratory experiment

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Background-Challenges

- Back-analysis based on Monte Carlo is time consuming (each layer controlling soil parameters can vary from 2 to 14)
- Probabilistic method: Bayesian inference is the basic mathematical tool for quantifying this uncertainty

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{1}$$

$P(A|B)$: posterior: Distribution of soil parameters;$P(B|A)$:likelihood: observed data and FE simulation based on priors; $P(A)$: prior: Soil parameters from lab/field

Background-Challenges

- Applying Bayesian methods in this setting is the cost of repeated likelihood computations
- How to get the best possible soil parameters distribution, based on the given priors, while avoiding extreme FE Monte Carlo calculations.

Solution-Introducing Markov Chain process

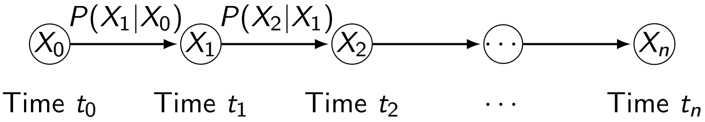

Figure 2: Markov Chain process

Markov Chain process :

- State transition of Markov chains depends only on the current state, thus Simplifying the modeling process
- Given the current state, a state transition probability distribution can be used to infer the likelihood of the next state

Bayesian inference based on Markov Chain process VS Bayesisan inference based on Monte Carlo:

- Common: They have the same priors (soil parameters from lab/field); They all use FE simulations to generate the likelihood (ICFEP)

- Differences: 1 Bayesian inference based on Markov Chain process can adapt to more complex models (with increasing soil parameters); 2 Iterative updating of parameter estimates because of Markov Chain's property (enables improve posterior in fewer sampling and calculations with updating priors in the markov chain)

Methods-Partially observed Markov decision process(POMDP)

To form the basis of digital twin, based on Markov Chain, we introduce **Rewards** and **actions** to form the basis of Partially observed Markov decision process:

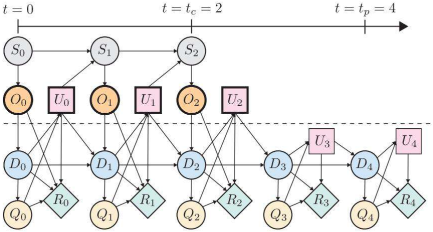

Figure 3: Digital Twin [2]

In digital twin, there are two parts:

- Calibration and Assimilation

$$p(D_0, ...D_{t_c}, Q_0, ..., Q_{t_c}, R_0, ..., R_{t_c} \mid o_0, ..., o_{t_c}, u_0, ..., u_{t_c})$$
$$= \prod_{t=0}^{t_c} \left[\phi_t^{\text{update}} \phi_t^{\text{QoI}} \phi_t^{\text{evaluation}} \right], \tag{1}$$

- Prediction:

$$p(D_0, \ldots, D_{t_p}, Q_0, \ldots, Q_{t_p}, R_0, \ldots, R_{t_p}, U_{t_c+1}, \ldots, U_{t_p} \mid o_0, \ldots, o_{t_c}, u_0, \ldots, u_{t_c})$$
$$\propto \prod_{t=0}^{t_p} \left[\phi_t^{\text{dynamics}} \phi_t^{\text{QoI}} \phi_t^{\text{evaluation}} \right] \prod_{t=0}^{t_c} \phi_t^{\text{assimilation}} \prod_{t=t_c+1}^{t_p} \phi_t^{\text{control}}$$

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Research Plan

Assume the probabilistic model with reference to Figure 3, and find own Q,R:

Stage 1: Calibrate the model in [1] with partially observed Markov decision process

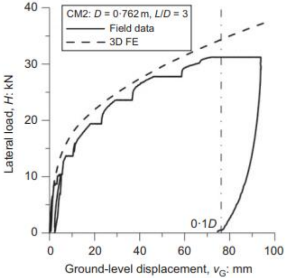

Figure 4: CM2 pile load displacement

- software: ICFEP-Likelihoods and observed data
- Constitutive model:clay in [1] and sand in [3]
- priors: soil parameters in [1] and sand in [3]
- Consider the soil profile variance-Create the random field (scale of fluctuation in ICFEP)

Objective: Ensure the soil parameters in digital model can reveal unique characteristics of piles

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Research Plan

- Stage 2 : In operational Phase, Based on Partially observed Markov decision process method, continue the assimilation process: extend the digital twin capability to capture the piles response during loading
- stage 3: Extension to Prediction

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Reference

[1] Lidija Zdravković et al. "Ground characterisation for PISA pile testing and analysis". In: *Géotechnique* 70.11 (2020), pp. 945–960.

[2] Michael G Kapteyn, Jacob VR Pretorius and Karen E Willcox. "A probabilistic graphical model foundation for enabling predictive digital twins at scale". In: *Nature Computational Science* 1.5 (2021), pp. 337–347.

[3] David MG Taborda et al. "Finite-element modelling of laterally loaded piles in a dense marine sand at Dunkirk". In: *Géotechnique* 70.11 (2020), pp. 1014–1029.