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Reliability-Based Design of Offshore Wind Turbine Monopiles Using CPT Data and Active Learning Metamodeling

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ABSTRACT: Monopiles are the most commonly used foundation type for offshore wind turbines (OWT). Ensuring a reliable design for monopiles is crucial for sustainable development of offshore wind energy but presents significant challenges due to inherent soil spatial variability. This paper introduces an integrated procedure for the reliability-based design of monopiles, encompassing soil spatial variability modeling, failure probability estimation, and design variable determination. Initially, modeling of soil vertical spatial variability is achieved using the cone penetration test data collected from the vicinity of the target monopile location. Following the creation of a numerical model for the monopile, active learning metamodeling is employed to estimate the failure probability concerning excessive inclination under ultimate loadings. Due to the high efficiency of the improved active learning algorithm, reliability-based design is performed to determine the minimum embedding depth that satisfies the required reliability index. The results reveal that the failure probability can be efficiently estimated using the procedure. The final determined design variable presents the minimum steel consumption while satisfying safety criteria. The introduced procedure proves to be a powerful tool for the reliability-based design of OWT monopiles. Future work aims to incorporate optimization algorithms into this procedure to simultaneously optimize multiple design variables, achieving a safe and cost-saving design.

Keywords: Offshore Wind Turbine Monopile; Reliability Analysis; CPT Data; Active Learning Metamodeling

1 INTRODUCTION

The foundation of offshore wind turbines (OWT) is one of the essential components to be considered at the design phase. Monopiles are the most used foundation type for OWT, which require a reliable design to withstand uncertainties such as soil spatial variability. Conventional deterministic calculations overlook these uncertainties.

Probabilistic approaches are generally employed to account for the uncertainties and estimate the failure probability (P_f) or reliability index (β) for a certain failure mode (e.g., excessive pile rotation) from a set of random variables (RV) as input. Results from these RV inputs do not consider explicitly the spatial variation of soil properties.

The random field (RF) approach is the commonly used method for representation of spatial variability of soils (Fenton and Griffiths, 2008, Vanmarcke, 2010, Guo et al., 2021). In order to model any problem combining the random field realizations as input, random finite element methods (RFEM) have been implemented in various geotechnical applications (Griffiths and Fenton, 2009, Al-Bittar et al., 2018, Wang et al., 2024). After obtaining the results from RFEM, a reliability assessment is performed using P_f or β estimated through reliability methods (e.g., first- and second-order reliability method FORM and SORM, or crude Monte Carlo Simulations (MCS)). However, FORM and SORM lose accuracy when dealing with highly nonlinear performance functions, and MCS requires a large number of simulations, which may become prohibitive when dealing with complex numerical models and/or low failure probabilities (Siacara et al., 2024).

Active learning reliability method combining kriging and crude MCS (AK-MCS) has been proposed to overcome the disadvantage of excessive number of iterations of mechanical model calculations (Enchard et al., 2011). This method adaptively constructs a surrogate (metamodel) of the original model with a smaller number of iterations and reaches an accurate estimate with minimum error for reliability assessment (Moustapha et al., 2022).

This paper presents a reliability-based design of OWT monopile using active learning metamodeling. Soil uncertainty was quantified through analyzing real-site investigation data. RFs of undrained shear strength (s_u) of soil have been generated as input using Karhunen-Loève expansion. The undrained deformation modulus of soil (E_u) has also been taken as a dependent input of s_u. A mechanical three-dimensional model has been constructed using Plaxis 3D to obtain initial results for active learning metamodeling. The mechanical model runs have been fully automated by Python code which integrates the quantity of interest (monopile rotation in this study) for further evaluation through the developed MATLAB script coupled with UQLab toolbox. Due to the high efficiency of the improved active learning algorithm, reliability-based design is performed to determine the minimum embedding depth that satisfies the required reliability index.

2 METHODOLOGY

2.1 Spatial Variability of Soils with Random Fields

Soil properties are generally spatially varied due to the geological processes. This is one of the main sources of uncertainty in soil properties which affects response of geotechnical systems (Phoon and Kulhawy, 1999). RF theory considers the spatial variation of a soil property as an infinite number of RVs over a continuous to express the spatial variability of soil. For practical usage of RF, however, the continuous function should be truncated in order that it contains a finite number of RVs which is called random field discretization. The main goal of RF discretization is to define the best approximation requiring a minimal number of random variables (Sudret and Der Kiureghian, 2000).

There are various discretization methods in the literature, and Karhunen Loève expansion (KLE) is one of the most commonly used ones. It is optimal among the series expansion methods in terms of the global mean square error with respect to the number of random variables in the discretization (Ghanem and Spanos, 1991). The KLE of a Gaussian random field $H(\boldsymbol{x},\ \theta)$ after discretization, with a mean $\mu(\boldsymbol{x})$ and standard deviation σ, can be written as follows (Moustapha et al., 2024):

$$\widehat{H}(\boldsymbol{x},\theta) \approx \mu(\boldsymbol{x}) + \sigma \sum_{i=1}^{M} \sqrt{\lambda_i \xi_i(\theta)} \varphi_i(\boldsymbol{x}) \qquad (1)$$

where λ_i and $\varphi(\boldsymbol{x})$ are eigenfunctions and eigenvalues of the covariance function $C(\boldsymbol{x},\boldsymbol{x}')$, which is the autocorrelation function $\rho(\boldsymbol{x},\boldsymbol{x}')$ multiplied by the standard deviations $\sigma(\boldsymbol{x})$ and $\sigma(\boldsymbol{x}')$. $\{\xi_i(\theta), i = 1, \ldots\}$ in Eq.1 are independent standard normal random variables, and M is the number of terms in the expansion having the largest eigenvalues after the truncation of the infinite RF. M is determined by taking 0.99 energy ratio as the threshold in this study obeying the suggested range in the literature (0.95-0.99). The squared exponential autocorrelation function is used in the present study (Moustapha et al., 2024b).

2.2 Reliability Analysis and Active Learning Metamodeling

Reliability analyses usually contain an assessment of P_f for a probabilistic model with uncertainty quantification in input parameters (such as soil properties). A limit-state function $g(\mathbf{X})$ is generally defined for uncertainty propagation which takes positive values in the safe domain (D_s) and negative values in the failure domain (D_f). The values of P_f are then calculated as follows (Malchers and Beck, 2018, Siacara et al, 2024):

$$P_f = P[g(\mathbf{X}) \leq 0] = \int_{D_f} f_{\mathbf{X}}(\boldsymbol{x}) d\boldsymbol{x} \qquad (2)$$

where $f_{\mathbf{X}}(\boldsymbol{x})$ in Eq.2 is the joint probability density function (PDF) of $\mathbf{X}$.

One of the methods for estimation of small P_f called subset simulation (SS) is employed in this study. SS is based on solving the sequence of conditional reliability analyses and combining them with Markov chain Monte Carlo simulation. There are two user-defined parameters for SS: the initial probability (P_0) and the number of samples in each subset, for which 0.2 and 200000 values are used in this study in combination with surrogate modeling, respectively. These values confirm that the SS analysis was performed with so-called “overkill settings” which are favorable for failure probability estimation with higher accuracy (Moustapha et al., 2022).

In order to reduce the computational cost for simulation-based P_f estimation techniques, active learning metamodeling (surrogate modeling) is usually used. The method is based on starting with an initial small set of samples for model estimations (experimental design), which is sequentially enriched by learning functions. The goal is to approximate the limit-state surface as close as possible (i.e., using the least number of model evaluations) to achieve the best possible accuracy for the estimated failure probability (Moustapha et al., 2022). In this study, the adaptive (or active learning) polynomial chaos kriging (A-PCK) technique was employed to create a surrogate model (Siacara et al., 2024).

2.3 Analysis Procedure in the Study

The procedure proposed in this work starts with modeling vertical soil spatial variability using cone penetration test data (CPT) from the vicinity of the target monopile location. 1D RFs of soil shear strength (s_u)

and stiffness (E_u) have been generated using the KLE method with the UQLab Matlab toolbox (Marelli and Sudret, 2014). An analysis framework has been developed using Plaxis 3D to create and get the response of the monopile mechanical model automatically through Python code. A surrogate model by A-PCK with SS (denoted as A-PCK/SS hereafter) has been then created using a Matlab script coupled with UQLab and Plaxis 3D-Python. The final surrogate model after the enrichment has been obtained for further reliability assessments. The procedure has been validated using a deterministic and a probabilistic model compared with a reference study. After the validation, a case study with real CPT data- generated RFs used as inputs in the mechanical model to obtain a final surrogate model. RBD of monopile embedded length has been performed to find the minimum length that satisfies the target reliability. A flowchart illustrating the procedure is given in Figure 1.

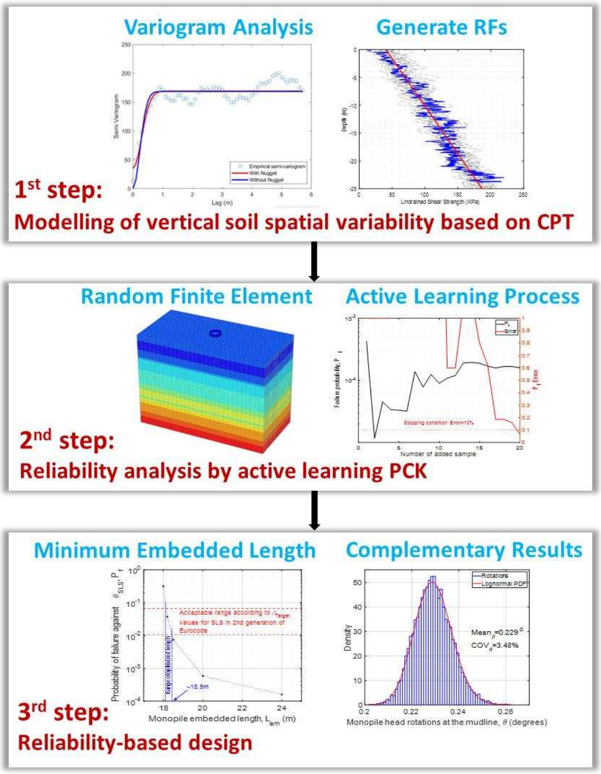

Figure 1. Flowchart of the proposed analysis procedure

3 MODELING OF OWT MONOPILE

The mechanical model (Figure 2) of a monopile has been created using Plaxis 3D software (Brinkgreve et al., 2024). The model was validated in both deterministic and probabilistic frameworks by comparing with published results.

3.1 Validation of the Model with Deterministic Input

An open-ended steel monopile of *3-4 m* diameters and *18-24 m* embedded lengths (L_{em}) was considered from chapters 2 (Model 1) and 3 (Model 2) in a reference study, respectively (El Haj, 2019). The wall thickness of the monopile was equal to *5 cm*. The monopile was extended by *1 m* above the seabed for both models to prevent the soil from going over the monopile. The self-weight of OWT was taken as $V=2000\ kN$ vertical force applied on the monopile head. The horizontal static forces applied for Models 1 and 2 are $H=550\ kN$ and $1600\ kN$, respectively. The point of application from the mudline is $h=38.6\ m$ for each model resulting in a bending moment at the pile head $M=H\times(h-1)=20680\ kN.m$ and $60160\ kN.m$, respectively. The dynamic effect of the forces is out of the scope of this study. A single layer of soil with constant $s_u=50\ kPa$ was used for Model 1. For Model 2, a single layer of soil with increasing s_u by depth was used with an initial value of 2 kPa and a rate of 1.68 kPa/m. The soil stiffness was dependent with $E_u=200\times s_u$ and $E_u=500\times s_u$ correlations for Model 1 and 2, respectively. Table 1 summarizes the validation results of the deterministic models compared for the monopile head rotations at the mudline (θ) from the reference case.

Table 1. Validation of the deterministic model (Pile rotation at the mudline)

	This study	**El Haj, 2019**
Model 1	0.22°	0.23°
Model 2	0.54°	0.55°

3.2 Probabilistic Model

The same model from Chapter 2 of the reference case has been employed for further validation in a probabilistic framework. The serviceability limit state (SLS) has been considered with monopile rotation limit at the mudline of $\theta_{SLS}=0.25°$. The deterministic parameters from Model 1 were taken as the mean values of the inputs, and the coefficient of variation was taken as $COV_{su}=25\%$. The model has been divided into small layers of soils to represent the spatial variation of soil with RF inputs. The correlation length of s_u was taken 2 m same to the reference case, and the layer thickness of the model was adjusted accordingly (Figure 2). The other settings of the model have been kept the same with Model 1.

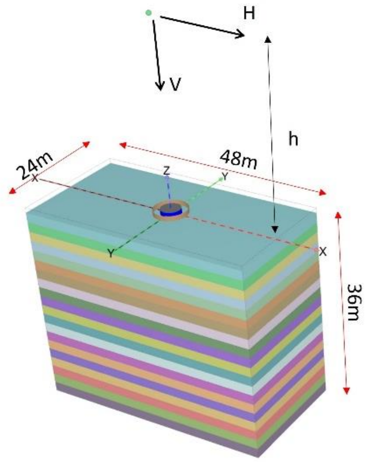

Figure 2. Mechanical model in Plaxis 3D

A-PCK/SS explained in section 2.3 was applied, and the resulting P_f values against θ_{SLS} were compared with the results from the reference case. The initial design of experiments (DoE) for the training of the surrogate was taken 15, the same as the reference case. The stopping error was taken ε=*10%*. Table 2 shows that there is a reasonable agreement in the last P_f values obtained, and the introduced method showed an efficient estimation of failure probabilities with a smaller number of enrichments.

Table 2. Validation results of the probabilistic model

	This study	EI Haj, 2019
P_f	2.1×10^{-3}	3.4×10^{-3}
COV_{Pf}, %	1.76	2.42
Initial DoE	15	15
Number of added samples	33	44

4 CASE STUDY

The similar geometry and loading conditions of Model 2 have been employed for further studies on RBD of OWT monopile using the proposed procedure. s_u values were taken from a CPT database of an offshore wind farm in the UK (Marine Data Exchange, 2024). The statistics (i.e., trend, standard deviation etc.) and the vertical scale of fluctuation of s_u were estimated using linear fitting and variogram analysis, which allow following generation of site-specific RFs using the KLE. The spatial variability was considered only in the vertical direction due to the large scale of horizontal fluctuations in marine soils (Wang et al., 2024) and the difficulty of estimating lateral variability from sparsly located CPTs. Also, a 1D random field was chosen for computational efficiency.

4.1 Generation of Soil Parameter RFs

A lognormal random field of undrained shear strength with linearly increasing mean along depth has been used in this study. s_u dependent stiffness with $E_u = 500 \times s_u$ was employed for considering spatial variation of E_u. All the parameters and settings in the RF generation by the KLE method are summarized in Table 3. It is noted that the correlation length is obtained by transforming from the scale of fluctuation.

Figure 3 shows the measured s_u profile, along with the fitted trend and 10 generated RF realizations using the settings of Table 3.

Table 3. RF Generation parameters

Parameters	Values
Initial shear strength, s_{u0} (kPa)	38.8
Increase rate of s_u (kPa/m)	5.8
Standard deviation of s_u (kPa)	13.5
Discretization scheme	KLE
Autocorrelation function	Gaussian
Number of terms in the expansion	16
Vertical correlation length, a_v (m)	1.41
RF Mesh size (m)	0.7

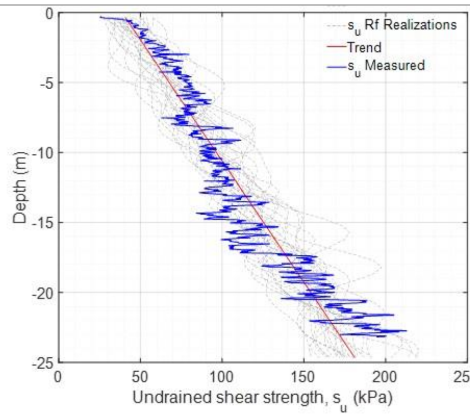

Figure 3. Sample random field realizations generated from the CPT sounding selected and trend of s_u by the depth

4.2 Deterministic Model and Reliability Analysis Results

Figure 4 shows the deterministic model used for the calculation of the monopile rotation at the mudline. One realization of s_u RFs is mapped to the model for illustration. The monopile is assessed in a Serviceability Limit State (SLS) by considering excessive rotation of pile at mudline as failure mode. The corresponding performance function is thus:

$$G = \frac{\theta_{SLS}}{\theta} - 1 = \frac{0.25°}{\theta} - 1 \quad (1)$$

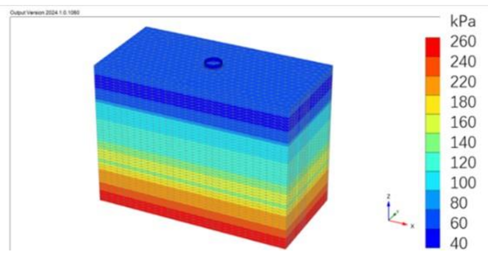

Figure 4. Sample RF realization of s_u in Model 2

The active learning metamodeling approach A-PCK/SS (Siacara et al., 2024) is then used to quantify the uncertainty propagation and provide Pf estimate. The number of initial DoE is set as 25, and the stopping error limit is 10%.

Figure 5 shows the active learning process of the A-PCK/SS. The convergence of Pf estimate is achieved after over 10 added samples and the process is stopped at the 20th iteration with satisfied Pf estimate error. The total number of model evaluations is thus 45, showing high efficiency of the method. The finally estimated Pf of the studied monopile with an embedded length of 24m is 1.6×10^{-4}.

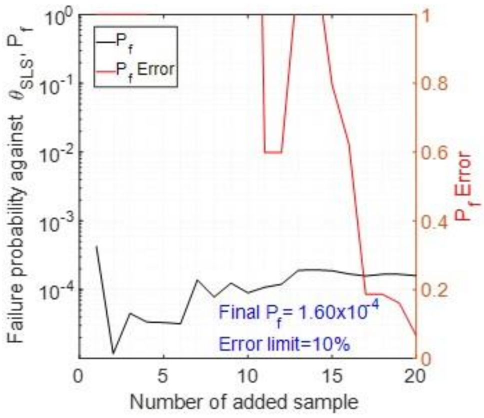

Figure 5. Analysis results of A-PCK/SS algorithm for L_{em}=24m

4.3 Reliability-Based Design of Monopile Embedded Length

The Pf of the monopile with the initial embedded length (L_{em}) is lower than the required maximum Pf indicated in the 2nd generation of Eurocode, which corresponds to a reliability index of 2 for SLS. Therefore, it is expected to reduce the L_{em} to find the minimum embedded depth that satisfies the target reliability index ($\beta_{Target} = 2$). This can be acheived by tuning the L_{em} and perfoming the reliability analsyes with the A-PCK/SS as shown in Figure 6 which indicates that the minimum L_{em} could be 18.5m showing a reduction from the initial embedment length.

Table 4 provides a summary of the analysis results for the monopile with a L_{em} of 18.5m. The Pf is 7.44×10^{-3}, corresponding to a reliability index of 2.4 being slightly larger than the target value. The average of the pile rotation under the uncertain soil properties is 0.229^o and the 95% interval is $[0.213^o, 0.245^o]$. Such information, along with the distribution of rotation angle (Figure 7), are complementary results to the conventional deterministic analysis, and provide useful insights into the monopile design/ evaluation for decision making.

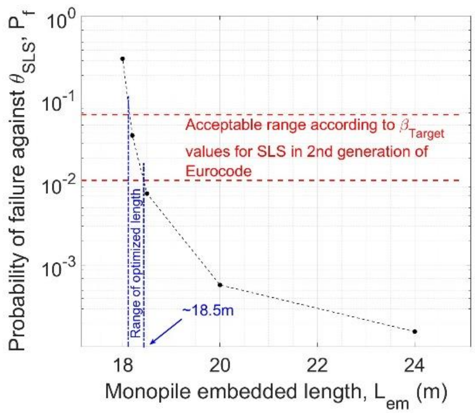

Figure 6. RBD results of L_{em} by A-PCK/SS algorithm

Table 4. Results summary of L_{em}=18.5m

Probabilistic analysis results	
Failure Probability:	7.44×10^{-3}
Reliability Index:	2.4
Mean θ	0.229^o
95% confidence interval of θ	0.213^o - 0.245^o
Deterministic analysis results	
θ with fitted trend	0.228^o

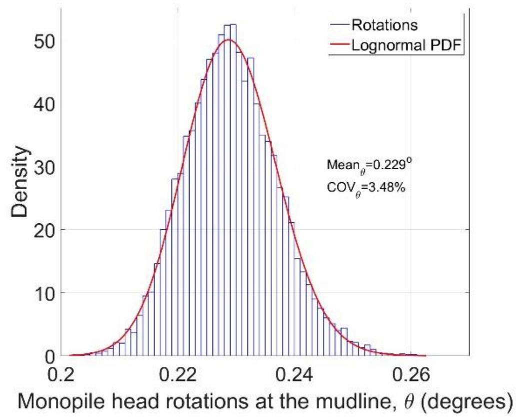

Figure 7. PDF of θ for Lem=18.5m model

5 CONCLUSIONS

This paper presents a reliability-based design procedure for offshore wind turbine monopiles against pile rotation under ultimate load conditions. The procedure models vertical soil variability using CPT data near the monopile site, represented as a 1D random field with a linearly increasing mean. It is integrated with a numerical monopile model and an active learning PCK framework for efficient reliability analysis. The final step determines the minimum embedment length to achieve a target reliability index, optimizing the design while considering site-specific uncertainties.

A case study using CPT data from an offshore wind farm demonstrates the procedure. Results show that the active learning approach enhances efficiency, while reliability-based design reduces the required monopile embedment length. The framework also provides failure probabilities and confidence intervals for informed decision-making.

The current work focused on optimizing the monopile length for a single case. The proposed procedure will further be tested on numerous cases containing varying RF soil parameters to validate the applicability of the procedure on different RF dimensions.

Future improvements include incorporating monitoring data to update soil property uncertainties and expanding the design scope to include additional variables and objectives.

AUTHOR CONTRIBUTION STATEMENT

Ahmet Can Mert: Methodology, Software, Formal Analysis, Visualization, Writing- Original draft. **Xiangfeng Guo**: Data curation, Conceptualization, Funding acquisition, Writing- Reviewing and Editing, Investigation. **Daniel Dias**: Supervision, Investigation, Reviewing and Editing.

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