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RELIABILITY-BASED DESIGN OF MONOPILES USING CPT DATA AND DEEP LEARNING ENHANCED ADAPTIVE METAMODELING

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Monopile is the most common type of foundations for offshore wind turbines (OWT). A reliable design of monopiles requires considering the uncertainty in soil conditions. This study presents an enhanced framework for reliability-based design (RBD) of monopiles for OWTs combining a deep learning algorithm with a commonly used reliability technique called adaptive (or active learning) metamodeling. First, the soil vertical spatial variability was modelled using random field approach with the CPT data collected from the vicinity of the target installation location of monopile. A mechanical model of monopile was consequently created to supply target outputs for a deep learning algorithm used in this study called long short-term memory (LSTM) neural networks. LSTM predicts the outputs of the mechanical model to be used in the adaptive metamodeling for enhanced failure probability estimation against excessive monopile rotation. Following the failure probability estimations, RBD is performed using the proposed procedure to determine the minimum embedded length which satisfies a target reliability. The results disclosed that the deep learning enhancement to the active learning reliability estimated the failure probabilities effectively. The procedure proposed in this paper proves to be an enhanced tool for RBD of OWT monopiles. The objective of the future works is to develop an integrated algorithm for multiple RF inputs and optimize multiple design variables confirming a safe and cost-effective design.

Keywords: Monopile, Reliability-Based Design, LSTM, Active Learning Metamodeling, CPT Data.

1. Introduction

A reliable design of monopiles requires taking the uncertainty in soil conditions into account. Probabilistic approaches are commonly used to consider the spatial variability of soils which estimate the probability of failure (P_f) for a given failure mode (e.g., excessive lateral displacement or rotation). One of these probabilistic approaches is the use of random fields (RFs) to represent the spatial variability of soil (Vanmarcke 2010). Random finite element methods (RFEM) have been used in many geotechnical problems to model the problem combining the random field samples as input (Griffiths and Fenton 2009, Al-Bittar et al. 2018, Wang et al. 2024). RFEM requires repeating calculations of the model for large number of RF realizations to estimate P_f for reliability assessment. One of the ways is called active learning reliability method combining kriging and crude MCS (AK-MCS) to overcome the disadvantage of excessive number of iterations (Enchard et al. 2011). This paper presents a reliability-based design of OWT monopile using deep learning enhanced active learning metamodeling. Soil spatial variability was quantified using real-site investigation data. RFs of undrained shear strength (s_u) of soil was generated as input using Karhunen-Loève expansion. The undrained deformation modulus of soil (E_u) was also taken as a dependent input of s_u. A mechanical 3D model has been constructed to supply target outputs for a deep learning algorithm used in this study called long short-term memory (LSTM) neural networks. LSTM predicts the outputs of the mechanical model used in the active metamodeling subsequently for failure probability estimation against excessive monopile rotation. Following the failure probability estimations, reliability-based design (RBD) is performed using the proposed procedure to determine the minimum embedded length of monopile which satisfies the target reliability.

2. Methodology

2.1. *Spatial Variability of Soils*

The inherent spatial variability is one of the main sources of uncertainty in soil properties (Phoon and Kulhawy 1999). RF theory is one of the commonly used methods to represent this uncertainty as an infinite number of random variables (RVs) over a continuous domain. This infinite RF must be discretized with the best approximation requiring a minimal number of RVs (Sudret and Der Kiureghian 2000). A well-known method for RF discretization was used in this study called Karhunen Loève expansion (KLE) (Moustapha et al. 2024).

2.2. *Deep Learning Enhanced Adaptive Metamodeling*

A reliability assessment involves P_f evaluation for a probabilistic model with inputs containing uncertainties (e.g., soil properties). A limit-state function (LSF) G is defined for uncertainty propagation which takes positive values in the safe domain and negative values in the failure domain. The detailed formulations regarding the calculation of P_f can be found in the literature (Malchers and Beck 2018). One of the methods for estimation of small P_f called subset simulation (SS) is employed in this study. 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 trainning (design of experiments DoE), 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 with SS (A-PCK/SS) technique was employed to create a surrogate model (Siacara et al., 2024). LSTM neural networks were included to train the target outputs obtained from the mechanical model. In our approach, we propose treating the s_u profile as a sequence, allowing LSTM to effectively learn the sequential correlations along depth. The sequence input layer takes RF of s_u along depth as a sequence with number of discretized points in RF. LSTM layer processes the sequence to learn the sequential correlation between each point in RF, providing additional fully connected layer fed with single output (the mechanical model response). The output of the LSTM captures the sequential correlation information extracted from the s_u RF realizations. This output (as a predicted mechanical model response) is then fed into the A-PCK model as DoEs, providing an additional input feature to the original input of PCK training, which is the random variables in KLE, aimed to enhance its accuracy (Figure 1).

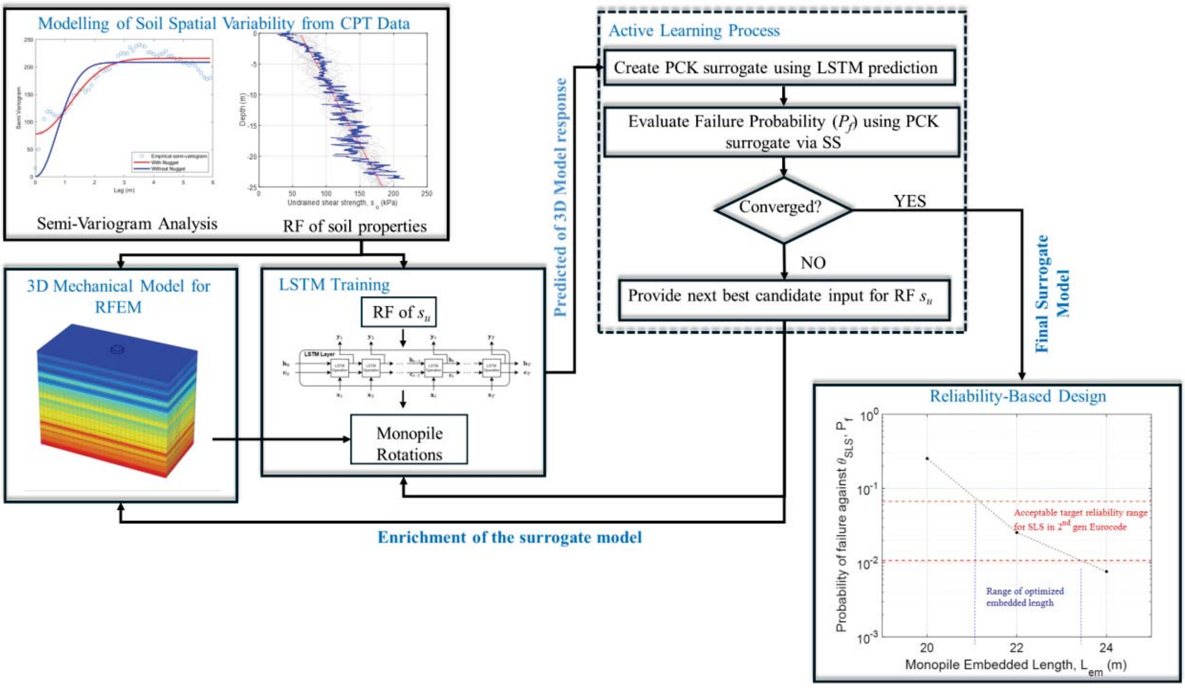

Figure 1. Flowchart of the proposed procedure for RBD of OWT monopiles

The procedure begins with uncertainty quantification of soil variability using cone penetration test (CPT) data collected from the vicinity of the target installation location of the monopile. One-dimensional RF of soil shear strength (s_u) and stiffness (E_u) were generated using the KLE method with the UQLab Matlab toolbox (Marelli and Sudret, 2014). A mechanical model was established using Plaxis 3D to get the response of the monopile automatically through Python code. The full model along the depth has been divide into small layers obeying the scale of fluctuation estimated from CPT data, and soil parameters have been assigned into these layers accordingly. The number of element and nodes in the finite element mesh are 127381 and 181541, respectively. The loading and model limits are given in Figure 2, and the bottom boundary is fixed in all directions. The four sides of the model allow vertical deformations, but they are fixed for lateral movement. In all soil layers, Mohr-Coulomb soil model was used with undrained condition (Tresca).

3. Validation of the Proposed Technique

Reliability assessment was performed for the pile lateral displacement (y) with a reference study which involves a laterally loaded reinforced concrete pile in spatially varying soil with 1D RF of s_u (Xiao-ling et al. 2021). The results showed that the deep learning enhanced algorithm gave very close results of P_f but with much fewer number of model simulations, compared to crude MCS in the reference which validated the efficiency and accuracy of the proposed procedure (Table 1). The validation study here is to show the accuracy of the method proposed on P_f estimation. The results revealed a promising accuracy for the method which can be considered as an alternative method to the existing techniques. However, more comparison should be performed to fully demonstrate the applicability and the efficiency of the method in future works.

Table 1. Validation for deterministic and probabilistic results

	This study	**Reference (Xiao-ling et al. 2021)**
Deterministic Comparison *(estimated lateral displacement of the monopile at mudline)*		
	0.0155 m	0.0154 m
Probabilistic Comparison *(estimated Pf , with total number of model simulation in parentheses)*		
	1.26% (33)*	1.14% (10000)#

Notes: *LSTM-PCK was used; #Crude MCS was used

4. Case Study

A monopile model was employed for a case study (El Haj 2019). An open-ended steel monopile of 4 m in diameter and 24 m in embedded length (L_{em}) was considered. The wall thickness of the monopile was equal to 5 cm. The monopile was extended by 1 m above the seabed to prevent the soil from going over the monopile. s_u values were derived 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 (Figure 2b). 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. The parameters for the RF generation by the KLE method are summarized in Table 2. Figure 2a illustrates the model geometry and a sample RF realization of s_u.

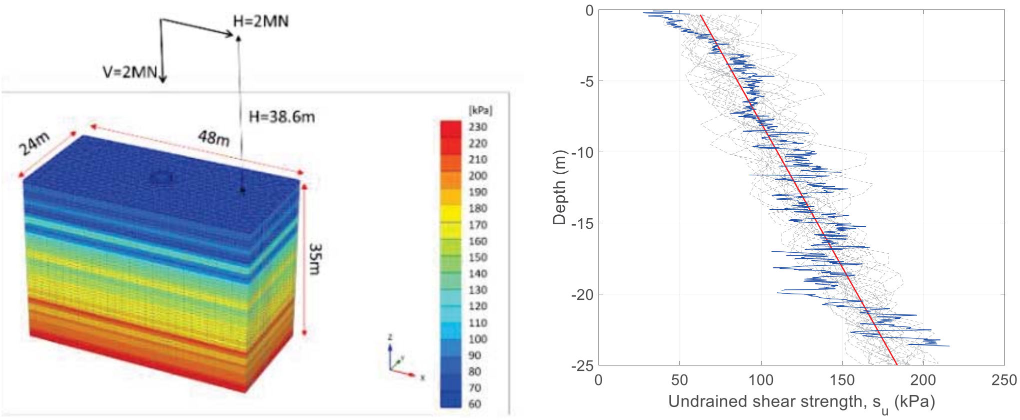

Figure 2. a) Model geometry and a sample RF realization of s_u, b) RF realizations, fitted trend and s_u from CPT data

Table 2. RF parameters used in this study

Parameters	**Values**
Initial shear strength, s_{u0} (kPa)	60.82
Increase rate of s_u (kPa/m)	4.92
Standard deviation of s_u (kPa)	14.32
Discretization scheme	KLE
Autocorrelation function	Gaussian
Number of terms in the expansion	31
Vertical correlation length, a_v (m)	0.72

The monopile was assessed in Serviceability Limit State (SLS) by considering excessive rotation of pile at mudline as failure mode. The corresponding performance function in Eq.1 is thus:

$$G = \frac{\theta_{SLS}}{\theta} - 1 = \frac{0.25°}{\theta} - 1 \tag{1}$$

LSTM-PCK is then used to quantify the uncertainty propagation and provide P_f estimate. The number of initial DoE is set as 25, and the stopping error limit is 10%. The convergence of P_f estimates for 24 m embedded length stopped at a value in the order of 7.6×10^{-3}. The method proposed in this study achieved after 43 added samples with satisfied error, showing a good efficiency. The P_f of the monopile with the initial embedded length (L_{em}) is lower than the required maximum P_f indicated in the JCSS probabilistic model code (JCSS 2001), which corresponds to a reliability index between 1.5 to 2.3 for SLS. Therefore, it is expected to reduce the L_{em} to find the minimum embedded depth which satisfies the target reliability index range. This was acheived by altering the

L_{em} and perfoming the reliability analyses with the LSTM-PCK in Figure 3a which indicates that the minimum L_{em} could be 22 m showing a reduction from the initial length, Figure 3b depicts the performance of LSTM-PCK during the active learning process for L_{em} = 22 m. Table 3 provides a summary of the results for the monopile with a L_{em} of 22m. The P_f is 2.6×10^{-2}, corresponding to a reliability index of 1.95 being within the target range.

Table 3. Summary results for L_{em} = 22 m

Probabilistic analysis results	
Failure probability	2.6×10^{-2}
Reliability index	1.95
Mean θ	0.2373°
95% confidence interval	0.2254° - 0.2501°
Deterministic θ with fitted trend	0.2367°

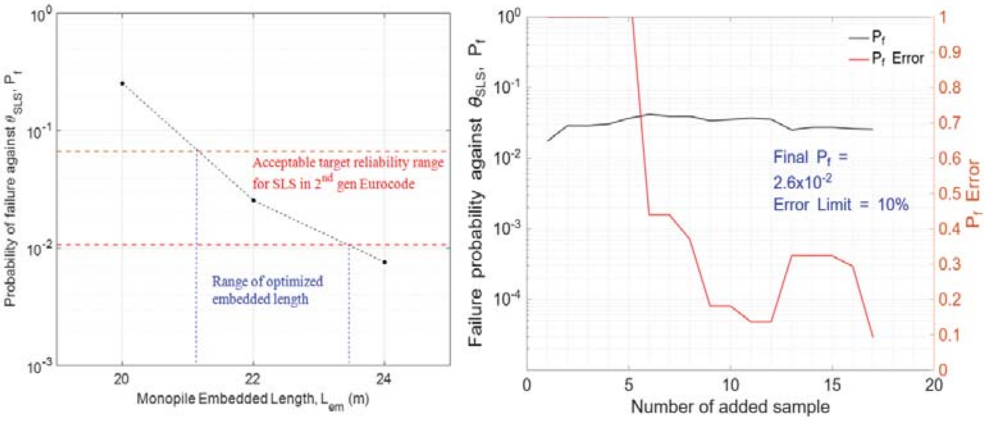

Figure 3. a) RBD results of L_{em} by LSTM-PCK, b) LSTM-PCK performance during the active learning process

5. Conclusion

The paper presented a reliability-based design framework for monopiles of offshore wind turbines in terms of serviceability limit states. The method quantified the spatial variability of soil through analysing CPT data with 1D random field. A mechanical model was created to perform RFEM analyses for RF soil inputs and get the monopile response. LSTM neural networks were proposed to extract sequential correlation information from soil random profiles and assist the PCK in constructing a more accurate surrogate model in active learning reliability analysis process. The proposed procedure efficiently enhanced the active learning process for RBD of OWT monopiles. The future work aims to further improve the framework with the development of combined training algorithm for LSTM and PCK.

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