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Machine learning to expedite concept monopile design

Apprentissage automatique pour accélérer la conception de monopieux conceptuels

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ABSTRACT: Offshore wind turbine generators (WTG)s are typically supported by monopile foundations in shallow water (<50m). The design of monopile foundations is usually conducted using rule-based soil reaction curves (SRC)s in a 1D or 0D model. For the derivation of SRCs, WTG location-specific 3D finite element analysis (FEA) is now typically adopted in industry to ensure optimised foundation design. However, this approach is time consuming to calibrate to new sites and hence not well suited for early-stage structural design and load simulations where thousands of calculations are performed to finalise the offshore wind farm layout. This paper presents a novel approach for early stage monopile design (i.e. concept or pre-FEED), in which a concept design surrogate model was trained on a database of 2000 3D FEA simulations using a machine learning algorithm. The surrogate model provides rapid estimations of monopile design for Natural Frequency Analysis (NFA) and Fatigue Limit State (FLS) conditions, while also intrinsically incorporating the fidelity of the 3D FEA simulations. The surrogate model predicts results close to that of 3D FEA, over 10000 times faster, for layered soil profiles and a wide range of monopile dimensions inside the training space. Published monopile lateral response results from field testing were used to further validate the model. Use of such a tool in practice will speed up the process of preliminary monopile design and load simulations, reducing risks and time for developers, whilst improving site feasibility studies and cost estimates.

RÉSUMÉ: Les générateurs d'éoliennes offshore (WTG) sont généralement soutenus par des fondations monopieux. La conception des fondations monopieux est généralement réalisée à l'aide de courbes de réaction du sol (SRC) basées sur des règles dans un modèle 1D ou 0D. Pour la dérivation des SRC, la FEA 3D spécifique à l'emplacement WTG est désormais généralement adoptée dans l'industrie pour garantir une conception optimisée des fondations. Cependant, cette approche prend du temps à calibrer sur de nouveaux sites et n'est donc pas bien adaptée à la conception structurelle et aux simulations de charges à un stade précoce, où des milliers de calculs sont effectués pour finaliser la configuration du parc éolien offshore. Cet article présente une nouvelle approche de la conception de monopieux à un stade précoce (c'est-à-dire concept ou pré-FEED), dans laquelle un modèle de substitution de conception de concept a été formé sur une base de données de 2000 simulations FEA 3D à l'aide d'un algorithme d'apprentissage automatique. Le modèle de substitution fournit des estimations rapides de la conception de monopieux pour les conditions d'analyse de fréquence naturelle (NFA) et d'état limite de fatigue (FLS), tout en intégrant intrinsèquement la fidélité des simulations FEA 3D. Le modèle de substitution prédit des résultats proches de ceux de la FEA 3D, plus de 10 000 fois plus rapides, pour des profils de sol en couches et une large gamme de dimensions de monopieux à l'intérieur de l'espace d'entraînement. Les résultats publiés de la réponse latérale du monopile du PISA JIP ont été utilisés pour valider davantage le modèle. L'utilisation pratique d'un tel outil accélérera le processus de conception préliminaire du monopieu et de simulations de charge, réduisant ainsi les risques et le temps pour les développeurs, tout en améliorant les études de faisabilité du site et les estimations de coûts.

Keywords: Offshore wind; monopiles; machine learning; concept design; finite element analysis.

1 INTRODUCTION

The offshore wind industry is currently experiencing a period of rapid growth and innovation due to the threat of the climate crisis and the finite supply of fossil fuels. As the scale of wind generating structures grows, impetus to optimise their construction increases. This is especially true for foundations, which can represent up to 30% of the total offshore wind farm (OWF)

CAPEX cost. Monopiles are the most common foundation type for WTGs and are typically used in water depths up to 60m, with diameters up to 12m and length to diameter ratios of 2.5-6. Identifying suitable locations where WTGs can be constructed economically at an early stage in the design process can lead to significant cost and time savings for developers. The approach explored herein, named the Rapid Monopile Design Surrogate (RMDS) tool, employs modern machine learning methods to allow NFA and FLS design assessments at proposed WTG locations to be carried out faster than is currently possible whilst retaining accuracy. The outputs can be easily integrated into established workflows to estimate the optimum monopile dimensions, and subsequently foundation cost, for the given location.

2 BACKGROUND

2.1 Current methods for NFA and FLS design

The monopile diameter and wall thickness, and hence feasibility, is typically driven by the NFA and FLS design; therefore, it is critical this is assessed at the early stage of the project. The current industry practice for early stage NFA and FLS assessments and aeroelastic WTG load simulations uses a combination of 3D FEA and SRCs. However, this is a slow process which is computationally expensive, and can demand a considerable amount of time and expertise to set-up. A macro element 0D model, consisting of a coupled three-spring configuration, is an alternative approach, suitable for early stage design. This simplifies the monopile by replacing it with a lateral spring (K_L), a rotational spring (K_R) and a cross-coupling spring (K_{LR}), where the springs represent the stiffness of the monopile at mudline. Vertical stiffness is generally omitted from calculations as it is large enough that zero displacement can be assumed. The values of the three springs can then be used directly as inputs for calculation of natural frequency and deformation of the monopile in the small displacement zone. To obtain values of each spring, empirical equations have been proposed. Arany (2017) provides a summary of commonly used equations. However, these equations can only be applied to idealised soil conditions and have been shown to lead to overly stiff designs .

2.2 Machine learning models

Few attempts have been made to predict monopile response using ML. Suryasentana (2020) showed that Gaussian Progress regression was effective in predicting *p-y* springs down the length of a monopile.

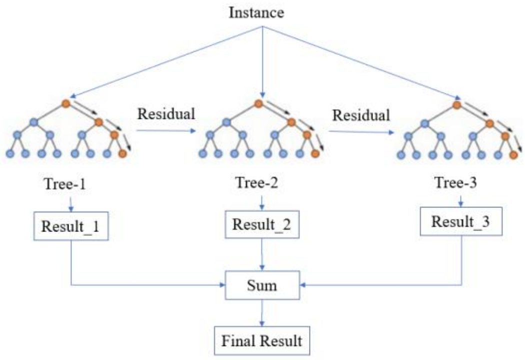

Figure 1. Simplified XGBoost model visualised (Wang et al., 2020).

Suryasentana notes that in their work the dataset was small and specific to one site and therefore, randomised 3D FEA would be a more suitable method to generate a database of monopile responses capable of generalising to a wider variety of soil conditions.

The ML model chosen for this study was the open-source package XGBoost (Chen *et al.* 2016). The algorithm is based on the concept of decision trees; a series of conditions are applied to the inputs of the tree (i.e., is depth greater than 15m?), to improve predictions of an output (Figure 1). XGboost is widely used in datascience due to its scalability and relatively low computational intensity and is increasingly used for regression problems in geotechnical engineering (see Kardani, 2020).

3 METHODOLOGY

3.1 Dataset formulation

The database on which the RMDS tool was trained consisted of results from 2000 FEA simulations with monopile dimensions, loading conditions and soil profiles as outlined in Table 1. These properties were randomly generated at small intervals to reduce the effects of overfitting to input parameters. This process was automated using a python script and employed the commercial FEA software PLAXIS 3D.

Table 1. Parameter space for dataset.

Header	Range	Step
Diameter (m)	6-12	0.25
Embedment length (m)	25-45	1
Lever arm (m)	20-120	1
Initial shear modulus (MPa)	1-350	1
Layer thickness (m)	2-10	1
Poisson's ratio	0.495	Constant
Diameter/pile wall thickness	120	Constant

NFA/FLS calculations are influenced by behaviour in the very small strain region where the behaviour is often close to linear. As a result, the FEA employed a linear elastic soil constitutive model. Two values were extracted from each simulation to train the RMDS tool, these are referred to as the target variables:

$$K_H = \frac{F_x * D}{u_x} \tag{1}$$

$$K_M = \frac{M_y}{\theta_y} \tag{2}$$

Where K_H is the uncoupled lateral stiffness (GN), F_x is the shear at mudline (GN), u_x is the lateral displacement at pile head (m), K_M is the uncoupled rotational stiffness (GNm/rad), M_y is the overturning moment and θ_y (GNm) is the pile rotation at mudline (rad).

Prior to model training, the format of the soil profile was altered to improve resolution and readability for training. This was accomplished by taking values of initial shear modulus (G_{max}) at 30 equally spaced points down the pile length, where each G_{max} value would be an individual input to the ML model.

3.2 Training of machine learning models

The RMDS tool consists of two XGBoost models that were trained using the same 33 input features: diameter, embedment length, lever arm and 30 G_{max} values. For one model K_H was the target variable and for the other it was K_M. The dataset was partitioned so that of the 2000 samples, 80% was used for training and 20% was held out for testing. A grid search was used to return the optimal hyperparameters (these are XGBoost parameters set by the user which govern how the model learns) for both models. It was found that no regularisation hyperparameters were required other than subsampling the data. This is likely because there is very little noise in the database generated by FEA, which is an advantage of using FEA for ML model training.

As a result of training the RMDS tool with different lever arms, the values of each spring in the three spring model can be calculated. This is achieved by solving for each term in the stiffness matrix using two different lever arms:

$$\begin{bmatrix} F_x \\ M_y \end{bmatrix} = \begin{bmatrix} K_L & K_{LR} \\ K_{RL} & K_R \end{bmatrix} \cdot \begin{bmatrix} u_x \\ \theta_y \end{bmatrix} \tag{3}$$

Due to small errors, the cross-coupling terms were not exactly equal, therefore an average of K_{LR} and K_{RL} can be taken as the value of the cross-coupling term.

4 RESULTS

4.1 Model fit

Figure 2 highlights the effectiveness of the RMDS tool in predicting both target variables (uncoupled lateral and uncoupled rotational stiffness) for 20% of the database that was set aside for testing. As shown by the high r^2 value, the variance in the target variables is explained very well by both ML models, and the mean absolute percentage error (MAPE) is very low for both models, most notably the rotational model.

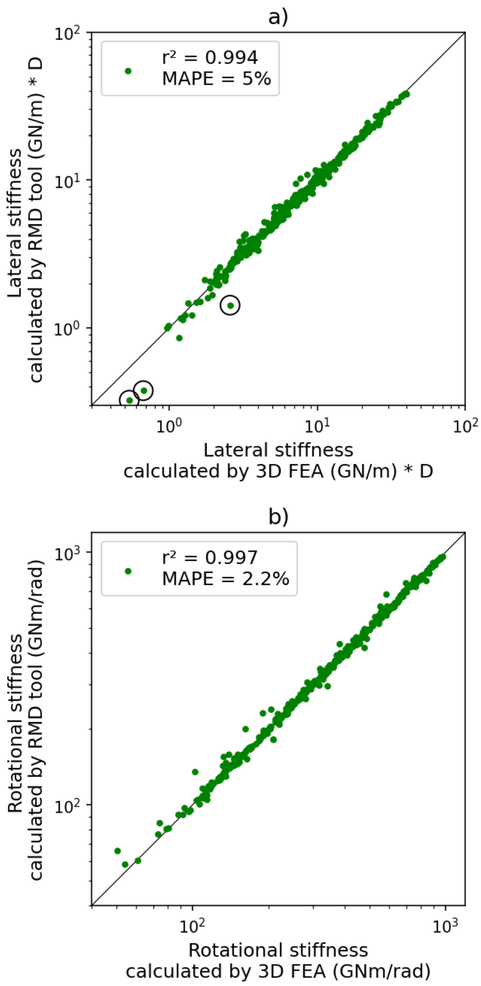

Figure 2. RMDS tool predictions versus 3D FEA predictions for a) uncoupled lateral stiffness and b) uncoupled rotational stiffness. Three poor predictions are circled in a) which corresponded to cases with unrealistic soil profiles.

It was found that the poorest predictions corresponded to an FEA simulation in which the randomised soil profile was unrealistically low. For example the circled points in Figure 2 had a median

G_{max} of 20MPa or lower down the length of the monopile.

The RMDS tool was able to predict both the lateral and rotational stiffness in 0.017 seconds, in comparison to 20 minutes, which is a representative time for the 3D FEA analysis. This highlights the potential time savings of implementing the RMDS tool in concept design. A benefit of the ML approach is that the tool can be continually improved by adding more training data and retraining the model.

4.2 Validation

To further establish the reliability of the RMDS tool, it was compared with 3D finite element calibration analysis conducted within the PISA JIP as presented in Byrne *et al*. (2020), which serves as the basis for industry-standard design methods. Specifically, the RMDS tool was compared to calibration analyses, and design cases for which there was data available and pile diameter and embedment length were within 25% of the corresponding ranges as outlined in Table 1. More details can be found in (Byrne *et al.*, 2020).

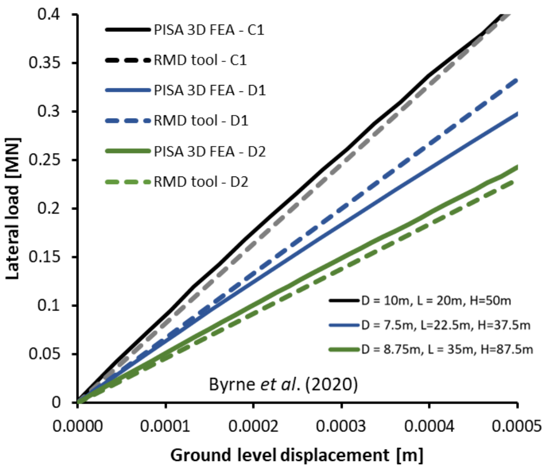

Figure 3. RMDS tool predictions of uncoupled lateral stiffness in the very small strain region, compared to 3D FEA results from PISA calibration analysis C1 and design cases D1 and D2 presented in Byrne et al. (2020).

Generally, very good agreement with the initial lateral stiffness is observed as shown in Figure 3. Therefore, the results provide confidence that the FEA set-up used to create the training database was accurate and that the RMDS tool was able to effectively learn the trends of the database to act as a surrogate FEA model.

5 CONCLUSIONS

The RMDS tool was developed using modern machine learning techniques to act as a surrogate model for 3D FEA, allowing rapid, accurate predictions of monopile stiffness in the very small strain region. This capability could result in significant time and cost savings for concept NFA and FLS assessments. However, unlike 3D FEA, the RMDS tool can only be used within its calibration range and in some instances, may overfit to its input parameters. The demonstrated proof-of-concept tool shows good predictive capabilities on results from well-established published field tests and can be continually improved by retraining the model on new data. This paper has focused on the small strain region, using a simplified linear elastic constitutive model; however, techniques presented in this study could also be used to train ML models for predicting non-linear soil response, using more advanced constitutive models, or predicting *p-y* springs along the length of a monopile.

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