MACHINE LEARNING TECHNIQUES TO ESTIMATE THE STIFFNESS OF OFFSHORE FOUNDATIONS

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INTRODUCTION

- The UK has pledged to become carbon neutral by 2050, with 15% of the UK's current total emissions coming from the power sector. This merits the investigation of quick, accurate design methods for renewable energy sources.
- The monopile is the most common foundation for offshore wind turbines (OWT's). It is a large diameter steel tube which is driven into the seabed, mobilising soil strength along its length and base.
- The natural frequency of an OWT is an important design parameter. This is because it must lie in the narrow band between the rotational frequency and the blade passing frequency (generally 3 x rotational frequency, as there is typically 3 blades).
- The monopile stiffness is a key parameter in the OWT's natural frequency. It can be modelled as a set of coupled springs attached to the tower. The stiffness of these springs is known as the pile head stiffness matrix, found from the initial portion of the pile's load displacement curve at the ground level. Lateral and moment loading are considered.

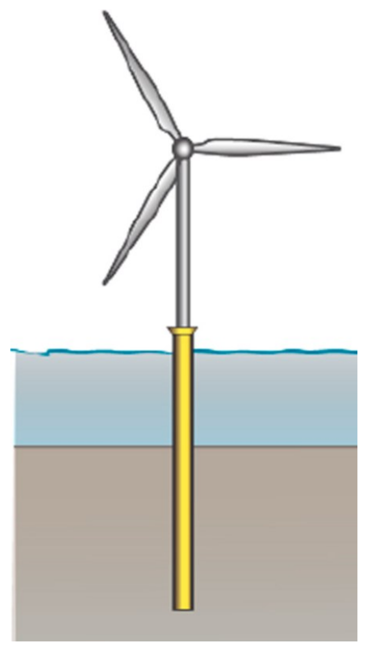

Figure 1– An OWT supported by a monopile (Kaynia 2019)

$$\begin{bmatrix} F \\ Fh \end{bmatrix} = \begin{bmatrix} K_L & K_{LR} \\ K_{LR} & K_R \end{bmatrix} \begin{bmatrix} v \\ \psi \end{bmatrix}$$

- The PISA project aimed to extend the p-y method commonly used in industry. The p-y method models the soil as a set of lateral non-linear Winkler springs characterised by soil reaction-displacement (p-y) curves, and the pile as an embedded Euler–Bernoulli beam. The PISA design method (Byrne et al. 2020; Burd et al. 2020a; Burd et al. 2020b) extends this by capturing other interaction effects relevant to large diameter monopiles. It includes a base horizontal force (H_B) and base moment (M_B), as well as a distributed moment (m) arising from vertical shear tractions along the pile shaft opposing the direction of applied moments. The pile is modelled as a Timoshenko beam.

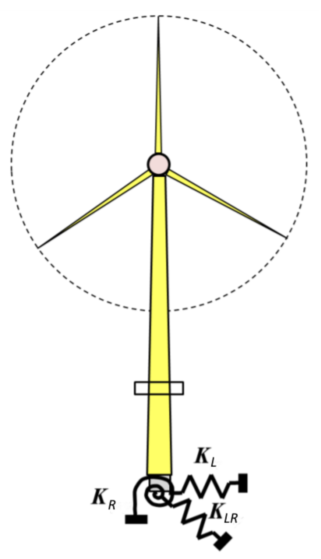

Figure 2– OWT with monopiles modelled as a set of coupled springs (Gupta 2018)

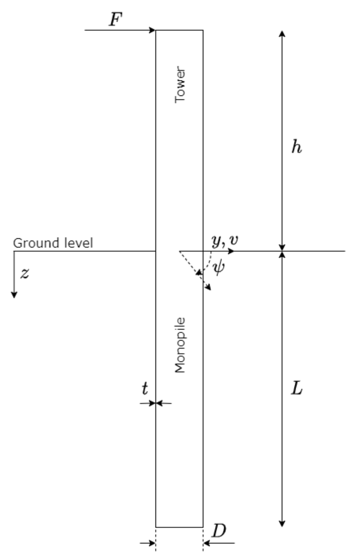

Figure 3– Problem space definition with the soil divided into 6 randomly sized strata

- Monopile geometries were based on those used in the PISA project, which aimed to model monopiles of today and tomorrow. Soil profiles used were also based on those modelled in the PISA project.
- This project presented a method of predicting the stiffness of offshore wind turbines using artificial neural networks. The objectives of the method developed in this project were to produce more accurate stiffness predictions than the PISA 1D model, approaching the accuracy of three-dimensional finite element analysis (3D-FEA) with a faster predictive speed than 3D-FEA. The 1D model prediction was used as an input feature.

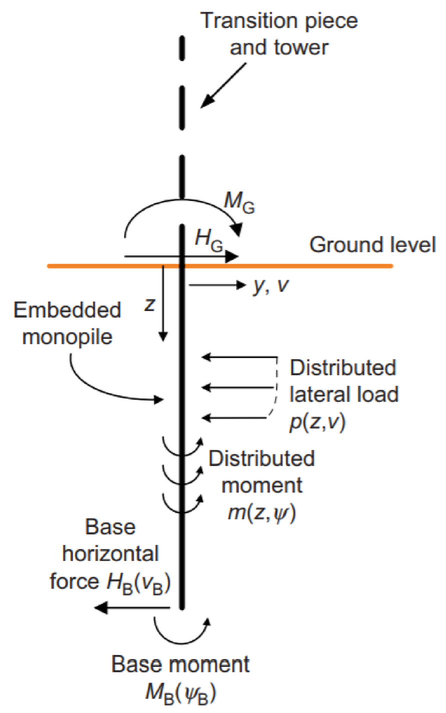

Figure 4– PISA 1D model (Burd et al. 2020a)

METHOD

- Training data was gathered by performing 3D-FEA in Abaqus on a range of monopile geometry/soil profile instantiations (samples). Soil profiles with a depth of 100m were split into 6 layers of random height. These layers were randomly assigned as coarse grained (sandy) or fine grained (clayey). The shear modulus-depth relationship was defined based on modelling in the PISA project, and parameters were bundled into a parameter α. This was randomly selected for each layer for each sample. Soil was modelled as elastic, with perfect contact along the shaft.

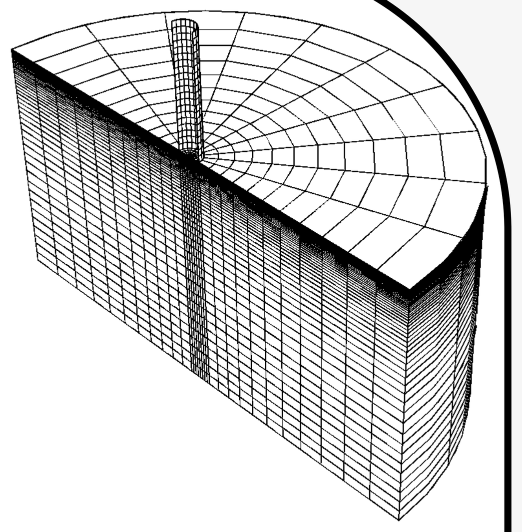

Figure 5- A mesh for performing 3D-FEA on a monopile embedded in soil. Only half the problem is discretised due to symmetry.

Sands	Clays
$G_0 = \frac{Bp'_{ref}}{0.3+0.7e^2}\sqrt{\frac{p'}{p'_{ref}}}$	$G_0 = Ap'$
$p' = \frac{(1+2K_0)}{3}\gamma' z$	$G_0 = \alpha_c z$
$e = e_{max} - I_d(e_{max} - e_{min})$	$3.027 \times 10^6 \leq \alpha_c \leq 12.108 \times 10^6$
$G_0 = \alpha_s \sqrt{z}$	
$24.669 \times 10^6 \leq \alpha_s \leq 43.263 \times 10^6$	

Pile	D(m)	h_1/D	h_1(m)	h_2/D	h_2(m)	L/D	L(m)	D/t	t(mm)
CP1	5	5	25	15	75	2	10	111	45
CP2	5	5	25	15	75	2	10	60	83
CP3	5	5	25	15	75	6	30	111	45
CP4	7.5	5	37.5	15	112.5	2	15	110	68
CP5	7.5	5	37.5	15	112.5	6	45	110	68
CP6	10	5	50	15	150	2	20	110	91
CP7	10	5	50	15	150	2	20	80	125
CP8	10	5	50	15	150	4	40	110	91
CP9	10	5	50	15	150	6	60	110	91
TP1	5	5	25	15	75	4	20	60	83
TP2	7.5	5	37.5	15	112.5	4	30	110	68
TP3	10	5	50	15	150	3	30	110	91
TP4	10	5	50	15	150	5	50	80	125
VP1	6	5	30	15	90	3	18	100	60
VP2	8.5	5	42.5	15	127.5	4.5	38.25	85	100
UP1	7	5	35	15	105	6	42	66	106

Table 1– Monopile geometries modelled

- Table 1 shows the monopile geometries modelled. CP1-9 and TP1-4 were used to generate training data for the neural network, whilst VP1-2 were used as validation data for model selection, to ensure the neural network had generalised well to unseen geometries. Models were selected using this, as well as their performance on a 20% holdback set of the training data (the test set). UP1 was used after model selection to ensure the network had truly generalised well to unseen geometries, and had not fit VP1 and VP2 well by chance. 1000 samples were generated for each of CP1-9 and TP1-4. 500 samples were generated for VP1-2, and 150 samples were generated for UP1.
- Feedforward neural networks (FNN's) were created for each stiffness term. A feedforward neural network (FNN), also known as a multi layer perception is made up of interconnected nodes, in which information only flows forwards. A feature vector is entered into an input layer, with each neuron representing an input feature. There are 22 features for the networks, representing the monopile geometry, soil profile and 1D model prediction. Subsequently there are hidden layers, and finally an output layer. Each neuron feeds forward into every neuron in the layer after it, with each link being characterised by a weight. Each neuron has a bias which it applies to all inputs linking into it. Weights and biases simply represent a linear transformation to the value of the neurons being fed forward. A non-linear activation function is typically applied before neurons in the hidden layer. This is required to introduce non-linearity to the model.

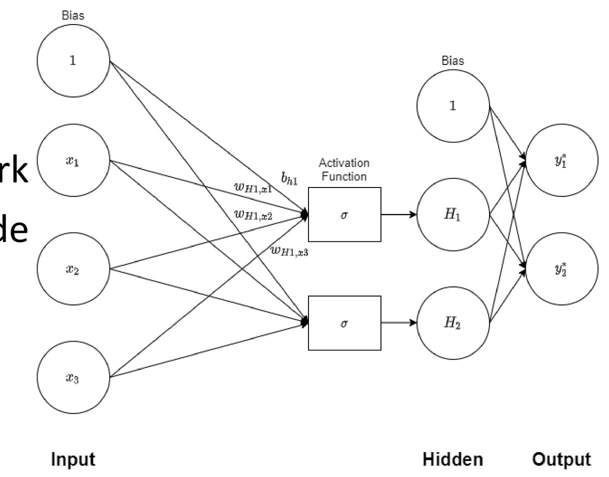

Figure 6– Simple FNN with three input neurons, a two noded hidden layer and two outputs

- The networks were optimized with stochastic gradient descent, with Nesterov Accelerated Gradients. For K_R the dataset was augmented with noise on the outputs, which introduced a regularizing effect. Hyperparameters were tuned using a grid based search. All networks have 3 hidden layers. K_L has 20,10 and 10 neurons on its hidden layers. K_{LR} has 50,50 and 10. K_R has 5,10 and 50.

RESULTS

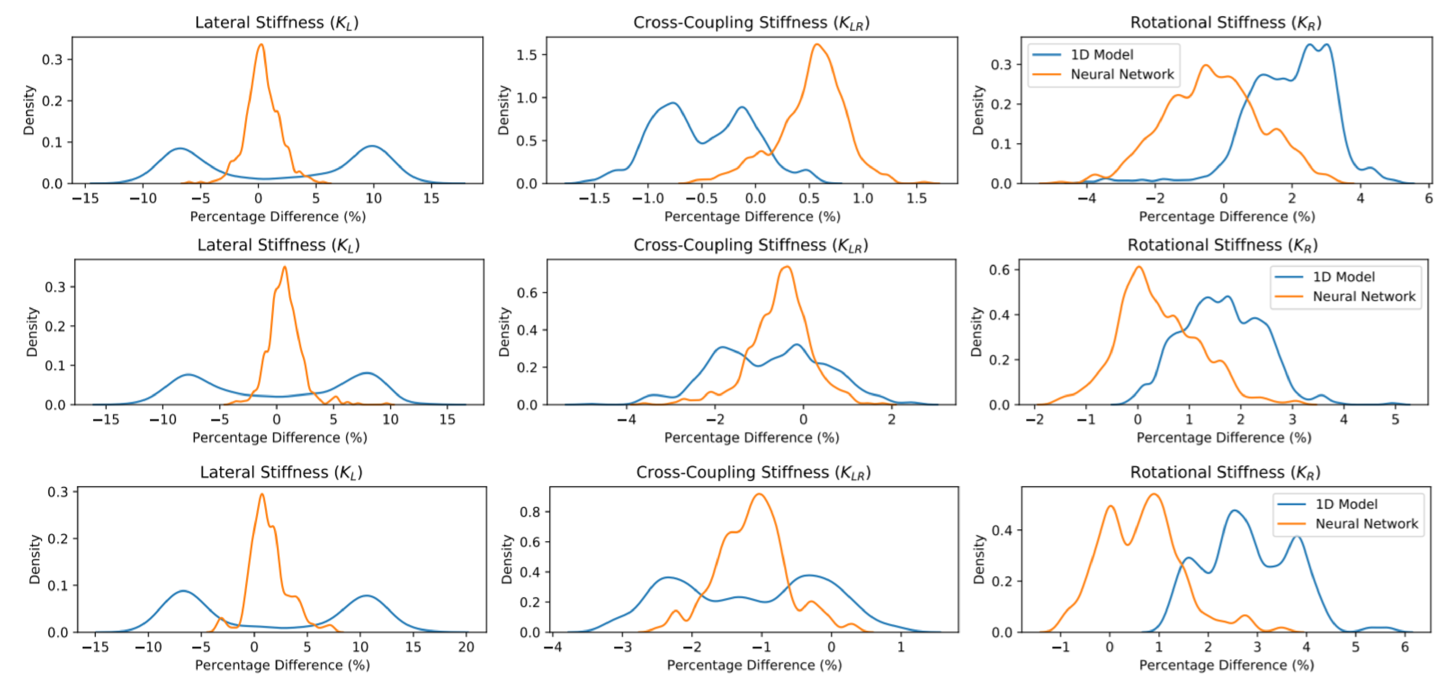

Figure 7– Kernel density estimations comparing percentage errors of 1D model to neural networks over the 3 stiffness terms. Validation piles VP1, VP2 and UP1 respectively are shown.

	MAPE (%)		APE >10% (%)		APE >5% (%)	
	1D	FNN	1D	FNN	1D	FNN
K_L	7.54	1.27	24.45	0	76.63	1.19
K_{LR}	2.88	0.67	2.40	0.07	18.45	0.46
K_R	1.97	1.46	1.55	0.49	6.07	3.07

Table 2– Mean absolute percentage error, absolute percentage greater than 10% and 5% for the FNN's compared to the 1D model. Results are averaged over the 20% holdback test set and the validation piles.

- The FNN's predicted the pile head stiffness matrix in 6.44×10^{-6} seconds. This is better than the 1D model (0.011 seconds) and the 3D-FEA (28.6 seconds), although a working model would have to include the 1D model's prediction.

DISCUSSION

- This project presented an initial exploration into using artificial neural networks to predict the pile head stiffness matrix of monopiles used for OWT's.
- It fulfilled its objective of producing predictions close in accuracy to those made by 3D-FEA, with a much smaller predictive time. This does not account for the time and user expertise required to set up the 3D-FEA model. Whilst the predictive speed of the 3D-FEA in this project was relatively low, this project demonstrates that it may be possible to expedite the problem with more complexities introduced (such as non-linear effects like friction, gapping and compliance). These would significantly increase the 3D-FEA solution time, whilst likely not significantly affecting the FNN's predictive speed.
- Figure 8 shows how FNN's could expedite the design process, iterating through monopile dimensions to find dimensions which satisfy the target natural frequency. It suggests all final dimensions are verified by techniques such as 3D-FEA.

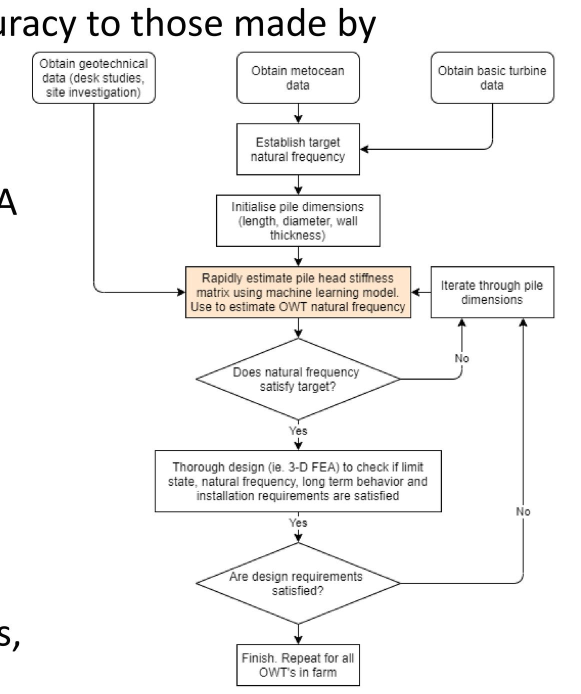

Figure 8– Simplified design flowchart demonstrating how methods developed in this report could aid design process of an OWT's foundation

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