Small strain shear modulus derived from offshore seismic reflection data

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ABSTRACT

Small strain shear modulus G_{max} is an important parameter for design of foundations of fixed offshore structures. The preferred reference method for G_{max} is the seismic velocity test (SVT) performed as part of a seismic cone penetration test (SCPT). SVTs provide in-situ G_{max} values for discrete depth sections of SCPTs.

This paper focusses on added value achieved by (1) generation of 15 million synthetic G_{max} profiles to 50 m depth and (2) a G_{max} zonation map for the IJmuiden Ver Wind Farm Sites Alpha and Beta (offshore Netherlands). The synthetic G_{max} profiles were derived from a data set of 51 SCPT profiles, 250 CPT profiles and 2D UHR seismic reflection traces along survey track lines spaced at about 70 m. The quality of the SCPT data and UHR seismic reflection data was state-of-the-art (as of 2021). The data process included the use of a (1) multi fidelity data fusion statistical framework and (2) machine learning by a convolutional neural network. The synthetic G_{max} data were the basis for the G_{max} zonation map used to enhance an integrated ground model for the wind farm sites. Particularly, the map can be used to quickly identify and constrain areas which are favourable and challenging for design of monopiles and other common foundation types typically considered for offshore wind turbines.

Keywords: shear modulus; machine learning; integrated ground model; synthetic G_{max}; zonation.

1. Introduction

The primary purpose of developing an integrated ground model for an offshore wind farm during the pre-FEED or concept design stage is to de-risk the site by reducing uncertainties where possible. This includes identifying and delineating spatial areas that have features impacting design.

Small strain shear modulus G_{max} is an important design driver of foundations of fixed offshore structures, with the preferred (in-situ) reference method for obtaining G_{max} being the seismic velocity test (SVT) performed as part of the seismic cone penetration test (SCPT).

This paper focusses on enhancement of an integrated ground model developed for IJmuiden Ver Wind Farm Sites Alpha and Beta (offshore Netherlands) in two ways:

- A first-ever large-scale prediction of shear modulus parameter values (i.e. 15 million synthetic (or predicted) G_{max} profiles to 50 m depth) based on 2D UHR (ultra high resolution) seismic reflection data used for incorporation into the integrated ground model is presented;
- An illustration of how 15 million synthetic G_{max} profiles can be used to add value to the integrated ground model by creating a zonation map to quickly identify and constrain areas which are favourable and challenging for design.

The presented approach is covered by ISO (2021) and meets key requirements for derived values of G_{max} for characterizing any site: (i) high quality data, (ii) abundantly available and (iii) cheap to acquire or obtain.

2. Project site and geology

Ijmuiden Ver Windfarm Sites Alpha and Beta (IJVWFS) is located approximately 62 km off the west coast of the Netherlands (Fig. 1) in the Dutch sector of the Southern North Sea. Fig. 1 shows the layout, with values of coordinates in metres. The total surface area of IJVWFS is approximately 439 km^2. Water depths range between 20 m and 45 m.

Site investigation data for IJVWFS include results from geological, geotechnical and marine geophysical data. A complete database of source data is in the public domain (offshorewind.rvo.nl). The source data of particular interest for this paper comprises of 51 SCPT investigation locations, 236 PCPT (excludes the CPTs from the SCPT locations) investigation locations, 10 PSSL (P & S suspension logger, borehole geophysical logging) investigation locations and 2D UHR data acquired along survey track lines spaced at about 70 m.

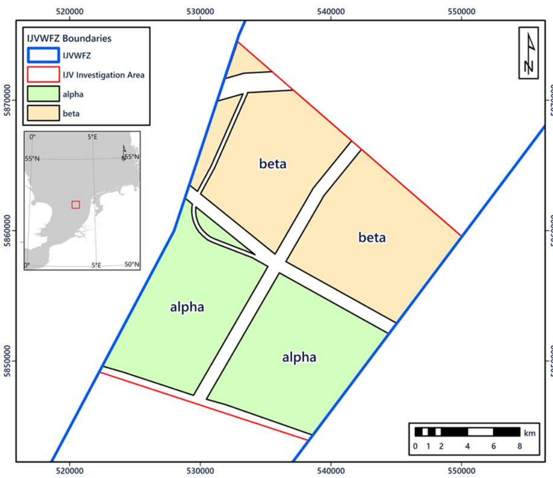

Figure 1. IJmuiden Ver Windfarm Sites Alpha and Beta (IJVWFS) Project Site.

The integrated ground model developed for this site includes six soil provinces and eight soil units. Fig. 2 and Fig. 3 give an overview of soil units encountered in the shallow subsurface (between seafloor and 50 m below seafloor BSF) and how their upper and lower boundaries correlate to the seismic horizons identified at IJVWFS. The IDs of the seismic horizons are R00 to R20 (Fig. 2). Sediments and post-depositional processes from the Pleistocene to Holocene dominate the geological framework of IJVWFS (Fugro, 2023a).

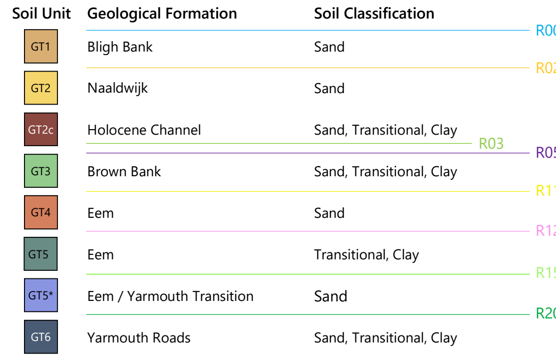

Figure 2. Soil Units at IJVWFS.

3. Synthetic small strain shear modulus

3.1. General workflow

The general workflow for synthetic G_{max} profiles is according to that described by Carpentier et al. (2021) for synthetic profiles of CPT cone resistance. Particularly, the workflow includes the use of convolutional neural networks (CNNs). Details are given in Fugro (2023b), available on offshorewind.rvo.nl.

3.2. Input data

Three key elements were used as input data for synthetic parameter generation.

- Geophysical data: 450 2D UHR lines, including stacking velocities per common depth point (CDP);
- Geotechnical data: profiles of q_n (net cone resistance) and v_s (shear wave velocity) from 287 unique geotechnical investigation locations (PCPT & SCPT) and values of v_s from SVT tests carried out at 51 SCPT locations;
- Ground model information: seismic horizons per soil unit along with soil density (ρ) information for all 2D UHR lines.

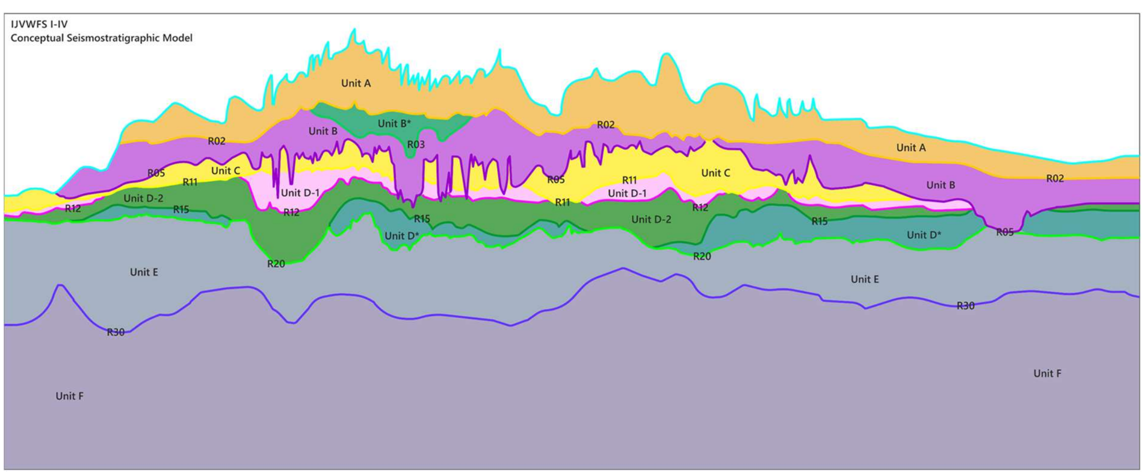

Figure 3. Conceptual model of soil units and seismic horizons at IJVWFS

For the geotechnical data, this paper also uses the term 'measured' to distinguish from synthetic (predicted). Strictly, q_n, v_s and G_{max} values derived from v_s values are derived values, not measured values.

The input geophysical data at a CDP location is called a 'seismic trace'. A seismic trace is associated with four data types or attributes in the form of 1D profiles. These attributes are: (i) soil unit; (ii) interval velocity; (iii) instantaneous amplitude; and (iv) acoustic impedance. Each seismic trace is also associated with fixed x-y coordinates of the CDP and information on depth in metres below seafloor and depth below LAT (lowest astronomical tide). To enhance the accuracy of synthetic G_{max} profiles and prevent a 'garbage-in-garbage-out' scenario, a key step was cleaning and processing of v_s input data (CPT profiles and SVT data points). This key step included (1) distinguishing a primary v_s dataset and a secondary v_s dataset and (2) application of a multi fidelity data fusion (MFDF) statistical approach, i.e. use of a higher accuracy sparse dataset (SVT) to enhance a lower accuracy larger dataset (CPT). It can be noted here that v_s data were used as input. Output values of v_s were converted to G_{max} values using the following equation:

$$G_{max} = v_s^2 \cdot \rho$$

The primary dataset refers to schematised v_s profiles at investigation locations where SCPTs were performed. The v_s profile schematisation was based on the SVT data and subsequently fine-tuned, where required, based on CPT data and PSSL v_s data, where available.

The secondary dataset refers to continuous v_s profiles at all 287 unique CPT investigation locations. Development of these v_s profiles included the use of a site-specific CPT-based correlation.

Comments on the MFDF methodology for the secondary dataset are as follows:

- v_s based on SVT data was used as reference;
- v_s correlation by Robertson and Cabal (2015) was used as a basis, modified using a yield stress ratio (YSR) based factor:

  $$v_s = YSR^b \cdot \left[\alpha_{vs} \cdot \frac{(q_t - \sigma_{v0})}{p_a}\right]^{0.5}$$

  where $\alpha_{vs} = 10^{(0.55\, I_c + 1.68)}$ and where shear wave velocity v_s is in m/s and corrected cone resistance q_t, total in situ vertical stress σ_{v0} and atmospheric pressure p_a are in kPa. Factor b is a soil unit specific exponent and I_c refers to (CPT) soil behaviour type index;
- Pairing of SCPT derived v_s values and CPT derived v_s values to determine the best fit YSR factor on a soil unit basis;
- Use of depth-specific weight factors where a higher weightage was assigned to a depth range between 5 m and 25 m BSF (below seafloor) accounting for (i) reliability of SCPT data, and (ii) the zone of influence for monopile and jacket pile designs.

Fig. 4 illustrates an example of v_s input data for an investigation location: CPT based profile (orange dashed line) as described above and datapoints from SVTs (black markers). Fig. 4 also includes soil unit information.

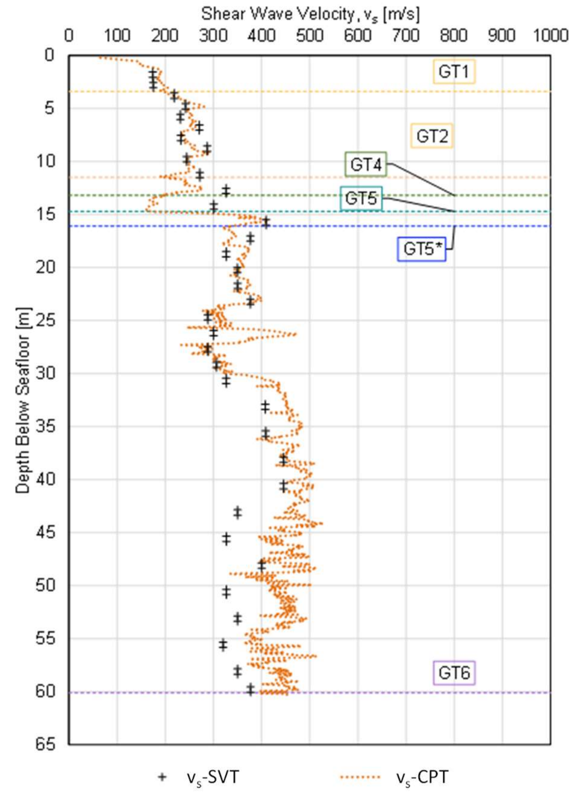

Figure 4. Example of v_s input data.

Another key step was pairing of the geotechnical data from the investigation locations with the seismic traces. The v_s data from each investigation location were paired with the 10 closest seismic traces in order to teach the CNN model that minor variations observed in the seismic traces should be considered as noise and can be disregarded, i.e. preventing the CNN from over-fitting.

The measured horizontal offset between each investigation location and the closest seismic trace was observed to be generally less than 10 m at seafloor. It is important to note however that expanded combined uncertainties (coverage factor $k = 2$) associated with geospatial positions of (S)CPT locations and seismic traces, are on the order of 2.0 m and 3.5 m respectively (Peuchen et al. 2023).

3.3. CNN phases

The CNN workflow included two phases: (i) a training phase for the CNN model to learn, and (ii) a validation phase where the performance of the trained model is evaluated with a validation dataset excluded from the training data (blind prediction).

Out of 287 unique investigation locations, 10 investigation locations were selected to form the validation dataset, i.e. for blind prediction (Fig. 5).

The training phase utilized the remaining 277 investigation locations, of which 222 investigation locations (approximately 80%) formed the network learning dataset, i.e. these were used to update the weights in the network. The remaining 55 locations (approximately 20%) formed the testing dataset, i.e. these were used to monitor the training progress and to terminate the process once the networks were sufficiently well trained. This 80-20 partition was found to secure a good amount of data for the model to learn, while also providing sufficient data for reliable monitoring.

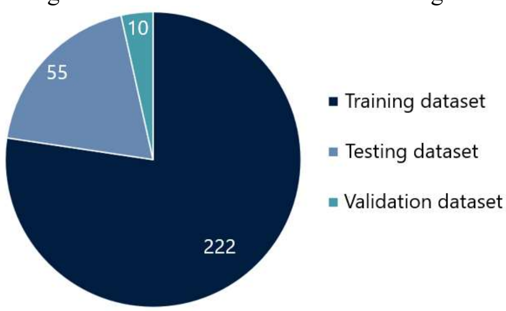

Figure 5. Division of input data into training, testing and validation datasets.

During the training phase, the CNN model was trained on the training dataset (222 locations) and evaluated on the testing dataset (55 locations) to assess the model's performance on new, unseen data. A single cycle of training the CNN model using a specific training dataset and testing dataset is termed an epoch. This training process is repeated by shuffling the locations assigned to the training and testing datasets between epochs. With each epoch, the CNN model is exposed to a different set of training locations. This allows the model to generalize better to new data.

The loss function, as shown in Fig. 6, measures how well the CNN model is performing on the testing dataset during the training phase. The loss function is the mean-squared error between the synthetic v_s parameter values (predicted values) and the measured v_s parameter (known values) in the testing dataset. As the CNN model improves during training with each epoch count, the loss function decreases. If the loss function stops decreasing significantly, it indicates that the model is no longer improving and may have reached the limit of what it can learn from the training data. Stopping training at this convergence point helps to prevent overfitting and ensures that the model generalizes well to new data.

At this stage the CNN model is considered fully trained. The model can then be used as a production tool to generate synthetic G_{max} profiles for all seismic lines.

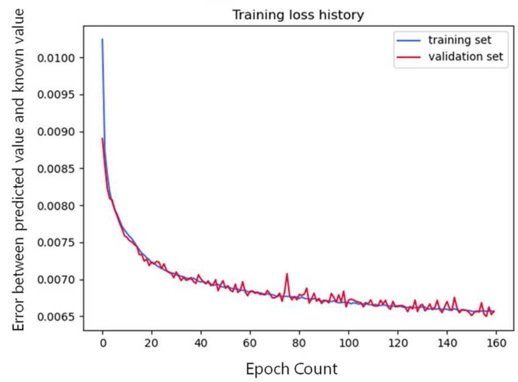

Figure 6. Example of convergence of loss function.

3.4. Synthetic G_{max} profiles

The complete dataset of synthetic G_{max} profiles for all 450 seismic lines can be found in the public domain (offshorewind.rvo.nl).

Fig. 7 shows a comparison of measured (black lines) and synthetic (green lines) G_{max} profiles values for the validation dataset (10 locations). In general, the predictions for the validation locations are assessed to be fair to good, with the mean profiles of the measured G_{max} parameter values captured well by the predicted profiles. Fig. 7 includes the soil units (background colours). The synthetic G_{max} profiles include a maximum likelihood prediction along with high and low estimates of 50% and 90% confidence intervals. Fig. 8 shows results of the (maximum likelihood) synthetic G_{max} parameter values along an example seismic line.

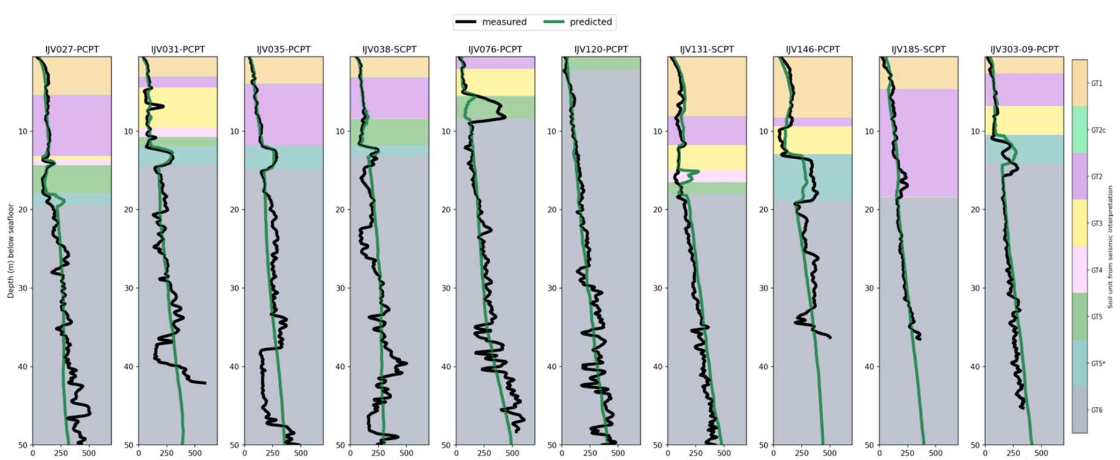

Figure 7. G_{max} predicted and measured values for the validation set of CPT locations (blind predictions).

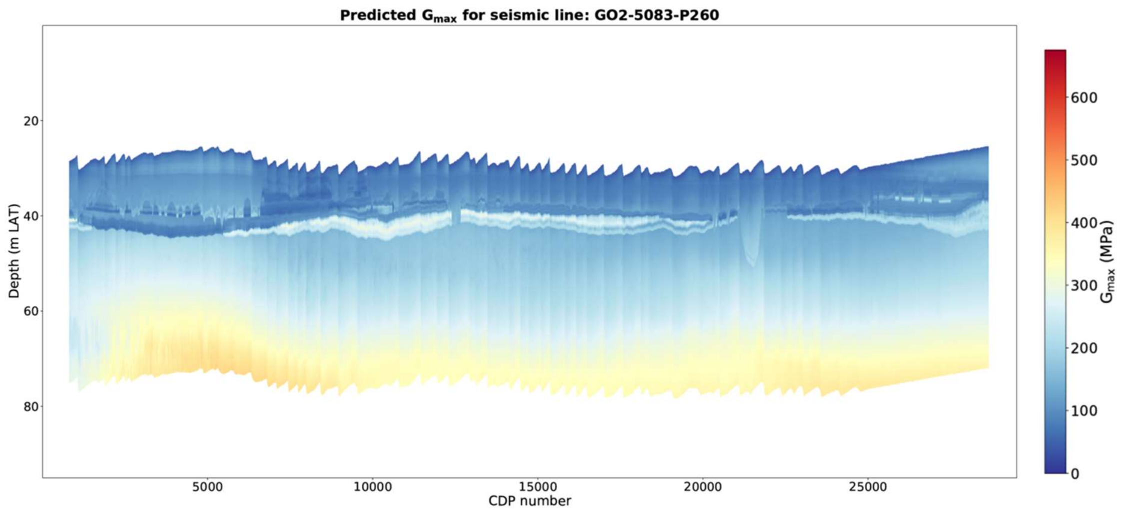

Figure 8. G_{max} prediction for UHR line G02-5083-P260 containing ~30,000 traces (~15 km long).

4. G_{max} zonation map

4.1. Map features

Fig. 9 shows the G_{max} zonation map developed for IJVWFS. In general, the conditions at this site are observed to be fairly uniform with no dramatic differences.

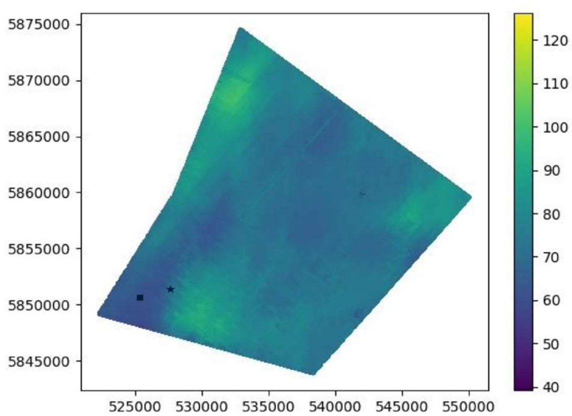

Figure 9. G_{max} zonation; colour bar shows $\overline{G_{max}}$ in MPa.

The synthetic G_{max} profiles provide high density and resolution of geotechnical data across the IJVWFS site, allowing the following fundamental features for the G_{max} zonation map:

- Enhanced spatial zonation of the site based on G_{max} profiles;
- A primary depth range of interest (i.e. from seafloor to 25 m BSF), considered as critical for geotechnical design of monopile foundations;

The G_{max} zonation map was developed according to the following procedure:

1. IJVWFS was divided into spatial grids with position coordinates associated with each synthetic G_{max} profile;
2. Synthetic G_{max} was considered the primary screening parameter;
3. Available synthetic G_{max} profiles were divided into 10 m depth segments and each depth segment was assigned a weight factor according to its expected significance with regards to foundation design (Table 1);
4. A weighted $\overline{G_{max}}$ was calculated at each position coordinate based on the G_{max} profiles. The following formula was used:
$$\overline{G_{max}} = \sum (w_i \cdot G_{max-i})/N_i$$
where w = weight factor, G_{max} = G_{max} values per depth segment, N= number of depth segments, i = 1 to n with n = total number of data points;
5. A colour scale was assigned to each value of weighted $\overline{G_{max}}$ as a visual aid.

Table 1. Weight factors for G_{max} zonation

Depth segment [m BSF]	Weight factor w [-]
0.5 to 10	0.4
10 to 20	0.3
20 to 30	0.2
30 to 40	0.1
40 to 50	0

4.2. Added value

Three key advantages are identified for developing a G_{max} zonation map to enhance understanding of the site.

- With G_{max} a driving parameter in most calculation models, the G_{max} zonation map can be used to quickly identify and constrain areas which are challenging for design;
- The zonation map targets monopiles and can be used for most foundation types typically considered for offshore wind turbines;
- A comparative assessment of the G_{max} zonation with other maps developed for the site, e.g. the soil province map provides an enhanced understanding of the site and serves as an

additional option to developers to refine cost and schedule estimates.

4.3. Example of use of zonation map

Fig. 10 presents an illustrative application of the use of this G_{max} zonation map. It shows normalised bending moment at seafloor versus monopile rotation from vertical (degrees) at seafloor, for the two locations shown in Fig. 9: square marker (location IJV107) in the dark blue region on the south-west corner of IJVWFS, and star marker (location IJV092) appearing on the periphery of the dark blue region in the south-west corner of IJVWFS. The bending moment at seafloor on the y-axis for all plates is normalised by the bending moment (at seafloor) mobilized at 1 degree rotation calculated for location IJV092.

The presented results were obtained by implementation of the 1D PISA approach (Byrne et al. 2017) using Plaxis MoDeTo (Monopile designer manual, 2023). Rule-based reaction curves of the Cowden clay and Dunkirk sand were used to model sand and clay layers at each location respectively (Byrne et al., 2017). Input parameters and parameter values for the analysis at the two locations can be found in Fugro (2023b). Monopile dimensions and loading conditions for the MoDeTo analysis were as follows:

- Outer diameter of 8 m;
- Wall thickness of 0.08 m;
- Range of embedment lengths, length to diameter L/D = 4 and L/D = 6;
- Horizontal load (monotonic and unidirectional) applied at 50 m above seafloor.

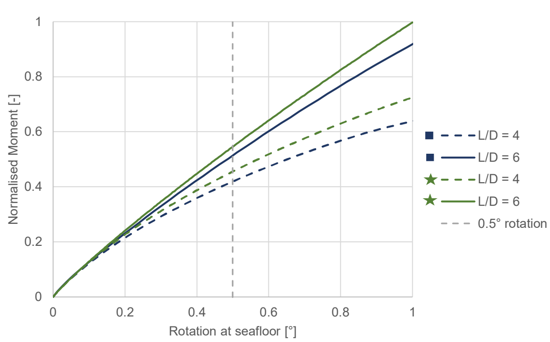

Figure 10. Normalised bending moment at seafloor versus monopile rotation (degrees) at seafloor for two locations.

5. Concluding remarks

This paper presented a first-ever large scale prediction of G_{max} profiles for a wind farm site using 2D UHR data. As for other synthetic geotechnical parameters (such as CPT cone resistance), it is important to note that the synthetic prediction process provides an approximation of relationships between (acoustic) seismic reflection data and (mechanical) geotechnical data.

The presented G_{max} zonation map illustrates opportunities for facilitating and optimizing foundation design. Further improvements could include:

- Addition of contour lines for mapping or tracking similar profiles;
- Addition of other supplementary screening parameters, such as synthetic (CPT) cone resistance;
- Multiple weight factors to tailor G_{max} zonation to specific foundation types, e.g. jacket foundations.

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