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# Upscaling 1 500 000 synthetic CPTs to voxel CPT models of offshore sites

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ABSTRACT: In 2020, the Dutch government published 1 500 000 synthetic CPT profiles for use in development of the Hollandse Kust (west) Wind Farm Zone, offshore Netherlands. The scale of this approach was novel at that time and possibly first-ever. The synthetic CPT profiles were derived from a training data set of 122 actual CPTs and ultra-high-resolution (UHR) seismic reflection traces, using machine learning by a convolutional neural network. The synthetic CPT profiles were limited to positions along the 162 UHR survey track lines (2D) and were limited to cone resistance to a depth of 50 m below seafloor. The UHR track lines were spaced at about 400 m. This paper explores upscaling the synthetic CPT approach to voxel (3D) models and adding (S)CPT-based parameters such as shear modulus at small strain $G_{max}$. Future added-value is expected from post-2020 improvements seen in seismic reflection data resolution, attribute extraction and neural network architecture.

## 1 INTRODUCTION

Reducing ground risk is important for the development of an offshore wind farm. This requires understanding of the geological and geotechnical conditions to depths in the order of 30 m to 100 m below seafloor (BSF), depending of type of support structure for the wind turbines.

The understanding of ground risk is typically expressed by a ground model or multiple ground models (ISO 2021). These models typically rely on integrated interpretation of geological information, geophysical (UHR and UUHR multichannel seismic reflection) data and geotechnical data (particularly cone penetration tests, CPTs.

Since the 1990's, there has been increasing focus on deriving geotechnical properties directly from geophysical data using methodologies developed in the oil and gas industry (e.g. Nauroy et al. 1998). More recently, trials were made with synthetic CPTs and geo technical properties generated by interpolating CPT data between investigated locations (Forsberg et al., 2017) and using statistical methods and multi-attribute regression through an artificial neural network (Sauvin et al. 2019). The general approach is covered by ISO 19901-10 Marine Geophysical Investigations (ISO 2021).

This paper describes the status quo for 2020 and explores future opportunities for upscaling the synthetic CPT approach. The status quo is presented by an example in the public domain (www.offshorewind.nl): the Hollandse Kust (west) Wind Farm Zone, HKW WFZ (Figure 1), offshore Netherlands (Fugro 2020a and 2020b). HKW WFZ data acquisition, data analysis and advice were largely completed in 2019 and 2020. The 1 500 000 synthetic CPT profiles were generated at no schedule impact. DNV GL (2020) sees this cutting edge development as *'a huge step forward in terms of project area overview with respect to geotechnical site conditions and also as a valuable tool to improve and understand the correlation between future geological, geophysical and geotechnical investigations.'*

## 2 HOLLANDSE KUST (WEST) WIND FARM ZONE

The site for the HKW WFZ is located approximately 53 km from the Dutch coast, covering an area of roughly 176 km2 in water depths ranging from 18 m to 36 m LAT.

Ground model input mainly included:
- Geological information;
- Geophysical data: multibeam echosounder, side scan sonar, magnetometer, sub-bottom profiler and 2D-UHR single channel and multi-channel

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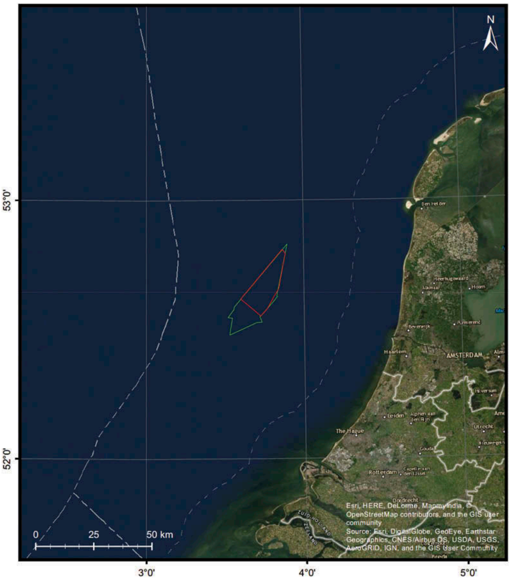


Figure 1. Location of the future Hollandse Kust (west) Wind Farm Zone.

seismic reflection data. The data were acquired according to a draft version of ISO (2021);

– Geotechnical data acquired from 57 boreholes with sampling and cone penetration testing (CPT) to a maximum depth of 90 m below seafloor (BSF), 122 seafloor CPTs to a maximum depth of 56 m BSF, 30 seafloor seismic cone penetration test to maximum depth of 56 m BSF, and laboratory testing. The data were acquired according to ISO (2014).

The acquired geophysical and geotechnical data were integrated into a traditional quasi-3D ground model, with seismic reflections tied to geotechnical boundaries derived from seafloor CPT and borehole information (Figure 2). The ground model comprised eight geological soil units, each having a distinct seismic character and spatial distribution.

Figure 2 provides cross sections that illustrate how the traditional ground model was enhanced by 1 500 000 synthetic CPT (cone resistance) profiles and associated error predictions to 50 m below seafloor (Carpentier et al. 2021). The presented cross section has a length of 11 500 m with 4 actual CPTs and about 9000 synthetic CPTs to a depth of 50 m.

The HKW WFZ synthetic CPT profiles were derived from a training data set of 122 actual CPTs and ultra-high-resolution seismic reflection traces, using machine learning by a convolutional neural network. The synthetic CPT profiles were limited to positions along the 162 UHR survey track lines (2D). The UHR track lines were spaced at about 400 m.

Figure 3 shows example checks on predictions. In general, the predicted and measured net cone resistance values showed reasonably good agreement, particularly in the upper 20 m BSF. Below 20 m, prediction was more trend-type. In addition, a trend-type prediction also applies to transitional and strongly layered (<1 metre scale) soil. It can be concluded that the prediction quality for the synthetic CPTs is such that added value can be derived to enhance the general ground model. The HKW WFZ prediction quality is inadequate for geotechnical design.

Reasons for the observed trend-type predictions include data conditioning, resolution of 2D-UHR seismic reflection data and limitations in refinement of the interpreted geological units. Data conditioning was applied by down sampling the CPT data to align

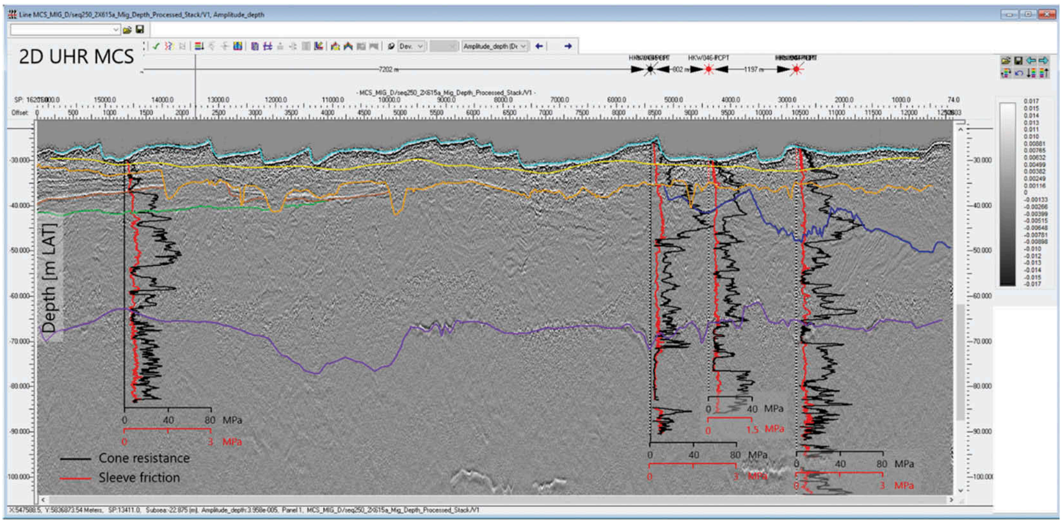


Figure 2a. Example of integrated interpretation of 2D-UHR multi-channel seismic line, aligning geophysical horizon interpretation to identified geotechnical boundaries from seafloor CPT and borehole data.

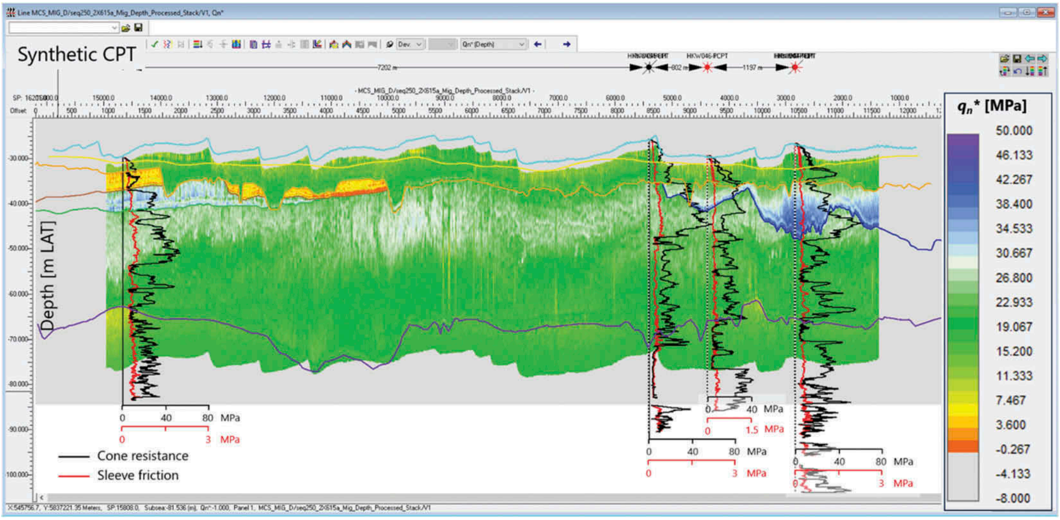


Figure 2b. Predictions of cone resistance (qn*) from 2D-UHR seismics (colors ranging from orange to purple) plotted together with measured cone resistance (black traces) and sleeve friction (red traces). See Figure 2a for comparison.

with vertical resolution of the 2D-UHR seismic data (i.e. sample rate of 0.1 m for prediction input versus 0.02 m as measured). Down sampling reduces net cone resistance effects of soil layering. The resolution of the 2D-UHR seismic data decreases with depth. This also affects the ability to identify additional geological units. This effect becomes more pronounced below approximately 20 m BSF.

As expected, training of the convolutional neural network showed decreasing prediction accuracy with increasing lateral distance between the seafloor CPT location and the nearest seismic trace along the 2D-UHR line. This is particularly significant where the correlation distance for spatial soil variability is less than the distance between the seafloor CPT location seismic trace selected for training.

Figures 3 and 4 illustrate prediction quality by means of a quality indicator per geological unit. It can be seen that the lower limits of the quality indicator can provide statistical values for $q_n$* that fall outside credible ranges for these specific soils.

## 3 UPSCALING

### 3.1 *Opportunities for future added value*

The following opportunities for upscaling are discussed:

– Enhanced geophysical interpretation
– Improved data pairing for training
– Impact of technology developments
– Predictions for multiple parameters
– Voxel model by geo-statistics
– Voxel model by 3D geophysics

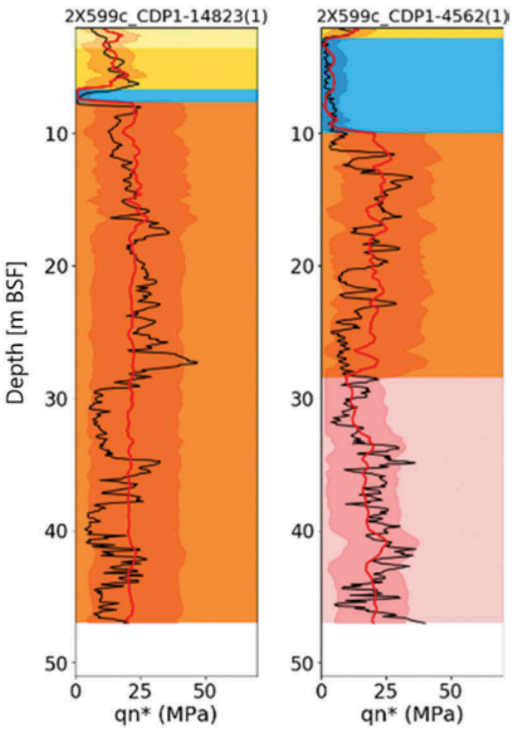


Figure 3. Comparison of actual net cone resistance (black line) versus synthetic net cone resistance (red line). The red halo represents the interval in which predictions are likely to fall (5th and 95th percentiles of the error misfit). Other colour infills indicate geological units.

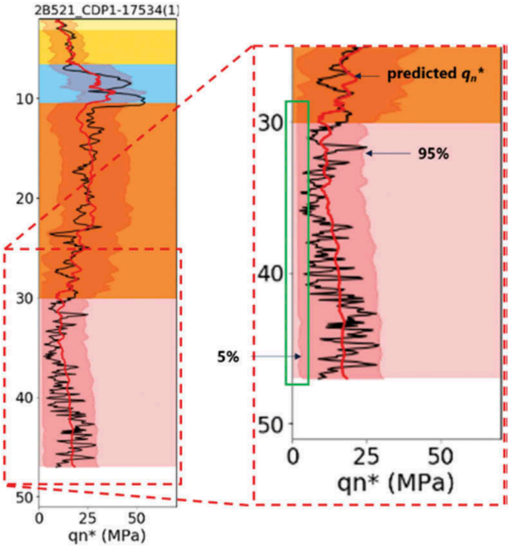


Figure 4. Statistical values for $q_n^*$ that fall outside credible ranges (green box).

The opportunities can be considered individually. However, combinations are expected to lead to a step change in added value.

The following sections discusses potential opportunities for a time window of 2020 to 2025.

### 3.2 *Enhanced geophysical interpretation*

Figure 2b Indicates that the synthetic CPTs can allow for further refinement of the geological model. This, in turn, helps steering future, turbine-specific geotechnical data acquisition, increasing safety and cost-efficiency.

For example, light green colours can be seen between approximately 40 m and 50 m LAT. These strength insights (i.e. trends in net cone resistance) may justify refining the geological model at this depth, by assigning a new geological soil unit to encompass these geotechnical conditions. It should be noted that this potential additional geological soil unit could not be identified from 'regular' seismic data (e.g. seismic amplitudes) alone. The example also indicates that synthetic CPT results (1) can give further insight into potential soil heterogeneity, (2) may aid in identifying areas of higher geotechnical uncertainty and (3) can identify where geotechnical conditions deviate from regional trends.

### 3.3 *Improved data pairing for training*

Quality of input data is important for success of machine learning.

Attention should be given to accuracy of spatial positions of paired data derived for actual CPT locations and seismic reflection data points: the closer the better. Particularly, logging of spatial trajectories of deep CPTs should be considered, compared to conventional assumptions for a vertical CPT. Seismic reflection survey should consider specific positioning of the source(s) and specific positioning of multiple points along the streamer(s). This is particularly important for situations where correlation distance for soil spatial variability is limited.

Mitigation options for pairing of spatially distant data can include point-specific matching checks and adjustments, using marker points in the profiles.

### 3.4 *Impact of technology developments*

For marine geophysics, significant technology developments are taking place, with high potential for added value in de-risking for ground conditions. For geophysical data acquisition, these include improvements in acoustic sources and streamer control. For processing methodology, notable improvements include de-ghosting algorithms, multiple removal algorithms and velocity models). These improvements will result in opportunities for very high resolution data and high quality seismic attributes.

Fast developments are taking place in neural network architecture. Technology developments for marine soil investigation (CPTs, other in situ testing and laboratory testing) are expected to be 'incremental', i.e. at a slow pace compared to marine geophysics and neural network architecture.

### 3.5 *Predictions for multiple parameters*

The HKW WFZ choice for synthetic profiles for cone resistance is obvious: input cone resistance data are accurate (Peuchen & Terwindt 2015) and typically show good correlation with geological units and other geotechnical parameters. Shear modulus at small strain $G_{max}$ is another candidate for synthetic predictions. Comments for $G_{max}$ are as follows:

- $G_{max}$ is an important parameter for geotechnical design of monopiles used for support of offshore wind turbines;
- $G_{max}$ is a low-strain soil parameter. Seismic reflection data are also low-strain and good predictive capability would seem obvious;
- Good predictive capability may be impeded by higher uncertainties (compared to CPT cone resistance) for actual $G_{max}$ profiles (Parasie et al. 2022) required for training a neural network. Actual $G_{max}$ values are typically derived from seismic cone penetration tests. These tests rely on time and distance measurements. Data processing requires estimates of input soil density. Premises include theories on acoustic wave propagation and assumptions about heterogenous soil behaving as an isotropic elastic medium.

### 3.6 *Voxel model by geo-statistics*

Commonly (2022), visualisation of a ground model is by means of 2D cross sections and 2D charts, i.e. in pixels. In some cases, 3D visualisation (e.g. Figure 5) is implemented, allowing interpretation in terms of voxels. Voxel data are typically generated by geo-statistics on a soil-unit basis. Synthetic CPTs can enhance this approach.

An important consideration is the volume of data. Can the information be made available within tight schedules required for energy transition? Can it be easily assessed for decision making?

### 3.7 *Voxel model by 3D geophysics*

ISO 19901-10 Marine Geophysical Investigations (ISO, 2021) covers acquisition of 3D UHR seismic reflection data. Currently (2022), acquisition of these data in the foundation zone (upper 100 m BSF) is performed only for occasional offshore wind sites, with some indications of growth in applications of this technology. The availability of 3D UHR seismic reflection data in combination with generation of synthetic geotechnical parameters has the potential for a step-change in voxel ground models and associated added value to offshore developments.

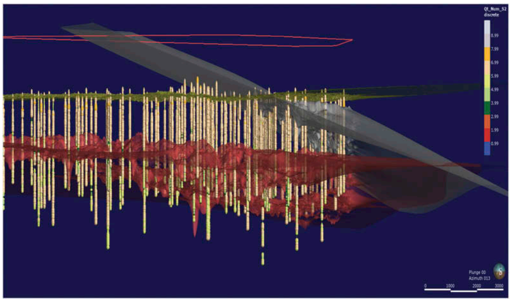

Figure 5. Excerpt of 3D HKW WFZ model in Leapfrog (Seequent, 2021) software.

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