Developing robustly predictable high resolution ground models by improving site investigations through machine learning applications & data analytics for offshore wind farms

Introduction

The integrated workflow discussed in this abstract is a combination of two-2 step approaches for creating predictive models for understanding the shallow sediment distribution effectively and to reduce the related uncertainty when it comes to designing and feasibility of piling foundations for Offshore Wind Farms. It is important to mention here that this workflow is essential and driven by the generation of answer products for reducing uncertainty on the foundation installation of Offshore Wind Farms, by creating predictive sediment models and use of these in estimating capacity for foundational installations. In Step 1 a predictive forward sediment-cum-stratigraphic model is used for creating a robust understanding of the shallow sediment distribution, associated with shallow sediments with mechanical properties and estimating foundation strength capacity of the area of interest. In the second step, the predictive shallow sediment model is used for integration with assisted property modelling, which helps in the data-driven distribution of key properties deciding the feasibility for foundation installation.

The forward stratigraphic modeling approach has been used to predict the sediment distribution across the Area of Interest (AOI) which helps in creating iterations-based simulations and representative models which capture the range of sediment types and associated rock properties. The forward stratigraphic modeling workflow may be integrated with several input datasets for creating representative and fit for piling iterations for reducing the foundational uncertainty for wind farm installations in an offshore environment. These inputs may vary from pre-existing installations and sediment information in the vicinity of a planned wind farm installation, to shallow seismic data which can help largely in the calibration of predictive models and increasing near reality predictability for offshore installations.

It is important to mention here that this part of the workflow will help in preserving the hard data points of CPT test data as calibration indexes with the value proposition of highlighting the potential application of robust sediment distribution of results away from these data points. In addition, it is also a key point to highlight that the potential CPT sediment boundaries can be used as key markers for creating and preserving the spatial distribution of such transitional interfaces across an Area of Interest (AOI). The forward sediment models, as part of this workflow, will also result in the generation of not only near slope bathymetric profiles but can also help largely in predicting the internal morphology of stratigraphy on high-resolution scales for making better feasibility plans on foundations.

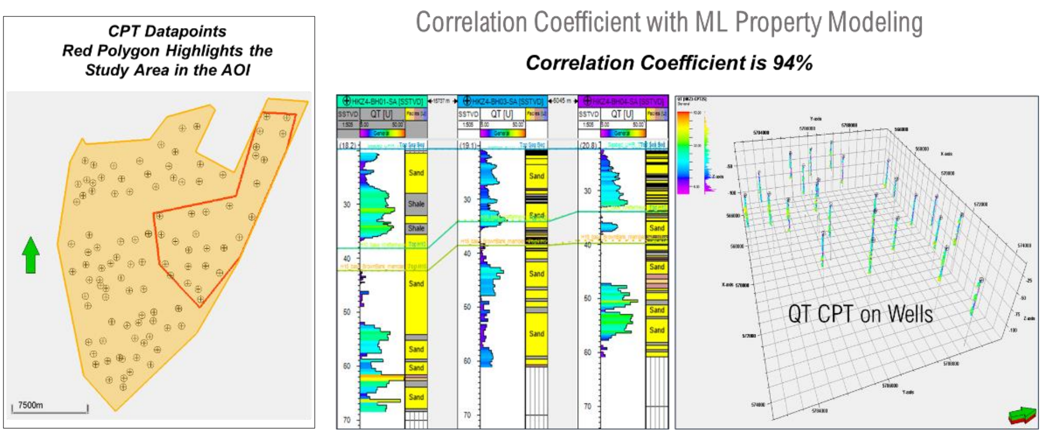

Figure 1 *The Area of Interest (AOI) shows the datapoints for geotechnical properties along with the availability of the Qt CPT property upscaled on the ground model for property distribution.*

Method and/or Theory

This workflow comprises of two step approaches; in which the first step is to create a predictive forward stratigraphic model using geological processes and in the second step a machine learning predictive property modeling workflow using random forest is used for propagation of geotechnical and CPT properties which are being conditioned to the sediment predictive model in the first step.

The forward stratigraphic predictive model helps in the generation of a robust predictive model which is based on the conditioning parameters of physical geological processes i.e., diffusion, steady flow, unsteady flow etc. The forward stratigraphic model also helps in the generation of several iterative simulations on the prediction of sediments based on the different lithological units added in the workflow. The forward stratigraphic model also helps in generation of key areas of geotechnical and CPT calibration points with the well calibration integration on extremely fine resolution grids. This not only helps in generating fine grid resolution for the sediment model but also helps in the preservation of the fine scale prediction to be integrated and ingested into the property modeling workflow in the later step. The forward stratigraphic model is also creating time step realizations for the sediment prediction hence making it comparable with the high layer resolution on the property grid.

Once the forward stratigraphic model is calibrated and generates the predictive realizations it is then used in the assisted property modeling step. In the machine learning solution of property modeling the predictive sediment model is used to guide the CPT and geotechnical properties by generating 100's of random forest realizations for each sample point. Hence the final property model is a combination of several training targets which was the sediment model in this case along with seismic generated volumes and the predictive targets which were the distribution of CPT and Geotechnical properties.

The assisted property modeling which is used in the second part of the workflow cycle where predictive shallow sediment models drive the overall distribution trends with the help of input data gives a full insight on documenting the risk areas for installations and potential foundational challenges, highlight the potential expected profiles across a larger area for future expansion of wind farms and helping in the generation of the dynamic database for regional scale wind farm installations. The CPT test data points can be used as upscaled logs for model scale distributions after performing the related QA / QC steps. The assisted property modeling will generate critical answer products like quantiles and uncertainty volumes for de-risking the piling foundations for offshore wind farms. The value proposition is by generating stochastic cellular models on high resolutions for planning and screening of potential sites.

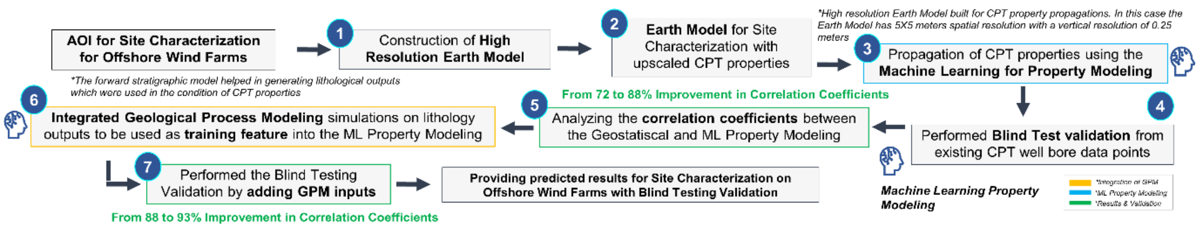

Figure 2 *This is an example of the implemented workflow where a ground model for offshore wind farms site characterization was populated for geotechnical and cone penetration test (CPT) properties using the Machine Learning property modeling workflow which was then later conditioned to a forward stratigraphic model for making inferences on sediment distributions. In the final step blind testing validation was performed with pre and post comparison of distributed properties using geostatistical algorithms and machine learning property modeling regression analysis. Improvements were observed in the correlation coefficients in cases where machine learning property modeling was used with conditioning of forward stratigraphic modeling.*

The site characterization workflow used the Machine Learning property modeling workflow to distribute the Cone Penetration Test (CPT) properties like cone resistance etc using the regression analysis. In the later part, the Geological Process Modeling (GPM) outputs like lithofractions were used in the regression analysis.

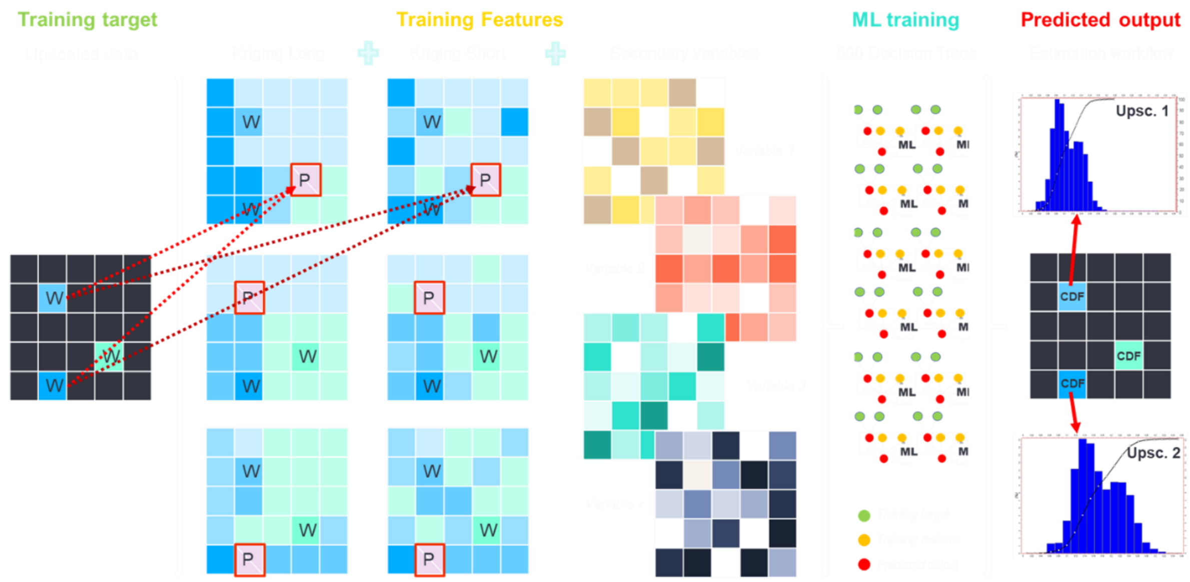

Figure 3 *Conceptual framework of the machine learning property modeling workflow highlighting the training targets and training features used in the machine learning workflow for creating trained decision trees to make predicted outputs.*

The workflow helped to reduce the turnaround time for modeling by 30 % as compared to the conventional way of property distribution. In addition, the model prediction increased from 72 to 93 %. The results observed by the integration of Machine Learning Property Modeling workflow show significant improvement within the CPT properties correlation coefficients which when compared to the geostatiscal model shows an improvement from 0.72 to 0.88. In the later step the Geological Process Modeling inputs were used within the workflow as training features which further improved the workflow for correlation coefficients from 0.88 to 0.93 hence confirming the blind testing validation up to 93 % predictability on the model.

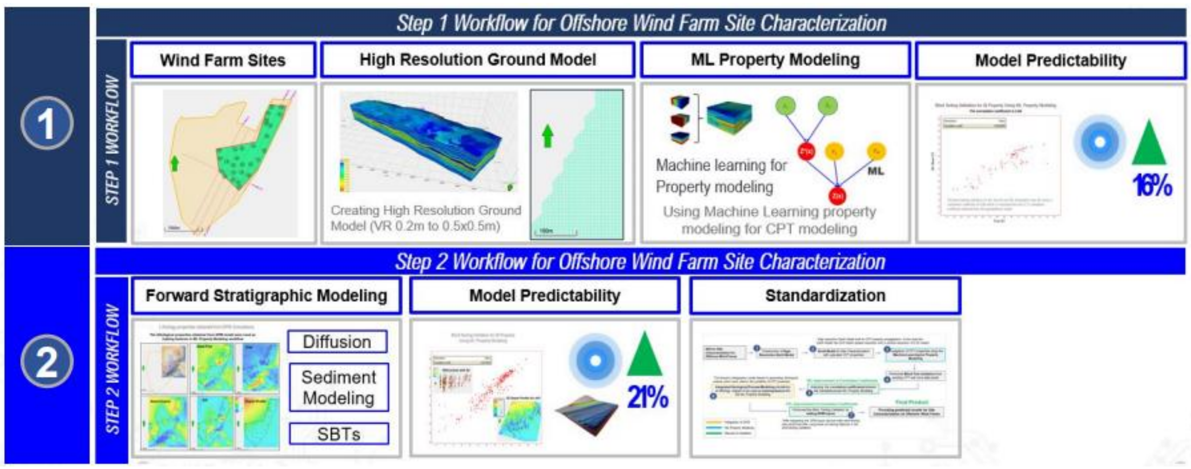

Figure 4 *Integrated workflow for creating high resolution ground models for offshore wind farm using machine learning application and data analytics for creating predictions.*

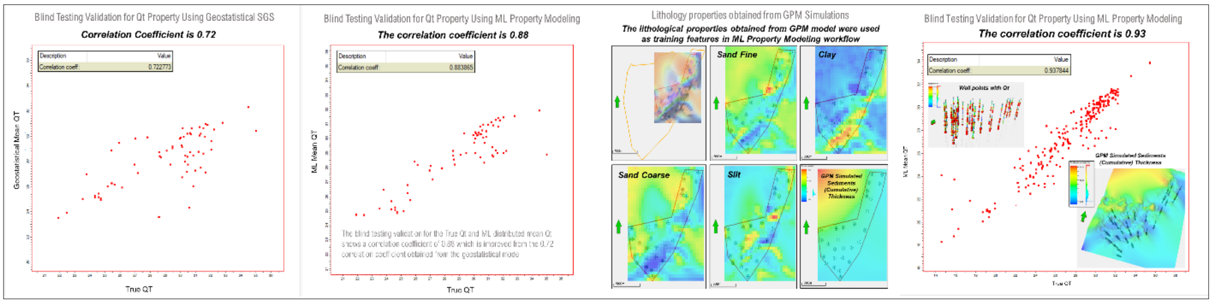

Figure 5 *This is an example of the results observed by the integration of Machine Learning Property Modeling workflow shows significant improvement within the CPT properties correlation coefficients which when compared to the geostatiscal model shows an improvement from 0.72 to 0.88. In the later step the Geological Process Modeling inputs were used within the workflow as training features which further improved the workflow for correlation coefficients from 0.88 to 0.93 hence confirming the blind testing validation up to 93 % predictability on the model.*

Conclusions

The combined workflow presented in this abstract is integration between predictability of stratigraphic sediment modeling which is later integrated with data-driven assisted property modeling giving key insights into the distribution patterns of geotechnical properties. It is quite evident that by integrating both these components we can deliver better less uncertain and fully quantified results at scale for planning, installation, and post-monitoring updates for offshore wind farms.

Acknowledgements (Optional)

We would like to acknowledge RVO for providing the Hollandse Kust (Zuid) public dataset for testing and validation of the detailed workflow.

References

A, Ahmad., et al., Applying Forward Stratigraphic & Machine Learning Property Modeling for Site Characterization of Offshore Wind Farms