

Visualisation of Probabilistic Access Forecasts for Offshore Operations

C Gilbert, J Browell and D McMillan

University of Strathclyde, 16 Richmond St, Glasgow G1 1XQ, UK

E-mail: ciaran.gilbert@strath.ac.uk

Abstract. Access forecasting aims to predict the quality of transfer of maintenance technicians to/from vessels and the constituent offshore structures at the wind farm. This is highly dependent on sea state conditions as well as other environmental factors such as visibility. Typically, scheduling or dispatch decisions are made on the basis of deterministic forecasts of significant wave height, often coupled with service contracts where transfers are expected to be attempted below a threshold significant wave height. However, there is always uncertainty in a weather prediction which can be accounted for by probabilistic forecasts. The aim of this work is to explore visualisation ideas for transforming vessel specific access forecasts into an interpretable and intuitive decision-support tool. Three simple methods are proposed based on a score out of 10, classification of transfer conditions, and a threshold score. Methods for summarising access conditions for 2–5 days ahead are also developed. This new forecasting and visualisation capability has significant implications for marine coordinators and skippers who will be able to make better informed safety-critical decisions, with the potential for reductions in the cost-of-energy offshore.

1. Introduction

Access forecasting for offshore wind farm operations is critical to ensure safe transfer of maintenance technicians to and from turbines and to maximise turbine availability. Improving access can reduce the cost of operations and maintenance (O&M) as well as construction costs. O&M is estimated to represent 25% of the levelised cost of offshore wind energy [1]. Independent studies show that that improved access to the turbine could comfortably shave £15m from the operating costs of an offshore wind farm [2]. Improved access in tandem with improved prognostic capability from condition monitoring has the potential to unlock even greater savings. However, the pressure to achieve increased access to the turbine implies a greater number of marginal-weather crew transfers, which potentially carry a greater safety risk. Improved access is especially valuable to the industry as the offshore fleet ages and life extension initiatives kick in, necessitating many more crew transfers for inspection and to deal with increased failures in late life.

In order to achieve O&M cost savings while maintaining high levels of safety, this project seeks to develop a new crew transfer access forecasting capability within the context of the wider decision-making processes which govern and incentivize behaviour on site. Information flows from assets, weather forecasts and data systems must be assimilated by the marine coordination team, who then form part of a crucial decision-making chain along with crew transfer vessel (CTV) skipper and crew, and finally maintenance technicians. Typically, these



scheduling/dispatch decisions are made on the basis of single-valued (deterministic) forecasts of significant wave height, often coupled with service contracts where transfers are expected to be attempted below a threshold significant wave height. However, there is always uncertainty in a weather prediction which can be accounted for by probabilistic forecasts. The economic benefit of probabilistic forecasting in O&M decision making has demonstrable value [3].

To forecast the quality of a CTV transfer given uncertainties in the ocean conditions requires vessel specific forecast scenarios of motion during transfer. Given this information content, the goal of this paper is to outline ways to best visualise forecasts for end-users. The communication of uncertainty forecasts is crucially important; one of the main barriers to uptake by industry (and therefore decision-makers) of uncertainty forecasts is the lack of clear communication of information content [4]. Stakeholders in this project have indicated that simplicity is key and that condensing complex information into the simplest form would help decision-makers uptake this information into their workflow.

Scenario forecasts [5] (i.e. trajectories) are required to inform time-dependent decision making [4], such as the case here. Consider that access to the turbine at one narrow point in time is not sufficient as technicians require to be dropped off, complete work, and picked up again before the end of the available work window. Since meteorological forecast errors can persist in time, if the forecast is incorrect at one time point then it is likely to be incorrect *in a similar way* at the adjacent time step. Therefore, uncertainty in the forecasts must be accounted for and linked between time horizons. This is the purpose of scenario forecasts and necessitates their inclusion in this study. Scenario forecasts can be compared to the more familiar physical ensemble forecasts which alternatively can be used in this type of application [4], although site specific ensemble re-calibration would equally be necessary [6]. The focus of this work is in transforming vessel specific scenario forecasts into a digestible format for decision-makers.

The site of interest is an east coast wind farm in the UK, from which we have historical forecasts from the European Centre for Medium Range Weather Forecasting (ECMWF), ocean measurements from a wave buoy, and vessel motion data including over 700 crew transfers.

This paper is organised as follows: Section 2 covers some background on how to obtain vessel specific scenario forecasts. Section 3 describes the problem and Section 4 details the proposed solutions. These are followed by discussion points in Section 5, and conclusions are drawn in Section 6.

2. Generating Vessel Specific Forecast Scenarios

For more information on this stage the reader is referred to related work by the authors [7]. The approach can be summarised in two stages: 1) post-processing of weather forecasts to generate site-specific forecasts; this involves mapping the relationship between concurrent measurements of the sea state from a measurement buoy at the site and the corresponding historical Numerical Weather Predictions (NWP) and 2) creating a crew transfer model which learns the relationship between the vessel motion during push-on and the corresponding met-ocean measurements from the wave buoy. Both stages involve statistical learning techniques to find patterns in the data and map the complex relationships. The block flow diagram in Figure 1 illustrates the modelling stages and how they interlink with each other, including the both the sources and streams of data used, for the training and operational stage of the decision-support tool.

Site specific post-processing of NWP data is known to significantly increase accuracy of the forecasts [8]. This involves using the historic NWP forecasts and observations (e.g. wave buoy or met mast) to identify systematic biases in the NWP and remove them from subsequent forecasts. In this study probabilistic forecasts are generated for each variable of interest (significant wave height and peak wave period) to quantify forecast uncertainty. Both quantile regression and parametric distribution regression are considered.

To refine the forecasting model, clustering is used to separate distinct sea states. In this

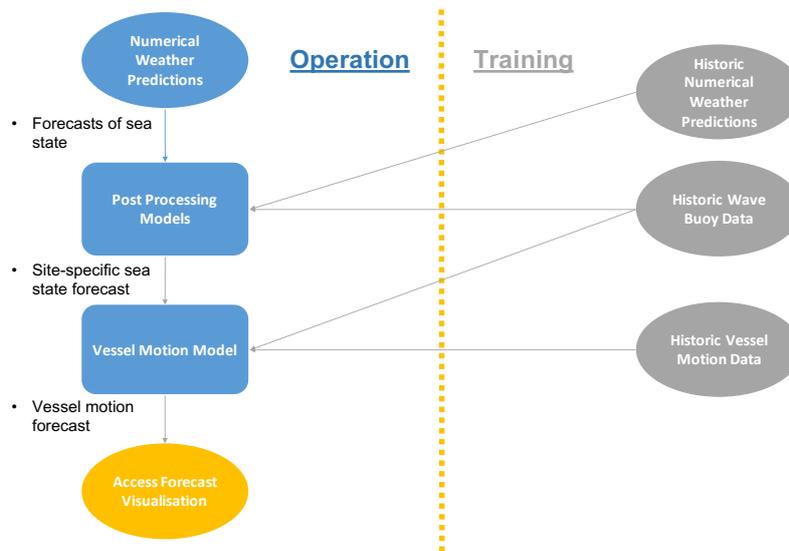


Figure 1. Summary of methodology to generate vessel specific scenarios

case, when either locally generated wind waves or swell from the North Sea dominate. Weather forecasts are used to predict the probability of cluster membership via logistic regression. This allows wave direction to enter the vessel motion modelling process in a straightforward manner.

An example of a probabilistic forecast of significant wave height for up to 5 days ahead is presented in Figure 2. The forecast has a high degree of confidence for the first 4 days for the forecast horizon, after which uncertainty increases significantly. The widest interval stipulates that there is a 90% chance that the observation will fall in this region at each time step.

To use post-processed forecasts as inputs to a vessel motion model, the joint distribution of each time horizon must be estimated using the marginal distributions (i.e. Figure 2) and a copula function [5]. Samples with the correct temporal dependency structure can then be drawn

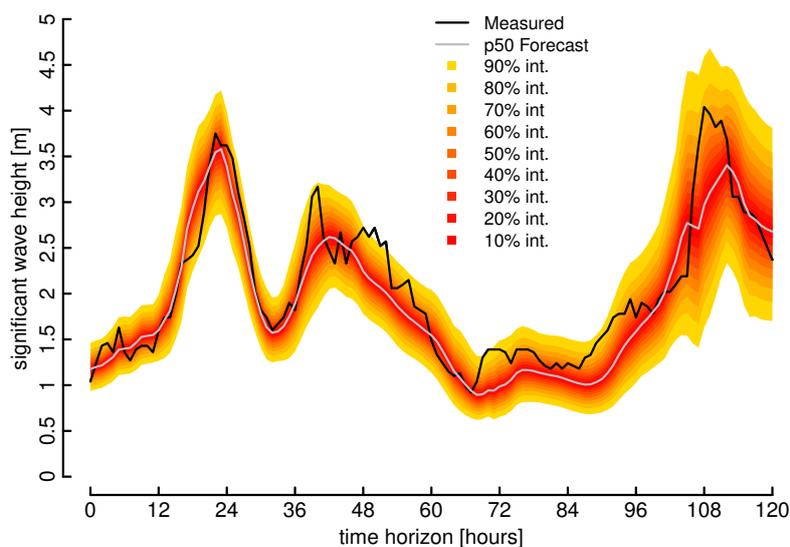


Figure 2. Example post-processed density forecast of significant wave height

from the joint distribution and used as temporal scenarios to a vessel motion model.

Accessibility is constrained by vessel motion during transfer, which is driven by the sea-state, and interactions between waves, the vessel and transition piece. Here we adopt a data-driven approach to estimate vessel motion during transfer. Data from two vessels with identical hull design comprising of detailed vessel motion and push-on instances (≈ 700) is available and has been analysed alongside corresponding buoy measurements and weather forecasts. There is a clear relationship between heave peak-to-peak vessel motion, which is a crucial metric for successful transfers, and the significant wave height measurements of the buoy — as shown in Figure 3. A large portion of the variation seen in Figure 3 is explained by other variables such as wave period and direction. To model the observed heave-to-peak versus observed sea-state distributional models are generated using general additive models for location, shape, and scale [9]. The relationship between sea state and vessel motion is used to forecast vessel motion during transfer from sea-state scenarios up to 5 days ahead. The next stage of this process, and the focus of this paper, involves innovative communication of forecast information content to end-users.

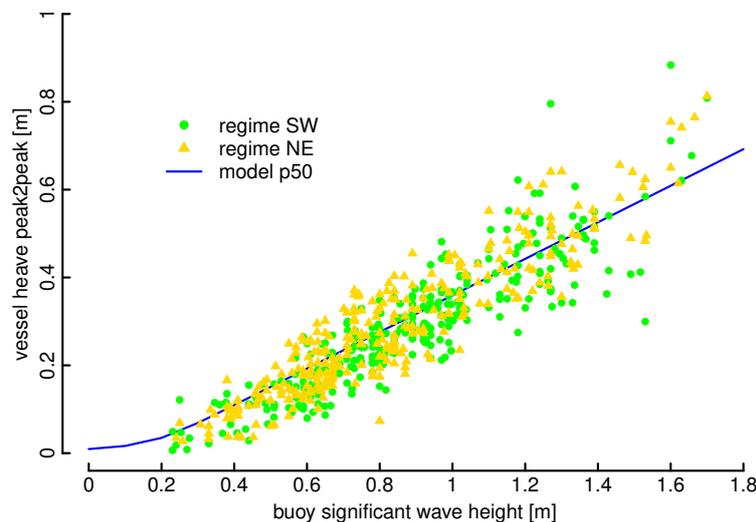


Figure 3. Vessel motion and measured significant wave height. Sea state is divided into two regimes defined on wave direction depending on whether to prevailing wave direction is from the South West (SW) or North East (NE). Blue line shows the median of the model fit in the south west regime.

3. Motivation for Forecast Visualisation Stage

The raw output of the vessel motion model driven by forecast scenarios of the sea-state is shown in Figure 4 and clearly illustrates the motivation behind this study. Although these equally-likely scenarios are useful for driving scheduling or dispatch tools, they present difficult information content for human interpretation. Note the similarity of the forecast profile compared to Figure 2.

Another important aspect to consider which motivates transformation of the forecasts is that often the forecast significant wave height is beyond the maximum measured wave height during transfer. This is understandable given that in reality a CTV skipper would not attempt a transfer in conditions which are unsafe. So beyond vessel heave peak to peak values of $\approx 0.9\text{m}$ access predictions should reflect that there is zero chance of a successful transfer. Forecasts must then be transformed to adhere to the physical reality of the problem.

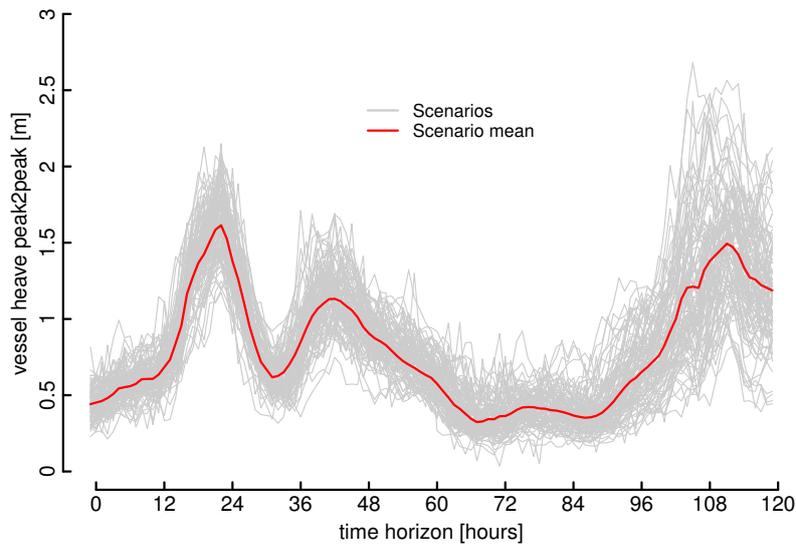


Figure 4. Scenario or trajectory forecasts contain temporal dependency structure that is important to consider in sequential decision making across extended periods of time; however, they are difficult to interpret in this form. Only 10% of the generated scenarios are plotted here.

4. Visualisation Options

This section proposes some methods to transform the vessel specific forecasts into more interpretable and realistic access scores. First it is important to consider what the end user requires; from discussions with industrial partners, marine coordinators desire simplicity from a decision support tool. To achieve this three simple functions are proposed to transfer the forecasts, based on a score out of 10, classification of access conditions, and a threshold score. The purpose of this paper is not to find the best method for communicating information content, it is to propose methods which can be built upon more rigorously in the future, and to introduce visualisation methods to the end-users for feedback. The plots described are implemented in R using the base graphics package and `ggplot2` [10, 11].

The user-defined functions for transforming the vessel scenarios into the score out of 10 and access classification are shown in Figures 5 and 6 respectively. The value used for the third

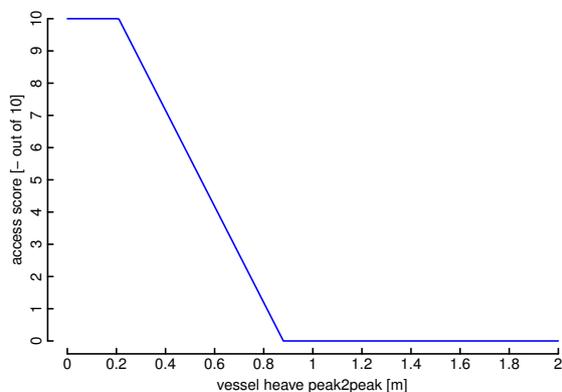


Figure 5. Example function for transforming scenarios into a continuous access score

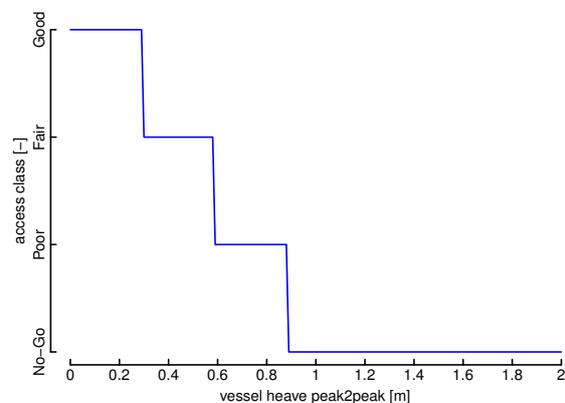


Figure 6. Example function for transforming scenarios into an access classification

method, i.e. the threshold access score, corresponds to a significant wave height value of 1.5m, which sites use operationally to define the maximum value for CTV accessibility. These scores are all flexible and can be user-defined based on the vessel capabilities, specific mission, experience of the site, and appetite for risk, for example.

The detailed forecast visualisation focuses on the 1-day-ahead region with further horizons summarised to the right of the main plot. This opens up the issue of summarising further horizons (2–5 days) information content; three ways of presenting this information are proposed. These are defined as the number of access days available, the number of available weather windows, and a panel plot showing more detailed information. This essentially gives 9 different propositions of visualising these forecasts as any combination of the 1-day-ahead forecast can be combined with three further horizon methods.

In Figure 7 an example of the continuous access score is shown in good access conditions, with further horizons summarised by the number of upcoming access days. This is the simplest of all the options described here and early feedback from marine coordinators have indicated a general preference for this visualisation based on analysis of the three proposed options. The advantages are obviously the simplicity and therefore ease of interpretation. Site and vessel experience are essential for defining the score function.

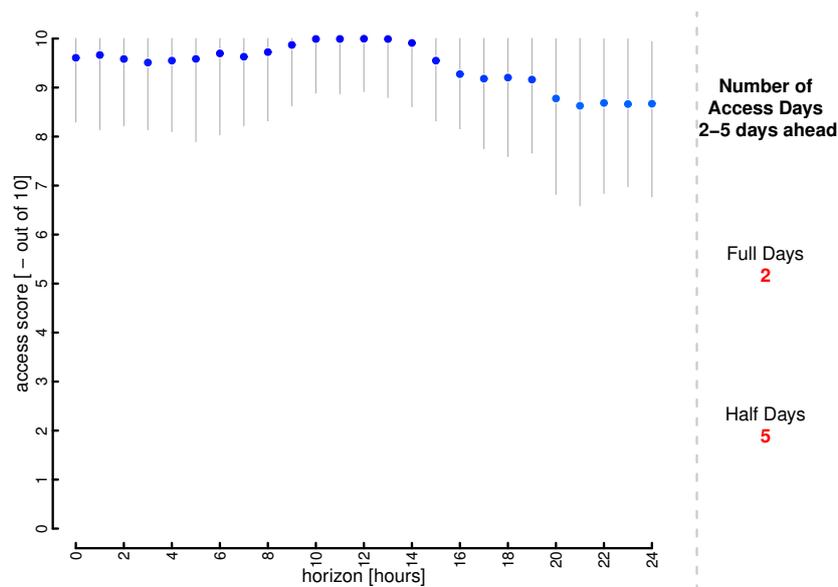


Figure 7. An example visualisation of a ‘transfer quality’ forecast. Large vessel motions and/or other factors deemed to degrade transfer quality result in a reduction in the score from a maximum of 10. The use of probabilistic forecast enables the uncertainty on this score to be quantified and communicated to the decision-maker. Longer-term forecasts of accessibility is shown for context: if this is the only chance of access for a long time, potential weather windows are more valuable. This plot indicates good access conditions.

An example of the access classification forecast is shown in Figure 8 in variable access conditions. Here the bars quantify the percentage of scenarios belonging to each class at every time step. Further horizon information is presented as the number of available weather windows for access. The advantages of this method is that every scenario produced here is accounted for and therefore the end user views a complete picture of the spread of possibilities at every time step. Additionally, the further horizon information would suit a more opportunistic operations scheduling method because the length of weather windows is flexible and user-defined. The

disadvantages of this method is that it is not as immediately intuitive compared to the other visualisation tools.

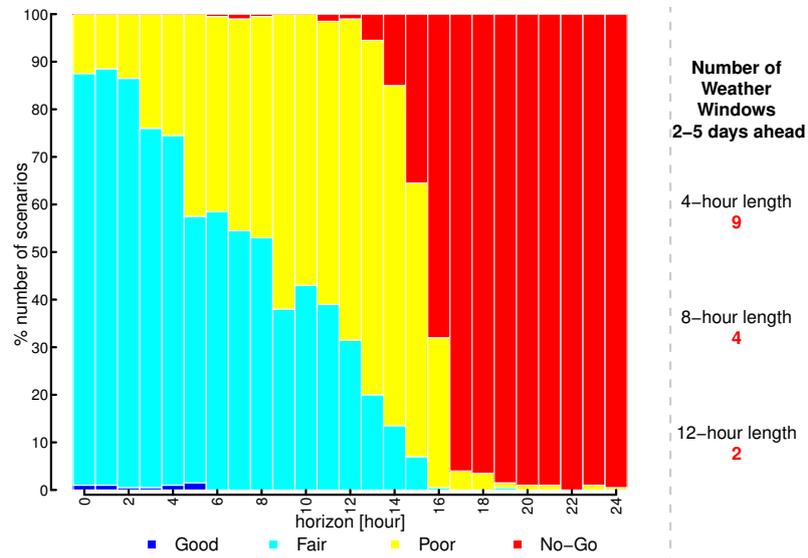


Figure 8. Similar to Figure 7 but scores are classified into descriptive categories. Note that all scenarios are visualised at each time step in this case. Slightly more detailed contextual information is provided in the left panel. This plot indicates variable access conditions.

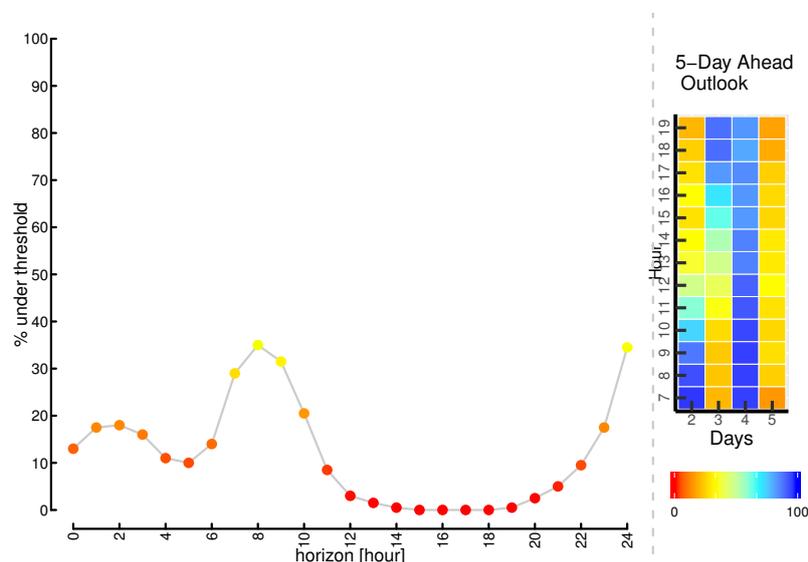


Figure 9. Threshold access score, where the limit is set approximately to the maximum observed vessel motion in 1.5m significant wave height. High values correspond to good access conditions. Further horizons shown in more detail via a panel plot where the colour of each panel corresponds to the percentage under threshold. This plot indicates poor access conditions.

Figure 9 is an example of the threshold score in bad access conditions. The plotted points quantify the percentage of scenarios under the defined limit; this means that high percentages

are desirable for access. Details on conditions further into the horizon are shown with more detail via a panel plot where the colour of each panel indicates the threshold score over the next 4 work-days. However, the extra detail is clearly valuable. In Figure 9 good access conditions are clearly visible the following working morning and 4 days ahead which would enable more informed scheduling dispatch decisions immediately. The main advantages of the threshold access score are that it could be easily incorporated within existing contractual vessel access limits and that this visualisation tool is not as sensitive to the user-defined score function. The disadvantage of this score is that it doesn't inform of the spread of the scenarios, consider that 90% of scenarios could be just below the threshold limit.

5. Discussion & Future Work

On marginal access days the opportunity cost of lost revenue can be large if they are followed by days of windy conditions with poor access. It was envisioned at the outset of this visualisation work that access forecasts would be shown concurrently with power forecasts, as shown in Figure 10. Other methods were considered such as a cost/loss model and real-options decision tools. However, operators are currently understandably reluctant to consider power forecasts alongside access forecasting as it implies a potential trade-off between revenue and safety. Alternatively, this information could be used in retrospective analysis to better understand the impact of vessel dispatch decisions and this aspect is reserved for future work.

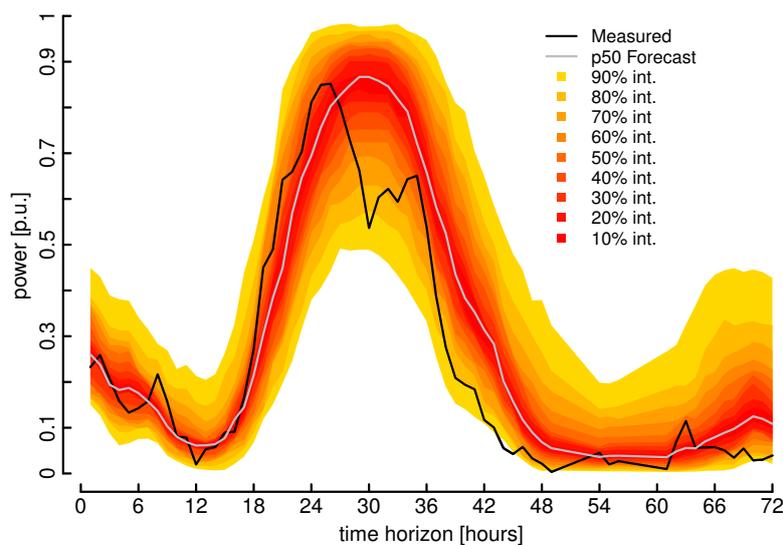


Figure 10. An example of a probabilistic power production forecast and out-turn

There are some crucial environmental factors for access quality which are also left for future work such as lightning risk, visibility, and wind speeds for craning. The intention of this work is to visualise the access forecast information content based on essential factors of wave height, period, and direction. For example, access scores in further work could simply be augmented to include lightning strike forecasts by simply over-riding the access scores to the minimum.

6. Conclusions

This work describes a visualisation strategy for forecasting access quality up to 5 days ahead considering vessel motion for offshore operations. Weather predictions are tuned via site-specific post-processing and forecast uncertainty is quantified using widely available historic data and

machine learning; please refer to [7] for more detail on the forecasting methodology. The raw output of the vessel motion model driven by forecast scenarios of the sea-state is transformed to better communicate information content. Three simple access forecasts are proposed based on a score out of 10, classification of transfer conditions, and a threshold score. The purpose of this paper is to propose methods which can be built upon more rigorously in the future, and to introduce visualisation methods to the end-users for feedback. This new forecasting and visualisation capability has significant implications for marine coordinators and skippers who will be able to make better-informed safety-critical decisions, with the potential for reductions in the cost of offshore wind energy.

Acknowledgments

This work is supported by the EPSRC Supergen Wind Hub project ORACLES, EP/L014106/1. The authors would like to thank Amine Hadjer, John Best, and Pete Leach at James Fisher Marine Services, Lars Johanning and Giovanni Rinaldi at Exeter University, Sally Shenton at Generating Better, and Christopher Briggs at SiemensGamesa for their excellent discussion points and feedback throughout this work. **Data Statement:** Due to confidentiality agreements with research collaborators, access to vessel motion data is restricted. Numerical weather predictions from ECMWF are available at www.ecmwf.int for qualifying research institutions or commercial customers. Wave buoy measurements from the Centre of Environment Fisheries and Aquaculture Science (CEFAS) are available at <http://wavenet.cefas.co.uk/>.

References

- [1] Shafiee M, Brennan F, Espinosa IA. A parametric whole life cost model for offshore wind farms. *International Journal of Life Cycle Assessment*. 2016;.
- [2] Catterson VM, McMillan D, Dinwoodie I, Revie M, Dowell J, Quigley J, et al. An economic impact metric for evaluating wave height forecasters for offshore wind maintenance access. *Wind Energy*. 2016 2;19(2):199–212.
- [3] Taylor JW, Jeon J. Probabilistic forecasting of wave height for offshore wind turbine maintenance. *European Journal of Operational Research*. 2018;.
- [4] Bessa R, Möhrle C, Fundel V, Siefert M, Browell J, Haglund El Gaidi S, et al. Towards Improved Understanding of the Applicability of Uncertainty Forecasts in the Electric Power Industry. *Energies*. 2017;10(9):1402.
- [5] Pinson P, Madsen H, Papaefthymiou G, Klöckl B. From Probabilistic Forecasts to Statistical Scenarios of Short-term Wind Power Production. *Wind Energy*. 2009;12(1):51–62.
- [6] Pinson P, Girard R. Evaluating the quality of scenarios of short-term wind power generation. *Applied Energy*. 2012;96:12–20.
- [7] Gilbert C, Browell J, McMillan D. Probabilistic Access Forecasting for Offshore Operations [in preparation]. 2019;.
- [8] Giebel G, Kariniotakis G. Wind power forecasting-a review of the state of the art. In: *Renewable Energy Forecasting: From Models to Applications*. Elsevier; 2017. p. 59–109.
- [9] Rigby RA, Stasinopoulos DM, Lane PW. Generalized additive models for location, scale and shape. *Journal of the Royal Statistical Society Series C: Applied Statistics*. 2005 6;54(3):507–554.
- [10] R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria; 2016. Available from: <https://www.r-project.org/>.
- [11] Wickham H. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York; 2016. Available from: <http://ggplot2.org>.