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Evaluating a novel approach to reliability decision support for offshore wind turbine installation

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ABSTRACT: This paper briefly describes a novel approach of estimating weather windows for decision support in offshore wind turbine installation projects. The proposed methodology is based on statistical analysis of extreme physical responses of the installation equipment (such as lifting cable loads, motions of lifted objects, etc.), subjected to offshore met-ocean environment and limited by maximum allowable responses of the equipment used. An important aspect of any novel methodology is evaluating how well it performs compared to the standard methods given the same input. Hence, the main focus of this paper is on benchmarking the new methodology against the standard method for weather window estimation—the *Alpha-factor* method proposed by (DNV, 2011). The evaluation is done in a form of synthetic case study—an offshore wind turbine rotor lift operation at the FINO3 met-mast location. Performance of both methods is measured in terms of number and length of predicted weather windows.

1 INTRODUCTION

Offshore wind industry is continuing to grow with new developments being pushed further offshore with expectations of greater power generation and already heavily developed near shore locations. The move further offshore implies increased expenditures related to transportation and installation of offshore wind turbine and their foundations, which already contribute 10–15% of the total capital expenditure of a wind farm (Brown, et al., 2015). In addition to that, Operation and Maintenance (O&M) activities typically contribute 25–30% to the total Levelized Cost of Energy (LCOE) of an offshore wind farm (Nielsen & Sørensen, 2011). Knowing that transportation costs are a major contributor—up to 73%, according to (Dalgic, et al., 2015)—to installation and O&M expenditures on a wind farm, it is important to estimate these costs accurately and reduce them as much as possible.

Majority of installation and O&M operations offshore are typically carried out by specialized ships and equipment that have to be hired for the duration of the operation. Ship lease costs are directly connected to the operation duration, which in turn is comprised of the time it takes to actually perform the required activities offshore and waiting time for suitable weather conditions (weather windows). Usually, the duration of offshore activities is clearly defined but changing met-ocean conditions limit the possibility to predict weather windows and waiting times. Predicting weather windows with higher accuracy would improve the estimates of transportation, installation and O&M costs of a wind farm and in turn could possibly reduce the LCOE of offshore wind energy.

1.1 *State of the art of weather window estimation and its drawbacks*

The state of the art for weather window estimation under uncertain met-ocean conditions offshore is application of the *alpha-factor* method in (DNV, 2011). The standard method is limited to use of simple met-ocean parameters such as wind speed and wave height, as indicators of whether the operation is safe to attempt, see section 3.4 and (DNV, 2011) for more details. However, the operational limiting factors are inherently physical—closely linked to physical properties and responses of the installation equipment and vessels, such as strength of liting cables, maximum alowable accelerations, motions and velocities of vessels and lifted components, etc.

Since weather forecasts used to predict the accessibility at an offshore location are not precise, the uncertainties related to weather forecasting have an impact on the quality of accessibility predictions. The alpha-factor methodology aims to account for these uncertainties and provide guidance on how to take them into consideration. However, the aforementioned uncertainties can be quantified quite well by multi-ensemble weather forecasts. Multi-ensemble weather forecasts are now available for industry use but cannot be taken into consideration when using the standard *alpha-factor* methodology. Nonetheless, it should be noted that (DNV, 2011) mentions that ensemble forecasts can be used as an alternative to tabulated *alpha-factors*, but the procedure is not explicitly defined.

1.2 *Proposed improvements to state of the art*

Computer software can be used to simulate installation equipment responses under given met-ocean conditions and statistical methods can be applied to assess the probabilities of occurrence of extreme responses. This would allow to move on from using simple met-ocean condition parameters to actual physical limitations of installation equipment/vessels as indicators of whether the operation should be attempted. Furthermore, since the proposed methodology uses statistical methods to predict weather windows, it is possible and desirable to use multi-ensemble weather forecasts instead of deterministic ones.

In addition to that, marine operations can be highly sensitive to the incoming wave period, but the current practice does not have explicit ways of taking wave periods into consideration. However, due to nature of the proposed approach, wave period is always used as an essential part of input for the simulation model, therefore it is always implicitly included in the analysis.

This paper briefly presents the novel methodology, see (Gintautas, et al., 2016) but the main focus is on assessing whether the new approach can be used in decision support for offshore wind turbine installation in place of (or as an addition to) the standard a*lpha-factor* methodology. The evaluation is done in a form of synthetic case study of a floating offshore wind turbine rotor lift operation at the FINO3 met-mast location (research meteorological measurement mast located in the North Sea). Performance of both methods is measured in terms of number and lengths of predicted weather windows.

2 PROPOSED METHODOLOGY

A full description of the novel approach for weather window estimation can be found in (Gintautas, et al., 2016). This section gives a brief overview of the proposed methodology with Figure 1 showing the general workflow chart.

Generally, the procedure follows these steps:

1. Developing a simulation model for the offshore operation using hydrodynamic simulation software of choice (Abaqus/Aqua, SIMO, etc.).
2. Retrieving multi-ensemble weather forecasts for the period in question.

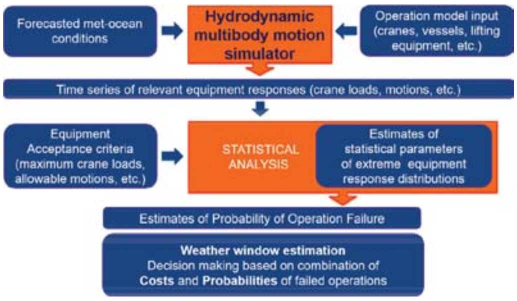

Figure 1. Flowchart of the proposed methodology, adopted from (Gintautas, et al., 2016).

3. Simulating the installation equipment response using forecasted met-ocean conditions as input and retrieving the time series of relevant responses.
4. Extracting extremes of relevant responses from simulated time series and estimating parameters for extreme response distributions.
5. Estimating the probabilities of relevant responses exceeding their respective *acceptance criteria*.
6. Estimating the total probability of operation failure by combining the probabilities of individual *acceptance criterion* exceedance events.
7. Obtaining weather windows suitable for successful operation by comparing the total probability of operation failure with the maximum allowable probability of operation failure recommended by (DNV, 2011) – 10^{-4}.
8. Comparing alternative weather windows based on their individual risk (a combination of probability of failure and monetary consequences), given that consequences in monetary terms are available.

It should be mentioned that the probability of failure and the resulting weather window predictions are directly linked to weather forecasts used for the analysis. This implies that the quality of said predictions depends on the quality and accuracy of initial weather forecasts.

3 EVALUATION OF THE NOVEL APPROACH

Due to limited availability of real data related to accessibility of offshore installation locations, the evaluation of the proposed methodology is done in a form of a synthetic case study. A description of the case study, forecasted met-ocean conditions and the evaluation procedure is given in this section.

3.1 *Test case and it's physical limitations*

Offshore rotor lift operation of the Hywind demo wind turbine was chosen as a test case. The model was developed in SIMO software and provided by MARINTEK (Vatne & Helian, 2014). It consists of a floating barge with a heavy lift crane, wind turbine rotor positioned on the barge and a floating wind turbine foundation-tower. The rotor is lifted off the barge, positioned in front of the nacelle and bolted to it, see Figure 2. When the barge is positioned at the installation location, the whole operation takes 1 hour to complete.

Although this particular rotor lift operation is more complex and weather sensitive than typical wind turbine installation operations using jack-up vessels to install onto fixed wind turbine foundation-towers, it was chosen as a reasonable representation of operations wind turbine industry will be performing in the near future.

Since the proposed methodology for weather window estimation focuses on analysis of physical responses of the installation equipment, Table 1 shows a summary of the critical responses and limits related to them.

3.2 *Test location and weather forecasts*

The location for the test case had to satisfy a few conditions to be feasible, namely:

- It has to be covered by ECMWF (European Centre for Medium-Range Weather Forecasts) weather forecasts.
- Measurements of met-ocean conditions should be available at the location.
- The location should be close to actual operating or planned wind farms.

FINO3 meteorological mast location in the North Sea (55° 11,7' N - 007° 09,5' E) satisfied the requirements—multiple planned and operating offshore wind farms in close proximity (see Figure 3), a ECMWF grid point nearby (55° 15' N - 007° E) and met-ocean condition measurements on site—thus it was selected for the test case.

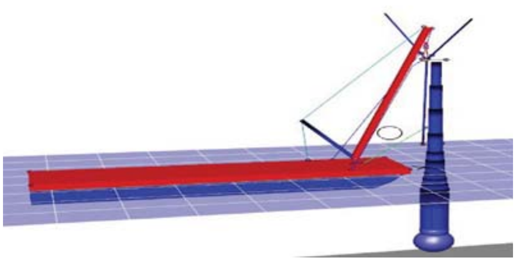

Figure 2. Hywind demo rotor lift test case. Rotor is lifted of the barge and ready to be bolted to the nacelle.

Having forecasts and measurements at the same location allows for a more comprehensive evaluation of the proposed methodology. Measurements at the test site could be interpreted as a "perfect forecast" implying exact predictions of weather windows with no uncertainty. Comparison of the number and length of weather windows obtained using uncertain ECMWF weather forecasts as input for simulations with the ones obtained using measurements gives insight on how weather forecast uncertainties affect weather window predictions.

The summer of 2014 was selected for the test period, more specifically May 1st to August 1st, 2014. Weather forecasts were retrieved and updated daily (at 00:00 hour) as it would be done during

Table 1. Physical limitations of Hywind rotor lift operation.

Critical response	Acceptance criteria
Airgap between blades and wave crests	> 3 m
Crane loads	< 6375 kN
Lift wire tension	> 0
Acceleration of rotor	< 4.8 m/s^2
Rotational acceleration of rotor	< 6 rad/s^2
Rotor sway and surge motions of lifted rotor	< 2 m
Airgap between blade 3 and tower	> 0 m
Yaw and tilt angle of lifted rotor	< 5 degrees
Relative angle between rotor and special tool	< 5 degrees
Relative radial velocity	< 0.4 m/s
Relative axial velocity	< 0.1 m/s

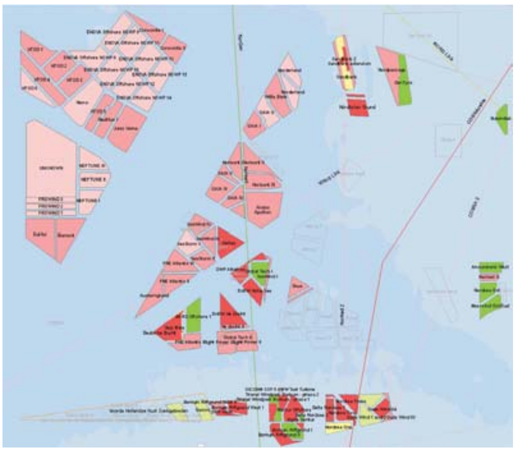

Figure 3. FINO3 and wind farm locations at North Sea, adopted from (4C Offshore, 2016).

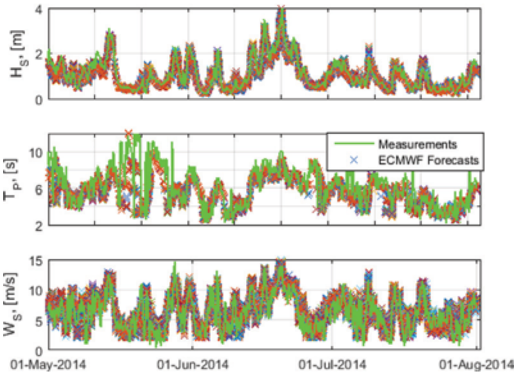

Figure 4. Weather conditions for the test period @ Fino3 location. Green lines—measurements from FINO3 met-mast, scatter—51 ensemble members of ECMWF forecasts.

day-to-day planning of offshore installation operations, see Figure 4.

Using all 51 ensemble members of the ECMWF weather forecasts to simulate installation equipment response gives a good grasp on the expected variability (uncertainty) of the responses under given weather forecast. Consequently it is assumed that 51 ensemble members are sufficient to cover the weather forecasting uncertainties and translate them into uncertainties of installation equipment responses.

3.3 *Weather restrictions of Hywind rotor lift operation*

In order to transparently evaluate the performance of the novel methodology of weather window estimation, all analyzed test cases have to be based on identical input—same location, weather conditions and operation limiting factors. Same location and input weather condition requirements are covered by using data from FINO3 location. However, leveling the operation limiting factors is more complicated—it is necessary to link multitude of physical limitations of Hywind rotor lift operation (Table 1) to limits on maximum allowable weather conditions for successful operation. This was done by simulating the operation with SIMO software with an array of possible weather conditions as input and analyzing the output time series. By comparing the simulated responses with their respective *acceptance criteria* from Table 1, it is possible to identify the weather conditions suitable for successful operation—e.g. looking into Crane Load time series and identifying whether the response is below (safe state) or above (failed state) the limit of 6375 kN. Weather conditions

Table 2. Weather restrictions of Hywind rotor lift operation.

Wave height H_s, [m]	Wave peak period T_p, [s]	Wind speed W_s, [m/s]
1.5	5	7

under which *all* relevant responses from *Table 1* are below their respective *acceptance criteria* were considered safe. Table 2 shows the weather restrictions of Hywind rotor lift operation.

It should be kept in mind that typically when multiple environmental limits are present a contour surface plot could be used to describe all possible combinations of weather limits. However due to multitude of different *acceptance criteria* in Table 1 and complex interactions between them, only the marginal case where all *acceptance criteria* are satisfied is presented in Table 2.

3.4 *Alpha-factor methodology and site specific alpha-factors*

The standard method to estimate weather windows for offshore operations is the a*lpha-factor* method in (DNV, 2011). The essence of the standard methodology is using an *alpha-factor* to reduce the weather restrictions of the operation thus making them more conservative. The reduction is done to account for uncertainties in weather forecasting. (DNV, 2011) gives sets of tabulated *alpha-factors* dependent on the duration, weather limits of the operation and the quality of weather forecasts. In practice *eq. (1)* is used to define operational weather restrictions for a given operation and weather forecast:

$$OP_{LIM,WF} = \alpha_{OP_{Lim}} \cdot OP_{LIM} \tag{1}$$

where $OP_{LIM,WF}$ = operational environmental limiting criteria (e.g. wave height or period); $OP_{LIM,WF}$ = forecasted operation limiting criteria; $\alpha_{OP,Lim}$ = factor accounting for uncertainties in weather forecasting ($\alpha_{OP,Lim} < 1$).

Alpha-factors for wave height and wind speed are explicitly given in the standard, however, no *alpha-factors* for wave period are given. Since the test case operation is highly sensitive to incoming wave period it is imperative to take uncertainties of wave period forecasting into consideration. Furthermore, (DNV, 2011) clearly states in note **B 703** that "<…> if the operation is particularly sensitive to some wave periods, uncertainty in the forecasted wave periods shall be considered". This can be done by estimating a site specific *alpha-factor* for wave periods using measurements and wave period forecasts at FINO3 location.

The typical procedure of using tabulated *alpha-factors* can be substituted by statistical analysis of weather forecasts and measurements. The methodology used to define tabulated *alpha-factors* in (DNV, 2011) can be found in (DNV JIP, 2007) and (Wilcken, 2012) and will be further used as basis to estimate site specific *alpha-factors*. Knowing that *alpha-factor* is a measure of uncertainty related to weather forecasting, measurement and weather forecast data, if properly analyzed, can be used to define specific *alpha-factors* for any given location. Generally, the *alpha-factor* is defined as follows:

$$\alpha_{OP_{Lim}} = \frac{OP_{Lim,Max}}{OP_{Lim,Max,Wf}} \tag{2}$$

where $\alpha_{OP,Lim}$ = *alpha-factor* for a given weather restriction (eg. wave height or period) of the operation; $OP_{Lim,Max}$ = maximum met-ocean condition (e.g. wave height or period) with a probability of exceedance of 10^{-4} during a certain period; $OP_{Lim,Max,Wf}$ = maximum met-ocean condition with a probability of exceedance of 10^{-4} during a certain period, taking into account the bias and variance of the weather forecast.

Maximum expected met-ocean conditions, $OP_{Lim,Max}$ or $OP_{Lim,Max,Wf}$, can be estimated from their respective distributions, assuming that maximum values have 10^{-4} probability of exceedance. For wave height and wave peak period, respectively:

$$1 - P(H \le H_{Max/Max,Wf}) = 10^{-4} \tag{3}$$

$$1 - P(\tau \le T_{Max/Max,Wf}) = 10^{-4} \tag{4}$$

where $H_{Max/Max,Wf}$ and $T_{Max/Max,Wf}$ correspond to $OP_{Lim,Max}$ and $OP_{Lim,Max,Wf}$ in eq.(1).

Here it should be noted that in principle it is possible to use a joint distribution function of wave heights and periods instead of the marginal ones. However, *alpha-factor* methodology uses individual *factors* for different met-ocean criteria (wind speed and wave height) thus, for the sake of consistency, definition of separate *alpha-factors* for wave period and wave height was necessary. Knowing that (DNV, 2011) does not provide explicit guidance on how wave periods should be incorporated in the analysis and following the methodology from (DNV JIP, 2007) and (Wilcken, 2012), marginal distributions were used.

H_{Max} *and* T_{Max} can be estimated from their short term distributions—Rayleigh and Bretschneider distributions respectively. Rayleigh is typically used as distribution of the heights of successive individual waves, conditioned on significant wave height of a certain sea state, and is defined as follows, see e.g. (Liu & Burcharth, 1998):

$$P(H \le H_{Max}) = \left[1 - e^{\left(-2\frac{H^2}{H_s^2}\right)}\right]^{\frac{t_f}{T_P}} \tag{5}$$

where H_s = significant wave height of a given sea state; T_p = wave peak period of a given sea state; t_f = duration of the sea state, in this case t_f = 3h = 3600s; H_{max} = expected maximum wave height.

Based on (Wist, 2003) and (Clauss, et al., 1994) the Bretschneider distribution can be used as a good descriptor of successive wave periods during a given sea state. The Bretschneider distribution is defined by the following equation:

$$P(\tau \le T_{Max}) = \left[1 - e^{\left(-0.675\frac{\tau^4}{T_{m01}^4}\right)}\right]^{\frac{t_f}{T_P}} \tag{6}$$

$$T_{m01} = \frac{T_P}{1.2} \tag{7}$$

where T_{m01} = mean wave period; H_{max} = expected maximum wave height; τ = wave period of successive waves.

Obtaining $H_{Max,Wf}$ and $T_{Max,Wf}$ is more complicated—it is necessary to take full weather forecasting uncertainty into account. This can be done by integrating the joint probability density functions for wave heights and wave periods:

$$p(H, H_S) = p(H \mid H_S) \cdot p(H_{S,F}) \tag{8}$$

$$p(\tau, T_P) = p(\tau \mid T_p) \cdot p(T_{P,F}) \tag{9}$$

where $p(H, H_s)$ = joint probability density function of wave height H and significant wave height H_s; $p(\tau, T_P)$ = joint probability density function of wave period τ and wave peak period T_P; $p(H|H_s)$ = conditional probability density function of wave height H—Rayleigh distribution, *eq. (4)*; $p(\tau|T_P)$ = conditional probability density function of wave period τ—Bretschneider distribution, *eq. (5)*; $p(H_{S,F})$ = probability density function of forecasted significant wave height $H_{s,F}$, assumed to be normal distributed with mean value of $H_{s,F}$ adjusted for bias and standard deviation of H_s forecasting, *eq. (10)*; $p(T_{P,F})$ = probability density function of forecasted wave peak period $T_{P,F}$, assumed to be normal distributed with mean value of $T_{P,F}$ adjusted for bias and standard deviation of $T_{P,F}$ forecasting, *eq. (14)*.

$p(H_{S,F})$ and $p(T_{P,F})$ are assumed to be Normal distributed as defined in *eq. (10)* and *eq. (14)* with parameters estimated from weather forecasts:

Table 3. Site specific alpha-factors for FINO3 location.

	Wave height ($H_{s,Lim} = 1.5$ m)	Wave peak period ($T_{P,Lim} = 5$ s)
Alpha-factor	0.81	0.78

$$p(H_{S,F}) = N(\mu_{H_{S,F}} + b_{H_{S,F}}, \sigma_{H_{S,F}}) \quad (10)$$

$$H_{S,F,error} = H_{S,forecasted} - H_{S,measured} \quad (11)$$

$$E\left[H_{S,F,error}\right] = b_{H_{S,F,}} = \frac{1}{n}\sum_{i=1}^{n} H_{S,F,error} \quad (12)$$

$$\sigma_{error,H_{S,F}} = \sqrt{\frac{\sum (H_{S,F,error} - E\left[H_{S,F,error}\right])^2}{1-n}} \quad (13)$$

$$p(T_{P,F}) = N(\mu_{T_{P,F}} + bT_{P,F}, \sigma_{error,T_{P,F}}) \quad (14)$$

$$T_{P,F,error} = T_{P,forecasted} - T_{P,measured} \quad (15)$$

$$E\left[T_{P,F,error}\right] = b_{T_{P,F}} = \frac{1}{n}\sum_{i=1}^{n} T_{P,F,error} \quad (16)$$

$$\sigma_{error,T_{P,F}} = \sqrt{\frac{\sum (T_{P,F,error} - E\left[T_{P,F,error}\right])^2}{1-n}} \quad (17)$$

where $p(H_{S,F})$ and $p(T_{P,F})$ = probability density functions of the forecasted parameter in question (significant wave height or peak period); $\mu_{HS,F}$ and $\mu_{TP,F}$ = mean value of the significant wave height and peak period, estimated from weather forecasts; $\sigma_{error,HS,F}$ and $\sigma_{error,TP,F}$ = standard deviation of the error terms; $b_{HS,F}$ and $b_{TP,F}$ = forecasting biases; $H_{S,forecasted}$ and $T_{P,forecasted}$ = forecasted significant wave height and peak period; $H_{S,measured}$ and $T_{P,measured}$ = measured significant wave heigh and peak period.

$H_{Max,Wf}$ and $T_{Max,Wf}$ are estimated from *eq. (18–19)*:

$$1 - \int_0^{H_{\max,Wf}} \int_0^{\infty} p(H \mid H_S) \cdot p(H_S) dH_s dH = 10^{-4} \quad (18)$$

$$1 - \int_0^{T_{\max,Wf}} \int_0^{\infty} p(\tau \mid T_P) \cdot p(T_P) dT_P d\tau = 10^{-4} \quad (19)$$

Applying *eq. (2–19*) to measured and forecasted met-ocean condition data for FINO3 location gives site specific *alpha-factors*, see Table 3.

3.5 *List of analyzed cases*

In order to properly evaluate the feasibility of the proposed new methodology, a comparison against the standard *Alpha-factor* method is done. Performance of both methods is measured in terms of number and length of predicted weather windows. Three cases from (DNV, 2011) are used as reference together with two cases where the novel approach is used, namely:

Table 4. Evaluation cases.

Method	Operation restrictions $H_S \le \alpha_{Hs} \cdot 1.5$ m	$T_P \le \alpha_{Tp} \cdot 5$ s	$W_S \le \alpha_{Ws} \cdot 7$ m/s
1 *α-factor*	$\alpha_{Hs} = 0.78$	$\alpha_{Tp} = 1$	$\alpha_{Ws} = 0.8$
2 *α-factor*	$\alpha_{Hs} = 0.78$	$\alpha_{Tp} = 0.78$	$\alpha_{Ws} = 0.8$
3 *α-factor*	$\alpha_{Hs} = 0.81$	$\alpha_{Tp} = 0.78$	$\alpha_{Ws} = 0.8$
4 Novel	$P_{F,Op} \le 10^{-4}$ with physical limits from *Table 1*		
5 Novel	$P_{F,Op} \le 10^{-4}$ with physical limits from *Table 1*		

Alpha-factor method with tabulated factors from (DNV, 2011) for wind speed, wave height. In this case $\alpha_{Tp} = 1$, knowing that (DNV, 2011) does not provide *alpha-factors* for wave period and assuming that wave peak period can be forecasted with no uncertainty (highly unlikely situation).

1. *Alpha-factor* method with tabulated factors from (DNV, 2011) for wind speed and wave height. In this case site specific $\alpha_{Tp} = 0.78$ for wave period is used—estimated using measurements and historical forecasts for FINO3 location.
2. *Alpha-factor* method with site specific *alpha-factors* for wave height and wave peak period and factor for wind speed taken from (DNV, 2011). In this case site specific $\alpha_{Tp} = 0.78$ and $\alpha_{Hs} = 0.81$ are used—estimated using measurements and historical forecasts for FINO3 location.
3. Novel approach using measurement data from FINO3 met-mast as input for the simulation model. This can be interpreted as a synthetic "perfect weather forecast" and allows evaluation of the effect of weather forecast uncertainty on weather window predictions.
4. Novel approach using ECMWF multi-ensemble weather forecasts as input for the simulation model. It is a good representation of a real-life situation when readily available weather forecasts would be used to predict future weather window opportunities.

Multiple reference cases (1–3) based on current standard practice gives a wider overview of the capabilities and limitations of the current methodology. In turn, comparison of those reference cases with the novel approach also provides insight on extended capabilities of the novel approach e.g. implicit and consistent inclusion of wave periods and wave period forecasting uncertainties into the analysis. All evaluation cases are summarized in the following Table 4.

4 RESULTS AND DISCUSSION

This section presents evaluation results of the proposed new methodology. Following Figures 5–6 show the predicted number and total length of weather windows for the test period (*1 May–1 August, 2014*). First 3 bars in the Figures represent first 3 test cases—different uses of *alpha-factor* methodology from (DNV, 2011). Bars 4–7 represent different uses of the proposed new methodology.

It is seen from the Figures 5 and 6, that there is a large influence of wave peak period uncertainty on the predicted weather windows. By comparing (1—*"perfect wave period forecast"*) and (2—*"wave period forecast with forecasting uncertainty"*) bars it can be stated with confidence that, at least for this specific operation, including uncertain wave peak period forecasts reduces the total number and length of predicted weather windows. Furthermore, since the 2nd and 3rd bars have the same heights in both Figures 5 and 6, this indicates that wave period is the leading limiting factor for this particular operation. This in turn indicates that it is necessary to include wave periods and wave period forecasting uncertainties when estimating weather windows, even though (DNV, 2011) does not provide tabulated *alpha-factors* for wave periods or explicitly explain how to include them into weather window analysis.

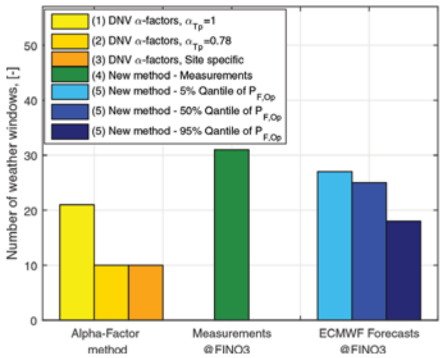

Figure 5. Evaluation results. Estimated number of weather windows for all 5 test cases. Test period 1 May–1 August, 2014.

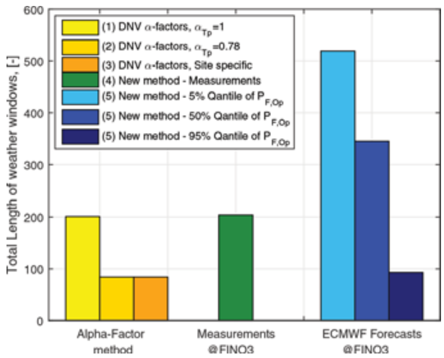

Figure 6. Evaluation results. Estimated total length of weather windows for all 5 test cases. Test period 1 May–1 August, 2014.

When it comes to evaluating the performance of the new methodology, it is important to note that the proposed methodology is based on probabilistic analysis of uncertain equipment responses, and consequently the resulting weather window estimates are also uncertain. The last 3 bars in the figures above show weather window estimation results using 5%, 50% and 95% quantiles of the total probability of operation failure ($P_{F,Op}$) distributions as basis. Moving from lower to higher quantiles results in less and shorter predicted weather windows but in turn implies more reliable results. For further comparisons, results obtained using 95% quantile of total probability of operation failure will be used, mainly because a high degree of confidence is necessary.

Comparing the total length of estimated weather windows for *case "3"* and the proposed methodology (with 95% quantile of $P_{F,Op}$) reveals that there is ~11% relative difference in favor of the novel approach (84 against 93 hours suitable for operation during the test period). When comparing the same cases in terms of number of predicted weather windows, there is even higher relative difference of ~80%—the proposed methodology predicts more weather windows. However, this difference can be attributed to the fact that the proposed methodology predicts larger number of shorter weather windows.

Another important investigated aspect was the impact that weather forecast uncertainty has on weather window predictions. As it was mentioned in previous sections, on-site measurements from FINO3 meteorological mast can be interpreted as a perfect weather forecast with *negligible* uncertainty. Using these measurements as input to operation simulation model and estimating weather windows based on simulation results gives an upper limit of the *best-case* performance of the proposed methodology. For this particular operation the theoretical upper limit would be 204 operational hours during the test period, or ~143% more operational hours when compared to *case "3"* of *alpha-factor* method. Even though it is impossible to have perfect forecasts of met-ocean conditions and reach the theoretical upper limit of performance, it can be stated that there is room for improvement. Numerous research activities are directed towards reduction of weather forecasting uncertainties—this would reduce the uncertainties of predicted total probability of operation failure and in turn the methodology would produce more and longer weather windows.

One more positive aspect of the proposed methodology is that it allows direct and transparent inclusion of weather forecasting uncertainty into weather window analysis—the uncertainties of weather forecasts are directly translated into uncertainty of total probability of operation failure and further into uncertainties of length and number of predicted weather windows.

5 CONCLUSIONS

This paper briefly presented a novel Reliability based decision support methodology for weather window estimation, with the main focus of the paper being on evaluation of the proposed methodology. The evaluation was done in a form of a synthetic case study—a floating offshore wind turbine rotor installation at FINO3 met-mast location. Even though the presented methodology is Reliability based, it can be easily extended to Risk based decision support by including consequences of operation failure in monetary terms and combining them with the total probability of operation failure. Also it is possible to use the proposed methodology for other offshore operation since the applicability is only limited by definition of equipment response limits and possibility to simulate those responses in terms of time series.

As a general conclusion it can be stated that the proposed methodology is performing better (with ~11% improvement in terms of total length of predicted weather windows for the test period in the example) than the standard *alpha-factor* method, described in (DNV, 2011). Even though an 11% improvement in predicted total length of weather windows is a significant improvement on its own, it should be kept in mind that the quality of decisions based on the novel approach is higher. This is simply due to use of multi-ensemble weather forecasts, covering the full range of expected weather conditions and including forecasting uncertainties, wave periods being an integral part of the analysis and simulating the actual behavior of installation equipment and vessels.

Furthermore, it can be stated that weather forecast uncertainty plays a central role in the number and duration of estimated weather windows. This claim is based on a comparison of "perfect" and "uncertain" weather forecasts for the same test period. More and longer weather window were obtained when using a "perfect weather forecast" case. This implies that that there is potential for even better performance of the proposed methodology if weather forecast quality is improved.

It should be noted that only one case study was performed in the evaluation phase. Therefore broad general conclusions have to be drawn with caution, simply because differences between *Alpha-factor* and the proposed new approach could partly be linked to this specific test case. Keeping this in mind it is still obvious that the proposed approach shows good promise and with further development could be used as decision support for offshore operations.

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