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Gintautas, Tomas; Sørensen, John Dalsgaard

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Influence of Met-Ocean Condition Forecasting Uncertainties on Weather Window Predictions for Offshore Operations

Tomas Gintautas, John Dalsgaard Sørensen
Department of Civil Engineering, Aalborg University
Aalborg, Denmark

ABSTRACT

The article briefly presents a novel methodology of weather window estimation for offshore operations and mainly focuses on effects of met-ocean condition forecasting uncertainties on weather window predictions when using the proposed methodology. It is demonstrated that the proposed methodology has the capacity to retain the uncertainties of met-ocean condition forecasting and transfer them into uncertainties of probability of operation failure. In addition to that, improvements to the failure function, used to define operation failure are presented. The failure function is modified to include stochastic variables, representing met-ocean forecasting uncertainties and the results of such modification are given in terms of predicted weather windows for a selected test case.

KEY WORDS: offshore, wind turbine, marine operations, transportation, installation, risk, probability, weather window, FORM, decision support.

INTRODUCTION

Typically, costs of installation of offshore wind turbines contribute significantly to initial capital expenditures (CAPEX) of an offshore wind farm. These costs can amount to 10-20% of CAPEX, according to (Brown, et al., 2015), (Esteva Fàbrega & Gomis Bellmunt, 2014) and (Moné, et al., 2015) and up to half of that can be attributed purely to costs of transportation equipment, (Fingersh, et al., 2006). Furthermore, as indicated in (Nielsen & Sørensen, 2011) and (Santos, et al., 2015), operation and maintenance costs contribute 25-30% to the total Levelized Cost of Energy (LCOE), where up to 73% of this contribution is again related entirely to costs of transportation systems. Since the European Commission set the 20-20-20 goals in 2008, among which the contribution of renewable energy in the total energy pool is expected to reach 20%, the total installed capacity of offshore wind turbines increased more than 7 times (from 1.5GW in 2008 to 11GW in 2015, according to (European Wind Energy Association, 2016)) and is expected to increase in the future. This implies that new offshore wind farms will have to move even further offshore, and the costs associated to installation and maintenance of such farms will increase accordingly.

All the aforementioned offshore operations are carried out by specialized vessels and equipment, that needs to be hired for the duration of the operation. Typically this duration includes the time it takes to perform the operation, transfer time from port to the farm and waiting time for suitable weather conditions. Generally, the duration of the operation and

the travel time to the farm is known from previous experience. However, it can be notably more difficult to estimate the waiting times for suitable weather conditions and the durations of weather windows themselves. With offshore wind farms moving further offshore, where the met-ocean condition forecasts can be considerably more uncertain, it is imperative to improve and validate the methodologies for weather window prediction in order to ensure that estimates of installation and maintenance costs of such farms stays as accurate and as low as possible.

Current practice in the industry for predicting weather windows (and waiting times) is the so called “*α-factor*” method, documented in (DNV, 2011). It uses basic met-ocean condition parameters (wind speed, significant wave height, etc.) as constraints for offshore operations. These *factors* are typically < 1 and thus make the operation constraints more conservative. However, the limitations of offshore operations are inherently physical – related to strength of installation equipment, maximum allowable motions of vessels and lifted objects, etc. Keeping in mind that operation limiting met-ocean parameters are typically determined in the design stage from numerical simulations of operation vessels and equipment response, the move from basic met-ocean condition constraints to physical operation limiting parameters would be even more reasonable. Furthermore, the *α-factor* methodology accounts for forecasting uncertainties (aleatory and epistemic) by introducing a set of tabulated *α-factors*. Currently it is possible to quantify these uncertainties in a transparent manner by using ensemble weather forecasts (from e.g. ECMWF) in combination with historical measurements of met-ocean conditions.

The methodology, briefly presented in this paper is an important improvement over the state of the art techniques because it relies on statistical analysis of offshore equipment response, in combination with maximum allowable equipment responses (maximum crane loads, motions and accelerations of vessels and equipment, etc.), to establish probabilities of operation failure and subsequently determine weather windows. It also uses ensemble met-ocean condition forecasts to quantify the forecasting uncertainties. Besides the brief presentation of the proposed methodology, the main objectives of the paper are as follows:

1. Investigate how the uncertainties and biases of offshore met-ocean condition forecasts affects weather window predictions.
2. Demonstrate the capabilities of uncertainty transfer within the proposed methodology.
3. Demonstrate how inclusion of additional stochastic variables, representing met-ocean condition forecasting uncertainties, in

the failure function definition can be used to reduce the computation power needed to estimate weather windows, when ECMWF ensemble weather forecasts are used as input to the model.

The paper is structured as follows. First, the proposed methodology is presented and modifications to it are described. In the same section, a description of the test case is given. Secondly, a section is dedicated to investigate the effects of weather forecasting uncertainties on weather window predictions and probability of operation failure. This section also serves as demonstration of capacity of the proposed methodology to retain and transfer met-ocean forecasting uncertainties to uncertainties of probabilities of operation failure. Thirdly, a section discussing the effects of updating the failure function with additional stochastic variables, accounting for statistical forecasting uncertainties, is given. Here the updated failure function is applied and results are presented and discussed. Finally, the results are summarized in the conclusion section.

METHODOLOGY AND TEST CASE SETUP

This section briefly describes the proposed methodology for weather window prediction, also a description of the test case is given. The goal here is to introduce the reader to the main ideas of the proposed methodology, while giving more details where it is necessary for the purposes of this paper. For a detailed description of the proposed methodology the reader is referred to (Gintautas, et al., 2016) and (Gintautas & Sørensen, 2016), where the initial methodology is presented in detail and evaluated, and to (Gintautas & Sørensen, 2017) where improvements to the methodology are described.

Proposed methodology

The methodology uses physical offshore vessel and equipment responses as basis for probability of operation failure calculations, which, in turn, can be compared to maximum allowable probability of failure to obtain weather windows. The following Fig. 1 shows the graphical representation of the proposed methodology, which can be summarized in the following steps, (Gintautas & Sørensen, 2017):

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 and location in question.
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 of extreme response distributions.
5. Estimating the probabilities of individual responses exceeding their respective acceptance criteria by solving limit state functions by FORM (First Order Reliability Method).
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} per operation.

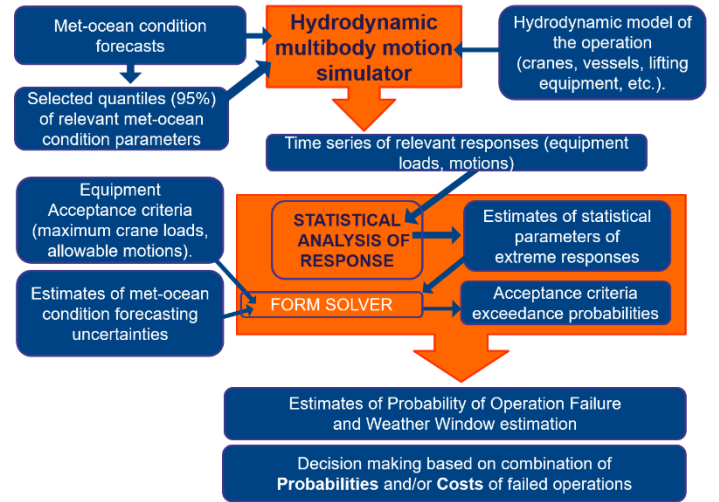


Fig. 1. Proposed methodology.

The methodology adopts failure function formulation for critical operation events in the form of Eq. (1) and uses FORM to solve these functions for probability of operation failure.

$$g(x) = X_R R(X) - X_E E(X) \quad (1)$$

Here X_R is uncertainty related to acceptance criteria definition and modelling, $R(X)$ is the acceptance criteria for particular equipment response (e.g. maximum allowed crane load, maximum allowed velocity/acceleration of lifted objects, etc.), X_E is the uncertainty related to equipment response modelling (e.g. hydrodynamic modelling uncertainties, weather forecast model uncertainty, etc.) and $E(X)$ models the relevant equipment response (crane load, acceleration and motion of lifted objects, etc.).

Such formulation of critical operation events allows relatively simple inclusion of modelling and other uncertainties to the weather window prediction model, by introducing additional stochastic variables. Having this capability makes it possible to use and evaluate the influence of met-ocean condition forecasting uncertainties directly, rather than by the use of an approximate α -factor, given that these uncertainties can be properly quantified. These uncertainties can be quantified using methods from e.g. (EN 1990, 2002) - by comparing the forecasted met-ocean conditions with measurements at the same location. The result of such comparison would be estimates of model biases and variance of model error terms for selected forecast components (e.g. significant wave height, period and/or wind speed). Then, based on the aforementioned forecasting model uncertainty estimates, stochastic variables, representing modelling uncertainties of each met-ocean forecast component, can be constructed and added to the failure function the following way:

$$g(x) = R(X) - \prod_{i=1}^{N_{par}} X_{Par,i} E(X) \quad (2)$$

Here $X_{Par,i}$ is the stochastic variable related to forecasting uncertainty of met-ocean parameter i , e.g. significant wave height or wind speed.

A significant shortcoming of the proposed methodology is that using multi-ensemble met-ocean forecasts requires hydrodynamic simulation of operation equipment responses of each individual forecast ensemble member. Since hydrodynamic simulations are quite time consuming, the total computation time requirements might be too high for the methodology to be practical. However, failure function definition in the form of Eq. (2) gives the opportunity to use estimates of forecasting uncertainties together with quantile estimates of forecasted met-ocean

parameters to obtain quantile estimates of probability of failure and, subsequently, quantile estimates of weather windows. This would allow simulation of installation equipment response using 1 set of forecasted met-ocean parameters (e.g. 95% quantile estimates of significant wave height, wind speed, etc.) instead of all 51 ensemble members of the ECMWF weather forecast. This approach will be discussed in more detail in Section 4 of this paper.

It should be noted here that uncertainty parameters related to equipment resistance modelling are not included in the analysis, and thus X_R is omitted from Eq.2.

Description of the operation model and equipment physical limits

The test case used in this paper is an offshore lift operation of Hywind Demo wind turbine rotor installation. The operation model consists of a barge coupled with heavy lift crane, a wind turbine rotor, positioned on the barge, and a floating foundation already positioned at the installation location. During the operation, a fully assembled wind turbine rotor is lifted up from the barge and mounted to the nacelle, positioned on top of a spar type floating wind turbine foundation, see Fig. 2 .

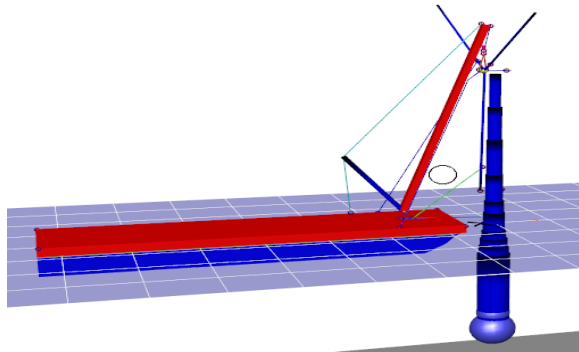


Fig. 2. Hywind rotor lift operation, adopted from (Vatne & Helian, 2014).

Since the proposed methodology deals with statistical analysis of installation equipment response and operation failure is defined as relevant equipment responses exceeding their maximum allowable values (strength, maximum allowable motions, etc.), the following Table 1 shows a summary of physical limitations of Hywind rotor lift operation. For a more detailed description of the physical limitations for this operation and for limits using the proposed methodology in general, the reader is referred to (Vatne & Helian, 2014) and (Gintautas & Sørensen, 2017).

Table 1. Physical limits of the operation.

Critical Response	Acceptance criteria
Crane loads	< 6375 kN
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
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

Selected location and met-ocean condition forecasts

Met-ocean condition forecasts were retrieved from ECMWF (European Centre for Medium-Range Weather Forecasts) for FINO3 met-mast location in the North Sea (55° 11,7' N - 007° 09,5' E). The location was chosen based on easy access to met-ocean condition measurement data, that is available from the met-mast. Measurement data will be later used to quantify the model uncertainties related to the ECMWF forecasts. A 3-month long period in summer of 2014 (May 1st to Aug 1st) was chosen for testing and 3 met-ocean condition forecast data sets were compiled from ECMWF forecast data, using different forecasting update frequencies. The conditions at the test site were described by multiple parameters – significant wave height and peak period, wind speed and the misalignment angle between the incoming wind and waves. The temporal resolution of ECMWF forecasts was 3 hours.

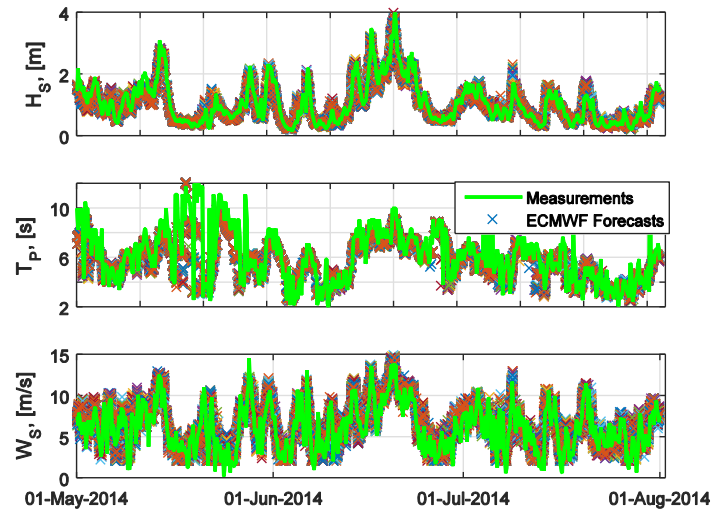


Fig. 3. Met-ocean condition forecasts at FINO3 location, forecasts updated daily.

Here the green line represents measurement data from FINO3 met-mast and the scatter around is the 51 ensemble members of ECMWF weather forecasts. Daily updated forecasts (at 00:00 hour, see Fig. 3) were used as base case, while forecasts for the other two cases were updated every 2nd and 3rd day. Having data sets with different update frequencies gives an opportunity to analyze the effects that weather forecasting uncertainties have on weather window predictions, and this will be discussed further in the paper.

WEATHER WINDOW PREDICTION UNDER UNCERTAIN MET-OCEAN CONDITION FORECASTS

This section focuses on demonstrating the effects that weather forecasting uncertainties have on weather window predictions and probabilities of operation failure. First, the effect of forecast updating frequency is investigated, followed by analysis of met-ocean forecast variability effects on variability of estimated probabilities of operation failure. Finally, the effects of forecasting biases (model uncertainties) on variability of operation failure probability are discussed.

Variability of met-ocean condition forecasts

As it was mentioned before, 3 data sets of met-ocean condition forecasts were constructed. The only difference among these data sets is the

frequency at which the forecasts are updated. In this section, coefficient of variation (COV) is chosen as a measure to quantify uncertainties related to forecasted met-ocean conditions (weather window prediction model input) and probabilities of operation failure (weather window prediction model output). However, due to multiparametric nature of forecasted met-ocean conditions, simple single-parameter COV would not be a completely suitable measure, therefore a more complex measure should be used. A multivariate coefficient of variation, based on (Albert & Zhang, 2010) Eq. (3), was chosen to represent the combined uncertainty of multi-parametric met ocean condition forecasts.

$$COV_M = \left[\frac{\bar{x}^T S \bar{x}}{(\bar{x}^T \bar{x})^2} \right]^{1/2} \quad (3)$$

Where \bar{x} is a vector of sample means of multiple input parameters (wind speed, wave height and period and their respective directions) and S is the dispersion (covariance) matrix.

The following Fig. 4 shows the combined COV_M for all 5 parameters used to describe the weather conditions at the test site.

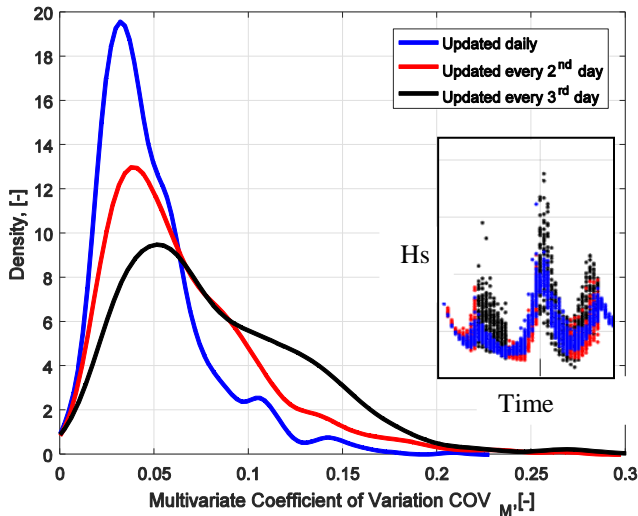


Fig. 4. Change of met-ocean condition forecast uncertainty based on forecast updating frequency.

Obviously, a lower forecast updating frequency implies higher uncertainty of forecasted met-ocean conditions, as indicated in Fig. 4. Lower updating frequency results in a wider, lower peaked distribution of COV_M . Furthermore, as it is seen in the zoomed section of wave height forecasts, the lower update frequency results in more extreme minima and maxima of the forecasted conditions.

Effect of weather forecasting variability on weather window estimates

All 3 previously mentioned data sets were used to simulate Hywind rotor lift operation at FINO3 location. Weather windows, suitable for operation, were obtained using the methodology depicted in Fig. 1. The following Fig. 5 shows the results of the analysis. Here the total length of predicted weather windows is normalized with respect to the case where weather forecasts were updated every day. Basis for weather window estimation, operation failure probabilities were evaluated at 5, 50 and 95% quantiles, by applying the quantile function, Eq. (4):

$$P_{F,Op} = P_{F,Q}(p) = \left[P_F : P(P_{F,ens(j)} \leq P_F) = p \right] \quad (4)$$

Here p is the desired quantile (5, 50 or 95%); $P_{F,Op}$ is the probability of operation failure and $P_{F,ens(j)}$ total probability of operation failure considering the (j -th) ensemble member of weather forecast.

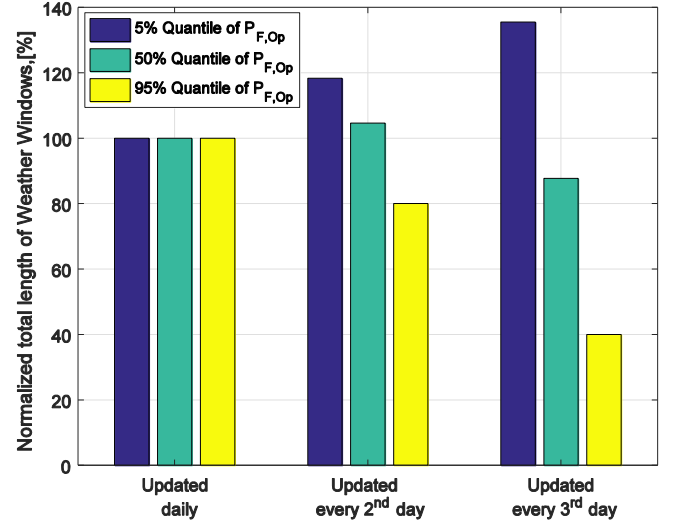


Fig. 5. Results of weather window estimation for Hywind rotor lift operation.

In the case when 95% quantile of operation failure probability ($P_{F,Op,95\%}$) is used to estimate weather windows (yellow bars), it is clearly visible that the total length of weather windows decreases when the forecasting frequency is decreased. This can be easily explained by the fact that estimates of $P_{F,Op,95\%}$ would be highly affected by simulations containing maxima of forecasted met-ocean condition parameters. And as was mentioned before, lower forecast updating frequency results in higher forecasted met-ocean condition maxima. When it comes to the case where $P_{F,Op,5\%}$ is used, the opposite is true – the total length of weather windows increases with the decrease of forecast updating frequency. This is because lower forecast updating frequency results in lower forecasted met-ocean condition minima, which in turn would significantly lower the estimates of $P_{F,Op,5\%}$ and thus increase the total number of predicted weather windows. The change of total length of predicted weather windows, when $P_{F,Op,50\%}$ is used, does not show a clear trend and indicates limitations imposed by the choice of test case duration. Increasing the test case duration from the chosen 3 months would stabilize the results of $P_{F,Op,50\%}$. However, due to heavy computational demand of running the hydrodynamic simulations, longer than 3 month test period was not considered, and thus is beyond the scope of this paper. Despite the shortcomings of the test case duration, some conclusions can still be drawn from this analysis. It is clear that the proposed methodology has the capacity to retain the information about extremes of forecasted met-ocean condition parameters and convert them into extremes of probability operation failure and, subsequently, into extremes of total length of predicted weather windows. Furthermore, knowing that variability of met-ocean condition forecasts effects the total length of predicted weather windows, this stands as good basis for more elaborate investigations of met-ocean forecasting uncertainty effects, which will be discussed in the following subsection.

Effect of statistical weather forecasting uncertainties on probabilities of operation failure

In order to explore the effects of forecasting uncertainties in more detail, this section focuses on the variability of probabilities of operation failure given a variable input of met-ocean condition forecasts. Here it should be noted that inherently the variability of met-ocean condition forecasts

increases with increasing forecast lead time (the further in time forecast predicts – the higher the variability/uncertainty). However, forecast time is not the only influencing factor – the variability of the forecasted met-ocean conditions also depends, among other things, on the stability and severity of atmospheric conditions. This implies that a simple look at the probabilities of operation failure just based on weather forecast lead time is not enough to clearly see the effects of forecasting uncertainties. Therefore, further analysis is based on the magnitude of COV_M , rather than on forecast lead time. Coefficient of variation of probability of operation failure is calculated using the following Eqs. (5-6):

$$COV_{P_{F,Op}} = \frac{\sqrt{VAR[P_{F,ens,Op} | COV_M]}}{E[P_{F,ens,Op} | COV_M]} \quad (5)$$

$$P_{F,ens(j)} = 1 - \prod_{i=1}^{N_{ac}} (1 - P_{F,ac(i),ens(j)}) \quad (6)$$

Here $COV_{P_{F,Op}}$ is the coefficient of variation of probability of operation failure; $E[P_{F,Op}/COV_M]$ is the expected value of total probability of operation failure, calculated at a given level of COV_M ; $VAR[P_{F,Op}/COV_M]$ is the variance of total probability of operation failure, calculated at a given level of COV_M ; N_{ac} is the number of acceptance criteria; $P_{F,ac(i),ens(j)}$ are ensemble probabilities of acceptance criteria exceedance events, estimated by FORM (probabilities of certain equipment responses exceeding their respective maximum allowable values).

The probabilities of operation failure were again obtained for the 3 previously mentioned data sets of met-ocean condition forecasts. However, here they are analyzed together, without separating them based on forecast updating frequency as this maximizes the number of observations in each COV_M bin. $COV_{P_{F,Op}}$ is arranged according to the magnitude of COV_M and the results are shown in the following Fig. 6.

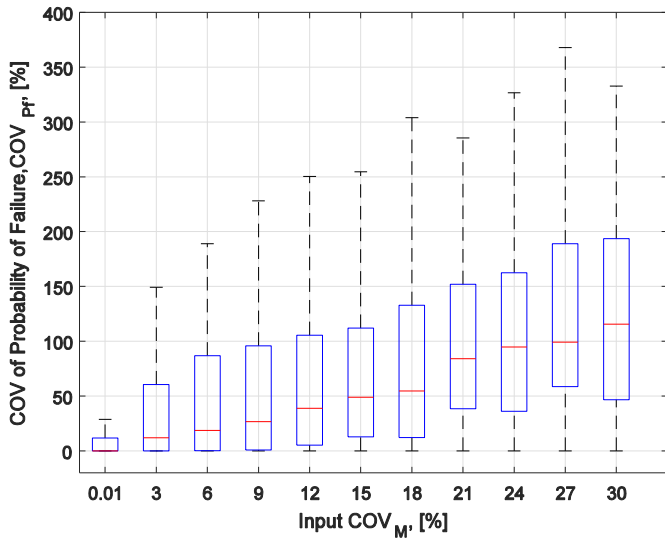


Fig. 6. Results of weather window estimation for Hywind rotor lift operation.

The red lines indicate the median of $COV_{P_{F,Op}}$ blue bars are the 25th and 75th percentiles and the black dashed lines cover the 99% range of $COV_{P_{F,Op}}$ distribution. A clear trend of increasing $COV_{P_{F,Op}}$ (in all measures – median, and all percentiles) is evident as COV_M increases. This is expected as the increase in variability of input forecasted met-ocean conditions should imply an increased in variability of probabilities of operation failure. This observation clearly implies that the proposed methodology has the capacity to transfer statistical uncertainties related

to met-ocean condition forecasting and convert them into uncertainties of probabilities of operation failure and, subsequently, to variability of predicted weather windows. The obvious advantage of the proposed methodology, among others, is that forecasting uncertainties are converted to uncertainties of weather window predictions in a consistent and transparent manner, rather than by using a single α -factor as it is done by using state of the art techniques, based on (DNV, 2011).

Effect of biases in weather forecasts on probabilities of operation failure

Another important aspect of using met-ocean condition forecasts to estimate accessibility to an offshore site is that generally forecasts may have inherent biases. Since FINO3 location was chosen as the test site, it is possible to retrieve the measurements of met-ocean conditions and then estimate the biases related to forecasting individual met-ocean condition parameters. It is done by comparing the measured met-ocean conditions against the forecasted ones. This analysis is based on guidance in (EN 1990, 2002). The bias and coefficient of variation of model error terms can be calculated using the following Eqs. (7-11):

$$b_{Par} = \frac{\sum Par_{meas,i} Par_{forec,i}}{\sum Par_{forec,i}^2} \quad (7)$$

$$\Delta_{i,Par} = \ln \left(\frac{E[Par_{forec,i}]}{Par_{forec,i}} \right) \quad (8)$$

$$\bar{\Delta}_{Par} = \frac{1}{n} \sum_{i=1}^n \Delta_{i,Par} \quad (9)$$

$$s_{\Delta,Par}^2 = \frac{1}{n-1} \sum_{i=1}^n (\Delta_{i,Par} - \bar{\Delta}_{Par})^2 \quad (10)$$

$$V_{\delta,Par} = \sqrt{\exp(s_{\Delta,Par}^2) - 1} \quad (11)$$

Here b_{Par} is the bias associated to a particular met-ocean forecast parameter (e.g. wind speed); Par_{meas} and Par_{forec} are the measurement and forecasts of that parameter; $\Delta_{i,Par}$ is the lognormal error term for a given set of parameter measurements and forecasts; $s_{\Delta,Par}^2$ is the variance of the lognormal error terms and V_{δ} is the coefficient of variation of the error terms.

The following Fig. 7-10 show the effect of individual met-ocean condition forecasting on the variability of probability of operation failure. Based on the figures, it can be stated that when the met-ocean condition forecasting model consistently under- or overestimates the conditions offshore (forecasting bias exists), there is an increase in variability of estimated probabilities of operation failure, at least when it comes to wave height, period and wind speed. However, the model does not seem to be heavily influenced by forecasting bias related to misalignment of wind and wave directions. The effect of forecasting bias can be explained by the fact that when the forecasting model miss predicts the met-ocean conditions, the miss prediction typically affects a certain number of forecast ensembles. The larger the number of miss-forecasted ensembles, the higher the variability of the subsequently calculated probability of operation failure, and thus $COV_{P_{F,Op}}$ increases. When it comes to the bias of wind-wave direction misalignment, the effect here does not show a trend because the influence of direction misalignment on the variability of probability of operation failure is negligible, when compared to other met-ocean parameters. However, it is still important not to omit the directional effects from the analysis, because certain combinations of all parameters can still result in a significant change of $P_{F,Op}$.

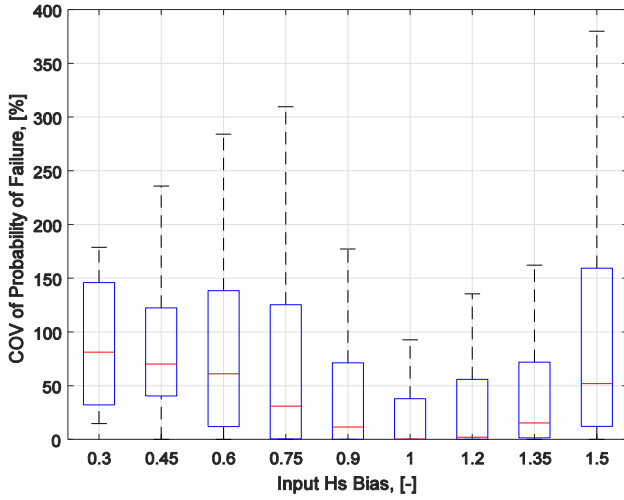


Fig. 7. Effect of significant wave height forecasting bias.

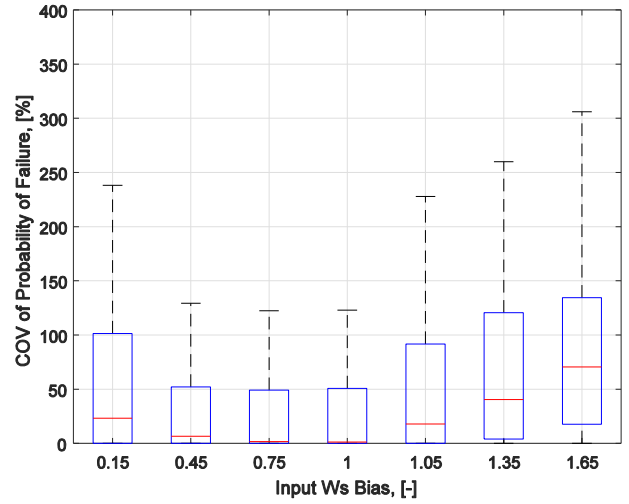


Fig. 8. Effect of wind speed forecasting bias.

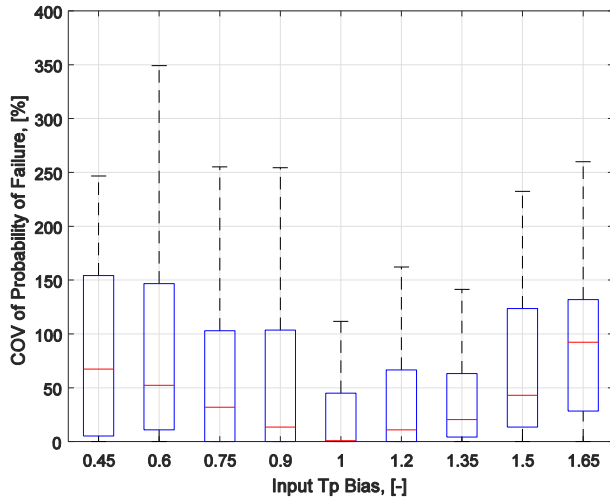


Fig. 9. Effect of wave peak period forecasting bias.

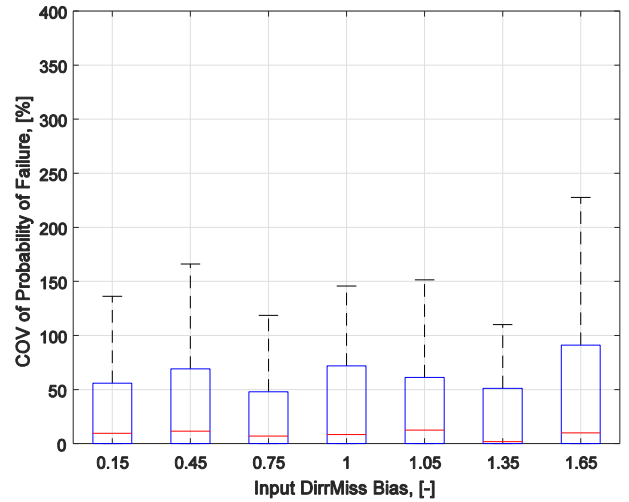


Fig. 10. Effect of wind-wave direction misalignment forecasting bias.

The observed change in variability of $P_{F,OP}$ ($COV_{F,OP}$) implies that reduction of biases in weather forecast model could improve the quality of weather window predictions when using the proposed methodology. Furthermore, a lower $COV_{F,OP}$, achieved by lowering b_{par} (through i.e. site calibration of forecasts or spatial and/or temporal downscaling), would also result in reduction of $P_{F,OP}$ quantile estimates (i.e. $P_{F,OP} | p = 95\%$, as per Eq.(5)) and in turn increase the number of predicted weather windows.

UPDATED FAILURE FUNCTION FORMULATION

This section describes the procedure of estimating and using met-ocean condition forecasting uncertainties within the proposed methodology. Focus here is directed towards demonstrating that usage of additional stochastic parameters in the failure function Eq. 2, describing the forecasting uncertainties, can reduce the computational demands resulting from usage of multi-ensemble ECMWF weather forecasts.

Estimation of statistical forecasting uncertainties and formulation of additional stochastic variables

It is possible to estimate the coefficient of variation of model error terms (normalized), $V_{\delta,Par}$, for every parameter that is used as input to the hydrodynamic simulation model. For the test case, these parameters are as follows – significant wave height (1), peak period (2) and wave direction (3); wind speed (4) and wind direction (5). Also, there is JONSWAP spectrum parameter γ (6), which is calculated using significant wave height and peak period. Therefore, 6 coefficients of variation will be calculated, using Eqs. (8-11), and further used to define stochastic variables describing met-ocean parameter forecasting model uncertainties. It should be noted here, that $V_{\delta,Par}$ coefficients are calculated for every forecast lead time individually, for each parameter. This is done by estimating the variance of all 51 ensemble members of the parameter in question around its' mean, (Eq. 8). The following Fig. 11 shows the distributions of coefficient of variation of model error terms for all 6 input parameters.

Table 2. Parameters of additional stochastic variables.

Variable	Par.	Distr.	Mean	Coefficient of Variation
Sig. Wave Height	X_{HS}	LN	1	$V_{\delta, Hs}$
Wave Peak Period	X_{TP}	LN	1	$V_{\delta, Tp}$
Wind Speed	X_{WS}	LN	1	$V_{\delta, Ws}$
Wave Direction	X_{HSDIR}	LN	1	$V_{\delta, HsDir}$
Wind Direction	X_{WSDIR}	LN	1	$V_{\delta, WsDir}$
JONSWAP γ	X_{γ}	LN	1	$V_{\delta, \gamma}$
Add. model unc.	X_M	LN	1	$0.03..0.05$

Now it is possible to construct a set of 6 stochastic variables for each forecast day and forecast lead-time, representing the uncertainties related to individual met-ocean parameters. Typically, for FORM analysis, model uncertainties are expressed as *lognormally* distributed stochastic variables with mean of 1 and a coefficient of variation – in this case $V_{\delta, Par}$. Table 2. shows a summary of these stochastic variables.

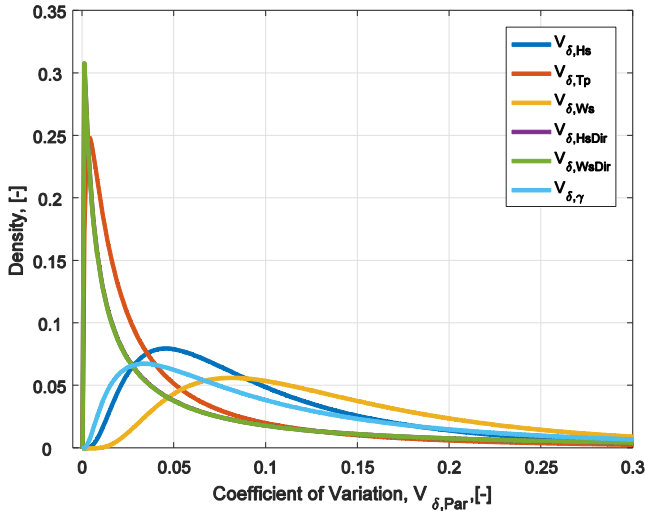


Fig. 11. Coefficients of variation of model error terms.

The failure function using all the additional stochastic variables would be as follows:

$$R(X) = X_{HS} X_{TP} X_{WS} X_{HSDIR} X_{WSDIR} X_{\gamma} X_M E_{P=95\%}(X) \quad (12)$$

Here $E_{P=95\%}$ denotes the equipment response variable, parameters for which are determined by simulating only 1 set of forecasted met-ocean condition parameters (using a desired quantile of met-ocean parameter distribution) instead of all 51 ensemble members. For the demonstration case in the following subsection, the quantile p is set to $p=95\%$.

Having defined the additional stochastic variables, it is possible to use the information about the statistical uncertainty, gained from ECMWF ensemble forecasts, directly in the weather window prediction model. The results of such analysis are presented and discussed in the following subsection.

Effect of additional stochastic variables

This subsection presents and discusses the results of using Eq. (12) to obtain weather windows from simulated response data related to 95% quantile estimates of input met-ocean parameters. The following Fig. 12 shows the effect of adding additional stochastic parameters, where the leftmost grouped bars show results from the analysis performed with Eq. (12) containing only one additional stochastic parameter for significant wave height uncertainty (X_{HS}). Every other group of bars indicates an

addition of one more stochastic variable. The last group of bars – “Target” – shows the results of simulating all 51 ensemble members of the met-ocean condition forecast and using the 95% quantile of probability of operation failure as basis for weather window estimation. The results in Fig. 12 are normalized with respect to “Target” total length of predicted weather windows.

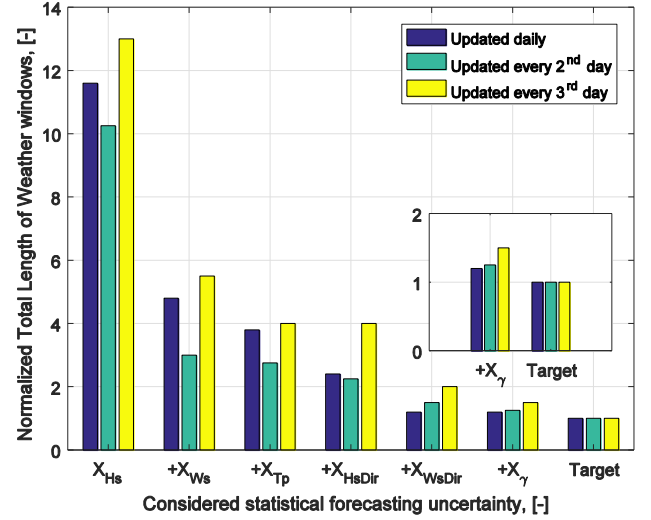


Fig. 12. Effect of additional stochastic variables on weather window predictions (95% quantile of $P_{F,OP}$).

It is clearly visible that adding more stochastic variables decreases the total length of predicted weather windows. However, the results are converging towards the “Target”. The zoomed in section shows the results when full Eq. (12) is used (uncertainties related to all 6 input parameters are included in the analysis). Here, if the bars at $+X_{\gamma}$ would be at height “1”, it would be an indication that such mapping is possible:

$$L_{Win}(P_{F,OP} | INP_{P=95\%}) = L_{Win}(P_{F,OP,P=95\%} | INP_{All_Ensembles}) \quad (13)$$

Here L_{Win} is the total length of predicted weather windows for the test period; $INP_{P=95\%}$ is the 95% quantile estimates of met-ocean condition parameter forecasts, used as input to hydrodynamic simulation model; $P_{F,OP,P=95\%}$ is 95% quantile probability of operation failure obtained from simulation results of all 51 ensemble members of ECMWF met-ocean forecast; $INP_{All_ensembles}$ is the full 51 ensemble member forecast used as input to hydrodynamic simulation model.

The possibility to define such mapping would significantly reduce the computation time requirements of the methodology. Instead of running all 51 ensemble members of ECMWF met-ocean condition forecast as input to hydrodynamic model, it would be sufficient to estimate the 95% quantile of each individual met-ocean condition parameter from the ensemble forecasts, and simulate only those. The implications for this particular test case and test duration would be running only 2300 simulations (92 days x 25 forecast lead times x 1 ensemble member, containing the 95% quantile estimates) instead of 117 300 (92 days x 25 forecast lead times x 51 ensemble members) simulations, resulting in a very significant simulation time reduction, which as mentioned before, is the most significant drawback of the proposed methodology.

Looking back at Fig. 12 it is clear that despite the fact that the results are converging to the “Target”, there are still uncertainties that are not accounted for by stochastic variables, related to met-ocean forecasting uncertainties – there is a slight mismatch between the “Target” and $+X_{\gamma}$ bars. This could be related to additional modelling uncertainties of the hydrodynamic simulation model, etc. It is possible to account for these

additional uncertainties, that are not covered by $X_{Par,i}$, by introducing another global lognormally distributed stochastic variable X_M and calibrate V_{X_M} such that the mismatch between “Target” and $+X_M$ bars is minimized. The following Fig. 13 shows the effect of additional modelling uncertainty and the results of a crude calibration.

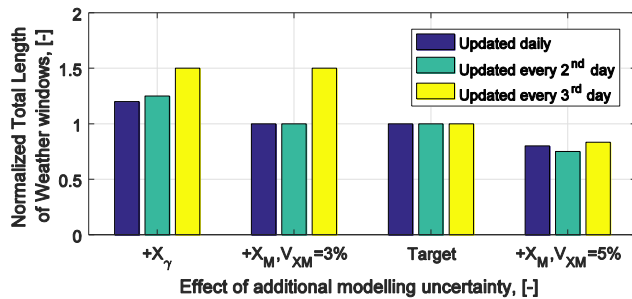


Fig. 13. Effect and calibration of X_M stochastic variable.

It is clear that by adding another stochastic variable X_M it is possible to remove the mismatch between the desired “Target” and “ $+X_M$ ” bars and thus prove that mapping from Eq. (13) is indeed possible. The true value of V_{X_M} lies between 3 and 5%, however, for practical uses V_{X_M} should be set to 5% - it introduces some additional conservatism by only reducing the total length of predicted weather windows by ~15%.

CONCLUSIONS

This paper briefly described a novel methodology for weather window estimation, based on statistical analysis of offshore operation and equipment response. The methodology uses simulated offshore equipment and vessel responses under forecasted met-ocean conditions to establish probabilities of operation failure and, subsequently, uses probability of operation failure to estimate weather windows suitable for operation. However, the focus of the paper was directed towards investigation of effects of weather forecasting uncertainties on weather window predictions and probabilities of operation failure.

It was demonstrated that the met-ocean condition forecasting uncertainties can significantly influence the results of weather window predictions. These uncertainties increase the variability of probability of operation failure estimates, which in turn reduce the total number of predicted weather windows for the test period. It was also demonstrated that the methodology can retain information about the extremes of forecasted met-ocean parameters and transferring those extremes into extremes of weather window estimates. Furthermore, the methodology is capable to also retain and transfer the information related to weather forecasting uncertainties into uncertainties of probabilities of operation failure – with increasing met-ocean parameter forecast variability there is a greater variability in estimated probabilities of operation failure. This is important because it allows for more explicit and more transparent inclusion of forecasting uncertainties into weather window predictions when compared to the standard α -factor methodology. Additional improvements to the failure function, accounting for weather forecasting uncertainties within the novel methodology, were proposed. The improvements involved using additional stochastic variables, representing the met-ocean condition forecasting uncertainties, in the failure function. Such failure function update gives an opportunity to substantially (up to 50 times, in this case) reduce the computation time requirements of the proposed methodology only altering the resulting weather window estimates by ~15%.

It should be noted that more studies with different offshore operation models are necessary to validate that the methodology produces consistent results irrespective of choice of operation. Furthermore, a

longer test period should also be used for further validation of the proposed methodology. Keeping this in mind, it is still apparent that the proposed approach looks promising and with further development could be used as decision support for offshore operation planning.

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