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Published in:
Energy Procedia

DOI (link to publication from Publisher):
10.1016/j.egypro.2016.09.225

Publication date:
2016

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Gintautas, T., Sørensen, J. D., & Vatne, S. R. (2016). Towards a Risk-based Decision Support for Offshore Wind Turbine Installation and Operation & Maintenance. *Energy Procedia*, *94*(September), 207-217. https://doi.org/10.1016/j.egypro.2016.09.225

Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 94 (2016) 207 – 217

Energy Procedia

13th Deep Sea Offshore Wind R&D Conference, EERA DeepWind'2016, 20-22 January 2016, Trondheim, Norway

Towards a risk-based decision support for offshore wind turbine installation and operation & maintenance

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Abstract

Costs of operation & maintenance, assembly, transport and installation of offshore wind turbines contribute significantly to the total cost of offshore wind farm. These operations are mostly carried out by specific ships that have to be hired for the operational phase and for duration of installation process, respectively. Duration, and therefore ship hiring costs is, among others, driven by waiting time for weather windows for weather-sensitive operations. Today, state of the art decision making criteria for weather-sensitive operations are restrictions to the significant wave height and the average wind velocity at reference height. However, actual limitations are physical, related to response of equipment used e.g. crane wire tension, rotor assembly motions while lifting, etc. Transition from weather condition limits to limits on physical equipment response in decision making would improve weather window predictions, potentially reducing cost of offshore wind energy. This paper presents a novel approach to weather window estimation using ensemble weather forecasts and statistical analysis of simulated installation equipment response.

Peer-review under responsibility of SINTEF Energi AS

Keywords: decision support, offshore, wind turbine, marine operations, installation, risk, probability, weather window.

1. Introduction

Cost of transport and installation of offshore wind turbines and foundations contributes to 15-20% [1] of total wind farm capital expenditure, furthermore, operation and maintenance activities typically contribute to 25-30% of the total Levelized Cost of Energy of an offshore wind farm. All these activities have one common limiting factor – limited access to an offshore location due to ever-changing met-ocean conditions. The high importance of met-ocean conditions offshore is usually a consequence of high weather sensitivity of the equipment and vessels used for transportation, installation or operation & maintenance activities.

Peer-review under responsibility of SINTEF Energi AS
doi:10.1016/j.egypro.2016.09.225

Typically, accessibility to a certain offshore location is expressed in terms of weather windows, during which operations can be performed, and waiting times for such weather windows. The state-of-the-art in weather window estimation today is limited to use of simple met-ocean parameters, such as wind speed at reference height and significant wave height. However, the limitations are inherently physical - related to response of equipment and vessels used for offshore operations, e.g. maximum lifting capacity of crane cables, allowable motions and accelerations of lifted components, etc. Computer software can be used to simulate responses of installation equipment under given met-ocean conditions and statistical methods can be applied to assess the probabilities of extreme response occurrence.

Moreover, weather forecasts used to predict accessibility to an offshore location are not precise. Uncertainties related to weather forecasting have an impact on the quality of accessibility predictions. The state-of-the-art way of addressing these uncertainties when predicting weather windows, is limited to simply scaling down the met-ocean condition limits by the use of an *"alpha-factor"* [2], thus making the limits more conservative. However, multi-ensemble forecasts capture the forecasting uncertainties quite well and can be used within the proposed new approach. It should be noted that use of ensemble forecasts is mentioned in [2] as an alternative to tabulated *alpha-factors*, but the procedure is not explicitly described. Also, some marine operations can be highly sensitive to incoming wave period. Current practice does not have clearly defined ways of taking wave periods or uncertainties, related to wave period forecasting, into consideration when estimating weather windows. Both are considered when using computer simulations, since ensemble forecasts of wave period is always used as part of met-ocean state description.

This paper looks into possible improvements on weather window predictions by using actual physical limits of transportation, lifting and other relevant installation equipment and proposes a new approach of assessing the effect of forecasting uncertainties on weather window predictions. This is done by statistically analyzing equipment response time series and estimating probabilities of responses exceeding certain critical limits. Furthermore, multi-ensemble weather forecasts are used to quantify the impact of forecasting uncertainties on the predicted weather windows.

"Proof of concept" of the proposed methodology is demonstrated by a case study of offshore wind turbine installation. It should be noted that the methodology is very general and field of application is relatively wide. The proposed methodology can be applied to any offshore operation, given that reasonable limits on equipment responses can be established and responses can be quantified.

Nomenclature

ECMWF	European Centre for Medium-Range Weather Forecasts
POT	Peak-Over-Threshold analysis
$F_{local}(r \le R_{ac(i)})$	Local cumulative distribution function of extreme equipment response
$E\,[n_p]$	Expected number response of peaks (extremes) per realization of forecasted ensemble sea state
$R_{ac(i)}$	Specific (*i*-th) acceptance criterion
$P_{non-exc,ens(j)}$	Cumulative distribution function of extreme equipment response, adjusted for number of peaks, when (*j*-th) weather forecast ensemble member is considered
$f(R \mid \mu_{LN}, \sigma_{LN})$	Probability density function of acceptance criterion, with μ_{LN}, σ_{LN} parameters.
$R, \Delta R$	Range of acceptance criteria used for acceptance criterion distribution
$P_{F,ac(i),ens(j)}$	Probability of failure when a specific (*i*-th) acceptance criterion is exceeded and one (*j*-th) weather forecast ensemble member is considered
N_{ac}	Number of acceptance criteria for a given operation and number of
N_{ens}	Number of ensemble members in a weather forecast
$P_{F,ac(i)}$	Probability of failure when a specific (*i*-th) acceptance criterion is exceeded
$P_{F,Op}$	Probability of failure of the whole operation

2. Overview of the proposed methodology

This section presents as a general overview of the proposed methodology. Fig. 1 shows the "work flow" of the proposed Risk-Based decision support framework.

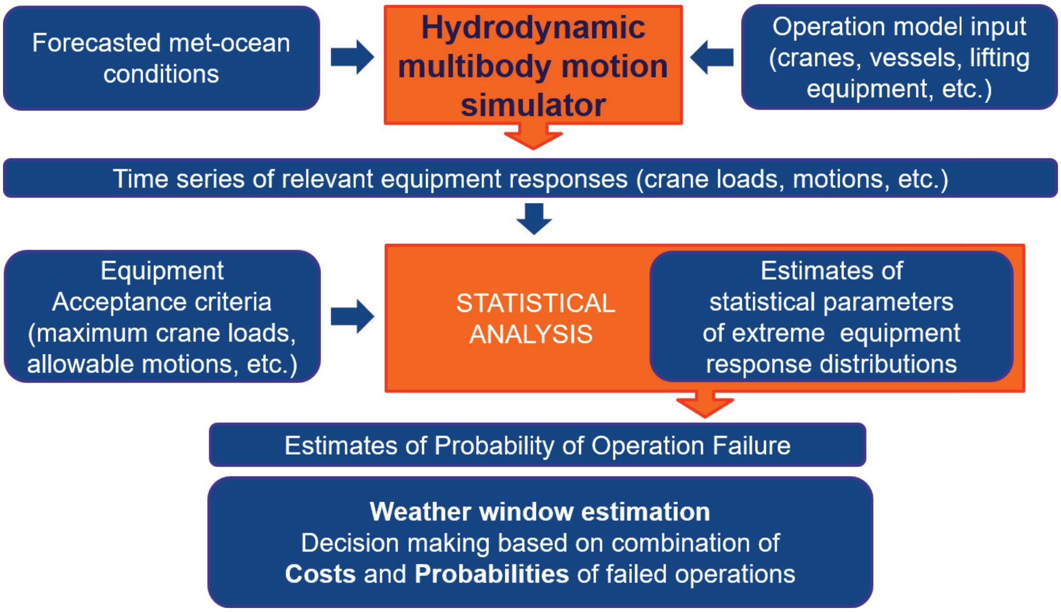

Fig. 1. Topology of the proposed methodology.

The procedure can be applied to any offshore operation and can be summarized in the following general steps:

1. Selecting weather forecasts for the analysis. Multi-ensemble forecasts are recommended.
2. Selecting a hydrodynamic multibody motion simulation model and software to quantify the response of equipment for a given offshore operation in terms of time series.
3. Simulating the operation and retrieving the relevant equipment response time series.
4. Estimating parameters of extreme equipment response distributions.
5. Estimating the likelihood of relevant responses exceeding equipment *acceptance criteria.*
6. Combining the likelihoods of individual *acceptance criterion* exceedance events to obtain total likelihood of operation failure.
7. Comparing total likelihood of operation failure with maximum allowable operation failure probability of 10^{-4}, defined by [2], in order to obtain weather windows suitable for successful operation.
8. If consequences of failure expressed in monetary terms are available, combining them with the likelihood of failure to allow for Risk-Based comparison among alternative weather windows.

Focus of this paper is mainly on statistical analysis of installation equipment response time series and estimation of probabilities of operation failure.

3. Estimating the probability of operation failure and weather windows

This section focuses on describing the statistical analysis of installation equipment response data and estimating the probability of operation failure. Probability of operation failure is used as basis for estimation of acceptable weather windows.

3.1. Types and meaning of Equipment Acceptance Criteria

In this paper term "*acceptance criteria"* is used to describe limitations of equipment used for offshore operations. These limits are related, but not limited to, physical properties of equipment such as tension strength of lifting cables, maximum allowable crane load or acceleration of lifted objects. Also, *acceptance criteria* can be derived from pure practical perspective, such as maximum allowable translations/rotations of lifted objects, assuming that excessive motions can lead to risk of losing control of lifted objects. Furthermore, velocities can be used as *acceptance criteria* when impact energy is important at contact between lifted objects and their final resting position. If the lifted object is controlled by tug wires attached to it, then tug wire tension can be used as *acceptance criterion* – load in the wire should not exceed breaking strength and should be non-zero, implying that the wire is not slack and control of lifted object can be maintained. If there is risk of waves colliding with e.g. lifted objects, minimum distance between wave crest and lowest point of the object can also serve as an *acceptance criterion.* To summarize, *acceptance criteria* can be grouped into two major groups:

- Non-exceedance *acceptance criteria* (type N), when the response should be below a certain level in order to avoid a "failure state". This type would include cable strength, motion or acceleration *acceptance criteria.*
- Exceedance *acceptance criteria* (type E), when the response should be above a certain level in order to avoid "failure state". This type would include *acceptance criteria* such as control wire slacking, clearance between lifted objects and wave crests or other fixed objects, etc.

It should be kept in mind that time series related to responses with different *acceptance criteria* should be analyzed separately. This is necessary because probability of responses exceeding their respective *acceptance criteria* will be estimated individually, and only combined into total probability of operation failure at the end of analysis. In addition, some *acceptance criteria* are not applicable or might change during operation; e.g. lifting velocity has a lower limit at lift-up and higher limit while moving objects mid-air, or might be completely irrelevant during transportation. In these situations responses related to non-constant *acceptance criteria* should be analyzed separately and probabilities of responses exceeding these *criteria* should be distinct.

Some *acceptance criteria,* such as lift wire strength, can be interpreted as deterministic or as stochastic. Both, exceedance and non-exceedance *acceptance criteria* mentioned above, can be regarded as stochastic, given that their distribution properties can be defined.

3.2. Simulating equipment response

The simulation time should represent the real duration of the operation, because the goal is to estimate the probability of operation failure within the actual operation timeframe – if operation takes 1 hour to complete, estimated probability of operation failure would be related to probability of one-hour extreme responses exceeding their respective *acceptance criteria.* However, it is necessary to simulate multiple realizations of every forecasted ensemble sea state (different colors in Fig. 2). This ensures sufficient number of extremes extracted for a good fit of the tail of extreme response distributions. Furthermore, care must be taken if the simulation software requires some time to reach a steady state solution, i.e. any initialization period, where the results have not yet stabilized, should be omitted from the analysis.

3.3. Equipment response analysis using Peak-Over-Threshold method

The Peak-Over-Threshold (POT) method is used to extract extremes (peaks or valleys) from historical data or simulated time series. Threshold selection and extracted extremes for different *acceptance criteria* are dependent on type of the *limit*:

- For *non-exceedance acceptance criteria* threshold is based on [3], and is set to **μ+1.4σ** (mean value + 1.4 standard deviation) of the response time series. Maximum extremes (peaks) are extracted.
- For *exceedance acceptance criteria* the threshold is set to **μ** (mean value) of the response time series. Minimum extremes (valleys) are extracted.

As previously mentioned, multiple realizations of every forecasted ensemble sea state have to be simulated. This implies that the dataset, used to fit an extreme response distribution function related to a particular forecasted ensemble sea state, should contain extremes extracted from all simulated realizations. However, unique thresholds should be applied for every realization to capture extremes from different realizations equally (see non-constant threshold in Fig. 2). For the sake of completion, Fig. 2 shows multiple realizations of one simulated ensemble sea state.

Another important aspect of a POT analysis is to make sure that the extracted extremes are statistically independent. This can be achieved using temporal separation between the local extremes. Annex G of [4] recommends minimum time separation between individual response extremes of three response cycles (defined by three mean crossings over the block size).

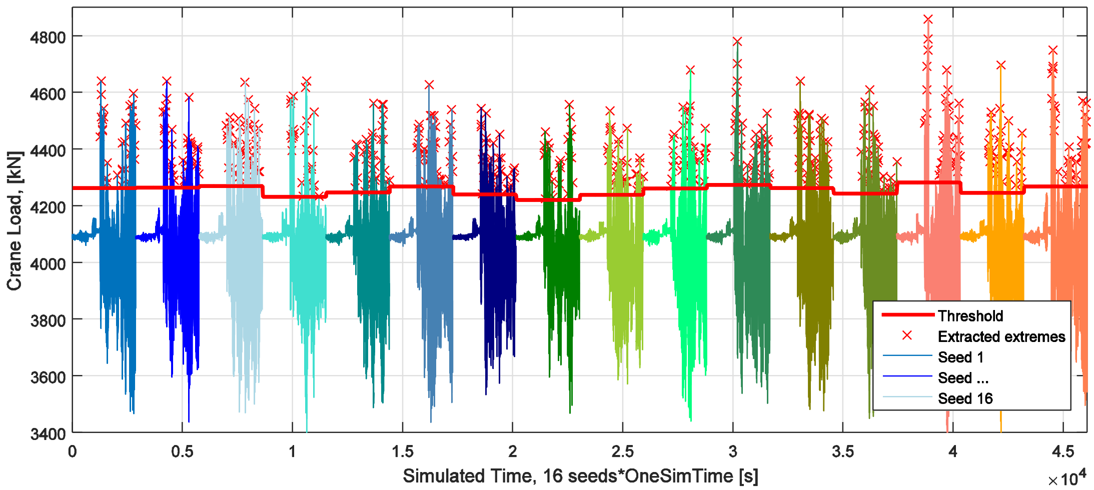

Fig. 2. POT analysis on example time series. 16 realizations (different colors) of one forecasted ensemble sea state (H_s=1.2m, T_p=3s, W_s=6m/s). Crane Load response while wind turbine rotor is lifted off the barge, rotated to vertical position mid-air and secured to nacelle.

3.4. Extreme response distributions for different acceptance criteria and weather window estimation

As mentioned in section 3.1, there are two general types of *acceptance criteria*, therefore two distributions are chosen. A two-parameter Weibull distribution is used for responses related to *non-exceedance acceptance criteria,* due to its versatility and usually good performance when predicting extreme events. However, Weibull distribution is not defined for negative values or *zero*. When *acceptance criterion* is *zero* or close to *zero,* the Normal distribution is used. This would typically be applicable to responses related to *exceedance acceptance criteria* (e.g. blade-tower clearance >0m, implying no collision between lifted wind turbine blade and tower).

Distribution parameters are estimated using the Maximum Likelihood parameter estimation method. Extreme response distributions obtained from POT results are termed *local* and have to be adjusted for the fact that multiple realizations of every ensemble sea state were simulated. This can be done using equation (1):

$$P_{non-exc,ens(j)}(r \le R_{ac(i)}) = F_{local}(r \le R_{ac(i)})^{E[n_P]} \tag{1}$$

where $F_{local}(r \le R_{ac(i)})$ is the local cumulative distribution function of extreme equipment response, fitted to the extremes extracted from all simulated realizations of forecasted ensemble sea state and $E[n_p]$ is the expected number of peaks (response extremes) per simulated realization of forecasted ensemble sea state.

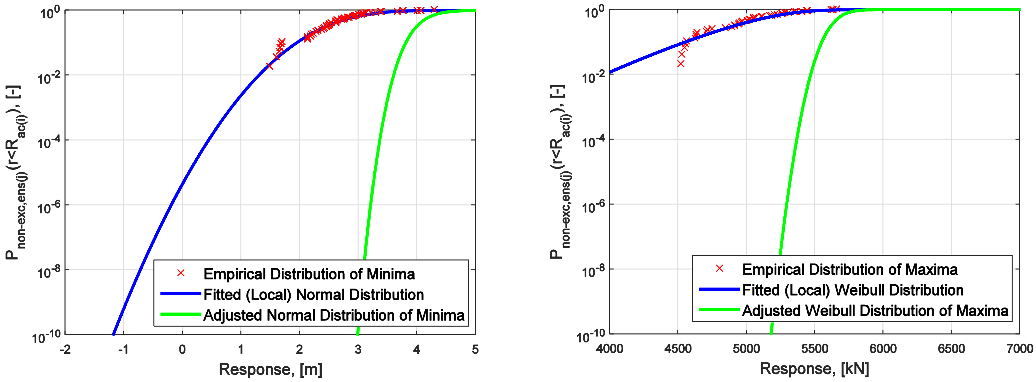

Fig. 3. Example of fitted Normal and Weibull distributions. One forecasted ensemble sea state (extremes extracted from all 16 realizations). Left – Normal distribution for minimum Airgap between tower and lifted rotor assembly (AirGap tower *acceptance criterion,* clearance >0m). Right – Weibull distribution for maximum Crane Load response (maximum Crane Load *acceptance criterion*).

Based on the type of *acceptance criterion*, the ensemble probability of failure for specific *acceptance criteria* is calculated using the following equations for the *j*-th ensemble for the *i*-th acceptance criteria:

$$P_{F,ac(i),ens(j)} = 1 - P_{non-exc,ens(j)}(R_{ac(i)}) \quad \text{for } \textit{Non-exceedance acceptance criteria} \tag{2}$$

$$P_{F,ac(i),ens(j)} = P_{non-exc,ens(j)}(R_{ac(i)}) \quad \text{for } \textit{Exceedance acceptance criteria} \tag{3}$$

It should be mentioned that when multi-ensemble forecasts are used, the number of distributions fitted per *acceptance criterion* is equal to number of ensemble members in the forecast. The same applies to number of ensemble probabilities of failure. Fig. 4 shows the extreme response distributions for 51 ensemble members of a typical ECMWF weather forecast.

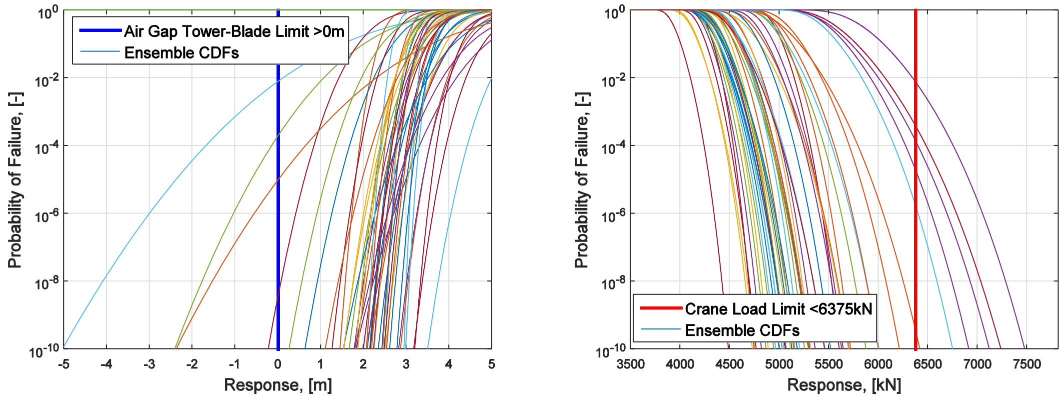

Fig. 4. Example of distributions of extreme equipment response for 51 ensemble members of typical ECMWF weather forecast. Left – Normal distributions with deterministic limit on minimum Airgap between tower and lifted rotor assembly. Right – Weibull distributions with deterministic maximum Crane Load limit.

Some of the *acceptance criteria* can be regarded as stochastic, thus equation (4) can be used to determine probability of failure for a particular stochastic *acceptance criterion.* It is estimated as the area marked in red in Fig. 5 (right) for a given realization of *R*, and integrated numerically by:

$$P_{F,ac(i),ens(j)} = \sum (1 - P_{non-exceedance,ens(j)}(R)) \cdot f(R \mid \mu_{LN}, \sigma_{LN}) \Delta R \tag{4}$$

where $f(R \mid \mu_{LN}, \sigma_{LN})$ is the probability density function of the *acceptance criteria*, with μ_{LN}, σ_{LN} being the distribution parameters (blue on the left of Fig. 5).

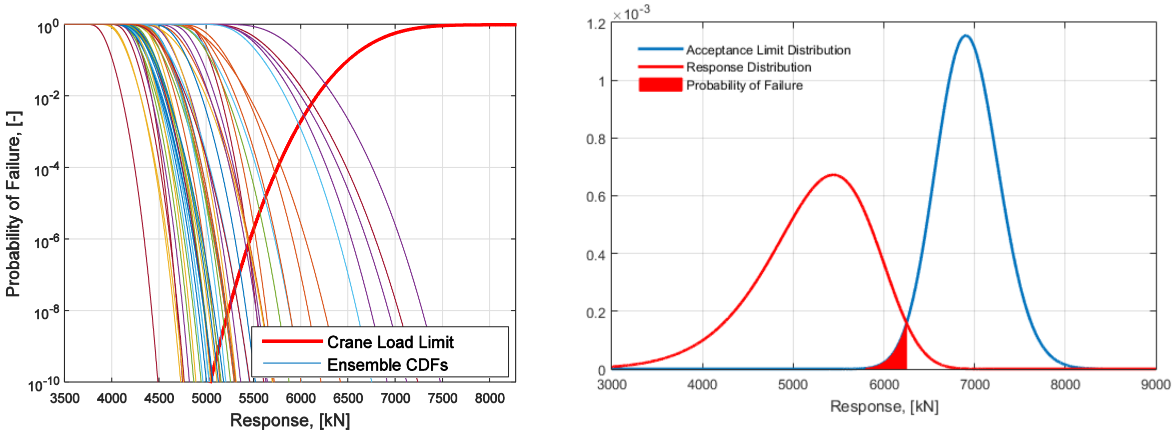

Fig. 5. Example of distributions of extreme equipment response for 51 ensemble members of typical ECMWF weather forecast. Left – Weibull distributions with stochastic maximum Crane Load limit, right – integration of load and resistance probability density functions.

Having calculated the ensemble probabilities of failure based on the type of *acceptance criteria* analyzed, the expected probability of failure for the operation can be calculated as average over all ensembles, eq. (5).

$$P_{F,ac(i)} = \frac{\sum_{j=1}^{N_{ens}} P_{F,ac(i),ens(j)}}{N_{ens}} \tag{5}$$

where N_{ens} is the number of ensemble members in a weather forecast.

If the operation has N_{ac} *acceptance criteria* and it is assumed that operation failure occurs if just one of these are exceeded then a series system of the multiple *acceptance criterion* exceedance events can be modelled, and the total probability of operation failure can be calculated by eq. (6) further assuming statistical independence between *acceptance criterion* exceedance events, despite the fact that aforementioned events might be somewhat correlated. However, correlation analysis of *acceptance criterion* exceedance events is beyond the scope of this paper.

$$P_{F,Op} = 1 - \prod_{i=1}^{N_{ac}} (1 - P_{F,ac(i)}) \tag{6}$$

Finally, the total probability of operation failure can be compared to the maximum allowable probability of failure of 10^{-4}, recommended by [2], and weather windows can be obtained.

4. Case study and proof of concept. Hywind Rotor Lift Operation

As an example test case and proof of concept, Hywind rotor lift operation was chosen. A time domain multibody motion model in SIMO software (SImulation of complex Marine Operations) was made available by MARINTEK together with model description [5]. The concept model was initially developed and used for Hywind Demo installation in 2009. The model was further improved for use as an offshore installation test case for the DECOFF project.

4.1. Description of Hywind Rotor Lift Operation and selected met-ocean conditions

During the operation, a barge transports assembled rotor to the intended installation location where the floating turbine tower is already positioned. After lift preparations, the rotor is lifted-up off the barge, rotated mid-air to a vertical position and secured to the nacelle. The whole operation model is split into 6 phases, but this study only focuses on phases 3 to 6, where the barge and the floating tower are already positioned at the installation location and the rotor lift-up – rotation – securing to the nacelle is commenced (see Fig. 6).

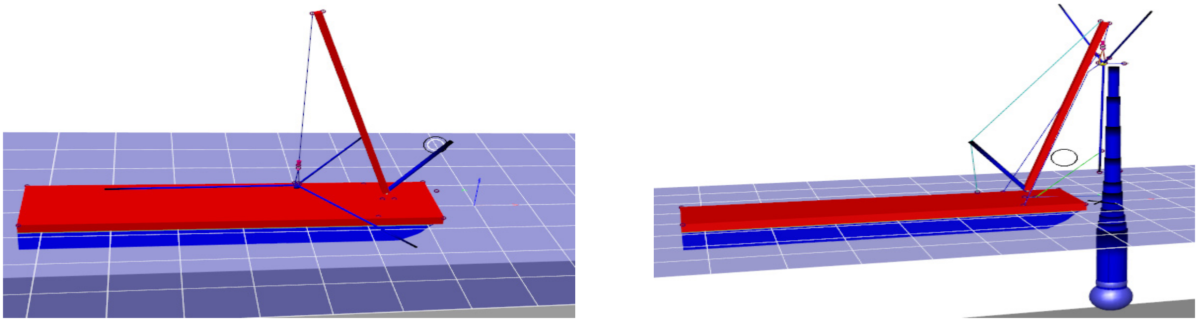

Fig. 6. Hywind rotor lift operation test case. Phases 3 – lift up (left) to 6 – securing to the nacelle (right).

Table 1 shows an overview of the rotor lift operation. Critical responses and *acceptance criteria* for different installation phases are indicated together with the duration of each phase. Also, the types of *acceptance criteria* is shown.

Table 1. Overview of the Hywind Rotor Lift Opertaion.

Critical Response	Phase number						Acceptance criteria	Type
	1	2	3	4	5	6		
Airgap between blades and waves	X	X	X				> 3 m	Deterministic (E)
Crane loads			X	X	X		< 6375 kN	Stochastic (N)
Lift wire tension			X	X	X		> 0	Deterministic (N)
Acceleration of rotor			X	X	X		< 4.8 m/s^2	Stochastic (N)
Rotational acceleration of rotor			X	X	X		< 6 rad/s^2	Stochastic (N)
Rotor sway and surge motion			X	X	X		< 2 m	Deterministic (N)
Airgap blade 3 and tower					X	X	> 0 m	Deterministic (E)
Yaw and tilt angle					X		< 5 degrees	Deterministic (N)
Relative yaw and tilt angle between rotor and special tool						X	< 5 degrees	Deterministic (N)
Relative radial velocity						X	< 0.4 m/s	Deterministic (N)
Relative axial velocity						X	< 0.1 m/s	Deterministic (N)
Phase Duration (hours)	**8**	**3**	**0.2**	**0.2**	**0.4**	**0.2**		
Total Operation duration (hours)	**12**							

Met-ocean condition forecast for the test case is ECMWF multi-ensemble weather forecast for FINO3 met mast location (7 º W 55.25 º N, North Sea). The forecast covers 3 days - 2013-08-06 00:00:00 to 2013-08-08 24:00:00 with temporal resolution of 3 hours. Met-ocean conditions at the installation site are described by the wind speed and direction, wind generated and swell wave heights, periods and their respective directions.

4.2. Simulation of response and results

ECMWF weather forecasts have 51 ensemble members; consequently, 51 simulations were performed for every forecasted 3-hour met-ocean state. Furthermore, in order to ensure sufficient data points for distribution fitting and convergence of estimated probabilities of failure, 16 realizations of equipment response for each forecasted ensemble sea state were simulated. 16 unique seeds are used to generate input wind and wave time series which are converted into equipment response within SIMO software. This totals in ~20000 simulations for the 3 day period.

Acceptance criteria for phases 3-6 from Table 1 were considered and the procedure described in section 3 was used. Fig. 7 shows average probabilities of failure related to different *acceptance criteria,* averaging is done over all 51 ensemble members of the weather forecast. Here, failure is an event when a given *acceptance criterion* is violated within forecasted 3 hour sea state.

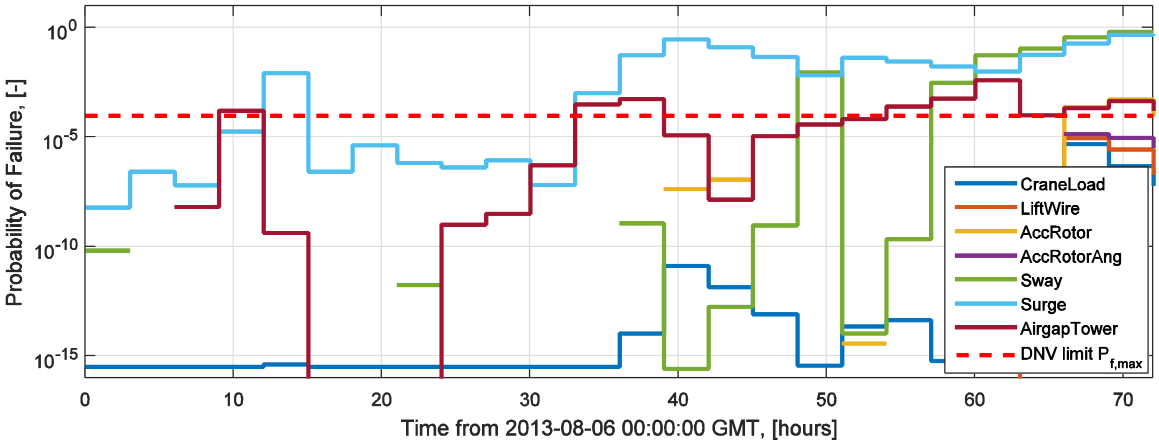

Fig. 7. Expected values of $P_{F,ac}$ of selected *acceptance criteria*.

It is seen that some of the individual *acceptance criteria* are violated. Probabilities of failure related to e.g. surge and sway motion *acceptance criteria* are above the recommended maximum probability of operation failure - 10^{-4}. This implies that for most of the 3 day forecast, operation should not be attempted. However, there are times when total probability of operation failure could be acceptable.

All the *acceptance criteria* have to be satisfied at all times for a successful completion of the operation. Therefore, the combination of all *acceptance criteria* exceedance events can be treated as a series system of "failure elements" as described in section 3. Equation (5) is used to obtain total probability of operation failure. Fig. 8 shows one of the input weather parameters (significant wave height) together with total probability of operation failure of Hywind rotor lift operation for 3 day weather forecast.

Fig. 8 indicates that there are 2 weather windows suitable for operation, a short 3 hour window in the start of the 3 day period and a longer, 15 hours long, later. It is also visible, that the probability of operation failure follows the trends of weather forecast – with bad weather conditions (increasing wave height) the probability of failure increases. Furthermore, the uncertainty of predicted probability of operation failure reflects the uncertainty of weather forecast – with increased spread of forecasted wave height, increased spread of predicted individual ensemble probabilities of failure can be observed.

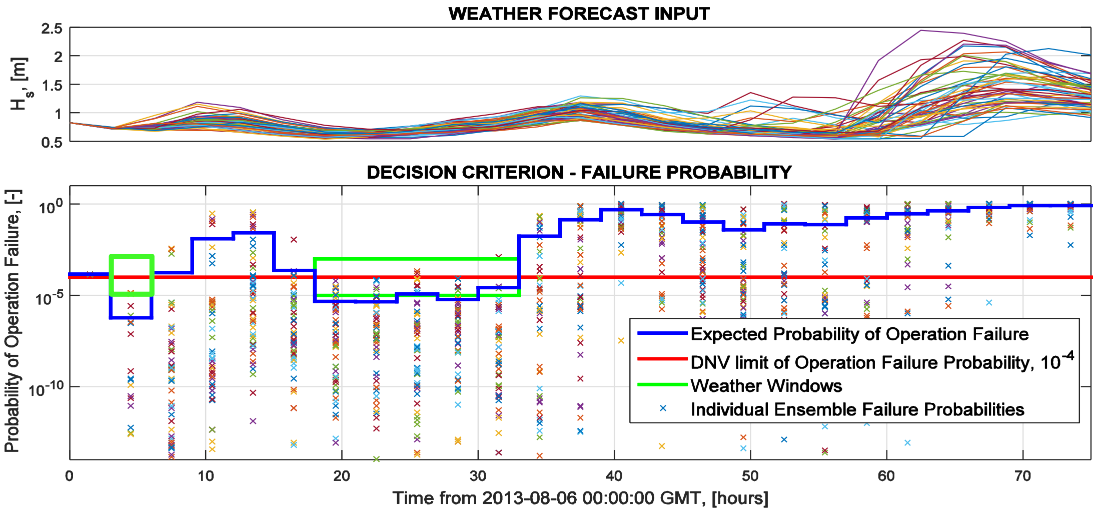

Fig. 8. Weather input and expected probability of operation failure of Hyhwid Rotor lift operation for a 3 day weather forecast.

Additionally, a crude comparison between the standard *alpha-factor* and the new approach is done. *Alpha-factors* for Hywind rotor lift operation were selected according to [2] section 4. Table 2 shows weather limitations of the operation and the *alpha-factors* used. Note that tabulated *alpha-factors* for wave peak period are not given in [2], it is only noted that uncertainties in wave period forecasting should be accounted for. Thus the *alpha-factor* for wave period was estimated using the procedure identical to one used to establish the tabulated *alpha-factors* for wave height in the standard, based on [6]. *Alpha-factor* methodology requires weather conditions at the installation site to be below *all* adjusted weather limits from Table 2. Fig. 9 shows weather windows estimated using both methodologies.

Table 2. Weather limits and alpha factors for Hywind rotor lift operation.

	Wave height H_s, [m]	**Wave peak period T_P, [s]**	**Wind speed W_s, [m/s]**
Weather limit	1.5	5	7
Alpha-factor	0.78	0.78	0.8
Adjusted weather limit	1.17	3.9	5.6

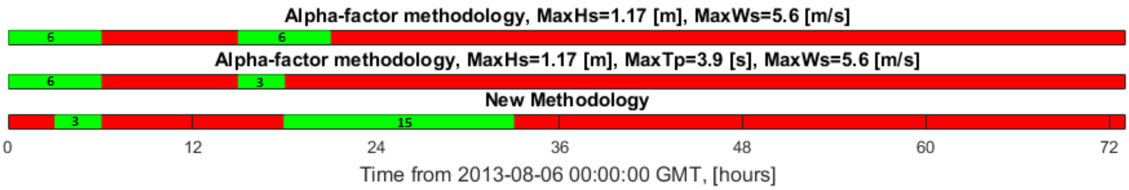

Fig. 9. Comparison between standard *Alpha-factor* and the proposed methodologies. Weather windows suitable for operation are shown in green. Top – *alpha-factor* methodology with limits on wind speed and wave height, middle - *alpha-factor* methodology with limits on wind speed, wave height and wave peak period, bottom – proposed new methodology with limits on equipment response (from Table 1).

It is visible that the new methodology predicts more operational hours during the forecasted 3 day period (18 hours against 12 or 9 hours for *alpha-factor* method variants). Furthermore, the weather windows for different methods are located in the same areas on the time axis, implying relatively consistent results between both methods.

However, it should be kept in mind that this is only a crude comparison between methodologies and a more thorough comparison is necessary in order to draw concrete conclusions about the performance of the new methodology. A thorough comparison is however beyond the scope of this paper.

5. Summary and conclusions

A methodology for Reliability Based decision support for weather window estimation was developed and presented. The methodology can easily be extended for Risk Based decision support. The methodology uses physical limitations of the equipment used for offshore operations as basis for estimation of weather windows. This is an improvement over the state-of-the art techniques used for offshore operation planning, which are limited to use of simple met-ocean parameters (wave height and wind speed) for decision making. Also, ensemble forecasts are used and wave periods are taken into account. This also represents improvements compared to the state-of-the-art and techniques currently applied.

A “proof of concept” case study of the offshore Hywind rotor lift operation was carried out. It was used to verify if the proposed methodology could be useful as decision support when predicting weather windows for offshore wind turbine installation. After extensive testing it can be concluded that the proposed methodology produces consistent results and has potential to be used as decision support for weather window estimation – predicted probabilities of operation failure follow the trends of weather forecast, including the uncertainty of input weather forecasts which is translated into larger predicted probability of operation failure.

Despite the fact that the “proof of concept” and demonstration case is an offshore wind turbine rotor lift, the methodology is very general and could be applied to any other marine operation. The applicability is only limited by the possibility to quantify the responses of the equipment by computer simulations and proper definition of equipment *acceptance criteria*.

6. Future Work

Some additional work has been done, but not published yet. This includes benchmarking of the proposed methodology against standard practice for weather window estimation – the “a*lpha-factor*” method, and investigating the effects of weather forecast uncertainty on performance of proposed methodology. Results of aforementioned analyses are to be presented in upcoming publications. However, more work is necessary and should include:

- Updating the model with Structural Reliability techniques in order to reduce the demand on computing power due to large amount of simulations necessary to obtain reliable results.
- Splitting the *acceptance criteria* into serviceability and ultimate limit states. This would allow the use of different maximum allowable probabilities of failure for the two, when estimating weather windows.
- Including costs of failure to produce a “Risk-Based” aspect allowing comparison among different weather windows in terms of expected Risk, rather than just probability of operation failure.
- Extending and testing the methodology on more general offshore operations (offshore oil and gas, wind turbine installation on monopoles/jackets, offshore wind turbine operation & maintenance access, etc.).
- Investigating effects of correlations among different *acceptance criteria* exceedance events.

Acknowledgements

The research is funded by The Research Council of Norway, project No. 225231/070 - Decision support for offshore wind turbine installation (DECOFF). The financial support is gratelly appreciated. The authors also acknowledge Christian Michelsen Research, Meteorologisk Institut (Norway), MARINTEK, Uni Research, University of Bergen (UiB) and STATOIL for their valuable inputs and support.

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