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Maintenance strategies for large offshore wind farms

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Abstract

Up to one third of the total cost of energy from offshore wind generation is contributed by operation and maintenance (O&M). Compared to its onshore counterpart, this fraction is significantly higher. Costs are not only caused by spare-parts and repair actions, but also by production losses due to downtime. The accessibility of a turbine in case of a failure is one main aspect affecting downtime. Therefore, a tool has been developed and implemented in MATLAB to simulate the operating phase of a wind farm with special emphasis toward the modeling of failures and repair. As an example application, a site at the UK east coast was chosen, and a few distinct scenarios were considered. Results include how sensitive availability changes with respect to changes in maintenance fleet and maintenance scheduling strategy. A quantification of potential cost savings due to an increase in availability is also stated.

Keywords: Offshore Wind Energy; Operation and Maintenance (O&M); Availability; Accessibility; Downtime; Markov Chain

1. Introduction

In order to be able to fund ambitious large-scale offshore wind projects, it is necessary to mitigate the risk for potential investors [1]. Wind turbine availability is a main risk-influencing factor, as it determines the obtainable income directly. Experiences from the UK round 1 offshore wind farms *Barrow, North Hoyle, Scroby Sands* and *Kentish Flats* show availabilities of 67-87%, which is far below expectations [2]. We have performed simulations to determine key factors to increase availability, and therefore the economical efficiency of offshore wind farms. Studies have been carried out showing the influence of variations in maintenance fleet. The effect of changes in wave height limits for the utilized equipment has been analyzed, and results with respect to changes in availability and quantified production losses due to downtime are discussed. Influences of changing the accuracy of weather forecasts have also been investigated. All studies have been performed using MATLAB, with the methodology described within

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this paper. Investigations have been carried out for a hypothetical 2.5 GW wind park close to the UK east coast that consists of 500 turbines, each with a rated power of 5 MW.

2. Methodology

The methodology for modeling the offshore wind farm is described in the following paragraphs, and is functionally divided into the five main modules *weather, failures, resources, scheduling* and *cost*.

Whether it is possible to perform offshore operations or not is mainly determined by *weather* conditions. Amongst all parameters, wave height is the most important limiting factor, in magnitude, as well as in persistence [3]. It is therefore important to have a method at one's disposal that allows for generating realistic sea state time series. The main available methods can be classified into three categories and are either based on Gaussian statistics, ARMA processes, or assume the Markov property [4]. The latter is particularly capable to not only represent correct wave height distributions, but to also capture their persistence [5], and has therefore been chosen for the present work.

Historical data for a given site was used to first estimate transition probabilities for a discrete Markov chain whose states represent different values of significant wave height. Time series of significant wave height were then obtained by random sampling. The transition matrices were estimated for each month separately to capture seasonal trends. Data for the past 22 years (1989-2010) was available in 6 h resolution from the ERA Interim dataset of the European Centre for Medium-Range Weather Forecasts[2]. The Markov chain consists of eighteen states, each representing an incremental change in significant wave height of 0.4 m, which results in a 18 x 18 transition matrix. The significant wave height is assumed to be constant throughout each 6 h period. The number of states is a compromise between resolution and having enough statistics available for reliable estimation of transition probabilities from one state to another. Corresponding wind speeds were generated, also assumed to be constant per 6 h time interval, based on their conditional probability distribution relative to the significant wave height value. The wind speeds ranged from one to thirty meter per second, and were represented with 1 m/s resolution.

The weather module was validated by comparing its output with the original time series, with respect to mean values, standard errors (SE) and cumulative distribution functions (CDFs) of significant wave height, wind speed and the length of weather windows fulfilling certain conditions. Table 1 compares mean values and standard errors of significant wave height and wind speed for the complete 22 year period, as well as their linear correlation coefficients.

Table 1. Mean values, standard errors, and wind-wave correlation; comparison of model results against observed data

	Wind		Waves	
	Modeled	Observed	Modeled	Observed
Mean Value	7.1394	7.1367	0.9802	0.9829
Standard Error	0.0187	0.0189	0.0035	0.0035
	Modeled		Observed	
Wind-Wave Correlation	0.8582		0.8787	

Regarding mean values and standard errors, both modeled wind speeds and wave heights lie within 2 percent of the values for the observed time series. Results for the CDFs, besides errors due to the finite number of states used for the synthetic data, agree well (Fig. 1). Considering correlations between wind speed and wave height, both modeled and observed data is showing similar results.

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[2] http://www.ecmwf.int/

Regarding maintenance tasks, the persistence of weather conditions is of particular importance. All offshore operations take a dedicated period of time to be performed, in which, for instance, wave height and wind speed must not exceed defined threshold levels. The persistence of wind speed and wave height has been evaluated by their CDFs [5]. Results indicate that modeled and observed persistence data agree reasonably well (not shown).

To summarize, the assumption of a Markov process for the sea state, in combination with wind speeds modeled by the conditional probability distribution relative to the sea state shows a good agreement with observed values. Considering all mentioned tests, the method is therefore suitable for the purpose of this investigation.

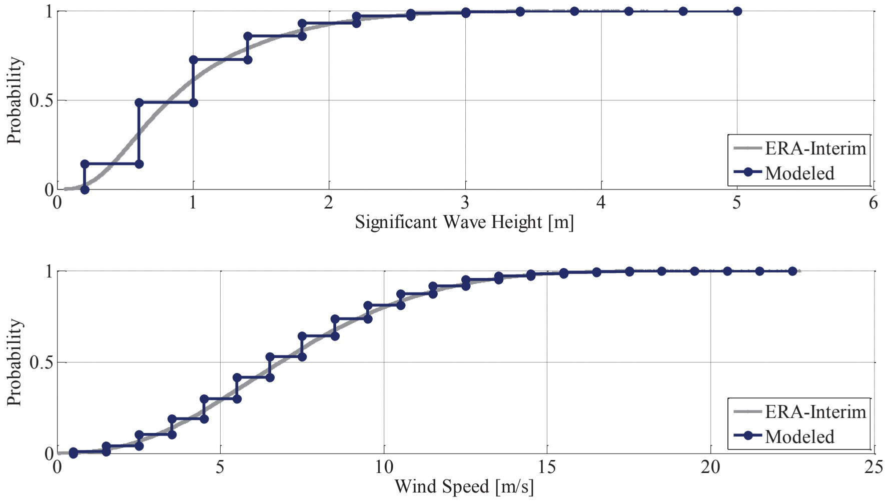

Fig. 1 Cumulative distribution function of significant wave height (top) and wind speed (bottom)

Annual failure rates and mean time to repair are the basis for the *failure* module. Data gathered from an ongoing onshore reliability study performed at the Fraunhofer Institute for Wind Energy and Energy System Technology has been used as input [6].

In accordance with that study, turbine failures for 12 subsystems were considered, assuming a Poisson process for the failure of each component. Failures are clustered into those which can be repaired without heavy lifting equipment, and those which need a crane. To concentrate on the essential features, repair times are assumed constant. For components which do not need a crane, a constant number of people needed for repair is assumed, which is referred to as a repair *crew*. Failures are generated for each component of all turbines independently. Malfunction of one subsystem always results in the breakdown of the whole turbine. Correlations between external conditions (wind speed, time of year) and failure rates are not considered. Bathtub curves of failure distribution during lifetime, as described in [6], are also neglected. Scheduled preventive maintenance has not been taken into account.

The module on *resources* defines which equipment and personnel is available for O&M activities. The equipment is specified by its characteristic properties: assumed transit time from harbor to park, its maximum capacity, and its operational constraints with respect to maximum wind speed and wave height.

For simplification, the transit time for a maintenance vessel is set to 6 h for an ordinary vessel, respectively 12 h for a crane vessel. The capacity of people to carry in a boat is adjustable. Wave height and wind speed constraints are also variable, in order to study the effect on the availability.

In order to consider limitations of working-hours for the crews, a maximum time offshore has been implemented and set to 7.5 days. If it is exceeded, an abortion stop of all ongoing operations at that moment proceeds and the affected vessel and its personnel returns to shore.

Whether an operation is going to be performed under different circumstances is defined in the *scheduling* module. A general overview of the procedure after a new failure occurs is shown in Figure 2 for an ordinary vessel (the scheduling of a crane ship being similar).

In case of the occurrence of a new failure, all ships operating in the wind park check if they transport enough personnel (from previous, completed repairs) without present task. If this is the case, a new crew is established for which the component is scheduled for repair, provided that the maintenance personnel has not been offshore too long and the weather conditions are sufficient. If a failure cannot be scheduled for all ships located in the park, it stays unscheduled (unreserved) and can then be scheduled for ships in harbor. First, all ships already containing crews (from previous time steps with bad weather) are trying to schedule the failure. Depending on each ship's capacity, it will either create and add a crew for this failure, or, if the maximum load is already reached, leaves the component unreserved and available for scheduling by other ships. If there are no suitable ships available, the failure remains unreserved and the procedure starts afresh six hours later, in the next time step. If a ship in harbor carries a crew, it will, as soon as weather conditions allow for, enter into transit to the park. For the weather check, a so-called *look-ahead-time* represents the accuracy of the weather forecast. This parameter determines the maximum time a ship can assume reliable information about future weather conditions. Weather conditions are sufficient, as long as wind speed and wave height are under the operational threshold levels for the total intended time offshore (maximum of all crews' expected time to repair). In the next time step after transit, the ship drops off all crews at the turbines with components that are scheduled for repair. Weather conditions and time offshore are reviewed every time step whenever a vessel is in park. After a crew arrives at a component, the respective repair time counts down every time step until zero. The crew is then collected by the ship in the next time step and can schedule further failures. Every ship can only handle the crews that were assigned to it in the harbor. It is presumed that all components which can be repaired without a crane do not require additional equipment from land.

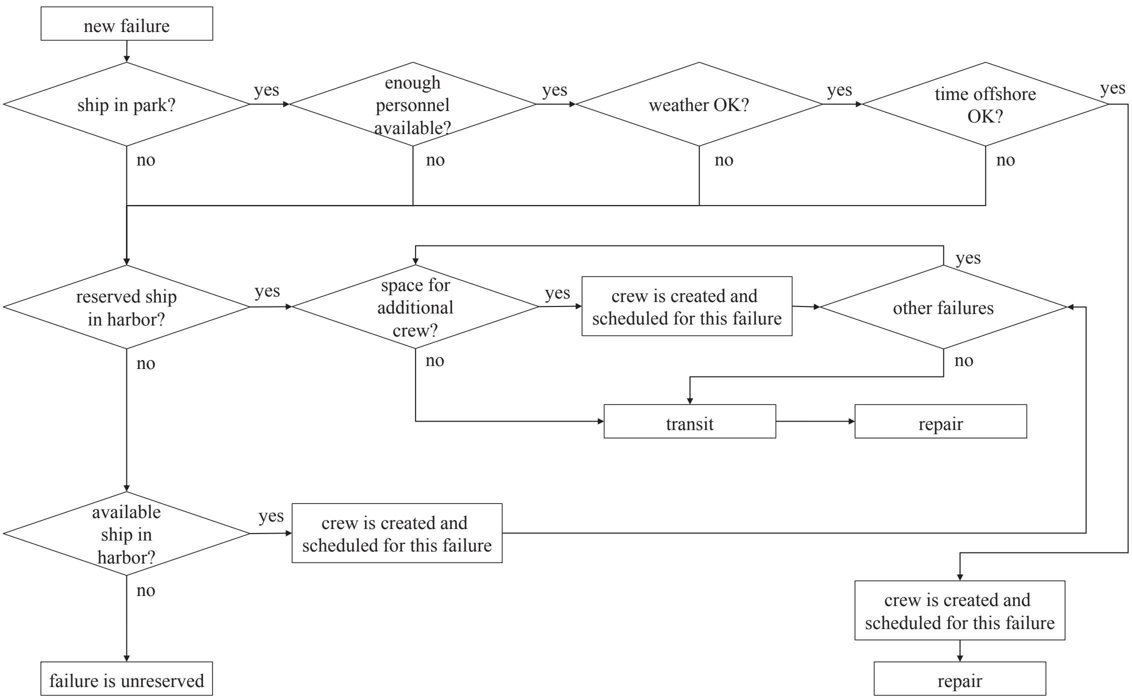

Fig. 2 Scheduling strategy flow chart

In contrast, a crane can only handle one repair task before returning back to the harbor. If a crew has to interrupt a repair, failures are reset to the state *unreserved* and repair times stay as they were before the interruption, assuming the next crew can continue immediately working on the failure.

There are diverse factors determining operating *costs* of an offshore wind farm. Here, the focus is set on production losses, as they can be handled in a simple manner and are strongly effecting the economical performance of an offshore wind park [7]. We quantify how much worth it would be to deploy more or better equipment in terms of an increase in availability. Spare-part and labor costs, as well as expenses due to vessel or crane deployment, are included in this value. To quantify production losses, a linearized power curve is evaluated for the modeled wind speeds during downtime. Potential production is equal for every turbine in park, i.e., there is only one wind speed considered and wake effects are neglected. In order to quantify losses in monetary terms, the summarized kilowatt hours are multiplied with the local feed-in tariff (FIT), assuming a compensation of 0.1801 €/kWh for British waters [8].

3. Results

Variations of maintenance fleet and weather forecast accuracy have been performed with respect to park-availability, cost savings and deployment of equipment. Each simulation represents one year of operation.

3.1. Influence of wave height constraint and equipment variation on park availability

Four different compositions of the maintenance fleet were taken into account for this study, as major effects can be clearly seen in those configurations (Figure 3):

Wave height boundaries were varied from 1.0 to 2.6 m in steps of 0.4 m (corresponding to the resolution of the sea state simulation). All other simulation parameter were held constant. The look-ahead-time was set to 48 h. The maximum number of people that could be carried on a ship was four. Each calculated availability value represents a mean over five runs, with standard errors less than a few percent.

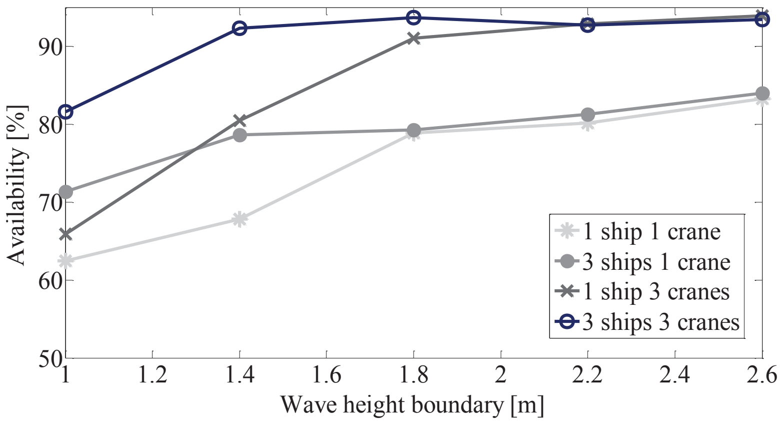

Fig. 3 Park availability against equipment characteristics, for four different fleet compositions

Regarding fleet variation, it can be seen that the highest availabilities have been achieved with three ships and three cranes, the largest fleet considered (Fig. 3). In reverse, lowest values occurred by considering only one ship and one crane. For assumed wave height boundaries less than 1.4 m, additional ships and cranes both lead to an increase of availability of the same magnitude, i.e., the availability changes (almost) linearly with the number of resources. For the regime from 1.4 to 2.2 m, additional ships have a lower influence on the availability than additional cranes have. The availability of more than one ship that can perform for boundaries greater than 2.2 m has almost no effect on availability anymore, i.e., there exist sufficient weather windows that one such ship can handle all repairs. The number of crane vessels still has an important influence, as each crane vessel can only handle one repair a time. In case of several failures, a greater number of cranes would directly lead to more repairs during a weather window.

3.2. Effects of accuracy of the weather-forecast

The decision whether an operation is going to be performed mainly depends on weather conditions. In case of a theoretical, fully accurate forecast (with a look-ahead-time of infinite length), ships or crane boats are only deployed if it is assured that they can finish their tasks. If the look-ahead-time is finite, as it is in reality, vessels have to cancel offshore operations from time to time, and need to access the turbine more than once for each repair. This is represented in Figure 4, where the number of deployments for an ordinary maintenance vessel (ship) and a crane vessel (crane) are displayed for five different cases. The look-ahead-time has been varied in a range from 6 h to 72 h.

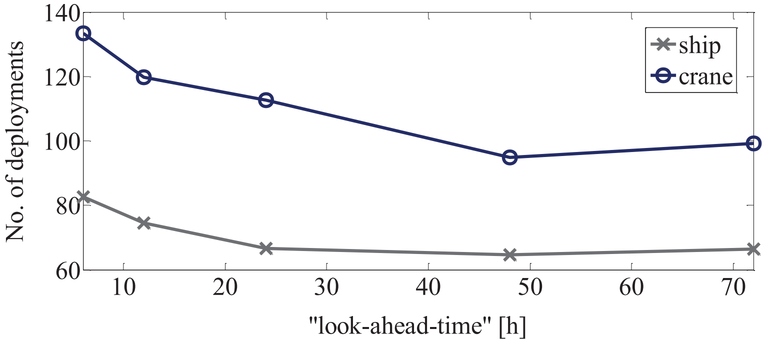

Fig. 4 No. of crane deployments against look-ahead-time

The total number of average operations carried out by both vessels is shown for a one year simulation in a three-ship-three-crane configuration, where five runs have been taken into account. Achieved availabilities have been on the same level for all runs. Both curves show a strong dependence of the amount of operations on the reliability of the weather forecast in regions of short look-ahead-times. Crane boats arrive at their optimal operating point if an accurate forecast of two days or more can be provided. Due to shorter transit and repair times, the saturation for ships is reached after 24 h, i.e., longer information about future weather conditions is not necessary for an optimum performance in this configuration. Especially for crane vessels, a slight increase of the number of deployments can be observed for long look-ahead-times. This phenomenon is assumed to be of statistical nature due to the limited amount of simulation runs.

3.3. Cost

For an estimation of potential cost savings due to higher availability, downtime losses have been quantified monetarily. For linearization of the power curve, data from the 5 MW reference turbine developed by the National Renewable Energy Laboratory [9] has been used. For the FIT, data from a KPMG market survey has been used [8], leading to an income of 0.1801 €/kWh for British waters. The dependence of yearly production losses on availability is visualized in Figure 5, where data is provided for the entire park. All different fleet combinations and wave height boundaries have been evaluated for this diagram.

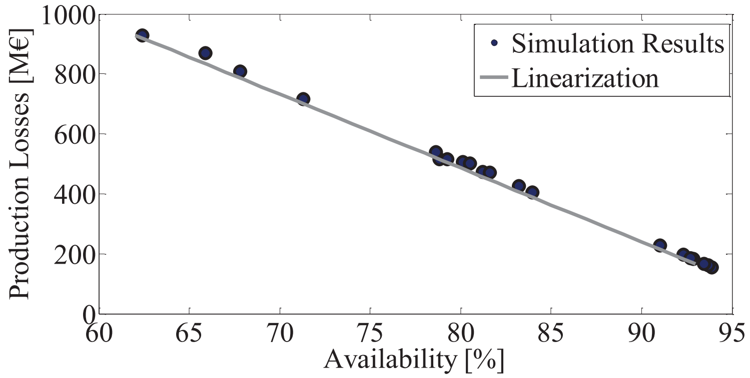

Fig. 5 Production losses against availability

A strong linear correlation between availability and production losses can be seen. Variations occur in regions of lower availabilities, as wind speed variations are then having some influence, due to the total amount of considered realizations.

Exemplarily, a change of wave height boundary from 1.0 m to 1.8 m for both access methods in a one-ship-one-crane configuration would decrease downtime losses by about 30 percent. In numbers, a yearly decrease of downtime losses of 393 M€ for the park, respectively more than 780 k€ on average per turbine, could be achieved by using a more advanced access system, according to the assumptions made for this investigation. For the simulated wind park, the correlation between production losses (PL) and availability (A) can be formulated as in Equation 1, when considering availability values from 62-93 % in order to approximate cost savings by variation of parameters:

$$PL(A) = (0.62 - A) \cdot 2460 \text{ M€} + 929 \text{ M€}. \tag{1}$$

A small increase in availability can therefore lead to high cost savings. Which parameters could effectively affect availability is stated in the above sections. As shown in Figure 3, the application of a three-ship-one-crane configuration with an assumed wave height boundary of 1.4 m leads to the same availability level as a one-ship-one-crane configuration with a wave height boundary of 1.8 m. The decision on which solution is providing the overall economical optimum has therefore to be decided considering aspects on various cost drivers.

4. Discussion

The intention of this project was to figure out the sensibility of the availability for an offshore wind park, under the variation of certain parameters. Calculated availabilities and potential cost savings shall not be understood as ultimate values, but allow for developing a sense for how the availability and costs could react due to parameter variation. Several simplifications have been made in order to concentrate on the parameters of interest.

Regarding the weather module, slightly better statistics could have been achieved by decreasing the wave height resolution, i.e., by decreasing the number of states of the Markov chain. At the same time, that would eliminate the possibility of varying wave height boundaries as it was done for this study. Selected tests of the weather module also show a sufficient accuracy of generated time series. Furthermore, the generation of wind speed time series based on wave heights would not have been possible in this accuracy. Especially for the cost module, a precise representation of wind speeds is essential.

Considered failure rates are based on an onshore survey. Values for offshore turbines might differ significantly, but, as the market still is quite young, only incomplete data is available. Failure rates for all considered systems can be readily adjusted, if required. The simplification of a total turbine breakdown, independent of which system fails, might be refined subject to each component.

The possibility of continuing a repair from the point it has been interrupted might also, especially for components repaired or replaced by a crane, not be realistic.

The definition of maintenance resources was held very simple. Only two different access systems were considered, an ordinary maintenance vessel or a crane vessel. Ships were only specified by the maximum number of personnel they can carry, a maximum weight capacity of transported material is neglected. In terms of restrictions, both access systems are only underlying wave height boundaries. In reality, depending on the planned operation, wind speed, fog, temperature or rainfall might also play a role. Alternative access methods, e.g., by helicopter, have not been taken into account. For ships in harbor, personnel is always available in the demanded quantity.

The scheduling strategy applied for this study could be refined by implementing more factors a ship, respectively a crane, can base its decisions on, including probabilistic aspects for weather forecast accuracy or repair time variations. If transit times and repairs could be supplied by costs, more optimal overall strategies could be developed. For the variation of maintenance fleet, wave height boundary and weather forecast accuracy, the applied scheduling is showing sufficient results.

Economical performance is solely investigated by evaluating production losses during downtime. Significant changes have been achieved by parameter variation, showing that especially the wave height boundary for access systems has a great influence on the economical performance. An implementation of the described methods to other wind farm cost models could be a possibility of accessing life cycle cost for an overall economical optimization.

5. Conclusion

The presented methodologies of modeling the operation phase of an offshore wind farm show promising results. An accurate weather model has been developed, based on Markov theory, which, to the authors knowledge has not been applied for wind park simulation before. Significant changes in availability, monetarily quantified by production losses, have been presented with respect to changes in maintenance fleet and vessel characteristic. The economical potential was shown with the perspective of implementing these methods in tools for wind park life cycle cost models. More detailed studies regarding the economical effect of different scheduling strategies and equipment specifications could be performed on this basis.

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