openO&M: Robust O&M open access tool for improving operation and maintenance of offshore wind turbines

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With O&M costs accounting between 25-30% of life-cycle costs, it becomes pertinent to model related activities analytically, accounting for all downtime-contributing factors and at the same time incorporating in the analysis practicalities of operations. Related analysis should be able to account for the accurate prediction of weather data, classification of maintenance interventions and modelling of failure rates, and finally, apply realistic strategies with respect to planned and unplanned maintenance activities. This paper reports the development of the initial version of an open-access tool, which allows the estimation of availability of a given wind farm with specified characteristics throughout its service life, allowing for the simulation of a number of scenarios related to reliability parameters, vessels specifications and availability, number of technicians etc, towards optimising a wind farm maintenance strategy. Here, we present initial results for a reference case study, showing applicability and responsiveness of the tool and sensitivity analysis of the jack-up vessel mobilisation time as a varying parameter as it was found to have a significant impact in the estimated availability.

Keywords: offshore wind energy, O&M, availability, numerical tool, open access, planned maintenance, unplanned maintenance, weather forecasting.

1. Introduction

The offshore wind industry is experiencing rampant growth in Europe and overseas. Based on WindEurope's statistics, by the end of 2018, a total of 18,499 MW of capacity was installed in Europe, corresponding to 4,543 grid-connected wind turbines across 11 countries (WindEurope 2019). This capacity is foreseen to increase by four times by 2030, making a cumulative installed capacity of 70GW. As a consequence of this rapid technology development, there is an increasing need to reduce the operation and maintenance (O&M) costs and therefore the Levelised Cost of Energy (LCoE) of this important source of renewable energy (Martinez-Luengo, Shafiee, and Kolios 2019; Ioannou, Angus, and Brennan 2018).

Several authors and wind energy organisations are developing models and computational tools for offshore wind O&M simulation and optimisation. A comprehensive literature review is provided by (Hofmann 2011; Kolios 2018). Most of the existing models are variants of risk-based methods grounded on reliability engineering and uncertainty quantification methods to model the relationship between availability, maintenance and cost at a whole-system wind-farm level, considering the variability of the sea climate.

Besides the similarities in the inputs required and outputs produced in most of the models, there are significant methodological differences between them, mainly regarding weather simulation and the way reliability and maintenance are represented (Scheu et al. 2017; Leimeister and Kolios 2018). In particular, at the

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level of reliability modelling, a number of tools consider constant failure rates for components and subsystems (i.e. CONTOFAX, NOWIcob), while others consider time-dependent or season-dependant failure rates, i.e., MWCOST and SIMLOX).

With respect to maintenance modelling, there is a spread of methodologies ranging from the consideration of repair and waiting times as deterministic variables (Rademakers LWMM, B.H., Zaaijer MB 2003), probabilistic variables and the consideration of maintenance tasks as a serialised process (Dinwoodie et al. 2013) or in parallel process (Joschko et al. 2015).

In regards to weather simulation, models are using just historical time-series as input (e.g., OMCE and MWCOST), while others use synthetically generated time-series using contrastingly different methods such as Markov chains, multivariate autoregressive models, or the Fast Fourier Transform (FFT). In addition, of the reviewed models, only a few of them are commercially available (the most relevant being ECN O&M, NOWIcob and O2M), while the rest are authored models not publicly available as computational tools, which constrains their spread throughout industry and academia.

In this paper, the development of a wide-applicable modular, open access tool for the simulation of O&M activities of offshore wind farms is documented. The tool, which is named as 'openO&M' has been developed in Matlab® and allows a versatile yet transparent simulation of the long-term availability of an offshore wind farm, along with its associated power production.

The input of the model consists of a user-defined description of the failure rates of the various subsystems, maintenance and repair policies, and simulated weather conditions. Then, stochastic simulations are run in the time domain, and failure modes are simulated based on the failure rates. Each failure type belongs to a specific maintenance category, which determines the weather limitations and vessel, crew, and time needed for the repair. These determine a series of operational downtimes along the lifespan of the plant whereby the availability and power are obtained. The applicability and versatility of the proposed tool are demonstrated and discussed using an illustrative case study.

The paper is structured as follows. After this brief introduction, the structure of the tool is presented through its modules. Then a case study is presented with some indicative results. Finally, some conclusions are listed together with recommendations for future work.

2. Structure of the openO&M tool

In order to ensure versatility of the tool, a modular approach has been adopted with four distinct modules, allowing for expansion and further investigation of certain functions depending on the focus of the analysis. In this section, each of the modules is briefly presented.

2.1 *Reliability module*

This module aims at simulating the occurrence and severity of the different failure types corresponding to the subsystems of the turbine, along with the overall mean time to failure (MTTF) of the turbine. To this end, each subsystem (e.g., the gearbox) is assumed to have three failure types according to their severity, namely:

- Minor failure (denoted by m), implying that the turbine continues working when the failure is detected, and it is shut down only during the repair time;
- Major failure (denoted by M), the turbine is stopped as soon as the failure is revealed, and remains out of service until the fault is restored;
- Replacement (denoted by R), the faulty subsystem needs a complete replacement, and the turbine is arrested during the waiting time and replacement, implying longer downtime.

The time to failure (TTF) associated with each failure mode for a particular subsystem i is assumed to be distributed by an exponential probability density function with parameter $\lambda_{i,mode}$, as follows:

$$f(t) = \lambda_{i,mode} \exp\left(-\lambda_{i,mode} t\right) \quad (1)$$

where $\lambda_{i,mode}$ is the failure rate for subsystem i under a particular failure mode (e.g., m, M, or R). Based on the equation above, the cumulative distribution function (CDF) of the time to failure is given by:

$$F(t) = 1 - exp(-\lambda_{i,mode} t) \quad (2)$$

which, according to the exponential reliability theory, coincides with the probability of failure (PoF) of subsystem i under a particular failure mode, ie. $PoF_{i,mode} = 1 - \exp(-\lambda_{i,mode} t)$. Therefore, by assuming that the subsystem fails when one of the failure modes takes place (i.e., serialised system), the probability of failure of the subsystem i can be obtained as

$$F(t) = 1 - exp(-\lambda_i t) \quad (3)$$

with $\lambda_i = \lambda_{i,m} + \lambda_{i,M} + \lambda_{i,R}$. Analogously, the probability of failure of the whole turbine is obtained by idealising the turbine as a serialised system of subsystems, therefore

$$F(t) = 1 - exp(-\lambda_{turb} t) \quad (4)$$

where $\lambda_{turb} = \sum_i \lambda_i$. From Eqs (2) to (4) and based on the exponential reliability theory, the MTTF of subsystem *i* under a particular failure mode will be given by $1/-\lambda_{i,mode}$, whereas $1/-\lambda_i$ and $1/-\lambda_{turb}$ provide the MTTF of subsystem *i* (i.e., under any failure mode) and the MTTF of the complete turbine, respectively. To simulate the occurrence of a particular failure mode for a particular subsystem, the time to failure of all the subsystems is simulated according to Eq (3) by substituting *t* using a uniform random number for $F(t)$. Therefore, the fault subsystem will be the one with the lowest time to failure. The same procedure is repeated using Eq (2) to determine the failure mode of the faulty subsystem.

2.2 *Power module*

A power model is used for the calculation of the generated energy of the entire wind farm. First, the generated energy of each turbine is determined based on the weather forecast model and the turbine's power curve. Second, the generation of all turbines is summed up to obtain the wind farm's total energy production.

In order to utilise the power curve, the wind speed at hub height is required. Wind data measured by a met mast is providing wind speeds at a reference height. It needs to be extrapolated to the wind speed at hub height, which can then be applied to the power curve. Therefore, the power law is utilised:

$$U_{hub\ height} = U_{reference} * \left(\frac{hub\ height}{reference\ height}\right)^{\alpha} \quad (5)$$

where $U_{reference}$ is the wind speed at reference height in m/s measured at the met mast. $Hub\ height$ and $reference\ height$ are given in $meters$. The power law exponent α is given by:

$$\alpha = \frac{0.37 - 0.088 * \ln(U_{reference})}{1 - 0.088 * \ln\left(\frac{reference\ height}{10}\right)} \quad (6)$$

Utilising wind speed data at a reference height of 10 meters simplifies above equation to:

$$\alpha = 0.37 - 0.088 * \ln(U_{reference}) \quad (7)$$

Afterwards, the power is determined as follows:

$$P(U_{hub\ height}) = 0, \text{ for } U_{hub\ eight} < U_{cut\ in}\ or\ U_{hub\ height} > U_{cut\ out} \quad (8)$$

and

$$P(U_{hub\ height}) = P_1 + \frac{U_{hub\ height} - U_1}{U_2 - U_1} * (P_2 - P_1), \text{ for } U_{cut\ in} \leq U_{hub\ height} \leq U_{cut\ out}$$

If the wind speed is lower than the turbine's cut-in wind speed or higher than its cut-out wind speed, the wind turbine is shut down and not producing power. Within the boundaries, values of the power curve are linearly interpolated for $U_1 \leq U_{hub\ height} \leq U_2$.

Afterwards, the energy can be calculated as:

$$E = P \times t \quad (9)$$

where t is the time given in $hours$.

Calculating the generated energy as mentioned above, underlies the assumption that the yaw controller always yaws into the current wind direction in order to retrieve 100% of the power. Furthermore, travel times of the yaw system when adjusting to a new wind direction are neglected in this approach as these ones have a minor impact considering the total lifetime of the wind farm.

2.3 *Weather Forecast module*

Weather conditions include random variables; hence, an appropriate approach must be adopted to forecast weather efficiently. Effective weather forecasting allows for appropriate planning of O&M related activities, reducing downtime and improving availability estimations.

The Markov model is a stochastic process, named after the Andrey Markov used in this study to forecast weather conditions. Accurate forecasting of wave height and wind speed are imperative to determine the availability and can set limits on whether it is possible or not to perform maintenance activities at sea, since vessels may have limitations when travelling to and accessing offshore wind turbines.

The Markov model is trained based on historical weather data and for the case study presented here, data from a past period of several years were obtained from FINO3 database to forecast weather conditions for the operational lifetime of an offshore wind farm. Historical weather data are discretised using a resolution of 0.2 m for wave height and of 1 m/s for wind speed. Due to this, a finite number of possible values for the variables are generated, which is necessary to apply discrete time Markov chains method. As the original database had a time step of 3 hours on the weather data, the same number was used for the forecast, providing a balance between the accuracy of the forecast and time resolution for availability simulations.

Once historical weather data were discretised, the Markov probability matrices are obtained next. Discrete-time Markov chains method is based on considering a finite number of states in a system (different wave heights in this case) and determining the probability each state has of evolving into any of the possible states in the system (including itself) which leads to a matrix of probabilities. To obtain them, the code checks the number of times each of the possible wave height values ("i") takes place in the historical dataset for each month and the number of times it evolves into each of the other wave height values ("j"). Then, it calculates the probability of wave height state "i" turning into "j" using the following expression:

$$p_{ij} = \frac{n_{ij}}{N_i} \tag{10}$$

Where n_{ij} is the number of transitions from wave height "i" to "j", and N_i is the total number of times state "i" appears. These probabilities are grouped per month in the form of the matrix for both wave height and wind speed prediction. Using these probability matrices, future values of wave height and wind speed can be predicted provided initial pair of values have been set.

2.4 *Maintenance module*

There are 2 types of maintenance activities considered in this model: planned and unplanned.

Planned maintenance is a scheduled service, whereas unplanned maintenance takes place as soon as a failure occurs. Downtimes are calculated accordingly, based on the maintenance duration, the weather conditions and the resource availability. It is assumed that for planned maintenance, workboats are filled to their maximum capacity, as they can perform operations to more than one turbine at once.

For unplanned maintenance, the O&M tool differentiates between failures which require a JUV (jack-up vessel) and failures which require a CTV (crew transfer vessel). In order to decrease downtimes, respective maintenance campaigns are implemented which do not only repair one turbine but store different maintenance tasks on a campaign list and follow this list during the campaign. While in one JUV campaign all turbines are maintained for which a failure occurred within the lead time of ordering a JUV, a CTV campaign repairs all failures which occurred during the night when technicians rest. This difference is due to the usage of vessel type. A JUV is costly and needs to be ordered at the market, and this takes time. Instead of just repairing one failure and ordering a JUV for another failure again, all pending turbines which need maintenance are served. Moreover, JUV campaigns are performed in shifts to utilise the JUV to capacity. In comparison, CTV campaigns are only performed during day-shifts as no accommodation is available on this vessel type. All failures which occurred during the night are scheduled for the next day-shift. In case not all turbines can be served, the campaign continues the next day.

2.4.1 Planned Maintenance

In the model presented, planned maintenance takes place at yearly intervals. Maintenance is performed in all subsystems of the turbine to ensure normal operation and avoid unscheduled breakdowns. Downtimes are calculated based on the maintenance activity duration which assumed to be fixed.

2.4.2 Unplanned Maintenance

Unplanned maintenance is performed on either individual machine failures or on wind farm infrastructure (e.g. cabling, transformers) failures. In case of a minor failure, the turbine is considered still operational. As soon as a major failure or need for replacement on a wind turbine subsystem occurs, the turbine is assumed to be in a non-operational state and maintenance or replacement activities need to be carried out. In the event of infrastructure failure, all turbines connected to it are considered to be in non-operational mode at that time.

Firstly, the vessel and crew availability is taken into account. Depending on the type of failure (e.g. minor, major or replacement), a different type of vessel might be required. If resources are not sufficient, downtime is calculated until enough vessels and crew are available to perform required maintenance on the respective wind turbine. This depends on the previous missions' travel times and repair times as well as the maximum number of vessels and crew available for the wind farm. If multiple shifts are required for a specific repair, the crew rest time is also added to the downtime.

Afterwards, the availability of the parts needed when maintenance activities occur is considered. The downtime of a wind turbine is affected by the time until the required spare part for maintenance is ready.

The mobilisation and demobilisation times need to be calculated, as well. These include the time needed to prepare the vessel, load the required tools and spare parts for each maintenance mission, and clean up the vessel after maintenance is complete to make it ready for the next mission.

Finally, the weather conditions for safe operations are considered. If the maximum wave height and maximum wind speed allowable for each vessel are exceeded, the downtime is increased until safe operation limits are reached.

Maintenance activities are carried out until the end of the lifetime of all wind turbines in the wind farm. Then, the downtimes of each turbine are added up, and the total wind farm availability is calculated, as shown below.

$$A = \frac{Lifetime_{wf} - Downtime_{wf}}{Lifetime_{wf}} \quad (11)$$

Where A is the calculated wind farm availability, $Lifetime_{wf}$ is the cumulative lifetime of all wind turbines in the wind farm and $Downtime_{wf}$ is the cumulative downtime.

A flowchart for unplanned maintenance is given in Figure 1.

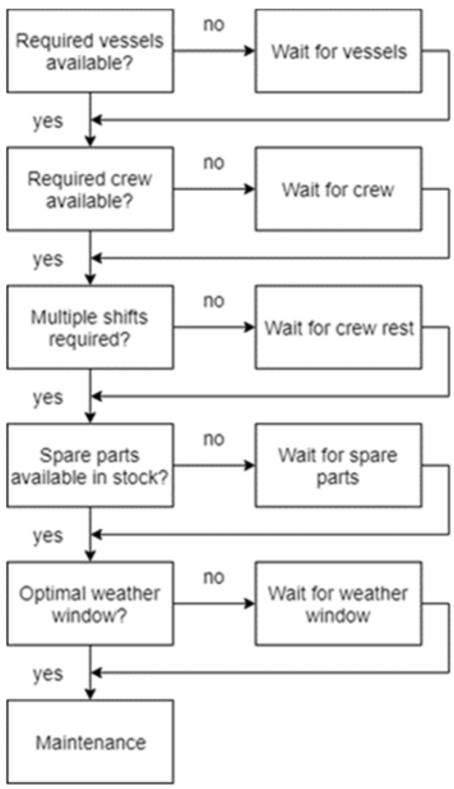

Fig. 1. Unplanned maintenance flowchart.

3. Case Study

The O3M tool is validated through a wind farm lifecycle scenario. This section will present a base case based on inputs from literature and a sensitivity analysis with respect to mobilisation time of the vessels.

3.1 Base Case

Failure rates are based on the DTU 10MW reference turbine. The components considered are the gearbox, generator, electrical system, pitch system, yaw system, blades and main shaft. The wind farm layout is based on (Bak et al. 2017) and the repair information -including times and resources needed- are based on (Carroll, McDonald, and McMillan 2016).

The availability of the wind farm of the O&M tool is shown in Table 1.

Table 1. Availability and Energy Production of the Wind Farm Lifecycle

Availability (%)	**Energy Production (GWh)**
94.49	246,852

A breakdown of the downtimes is shown in Figure 2, and the energy produced by each turbine in the wind farm is shown in Figure 3.

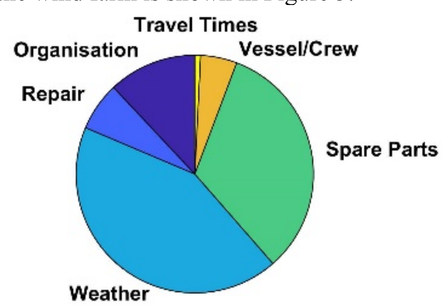

Fig. 2. Energy generated by each wind turbine in its whole life

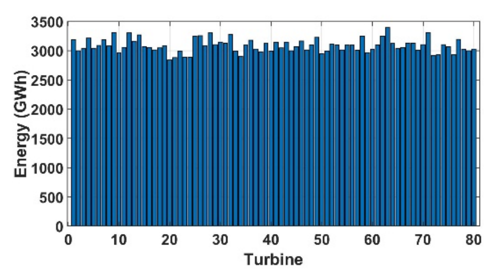

Fig. 3. Breakdown of windfarm downtimes

3.2 Sensitivity Analysis

A sensitivity analysis scenario is performed with respect to the mobilisation time of the jack-up vessel. It is expected that a decrease in the vessel mobilisation time will cause an increase in availability. The results of the sensitivity analysis are shown in Figure 4. The availability increases by 2.8% if the mobilisation time is decreased from

40 to 2 days. Hiring an external jack-up vessel with the cost of higher mobilisation time or owning one, is decided by the wind farm operator, and this tool can aid in the decision-making process.

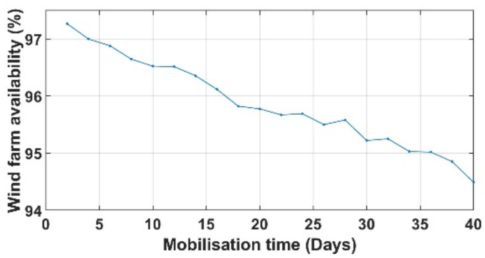

Fig. 4. Availability vs jack-up vessel mobilisation time

4. Conclusions

This paper documents the development of an open-access tool for the simulation of O&M activities and determination of values of availability for given scenarios and towards optimisation of operational strategies. This tool can be useful to researchers and practitioners due to its modular format and ability to perform simulations at a low computational cost.

As this is the initial version of the tool, there are a number of additions that are already under development. This includes a more detailed investigation of the most appropriate reliability model, study of advanced weather forecasting models and a more realistic maintenance strategy module with smart features for the determination of maintenance campaigns.

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