Influence of the Personnel Availability on Offshore Wind Farm Maintenance

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Offshore Wind Farms (OWFs) have rising importance for energy provision of many regions worldwide. However, their harsh environment leads to considerably higher failure rates and degradation compared to its onshore counterparts. Consequently, OWFs require well-established maintenance processes in order to provide required operational availability of all wind turbines. Amongst the several factors impacting these processes the personnel plays an important role, bearing in mind that no maintenance is possible without having access to technicians or seamen operating the required vessel. This work proposes a comprehensive model for evaluating the actual impact the personnel availability has on the corrective maintenance processes of an OWF and, consequently, its energy production. Therefore, maintenance processes and WT failure rates based on reported data are considered. Furthermore, a pandemic model is employed in order to elaborate the possible impact a health crisis can have on the operational availability of an OWF. Results indicate that the monthly energy production can drop by up to 74% in case of a constant reduction of the personnel by 50%, while a worst case pandemic scenario results in a 23% lower energy production over the whole year.

Keywords: Offshore Wind Farm, Maintenance, Modelling, Pandemic, Maritime Systems.

1. Introduction

With annual growth rates of nearly 30%, the offshore wind industry continuously increases its importance for energy provision, O'Sullivan (2020). For example, the total offshore wind energy production in Europe in 2019 was 67TWh, which corresponded to 2.3% of the total EU electricity consumption, Komusanac et al. (2020). Furthermore, it is predicted that by 2030 the offshore wind power will be responsible for 8% of the total ocean economy adding USD 230 billion of value, OECD (2016).

Offshore Wind Farms (OWFs) are complex infrastructures located in harsh environments, such that well-established maintenance processes are required in order to guarantee high operational availability. Several factors impact these processes, e.g. weather conditions, availability of spare parts or available maintenance vessels. The recent COVID-19 pandemic crisis highlighted another important factor – the number of available personnel. This can be affected not only by health issues, but also by organizational problems, strikes, bankruptcies etc.

There are several scientific articles discussing maintenance process modelling in OWFs, e.g. Chan and Mo (2017); Gutschi et al. (2019); Sahnoun, M. et al. (2019). However, to the best of our knowledge, there has been no work published that analyses the impact of the changing personnel availability on the maintenance processes and consequently on the operational availability of an OWF. Based on this observation, the intention of this work is the conception a model that enables such an analysis. This model can be a powerful tool for comparing the outcome of different adverse events leading to a reduction of the available personnel and of potential countermeasures.

The rest of this work is structured as follows. Section 2 discusses basic information about the structure of OWF and related maintenance processes. Section 3 presents the personnel-dependent maintenance model, while Section 4 discusses exemplary results. Finally, Section 5 concludes this work.

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2. Preliminaries

2.1 *OFFSHORE WIND FARMS*

OWFs are complex cyber-physical systems with human interaction exhibiting an automated main operational mode. As such, OWFs possess all the basic traits common of critical infrastructures, Sansavini (2017); Schütt (2014); Lichte and Wolf (2019). Multiple interacting layers exist with multiple interdependences between them – physical structures, energy conversion, measurement alongside with control and protection (automation), manual operation and maintenance (O&M), management. Accordingly different interacting flows are produced and distributed within the system boundary and across it – energy, information (signals/data), vehicles, people, replacement parts, maintenance services – through which the function and the operation are ensured. The main OWF elements as physical structures are: Wind Turbines (WTs), offshore and onshore substations, control and O&M centre as well as power and communication cables.

The operation, functionality and performance of an infrastructure can be represented by functional models characterizing the interaction of the above mentioned layers and flows. These models describe the technical behavior of the system in relation to its intended task or result. Such a generic OWF model was presented in Kulev et al. (2019). Accordingly, in this paper we investigate the influence of the change of the maintenance process (flows), due to the reduced personnel availability, on the energy provision process (flow) as a consequence of the interaction.

Different system states can be assigned to the values of parameters (operational parameters) pertaining to the flows and to the required conditions (operating/environmental/work) in relation to the requirements. However, regarding the energy provision within the OWF we consider only system states depending on the wind speed and the failures of the main WT components, as the single cause for the degradation of the energy provision.

This degradation can not only impact the produced energy by the OWF but its operational safety and its ability to fulfill the grid requirements, too. One of these requirements is the so called Fault Ride-Through (FRT) capability. Our simulations with the modified wind farm models provided within Simscape Electrical by MathWorks show that a reduced number of operating WTs leads to a reduced FRT capability. A voltage drop with a given magnitude at the grid connection point which can be endured with all WTs functioning leads to an OWF downtime if 1/3 of the WTs operate. A 3-phase short-circuit disturbance at the remote end of the export cable (away from the WTs) cannot be endured by the OWF when only 2/3 of WTs are operational.

2.2 *OWF Maintenance processes*

In general, one can distinguish two types of O&M processes: preventive maintenance and corrective maintenance. According to IEC (2015), preventive maintenance is carried out to mitigate the degradation and to reduce the probability of failure. The preventive maintenance can be further classified as condition-based or scheduled maintenance. The condition-based maintenance is carried out based on item condition and/or forecast of the condition degradation. Scheduled maintenance is carried out in accordance with a specified time schedule. These schedules can be developed with regard to, among others, prediction of wind turbine degradation, wind turbine manufacturer guidelines, spare parts availability or support vessels/item accessibility. In case of a WT, a typical preventive maintenance intervention consists of a thorough inspection of the entire system, replacement of fluids, lubrication and servicing of mechanical parts, Chan and Mo (2017).

The scheduling process is even more complicated when one takes into account failures, which are in the domain of corrective maintenance. It is worth mentioning that all maintenance tasks are concurrent processes competing against each other for a pool of resources.

One of the most important factors that have an influence on the WT and ipso facto on the OWF maintenance is weather. The influence is a subject of discussion in Battisti et al. (2006); Carroll et al. (2016); and Wilkie and Galasso (2020). In this paper, it is also considered as a

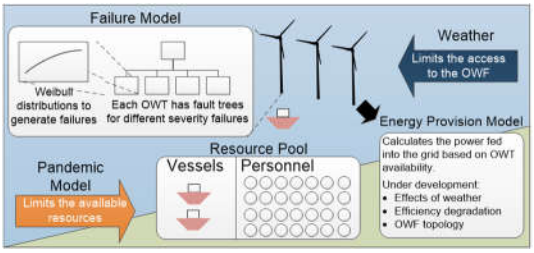

Fig. 1. Schematic overview of the O&M concept

major constraint on the performance of maintenance tasks. In the context of various transportation units (e.g. FSV – Fast Supply Vessel, helicopters) or available technology (e.g. W2W – Walk to Work, de-icing systems) acceptable weather conditions may vary. In case of basic models of FSVs, the main weather factor is described as a significant wave height. Operational condition for that parameter is set to < 2 m. However, for the research purpose other weather indicators are introduced: wind speed, temperature and ambient light. Moreover, among many not weather-related parameters, presented example scenarios incorporate the distance of the transport vessel to the offshore installation. All these aspects form a meaningful interaction with the maintenance process.

3. Personnel-dependent maintenance model

This section presents the developed maintenance model for the analysis of the impact of available human resources on the fulfillment of maintenance. Fig. 1 depicts a general overview that shall be discussed in the following subsections

3.1 *OWF Maintenance model*

Fig. 2 depicts the process and information flow in the O&M model domain. The major signals considered in this case are: weather conditions and available human resources.

The weather data used in the model are based on National Data Buoy Center (NDBC) of National Oceanic and Atmospheric Administration (NOAA), NOAA (2019). In addition, the second source of weather data was used as a test – UFS "German Bight", DWD (2016). Both of those data sources provide one year weather information related to similar geographical latitude: NDBC station 46083 - 58°16'N, UFS "German Bight" - 54°10'N. There is also an option in the model to use artificial weather generators. Apart from typical meteorological measure data sets, the model includes such phenomena as nautical and civil twilight based on 54°N latitude. All of the weather data sets are considered as discrete values with a one hour resolution. In the course of the simulation run, the weather data are called at various points, e.g. when the vessel needs to outbound to the offshore installation, when the maintenance process proceeds, or when there is a need to calculate an estimation time of arrival. The weather conditions can delay the tasks and procedures connected to the O&M processes.

The O&M discrete event model uses a number of resource pools, e.g. Fast Service Vessel (FSV) pool, Heavy Lift Vessel (HLV) pool, personnel pool. The construction of the failure model and

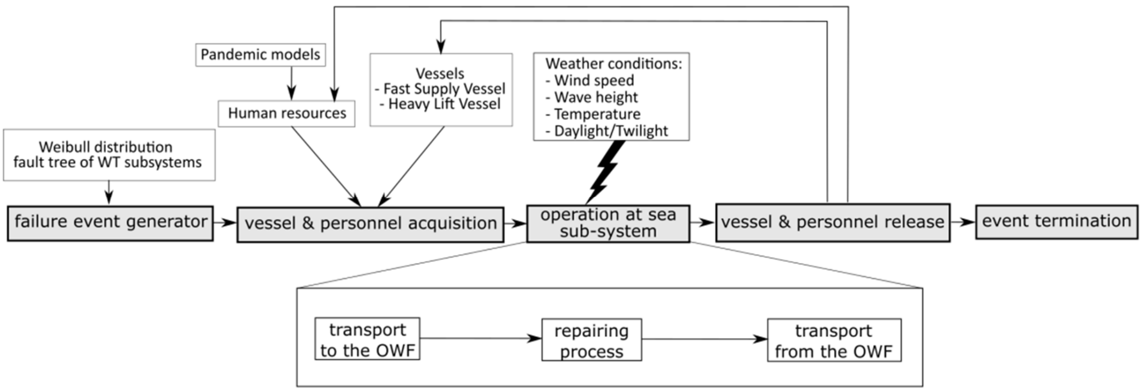

Fig. 2. Simplified schema of the O&M model

its implication for the O&M model are presented in sections 3.2.2 and 3.2.3. One should note that this model shall not represent the detailed execution of maintenance tasks, but to enable a global analysis of factors that influence maintenance activities.

The model provides following established KPIs: Operational Availability (OA) and Mean Time To Repair (MTTR), both described by the EN 15341 norm as T2 and T21 indicators respectively, BSI (2007). As a result of OA and wind speed data implementation, it is possible to estimate OWF energy provision, as described in section 3.2.1.

3.2 *WT Degradation model*

3.2.1 OWF energy provision model and degradation

Regarding the energy provision, we differentiate four WT system states in terms of the power flow, depending on the wind speed and presence of failures: full load operational, partial load operational, non-operational due to out-of-range wind speeds and dysfunctional (down-time) due to a main component failure and maintenance, Schütt (2014).

The ratio of the power $P_{OWF}(t)$ fed at given time t into the grid by an OWF with N WTs to the maximal possible power OWF P_{OWFR} can be expressed as a dependence on the wind speed and the operating conditions by following approximation, Schütt (2014):

$$\frac{P_{OWF}(t)}{P_{OWFR}} = \sum_{i=1}^{N} C_i(t) \left(\frac{v_i(t)}{v_R}\right)^{m_i} \#(1)$$

with $C_i(t)$ as a utilization coefficient of the i-th WT according to the control/protection strategy regarding the wind speed $v_i(t)$ and the fault conditions/maintenance. The exponent m_i is a control parameter depending on the wind speed. The constant v_R is the rated wind speed, with a typical value v_R = 13 m/s chosen by us. The maximal possible P_{OWFR} is the power generated by all WTs by $v_i(t)= v_R$. So $C_i(t)$ can have only 2 values - 0 and 1. A zero value occurs in case of WT main component failures/maintenance and by wind speeds outside of the range [v_{cin}, v_{out}] where v_{cin} is the cut-in speed (typical value is v_{cin} = 3.5 m/s) and v_{cout} is the cut-out speed (typical value is v_{cout} = 25 m/s). A value of 1 is assigned by operational WT and wind speeds within the [v_{cin}, v_{out}]. The above mentioned exponent is m_i = 3 for partial loads under $v_i(t)$ within [v_{cin}, v_R] and mi = 0 for full load under vi(t) within [v_R, v_{cout}]. Thus, Eq. (1) models the OWF energy production interrupted only by out-of-range wind speeds and down-times due to WT failures with the corresponding maintenance.

The rated WT power is the power generated by the WT by $v_i(t) = v_R$ and can be expressed through the efficiencies of these main WT systems where the energy conversion occurs, Schütt (2014):

$$P_{WTR,i} = \eta_{rot}\eta_{dt}\eta_{gen}\eta_{rct}\eta_{itr}P_{w,r}\#(2)$$

with η_{rot}, η_{dt}, η_{gen}, η_{rct}, η_{itr} are the efficiencies of the rotor system, the drive train (with/without a gearbox), the generator, the rectifier and the inverter/transformer, respectively. $P_{w,r}$ indicates the mechanical power of the wind at wind speeds corresponding to the rated generation power. Conversion efficiency is practically a constant in a healthy system and a fault leads to its decrease, e.g. at the WT gearbox, Feng et al. (2011).

It was also suggested by Staffell and Green (2014) that the decrease of the conversion efficiency is one of three causes for the performance decrease of wind farms during the life cycle. Their work indicated that the performance of WTs declines about 1.6% each year and that the aging may increase the likelihood of severe failures. The associated decline of the ideal performance can be modelled with approach shown in Staffell and Green (2014), where the performance is treated as a function of age. Through Eq. (2), this can be implemented with age dependent efficiency factors. In a scenario where the maintenance is extremely limited, OWF could be operated without preventive maintenance. In our view, this may severely affect the reliability. For example, insufficient lubrication accelerates the aging which will increase the failure rate and decrease the remaining useful life of components. So, extremely limited maintenance can lead to severe failures with large lead times caused by the lack of the spare parts and/or times to repair, e.g. drive train/gearbox, generator.

3.2.2 Failure model design

Wind turbines suffer from failures during operations. In our model, this trait is represented by the failure model. The model contains one or more fault trees for each of the turbine within OWF, Vesely et al. (1981). Different fault trees represent different top events. These events can require different maintenance actions or resources to restore the operations. This aspect is discussed further in other sections. In this paper, each turbine has two different fault trees to represent failures with different severities.

Each basic event within a fault tree has a failure distribution to generate failure times during a simulation. Technically any distribution function can be used for this. We chose the Weibull distribution, Rausand and Høyland (2004), for our initial implementation as it is well proven in reliability analyses. The distribution is simple but versatile, as it can model either age related degradation or a failure rate that is decreasing over the time. The random failure time t_1 as a function of random variable u, which is within range 0 - 1, follows from:

$$t_1(u) = t_0 + \xi + \lambda(-\log u)^{\frac{1}{\alpha}} \#(3)$$

with t_0 is the current time in simulation, ξ is a so-called threshold parameter that can be used for modelling failure free life, λ indicates the scale parameter, and α is the shape parameter.

The maintenance model interacts with the failure model using following methods:

checkNextFailure: provides information on when the next failure will occur, which turbine it will affect, severity of the failure, and the specific system that will fail.

activateNextFault: activates the aforementioned failure.

restoreItem: restores the condition of an item that is specified by the turbine number, severity, and event. The current time value is used for calculating the next time when the same failure will re-occur.

getStatusList: lists the statuses of each turbine that specifies if a turbine is functional or has failed. In the latter case, the method provides also the severity of the most critical failure within a turbine.

3.2.3 Failure data

Today, several publications of WT failure data exist. We chose to use reference Carroll et al. (2016) as the basis for our failure rates because the publication also includes information on the required number of technicians for different maintenance activities. Alternatively, we considered using Dao et al. (2019) as a more resent source of information, or Athamna (2015), which presents a bottom-up approach for deriving failure rates for main systems of a WT based on failure rates of system components. The thesis presents failure rates for the main WT types.

Data in Carroll et al. (2016) are acquired from about 350 OWTs that were 3 – 10 years old and have a nominal power of 2 – 4 MW. In total, the data set consists of 1768 turbine years of operations. In that paper, the failures are classified based on repair material cost. Our analysis does not consider this. Thus, we chose to combine categories “no cost data”, “minor repair”, and “major repair” as one category as there were no major differences between required number of technicians or the repair time. In the fourth category, “major replacement”, these values are generally more severe and so we kept it as a separate class. We use these data to form a fault trees with a so-called "Parts Count" approach that was introduced in Vesely et al. (1981). With this approach, we assume that any failure of a main component will cause a WT to be unavailable.

3.3 *Pandemic model*

There are several reasons that can lead to a reduction of the available personnel for maintenance activities in an OWF. This also includes pandemics, like the COVID-19 crisis. For the sake of illustration and out of curiosity, we opted for modelling the impact of such a pandemic on the available personnel.

In order to represent the typical progress of the COVID-19 pandemic, we employed the Susceptible-Exposed-Infectious-Removed (SEIR) model presented by Wu et al. (2020),

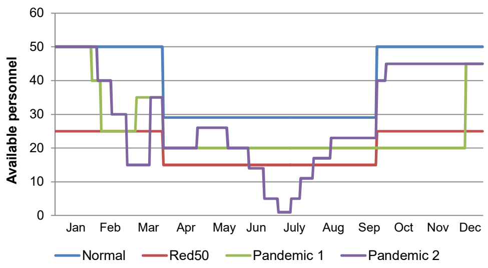

Fig. 3. Available personnel throughout the year for considered scenarios

which divides the population into these categories, with the removed representing the recovered or deceased individuals. This model uses ordinary differential equations for estimating when an individual changes from one state to another, whereas a change can only be from susceptible to exposed to infectious and, finally, to removed.

With help of the project SEIR-fit, we parametrized the model with real case data from Germany provided by the Johns Hopkins University. Next, we extracted the resulting basic reproductive number R_0 for each type of intervention, which are: no interventions (int0), curfew (int1), relaxed contact ban (int2) and contact ban (int3). Using the SEIR model and the respective R_0 values, one can estimate the pandemic progress for alternative times of the interventions. That means, in the pandemic 1 scenario (see Fig. 3.), no changes to the times of interventions have been done. In the worst pandemic case scenario, named pandemic 2, we delayed the time of establishing the interventions by 50% and anticipated the time of removal of the interventions by 50%. Furthermore, we defined for each intervention a planned reduction of personnel with following reduction values: int1: 20%, int2: 30% and int3: 50%. Additionally, we defined that each exposed or infected individual affects on average nine other people that must also stay in lockdown. Finally, we estimated for each of the two pandemic scenarios the daily percentage reduction of available personnel by adding the decrease due to interventions and ordered lockdown.

As can be seen in Fig. 3, pandemic model delivers data for two scenarios: pandemic 1 and pandemic 2. Scenarios named normal and red50 (reduction ca. 50%) are introduced in the section 4.1.

4. Experiments

This section presents the results obtained for four personnel availability scenarios. All of the experiments were conducted with the same failure events provided and with the same weather conditions.

4.1 *Parameters*

We set up an OWF consisting of 30 WTs that have an average distance of 30 km from the shore, which corresponds to halve of the distance a vessel has to travel per mission. The corrective maintenance personnel have access to 1 HLV and 5 FSVs in normal scenario. Furthermore, we divided the standard available personnel for unscheduled maintenance activities into a summer and winter allocations. This follows from the observation that during winter season the times of acceptable weather conditions for maintenance activities are strongly reduced, which requires a higher parallelism of missions in order to assure acceptable Operational Availability (OA) of the OWF. That means the scenario normal employs during winter season a personnel of 50 people, while during summer season the personnel amount drops to 25. Based on these numbers, three additional scenarios have been constructed – pandemic 1 and pandemic 2 (see also Section 3.3) as well as red50, during which the available personnel corresponds to 50% of the standard personnel. The resulting values of the available personnel are depicted in Fig. 3. The weather values are taken from NOAA, (2019) for the period of 12 months of 2019. The failure rates are based on Carroll et al. (2016), as described in Section 3.2. The energy production has been calculated assuming WTs capacity of 3.5MW each.

For the sake of the presented analysis, we assumed a constant availability of all maintenance vessels as well as spare parts.

4.2 *Scenario Analysis*

Fig. 4 and Fig. 5 focus on the OA in a yearly and monthly view. It is shown in Fig. 4 that the

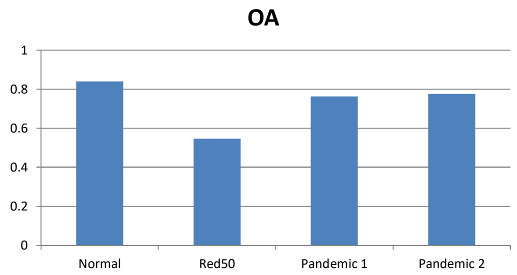

Fig. 4. Operational Availability (OA) after one year for considered scenarios

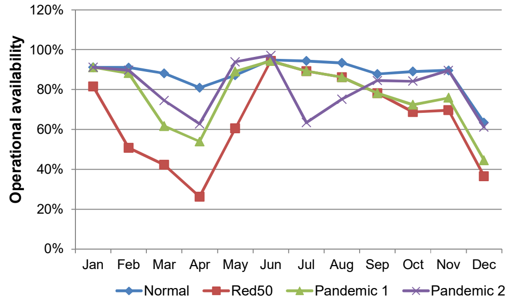

Fig. 5. OA for each month of considered scenarios

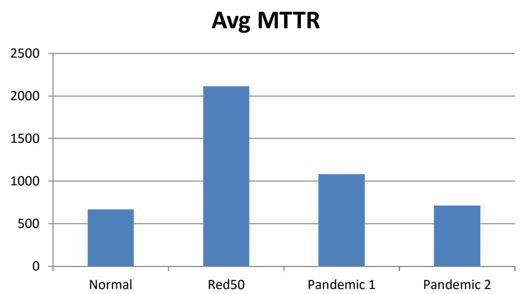

Fig. 6. the Mean Time To Repair (MTTR) for one year of considered scenarios

lowest yearly OA level of ca. 55% was reached by the red50 scenario. Meanwhile, the normal scenario resulted in yearly OA of ca. 84%. Both pandemic scenarios results in ca. OA of 76% and 78%, respectively what may suggest that constant reduction of available personnel has more impact on the OA KPI than short-term (up to 2 months) absences of significant number of personnel. However, one can notice in Fig. 5 for the pandemic 2 scenario that the highest drop pf OA is coincidentally during the summer time, which usually has good weather conditions. Shifting the pandemic 2 personnel unavailability

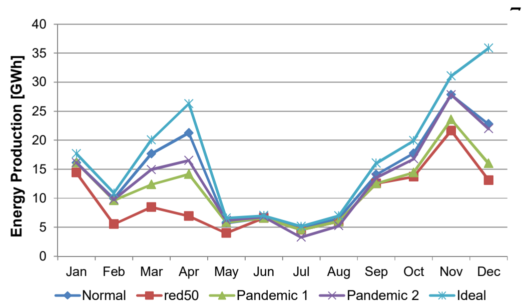

Fig. 7. Monthly energy production in GWh for one year of considered scenarios

"valley" from summer to winter time may influence the OA KPI in a significant way.

Fig. 6 depicts the Mean Time To Repair (MTTR) values for one year, which correlate with the results shown in Fig. 4. The results indicate that a 50% reduced crew availability leads to up to 30% reduction of the OA in comparison to normal scenario. This reduction further results in a MTTR that is 3 times higher than in the normal scenario.

When regarding OA and MTTR values obtained for pandemic scenarios one should keep in mind that the market integrals of pandemic 1 and pandemic 2 curves have similar values (see Fig 3). That might explain lack of significant differences between both pandemic models.

Fig. 7 shows the monthly values of energy production in GWh. The ideal values were estimated based on available wind speed data and can be regarded as potential energy production levels. The results indicate that in the beginning of the year, the red50 scenario is heavily affected by the lack of personnel. The drops in energy production reach the level of 3.97GWh in May. In contrast, pandemic 1 and pandemic 2 scenarios produced 5.85GWh and 6.17GWh of energy respectively. One can also observe how close to the ideal energy production levels all considered scenarios are located in a May-August period.

5. Conclusions

In this work, we present a model for the analysis of the impact of personnel availability on maintenance processes in Offshore Wind Farms (OWF). The model consists of the four subsystems O&M, failure generation, pandemic and energy provision. Results indicate that the time between occurrence of a failure and its repair can increase by more than factor 3 in case of a constant reduction of the personnel by 50%, while a worst case pandemic scenario resulted in a 17% lower energy production over the whole year. This clearly shows that future works should explore how O&M must be improved in order to reduce its susceptibility against the loss of maintenance personnel.

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