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EVALUATING THE PERFORMANCE OF MAINTENANCE STRATEGIES: A SIMULATION-BASED APPROACH FOR WIND TURBINES

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ABSTRACT

The performance of multi-component systems is heavily influenced by the individual maintenance strategy applied on each subsystem, its costs and the impact of subsystem fails on the performance of the whole system. For an assessment of different combinations of maintenance strategies, we present a simulation-based evaluation approach applied to an offshore wind farm, investigating the produced energy and levelized costs of electricity. The evaluation is carried out by breaking wind turbines down into major subsystems, applying different suitable maintenance strategies to them and monitoring the performance of the entire wind farm. The investigated configurations include corrective, predictive and reliability-centered maintenance strategies. Thereby we investigate limits regarding minimum and maximum performance as well as the impact of a realistic application of monitoring systems on system performance.

1 INTRODUCTION

Driven by European climate and energy policies, wind energy has become one of the key sources for renewable energy. Walsh and Pineda (2019) reports that in 2018 wind power has reached a total of 189GW installed capacity in Europe, where onshore wind accounts for 170GW and offshore wind for 19GW. Levelized Costs of Electricity (LCoE) range from 39.9€/MWh to 83.3€/MWh for onshore wind. In contrast LCoE of offshore wind turbines are significantly higher and range between 74.9€/MWh and 137.9€/MWh, due to the use of more resistant materials and higher efforts for installation and maintenance (Kost et al. 2013). Main components of LCoE in wind energy are capital costs, financing costs and Operation and Maintenance (O&M) costs. Typically O&M costs account for 20%-25% of the overall LCoE (Taylor et al. 2015). As Tardieu (2017) expects wind energy investments in Europe reaching 239B€ until 2030, the importance of cost saving O&M strategies for wind energy becomes evident.

Overall Wind Farm (WF) performance is a complex measure and has multiple dimensions to be considered. The main objective of a WF operator is to maximize the electricity output while minimizing the operational costs. Minimizing downtime by applying a preventive maintenance strategy can certainly increase the total electricity output of the Wind Turbine (WT). However, due to the associated higher intensity of maintenance activities and increased number of use of spare parts, total operational costs will most likely also increase. Furthermore, increasing maintenance intensity may lead to bottlenecks in the maintenance process chain due to limited resources like staff and vessels. Thus, there is a conflict of objectives between minimizing the efforts for operation and maintenance on the one hand and maximizing the availability of the WF on the other.

Maintenance Strategy Selection (MSS) is described as a Multi-Criteria Decision-Making (MCDM) process where several attributes have to be taken into account. These include, but not limited to: required investment costs, safety aspects, failure costs, mean time between failures, mean time to repairs, resource utilization, and further constraints. Many of these factors are hard to evaluate and some may not even be quantifiable. Thus, the optimal selection of maintenance strategies is very critical for the success of a company. Shafiee (2015) reviewed 82 scientific publications between 1995 and 2013 dealing with the MSS as a MCDM problem. His research shows that the maintenance strategy selection problem has already received reasonable amount of attention in the literature. However he also identifies need for improvements which he summarizes in an extensive list, e.g., the development of MCDM-models for selecting the best maintenance strategy using all kinds of necessary information. However, from a practical point of view maintenance strategy selection is often a tedious task and is in many cases described as the gap between academic and industrial application. Common issues are difficulties in collecting data about maintenance activities, as well as assessing the impact of functional unit breakdowns on the entire system. The failure behavior of any kind of equipment can be determined by analyzing collected data and is fundamental for selecting maintenance strategies properly. (Shafiee 2015; Bertolini and Bevilacqua 2006; Sherwin 2000; Bevilacqua and Braglia 2000)

In wind energy production, understanding WT failures plays a key role in reducing O&M costs as pointed out by Carroll et al. (2016). Therefore, a WT must be seen as a system of functional units with different failure behaviors and maintenance strategies for reducing O&M cost.

This paper presents a simulation-based approach that enables the quantitative assessment of the performance of an offshore WF when using MSS. While the performance of a WF is measured through total produced energy, the increased effort for applying different maintenance strategies is expressed as an additional O&M cost. With that the influence of different maintenance strategies on LCoE can be investigated. We model single WTs consisting of main subsystems and consider maintenance operations by staff, involved vessels, needed spare parts and time. The selection guidelines for applicable maintenance strategies are based on results from recent publications in the areas of wind energy and diagnostics.

This paper is organized as follows: Section 2 provides further information on maintenance strategies, failure modeling, cost assessment and simulation in wind energy production. Section 3 presents the conceptual model for the simulation-based evaluation. In Section 4 scenarios for the simulation-based evaluation are defined. Section 5 presents the simulation results of all scenarios. Finally, the paper concludes with a discussion of the results and an outlook for further research.

2 BACKGROUND

This section provides an overview on maintenance strategies, failure modeling, cost assessment, and the role of simulation in offshore wind energy production. First, we introduce common maintenance strategies, which are most relevant in this case study. Second, possible modeling techniques for failure behavior modeling are introduced. Third, a cost assessment framework for offshore WFs is presented and finally, the application of simulation for MSS and the cost framework is discussed.

2.1 Maintenance Strategies

Maintenance strategies can be classified in corrective and preventive strategies. Corrective Maintenance (CM) is a 'fire-fighting' strategy, which only reacts after failures have occurred. In contrast, the aim of Preventive Maintenance (PM) strategies is to prevent equipment breakdowns and to prolong its residual lifetime. PM is based on collecting data on maintenance activities and prescribed criteria in order to reduce the probability of failures. PM can be further divided into time-based, condition-based, and predictive maintenance. Time-based Maintenance (TbM) is a simple strategy, which prescribes periodical maintenance activities at predefined intervals (e.g., time or mileage). Condition-based Maintenance (CbM) is applied if the degradation (deterioration) of equipment is dependent on measurable factors (e.g., vibrations, level of wear) and can be processed by computerized measurement systems. Therefore, CbM is more cost intensive than TbM and not always feasible. However, CbM is more reliable than TbM especially in case of non-periodic breakdowns. Predictive Maintenance (PdM) strategies apply prognostic models to forecast the condition of a machine's function and to compare it with a predetermined threshold - thus providing information about the residual life. PdM based maintenance activities can be scheduled and executed before deterioration and reliability reach a critical level (Van Horenbeek and Pintelon 2013).

For efficiently assigning these strategies to subsystems, Reliability Centered Maintenance (RCM) can be utilized. It supports models like Failure Mode and Effects and Criticality Analysis (FMECA) and Root Cause Failure Analysis (RCFA) to identify the impact of possible failure modes on the function of the complete system. Furthermore, it directs maintenance efforts to functions of equipment where reliability is critical. According to Moubray (1991), RCM originated in aircraft maintenance in the 1960s where breakdowns can cause fatal effects. Nowadays, it is one of the most used maintenance management systems and predominant in the field of WTs (Sherwin 2000; Garg and Deshmukh 2006).

2.2 Failure and Deterioration Modeling

In general, failures of WTs can be defined as breakdowns, which occur if the deterioration of a subsystem falls below a critical limit. Thereby, the behavior of degradation over time plays a major role. Degradation is often modeled through failure rate functions. Following Stapelberg (2009), the 'failure rate' is the probability of system fails within a time interval. Several distribution functions are commonly used for failure rate modeling, especially Weibull or Exponential distributions. The two parametric Weibull distribution is defined by a shape parameter (β) and a scale parameter (η). The shape parameter allows for modeling decreasing ($\beta < 1$), constant ($\beta \approx 1$) and increasing ($\beta > 1$) failure rates. The Exponential distribution is defined by a single scale parameter (η) and can be applied in case of constant failure rates.

Deterioration modeling is based on the PF-curve concept which represents the condition of a system over time. Moubray (1991) describes the PF-curve (compare Figure 1) with an potential failure (P) as the point where a failure (F) can be discovered. For the simulation-based evaluation, we assume the interval between P and F to be long enough to prepare maintenance operations and travel to the WT which is predicted to fail. Furthermore, the condition of the subsystem is assumed to start degrading immediately after a repair. Downtime (DT) is just as long as Repair Time (RT) for failures of subsystems where CbM or PdM is applied. DT of CM includes all Preparation and Travel Time (PTT) as well as the RT itself.

2.3 Cost Assessment Framework for Offshore Wind Farms

To accurately evaluate the economic feasibility of offshore WF projects, the capital expenditure (CAPEX), operating expenditure (OPEX) and LCoE over a projects life cycle must be considered. Therefore, Shafiee et al. (2016) propose a whole life cost analysis framework for offshore WFs. They present a cost breakdown structure covering all five phases of offshore WF projects. These phases contain all costs associated with Pre-development and Consenting (P&C), Production and Acquisition (P&A), Installation and Commissioning (I&C), Operation and Maintenance (O&M) as well as Decommissioning and Disposal (D&D). Table 1

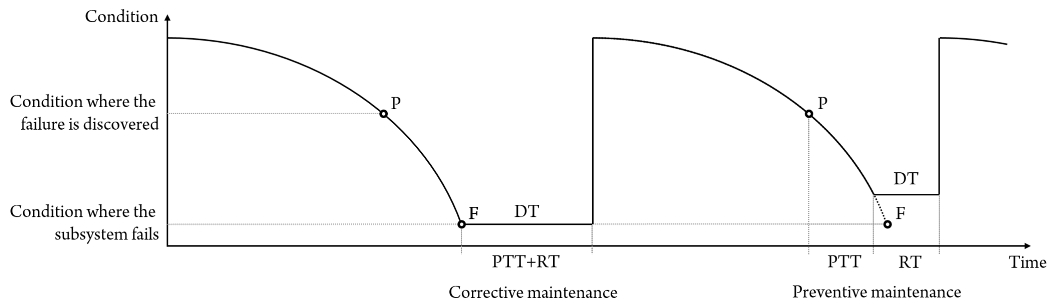

Figure 1: Schematic PF-curve including RT for preventive and corrective maintenance.

Table 1: Cost breakdown structure according to Shafiee et al. (2016).

Phase	**Included costs**
P&C	Project management, legal authorization, surveys, engineering, contingencies
P&A	WTs, support structures, power transmission systems, monitoring systems
I&C	Port, installation of the components, commissioning, insurance
O&M	Operation, maintenance
D&D	Decommissioning, waste management, site clearance, post monitoring

presents a list of considered costs in each phase. The calculation of LCoE considers costs of all phases and Produced Electricity (PE) discounted by Weighted Average Cost of Capital (WACC).

In the model presented in this paper, phases I&C and O&M are affected by maintenance strategies and hence described in detail. Costs for installing monitoring systems which enable CbM and PdM are considered by I&C costs. O&M costs include operation (rental, insurance costs, and transmission charges) and maintenance costs (direct and indirect costs). Direct maintenance costs represent all costs of CM and PM (compare Section 2.1) related to transport of failed components, maintenance staff and spare parts required. Indirect maintenance costs may either be fixed or variable and consider port fees for spare parts storage and quayside facilities, as well as costs for hired vessels and labor costs for maintenance planning and coordination.

2.4 Simulation

Simulation models have been used for multiple purposes in the maintenance sectors including maintenance policy or MSS, scheduling, staffing, inventory management, operational performance, reliability, etc. For a comprehensive review the reader is referred to Alabdulkarim et al. (2013). Also Ding and Kamaruddin (2015) provide a survey of optimization approaches, including simulation based methods, for MSS. According to Ding and Kamaruddin (2015) “Monte Carlo Simulation” is the most widely used method among simulation-based models for MSS. For example Besnard and Bertling (2010) use “Monte Carlo Simulation” for the optimization of CbM strategies of WT blades or McMillan and Ault (2008) investigate the sensitivity of condition monitoring benefits to operational parameters. Examples of studies based on other simulation paradigms are given by Byon et al. (2011) using discrete event system specification to include stochastic weather patterns for MSS and Sahnoun et al. (2015) combining an agent based model of offshore WFs and a cost model for maintenance strategy optimization. Tian et al. (2011) propose a method that aims to reduce O&M costs by bundling maintenance tasks regarding multiple components of different WTs of a given offshore park to combined maintenance orders. Thereby, different levels of criticality or risk are considered to find cost optimal maintenance plans. As concluded by Ding and Kamaruddin (2015) and Alabdulkarim et al. (2013), investigating a systems performance using prognostics and realistic limitations on maintenance operations is still not well covered by literature.

3 MODEL DESCRIPTION

This section provides a detailed description of the simulation model based on the Hierarchical Control Conceptual Modeling (HCCM) framework which was introduced by Furian et al. (2015). First, the problem definition and objectives of the simulation study are given in Section 3.1. Then, Sections 3.2 and 3.3 are defining the input and output measures. The content of the simulation model is presented in Section 3.4 including all modeled entities and processes as well as system control.

3.1 Problem Definition and Objectives

The economic feasibility of a WF project is highly depending on the cost efficiency of O&M. In order to estimate resulting efforts for O&M as well as the PE of the WF, a model which considers all relevant influencing parameters is needed.

The model we are presenting here is intended to serve as a generic approach rather than a tailored solution for a specific WF. Figure 2 shows a possible system under consideration of an offshore WF with WTs at a certain distance from a service port. Without loss of generality it is assumed that all maintenance activities are operated from this service port. Consequently, service vessels and maintenance staff are based at this port and all travel activities take place between the service port and the WF. Travel times are estimated based on vessel speed and distance. The spare part storage is also located at the service port. Besides order waiting times, there are no further waiting times connected to the spare part supply. WTs are

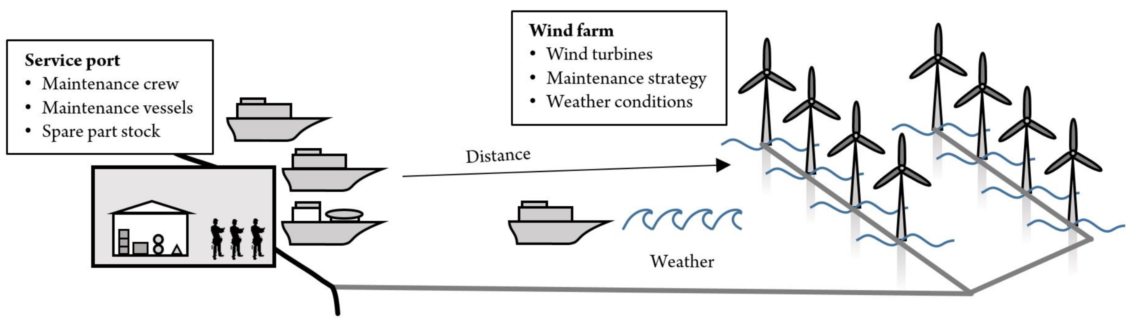

Figure 2: Offshore wind farm and onshore service port.

multi component systems which require maintenance activities over their lifetime. The overall goal of these activities is to keep the WFs in an available operative state and maximize Availability (A) over time. DTs caused by planned or unplanned maintenance activities are directly affecting the profitability and the LCoE of a WF. To enable a realistic cost estimation the simulation must be able to represent different applied maintenance strategies. Furthermore, meteorological effects have to be included in the model, which affect the WF operations in two ways: Wind speed defines the turbines PE based on a specific power curve. On the other hand, Significant Wave Height (SWH) influences the maintenance process, since safe operations are only possible up to a maximum SWH which is defined for each maintenance vessel type.

The objective of the simulation-based evaluation is to evaluate the overall performance of a WF under a particular combination of maintenance strategies. Furthermore, the result should provide economic-based arguments for applying efficient maintenance strategies.

3.2 Inputs

Input parameters of the simulation model can be grouped in fixed and variable input parameters. Fixed model parameters define the WF and all boundary conditions. Variable input parameters are used to define different applied combinations of maintenance strategies and their dependencies, i.e., scenarios.

An essential part of the model is the simulation of the failure behavior of WT subsystems which are modeled as described in Section 2.2. Table 2 presents empirically gathered failure rates λ as well as

Table 2: Subsystems and failure modes of a wind turbine.

	Minor repair				Major repair				Major replacement			
Subsystem i	$\lambda_{i,1}$	RT	RS	I	$\lambda_{i,2}$	RT	RS	I	$\lambda_{i,3}$	RT	RS	I
Pitch	0.82	9	2.3	**7.4**	0.18	19	2.9	3.4	0.001	25	4	0.0
Other Components	0.81	5	2	**4.1**	0.04	21	3.2	0.9	0.001	36	5	0.0
Generator	0.49	7	2.2	3.4	0.32	24	2.7	7.7	0.095	81	7.9	**7.7**
Gearbox	0.40	8	2.2	3.2	0.04	22	3.2	0.8	0.154	231	17.2	**35.6**
Blades	0.46	9	2.1	**4.1**	0.01	21	3.3	0.2	0.001	288	21	0.3
Grease/oil/cooling liq.	0.41	4	2	1.6	0.01	18	3.2	0.1	0	0	0	0
Electrical components	0.36	5	2.2	1.8	0.02	14	2.9	0.2	0.002	18	3.5	0.0
Contactor/circuit	0.33	4	2.2	1.3	0.05	19	3	1.0	0.002	150	8.3	0.3
Controls	0.36	8	2.2	2.8	0.05	14	3.1	0.8	0.001	12	2	0.0
Safety	0.37	2	1.8	0.7	0.00	7	3.3	0.0	0	0	0	0
Sensors	0.25	8	2.3	2.0	0.07	6	2.2	0.4	0	0	0	0
Pumps/motors	0.28	4	1.9	1.1	0.04	10	2.5	0.4	0	0	0	0
Hub	0.18	10	2.3	1.8	0.04	40	4.2	1.5	0.001	298	10	0.3
Heaters/coolers	0.19	5	2.3	1.0	0.01	14	3	0.1	0	0	0	0
Yaw system	0.16	5	2.2	0.8	0.01	20	2.6	0.1	0.001	49	5	0.0
Tower/foundation	0.09	5	2.6	0.5	0.09	2	1.4	0.2	0	0	0	0
Power supply	0.08	7	2.2	0.5	0.08	14	2.3	1.1	0.005	57	5.9	0.3
Service items	0.11	7	2.2	0.8	0.00	0	0	0.0	0	0	0	0
Transformer	0.05	7	2.5	0.4	0.00	26	3.4	0.1	0.001	1	1	0.0

operational maintenance data of offshore WTs from a previous publication of Ioannou et al. (2018), who are summarizing a detailed analysis of offshore WTs by Carroll et al. (2016). Thereby, WTs are divided into 19 subsystems, with each subsystem having three possible failure modes. For each failure mode, additional parameters define the number of Required Staff (RS), the average RT, and the Impact (I = $\lambda \cdot$RT) of a breakdown. For Material Costs (MC), the reader is referred to Ioannou et al. (2018).

The maintenance process is further determined by parameters describing the number of available vessels per type, a mission preparation time, the number of available maintenance staff and travel times from the service port to the WF. It is assumed that the travel time to the WT as also the mission preparation time is a mean value, summarized in PTT, only depending on the vessel type. Initial spare part inventory is given as an input value. For components which are maintained by applying CbM or PdM a condition threshold value of 40% (see Figure 1) for each failure mode which triggers an intervention is defined.

The weather prediction is based on a Markov-chain approach and uses a historic set of weather data including wind speed, wind direction and SWH. This weather model is used for the calculation of WT power production which is defined by a WT specific power curve. The power curve defines the PE as a function of wind speed including cut-in and cut-out wind speed (Shafiee et al. 2016). SWH determines if specific vessel types are able to operate or not.

Beside the fixed input parameters, variable input parameters are used for assigning maintenance strategies on each subsystem. Since the scenarios (see Table 5) are characterized by different combinations of maintenance strategies, the input parameters are values defining whether a CM or PdM strategy is applied on a subsystem. Furthermore, the deterioration processes (see Section 3.4) are concatenated to the maintenance strategies and thereby selected indirectly.

3.3 Outputs

Output parameters are aggregated Key Performance Indicators (KPIs) which are collected and calculated during the run-time of the simulation in order to describe relevant system characteristics. The output parameters are finally used to answer the questions defined in the objectives of the simulation study.

To assess the total effort for maintenance activities all processed Work Orders (WOs) and relevant information during the simulation period are gathered. This includes the number of WOs classified in CM, PdM, and TbM. For each WO the DT due to PTT and RT are accessible for analysis. This information is used for cost assessment and the final calculation of LCoE during post processing.

An important measure which is commonly used to assess WF performance is the Availability (A) as defined by IEC 61400 26: A is the number of available hours divided by the total number of hours (available and unavailable) the WT could operate during a time interval. It provides the percentage of time in which the WT was technically available disregarding if electricity was produced or not. Based on operational status information of each WT and wind speeds per time step the total amount of PE during the simulation period is calculated as an output. This output serves for the calculation of LCoE in the post processing.

3.4 Content

This section describes the model content including structure, processes and system control. The model structure is represented by Table 3 listing all entities and associated attributes included in the simulation.

Table 3: Model structure.

Entity	Attribute	Description
WF	n_{WT}	Number of Wind Turbine (WT) in the Wind Farm (WF)
	Distance	Distance to the service port
WT	Structure	Each WT is composed of 19 subsystems i as given in Table 2
	Failure modes	Each subsystem i has three different failure modes j: Minor repair, major repair, major replacement. Each of them contains specific λ, RT, RS, and MC
	Operational state	The operational state vector s of a WT defines if the WT is available or unavailable at a specific time interval
	Power Curve	The power curves provide the relation between wind speed and power output including cut-in and cut-out wind speeds
Vessel	Type	Defines the type t of the vessel
	$n_{t,Vessels}$	Total number of vessels v of type t
	$n_{t,v,Staff}$	Total number of staff members a vessel of this type can carry
	max_{SWH}	Maximum SWH the vessel can operate safely
	Availability	Defines if a vessel is available or in operation
Staff	n_{staff}	Total number of maintenance staff
	Availability	Defines if a staff member is available or in operation

For modeling the maintenance processes, we assume subsystems to be maintained either using PdM or CM. In particular, subsystems which are maintained with respect to PdM are assumed not to fail nor to cause CM activities. To model failures which cause the generation of a CM WO, all subsystems which are maintained according to CM are pooled to a serial overall system without redundancy. The occurrence of a failure is modeled using an exponentially distributed reliability function with a constant failure rate λ. As depicted in Table 4 the total failure rate λ_{total} is the sum of all subsystem failure rates λ_i and λ_i is the sum of the failure rates $\lambda_{i,j}$ for failure modes j. The reliability distribution function $R(t)$ and failure distribution function $F(t)$ of the entire system are given by $R(t) = e^{-\lambda_{total} \cdot t}$ and $F(t) = 1 - e^{-\lambda_{total} \cdot t}$. The

Table 4: Failure rate aggregation for subsystems and failure modes.

	Failure Mode 1	Failure Mode 2	Failure Mode 3	$\sum$ Subsystem i
Subsystem 1	$\lambda_{i=1,j=1}$	$\cdots$	$\lambda_{i=1,j=3}$	$\lambda_i = \sum_{j=1}^{3} \lambda_{i=1,j}$
$\vdots$	$\vdots$	$\ddots$		
Subsystem n	$\lambda_{i=n,j=1}$		$\lambda_{i=n,j=3}$	
			$\sum total$	$\lambda_{total} = \sum_{i=1}^{n} \lambda_i$

Time To Failure (TTF) is sampled from $F(t)$. Given the TTF, the affected subsystem and failure mode have to be determined. This calculation is based on TTF of the overall system and the time duration the subsystems have been operating since the last breakdown. Following Figure 3, a failure triggers the change of the operational status of a WT from 'available' to 'unavailable'. Furthermore, the generation of a WO defines the necessary activities to bring the WT in an operational state again. To simulate a PdM WO event, the reliability function of each failure mode of the affected subsystem as well as the time a predefined reliability threshold falls short, needs to be calculated. The statistical variation of a threshold shortfall is modeled by adding a uniform distributed proportion of $\pm 0.5 \cdot$MTBF

$$t = -\frac{ln(R_{threshold})}{\lambda} + \Delta t \text{ with } R_{threshold} = 0.4 \text{ and } \Delta t \subset \left(-\frac{0.5}{\lambda}, \frac{0.5}{\lambda}\right). \quad (1)$$

When this reliability threshold time is exceeded, a PdM WO is created and a maintenance task is triggered and the WT remains operational until the maintenance activity starts. TbM is assumed to take place once a year and for TbM WOs, the WT remains operational except during the maintenance activity itself.

In all cases WOs contain all relevant information of the subsystem and failure mode as well as required staff, vessel and spare parts. Figure 3 shows the failure simulation process and the operational states of the WTs which are either set by the occurrence of a failure or the maintenance process itself.

Vessels, maintenance staff members, and spare parts belong to resources required for the maintenance process. Within the maintenance process their availability is checked. Vessels and maintenance staff members are located in pools of available units. If a maintenance process requires a certain type and number of vessels and maintenance staff members, the respective units are blocked. Upon the completion of the maintenance process the respective vessels and maintenance staff members travel back to the service port and become available again. Spare part availabilities are modeled differently for different spare part types. Parts needed for minor and major repairs are held on stock, reordered as soon as a predefined safety stock level is reached. Spare parts for major replacements are not held on stock and ordered when required. Both type of parts become available after a predefined individual order lead time.

The maintenance process itself is the same for all type of maintenance strategies and shown in Figure 3. After receiving a WO the availability of required vessels, staff, and spare parts is checked. If resources are not available the process is paused until they become available. When all resources are available, total navigational time is calculated considering preparation times, travel times, RT and demobilization times. Next, weather conditions are checked whether they allow traveling or not. Therefore, the SWH must stay below the limit max_{SWH} during the entire operation.

In terms of system control, the dispatching of WOs is done in the following way: CM WOs are assigned a high priority followed by PdM with a medium priority and TbM with a low priority. Within a category, WOs are dispatched according to a FIFO principle.

4 SCENARIOS

Three scenarios are considered: In the base scenario SI, CM is applied to all subsystems and failure modes. This scenario will exploit the maximum time between failures, since there is no intervention before failures (compare Figure 1). Hence, there will be the least number of work orders and the lowest O&M costs

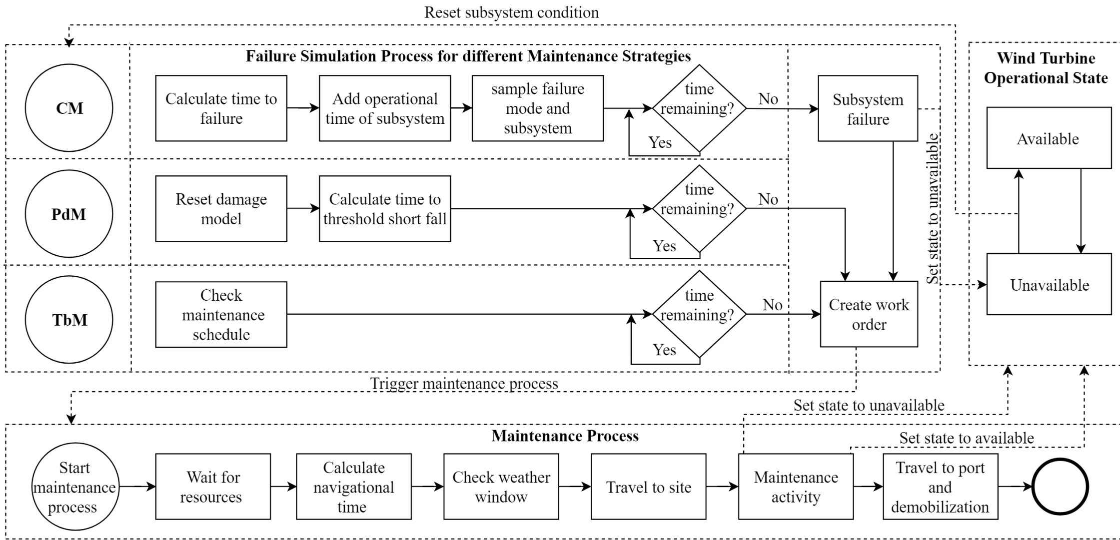

Figure 3: Failure simulation processes, maintenance process, and WT operational state.

are expected. However, the downtime includes also PTT and RT and therefore may have a high negative influence on the total produced electricity. Scenario SII applies PdM to each subsystem and failure mode. PTTs are excluded from DTs, but WOs will be executed before the subsystem fails and residual lifetime may get lost. Consequently, this leads to a larger number of WOs. The potential loss of PE is monitored and reported over simulation runs. The goal of scenario SIII is to apply RCM, and thereby PdM is just performed on critical subsystems where tools for monitoring the behavior are known in literature. We define the impact by means of the failure rate and the average repair time ($\lambda \cdot$RT) which is given in Table 2. Andrawus et al. (2006) list subsystems of WTs where monitoring through vibration analysis and strain gauges is possible. Matching this list with high impacts, all subsystems with an impact higher than 4.0 are considered as applicable for PdM. For simplicity reasons, only components that can be monitored via vibration sensors (gearbox and generator) are considered for PdM. It is further assumed, that all failure modes of monitored subsystems are detectable. Table 5 summarizes the scenarios. To consider service activities in O&M costs and PE, TbM is applied to all scenarios.

Table 5: Scenario definition through assigning maintenance strategies to subsystems.

Scenario	Name	TbM	CM	PdM
SI	Baseline	all	all	
SII	PdM	all		all
SIII	RCM	all	some	Gearbox and generator; all others are assigned to CM

5 RESULTS

First, all boundary conditions and simulation parameters for the simulation-based evaluation are introduced. Then the results of scenarios SI to SIII on O&M costs are presented. Finally, simulated O&M costs are applied on the cost analysis framework presented in Section 2.3 to discuss the influence on LCoE.

The WF modeled in this case study consists of $n_{WT} = 100$ offshore WTs with a power rating of 5MW and an operational lifespan of 20 years. The power output of the WTs is characterized by a power curve with a cut-in speed of 5m/s and a cut-out speed of 25m/s at a hub height of 85m. All maintenance activities require one or more Staff Transfer Vessel (STV) with a capacity of 12 maintenance staff members. Maintenance activities on the foundation require an additional special diving vessel while major replacements on the transformer system require an additional jack up vessel. The WF is in a distance of 75km from the service port which results in a travel time of 2h for STVs and diving vessels, and 3h for jack up vessels. There are 80 maintenance staff members and 15 STVs available for use. In addition, there is one jack up vessel and one diving vessel available. For all vessel types a fixed hourly rate is assumed (STV: 135€, Diving: 2500€, Jack-up: 4700€) and each required staff member cause costs of 250€ per mission hour. Failure rates, RS, and RT are used as given in Table 2. Further, we assume that these costs include all rental and insurance costs as well as direct and indirect maintenance costs as described in Section 2.3 and there are no additional transmission costs. The simulation period is set to 2+20 years, with the first 2 years used for simulation warm up. To achieve statistical confidence, 100 runs per scenario are performed. For applying the results to the cost analysis framework, life cycle costs of phases P&C, P&A, I&C, and D&D are taken from a previous study of Graefe (2019) for following periods. In the first period $0 \leq t < 3$ costs for P&C ($C_{P\&C,0} = 199{,}567{,}961$€), P&A ($C_{P\&A,0} = 853{,}484{,}173$€), and I&C ($C_{I\&C,0} = 325{,}833{,}883$€) are given. The costs for O&M ($C_{O\&M}$) in period $3 \leq t < 23$ are evaluated for each scenario. The third period at $t = 23$ is used for D&D and therefore costs of $C_{D\&D,0} = 87{,}719{,}950$€ are defined. All capital costs and PE for calculating LCoE are discounted to year $t = 0$ by $C_{X,0} = \sum C_{X,t} \cdot (1 + WACC)^t$ considering $WACC = 6.15\%$.

Table 6 presents the simulation results of all scenarios and the application on the cost framework for the entire Wind Farm. SI has implemented CM and is thus used as the baseline scenario for comparison. As expected comparing SI and SII, the total number of WOs is increasing, as WOs are generated before the subsystem fails. On the other hand, the results show that the total (DT_{total}) and average downtime (DT_{av}) is significantly smaller when applying PdM. Furthermore, the average availability (A_{av}) is at a maximum level, which is also reflected in total produced electricity (PE_{total}). However the O&M costs ($C_{O\&M,0}$) are at a high level due to the larger number of WOs. Scenario SIII represents a realistic application of RCM, where monitoring systems are applied on subsystems where the impact of a sudden failure is high and degradation monitoring is feasible (see Table 5). The number of WOs and O&M costs are similar to the numbers observed in SII, what can be explained by the impact ($RT \cdot \lambda$) and MC of these subsystems. On the other hand, A_{av} and PE_{total} are increasing significantly by monitoring only 2 of 19 subsystems. The average DT of SIII is more or less on an average level of SI and SII, which is mainly caused by the high number of CM WO as shown by Figure 4. Figure 4 presents the distribution of WOs along all available maintenance strategies and PE_{total}. Comparing SI with SIII, the positive influence of applying PdM to just two critical subsystems is depicted by the level of PE.

Table 6: Simulation results for SI - SIII and assessment of LCoE.

	WO_{total}	DT_{total}	DT_{av}	A_{av}	PE_{total}	$C_{O\&M,0}$	$C_{total,0}$	$PE_{total,0}$	$LCoE$	SP_0
	[#]	[1000h]	[h]	[%]	[GWh]	[MM€]	[MM€]	[GWh]	$[\frac{€}{MWh}]$	[MM€]
SI	15,114	2,168	143.5	87.8	27,453	363.0	1,829.2	14,146	129.34	-
SII	16,582	289	17.4	98.5	31,294	411.6	1,878.2	16,125	116.48	207.4
SIII	16,164	1,197	74.0	93.6	29,619	406.9	1,873.6	15,262	122.76	100.4

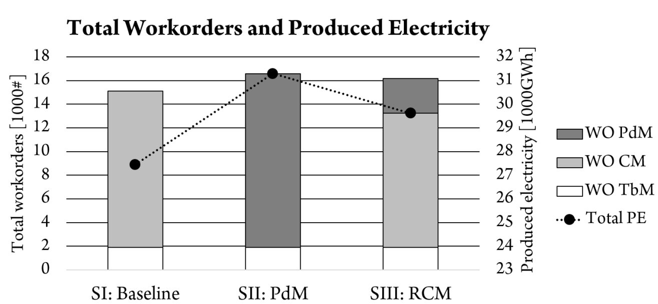

Figure 4: Distribution of WOs and total produced electricity.

For the application of the simulation results to the cost analysis framework the Saving Potential (SP_0) is calculated as the difference in $LCoE$ compared to the baseline scenario multiplied with the discounted total produced electricity $PE_{total,0}$. As we did not consider any additional costs for monitoring systems on I&C, SP_0 accounts for the monetary gap for installing and operating such systems to be profitable in an economic measure. Comparing $C_{O\&M,0}$ with SP_0 suggests that investing in CbM/PdM strategies leads to higher $C_{O\&M,0}$. However, decreasing $LCoE$ and increasing PE_{total} shows an economic potential up to 100MM€ at SIII. All confidence intervals are within $\pm 1.54\%$ and non-overlapping for all simulation results across each scenario. Summarizing, this case study demonstrates that an additional investment in O&M solutions can decrease the LCoE and thus raise the economic performance of a WF significantly.

6 CONCLUSION AND FURTHER RESEARCH

This paper presents a simulation-based approach for selecting maintenance strategies for offshore wind farms. All relevant entities of an offshore WF were modeled to simulate the production of electricity as a consequence of failure behaviors, maintenance processes, maintenance resources, and meteorological conditions. Since the produced electricity and associated levelized costs of electricity of offshore WFs are heavily dependent on the availability, downtime and operation and maintenance costs, we evaluate different combinations of maintenance strategies and conclude optimistic and realistic savings potentials. Our analysis shows that investments in maintenance yields a decrease of levelized costs of electricity, which results in a saving potential up to one million € over the lifetime of a single wind turbine. The proposed simulation model can be utilized and extended for further research in various directions. These include, but are not limited to: the incorporation of market factors influencing the economic success of a WF; the design and integration of maintenance planning procedures to further minimize O&M costs; and the investigation of environmental impacts of WF projects over their life cycle and associated cost factors. According to Arvesen and Hertwich (2012), environmental impact assessment including especially the O&M phase would create transparency and could accelerate the shift towards renewable energy generation.

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