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Joint optimization of preventive and condition-based maintenance for offshore wind farms

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Abstract. High costs of maintenance and lost production during downtime are a challenge to the offshore wind industry, and there is a great potential to improve cost efficiency by improved maintenance and control strategies utilizing condition monitoring information. As wind farms get older, there is also an increased need to find ways of extending the lifetime of wind turbines allowing continued operation. This may be obtained by de-rating strategies, meaning adjustments of the power production to reduce the fatigue loads on the turbines. This subsequently means wind farm operators are faced with a trade-off between maximizing power production while limiting the degradation of the turbines. To investigate the best trade-off, this paper presents an optimization framework that considers component condition and planned power production to find the best times to perform predetermined preventive and condition-based maintenance on an offshore wind farm. To solve the scheduling problem, it is formulated as a constrained integer linear program, maximizing the net income for the planning horizon. The proposed method considers logistic restrictions, wind and electricity price forecasts, control strategies, component condition and probability of failure. Moreover, the method uses a short time horizon (days) to utilise weather forecasts and a long time horizon (weeks) to better capture the impact of deteriorating condition. The model is presented in a general framework for accounting for component condition in offshore wind farm operation and maintenance. It is illustrated for a specific potential application, considering condition monitoring of main bearings and corrosion of structural elements as examples.

1. Introduction

Offshore wind power is growing rapidly, but high costs of maintenance and long turbine outage times is still a challenge. These challenges may be solved by condition monitoring solutions [1, 2]. To fully utilize condition monitoring it is necessary to include condition information in decision making for operation and maintenance (O&M) of the wind farms.

Maintenance tasks can be classified as either corrective maintenance (CM) or preventive maintenance (PM). PM tasks can in turn be classified as either predetermined or condition-based [3], but for simplicity we reserve PM to denote predetermined preventive maintenance in this paper. Condition-based maintenance (CBM) tasks are associated with a component, one or more failure modes, and a condition monitoring technique. Examples of failure that can be monitored include generator and gear box bearings [4], or damaged coating and subsequent corrosion of structural elements. Incipient bearing failures are typically monitored by analysing vibration data, while corrosion may initially be detected on inspections, either through manual inspections or by developing drone-based monitoring systems [5]. Based on inspection results it

Nomenclature

Functions

$F_Z(z)$	Cumulative distribution function of the random variable Z
$P(w)$	Power curve (kW)

Indices

i	Wind turbine
k	Wind power production level
t	Time stage

Parameters

ΔT_{tk}	Hours in time step and production level
ΔT_t	Hours in time step
λ	Electricity price (€ /MWh)
μ_s	Mean time from state $s-1$ to state s
ρ_{ti}	Failure probability
τ^x	Time for PM (h)
τ^y	Time for CBM of type y (h)
τ^z	Time for CBM of type z (h)
C^f	Cost of failure (€)
C^{tr}	Transportation cost (€)
C^{turb}	Capital cost of wind turbine (€)
C^{vis}	Cost visiting a turbine (€)
H^{max}_{tk}	Available work-hours long-term (h)
P^1_{ti}	Power production after CBM (MW)
P^0_{tki}	Initial production level k (MW)
P^1_{tki}	Production level k after CBM (MW)
P^0_{ti}	Initial wind power production (MW)
q	Discount rate
Q_t	Number of available technician teams
S_{ti}	Technical condition of wind turbine
T^L	Nominal lifetime of a wind turbine
T^s	Workday hours (h)
T^{RUL}	Remaining useful life of wind turbine
w_t	Wind speed (m/s)

Sets

$\mathcal{K}$	Wind power production levels
$\mathcal{T}$	Time step
$\mathcal{T}^{long}$	Time step in the long horizon
$\mathcal{T}^{short}$	Time step in the short horizon
$\mathcal{W}$	Wind turbines

Variables

$\bar{y}_{ti}$	CBM task of type y is performed in previous time steps (binary)
$\bar{z}_{ti}$	CBM task of type z is performed in previous time steps (binary)
a_{ti}	Time available for production (h)
b_{ti}	Restored turbine operation time in the short term
c_{tki}	Operation time at production level k
d_{tki}	Restored turbine operation time at production level k
h_{tki}	Worked hours (h)
r_{ti}	Turbine visited (binary)
v_t	Wind farm visited (binary)
x_{ti}	PM task is performed (binary)
y_{ti}	CBM task of type y is performed (binary)
z_{ti}	CBM task of type z is performed (binary)

may be decided to intensify inspections or to install additional sensors on critical points of the construction. Possible CBM actions in case of corrosion include recoating.

Offshore wind farms are typically placed in remote locations and are subject to harsh weather conditions. This means maintenance activities include long travel times and are subject to restrictions on when maintenance can be executed. These facts imply a large value of carefully planning maintenance operations, and that a failure usually leads to long down times and large production losses. Moreover, information about the technical condition of turbines may be used to reduce the fatigue load for deteriorated turbines by control strategies involving turbine derating [6]. CBM actions may in that case bring the turbine back to full capacity but requires shutdown of production during maintenance. In other words, the wind farm operator must balance short-term losses against long-term gains. To jointly consider wind farm control and maintenance planning thus makes O&M decisions even more complex.

There is an extensive literature on scheduling of maintenance actions for offshore wind farms [7, 1]. Daily scheduling including service maintenance (i.e., PM) and CM was considered in [8] and [9] more than a decade ago, while much of the subsequent work has focused on both scheduling and routing of maintenance vessels [10, 11]. An overview of related research on maintenance scheduling for offshore wind farms is shown in Table 1. It shows that most of the previous work considers the scheduling of CM and PM, while some do not specifically define the type of maintenance tasks considered. Routing and scheduling models consider a short-term planning horizon (from two to 30 days), but some scheduling models also consider an additional long-term (LT) planning horizon. The column "Risk of failure" indicate works

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Table 1: Overview of related research and the contributions of this work. The symbols indicate if the feature is: x = included, (x) = indirectly included.

Ref.	Maint. tasks	Horizon (days)	Routing	Downtime cost	Risk of failure	Control/ derating	Degradation
[9]	PM+CM	7 + LT		x			
[13]	PM	365		x			
[14]	PM+CM	12	x		(x)		
[11]	n/a	2-3	x	x	(x)		
[15]	PM+CM	3-7	x	x	(x)		
[10]	PM+CM	3-7	x		(x)		
[16]	CM+CBM	200		x			x
[17]	PM	365					(x)
[18]	PM+CM	3-7	x		(x)		
[19]	PM+CM	1	x		x		
[20]	n/a	7					
[21]	PM+CM	7 + LT			(x)		
[22]	PM+CM	14	x	(x)			x
[23]	PM+CM	1	x	x	(x)		
[24]	n/a	30		x		x	
This work	PM+CBM	7 + LT		x	x	x	x

that indirectly or directly account for the risk of failure occurring after the planning horizon if maintenance is not completed. Most optimization models for maintenance scheduling considers this indirectly through a penalty term for non-completion of maintenance tasks. Very few of these works consider control strategies, including derating, or account for the degradation of component condition.

This paper contributes to the literature by proposing a modelling framework for including condition-based maintenance in the short-term maintenance scheduling. As shown in Table 1, the proposed models consider control strategies, component condition and probability of failure, in addition to wind power production forecasts and logistic restrictions. The optimal maintenance schedule is defined as the one that maximizes the net expected revenue, i.e. the revenue minus the maintenance costs. Both i) the potential power production and thus the revenue and ii) the accessibility to wind turbines will depend on the weather conditions. Precise weather forecasts for a few days ahead are usually available, while for a longer time horizon the weather forecast is uncertain [12]. The proposed model therefore adopts the approach used in [8] and [9] and considers two different time horizons. For the short-term time horizon it is assumed that production forecasts are available. This work does not consider routing, which is a simplification and means intra-day logistics are omitted.

The paper is organized as follows. In Section 2 the optimization model is formulated and explained. The modelling of power production forecasts is presented in Section 3, and Section 4 shows the condition monitoring framework used in this study. In Section 5 the methods from the previous sections are combined in an illustrative case study considering as examples the condition monitoring of i) the main bearing and ii) corrosion of structural elements. Section 6 concludes the paper.

2. Method

The objective of the maintenance scheduling problem is to maximize the revenues from wind power operations while minimizing the costs of preventive and condition-based maintenance tasks and failures. To this end we define a model that considers predetermined maintenance tasks x_{ti}, and two types of condition-based maintenance tasks, y_{ti} and z_{ti}. Predetermined tasks are required to be performed once within the planning horizon. Tasks of type y can be performed to prevent failure, while tasks of type z can be performed to bring the turbine back to full capacity. Performing any maintenance task requires the turbine to be shut down and leads to lost revenue. We divide the model horizon into two periods, short and long term. In the short term, the model has a temporal resolution of days and wind power is represented by production scenarios. In the long term, statistical data is used to estimate the production losses related to maintenance activities with a weekly temporal resolution.

2.1. Mathematical formulation

The method may be formulated as a mixed integer linear program (MILP) with objective function given in (1), where the short and long term is accounted for in the first and second lines respectively.

$$\max \sum_{t \in \mathcal{T}^{short}} \left[\sum_{i \in \mathcal{W}} \left[\lambda (P^0_{ti} a_{ti} + (P^1_{ti} - P^0_{ti}) b_{ti}) - C^f \rho_{ti} (1 - \bar{y}_{ti}) - C^{vis} r_{ti} \right] - C^{tr} v_t \right] + \tag{1}$$
$$\sum_{t \in \mathcal{T}^{long}} \sum_{i \in \mathcal{W}} \Big[\sum_{k \in \mathcal{K}} \left[\lambda (P^0_{tki} c_{tki} + (P^1_{tki} - P^0_{tki}) d_{tki}) - \frac{C^{tr} + C^{vis}}{\tau^x + \tau^y + \tau^z} h_{tki} \right] - C^f \rho_{ti} (1 - 0.5 y_{ti} - \bar{y}_{ti}) \Big]$$

Revenue is given by the product of the electricity price λ the produced power P^0_{ti} and the hours available for production a_{ti}. Wind turbines that are operating with a derated capacity have a power production P^0_{ti} and can return to full capacity P^1_{ti} after condition-based maintenance is performed. This is expressed by the term $(P^1_{ti} - P^0_{ti}) b_{ti}$, where $b_{ti} = a_{ti} \bar{z}_{ti}$ and $\bar{z}_{ti}$ is a binary variable indicating whether CBM of type z has been performed before time step t. The expected costs of faults are accounted for by the term $C^f \rho_{ti} (1 - \bar{y}_{ti})$, where $\bar{y}_{ti}$ is a binary variable indicating whether CBM of type y has been performed before time step t. The costs of traveling to the wind farm and to visit a turbine is accounted for by the terms $C^{tr} v_t$ and $C^{vis} r_{ti}$. The same terms are included in the long term, but production is discretized in a set of production levels. This means the produced power at power level k is given by $P^0_{tki} c_{tki}$ where c_{tki} is the hours available for production. The term $(P^1_{tki} - P^0_{tki}) d_{tki}$, where $d_{tki} = c_{tki} \bar{z}_{ti}$, is added to account for additional power production possible after CBM tasks are performed. Travel and turbine visit costs are accounted for by the aggregate cost multiplied by the worked hours. Finally, failure costs are accounted for in a similar way as for the short term but because the time steps are longer we include the probability that a failure happens in the same time step but before maintenance is actually performed.

Predetermined preventive maintenance tasks are carried out once for each wind turbine during the model horizon as stated in (2) and condition-based maintenance of type y can be done at most once as stated in (3).

$$\sum_{t \in \mathcal{T}} x_{ti} = 1 \qquad \forall i \in \mathcal{W} \tag{2}$$

$$\sum_{t \in \mathcal{T}} y_{ti} \leq 1 \qquad \forall i \in \mathcal{W} \tag{3}$$

The amount of work that can be carried out on maintenance tasks is limited by the number of teams of technicians and available work hours during the work-day as shown in (4). We do not specify the number of technicians per team in this model, but technicians typically work together at the turbines in teams of 2 to 5 persons. In the long term, available work hours are grouped based on how they statistically coincide with wind power production. In this way, the amount of work carried out during a discretized wind power production level is accounted for in (5) and limited by the statistics of wind power production in (6).

$$\sum_{i\in\mathcal{W}}(\tau^x x_{ti} + \tau^y y_{ti} + \tau^z z_{ti}) \le Q_t T^s \qquad \forall t \in \mathcal{T}^{short} \tag{4}$$

$$\tau^x x_{ti} + \tau^y y_{ti} + \tau^z z_{ti} = \sum_{k\in\mathcal{K}} h_{tki} \qquad \forall i \in \mathcal{W}, \forall t \in \mathcal{T}^{long} \tag{5}$$

$$\sum_{i\in\mathcal{W}} h_{tki} \le Q_t H^{max}_{tk} \qquad \forall t \in \mathcal{T}^{long},\ \forall k \in \mathcal{K} \tag{6}$$

The time available for power production is initially ΔT_t in each time step. In the long term it is necessary to divide the available time into power production levels and let ΔT_{tk} be the time available in power production level k. The available time when accounting for performed maintenance, is given by the auxiliary variables a_{ti}, and c_{tki}, which are calculated by subtracting the time used for maintenance from the total time as shown in (7) and (8). Note that in this formulation there is an implicit assumption that different tasks on the same turbine are done sequentially.

$$a_{ti} = \Delta T_t - \tau^y y_{ti} - \tau^z z_{ti} - \tau^x x_{ti} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{7}$$

$$c_{tki} = \Delta T_{tk} - h_{tki} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{long},\ \forall k \in \mathcal{K} \tag{8}$$

The auxiliary variables $\bar{y}_{ti}$ and $\bar{z}_{ti}$ are updated by the inventory constraints in (9) and (10).

$$\bar{y}_{ti} = \bar{y}_{(t-1)i} + y_{(t-1)i} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T} \setminus t_0 \tag{9}$$

$$\bar{z}_{ti} = \bar{z}_{(t-1)i} + z_{(t-1)i} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T} \setminus t_0 \tag{10}$$

We need the products $a_{ti}\bar{z}_{ti}$ and $c_{tki}\bar{z}_{ti}$ to calculate the wind power production after performing condition-based maintenance. This can not be included directly in the problem when using a MILP solver as the problem becomes quadratic. However, by utilizing the big M-method we can linearize the products to be represented by the continuous variables, b_{ti} and d_{tki}, as shown in (11) to (16).

$$b_{ti} \le M_b \bar{z}_{ti} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{11}$$

$$b_{ti} \le a_{ti} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{12}$$

$$b_{ti} \ge a_{ti} - M_b(1 - \bar{z}_{ti}) \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{13}$$

$$d_{tki} \le M_c \bar{z}_{ti} \qquad \forall i \in \mathcal{W},\ \forall k \in \mathcal{K},\ \forall t \in \mathcal{T}^{long} \tag{14}$$

$$d_{tki} \le c_{tki} \qquad \forall i \in \mathcal{W},\ \forall k \in \mathcal{K},\ \forall t \in \mathcal{T}^{long} \tag{15}$$

$$d_{tki} \ge c_{tki} - M_c(1 - \bar{z}_{ti}) \qquad \forall i \in \mathcal{W},\ \forall k \in \mathcal{K},\ \forall t \in \mathcal{T}^{long} \tag{16}$$

The big M should be equal to the upper bound of the continuous variable of the original products. For our problem this bound is ΔT_t and ΔT_{tk}, which can be derived from (7) and (8). The variable r_{ti} keeps track of whether a turbine is visited on a given day. This is obtained by the constraints in (17) to (19)

$$x_{ti} \le r_{ti} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{17}$$

$$y_{ti} \le r_{ti} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{18}$$

$$z_{ti} \le r_{ti} \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{19}$$

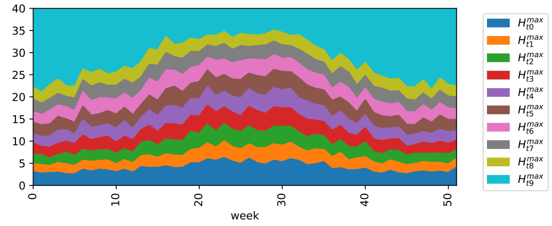

Figure 1: Available hours at each production level for an average year.

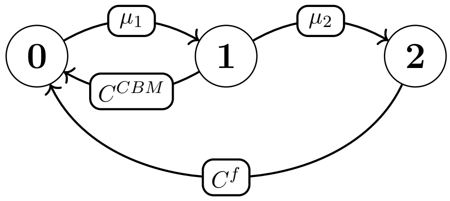

Figure 2: A Markov diagram illustrating the probabilistic failure model.

The variable v_t indicates whether the wind farm is visited and is subject to the constraint in (20).

$$v_{ti} \leq v_t \qquad \forall i \in \mathcal{W},\ \forall t \in \mathcal{T}^{short} \tag{20}$$

3. Production forecast

In the general case, wind power production depends on many factors and may be the output of a wind farm control module. However, as wind speed is the most important factor, in this paper power production is forecast based on the forecast wind speed. The relation between wind speed w and power production is given by a power curve $P(w)$. In the current framework it is assumed that a precise wind forecast is available within the short-term time horizon, and scenarios for the power production is thus obtained by $P_t = P(w_t)$.

3.1. Long-term forecast

For the long-term time horizon, the approach of [25] is adopted and extended for the current context. The relevant parameters are the power production levels P_{tk}^{loss}, and the available hours at each level. Power production levels are given by discretizing the power curve $P(w)$, while available hours at each level may be obtained by statistical weather data for the wind farm. As an illustration, the available hours per week based on 50 years of data from a location in the North Sea have been calculated. The result is shown in Figure 1 where it can be observed that there are more high speed wind conditions in the winter than in the summer.

3.2. Derating

In some cases it may be possible to avoid or postpone failure of a degraded wind turbine by operating at a lower load. If this is the case, the wind turbine is in a derated state. As long as the wind turbine is derated the turbine will produce less energy than it would when operating at full capacity. A CBM task may be performed to bring it back to full capacity. To account for derating in the optimization problem, the required inputs are the power production forecast without derating, P_{ti}, and the power production forecast with derating, P_{ti}^0. In the general case the power production P_{ti1} and P_{ti}^0 may also be an output from a wind farm control module. In this work the derating is modelled by an alternative power curve.

4. Condition-based maintenance

The proposed framework is agnostic to which specific failure modes are considered, and aims to be general enough to be applicable in a variety of situations. The applicability will depend on the time frame of deterioration and the repairability of the failure mode. By repairability we mean whether the damaged equipment can be repaired and to what degree the component is as good as new after a repair.

4.1. Failure modelling

The model requires a probability of failure as input, which means it is necessary to establish a relation between condition information and the probability of failure ρ_{ti}. In this paper, a Markov state model similar to the ones proposed in e.g. [26, 25, 27] is adopted as illustrated in Figure 2. State 0 represents no deterioration, state 1 represents that some failure progression is detected, while state 2 represents a fault. As indicated by the diagram, the transition time from state 0 to state 1 is exponentially distributed with parameter μ_1, while the transition time from state 1 to state 2 is exponentially distributed with parameter μ_2. If the component is in state 1 it may be returned to state 0 by a condition-based maintenance task at a cost C^{CBM}, while if in state 2 it may be returned to state 0 at a cost C^f. The exact interpretation of the states will depend the failure mode as illustrated in Section 4.1.1.

The probability of failure may be obtained by considering the probability distribution function $F_Z(z|\lambda_1, \lambda_2, S_0)$ of the time to failure Z_{0i}. The probability of failure in time step t is given by $\rho_{ti} = F_{Z_{0i}}(T_{t+1}) - F_{Z_{0i}}(T_t)$ where T_t is the time from the start of time step 0 to the start of time step t, and $T_0 = 0$. The expected time spent in a state depends on the specific situation but typically the time spent in state 0, given by $1/\mu_1$ is in the range of decades, while the expected time spent in state 1, given by $1/\mu_2$, is in the range of days, weeks, or months. This section presents an example where the proposed model may be useful.

4.1.1. Corrosion condition monitoring system We consider a condition monitoring system to track corrosion on the wind turbine structural elements. A system may consist of periodic inspections made by people, or possibly drones. Corrosion will in the long term decrease the structural integrity of the wind turbine. To maintain safe operation, the turbines are designed with an extra wall thickness, called corrosion allowance, which ensures sufficient wall thickness even with some corrosion [28].

Assume that the state of corrosion can be categorized in three states: 0) no indication of corrosion, 1) corrosion detected, and 2) corrosion allowance depleted. Assume that when condition is in state 1, it is sufficient to grind and recoat, which means τ_y is the time it takes to grind and recoat the corroded area. When corrosion has reached state 2, the damage is irreversible. The cost of doing maintenance too late is C^f, and includes the cost of decommissioning or replacing the turbine. Here, we define this cost of failure as the difference in net present value of the cost of replacing the turbine now (renewal) as compared to replacing it later (e.g., when repowering the entire wind farm after the end of the its useful lifetime):

$$C^f = \frac{C^{turb}(1 - (1+q)^{T^{RUL}})}{1 - (1+q)^{T^L}}. \tag{21}$$

Consequently the cost C^f will be smaller for an old turbine than for a new turbine.

4.2. Derating to avoid main bearing failure

A common way to monitor the drivetrain main bearing is to use vibration data [29]. Assume that vibration analysis shows that main bearing is in a degraded state, and it may break if run at full capacity. To avoid failure of the drivetrain a derating strategy is used. An appropriate strategy may be obtained e.g. through model predictive control as suggested in [30]. For simplicity assume that the derating strategy is to run the turbine at a proportion $R_i < 1$ of full capacity. This is equivalent to setting $P^0(w) = R_i P(w)$, which in turn means $P^0_{ti} = R_i P_{ti}$.

5. Case study

A case study has been constructed to illustrate the methodology. We consider a wind farm with $N = 16$ wind turbines. All turbines are of the DTU 10 MW reference wind turbine [31]

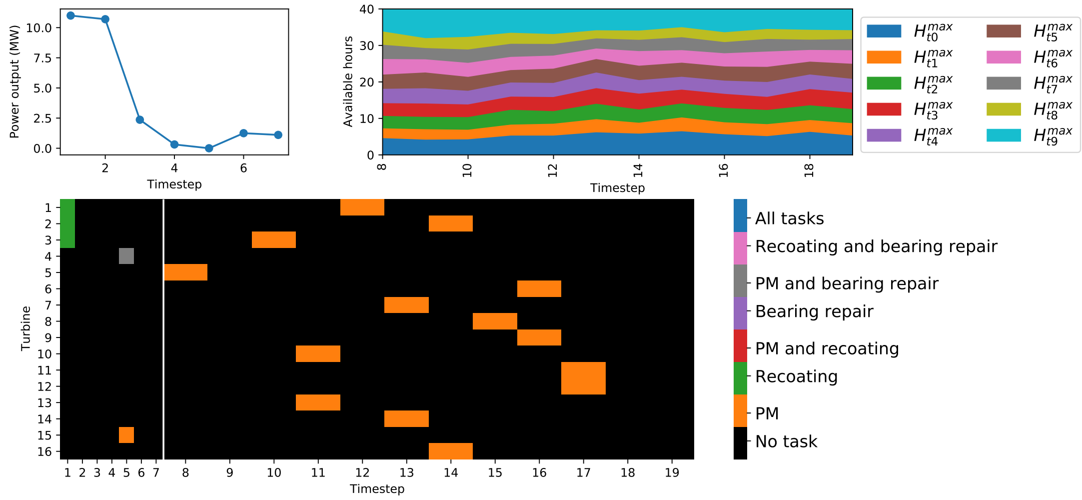

Figure 3: Summary of the case study. Upper left: Short term wind forecast, Upper right: Available hours at each production level in the long term. Lower: The optimal plan for executing maintenance tasks per turbine and time step. The short-term horizon is from time step 1-7 with daily resolution, while the long horizon spans time steps 8-19 with weekly resolution.

type, with associated power curve $P(w)$. For each wind turbine there is one annual service maintenance task, which is due within the end of the long-term time horizon $\mathcal{T}^{long}$. In addition, condition information is available about corrosion status and the main bearing. We plan the PM and CBM tasks using the optimization model presented in Section 2.

The corrosion status follows the model presented in Section 4.1.1. Specifically, if no corrosion is detected, the mean time until corrosion is detected is assumed to 20 years, which means $\mu_1 = 1/20$. If, on the other hand, corrosion is detected, the mean time to failure is 6 weeks, which means $\mu_2 = 52/12$, assuming there are exactly 52 weeks in a year. We assume that corrosion is detected on wind turbine 1, 2 and 3, i.e. $S_{i0} = 1$ for $i \in \{1, 2, 3\}$ and $S_{i0} = 0$ otherwise. The nominal lifetime of a wind turbine T^L is 20 years. The age of all wind turbines is 10 years, which means $T^{RUL} = 10$ years for all wind turbines. Assuming a discount rate of $q = 4\%$, and the cost of a new wind turbine to be 23 million € [32], the cost of failure C^f, calculated by equation (21), is found to be 13.7 million €. A degraded condition of the main bearing is detected at turbine 4, and this follows the derating strategy described in Section 4.2 and runs at 60% capacity, i.e. $R_4 = 0.6$ while $R_i = 1$ for all $i \neq 4$.

The short time horizon spans one week and the time steps are 1 day, while the long time horizon spans 12 weeks and time steps are 1 week. The choice of the long time horizon means that there is a high probability that turbines in a degraded state will fail within the time horizon if no CBM action is taken. The planning horizon starts in week 15, and implies the weather and production forecasts shown on the top row in Figure 3. Week 15 is in April and just prior to the season that is typically best for planning predetermined maintenance work. The electricity price is 60 €/MWh, there are $Q_t = 2$ teams of technicians available at all time steps, a PM task requires $\tau^x = 6$ hours, recoating requires $\tau^y = 8$ hours, and bearing repair requires $\tau^z = 8$ hours. Each work day is 12 hours and the transportation cost is $C^{tr} = 500$ € [8] and turbine visit cost $C^{vis} = 100$ €.

The optimal plan for when to execute the different maintenance tasks is shown in Figure 3. Recoating is prioritized on the first day of the planning horizon. Low wind speeds on day five are utilized to do bearing repair on wind turbine 4. During the visit to wind turbine 4, preventive tasks are done on turbine 4 and one other turbine. Preventive tasks on other turbines are planned

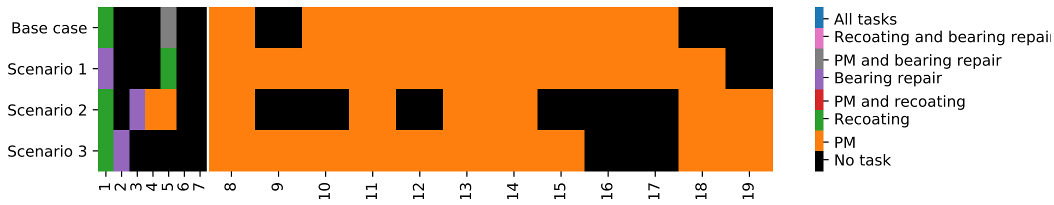

Figure 4: Summary of all scenarios. The color indicates whether at least one task of the given types are planned for the given time step.

for the long-term time horizon, utilizing the expectation of hours of low power production.

To investigate the effect that different input parameters have on the optimization, three additional scenarios have been designed. In Scenario 1, the failure cost C^f is set to 5000 €, in scenario 2 it is assumed that the number of available hours for power production levels 0 to 3 are all assigned to power production level 3, emulating a situation where the long term is less favourable for maintenance. In scenario 3, the derating factor for wind turbine 4 is 0.1. A comparison between the base case and the alternative scenarios is shown in Figure 4. Scenario 1 illustrates that a low failure cost means bearing repair is prioritized before recoating. Scenario 2 shows that less favourable long term wind expectations means more tasks are planned for the short term. Scenario 3 shows that a more severe derating strategy means bearing repair is planned for day 2 despite higher forecasted power production.

6. Conclusion

Maintenance costs of offshore wind farms may be greatly reduced by the use of condition monitoring, reducing the amount of maintenance which is performed and the number of component failures. There is a need for tools to determine the optimal plan for performing maintenance taking into account the information from condition monitoring systems.

This paper has presented a modelling framework for including condition-based maintenance when optimizing the short-term maintenance schedule for an offshore wind farm. It has been illustrated for an example application where condition information is utilized to jointly plan two different condition-based maintenance tasks and a predetermined preventive task for each wind turbine, where a degraded condition is assigned to a subset of the turbines. The framework is general, and the optimization model could easily be extended to consider additional types of condition-based maintenance tasks. It is also a first step towards integrating wind farm control in O&M decision making. This work is part of the WATEREYE project (O&M tools integrating accurate structural health in offshore energy), and one of its objectives is to find the best balance between energy production, protective control, and predictive maintenance. The method proposed in this paper can interact with a wind farm operations and control module to provide the best joint decisions, co-optimizing control and maintenance strategies.

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