WATEREYE

Project Title:	O&M tools integrating accurate structural health in offshore energy
Starting date:	2019/11/01
Duration in months:	36
Call (part) identifier:	H2020-LC-SC3-2019-RES-TwoStages
Grant agreement no:	851207

Consortium Members

Organisation	Abbreviation	Country
Centro Tecnológico Ceit-IK4	CEIT	Spain
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Deliverable D4.4

Wind farm controller including maintenance scheduling based on corrosion prediction

Due date of deliverable	Month 36
Actual submission date	2022-10-31
Organisation name of lead contractor for this deliverable	SINTEF Energy Research
Dissemination level	Public
Revision	0.0

The WATEREYE project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 851207

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DRAFT PREPARATION			
Version	**Publication date**	**Content**	**Author**
0.0	31/03/2022	▪ Maintenance planning	▪ Håkon Toftaker (SINTEF-E)
0.1	15/05/2022	▪ Overall structure	▪ Konstanze Kölle (SINTEF-E)
1.0	27/10/2022	▪ First draft of whole document	▪ Konstanze Kölle, Spyridon Chapaloglou, Valentin Chabaud (SINTEF-E)
1.1	28/10/2022	▪ Internal review	▪ Thibault Crepain (FMAKE)
2.0	31/10/2022	▪ Final version	▪ Konstanze Kölle, Spyridon Chapaloglou, Valentin Chabaud (SINTEF-E)

HISTORY OF CHANGES		
Version	**Publication date**	**Change**
1.0	27/10/2022	▪ First draft of the document
2.0	31/10/2022	▪ Final version

EXECUTIVE SUMMARY

The present document constitutes the report about the wind farm control and maintenance strategy developed as part of the project titled “O&M tools integrating accurate structural health in offshore energy” (Project acronym: WATEREYE; Grant Agreement No. 851207).

This study suggests an approach for multidisciplinary probabilistic decision making through the joint effect of fatigue- and corrosion-induced failures on O&M planning for offshore wind farms. The focus is set on the methodology of integrating aero-hydro servo analyses of wind farms (and not only their individual turbines) and subsequent fatigue damage calculations into medium-term decision making (weeks-ahead O&M planning), opening the way for combination with corrosion-related inspections or hypothetical repairs.

TABLE OF CONTENTS

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

Abbreviations / Acronyms	Description
CBM	Condition-Based Maintenance
CM	Condition Monitoring
DSS	Decision Support Systems
DTU	Technical University of Denmark
IPS	Indoor Positioning System
LCOE	Levelized Cost of Energy
MILP	Mixed integer linear program
MPC	Model Predictive Control
NREL	National Renewable Energy Laboratory
OPEX	Operational Expenditures
O&M	Operation and Maintenance
PI	Proportional Integral
PM	Preventive Maintenance
RUL	Remaining Useful Lifetime
RWT	Reference Wind Turbine
SCADA	Supervisory Control and Data Acquisition
TC-RWP	TotalControl Reference Wind Power Plant
UAV	Unmanned Aerial Vehicle
US	Ultrasound
UWB	Ultra-Wide Band
WT	Wind Turbine
WF	Wind Farm
WFC	Wind Farm Control
WFO	Wind Farm Operator

1 INTRODUCTION

The operation of wind farms has focused on maximum power production. Therefore, power maximization has also been the dominant operational objective of most research on wind farm flow control which considers the aerodynamic turbine interactions. However, the expected higher share of renewable sources in the energy mix can provide incentives for wind farm operators to not maximize power at any time but rather to maximize the revenue over the entire lifetime. This can include the provision of ancillary services to the grid operator and the mitigation of structural degradation. A relevant ancillary service is the provision of power reserve, consisting in following a below-maximum desired power reference from the grid operator. This is known as power curtailment or derating, leading to curtailed or derated operation.

Maximizing the revenue means to balance the short-term revenue gains from power production and the long-term (potential) revenue gains from decreased fatigue loads. Decreasing the accumulated fatigue damage extends the lifetime of components which again reduces the need for maintenance. This motivates the use of control strategies that mitigate fatigue loading, where curtailed operation particularly leaves degrees of freedom to operate the wind farm. The wind farm controller can apply a smart power dispatch to mitigate fatigue damage at key components of the wind turbines. The farm operator can also decide to purposedly curtail his farm, however, there exist no proven measures today to quantitatively estimate the cost savings from load reductions in real time.

Yet, downtime and repairs are costly. The general trend is that new wind farms have more and larger turbines and can also be located further offshore than before. All this leads to higher maintenance costs where in particular the potentially remote location complicates the access, making a good operation and maintenance (O&M) planning even more important to reduce the number of manned trips. The need of suitable weather windows to approach the wind turbines further constrains the execution of offshore O&M tasks. This can motivate the use of preventive load mitigation and smart planning to increase the overall profit. A typical example is failures on drivetrain components, which typically show early signs of failure weeks ahead in the form of abnormal vibrations. Seeking to maximize power without mid-term load mitigation nor maintenance planning can easily wipe out short-term profit.

This illustrates that control and maintenance strategies that reduce the levelized cost of energy are a timely research topic as the installed capacity of offshore wind power is increasing. Following the introduction, this report continues in Section 2 with a method that optimizes the maintenance planning of offshore wind farms. An optimization problem is defined that considers both lost production due to present failures and shutdowns for maintenance as well as weather windows. Two failure modes and related maintenance tasks are included in the example, namely corrosion that can be completely removed by recoating and a drivetrain fault that requires repair.

The tool TurbSim.Farm[xxxi] for mid-fidelity wind farm simulators enables stochastic analyses of farm-wide turbulences. In Section 3, a control framework is proposed that includes a damage database linking statistical quantities from farm simulations to the accumulated damage at each turbine's drivetrain, a component with a lot of wear and thus frequent failures. The included farm-

based quantities consist of inflow wind speed, direction and turbulence intensity at each turbine as well as the power command sent by the wind farm controller. The latter introduces derating control to the wind turbines.

The farm control framework in Section 3 returns an estimate of the accumulated drivetrain fatigue depending on the wind farm control strategy which can feed the O&M planning in Section 2 with information about the estimated component state. The co-optimization of the proposed maintenance and control strategy is discussed in Section 4 before the report closes with summary and future work in Section 5.

2 WIND FARM MAINTENANCE OPTIMIZATION

Offshore wind power is growing rapidly, but high costs of maintenance and long turbine outage times are still a challenge. These challenges may be solved by condition monitoring solutions[i],[ii]. Condition monitoring provides necessary information to make decisions in the operation and maintenance (O&M) of 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[iii], but for simplicity we reserve PM to denote predetermined preventive maintenance here. 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[iv], 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[v]. Based on inspection results, it 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 may often be subject to harsh weather conditions. This means that maintenance activities include long travel times and may be restricted due to limited accessibility. These factors imply a large value of carefully planned 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[vi]. In that case, CBM actions may bring the turbine back to full capacity but require a shutdown 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 renders O&M decision making even more complex.

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.

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

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).

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

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

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 workday 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 two to five 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).

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

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

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

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 cannot 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).

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

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

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

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

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

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

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):

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

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

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

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

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

2.2 Production forecast

In the general case, the 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, power production in the maintenance planning is forecasted 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 are thus obtained by $P_t = P(w_t)$.

2.2.1 Long-term forecast

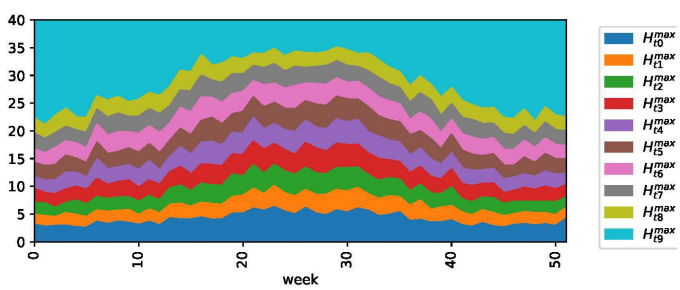

Figure 1. Available hours at each production level for an average year.

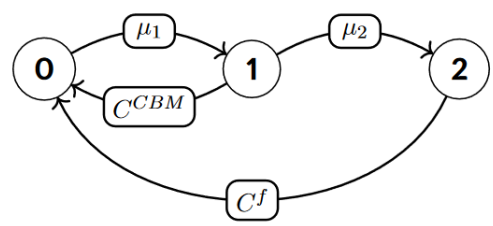

Figure 2. A Markov diagram illustrating the probabilistic failure model.

For the long-term time horizon, the approach of Besnard and Bertling (2010)[vii] 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.

2.2.2 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_{ti}^1 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.

2.3 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.

2.3.1 Failure modelling

The model requires a probability of failure as input, which means that 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., [vii],[viii],[ix] 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 on the failure mode as illustrated in the following Section.

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. 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.

2.3.2 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[x].

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 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.

2.4 Derating to avoid main bearing failure

A common way to monitor the drivetrain main bearing is to use vibration data[xi]. Assume that vibration analysis shows that the main bearing is in a degraded state, and it may break if run at full capacity. A derating strategy is used to avoid failure of the drivetrain. An appropriate strategy may be obtained e.g., through model predictive control as suggested by Brandtstaedter et al. (2018)[xii]. 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 $P_{ti}^0 = R_i P_{ti}$.

2.5 Example

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[xiii] 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 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 2.1.

The corrosion status follows the model presented in Section 2.3.2. Specifically, if no corrosion is detected, the mean time until corrosion is detected is assumed to be 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 $\mathrm{T}^{RUL} = 10$ years for all wind turbines. Assuming a discount rate of q = 4%, and the cost of a new wind turbine to be 23 million € [xiv], 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 2.4 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 workday is 12 hours and the transportation cost is C^{tr}= 500 € [xv] 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 for the long-term time horizon, utilizing the expectation of hours of low power production.

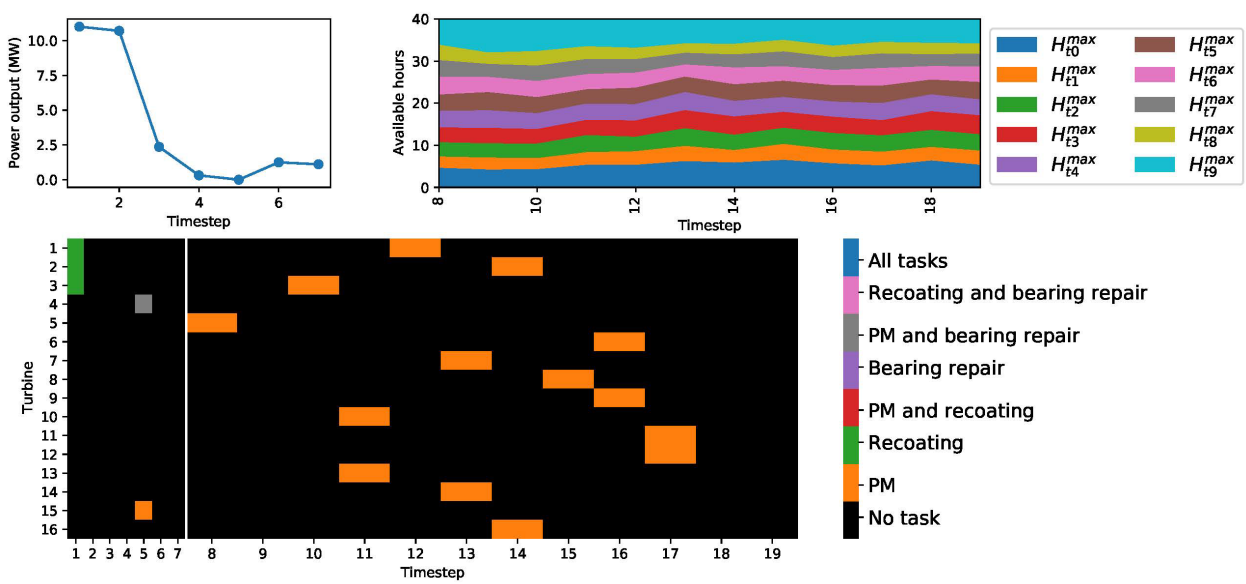

Figure 3. Summary of the case study. Upper left: Short-term wind forecast, Upper right: Available hours at each production level in the long term. Lower: The optimal plan for executing maintenance tasks per turbine and time step. The short-term horizon is from time step 1-7 with daily resolution, while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

3 WIND FARM CONTROL FRAMEWORK FOR DAMAGE ESTIMATION

A wind farm controller coordinates the operation of the wind turbines within a wind farm. The traditional goal of maximizing the power output at any time will be challenged in the future when more power plants will be driven by renewable energy sources. In electrical studies focusing on grid integration, active power control may refer to grid frequency support, to be opposed to voltage and reactive power control[xvi]. Wind farm control can have multiple objectives purely on the mechanical side without even considering the electrical connection to the power system[xvii]. In these studies (referred to as wind farm flow control[xviii]), active power control rather refers to dynamic power dispatch (to be opposed to passive control rather than reactive power). A first objective is power tracking of a reference provided by the grid operator [xix,xx].

Control actions and environmental disturbances change the external forces and moments that act on the turbine structures and components. These loads cause stress on the affected turbine parts by structural deflection and rotation, and eventually, structural damage occurs. This fatigue damage is a function of turbine-level thrust and power fluctuations, themselves dependent on the power setpoint (result from farm-level power dispatch) and the way this setpoint is tracked by the turbine controller. The effect of the latter on fatigue has received sizable attention in the literature [xxxi,xxvii,xix]. However, the turbine controller being proprietary to the turbine manufacturer and in practice a black box that the farm operator cannot tweak sets limitations to the feasibility of this approach. Therefore, in this study we focus on the effect of the power setpoint itself, whose choice is up to the farm operator, assuming a standard (conservative) tracking functionality in the turbine controller.

Most of studies on active power control that consider fatigue loading at the farm level can be divided into two general types:

- Advanced control formulations such as Model Predictive Control (MPC) based on analytical simplified models [xxi,xxii]
- Control design and testing based on high-fidelity simulations[xxiii,xix]

Studies of the first type apply a model-based controller to optimize the operation. In order to describe the whole wind farm in a feasible optimization problem, simplified analytical models are typically used which are unable to capture farm-scale turbulent fluctuations and hence do not consider situations with low available power within a simulation. Moreover, the complexity of model-based optimal control algorithm can act as barrier for scalability and transferability. Those studies typically also do not consider the effect of uncertainties on the controller performance, and their feasibility is therefore discussable. Studies of the second type are centred around designing and testing control strategies using high-fidelity simulations. These require high computational costs and are usually too expensive for stochastic analyses of structural loading and fatigue damage.

Mid-fidelity approaches can build a good comprise between simplified engineering models and computationally expensive high-fidelity simulations. An example of a mid-fidelity wind farm simulator is StrathFarm which has already been applied for multi-objective active power control[xxiv]. The open-source wind farm simulator FAST.Farm by NREL provides a perfect background for studying wind farm operation with medium fidelity. The module TurbSim.Farm[xxxi], developed partly in WATEREYE, enables the analysis of farm-wide power tracking, for example in FAST.Farm, while considering turbulent fluctuations in a stochastic manner.

The drivetrain is the power conversion system of the wind turbine including main bearing, main shaft, gearbox with a number of gears, bearings and shafts, generator and power converter[xxv]. With all these components, the drivetrain is one of the most often failing parts of wind turbines with long downtime and fastidious repairs, but received, nevertheless, significantly less attention in load-mitigating wind farm control than tower or blades. If the drivetrain is considered, it is often modelled in a very simplistic way, see e.g.[xxvi],[xxvii]. The latter work focuses on the damage on the shaft (simplistic drivetrain model) using hysteresis operators by generating a database for the fatigue damage at the turbine level[xxvii]. Such databases are becoming a common approach to circumvent the challenge of supporting control decisions with loading information in real time. Another example is the surrogate modelling (database) approach used in DNV's tool LongSim to include damage equivalent loads in control-oriented farm simulations[xxviii].

The wind farm control framework suggested in the present study combines the advantages of mid-fidelity simulations, the knowledge of farm-wide turbulence and a pre-computed database for the drivetrain damage. The outcome are estimates of the drivetrain damage depending on the control strategy.

The main contribution (advance beyond state of the art) of this work is the provision of a mid-fidelity solution for a multiscale problem bringing component level degradation to the farm control and production scheduling level (hours to weeks), where only simplified low-fidelity approaches have been used before. This may be broken down into individual advances:

- Power fluctuations due to farm-wide turbulence are considered by using TurbSim.Farm[xxxi]
- More realistic modelling of degradation of drivetrain components using a database approach[xxxii]
- Consistent use of NREL's FLORIS in curtailed conditions (see Section 3.3)
- Adaptation of the original hierarchical controller to encompass time-varying damage and sporadic saturation events

3.1 Wind farm control strategy

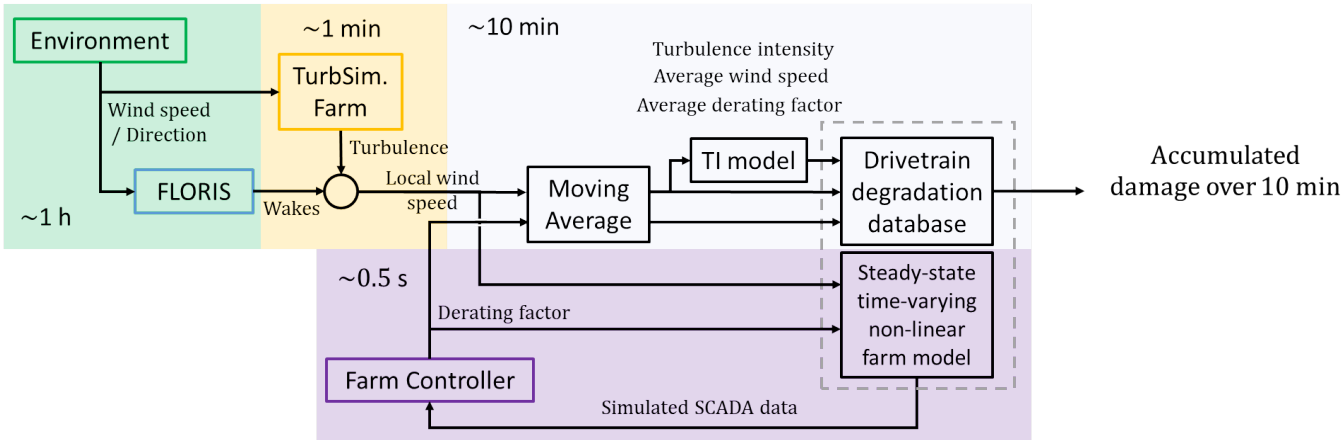

Figure 4. Set-up of the wind farm control framework including a calculation of the accumulated damage depending on environmental conditions and farm control.

Maintenance planning and optimization requires information about the condition of the relevant turbine components to be considered. Concerning fatigue loads, the accumulated damage cannot be easily monitored. However, drivetrain components may show early signs of failure. In this case it is beneficial to spare the damaged turbine, before planned maintenance in the coming weeks (referred to as mid-term, short-term being hour(s) and long-term months to years). Wind farm control will then try to balance power production with damage rate, so that the accumulated damage over the mid-term horizon is reduced for the damage turbine, in the hope of avoiding premature failure and hence downtime. Wind farm control may also be used without signs of failure, just trying to reduce the overall damage over all turbines by loading more turbines with a lower damage rate.

We seek to get an estimate of the damage that accumulates during operation including the effect of wind farm control. The problem we are facing is multiscale: the time horizon is one or two weeks, environmental conditions (wind speed and direction) are typically given on a 1-hour basis, damage is calculated in 10-min long simulations, power fluctuations due to turbulence are from periods of 5 min and above and hence require a 1-min resolution, while the controller itself has dynamics of the order of seconds. Damage calculations involve much faster dynamics requiring a sampling of 40Hz. Solving for all of these scales simultaneously would lead to exceeding complexity and computational cost. Therefore, we suggest a database approach to split farm and turbine levels: fatigue damage is computed beforehand and put in a parametric look-up table used during farm simulations. Moreover, a quasi-steady approach for wake and turbine modelling is used in farm simulations to reduce complexity and improve computational efficiency. These simplifications are deemed reasonable:

- As power tracking is always prioritized to load mitigation, modelling of power fluctuations is crucial. There, it has been observed that the effect of wake dynamics is negligible[xxxi].

- Wake dynamics do have an effect on turbulent mixing and hence on wake velocity deficit and in turn mean wind speed, but this is typically well modelled in a statistical/empirical manner in quasi-steady approaches

- Wake-induced turbulence partly deriving from wake dynamics (wake meandering) is important for fatigue loads, so decoupling turbine- and farm-levels by means of a database lookup approach may seem oversimplifying. Yet, the suggested method is in line with the simpler way of including wake-added turbulence through analytical formulas for the turbulence intensity as defined in the IEC standard[xxix].

- Turbine dynamics are much faster, so it is reasonable to assume equilibrium at the minutes scale

The block diagram in Figure 4 presents the proposed setup. The following list summarises the function of each block:

- **Farm**: The wind farm composed of a number of turbines with their dynamics and interactions including the local wind turbine controllers. In real-life applications, this block would provide measurements (SCADA data) from the farm. In this study, the wind farm is simulated in a simplistic quasi-steady manner to demonstrate the set-up for the use case in Section 3.4.

- **Farm Controller**: The wind farm controller defines the power set-points for the wind turbines in the farm. The controller is described in more detail in Section 3.2.

- **Environment**: Relevant environmental parameters are the wind speed and direction which are included here as time series with hourly resolution.

- **FLORIS[xxx]**: A quasi-steady wake model calculates the wake effects between the wind turbines for the environmental conditions.

- **TurbSim.Farm[xxxi]**: A turbulence generator calculates coherent farm-wide turbulence for the environmental conditions. The generated turbulence has a resolution of 1 min.

- **Moving Average**: A filter builds 10 min-averages of the turbulence, the wind speed after superposing wake and turbulence as well as power commands from the wind farm controller.

- **Drivetrain degradation database**: A database linking derating to drivetrain loads was created from turbine simulations using OpenFAST and a mid-fidelity degradation model[xxxii]. The accumulated damage for each turbine is defined based on the local wind speed, turbulence intensity and power control command.

3.2 Wind farm controller

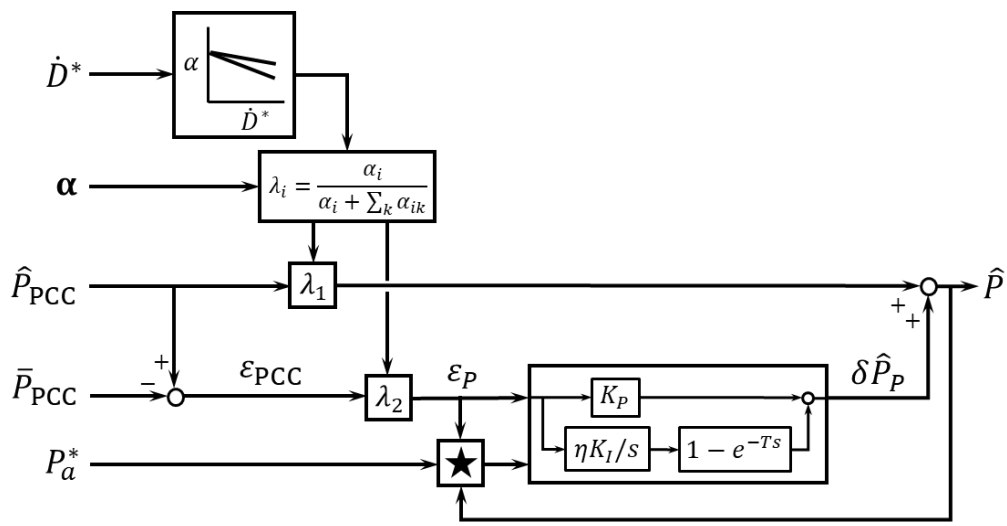

Figure 5. Architecture of the hierarchical wind power plant supervisory controller. The controller is an adaptation of previous work by Merz et al. (2021)[xxxiii].

The hierarchical wind farm controller implements a baseline plant controller that uses only typically available data from the Supervisory Control and Data Acquisition (SCADA) system. It balances two control objectives: (1) power tracking and (2) damage mitigation, using the control architecture shown in Figure 5 at each wind turbine. It follows the concept of distributed control for enhanced scalability, where a specific turbine only has limited knowledge about other turbines: the only quantities transmitted from farm level are the reference power, the actual farm power output, and the sum of damage indices over all turbines. The final controller output is the power command $\hat{P}$ that is sent to the turbine controller.

A feedforward loop dispatches the farm-scale power command $\hat{P}_{PCC}$ among the turbines according to the weighting λ_1. A proportional-integral (PI) feedback loop reduces the error ε_{PCC} between the commanded power $\hat{P}_{PCC}$ and measured power $\bar{P}_{PCC}$ at the point of common coupling considering also the available power P_a^* and the turbine-level power command $\hat{P}$ as feedback. The block marked with a star implements anti-windup that discharges the integrated feedback when the error approaches zero, through the saturation variable η.

Both the feedforward and the feedback loop are weighted depending on the damage rate at the considered component in relation to the damage rate at the other turbines. This ratio is considered in the weights λ_i for $i\epsilon\{1,2\}$ that adjust the distribution of power commands among the turbines. The controller can be tuned using the factors $\boldsymbol{\alpha} = \{\alpha_1, \alpha_2\}$ which scale the damage rate $\dot{D}^*$ before calculating the weights. Thus, one of the loops can be prioritized.

The wind farm controller in Figure 5 is an adaptation of the hierarchical supervisory controller of earlier work[xxxiii] conducted as part of the H2020 project TotalControl. In the proposed control framework, the wind farm controller is demonstrated for the first time with wake effects between turbines and more realistic damage rates depending on the operational state.

The controller has the following advantages:

- The control structure respects the proprietary structure of wind energy systems without intruding the wind turbine controller.
- A distributed — rather than centralized— control approach is used for scalability, where each wind turbine is treated quasi-independently on the others in the farm controller.
- Wind farm controller using human understandable, feedforward and feedback PI control loops which provide human understandable solutions and are easier to tune and more robust than farm-wide optimizations

3.3 FLORIS

To facilitate the readability of the control methods comparison described later in 3.4, the basic wind farm setup and relevant information regarding the wake modeling will be given first. The effect of the derating on the wake of the turbines is in the wind farm was captured by using the Floris simulation tool. Analytical and validated expressions are used to describe the flow fields behind each turbine, using information about the C_p and C_t characteristics of the turbines. For that purpose, the *Gauss-Curl-Hybrid (GCH)* model was selected being one of the most accurate in terms of modelling wake deflection, velocity deficit and second-order wake steering effects. The DTU-RWF composed of the DTU-10MW-RWT was given as input to Floris.

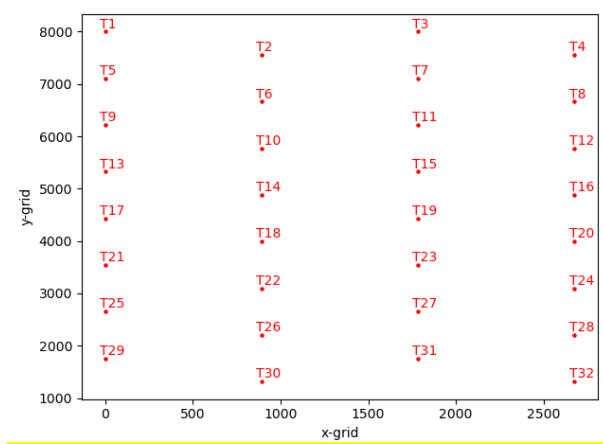

Figure 6. TC-RWP layout for wake modelling with DTU 10 MW turbines

The wind farm layout is presented in Figure 6 where the main wind direction is 270° (west wind). Thus, for this wind direction and there are two rows of upstream and downstream turbines

separated by 10D due to the staggered layout. From now, we will refer to the turbine sequence {1,2,5,9,10,…,29,30} as "*upstream*" and the sequence {3,4,7,8,11,…,28,32} as "*downstream*". In addition, we will refer to the turbines group {1,2,3,4} as the "northern" and the group {29,30,31,320 as the "southern". Thus, the in-between rows represent turbine groups spanning the north to south orientation. The derating command is given through pitch control of the wind turbines. To integrate the effect of derating into the wake modeling calculated with Floris, individual C_p and C_t equilibrium curves were given to each turbine, depending on the equilibrium rotator speed and pitch angle, as instructed by the database. Then the $C_p(\lambda, \beta)$ and $C_t(\lambda, \beta)$ curves were sampled to derive case-specific power and thrust coefficient curves as a function of wind speed, that is $C_p(u)$, $C_t(u)$. The case specific power curves are illustrated below.

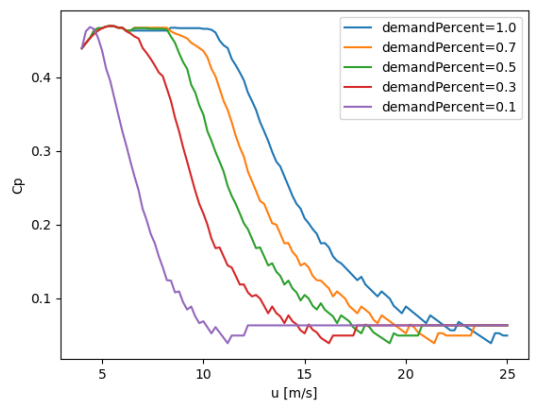

Figure 7. Power coefficient curve of DTU-10MW-RWT as a function of wind speed and derating.

As an example of how this functionality affects the wake, we present the following cases, in which all turbines are equally derated to 80% (Figure 8 and Figure 9) initially, and then, the power commands are updated from the controller, leading to different derating per turbine (Figure 10 and Figure 11). From Figure 8 and Figure 10 we observe the flow field inside the wind farm and how the wakes are evolving based on the update derating commands. More precisely we see that the wake effects are reduced for higher derating, since the corresponding thrust coefficients are reduced (Figure 9 and Figure 11) and thus the overall wind speed distribution in the farm increases, leaving increased wind speed for the "downstream" turbines. However, such a change is also reflected on the turbine's power coefficient curves which also change. It is also worth noticing that the controller's command is saturated by the available wind power of the turbine thus affecting the capabilities of each turbine not only with respect to power production but also contributing to reducing wakes as a consequence of the corresponding derating commands.

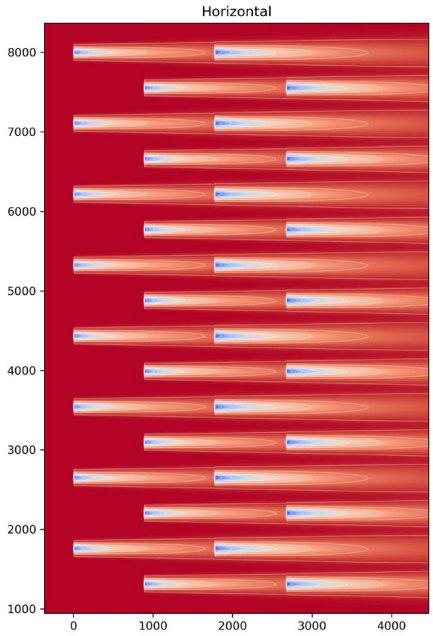

Figure 8. Wake modelling and flow field in the farm for equal derating

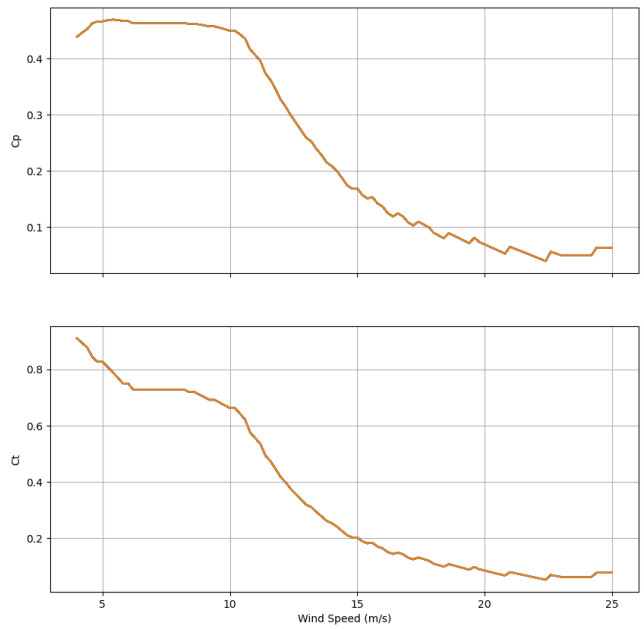

Figure 9. Power and thrust coefficient curves for equal derating

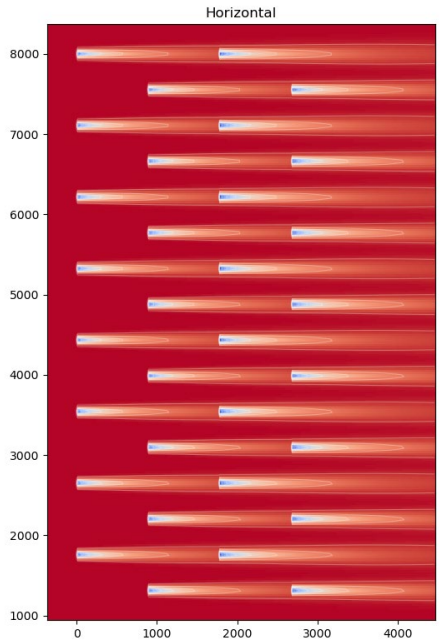

Figure 10. Wake modelling and flow field in the wind far for different derating commands

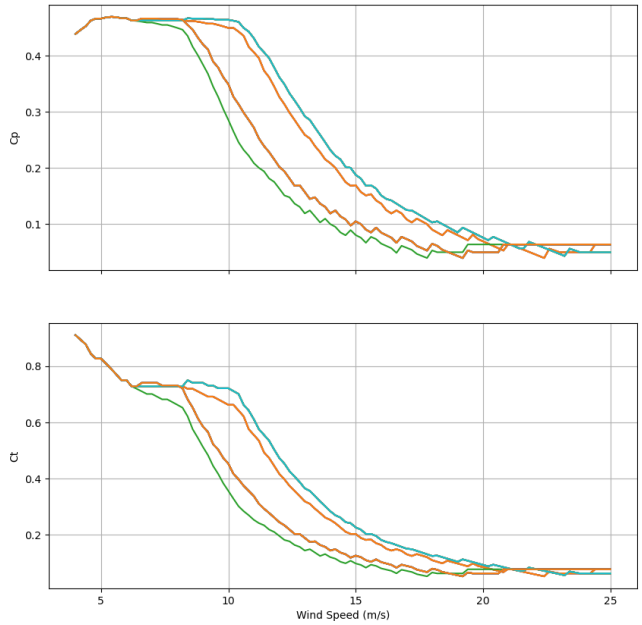

Figure 11. Power and thrust coefficient curves for different derating commands

3.4 Use case

Different derating strategies will lead to different power dispatch distributions for the wind turbines in the farm and eventually different damage rates on each turbine's drivetrain. To demonstrate the effectiveness of the proposed strategy ("*load mitigation"*), where the wind farm controller is informed of each turbine's damage, one additional benchmark strategy is evaluated and compared. The benchmark strategy ("*equal sharing"*) consists of choosing an equal splitting of the total PCC power reference. In this way, the turbines have as equal contribution to the power tracking task as possible, restricted only by the locally available power (determined from the environmental conditions, the wake effects, and the added turbulence). Even though this method is simple and intuitive, it does not take into account the damage to each turbine. In addition, to further demonstrate the effect of considering the damage in the *load mitigation* method, one additional case is presented, where a single turbine is heavily damaged, and the others are not. This case will be referred to as "*one-damaged"*.

A case study is run on the TotalControl Reference Wind Power Plant[xxxiv] (TC-RWP) with 32 x DTU 10MW reference wind turbines placed in a staggered layout (Figure 6). Realizations of 1-h correlated timeseries for each turbine are computed by TurbSim.Farm for all relevant wind speeds and directions.

To demonstrate the effect of the load mitigation controller and benchmark it against the alternative equal sharing, two case studies were considered. For both cases the ambient wind speed and power reference command from the PCC were set equal while for the one case the wind direction was set aligned to the farm main direction (west wind - 270°) and for the other the wind direction was set to be perpendicular to the farm's main direction (north wind - 0°) representing a worst-case in terms of wake evolution. Additionally, for both cases the ambient wind speed was 12.4 m/s (selected from FarmConners Market Showcases dataset[xxxv, xxxvi]) and the PCC power reference was set equal to 80% of the total nominal wind farm power. The results are summarized below.

<u>Case A: (*west wind*)</u>

In Figure 12, Figure 13, and Figure 14 we see the accumulated damage of each turbine over the period of 1 hour. More precisely, in Figure 12 we see the effect of "*equal sharing*" strategy, in Figure 13 the effect of "*load mitigation*" and in Figure 14 the effect of "*load mitigation*" for the "*one damaged*" case. Observing the first figure it is obvious that under those environmental conditions, if all turbines participated equally in the power-sharing, the damage that the "downstream" turbines would experience is greater than that of the "upstream" ones, causing the former to end up with higher damage accumulation at the end of the hour. On the other hand, using the reactive "*load mitigation*" strategy, and observing Figure 13, we can notice a trend reversal where the turbines that would otherwise take a lot of damage ("downstream") are controlled in such a way to reduce their accumulated damage in the end of the period. As a result, the farm's turbines end up with a more uniform damage, which can be noticed from the smaller spread at the end of the period,

compared to the previous case (Figure 12). Moreover, the effect of load mitigation is clearly depicted in Figure 14. In this case turbine #1 (see Figure 6) is heavily damaged while the rest are completely healthy. In this extreme case, the "*load mitigation*" strategy reacts to the damaged turbine and controls it in a way that is associated with accumulating less damage over the simulation period. This can be observed by the red line in Figure 14 which not only diverges compared to their neighbors but also ends up being the one with the smallest accumulated damage in the end of the period.

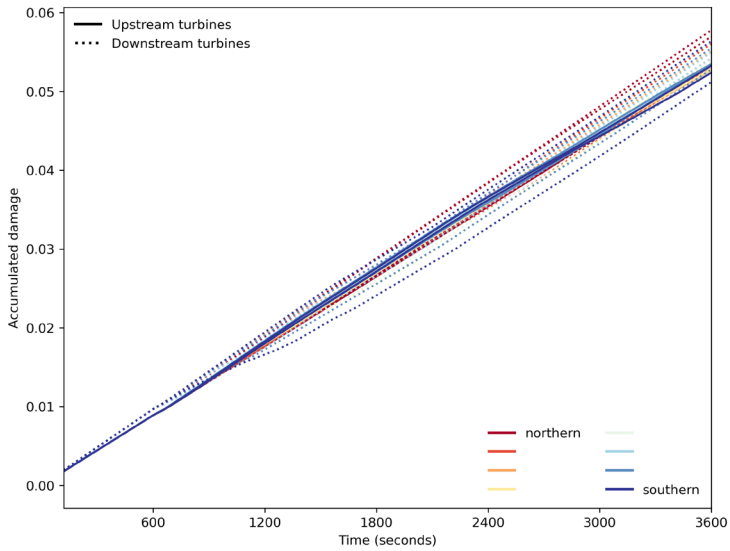

Figure 12. Accumulated damage - "equal sharing"

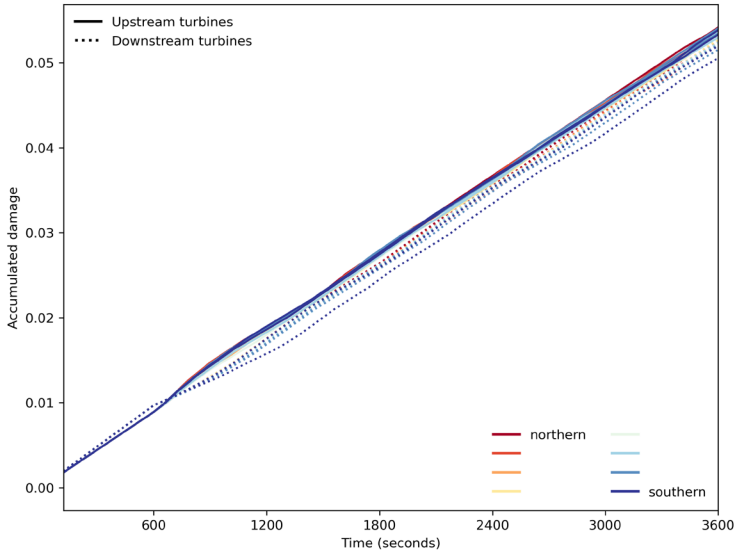

Figure 13. Accumulated damage - "load mitigation"

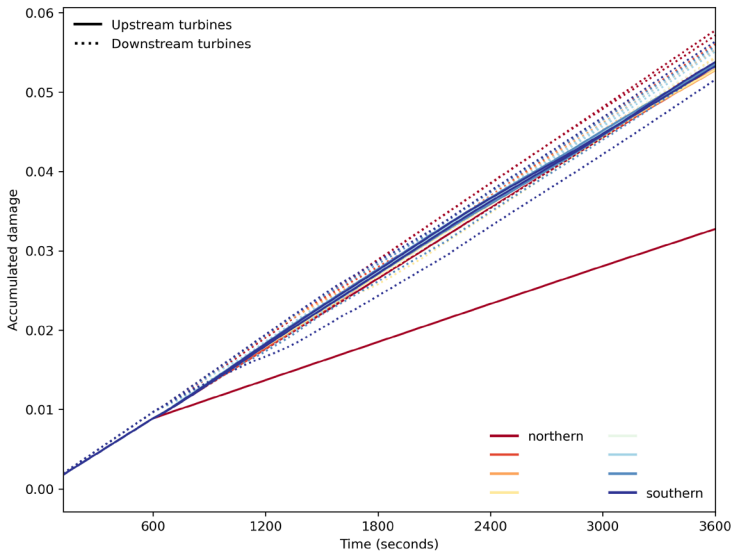

Figure 14. Accumulated damage - "one damaged"

Case B: (*north wind*)

Similar results can be derived for the second case, where the effect of the wakes in the specified north to south direction is more significant, making the differences among the control strategies more noticeable. In Figure 15 we observe the accumulated damage for the turbines following the equal power sharing strategy while in Figure 16 we observe the effect of the load mitigation in the accumulated damage. From both figures it is clear that three group of turbines are created with the ones to the norther part taking the highest damage and the ones in the southern the least, being justified from the considerably lower wind speed caused from the reinforced wakes. Even though the group trends did not change, from Figure 16 it is obvious that, once more the spread of damage over the turbines is highly reduced. In addition, similar effects for the single damaged turbine (turbine 1) are noticed from Figure 17, where the already damaged turbine accumulated the least damage.

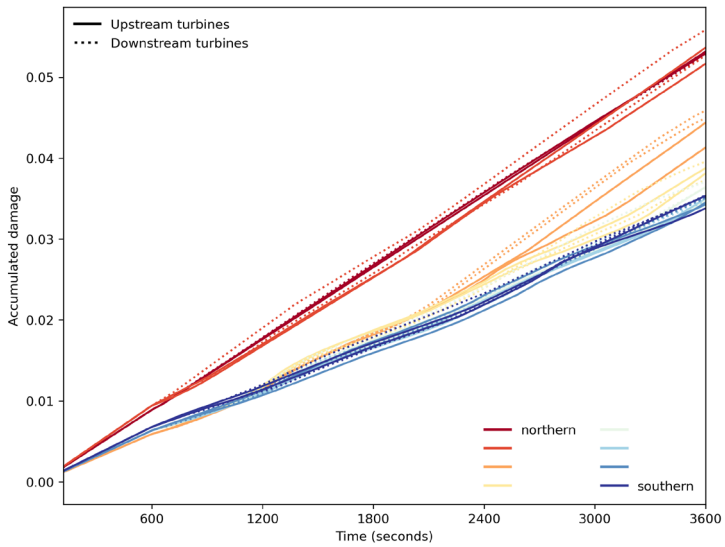

Figure 15. Accumulated damage - "equal sharing"

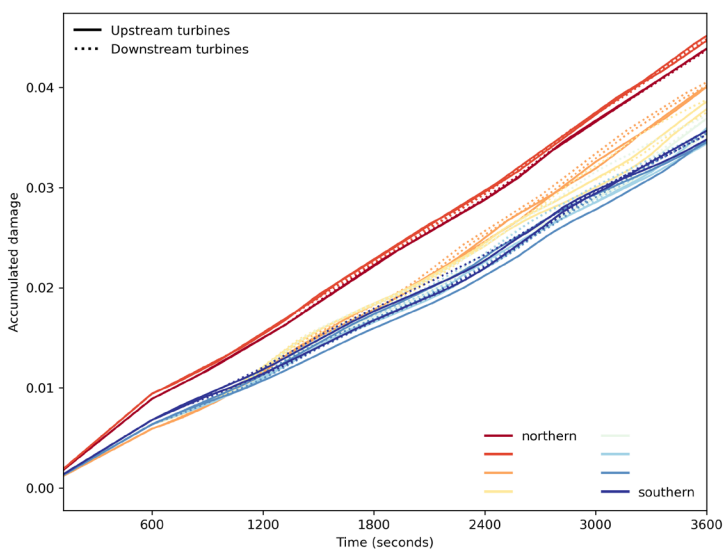

Figure 16. Accumulated damage - "load mitigation"

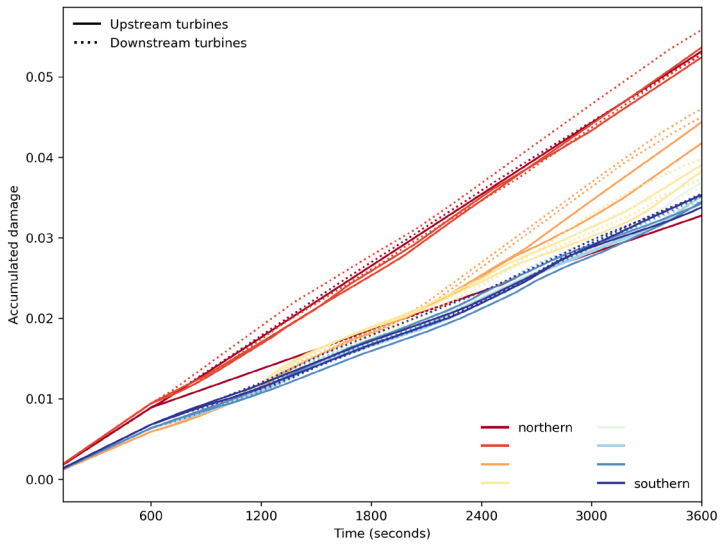

Figure 17. Accumulated damage - "one damaged"

4 CO-OPTIMIZATION OF CONTROL AND MAINTENANCE STRATEGY

The overall objective of the WATEREYE project is to reduce the LCOE of offshore wind farms. Both maintenance planning and farm-wide control can contribute to extend the lifetime of turbine components and to increase the revenue. However, these two wind farm management tools operate on different timescales.

Maintenance activities are performed when a component is in degraded condition or has already failed. The degradation leading to failure is usually a slow process that occurs over weeks to months, or even years.

Commands from the wind farm control, on the other hand, are implemented on smaller timescales of seconds to minutes. These affect the dynamic loading on the turbine components that can eventually lead to damage and require maintenance.

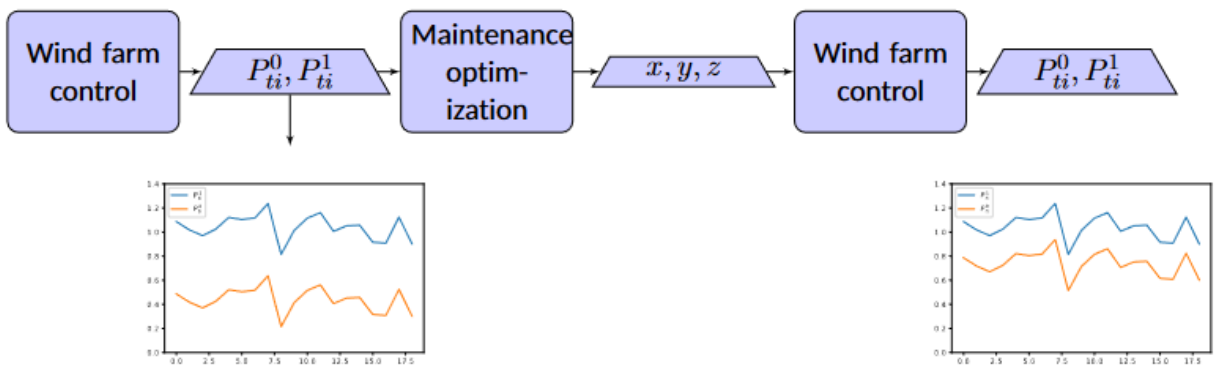

Figure 18. Illustration of the iterative scheme used to perform co-optimization of wind farm control and maintenance.

This illustrates that, on the one hand, the optimal wind farm control settings depend on the planned maintenance, for example, because wind turbines can be shut down for repair. On the other hand, the optimal maintenance plan depends on the planned production. This interdependence means the two problems should ideally be solved as a single joint optimization problem. Solving the joint optimization is not feasible as it would lead result in a large planning problem covering different time scales. Instead, we propose an iterative scheme which combines the maintenance optimization described in Section 2 and the mid-term effect of wind farm control strategy described in Section 3.

Assume that the wind farm controller lacks information about the maintenance plan and the maintenance optimization lacks information about the planned production. Assume first power tracking only (load mitigation is introduced in Section 4.1) as control objective. The procedure would be the following:

1. Planning the production (scheduling) of the wind farm is the first step to initiate the co-optimization. As the maintenance plan has not been settled yet, the wind farm controller assumes that no maintenance will be performed.

2. The planned production is then used as input to the maintenance optimization which returns an optimal maintenance plan.

3. Next, the optimal maintenance plan is used as input to the wind farm controller which is run for a second time. The procedure is illustrated in Figure 18.

4.1 Derating as part of maintenance optimization

The maintenance optimization is designed to account for derating strategies being employed. A simple example of such a strategy is described in Section 2.2.2. The proposed strategy is not a realistic way of implementing derating as its goal is to prevent failure until a repair can be performed which represents another dependence between the wind farm controller and the maintenance optimization. To account for derating, the maintenance optimization module needs to know both the planned production P_{ti}^{0}, and the planned production if condition-based maintenance is performed P_{ti}^{1}. Note that this involves forecasting the electricity price and need for power reserve, which is nontrivial.

To illustrate how derating strategy and maintenance planning can be combined, assume that the wind farm controller can account for the amount of wear and subsequently the remaining useful life of a component. The procedure then reads:

1. We follow the iterative scheme illustrated in Figure 18 and initiate the iteration by running the wind farm controller. As there is initially no plan to perform a repair of the main bearing, one must assume that the derating strategy should ensure that no failure happens until the end of the planning horizon.

2. The procedure continues by running the maintenance optimization with the planned production as input. The result of the optimization will most likely be that a bearing repair is planned within the planning horizon.

3. This changes the assumptions for the wind farm control unit, i.e., it means that if maintenance is planned for day t the bearing only needs to survive until day $t+1$ which means a higher production is possible.

This co-optimization does not ensure a globally optimal solution, but it is clear from the cross-coupling of farm control and maintenance planning that it provides a better solution than what would be possible if the two modules were used separately.

5 SUMMARY AND FUTURE WORK

A tool for optimal maintenance planning of offshore wind farms is designed that takes into account the planned power production, weather forecast and possibly needed derating when scheduling condition-based and preventive maintenance. An example with 16 wind turbines is presented that includes recoating and bearing repair as maintenance tasks. It is assumed that both tasks bring the system back to an as-good-as-new state, i.e., the recoating completely removes the detected signs of corrosion, and the bearing can withstand full power production again. The results show that condition-based maintenance is prioritized in the short term to repair occurred failures. Moreover, maintenance tasks are planned at times with predicted low production and clustered on the same days which reduces the travel costs to the offshore location.

Future work should include extending the maintenance optimization with time-dependent electricity prices to make it more realistic towards profit maximization. Moreover, tracking a power reference could be introduced as constraint to account for imbalance costs and market operation (bidding).

The optimization framework is general and flexible and can be applied to other failure modes and repair tasks. It can also be extended for the maintenance planning of other power plants using dispatchable renewable energy sources.

Maintenance planning and wind farm control are linked through the damage that accumulates during wind farm operation and requires repair on the long term. A framework providing an estimate of the accumulated damage including the effect of wind farm control is proposed. For this purpose, a hierarchical wind farm controller is adapted using well established proportional-integral feedforward and feedback control loops. The farm controller respects the usual hierarchy levels in wind energy systems without attempting to change the turbine controller. It is rather assumed that the local wind turbine controllers implement the power command they receive from the farm control while ensuring their safety functions. This wind farm controller ensures power tracking while it reduces the structural loads at the most damaged turbines by dispatching the power commands among the wind turbines in a smart way. In the larger control framework, the wind conditions at each wind turbine are calculated based on environmental conditions as input by superposing wakes and farm-wide turbulence. The power commands from the wind farm controller are used together with these local wind conditions at each wind turbine to extract the accumulated damage from a database built from turbine simulations under various conditions.

The presented use case for the TotalControl Reference Wind Power Plant highlights the significance of embedding information of turbine damage in the wind farm controller and demonstrates how each control strategy affects the accumulated damage. It was shown that using the proposed "*load mitigation*" method, the total accumulated damage could be spread more uniformly across the various turbines in the farm while ensuring the primary goal of power tracking, to the extent possible, restricted by the locally available power.

A roadmap for co-optimization of control and maintenance strategy is presented and discussed in the sense of loose coupling between separate modules, with a single iteration of each. The interactions are modelled in an "open loop" simulation of scenarios rather than "closed loop" integration of control and maintenance. Simulations of longer duration could be performed to gain long-term damage estimates depending on the wind farm control strategy. However, this would require simulating several weeks or months to see an effect on the degradation. Here, the concept was successfully demonstrated, and the short-term results can be extrapolated to the long-term damage. Future work should focus on tuning, calibrating and validating the solution using measurement data.

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