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Influence of extended potential-to-functional failure intervals through condition monitoring systems on offshore wind turbine availability

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ABSTRACT

Condition monitoring systems are deployed in various industries for decades contributing to optimizing operational performance and maintenance efforts. Several publications address this potential for application in the offshore wind energy industry; however, none attempts to quantify the impact that longer warning times ahead of a failure would have on asset availability. The aim of this paper is to bridge this gap by considering particularly the access restrictions for offshore operations through a probabilistic model which simulates existence of different condition monitoring systems on offshore wind turbines in the time domain. Results of this study quantify the positive impact that a longer warning time of potential-to-functional failure (P-F interval) has on availability, highlighting that variation of maintenance strategy through transformation of unplanned activities into planned interventions that can be conducted during a suitable weather window ahead of a component failure can lead to reduced operation and maintenance (O&M) costs.

1. Introduction

Achieving high asset availability in the operation of offshore wind power plants has been a challenge for many years. Today, availabilities of approximately 95 % are industry standard [1,2]. The efforts made to achieve these availability figures are considerable [3]. They include preventive maintenance measures such as the scheduled replacement of wearing parts, oil or grease and the response to unforeseen scenarios such as wind turbine failures, for example by providing appropriate access for different types of vessels and/or helicopters, spare parts, tools and technicians [4]. A failure is defined as the 'inability of a system or component to perform its required functions within specified performance requirements' [5,6].

One approach that reduces the need for (i) holding means of access available even when not needed, (ii) preventive replacement of parts when their effective life has not yet been reached by (iii) continuing to ensure that the asset is fully functional is the application of condition-based maintenance (CBM) strategies [7–10,45].

The principle of CBM is to initiate a maintenance activity based on the physical condition of an item, i.e. maintenance is performed prior to failure as soon as a specified threshold value of a condition indicator is exceeded. This assessment can be performed, for example, by observation, inspection, testing, or continuous online or offline monitoring of one or more parameters by the operator. Considerable efforts are being made to investigate various CBM solutions. The first publications date back to the early 2000s [11] and the topic is still of great interest to the industry today and presumably also in the future. Recent developments are described in detail in [3].

Most of the contributions in this area show developments of direct and indirect condition monitoring systems (CMS) or structural health monitoring systems (SHM) [12–15]. Very few attempt to quantify the value of these systems in terms of cost optimisation or availability. One early publication that specifically addresses the impact on costs and revenues is [16].

In this research, a time-based simulation based on Hidden Markov theory [17] is used to simulate the impact of CMS performance on life cycle costs. CMS performance is measured by the probability that a developing failure of a WT subsystem is detected. A false alarm of the system (i.e. the monitoring system indicates a component failure, but there is none) is reflected in their methodology. This effect is generally referred to as "false positive". Since monitoring systems do not function without failures, this consideration reflects the actual cost of monitoring as it takes into account that any unnecessary offshore operation would have monetary effects. The results compare the operating costs for

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preventive maintenance with condition-based strategies. The availability gains from early failure detection are quantified with a generic correction factor for a base capacity factor. The study does not examine the impact that a longer period of offshore intervention planning enabled by CMS degradation warnings would have on plant availability. In [18], preventive and condition-based maintenance is compared in terms of cost and return. The authors come to the conclusion that the use of CMS for the given case is of rather low value. Some downsides of malfunctioning CMS are discussed in [19] where machine learning methods are used to detect failures, where false alarms can lead to redundant inspection, while missed detections can be more sever because they can lead to critical failures.

None of the reviewed studies (i) compare corrective with condition-based maintenance, (ii) deploy time-based analysis for quantifying availability gains through CBM or (iii) investigate the performance of CMS with respect to their time-dependant failure detection capability; i.e. the question of how valuable the information about a developing failure is, e.g., 3 months, 2 weeks or only a few days prior to failure. The main aim of this study is to examine and better understand the effects of extended intervals between the warning about and occurrence of failures in critical offshore wind turbine systems. This is achieved through the development of a probabilistic simulation model relying on proven modelling methodologies with a dedicated module that simulates monitoring systems. Application of the methodology in a hypothetical offshore wind farm application illustrates its applicability deriving a quantitative assessment of the benefits of increased warning periods for potential failures.

The paper is organised as follows: Section 2 presents basic terminology on availability, maintenance intervals and the potential-to-functional failure (P-F) concept for characterisation of monitoring options, Section 3 develops the methodology, documents the numerical model developed and presents the baseline case, Section 4 presents the results from the application to a realistic offshore wind farm, Section 5 discusses the implications of this method and finally Section 6 summarises the findings of this work offering some concluding remarks.

2. Terminology

2.1. Availability

One of the most common indicators used to describe operating performance in the wind industry is availability. It is defined as the proportion of time that the wind turbine generates electricity over the entire duration of a given time interval, or the electricity that is generated over the theoretically producible electricity during a time interval [20]. Optimising availability is at the top priorities of offshore wind operators as revenues can only be achieved when electricity is generated and fed into a grid [21–23].

In the early years of offshore wind energy, low availabilities were achieved that did not meet the expectations of the operators. Indicative examples are the wind farms Barrow, North Hoyle, Scroby Sands or Kentish Flats (WFs) in the United Kingdom (UK), which had an availability of two thirds to 80% [24]. The main reasons for this shortcoming have been identified in early studies and are mainly: (i) low reliability of wind turbines (WTs) [25], (ii) underestimation of access restrictions for maintenance work [26], (iii) non-availability of specialised vessels for the above activities [27] and (iv) the application of corrective maintenance strategies – i.e. the reactive initialisation of maintenance operations after the failure of a component or part within the WT system [28]. Further details on maintenance strategies and in particular on the concept of condition-based maintenance (CBM) are explained in Section 2.2.

2.2. Maintenance strategies

WT components are subject to preventive and corrective maintenance measures; preventive measures to avoid failures and corrective measures that are carried out after a component failure [5], Fig. 1.

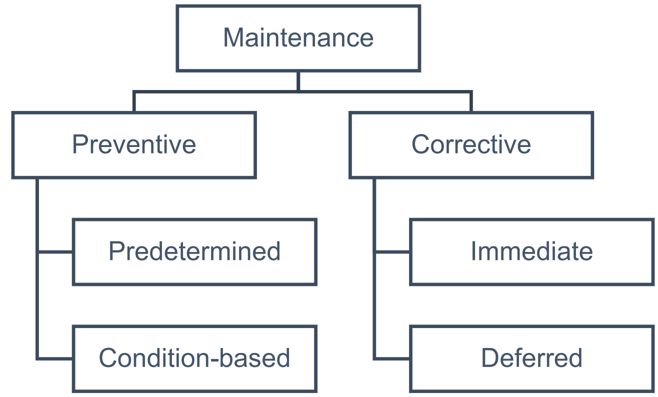

Fig. 1. Maintenance types.

Monitoring systems or predetermined inspections can generally enable CBM, which can be translated into a predictive maintenance strategy in a more sophisticated approach if extracted characteristics are linked to key performance indicators of the asset to support decisions on interventions. Preventive maintenance is defined as 'CBM carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item' [5]. This form of maintenance offers inherent optimisation potential for both preventive and corrective maintenance.

A corrective maintenance strategy has the advantage that the useful life of the asset is always fully utilized. This means that there is no 'waste' of resources (capacity underutilization) caused, for example, by preventive replacement of the asset or parts thereof. On the other hand, the disadvantages of a corrective maintenance strategy are that (i) it depends on a fast response time to avoid significant production downtime during a shutdown, and (ii) it can potentially cause greater direct costs, e.g. if consequential damage is caused when the item fails. The offshore wind industry is increasingly relying on preventive maintenance strategies, as long periods of inaccessibility can cause significant financial losses if a wind turbine is out of production and cannot be brought back to a running state.

A preventive maintenance strategy has the advantage that the asset delivers more predictable and reliable electricity, thus ensuring an optimised financial return. The disadvantage of a preventive maintenance strategy is that it is associated (at least initially) with higher costs. Every preventive inspection, overhaul, replacement or test campaign is associated with costs. Therefore, a workable balance must be found between the efforts of a preventive maintenance campaign and the risk of component failure. This is the main objective of the Reliability-centred maintenance approach as a strategy. Depending on the details of the preventive maintenance strategy, there is the possibility of over-maintenance. This means, for example, that a component is typically replaced well before the end of its nominal life - a scenario that would be avoided by a corrective maintenance strategy.

One way to mitigate the disadvantages of each of the above strategies is to apply a condition-based or predictive maintenance approach. Here, maintenance work is only carried out when it is necessary, i.e. the item is not unnecessarily over-maintained, but it also does not fail unexpectedly. This is always made possible by obtaining accurate information about the condition of the object and its degradation mechanisms.

Condition-based strategies rely on information based on data collected by continuous or periodic, online or offline CMS [29–32]. A clear distinction between diagnostic and prognostic systems becomes relevant. The following definition can be used to distinguish between the two: 'Diagnosis is an assessment about the current (and past) health of a system based on observed symptoms, and prognosis is an assessment

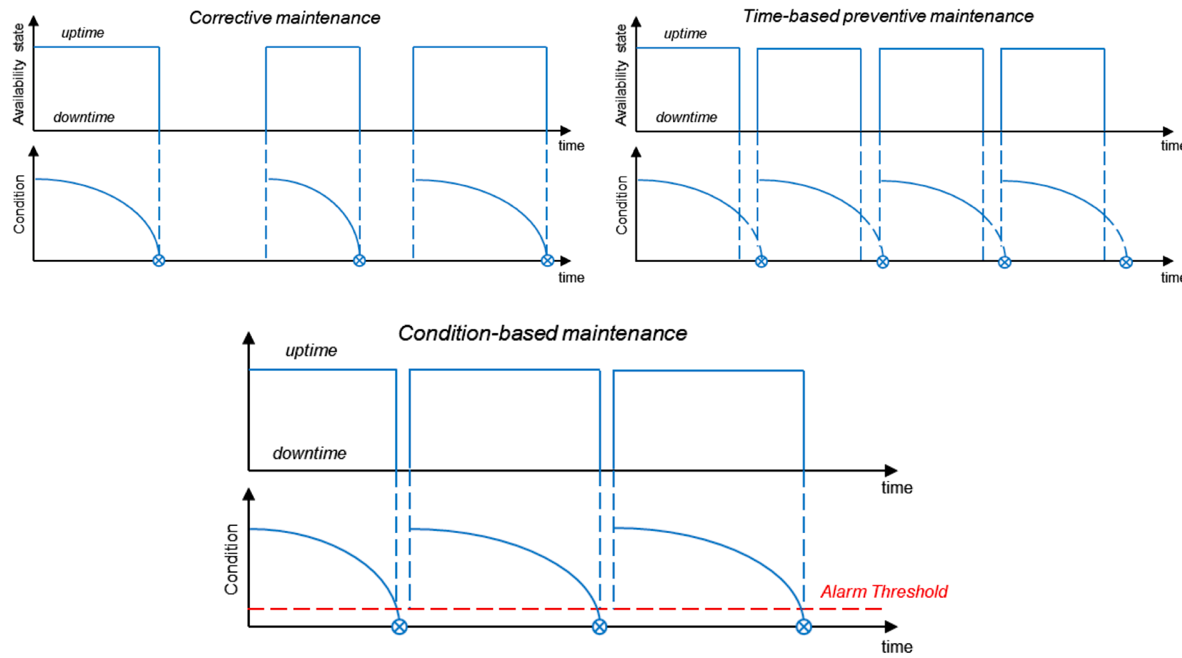

Fig. 2. Main implications of maintenance types.

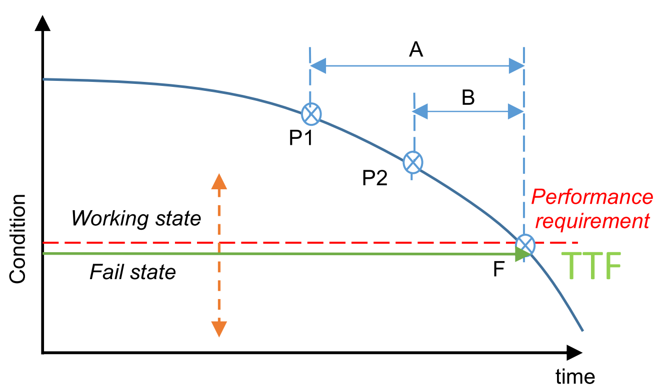

Fig. 3. Schematic representation of a P-F interval.

of the future health' [33].

The different maintenance strategies discussed above are illustrated in a simplified, conceptual manner in order to establish understanding of the main implications (Fig. 2). The alarm threshold in the condition-based maintenance strategy is often set based on experience. For example, if a sensor value or a processed health indicator exceeds a limit, the alarm is activated.

2.3. P-F intervals

In order to apply a CBM strategy, the failure behaviour, or physics of failure, of a component must be known; whereas, usually, a CBM strategy is most efficient if a developing failure can be detected well in advance. A common way to evaluate this, is the concept of P-F intervals [34]. It describes the interval between the point in time a developing failure can be detected until the failure occurrence. As defined in Section 1, a failure is defined as the 'inability of a system or component to perform its required functions within specified performance requirements' [5,6]. In a case of a wind turbine, this means that a component is not functioning and as a result a turbine is not fully operational. The P-F interval is therefore smaller than the lead time to failure (TTF), since the detection of the failure is fundamentally possible after the functional period has started. This is indicatively illustrated in Fig. 3 below. This example shows damage accumulation of a hypothetical component with time and according to a certain performance requirement. As soon as the performance requirement falls below a threshold, the component is in a failed state. This represents the F of the P-F interval. A and B represent CMS – in this example, A is capable to detect the failure development at time P1 and B is capable to detect the failure at time P2. The interval between the potential failure detection (here: P1 considering monitoring system A and P2 considering monitoring system B) and the actual failure F is defined as P-F interval. In this case, system A offers an earlier warning to enable a better-informed intervention to restore its operational capability.

The P-F interval is used as a performance indicator for CMS. The duration of the PF interval affects maintenance panning. A CMS with diagnostic capability detects a potential failure and after the fault detection, it is necessary to predict the time to functional failure [35]. The longer this interval is and the more accurately the exact point in time of failure occurrence can be estimated, the more benefits can be obtained by applying the system in a CBM strategy [36]. Several other terms may be used to describe the P-F interval: warning period, TTF or failure development period [34]. The P-F interval can be estimated based on experience (reliability and maintenance track records) or based on expert judgement, which is particularly the case for novel equipment [37]. Development of this type of condition deterioration/damage accumulation curves is based on a number of experiments which should then be statistically processed, taking a conservative curve as the characteristic for the purposes of design and further support maintenance related decisions.

While developing a maintenance strategy, the benefits of each maintenance approach should be evaluated considering the criticality of certain components and the actual benefit that monitoring brings, aiming to optimise life cycle costs and residual risks. Quantification of the benefits of monitoring in this context is the aim of this paper, hence a more extensive reference on CMS is not further included as the main focus is at supporting the understanding of the value that such systems may have in terms of increased asset availability. A methodology to quantify those benefits is presented in the next sections, followed by presentation and discussion of results. For further detail on CMS, it is referred to [3,12,38].

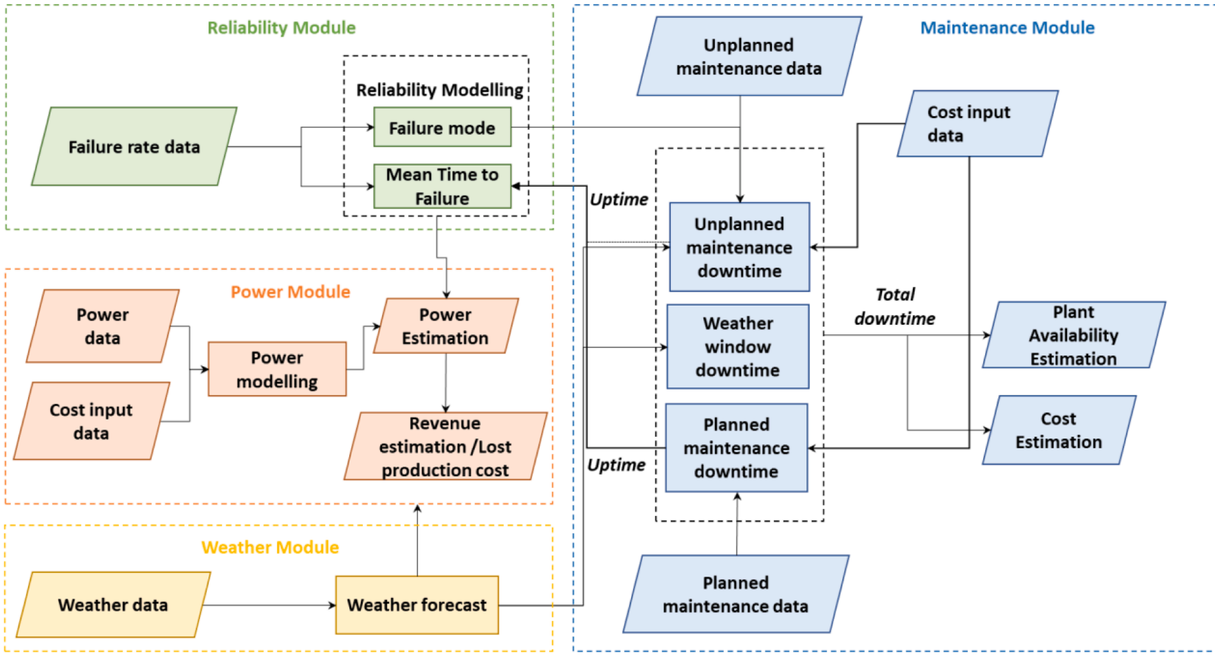

Fig. 4. Structure of O&M simulation tool.

3. Methodology and baseline case

A time-based simulation model relying on Markov chains and stochastic modelling has been developed and deployed for solving the research question addressed in this paper. The model was initially programmed by the authors and had been used to assess availability of various operating scenarios of current large-scale offshore wind farms. The new tool that has been employed for this study, is capable to simulate CMS and to assess wind farm availability sensitivity related to varying P-F intervals for WT system failures. A brief explanation of the tools' structure and individual modules is provided in the following and illustrated in Fig. 4, where the main focus is on a further extension for the post-processing capability that is used to analyse CMS. For further information on the functionalities, the reader is referred to the referenced work [39].

Weather Module: Historic met-ocean data has been obtained from the FINO3 database. Time series of wind speed and wave height from 10 years (2000 - 2010) in 3 h resolution was used to provide a solid representation of local conditions. A Markov chain is employed, considering a finite number of states, each representing and incremental change in significant wave height of 0.2 m and in wind speed of 1m/s. This module was validated for a typical case study by comparing the predicted outputs to the input values and acceptable values of standard errors were observed hence the selected method was deemed appropriate (less than 2% error).

Power Module: The calculation of the generated energy for the entire wind farm is calculated in this module. The actual power output in each time step is calculated based on the wind speed, the wind turbine hub height and the power curve [46]. Met mast measurements provide wind speed, which is extrapolated at hub height using the power law:

$$U_{hub\ height} = U_{reference} * \left(\frac{hub\ height}{reference\ height}\right)^{\alpha} \tag{1}$$

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

$$\alpha = \frac{0.37 - 0.088 * \ln\left(U_{reference}\right)}{1 - 0.088 * \ln\left(\frac{reference\ height}{10}\right)} \tag{2}$$

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

$$\alpha = 0.37 - 0.088 * \ln\left(U_{reference}\right) \tag{3}$$

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

Afterwards, the energy can be calculated as:

$$\mathrm{E} = \mathrm{P} \times \mathrm{t} \tag{4}$$

where t is the time given in (hr).

Calculating the generated energy as mentioned above, underlies the assumption that the yaw controller always yaws into the current wind direction in order to retrieve 100% of the power. Furthermore, travel times of the yaw system when adjusting to a new wind direction are neglected in this analysis as these ones have a minor impact considering the total lifetime of the wind farm. It is important to note that the power module, is necessary in order to calculate the power based on the forecasted wind speeds of the wind farm as well as to calculate the power not produced/revenue loss due to failures which will account for the actual power production also considering downtime due to various sources.

Reliability Module: There are various recent studies on offshore wind reliability studies – most relevant [40] and [3]. Ideally, reliability characteristics would rely on the actual physics of failure of each of the components, which would allow for a more realistic representation of the asset under consideration. For the specific questions addressed in this paper, however, the approach followed is considered appropriate as the core question is to quantify the time-related impact of CMS; which can be answered on a generic level here but asset-specific analyses are recommended in case a more elaborate reliability database is available. Such an approach should consider the different failure modes relevant for each of the WT systems, their likelihood, cause and mechanism. It is referred to [41] for further details on this topic.

Table 1
Annual failure rates and repair times baseline scenario.

System	Failure rates [Per year/Turbine] Minor	Major	Replacement	Repair times [h] Minor	Major	Replacement
Gearbox	0.644	0.157	0.028	8	22	231
Generator	0.049	0.018	0.008	7	24	81
Electrical system	0.37	0.043	0.002	5	14	18
Pitch system	0.397	0.02	0.008	9	19	25
Yaw system	0.259	0.036	0.012	5	20	49
Blades	0.2	0.045	0.04	9	21	288
Main shaft	0.231	0.026	0.009	5	18	48

Table 2
Site conditions baseline scenario.

Parameter	Value
Site	Bak et al 2017
Mean wind speed at hub height	7.9 m/s
Mean wave height	1.51 m Hs (significant wave height)
Number of turbines	80
Rated power	10 MW
Total capacity	800 MW
Lifetime	25 years
Distance from shore	80 km

Table 3
Vessel and crew characteristics.

Parameter	**Value**	
	Crew Transfer Vessel	Jack-up Vessel
Number of vessels	4	1
Transit Time	1.9	4.1
Maximum Wave Height [m]	1.5/1.9/2.1 (varied parameter)	2/1.7/2.5 (varied parameter)
Mobilisation Times [h]	0.1	960
Crew Capacity	12	35

Failure rates and representative repair times are estimated based on past literature [40] (the repair time does only reflect active maintenance periods – waiting times for weather windows (WW) are dependent on the conditions during the failure event). Failure rates and repair times for the considered systems are presented in Table 1.

Failure rates are processed into WT failures at discrete time steps, which is determined by generating a random number according to a selected statistical distribution function around the failure. For this study, the exponential distribution for failure generation is selected according to industry practice. In time step zero, i.e. during simulation initialization, a TTF value is generated for each of the systems. If a failure occurs on the turbine in one or more of the 7 subsystems, the demand for a repair or replacement activity is triggered. The failure rates of each system are used to generate exponential distribution functions. Random points of these distributions are selected, and the failure that occurs earliest in time corresponds to the respective modelled failure of the turbine. For modeling reasons, only one system at a time is supposed to fail for each turbine.

P-F Intervals: For computational simplicity purposes, the P-F intervals are incorporated in the lifecycle simulation model assuming linear degradation. After each replacement the component is assumed to return to a fully functional operating state and degradation begins after that, depending on the type of failure mode. Only failures that lead to replacement are considered for P-F interval analysis. The failed state is assumed to be proportional to the MTTF. Altering the failed state point affects the uptime of the wind turbine. This will be elaborated more in the sensitivity analysis section.

Maintenance Module: This module takes into account the basic technical data of the wind turbine and the farm that the simulation investigates in the analysis. The values used in the following analyses are summarized in Table 2. The metocean data is used as described above. Electricity production is not used for time-based availability as calculated in this paper. The lifetime corresponds to the number of simulated years, i.e. the final availability is calculated as an average over the entire lifetime. Crew transfer vessels are used for minor and major repairs, while jack-up vessels are used for replacements, as categorized in Table 3. The number of ships and crane barges and their wave bearing capacity are included in the available means of transport considerations, as described in more detail in Module 4. This means that up to a wave height limit of 1.5 m, a maximum of 4 crew transfer vessels and one

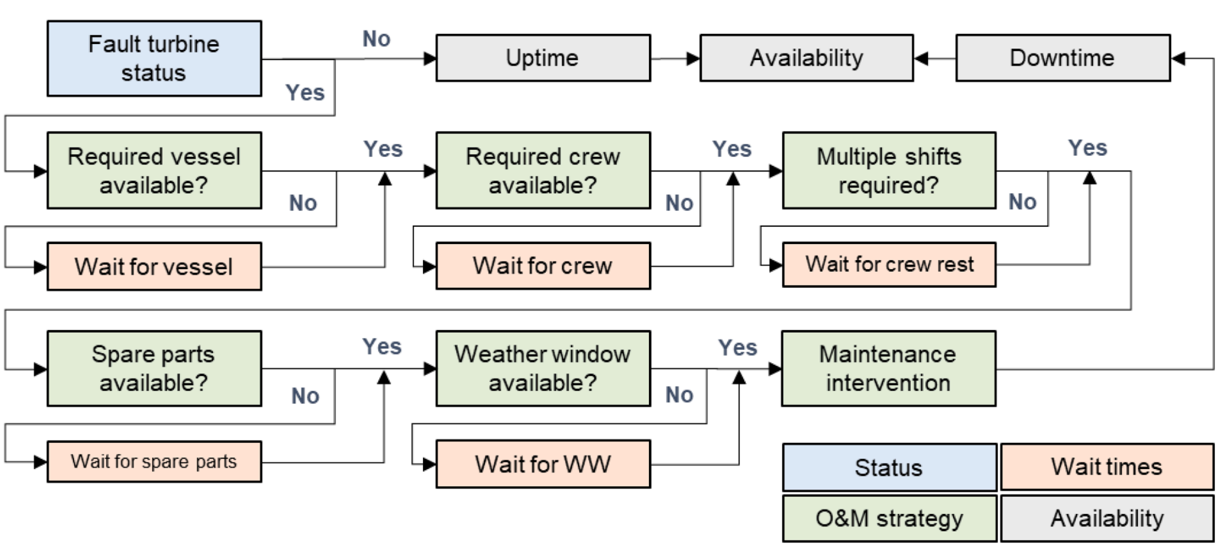

Fig. 5. Unplanned maintenance.

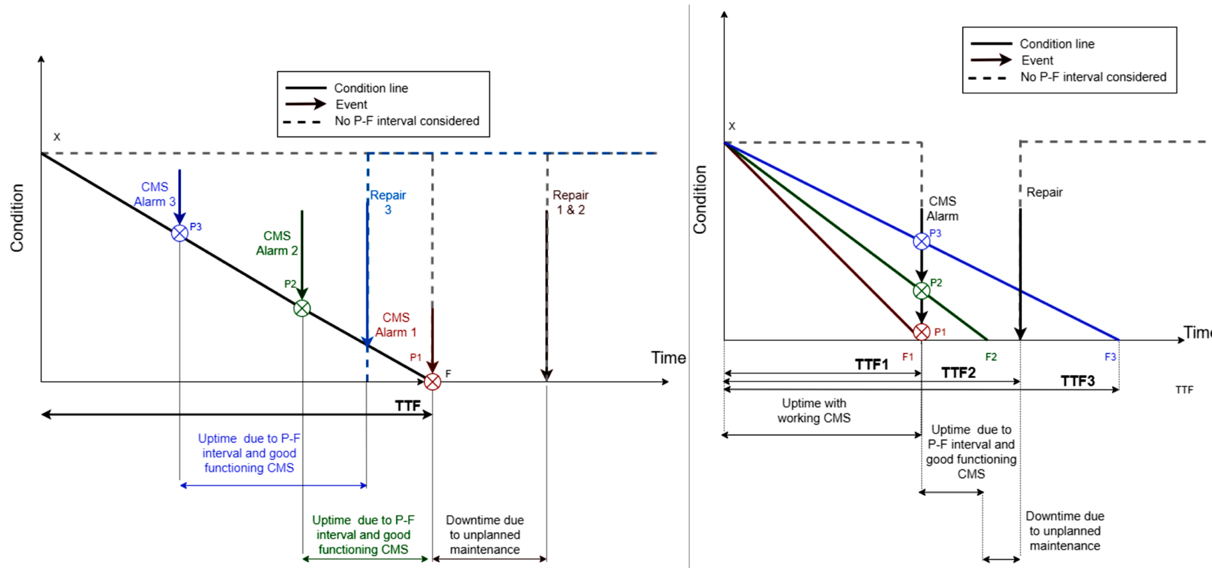

Fig. 6. Modelling of different CMS systems with respect to TTF. The P-F intervals of different CMS alarms are shown on the left and the modelling implemented is shown on the right.

crane barge can be active simultaneously. The values of the maximum wave heights for the 2 different vessels are altered in the sensitivity analysis.

The O&M strategy is based on a decision tree that follows a system failure in one or more wind turbines (Fig. 5). In the event of a failure, it is first checked whether a crew and a ship suitable for the type of repair required are already on site. The number of shifts required for each respective repair or replacement is taken into account. Component replacements are considered to require a jack-up crane vessel, while all other system repairs are assumed to require a crew transfer vessel. The activated vessel or barge will continue its transfer to the failed WT as soon as weather conditions permit; environmental restrictions are limited to a certain wave height limit. The use of ships or crane vessels is further limited by the number and type of equipment available. This depends on the fleet structure considered (summarized in Table 2).

As soon as a failed system is put back into operation (status reached, as soon as a crew ship combination has been placed on the failed WT for the assigned repair duration), the next failure for this system is determined in the same way as the original TTF was generated. This process is repeated accordingly if a failed component is repaired or replaced. Note that system failures are neither related to each other nor dependent on external conditions.

Sensitivity Analysis: The existence of a CMS is modelled by assuming that the alarm is triggered on the respective TTF. In case of a good functioning CMS, the model is hypothetically provided with information about an upcoming failure of any system at a duration equal to the difference between the TTF (CMS alarm time) and the functional failure, as shown in Fig. 6. On the left hand side, CMS systems with different capabilities are shown, similarly to what is presented in the theoretical background in Fig. 3. CMS Alarm 1 has poor functioning capabilities, as the fault is not detected before functional failure. CMS Alarms 2 and 3 both detect incipient fault before functional failure, with CMS 3 being more effective. Different repair times also demonstrate the effects on downtime. Repair time 1&2 shows that there is downtime due to unplanned maintenance. On the contrary, repair 3 shows that the CMS system 3 provides enough time for maintenance planning and therefore the turbine is repaired before functional failure.

For modelling reasons, the concept of different CMS capabilities and the effect on uptime is implemented by varying the P-F interval durations for each analysis. The P-F interval is modelled as a line, with the slope being a variable parameter that varies respectively with the Mean Time To Failure (MTTF) of each subsystem, allowing for analysis of different CMS capability. The intercept of the line (denoted by X) is the time of completion of the previous repair of the turbine and therefore the start of counting of the new uptime. This allows for a conservative analysis, assuming the start of degradation of a component right after repair. This can include modelling of a poorly functional or inexistent CMS, if no alarm is triggered before the failed state (Fig. 6). Line X-F1 shows a poorly functioning CMS, that doesn't give an indication of an incipient fault before a functional failure. Lines X-F2 and X-F3 both show

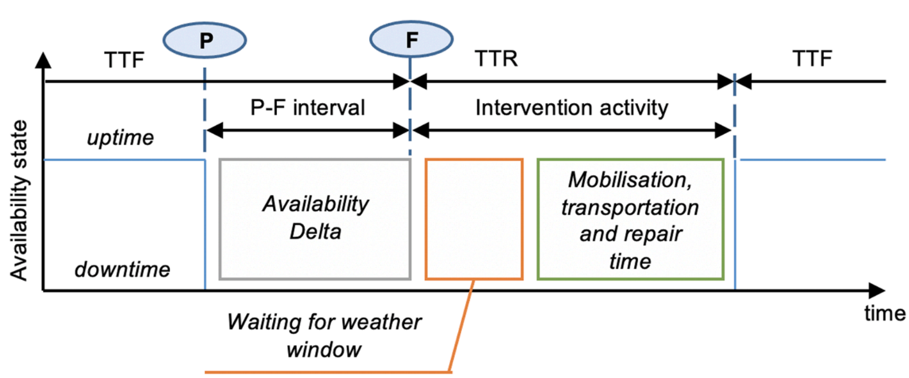

Fig. 7. Application of P-F intervals in the analysis.

Table 4
P-F interval coefficients β_{pf} used in study as percentage of MTTF.

MTTF%	60	70	80	90	100	110	120	130	140

Table 5
Wave height sensitivity analysis for each PF interval.

Simulation group	CTV Wave Height	JUV Wave Height
1	1.5	2
2	1.9	2
3	2.3	2
5	1.5	1.7
6	1,5	2.5

well-functioning CMS with different detection capabilities. In the case of X-F2, the CMS system detects degradation, but the functional failure happens before the crew reaches and repairs the turbine. In the case of X-F3, the repair of the turbine happens before functional failure, so there is no downtime. This would model a CMS with a good diagnostic and prognostic capability, however the life of the asset is not fully utilised. The trade-off of installing CMS is that the revenue lost from partial asset life utilisation and sensor costs, can be gained from extra repair costs and uptime.

The modelling of the P-F intervals and the CMS is shown by the equations 5 and 6, where λ is the corresponding failure rate of each turbine subsystem according to Table 1.

$$MTTF = \frac{1}{\lambda} \tag{5}$$

$$Y_{PF} = \beta_{pf} * MTTF + X \tag{6}$$

The ‘delta’ in achieved availability through CBM is calculated thereafter. Any gain achieved by increased uptime is illustrated in Fig. 7. The application of CMS can directly be translated into reduced waiting times for suitable weather windows and general maintenance planning, or extra downtime if the alarm is triggered after functional failure.

The P-F intervals considered in this paper are presented in Table 4. The coefficients β_{pf} vary from 60% of MTTF to 140% of MTTF. It should be clarified that MTTF is constant and depends on the failure rates of each subassembly, whereas the TTF is a random number that is provided by the exponential reliability distribution function. Since P-F intervals are applied to various subassemblies with different technical characteristics and degradation patterns, a wide range of intervals has been used. It reaches from zero days (corrective maintenance) over a few days and weeks to several months, depending on the failure mode and the corresponding TTF. The various PF interval coefficients shown in Table 4 are simulated for different wave heights for the 2 vessels used in the case study, in order to investigate the effect of access limitations on the value of CMS. Table 5 shows the wave heights simulated.

Outputs: The output value of interest here is availability. For this study, time-based availability is calculated for the lifecycle of the wind farm’s operational activities, with downtime being calculated as illustrated in the top of Fig. 7. In accordance with the procedure presented in the Maintenance Module, the corresponding availability figures deploying a condition-based maintenance strategy are then calculated.

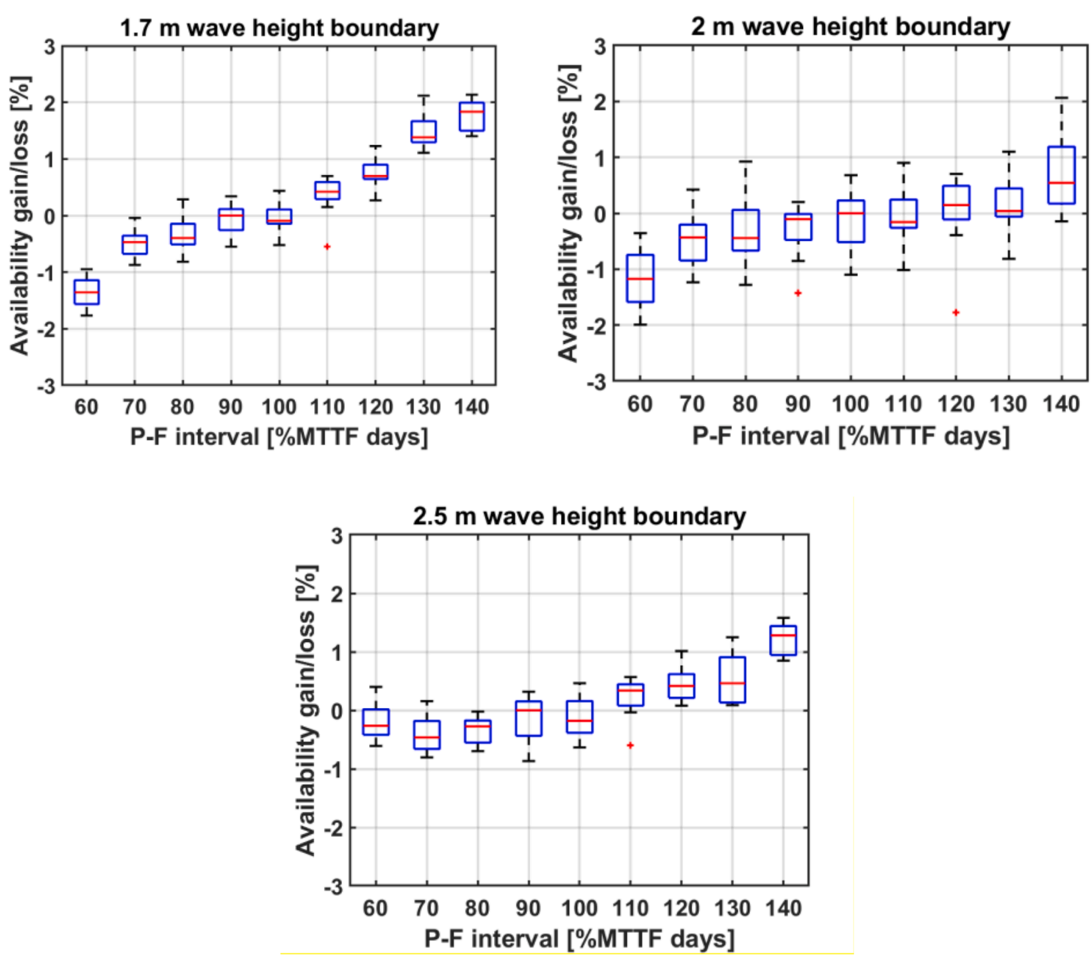

Fig. 8. Availability gains through extended P-F intervals at different wave height boundaries of JUVs.

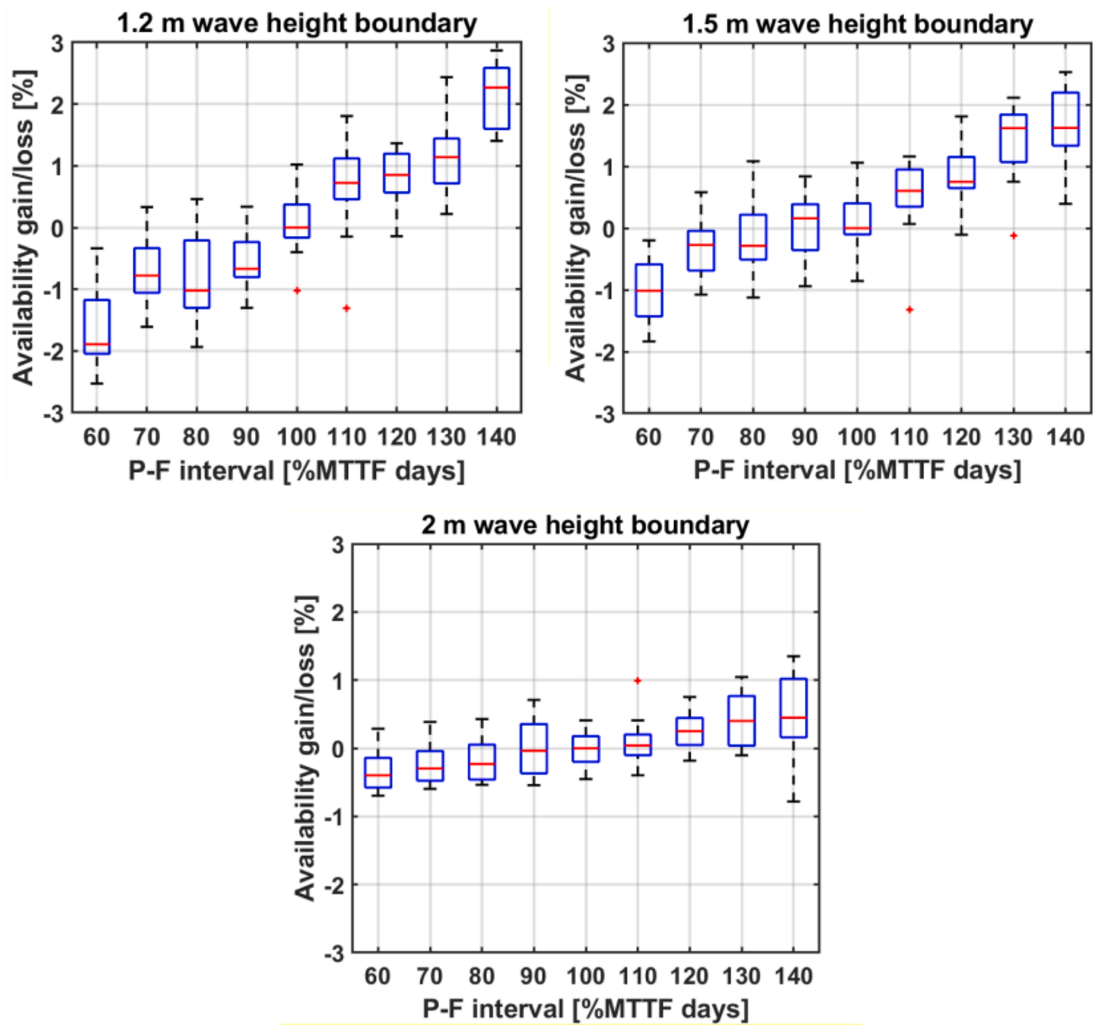

Fig. 9. Availability gains through extended P-F intervals at different wave height boundaries of CTVs.

Table 6
Average availability gains at different P-F intervals.

P-F interval [%MTTF]	Hs Boundary / Availability Gain for JUV [%]			Hs Boundary / Availability Gain for CTV [%]		
	1.7 m	2 m	2.5 m	1.2 m	1.5 m	2 m
60	-1.15	-0.21	-1.35	-1.69	-0.99	-0.33
70	-0.41	-0.41	-0.46	-0.70	-0.26	-0.23
80	-0.30	-0.33	-0.33	-0.88	-0.14	-0.18
90	-0.31	-0.12	-0.03	-0.59	0.11	-0.01
100	-0.05	-0.14	-0.05	0.03	0.09	-0.02
110	-0.07	0.53	0.35	0.63	0.47	0.11
120	0.02	1.02	0.74	0.81	0.84	0.27
130	0.13	0.53	1.48	1.15	1.41	0.40
140	0.69	1.04	1.79	2.18	1.63	0.45

The difference of both reflects the availability gain which is reported in the next section.

4. Results

The baseline scenario for the simulations is summarized in Tables 2 and 3. Fifty simulations were run and analysed for each scenario: three different wave height boundary level combinations for the two different types of vessels used and nine P-F intervals applied to all components and failures similarly (see Tables 4 and 5). The wave height boundary levels have been introduced as reduced waiting times through early failure detection which are expected to be more significant if access is restricted for longer periods. The number of simulation runs has been

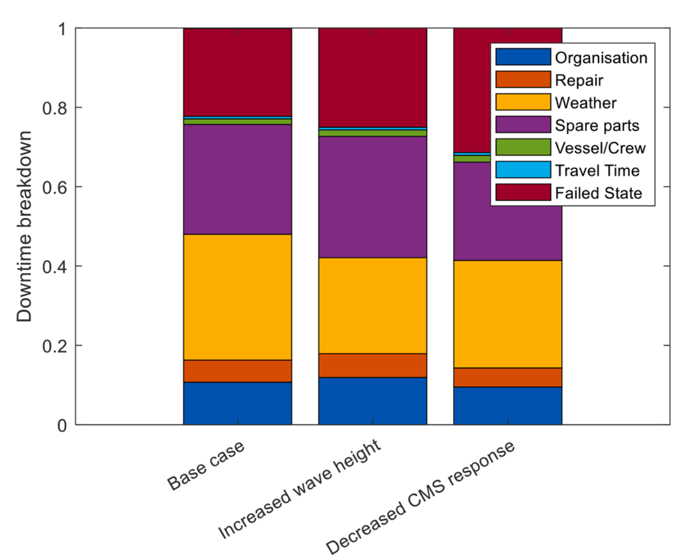

Fig. 10. Downtime breakdowns. Base case (left), increased wave height boundaries (middle) and decreased CMS response (right).

determined based on the standard error observed in the results that converged to approximately 6e-05 at a number of forty runs. Figs. 8 and 9 show an overview of all simulation results as boxplots. The bottom and top edges of the boxes indicate the 25th and 75th percentiles, respectively, while the centre is the median. The most extreme data points that are not considered outliers are plotted through the whiskers and the outliers are indicated by the '+' symbol.

The average availability gains per P-F interval at the three different wave height boundary levels is presented in Table 6.

It can clearly be seen that longer P-F intervals have a positive effect on availability. The effect is greatest at stricter access boundaries. A gain in availability up to more than 2% can be gained in a good functioning CMS. On the contrary, missed detections or inexistent alarm systems can lead to decreased production and availability. A coefficient of $\beta_{pf} = 100\% MTTF$ corresponds to a CMS alarm at roughly the time of functional failure, which is the base case. Obviously the actual TTF is different each time and depends on the exponential distribution function, but a check loop is included so as to ensure that PF values cannot exceed randomly generated values of TTF.

A breakdown of downtimes is presented in Fig. 10. The base case is shown on the left with 80% MTTF. The figure in the middle has the same P-F interval/ CMS response but increased wave height boundaries. It can be observed that as expected, there is decreased downtime due to weather conditions, since accessibility is easier. The figure on the right has the same wave height boundaries as the base case, but decreased CMS response and consequently increased failed state downtime.

Considering the above described results, it is now possible to estimate the potential value of monitoring information in terms of availability gains. It shall be noted that not all monitoring systems within the wind turbine enable the same warning time at the same quality. However, this consideration strongly depends on the type of wind turbine deployed and the respective CMS. It is therefore omitted to present eventual combinations of those systems in this paper as the focus is on quantifying the potential, however the framework that has been implemented into the numerical tool utilised can apply different P-F intervals for different classes of failure considered.

5. Discussion

Increased availabilities are expected when moving from a corrective to a condition-based maintenance strategy. The greatest advantages of condition-based maintenance strategies are seen in (i) the possibility to use equipment for (almost) the full theoretical useful lifetime and (ii) the possibility to plan offshore interventions well in advance resulting in decreased downtimes and increased availability. CMS, on the other hand, require investments for the installation of a suitable system and furthermore for data transfer, handling, analysis and storage [42]. The financial implications should carefully be compared with the gains expected from the system in order to make the right decision.

The proposed methodology relies on concepts that are proven in the offshore wind energy industry. However, particularly reliability estimates are subject to uncertainty. A methodology has therefore been suggested that isolates the problem allowing for further analyses based on any chosen set of base parameters. Results are in agreement with other studies, such as [18,35,43,44]: there is a potential value in the application of condition-monitoring technology in offshore wind. This paper, however, is the first of its kind that provides a quantification of availability gains through application of CBM. The methodology and results are applicable for practical implementation in commercial projects and further academic research. It enables a first estimate of the value of a monitoring system with respect to availability gains. For practical implementation though, not only corrective and condition-based maintenance strategies should be compared. Increased scheduled preventive maintenance may also be a suitable means for failure prevention and maintenance optimization. Such decisions depend on various other factors such as spare part lead times, the availability of a suitable means of transport or the availability of skilled technicians. Understanding those implications along with the potential revenue gains will enable better informed decision-making for O&M of offshore wind farms.

While choosing appropriate CMS or inspection strategies, a number of key performance indicators (KPIs) should be considered including their potential to reduce inspection frequency and inspection extent, mitigate unplanned maintenance, update operational capacity, avoid secondary damages and of course their maturity level. Further, their expected accuracy should also be considered in terms of probability of detection and sizing which are very relevant to both inspection and monitoring. In this current study the element of accuracy of monitoring is not covered as the scope of the paper lies elsewhere. In a subsequent study, an extra level of analysis introducing failure rates for the CMS can occur in order to study their effect on availability.

6. Conclusion

The ability to plan offshore interventions in advance through warnings from condition monitoring systems increases availability of offshore wind farms. It offers the possibility to save cost for preventive activities and gain availability by replacing corrective activities with planned interventions as shown in this study. The methodology presented is flexible in its application to several cases and may directly be used in further commercial and research applications. Results show in a quantitative manner that better performance of access means (higher wave height restrictions) would decrease the impact of CMS on availability since the plannability of interventions is increasing in importance with stricter access restrictions. A large potential for improving the revenue-to-cost structure in project execution and the risk-return balance in investments is expected to result from the application of accurate and reliable monitoring systems.

CRediT authorship contribution statement

Sofia Koukoura: Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft. **Matti Niclas Scheu:** Conceptualization, Investigation, Methodology, Writing - review & editing. **Athanasios Kolios:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Supervision, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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