Predictive maintenance scheduling framework for offshore wind turbines based on condition monitoring

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Predictive maintenance scheduling framework for offshore wind turbines based on condition monitoring: A review

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ABSTRACT: This study investigates the optimization of the operation and maintenance of offshore wind turbines based on condition monitoring data. Due to their increasingly remote and challenging location, a decision framework is proposed that optimizes the cost and risk of maintenance scheduling based on, dynamic Bayesian network based, iterative estimation of turbine lifetime. This allows for the combining of predictive and opportunistic maintenance strategies, scheduling preventative component replacements to minimize lost production, while maximizing lifetime and optimizing use of resources. Assessment of related literature and applications suggests the approach could lead to a reduction of maintenance costs that exceeds 30%. The proposed framework relies on effective fault detection and prognosis of wind turbine components, realised through the implementation of machine learning techniques on the turbine's own SCADA system. The installing of additional sensors can potentially increase the capability of this system for more advanced diagnosis and localization of a fault.

1 INTRODUCTION

The rapidly increasing demand for renewable energy sources has made wind energy one of the most promising alternatives to fossil fuels (Office of Energy Efficiency and Renewable Energy nd). With offshore wind energy projected to triple its capacity by 2026 (International Energy Agency 2021), it offers an efficient energy generation solution at a reduced environmental impact (National Grid nd).

However, the working conditions imposed by the marine environment present significant challenges for the construction, infrastructure, but mostly maintenance of offshore wind turbines (Duffy 2020). Increased loads from waves and strong winds, along with increased humidity, contribute to heightened failure rates among various turbine components, leading to costlier repairs and an increased need for maintenance (Zhu & Li 2018). Offshore working conditions also increase the wind turbine downtime required for repairs, resulting in further loss of revenue (Faulstich et al. 2011). Notably, the costs associated with offshore Operations and Maintenance (O&M) make up a considerable 23-35% of the overall investment, exceeding the 5-25% range typical for onshore wind (Dinwoodie & Mcmillan 2014, Blanco 2009, Sinha & Steel 2015b). As a consequence, 25% to 50% of the total energy generation cost of an offshore wind farm originates from maintenance expenses.

While research on onshore wind has traditionally emphasized cost-effective design and maximizing performance to minimize the initial capital cost of wind turbines (Molenaar 2003), the increased cost of O&M has brought forward new research priorities to ensure the long-term viability of the energy source (Barthelmie & Pryor 2001, Li et al. 2020).

This study investigates the implementation of a predictive maintenance decision framework that enables the application of strategic measures to enhance the critical aspects of wind turbine reliability, minimize the frequency of costly on-site visits, and aim to reduce the failure rates of high-risk components (Nikitas et al. 2020, Le & Andrews 2016, Carroll et al. 2017). Notably, the electric and control systems, gearbox, generator, and blades emerge as key contributors, accounting for 90% of the repair and replacement costs over a turbine's lifetime (Carroll et al. 2016, Artigao et al. 2018).

Recent studies into wind turbine condition monitoring are discussed to assess the prerequisites and potential capabilities of a fault prognosis system. Based on this predictive assessment of the turbine's health, it is discussed how well-informed maintenance decisions can be implemented to optimize O&M expenses, while mitigating risk and maximizing component lifetime.

2 INTELLIGENT CONDITION MONITORING

Predictive and condition-based maintenance decisions rely on accurate determination of the health of the system, which can be achieved by condition monitoring (CM) (Ren et al. 2021). A Condition Monitoring System (CMS) allows for the initiation of maintenance decisions by providing information on the condition of turbine subsystems.

While CM methods are initially ported from other machinery types, often based on vibration monitoring, the condition monitoring of wind turbines proved to be more complex due to the increase of stress and fatigue that originates from the inherently random load spectrum (Barszcz 2019). Combined with the increased remoteness of offshore turbines, a wide variety of online monitoring methods is developed that varies per type of component. Analysis of the operational data provided by SCADA systems as well as additionally installed sensors that perform measurements and report on the condition of the turbine allow for appropriate maintenance decisions that improve availability, reliability and lifespan, to provide the best economic maintenance solution (Walgern et al. 2017).

2.1 *SCADA data*

Signals and alarms from monitoring instrumentation, together with real-time performance and operational parameters, are collected by the SCADA system (Turbines 2005).

Thorough analysis of this comprehensive data set can potentially result in a cost-effective and easy-to-implement tool for evaluation of the wind turbine's health condition. Component specific CM approaches based on SCADA data often employ a wide array of parameters to evaluate anomalies in the turbine state, as well as accompanying minima, maxima and standard deviations. These methods generally estimate expected parameters, such as a component its temperature, and consider deviations from the simulated state as abnormal. An approach that considers the turbine as a whole, generates an expected power curve based on the set of SCADA parameters to compare with the actual power curve in the localization of anomalies (Papatheou et al. 2015, Pandit et al. 2019).

As wind turbine components deteriorate, the efficiency of the energy conversion process decreases, reducing the performance of the wind turbine. Therefore, deviations in the relationship between parameters such as power output, blade pitch angle, generator torque and rotor speed can be used as an assessment of the turbine condition and the early detection of faults (Sørensen et al. 2002).

The major difficulty of fault detection based on power output or other parameters is the variation in operating point that influences the measured data. Information on the operating point is not often available, so in abnormal events, data interpretation systems are required to distinguish between the existence of a fault or a harmless internal or external influence.

A common method to improve accuracy and robustness of the fault detection system is the deployment of machine learning methods (Zaher et al. 2009). These algorithms are well suited to process large amounts of SCADA data, while being able to deal with changes in operating point and complex system interactions (Barszcz 2019).

Supervised methods learn signal patterns for different technical states using data from both malfunctioning as well as healthy turbines. The data is labeled with information about the occurrence or type of faults, to train a machine learning model to predict the type of fault based on new input data. Unsupervised learning can also be used for fault diagnosis when there is no labeled data available. In this case, the goal is to identify patterns or anomalies in the data that may be indicative of a fault (El Bouchefry & de Souza 2020, Schneider & Xhafa 2022).

A common limitation originates from the low resolution of SCADA data, which is predominantly only stored every 10 minutes. Therefore, most studies into SCADA-based CM consider this sampling frequency (Maldonado-Correa et al. 2020). This constraint introduces the risk of overlooking spikes in temperatures, power curve anomalies or oddities in voltages and currents, causing SCADA-based CM applications difficulty to match the capability of traditional sensor-based CMSs. Recent studies investigate the possibility of using 1-s high frequency sampling of SCADA data to overcome this issue, with promising results (Bi et al. 2016, Gonzalez et al. 2017, Gonzalez et al. 2019, Lin et al. 2020).

2.2 *CM sensor data*

A common approach to CM is to equip the system with additional hardware, such as separate sensors dedicated to monitoring particular conditions like oil quality, vibrations, and sound emissions. Unlike SCADA systems, these devices can provide more precise readings at faster intervals, giving a more detailed understanding of the wind turbine's condition. However, this introduces additional costs, which are influenced by factors like measurement accuracy, sampling frequency, system capabilities, and the operating environment. Table 1 summarizes the sensing methods and their applications on turbine components according to existing research and reviews (e.g. (Pérez & Márquez 2015, Qiao & Lu 2015, Tchakoua et al. 2014, Hameed et al. 2011, García Márquez et al. 2012, Du et al. 2020)), with cost indications of implementations based on a study by Yang et al. (2014).

Analysis of a survey into commercially available CM systems performed by Crabtree et al. (2014) identifies vibration analysis applied to drive-train components as the most dominant CM method for wind turbines. In fact, 27 of the 36 total reviewed systems rely on vibration monitoring through accelerometers. After the drivetrain components, the blade is the most popular component, often associated with acoustic emission (AE) analysis (Verbruggen 2003). As most of the reviewed methods rely on time-domain, Fast Fourier Transform (FFT) or envelope analysis, there remains a notable absence in the adoption of more advanced machine learning methods.

Table 1: Condition monitoring sensor techniques for turbine components and their costs as adapted from Yang et al, each € = ± 2000 euro

	Blades	Rotor	Gearbox	Generator	Bearings	Tower
Vibration €	✔	✔	✔	✔	✔	✔
A.E. €€€€	✔	✔	✔		✔	✔
Ultrasonic €€	✔	✔				✔
Oil debris €€€			✔			
Strain €€€€€	✔					✔
Shock Pulse €€			✔	✔	✔	
Thermography €€€€€	✔	✔	✔	✔	✔	

2.3 *Wind Turbine CM Applications*

Based on a thorough analysis of recent studies by Hes in (Hes 2023), the most promising techniques for offshore wind CM, are established. Building on the comprehensive study performed by Badihi et al. (2022), the analysis discusses the capability and accuracy of CM methods from a practical perspective. The following sections brings forth recommendations based on his findings, which are summarized at the end of the section in Table 2.

2.3.1 *Blade Condition Monitoring*

Deterioration of the blade is quickly noticeable through a decreased performance of the turbine's power output. Combined with other SCADA parameters such as wind- and rotor speeds, studies suggest a fault warning can be produced hours (Wang et al. 2018), to days (Chen et al. 2013, Chen et al. 2015) and months (Chen et al. 2017) in advance. However, at this point, further localization and estimation of the fault severity of the fault solely based on analyzing SCADA parameters is difficult.

The most effective method to classify blade damage applies acoustic emission sensors. By clustering acoustic emissions picked up by two spaced sensors, the developed machine learning model localizes the fault. Xu et al. (2020) demonstrate accurate diagnosis of structural defects and delamination. Much cheaper vibration sensors potentially demonstrate the same diagnostic capability as AE sensors (Pacheco-Chérrez & Probst 2022), but need further research as they are not yet fully sensitive to damage and fail to obtain high accuracies (Oliveira et al. 2018). These sensors should also allow for the detection of icing and mud levels when supported by analysis of the power curve (Skrimpas et al. 2016).

Alternatively, a promising method to monitor structural defects, as well as erosion and the accumulation of mud and ice, is based on UAV-based thermography (Wang & Zhang 2017, Hwang et al. 2019, Sousa et al. 2020). However, this technique is still in an experimental stage and requires additional development.

2.3.2 *Generator Condition Monitoring*

Zhang & Lang (2020) demonstrate that nonlinear system frequency analysis of the power curve, as well as the generator temperature referenced with other SCADA parameters, is capable of producing a fault warning one year ahead of time. By adding analysis of generator currents, Brigham et al. (2020) demonstrate potential SCADA-based severity estimation and fault localization.

Even though some additional development of the technique is required for implementation, both methods display high accuracies. Therefore generator maintenance based only on SCADA data CM is very promising. This fact is supported by Gangsar & Tiwari (2017), who state that current-based fault detection of electrical generator faults is the most effective method for detecting and predicting generator faults.

2.3.3 *Gearbox Condition Monitoring*

Even though vibration analysis is still a very popular gearbox CM technique, recent literature shows that SCADA data can be used for the diagnosis and prognosis of many complex gearbox faults. By deploying a machine learning model, Rashid et al. (2020) demonstrate the detection of faults 2 months before critical failure based on analysis of the interaction between gearbox temperature and the produced power. The method is able to assess severity, but to provide a cheap preventative solution to gearbox fault detection, it is required that the model can effectively recognize the health state of the turbine and characterize the fault. Therefore, the model should be combined with models that allow for diagnosis, such as proposed by Bravo-Imaz et al. (2017) and He et al. (2020). They propose deviating between wear, crack, and pitting through the application of high-level feature extraction methods on the current signal.

If a longer prediction horizon is preferred, while also obtaining additional diagnostic information, additional vibration sensors should be installed. For instance, Teng et al. demonstrate a potential fault warning two years before critical failure by performing wavelet analysis on the vibration data (Teng et al. 2019). Other studies show that, based on vibration data, faults can be diagnosed very accurately in multiple gearbox stages (Carroll et al. 2019, Vamsi et al. 2019).

2.3.4 *Bearing Condition Monitoring*

Xiang et al. (2021) utilized convolutional, as well as long-, and short-term memory neural networks to analyze both temporal and spatial aspects of input data. Combined with an attention mechanism, the model predicts a bearing temperature based on SCADA data trends.

In this model, discrepancies between the predicted and actual bearing temperature trend serve as early indicators of an impending defect, signaling its emergence approximately two months before the eventual failure. Leveraging the local measurement of SCADA component temperatures, the model allows for diagnosis, facilitating the identification of the specific bearing responsible for the temperature irregularity and the evaluation of fault severity. This result is strengthened by Hu et al. (2018) and Carroll et al. (2019) who demonstrate accurate temperature-based bearing diagnosis and prognosis.

These studies suggest that temperature deviations could be detectable 4 to 6 months in advance. Although this fault prediction may not be highly accurate, about 70%, it can still provide valuable insights for strategic maintenance decisions.

While SCADA data analysis is the cheapest and least complex implementation, it is also the most accurate and effective. In the current state of bearing CM research, the implementation of SCADA-based is able to replace traditional vibration analysis. While the integration of vibration analysis alongside temperature analysis does not improve diagnostic accuracy, it does contribute to the accuracy of the RUL estimation (Carroll et al. 2019). This option could be considered if increased prognostic accuracy is required for effective maintenance decisions.

2.3.5 *Condition Monitoring of Other Faults*

Faults in the electrical- and auxiliary system are not studied as extensively as the blade and drive-train. Literature does suggest however that most of these faults can be detected or even predicted based on the analysis of SCADA parameters such as temperatures and error codes. While some studies are still in an experimental phase, after additional development, proposed models should be able to accurately monitor converter-, controller-, transformer-, hydraulic-, yaw-, pitch- and anemometer defects (Schlechtingen & Santos 2014, Teimourzadeh Baboli et al. 2021, Chen et al. 2017, Astolfi et al. 2019, Guo & Infield 2020), respectively.

The current state of research in turbine tower and foundation CM is insufficient establish the advantages of either AE or vibration implementation. However, installing vibration sensors to allow implementation of an ANN, as proposed by Nguyen et al. (2018), while also running regression models as proposed by Oliveira et al. (2018), can provide a cost effective and accurate CM solution to both foundation cracks, tower damage, and scour. This can provide an inclusive CM solution for structure defects, in contrast to AE appliances, which are currently limited to foundation cracks (Tziavos et al. 2020).

Machine vision methods that assess component condition with cameras, can also present possible solutions to the maintenance of wind turbine structures (Badihi et al. 2022).

2.3.6 *Concluding Remarks on CM Application*

Study of recent literature demonstrates that SCADA data can provide an easy-to-implement and cost-effective CM solution for every component except for the tower and the foundation. While some of these methods are still in an experimental or untested shape, most component-specific cases demonstrate an accurate indication of developing faults at least 2 months before a failure turns critical. In the meanwhile, continuing analysis of deviations in the wind turbine's power curve can serve as a turbine-wide indicator for damage. Currently, modelling of the power curve based on Gaussian processes is demonstrated to be most effective method (Pandit et al. 2019, Morrison et al. 2022).

Installing additional sensors, such as vibration or acoustic emission (AE) sensors, can potentially increase the capability of a SCADA-based system, for more advanced diagnosis and localization of a fault. However, as this is not a given fact for every component, this decision should be evaluated on a component-specific basis, considering the operator's requirements.

Table 2 summarizes these findings, showing if developing defects are noticeable through power curve analysis and what the suggested methods are for online prognosis and diagnosis of faults.

Table 2: CM Recommendations summarized in a table

Component	**Power Curve**	**Diagnosis**	**Prognosis**
Blade	✓	Vibration or AE	SCADA
Generator	✓	SCADA	SCADA
Gearbox	✓	SCADA or Vibration	SCADA or Vibration
Bearing	✓	SCADA or Vibration	SCADA or Vibration
Auxiliary		SCADA	SCADA
Structures		SCADA	-

3 MAINTENANCE ARCHITECTURE

Pattison et al. (2016) present an architecture to allow for structured and systematic handling of preventive or predictive maintenance decisions based on the data provided by CM techniques.

In contrast to other studies into maintenance scheduling (e.g. (Rademakers et al. , Hofmann & Sperstad 2013, Stålhane et al. 2016, Ioannou et al. 2019)), this maintenance architecture supports an automated and intelligent approach to identify failure patterns or modes without the need for expert knowledge. Short-term decisions can be made concerning

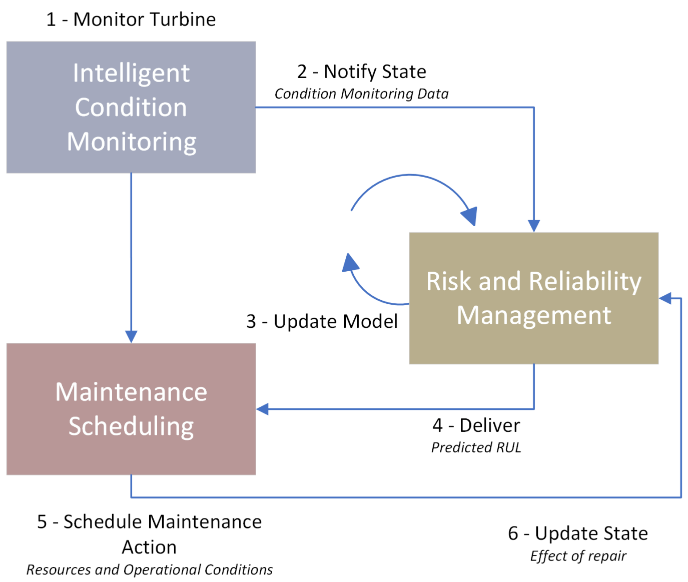

Figure 1: High-level information flow of maintenance system

maintenance activities based on the current state of external influences such as environmental- and logistical conditions. In addition, the modular structure allows for individual development of each module and constant re-evaluation of the proposed solution through feedback of the state of the other modules.

However, the architecture proposed by Pattison et al. (2016) is limited to the use of fault detection and diagnosis. As a result, the model can only directly incorporate data inputs related to the faulty component, fault severity, and the confidence level of the diagnosis. In the principles of Industry 4.0, Cachada et al. (2018) propose an intelligent and predictive maintenance architecture for early fault detection of machine failures, raising the question of how both real-time monitoring as well as prognosis can be applied to schedule maintenance actions in offshore wind maintenance. Consequently, this paper proposes an adapted architecture.

Figure 1 illustrates three modules, that collectively generate a solution in six high-level steps, from an information flow perspective.

Here, the Intelligent condition monitoring (ICM) module includes data analysis methods based on SCADA or deployed sensors to identify anomalous behavior (step 1). If any such deviation/anomaly is found, the system identifies t his s tate a nd informs the Risk and Reliability Management (RRM) module (step 2). Based on the ICM input, this module evaluates a component's probability of survival across the duration of its intended service life and adapts a generic lifetime model to the observed state of the component (step 3).

This expected remaining useful life (RUL) is delivered to the Maintenance Scheduling (MS) module (step 4). Based on this, as well as ICM module fault descriptive data, the module is able to propose the best type and timing of maintenance actions (step 5). The output will subsequently impact the turbine survivability within the RRM (step 6).

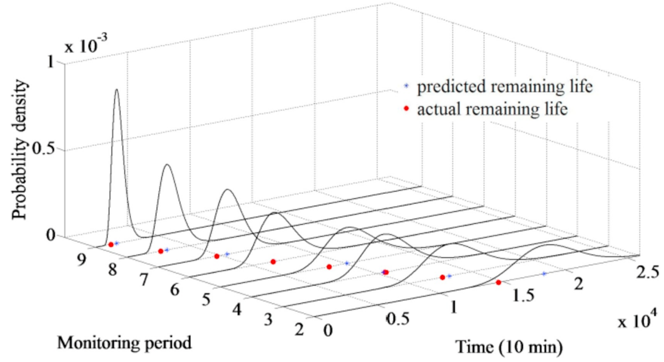

Figure 2: Comparisons of Gaussian probability distributions of RUL prediction results for turbine generator rear bearing, where each monitoring period consists of 2 weeks, up to a total of about 18 weeks at period 9 (Hu et al. 2018)

4 RISK AND RELIABILITY MANAGEMENT

Under the effect of a wide variety of external influences and a complex load pattern, a wind turbine's behaviour is difficult to predict. Combined with uncertainty concerning the effect of a maintenance action, the turbine state is under constant change.

For this reason, maintenance schedules are usually only prepared for a short period of three to seven days. Then, the schedule is updated every morning, as usually only the tasks of the first day are executed as planned (Kovacs et al. 2011).

To address this dynamic and random behaviour, the risk and reliability management module should be able to react to varying conditions and uncertainty and re-inform the scheduling process accordingly. This uncertainty can arise from the unpredictability in performance and power output due to for instance: (i) Variation in wind direction and velocity, (ii) Reliability of the turbine and grid connection, (iii) Regulatory changes in the allowable operating hours (iv) Inaccuracy of data (Dinwoodie & McMillan 2014, Ioannou et al. 2019, Dao et al. 2020).

The integration of prognosis allows for decisions to be made further into the future, requiring the increased alleviation of uncertainties due to inherently random behavior in the development of the fault. This uncertainty in degradation is influenced by factors such as: (i) Environmental conditions, including saltwater, winds, waves and temperature variations that influence the rate at which components degrade and corrode, (ii) Variation in operational factors influencing its rate of degradation, such as high loads or extended operation at rated capacity, (iii) Effectiveness and frequency of maintenance, (iv) Age of the turbine, (v) Uncertainties in the data and models.

In the estimation of remaining useful life, these uncertainties generally causes a decrease in prediction accuracy for a longer prediction horizon. This behavior can be seen in Figure 2, where the certainty of the prediction converges to the actual remaining life when the prediction horizon decreases.

As an example, Figure 2 is considered at 18 weeks lead time. Here, the model estimates RUL as a probability function between 12.5 and 25 weeks. While this can be considered an inaccurate estimate, it can actually already provide sufficient information to initialize maintenance scheduling, because the failure will occur somewhere in that time period. Through continuous monitoring of the development of the fault, the RMM module should update the estimation based on new turbine inspection data, and update the maintenance schedule.

4.1 *Machine Learning Methods*

Due to the required compatibility with CM data, data-driven machine learning methods are considered (Zonta et al. 2020). Ferreira & Gonçalves (2022) reviewed machine learning methods for RUL prediction, pointing out difficulties related to traditional ML methods such as Kalman Filters and Support Vector Machines. These methods do not consider the relevance of time-series signals reflecting changes in the health condition and often rely on manual feature extraction from raw sensor data (Wu et al. 2020).

The application discussed in this paper introduces additional stochastic requirements, that can be met with approaches such as Bayesian Networks (BNs) or fuzzy logic. Introduction of temporal dependencies into these models, provide more advanced versions such as Dynamic Bayesian Networks (DBNs), which includes the Hidden Markov Model, or fuzzified long short-term memory networks. The Dynamic Bayesian network then emerges as the most promising method for the continuous refinement of estimations in the face of external disturbances that influence the lifetime prediction, such as differences in operating conditions and failure modes or unexpected correlation between faults (Straub & Kiureghian 2010, Adedipe et al. 2020).

4.2 *Dynamic Bayesian Network*

The versatility of BNs is widely acknowledged across industries, particularly because of their ability to cope with uncertainties present in organizational operations and decision-making. In structural reliability, Straub & Kiureghian (2010) implemented a DBN, which facilitates Bayesian updating of the model when new information becomes available, including both continuous and discrete random variables. Similarly, a study focusing on battery health estimation demonstrates the effectiveness of statistical forecasting (Richardson et al. 2017). While this study uses a more straightforward method based on Gaussian regression, their results as displayed in Figure 3, serve as an insightful demonstration of a continuously updated lifetime estimation at different points in time.
The applicability of DBNs for wind turbines is demonstrated by Nielsen & Sørensen (2017). To analyze the degradation process and estimate the RUL of wind turbine blades, the model produces an initial prediction based on detected damage, which is updated using CM and inspections.

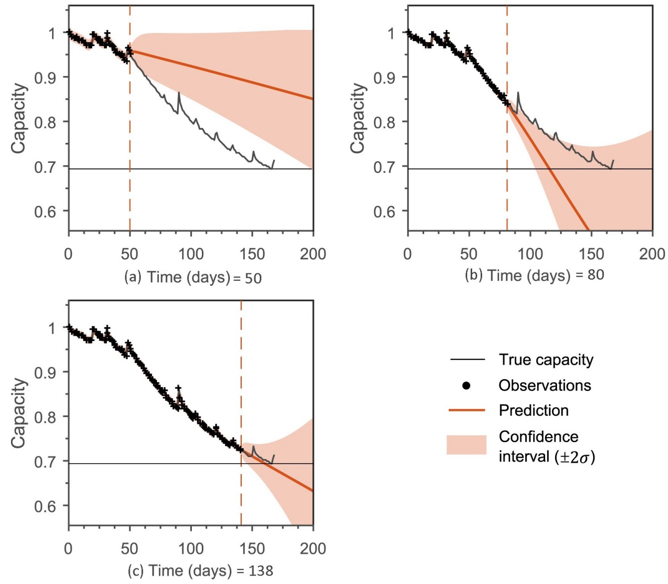

Figure 3: Remaining useful life prediction of a battery at three different points in time. Edited from: (Richardson et al. 2017).

Implementation of a DBN allows for the capturing of the dynamic nature of current- and future degradation, while capable of updating the reliability of the system based on data obtained through CM. Moreover, the DBN facilitates accurate estimations of the resulting system state following various maintenance interventions (Pattison et al. 2016).

5 MAINTENANCE SCHEDULING

The ability to identify faults preemptively, preventing them from progressing into critical failures, gives time to optimize maintenance activities and costs (Sinha & Steel 2015a, Kandukuri et al. 2016). Based on SCADA or sensor data, maintenance tasks can be initiated while considering factors such as downtime, repair costs, risk of failure and the cost of lacking performance.

During maintenance scheduling, it may be necessary to temporarily halt turbine operation to extend the available time for maintenance actions. Alternatively, Fault-tolerant and Condition-based control can be applied to accommodate the effects of noncritical faults in wind turbines, or modify the operational state of components depending on their health-condition to avoid unnecessary shutdowns and missed production, and increase the time window for maintenance (Badihi et al. 2022).

By replacing components in anticipation of their failure, while also assessing the most convenient and efficient time and method, the inclusion of opportunistic scheduling strategies into predictive maintenance can provide a promising step in the minimization of maintenance costs de Pater & Mitici (2021). Research that combines predictions with maritime logistics optimisation has yet to be performed, however (Halvorsen-Weare & Nonås 2022).

To consider the application of this hybrid solution to offshore wind, first, the separate aspects of predictive and opportunistic maintenance scheduling are discussed.

5.1 *Predictive Maintenance Scheduling*

To determine if maintenance should be carried out preventively, Zhu et al. (2017) assess the costs originating from a preventative or, future corrective maintenance action based on stochastic lifetime predictions. Evaluation of these costs produces a control limit used to notify the need for preventative replacement. This ensures that component lifetime is maximized without unnecessary early replacements. A similar threshold is applied by Zhou & Yin (2019), while also allowing for preventative replacement of other turbine components in the same action, if the cost of this preventative action is lower than a condition-based maintenance action later on.

Instead of a cost-based threshold to maximize the effective RUL, Schenkelberg et al. (2020) propose that the balancing of a failure risk in a maintenance optimization problem can be done by estimating the impact of failure on profitability. Through the application of a DBN, the model predicts costs associated with a possible failure escalation and compares that with the cost of preventative replacement.

5.2 *Opportunistic Maintenance Scheduling*

Opportunistic maintenance aims to find the most ideal moment to perform maintenance based on resources and costs related to O&M. Each individual task poses its own requirements on these resources, encompassing the management of personnel and spare parts as well as the arranging and routing of vessels (Karyotakis 2011). Importantly, transportation costs constitute to 30% of a turbine's maintenance expenses (Irawan et al. 2017).

Maintenance costs can also arise due to lost production. This lost revenue is a direct consequence of maintenance activities, as turbines may need to be temporarily halted for maintenance purposes. The servicing of one turbine can result in the interruption of other turbines as well, because multiple turbines are connected in series to the power grid (Pattison et al. 2016).

Lost production can be minimized by the incorporation of forecasted wind speed, or analysis of energy prices, aligning turbine shutdown with periods of low yield. Proposed by Petros Papadopoulos & Ezzat (2023), this method demonstrates promising results in the optimization of total cost, downtime, resource utilization, and maintenance interruptions.

Nguyen et al. (2022) propose a maintenance scheduling approach, designed to maximize cost-effectiveness while minimizing lost production and environmental and safety risks. This is obtained by the intelligent optimization of resources, minimization of production losses and efficient vessel routing. The proposed model utilizes fuzzy probabilities to assess environmental- and safety risks associated with marine environments.

Incorporation of these fuzzified risks into scheduling decisions enables stochastic inputs into the model. In a similar way, a probability density function associated with a prognosis, as shown in Figure 2, can be incorporated into the scheduling decision. Increased risk of failure could be balanced with maintenance opportunities, such periods of low yield and lower safety risks due to calm weather, or increased consolidation of maintenance tasks. Careful evaluation of the risk of component failure is required when seeking maximization of the RUL, as the preventative replacement of a component is usually beneficial over the risk of having to perform a more severe repair (Turnbull & Carroll 2021).

5.3 *Optimization solution methods*

Based on the discussed literature, solving the predictive maintenance scheduling optimization problem describes the scheduling of tasks and allocation of resources such as vessels and spare parts, while optimizing risk and costs.

When reviewing maintenance optimization studies, the mathematical handling of these tasks can often be found to be based on Mixed Integer Linear Programming (MILP). Given the magnitude of transportation costs of offshore O&M, proper management and routing of a suitable fleet of vessels is required. Stålhane et al. (2016) demonstrate a MILP model for optimal fleet deployment and long-term decision-making on the fleet size and composition. This includes the acquisition and routing of crew transfer vehicles, service operation vessels, jack-up vessels and helicopters. In this decision, which is made one year ahead of time, environmental conditions as well as failures are taken as a-priori information.

When the model is confronted with unexpected weather conditions and turbine failures, unplanned corrective maintenance actions drive up the O&M cost. This also means that maintenance costs are often underestimated. To achieve a better MILP estimate of costs, an heuristic is presented by Gutierrez-Alcoba et al. (2019). While this solution increases the initial investment costs, the capability to react to uncertain events reduces the risk of unexpected cost increases.

This prompts Magnus Stålhane & Hvattum (2021) to include a broader field of strategic uncertainties as well, such as economic trends, gradual development of wind farms, and vessel technology development. These approaches show that a more realistic description of the system, as well as associated costs allows for more accurate predictions of decision outcomes, and a overall more optimal scheduling solution.

Addressing maintenance task management from a different point-of-view, Schrotenboer et al. solve the optimization problem in the context of a single maintenance provider responsible for multiple wind farms (Schrotenboer et al. 2020). In the Netherlands, for instance, offshore wind practices demonstrate that maintenance is performed by a service provider that does not own the farms and, therefore, does not risk uncertain production revenues due to alternating energy prices or the risk of production losses due to downtime.

Ge et al. (2020) as well as Sang et al. (2021) demonstrate that proper evaluation of downtime related wind costs should include power generation losses due to wake effects. The proposed approach consists of two stages, where the first stage determines the required amount of ships and technicians, and the second stage determines which turbines should be maintained while minimizing cost or travel distance per day. This allows for the short term updating of maintenance tasks if unexpected environmental conditions or faults are revealed after the initial schedule made in stage one.

The mathematical model of Irawan et al. (2017) is considered to include spare part allocation. The model includes constraints related to spare parts and describes the not only the availability of spare parts, but also limitations related to the weight and required storage space when considering transportation.

Due to the uncertain nature of the marine environment, the discussed MILP-based studies consider heuristics and complex multi-layer solution frameworks (Zhong et al. 2018). Other non-deterministic methods can also be considered, including fuzzy-based programming (Zhong et al. 2019), integration of a rolling-horizon (Petros Papadopoulos & Ezzat 2023, Papadopoulos et al. 2022), discrete heuristic optimization machine learning (Fan et al. 2019), and meta-heuristic Genetic Algorithms (Stock-Williams & Swamy 2019).

The model should be able to meet the opportunistic demands of the maintenance scheduling module within a given time-frame. When integrated into the proposed architecture, the RUL probability function from the RRM module replaces fixed predictions or heuristic approaches to address unexpected failures and degradation uncertainty. This integration allows the optimization model to make advanced decisions, leading to a more optimal solution.

5.4 *Integrated Architecture*

After evaluation of the proposed architecture's required functions, a more detailed information flow visualization of the maintenance decision model can be made. Figure 4 depicts the three discussed major modules, as well as their interaction with each other and external data-sets.

Novel CM systems monitor the health of the turbine. After detection of a fault, its location and severity are used to initiate maintenance decisions. Based on the evaluation of component or turbine health, the RRM module estimates the RUL utilizing a DBN. In an iterative process, the RRM module converges step by step to refine its estimation as the turbine condition approaches its point of failure.

This estimated point of failure defines the amount of time that is available to solve the maintenance scheduling optimization problem. The required maintenance action is derived from the ICM module its diagnosis. This maintenance action includes task characteristics, such as time and cost, as well as conditional constraints such as equipment, stock or weather requirements.

Meeting the scheduling demands is done in multiple stages. First, the mid-term comprises the availability of stock and, if applicable to the service provider, the management of the fleet. This is followed by the assigning of vessels as well as personnel within any imposed environmental limitations. Finally, the short-term stage, covers the optimal routing of tasks. Based on the proposed schedule, the model verifies if a more optimal solution can be found at a higher risk of critical failure. Even when a maintenance schedule is produced the proposed solution might require updating in the face of changing environmental conditions. In turn, the performed maintenance action influences the predicted RUL.

6 COST

To estimate the potential financial impact of the implementation of the proposed maintenance strategy, several studies into the effect of predictive maintenance or optimization of a maintenance problem are discussed.

6.1 *Predictive Maintenance*

Through time-based simulation of wind farm operations, Turnbull & Carroll (2021) quantify the cost benefits associated with different maintenance strategies, taking into consideration both direct maintenance costs and lost production.

Their results indicate that O&M costs can be reduced up to 8% along with a reduction of lost production up to 11%. However in obtaining these values, Turnbull & Carroll assume that, after fault detection of monitoring systems, only 25% of major failures of the generator and gearbox can be repaired before major replacement is required.

6.2 *Opportunistic Maintenance*

A comprehensive review performed by Tusar & Sarker (2022) reviews a vast amount of maintenance models to assess the cost benefits associated

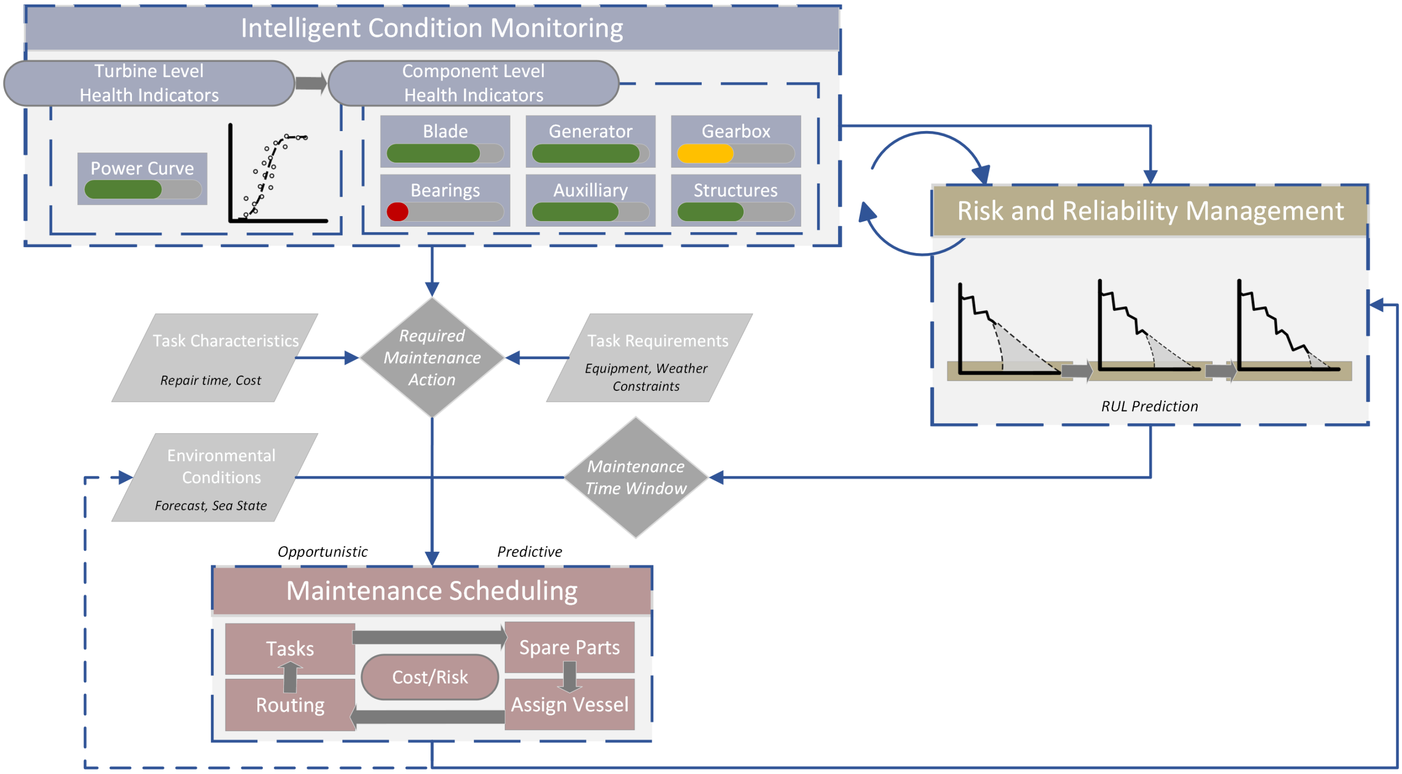

Figure 4: Integrated high-level information flow of opportunistic and predictive maintenance system

with different strategic approaches. Certain risk and reliability-based models reduce annual O&M costs by 23%, whereas opportunistic maintenance strategies suggest the ability to minimize 32% of production losses and transportation costs.

The most cost-efficient model in the review performed by Tusar & Sarker reduced the cost of maintenance by 48.2% compared to corrective maintenance. This method applied opportunistic maintenance for wind farms, proposing the efficient scheduling of tasks by grouping tasks of multiple components of a single turbine or combining tasks of multiple proximate turbines in a farm (Ding & Tian 2012). To provide enough room for these decisions, the model allows for performing incomplete or imperfect maintenance tasks, not always returning the component to a good-as-new state.

In a different approach, Besnard et al. (2011) propose stochastic scheduling at the lowest cost based on a wind forecast. The schedule is updated daily based on changes in the production and weather forecast. After evaluation of real wind data, the proposed approach demonstrated a 32% reduction in maintenance cost due to reduced production losses and saved transportation costs.

6.3 *Hybrid Maintenance Approach*

To assess the cost benefit of the hybrid opportunistic and predictive maintenance strategy as proposed in this paper, the model proposed by Tian et al. (2011) is considered. It uses predictive sensor data to determine a cost-effective solution that incorporates both opportunistic as well as predictive maintenance aspects. After comparing this method with traditional methods, Tian et al. suggest a cost saving of 44.42%.

In these examples, it is crucial to ensure that the benefits derived from implementing more advanced methods surpass the associated increased costs. This evaluation is contingent on the reliability and conditions of each unique component. As a consequence, the optimal maintenance solution must be assessed independently for each component (Zhong et al. 2019).

7 CONCLUSION

Optimization of the operation and maintenance costs of offshore wind turbines is realized through informed and strategic predictive decisions grounded on condition monitoring data. Based on lifetime predictions made by a dynamic Bayesian neural network, preventative component replacements are scheduled in a way that minimizes downtime and lost production, while maximizing lifetime and optimizing the use of maintenance related resources.

Studied applications consistently show a potential predicted lead time to failure of at least 2 months. Applying machine learning techniques on the turbine's own SCADA system provides an effective fault detection and prognosis system for many turbine components, while the installing of additional sensors can potentially increase the capability of this system, for more advanced diagnosis and localization of a fault.

Analysis of similar studies in offshore wind and other fields suggests the combination of predictive and opportunistic maintenance approaches could lead to significant reductions in O&M costs.

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