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Model predictive control framework for optimizing offshore wind O&M

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ABSTRACT: Offshore wind farms are a promising source of renewable energy, but they face significant challenges in terms of operation and maintenance (O&M). Traditional scheduling models often overlook the potential of condition-based maintenance (CBM). Addressing this gap, this paper introduces a novel framework, incorporating principles of Model Predictive Control (MPC), to optimize the O&M scheduling of offshore wind farms using prognostic-driven maintenance. The framework integrates probabilistic remaining useful life (RUL) prognosis in a mixed-integer linear programming (MILP) optimization model with a rolling horizon approach, in alignment with MPC's predictive and adaptive decision-making approach. The optimization model determines the optimal time to replace each component by minimizing the expected cost over the expected lifetime. This approach seeks to achieve the lowest expense while guaranteeing the highest utilization rate of each component. For the case study presented, the total O&M costs are reduced by up to 15% with respect to corrective maintenance strategies.

1 INTRODUCTION

In recent years, the global focus on renewable energy sources has intensified, partly driven by the urgent need to address climate change. Offshore wind farms have emerged as a promising and significant contributor in this domain. In 2021, a record number of offshore wind farm projects were commissioned, indicating a robust growth trajectory for this sector. The cumulative deployment of offshore wind energy is estimated to reach approximately 117 GW by 2027, and potentially 370 GW by 2031, according to the US Department of Energy (2022) (US Department of Energy 2022). This expected growth positions offshore wind as a pivotal component in achieving global electricity generation targets and in assisting countries to meet their climate and renewable energy objectives.

However, the high cost of offshore wind, compared to other renewable technologies, remains a significant challenge (NREL 2023). A critical factor influencing this cost is Operation and Maintenance (O&M), which accounts for a substantial portion of the total lifecycle costs of offshore wind projects, estimated to be between 25-30%, as opposed to 10-15% for onshore wind farms (National Renewable Energy Laboratory 2022), (van Bussel & Schöntag 1997).

Efficient and effective O&M strategies are essential to minimize downtime, enhance the performance and availability of the wind farm, and thereby reduce the overall Levelized Cost of Electricity (LCoE). These strategies include reactive and proactive maintenance (Ren et al. 2021).

Proactive strategies such as predictive maintenance are based on Condition Based Monitoring (CBM) and can substantially reduce the cost of O&M (Van Horenbeek & Pintelon 2012b), CBM involves monitoring the health and performance of wind turbine components in real-time or periodically, using sensors and other monitoring systems (Kou et al. 2022). By analyzing the collected data, trends and patterns, anomalies can be detected, allowing for timely maintenance actions (Le & Andrews 2016).

Nevertheless, traditional scheduling models in offshore wind farm maintenance primarily rely on fixed age thresholds for the planning of maintenance tasks, while overlooking the potential of CBM (May et al. 2015). This approach can often lead to inefficiencies since it does not account for the actual condition of the components, leading to scenarios where maintenance is either performed too early, resulting in unnecessary costs, or too late, leading to unexpected failures and extended downtimes (Fox et al. 2022).

In recent years, the advent of advanced control strategies has significantly impacted the operational efficiency of complex systems. Among these, Model Predictive Control (MPC) stands out as a form of control strategy that utilizes a model of the process to predict future outcomes and make decisions that optimize a set of predefined objectives over a future time horizon. It is characterized by its ability to anticipate future events and take control actions accordingly, making it an ideal framework for managing systems where the cost of operational decisions is high and the need for reliability is critical (Mayne et al. 2000).

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Table 1. Acronyms and nomenclature.

Symbol	Definition
OFW	Offshore Wind Farm
O&M	Operation and Maintenance
CBM	Condition-Based Maintenance
MPC	Model Predictive Control
RUL	Remaining Useful Life
MILP	Mixed-Integer Linear Programming
CTV	Crew Transfer Vessel
SOV	Service Operation Vessel
LCoE	Levelized Cost of Electricity
JUV	Jack-Up Vessel
HLV	Heavy Lift Vessel
t	Time in days since the beginning of the observation period
k	The current day or time step since the beginning of component operation
t_k	The time in days since the component V has been in operation, considering the current day k
L	Length of the maintenance planning horizon
d_p	Present day in the planning horizon
τ	Time step in the planning horizon
S	Set of all possible maintenance schedules
V	Set of components in the wind turbine
j^V	Vessel used for the replacement of component V
$c^V_{preventive}$	Cost of preventive replacement of component V
$c^V_{corrective}$	Cost of corrective replacement of component V
$T^V_{preventive}$	Preventive replacement time for component V
$T^V_{corrective}$	Corrective replacement time for component V
N_{tech}	Number of technicians necessary for replacement
R_{hour}	Hourly rate of a technician
C_{el}	Cost of electricity
$P(V)$	Power curve of a turbine
v_{mean}	Average wind speed
$\phi^V_k(i)$	Probability that the RUL of component V is exactly i days, after being used for k days
$c^V_{dt}(t_k)$	Expected cost of potential downtime losses for component V over time
x^V_s	Binary decision variable indicating if component V is replaced at time s
W_s	Binary variable indicating if weather conditions are suitable at time s
$Y^{j^V}_s$	Binary variable indicating if vessel j^V is available at time s
T^V_s	Binary variable indicating if technicians with the required skills to replace component V are available at time s
$E_R[C_V(k,t_k)]$	Expected cost of replacement after t_k days
$E_{DN}[C_V(k, L)]$	Expected cost of doing nothing over the planning horizon L
$E_R[L_V(k,t_k)]$	Expected lifetime after replacement at time t_k

(*Continued*)

Table 1. (*Continued*)

Symbol	Definition
$E_{DN}[L_V(k,L)]$	Expected lifetime without replacement over the planning horizon L
C^V_R	Cost over expected lifetime ratio for replacement
C^V_{DN}	Cost over expected lifetime ratio for doing nothing

The integration of MPC principles into these maintenance strategies offers a promising approach to further address these challenges. By adopting a framework that includes both predictive and adaptive elements, we can more effectively balance maintenance needs with operational efficiency.

The methodological innovation in O&M scheduling proposed in this paper involves the development of a novel framework that incorporates probabilistic RUL prognosis into a mixed-integer linear programming (MILP) model. Such an approach not only aims to minimize O&M costs but also to maximize the utilization rate of each component, a critical factor in the profitability, viability, and sustainability of offshore wind farms.

1.1 *Paper structure*

This paper will explore the concept of prognostic-driven maintenance in depth, elaborating on its methodology, implementation, and benefits. It aims to contribute to the existing body of knowledge by addressing the gap in current O&M scheduling practices and demonstrating the potential advantages of a prognostic-driven approach.

An extensive review of current methodologies in O&M for offshore wind farms is outlined in Section 2, showcasing how current strategies incorporate fault detection, but often overlook the integration of fault prognosis. This section identifies gaps in the literature and positions the paper within the context of existing research. The methodology is explained in Section 3, detailing the proposed prognostic-driven maintenance model. It explains how the model is constructed, the synthetic model used for RUL prediction in the absence of real-time data, and the mathematical formulations used for the optimization of maintenance scheduling. A hypothetical case scenario is outlined in Section 4, detailing the specific components, operational parameters, and maintenance requirements of a single offshore wind turbine. This scenario serves as a practical example to illustrate the application of the prognostic-driven scheduling model. The findings from applying the model to the case scenario are finally presented in Section 5. The results section includes graphs and figures to visualize the cost implications of different maintenance strategies over time, offering insights into the model's effectiveness. Lastly, in Section 6, the reader will find a critical analysis of the model's outcomes, its implications for the O&M of offshore wind farms, and a discussion on potential areas for further research and model refinement.

2 LITERATURE REVIEW

Short-term scheduling in offshore wind farm O&M is a critical factor for ensuring operational efficiency and reliability. This horizon focuses on the daily or weekly planning of maintenance tasks, influenced by real-time factors like weather conditions, component health, and logistical considerations (Irawan et al. 2017).

Recent advancements in technology, particularly in data analytics and predictive modelling, have enabled new, sophisticated approaches to short-term scheduling. The integration of real-time data from sensors, coupled with advanced prognostic models, allows for more accurate predictions of component health and maintenance needs (Le & Andrews 2016).

Several studies have highlighted the effectiveness of prognostic-driven approaches in short-term scheduling. These case studies provide valuable insights into the practical applications and benefits of adopting a prognostic-driven approach in short-term scheduling scenarios (Van Horenbeek & Pintelon 2012a).

The ongoing research in short-term scheduling is oriented towards further refining prognostic models and integrating them with dynamic scheduling systems. The focus is on enhancing the accuracy of predictions and developing more agile scheduling tools that can respond in real-time to changes in component conditions and environmental factors.

2.1 *Short-term scheduling in offshore wind farms*

Short-term scheduling within offshore wind farms O&M remains an intricate process that demands meticulous analysis and planning. The state of the art in short-term scheduling predominantly revolves around optimizing the routing of vessels and timing of maintenance activities.

In the literature, various strategies have been proposed to tackle these challenges. The routing and scheduling problem is often addressed by optimizing the paths and schedules for vessels to service wind turbines (Irawan et al. 2017). These models aim to minimize costs by reducing travel times, optimizing resource allocation, and ensuring safe and efficient transportation (Ade Irawan et al. 2023).

However, a significant aspect of these strategies is the reliance on fixed age thresholds for maintenance actions. These thresholds are identified using methodologies that optimize the maintenance schedule based on the age of the components (Sarker & Ibn Faiz 2016). This approach has been the traditional method for maintenance planning, where tasks are scheduled at predetermined intervals, regardless of the actual condition of the components.

Age threshold optimization techniques in the literature underscore the influence of age groups and thresholds on the overall maintenance costs (Sarker & Ibn Faiz 2016),(Li et al. 2022). These techniques utilize various decision rules and stochastic models to determine the most cost-effective moments for maintenance actions (Safaei et al. 2020). However, they do not fully exploit the potential benefits of prognostic information that could further optimize scheduling.

In contrast to this traditional approach, recent advancements have seen a shift towards prognostic-driven scheduling models. These models deviate from fixed age thresholds by employing probabilistic RUL predictions to inform maintenance decisions (Li et al. 2020). Prognostic-driven scheduling considers the actual condition and predicted future state of health of the components, potentially offering a more dynamic and cost-effective maintenance strategy.

The integration of prognostics into maintenance planning for OWFs represents a paradigm shift from a purely reactive to a more predictive and proactive approach. The impact that advanced monitoring strategies can have on lifetime O&M costs for offshore wind turbines is evaluated in (Turnbull & Carroll 2021), here the authors showed a potential cost reduction of up to 8% in direct O&M costs (transport, staff and repair costs) and up to 11% reduction in lost production, where the major source of savings are obtained through early intervention to avoid failure and major component replacement.

In conclusion, while fixed age threshold optimization has served as a foundational approach for short-term scheduling in OWFs, the advent of prognostic-driven models is suggesting the beginning of a new era in maintenance strategy. This emerging approach, grounded in probabilistic RUL predictions, aims to redefine the maintenance optimization landscape, promising increased efficiency, reduced costs, and improved system reliability for OWFs.

2.2 *Short-term scheduling in other industries*

A review of contemporary literature in the domain of maintenance scheduling for aircrafts, reveals a variety of methodological approaches, each contributing uniquely to the development of more refined and predictive O&M scheduling models. Prognostic models are central to forecasting the RUL of components. The methodologies employed across recent studies vary, with some common approaches being highlighted.

Convolutional Neural Networks (CNN) and Monte-Carlo dropout have been used by (Mitici et al. 2023), (Lee & Mitici 2023), (de Pater et al. 2022), (de Pater & Mitici 2021), employing a probabilistic Remaining Useful Life approach that estimates the likelihood of component failure within a given time frame, contributing to a more precise and cost-effective scheduling process.

Similarly, Bayesian Deep Learning (BDL), Long Short-Term Memory networks (LSTM) and Feed-forward Neural Networks (FNN) are used by (Zhuang et al. 2023). Kalman Filters are employed by (Vianna & Yoneyama 2018), where degradation trends and future wear values are estimated considering an implementation of a multiple model approach of the extended Kalman filter technique. The RUL prognosis methodologies presented are summarized in Table 2

Table 2. RUL Prognosis methodologies.

Authors	CNN	BDL	LSTM	FNN	Kalman Filter	NA
(Mitici et al. 2023)	✓					
(Zhuang et al. 2023)		✓	✓	✓		
(Lee & Mitici 2023)	✓					
(de Pater et al. 2022)	✓					
(de Pater & Mitici 2021)	✓					
(Chen et al. 2021)			✓			
(Camci et al. 2019)						✓
(Vianna & Yoneyama 2018)					✓	
(Li et al. 2016)						✓

The optimization of maintenance scheduling is influenced by the predicted RUL, where various methods are employed to ensure cost-effectiveness and high component utilization.

Mixed-Integer Linear Programming (MILP) is a widely adopted method, seen in most of the reviewed papers such as (Mitici et al. 2023), (Zhuang et al. 2023), (de Pater et al. 2022),(de Pater and Mitici 2021), (Chen et al. 2021), (Camci et al. 2019), providing a structured approach to optimizing cost while maintaining high component utilization rates; in (Mitici et al. 2023) the authors claim that through their novel approach, 95.6% of unscheduled maintenance can be prevented.

The predictive maintenance planning can also be formulated as a Deep Reinforcement Learning (DRL) problem, as seen in (Lee & Mitici 2023), this approach can be particularly useful in dealing with the dynamic and complex nature of maintenance scheduling. Exhaustive search methods, although computationally intensive, provide a thorough exploration of all possible solutions and are used in (Vianna & Yoneyama 2018).

Rolling-Horizon strategies, as seen in (Mitici et al. 2023) and (Zhuang et al. 2023), are employed for their adaptability and the capacity to update decisions with new information over time. The main scheduling optimization methods discussed are summarized in Table 3.

Table 3. Scheduling optimization methods.

Authors	MILP	DRL	Exhaustive search	Rolling-Horizon
(Mitici et al. 2023)	✓			✓
(Zhuang et al. 2023)	✓			✓
(Lee & Mitici 2023)		✓		
(de Pater et al. 2022)	✓			✓
(de Pater & Mitici 2021)	✓			✓
(Chen et al. 2021)	✓			
(Camci et al. 2019)	✓			
(Vianna & Yoneyama 2018)			✓	
(Li et al. 2016)	✓			

The objective functions in these models often include maintenance costs and the utilization rate of the system. For instance, (Chen et al. 2021) minimizes the expected costs over the component's expected lifespan (cost rate) while others only minimize maintenance cost (Li, Guo, & Zhou 2016). An overview of the objective functions used by each author is presented in Table 4

Table 4. Objective functions in scheduling models.

Authors	Maintenance Cost Rate	Maintenance Cost
(Mitici et al. 2023)	✓	
(Zhuang et al. 2023)	✓	
(Lee & Mitici 2023)	✓	
(de Pater et al. 2022)	✓	
(de Pater & Mitici 2021)	✓	
(Chen et al. 2021)	✓	
(Camci et al. 2019)		✓
(Vianna & Yoneyama 2018)		✓
(Li et al. 2016)		✓

In summary, the literature presents a rich tapestry of methodologies aimed at optimizing short-term scheduling. The trend towards integrating predictive analytics and probabilistic models is clear, with a strong focus on optimizing maintenance activities based on real-time data and advanced diagnostic techniques. These studies form the bedrock upon which future operational frameworks can be developed for offshore wind farms.

2.3 *Research gap*

As we have seen, the state of the art in scheduling for offshore wind farms (OWFs) primarily focuses on optimizing the allocation of resources, minimizing travel time and costs, and ensuring the timely completion of maintenance tasks. The literature reveals that, while fault detection is commonly accounted for in current methodologies, there is a lack of integration of fault prognosis and future component health predictions into these scheduling models.

Task sequencing and scheduling play crucial roles in minimizing downtime and maximizing resource utilization, however, current approaches typically do not integrate prognostic-driven strategies that can predict the future state of health of components. This represents a significant gap in the literature, as the incorporation of such strategies could potentially lead to more effective and cost-efficient scheduling by anticipating future maintenance needs and avoiding the pitfalls of reactive maintenance approaches.

Table 5. Maintenance scheduling in literature.

Authors	Consider fault detection	Consider fault prediction
(Irawan et al. 2017)	✓	
(Dai et al. 2015)	✓	
(Stock-Williams & Swamy 2019)	✓	
(Pattison et al. 2016)	✓	
(Raknes et al. 2017)	✓	
(Ade Irawan et al. 2023)	✓	
(Nachimuthu et al. 2019)	✓	
(Lazakis & Khan 2021)	✓	
(Mazidi et al. 2017)	✓	
(Sinha et al. 2013)	✓	
(Dawid et al. 2018)	✓	
(Liu et al. 2019)	✓	
(Mitici et al. 2023)[1]	✓	✓
(Zhuang et al. 2023)[1]	✓	✓
(Tseremoglou et al. 2023)[1]	✓	✓
(Lee & Mitici 2023)[1]	✓	✓
(de Pater et al. 2022)[1]	✓	✓
(de Pater & Mitici 2021)[1]	✓	✓
(Chen et al. 2021)[1]	✓	✓
(Camci et al. 2019)[1]	✓	✓
(Vianna & Yoneyama 2018)[1]	✓	✓
(Gogu 2018)[1]	✓	✓
(Li, Guo, & Zhou 2016)[1]	✓	✓
(Rodrigues et al. 2015)[1]	✓	✓

Note: Papers marked with[1] are related to the maintenance of aircrafts, the rest is related to the maintenance of OWFs.

On the other hand, as illustrated in Table 5, while research in the field of offshore wind maintenance is currently considering only fault detection, the aircraft maintenance industry has made significant strides in incorporating prognostic information and fault predictions into its scheduling models. The advanced adoption of CBM in aircraft maintenance provides a framework from which OWF maintenance can draw inspiration. The similarities between the two industries, such as the criticality of maintenance for safety and efficiency, the high costs associated with downtime, and the technical complexity of the systems involved, justify the adoption of similar methodologies in O&M scheduling for OWFs.

Addressing these challenges, the primary objective of this research is to propose a novel framework that not only integrates a prognostic-driven maintenance approach into the O&M scheduling process of offshore wind farms but also makes use of the predictive and adaptive capabilities of MPC. This framework aims to optimize maintenance activities based on probabilistic RUL predictions, thereby reducing costs and maximizing operational efficiency and energy production. By incorporating MPC, the research seeks to bridge the gap in current O&M practices, offering a dynamic scheduling model that can anticipate and adapt to the operational state of the wind farm components.

3 METHODOLOGY

The methodology applied in this research constructs a prognostic-driven optimization model for the short-term scheduling of maintenance activities in offshore wind farms. The proposed model is designed to integrate the probabilistic estimation of Remaining Useful Life (RUL) for components within a cost optimization framework, enriched by the principles of Model Predictive Control (MPC). MPC's predictive capabilities enable the model to consider not just current component states but also forecast future conditions, thereby allowing for proactive maintenance decisions that can adapt to changing operational needs.

This chapter describes the foundational framework of the model.

3.1 *Synthetic model for probabilistic RUL prediction*

To address the inherent uncertainties in predicting the Remaining Useful Life (RUL) of offshore wind turbine components, our study employs a synthetic model. This model is instrumental in generating probabilistic RUL predictions in the absence of real-time condition-based monitoring data.

The true RUL (RUL_{true}) of the components is considered a latent variable that follows a Weibull distribution, a common choice for modeling the life of mechanical systems. The probability density function of the Weibull distribution is defined as:

$$f(t; \lambda, \alpha) = \frac{\alpha}{\lambda}\left(\frac{t}{\lambda}\right)^{\alpha-1} e^{-\left(\frac{t}{\lambda}\right)^{\alpha}} \qquad (1)$$

where t is the ime in days since the beginning of the observation period, λ is the scale parameter and α is the shape parameter. To simulate the true RUL, we use inverse transform sampling, where:

$$RUL_{true} = \lambda(-\ln(U))^{1/\alpha}, \quad U \sim \text{Unif}(0, 1) \qquad (2)$$

where U is a random variable uniformly distributed between 0 and 1, used in the inverse transform sampling method.

Our model generates point predictions of RUL and characterizes the uncertainty around these predictions, which decreases over time as more information becomes available. The range for the standard deviation of the predictions is set by:

$$\text{std}_{max} = RUL_{true} \cdot (\text{large uncertainty}) \qquad (3)$$

$$\text{std}_{min} = RUL_{true} \cdot (\text{small uncertainty}) \qquad (4)$$

where std_{max} is the maximum standard deviation representing the initial uncertainty in the RUL prediction and std_{min} is the minimum standard deviation representing the reduced uncertainty as more information becomes available over time.

The confidence in the prediction increases with time, converging towards the lower bound of uncertainty. This is modeled as:

$$\text{std}(t) = \text{std}_{max} - (\text{std}_{max} - \text{std}_{min}) \cdot \left(\frac{1}{1 + \exp\left(-\frac{t - a \cdot RUL_{true}}{b \cdot RUL_{true}}\right)}\right) \qquad (5)$$

where std(t) is the confidence in the RUL prediction at time t, which is a function of time reflecting decreasing uncertainty. The maximum and minimum standard deviation, as well as the values of parameters a and b used in Equation 5, can be modified to represent different behaviours of the RUL predictions in time. Subsequently, the RUL prediction adjusted for error at time t is calculated as:

$$RUL_{pred}(t) = RUL_{true} - t + \text{error}(t) \qquad (6)$$

with the error term modeled as a normally distributed random variable with mean 0 and standard deviation corresponding to the confidence at time t is calculated as:

$$\text{error}(t) \sim N(0, \text{std}(t)) \qquad (7)$$

The synthetic model allows us to construct a probability distribution for the RUL at any given day d, denoted by ϕ^d. This distribution is a normal distribution centered around the point prediction $RUL_{pred}(t)$ with a standard deviation std(t):

$$\phi^d(t) = N\big(RUL_{pred}(t), \text{std}(t)\big) \qquad (8)$$

The synthetic model serves as a stand-in for actual condition-based monitoring data, which is often scarce or unavailable. By creating a simulated environment, we can test the robustness of our prognostic framework and its underlying assumptions. Furthermore, this model provides a controlled setup to assess the performance of maintenance scheduling algorithms and to investigate the effects of different parameters on the maintenance optimization process. Despite the benefits of using real sensor data for condition monitoring and prognostics, the synthetic model offers a valuable alternative for conducting preliminary analyses.

Ultimately, while the synthetic model provides valuable insights, it is designed to be supplanted by real-life condition-based monitoring systems as they become more prevalent and integrated into wind farm O&M practices.

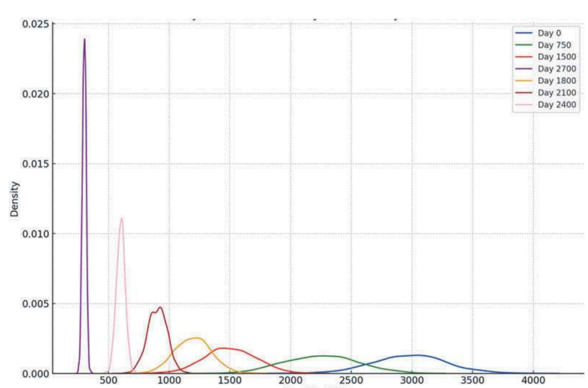

Figure 1. Probability Distributions of Synthetic Daily RUL Predictions.

In Figure 1, we observe the evolution of the probability distributions of the predicted Remaining Useful Life (RUL) at different moments of a component's operational span. This visualization is critical for understanding how the prognostic model's certainty improves as the component ages.

The graph illustrates several Gaussian distributions corresponding to different days in the component's lifecycle. Each curve represents the probability density function $\phi^d(t)$ for the RUL prediction on given days. The values of the days visualized in the graph have been chosen arbitrarily at intervals that give a comprehensive overview of the behavior of the curves during the lifetime of a component, while also highlighting the transition from early uncertainty to later confidence in RUL predictions. As time progresses, these distributions evolve in the following manner:

Early Life (Day 0, Blue Curve): Initially, the RUL distribution is wide with a peak far from zero, indicating that the component has a long expected lifespan ahead. However, the broad spread of the curve reflects significant uncertainty in this early prediction. This uncertainty is due to the lack of operational data and the inherent unpredictability at the beginning of the lifecycle.

Mid Life (Days 750 and 1500, Green and Red Curves): As the component transitions into its midlife, the distributions start to narrow, indicating an increase in confidence regarding the RUL. The peak of the distributions starts to shift left, towards lower RUL values, as the component naturally ages and accumulates wear and tear.

Approaching End of Life (Days 1800 to 2400, Yellow to Purple Curves): As the component nears its end of life, the distributions become increasingly sharper and more skewed towards the left, indicating that the remaining lifespan is diminishing. The peak of these distributions gets closer to zero, and the narrowing of the curves signifies a higher confidence in the RUL prediction. This increased precision is likely due to the accumulation of more significant operational data and wear patterns, allowing the model to make more accurate forecasts.

The sharpening of the distributions towards the end of the component's life is a crucial aspect of the prognostic model. It represents a condition-monitoring framework where, as more operational data becomes available over time, the RUL can be predicted with greater accuracy.

3.2 *Computation of maintenance costs*

Maintenance activities for offshore wind farms, for the purpose of this study, consist of corrective and preventive replacements. The costs associated with these activities are computed by considering various factors such as transportation, labor, materials, and potential downtimes. We disregard major and minor repairs, focusing solely on replacements. Each cost component is detailed below.

The transportation cost is associated with the usage of vessels to carry out maintenance activities. It is computed based on the type of vessel used, the duration of the activity, and the distance to the wind farm. The transportation cost C_{trans} is given by:

$$C_{trans} = C_{mobil} + (F_{consumption} \times D_{travel} \times 2) + (R_{day} \times T_{duration}) \tag{9}$$

Equation (9) includes three elements: C_{mobil} is the mobilization cost i.e. the initial cost to deploy the vessel, $F_{consumption}$ is the fuel consumption, calculated by multiplying the vessel's fuel consumption rate by the travel distance D_{travel} multiplied by two to take into account both travels, the first one to reach the wind turbine and the second one to get back to the onshore base, R_{day} is the operational cost of the vessel per day, multiplied by the duration of the activity $T_{duration}$ expressed in days.

The cost of labor is determined by the number of technicians needed, the duration of the activity, and the hourly rate. The technician cost formula is:

$$C_{tech} = N_{tech} \times R_{hour} \times T_{duration} \tag{10}$$

where C_{tech} is the technician cost, N_{tech} is the number of technicians, R_{hour} is the hourly rate, and $T_{duration}$ is the duration of the maintenance activity in hours.

Downtime costs refer to the loss of revenue due to the turbine being non-operational during maintenance. It is calculated by considering the electricity cost rate, the duration of downtime, and the rated power output of the turbine, the formula is:

$$C_{dt} = C_{el} \times P(v_{mean}) \times T_{duration} \tag{11}$$

where C_{dt} is the downtime cost, C_{el} is the cost of electricity per kWh, T_{dt} is the downtime duration, and $P(v)$ represents the power curve of the turbine i.e. its power output as a function of wind speed, therefore $P(v_{mean})$ is the power output at the average wind speed at the selected location.

The total cost of maintenance is the sum of the replacement material cost which is given, transportation cost, technician cost, and downtime cost. The formula is as follows:

$$C_{maintenance} = C_{material} + C_{trans} + C_{tech} + C_{dt} \tag{12}$$

These computations ensure a comprehensive understanding of the costs involved in the maintenance of offshore wind farms.

3.3 *Expected costs*

Two key cost considerations form the basis of the model: the expected cost of replacement and the expected cost of doing nothing, denoted by

$E_R[C_V(k,t_k)]$ and $E_{DN}[C_V(k,L)]$, respectively. The expected cost of replacement after t_k days is calculated using equation (13) which computes the expected total cost by considering both the risks of failure and the costs associated with preventive actions.

Furthermore, in the offshore wind farm O&M scheduling, downtime can significantly affect the total cost due to lost production. Thus, it is necessary to incorporate the expected cost of downtime losses due to potential unexpected failures, c^V_{dt}, into the optimization model. This cost is associated with the expected production losses when the turbine is unavailable due to the failure of component V, in contrast to the downtime cost computed in Equation 11 which is used to evaluate only the downtime and power losses during the maintenance activity itself.

The expected cost of potential downtime losses is calculated over the time horizon t_k and is a function of the cost of electricity C_{el}, the probability of component V failing at each time i, denoted as $\phi^V_k(i)$, the average power production of the turbine $P(v_{mean})$, and the average electricity market price. The cost is accumulated over all possible failure moments within the planning horizon, weighted by the duration of downtime that would result from a failure at each moment.

$$E_R[C_V(k,t_k)] = c^V_{corrective}\sum_{i=0}^{t_k-1}\phi^V_k(i) + c^V_{preventive}\left(1-\sum_{i=0}^{t_k-1}\phi^V_k(i)\right) + c^V_{dt}\sum_{i=0}^{t_k-1}\phi^V_k(i)(t_k-i-1) \tag{13}$$

8where $E_R[C_V(k,t_k)]$ is the expected cost of replacement after the component V has been used for $k + t_k$ days. $\phi^V_k(i)$ is the probability that the RUL of component V is exactly i days, after being used for k days. $c_{preventive}$ is the cost of preventive maintenance. $c_{corrective}$ is the cost of corrective maintenance, including downtime and potential penalties and the daily cost of downtime losses due to delayed maintenance, c^V_{dt}, is given by the equation:

$$c^V_{dt} = C_{el}\cdot P(v_{mean})\cdot 24 \tag{14}$$

The expected cost of doing nothing denotes the expected cost if no maintenance action is taken within the planning horizon L. Here, the cost is purely the cost of corrective actions, as no preventive maintenance is performed. It is calculated by summing the probabilities of failure for each day within the planning horizon and multiplying by the cost of corrective maintenance. The expected cost of doing nothing if the component is not replaced within the period $[k,k+L]$ is given by:

$$E_{DN}[C_V(k,L)] = c^V_{corrective}\sum_{i=0}^{L-1}\phi^V_k(i) + c^V_{dt}\sum_{i=0}^{L-1}\phi^V_k(i)(L-i-1) \tag{15}$$

3.4 *Expected cost/lifetime ratio*

The model also estimates the expected lifetime for both replacement and doing nothing scenarios.

$$E_R[L_V(k,t_k)] = k + \sum_{i=0}^{t_k-1} i\cdot\phi^V_k(i) + t_k\cdot\left(1-\sum_{i=0}^{t_k-1}\phi^V_k(i)\right) \tag{16}$$

$E_R[L_V(k,t_k)]$ is the sum of the days the component has been in service k, the remaining useful life weighted against its probability distribution $\phi^V_k(i)$, and the additional lifetime t_k if no failure occurs. This gives a comprehensive view of the expected operational life of a component considering both scenarios, failure and no failure within the time to replacement. Furthermore, it accounts for the risk of early interventions and the potential reduction in component life due to the accumulated probability of failure.

$$E_{DN}[L_V(k,L)] = k + \sum_{i=0}^{L-1} i\cdot\phi^V_k(i) + L\cdot\left(1-\sum_{i=0}^{L-1}\phi^V_k(i)\right) \tag{17}$$

$E_{DN}[L_V(k,L)]$ takes into account the component's current service life k and the weighted sum of the remaining useful life throughout the planning horizon L in both scenarios, failure and no failure within the planning horizon.

The decision-making process involves comparing the cost over the expected lifetime for replacement and doing nothing, for this reason we defined C^V_R as the ratio of the expected replacement cost over the expected lifetime and C^V_{DN} as the ratio of the expected cost of doing nothing over the expected lifetime without intervention, offering a perspective on the long-term cost implications of deferring maintenance.

$$C^V_R = \frac{E_R[C_V(k,t_k)]}{E_R[L_V(k,t_k)]} \tag{18}$$

$$C_{DN}^{V}=\frac{E_{DN}[C_V(k,L)]}{E_{DN}[L_V(k,L)]} \tag{19}$$

3.5 *Optimization model*

The optimization model is formulated to determine the optimal time to maintain a component to minimize the total expected cost of maintenance over the expected lifetimes of the components.

The decision variable is a binary variable that indicates whether component V is to be replaced at a specific time s.

$$x_s^V=\begin{cases} 1 & \text{if component V is replaced at time s} \\ 0 & \text{if component V is not replaced at time s} \end{cases} \tag{20}$$

The model aims to minimize the sum of the cost rates over the expected lifetime for all components, providing a decision framework that balances cost with component health and operational effectiveness. The objective function to be minimized is:

$$\min\left[\sum_{V\in V}\left(C_R^V\cdot x_s^V+C_{DN}^V\cdot(1-x_s^V)\right)\right] \tag{21}$$

The model is subject to logical constraints to ensure feasibility:

$$\sum_{s\in S}x_s^V\leq 1 \quad \forall V\in V \tag{22}$$

$$x_s^V\in\{0,1\} \quad \forall V\in V,\forall s\in S \tag{23}$$

Equation 22 ensures that for any given component V, at most one maintenance activity can be scheduled within the planning horizon.

Equation 23 defines the decision variable x_s^V as binary, where $x_s^V=1$ indicates that maintenance is scheduled for component V at time s, and $x_s^V=0$ indicates that no maintenance is scheduled.

Although the model currently focuses on these logical constraints, it is designed to be extensible. Future iterations should include operational constraints to account for the following factors:

Weather Window: Scheduling must consider the availability of suitable weather conditions for safe maintenance operations. The constraint ensures that maintenance is only scheduled when weather conditions are favorable.

$$x_s^V\leq W_s \quad \forall V\in V,\forall s\in S \tag{24}$$

Where W_s is a binary variable indicating if weather conditions are suitable at time s, depending on the available weather forecast and the operational limits of the vessels.

Vessel Capacity and Availability: Maintenance scheduling depends on the availability of vessels with the necessary capacity to transport technicians and equipment to the turbines. This constraint ensures that maintenance is only scheduled when a suitable vessel is available.

$$x_s^V\leq\sum_{j\in J}Y_s^{j^V} \quad \forall V\in V,\forall s\in S \tag{25}$$

Where $Y_s^{j^V}$ is a binary variable representing the availability of vessel j^V at time s, j^V being a vessel with a suitable capacity for carrying out the replacement of component V.

Spare Parts Availability: The availability of necessary spare parts must be assured for scheduled maintenance activities. This constraint ensures that maintenance is only scheduled when the required spare parts are available.

$$x_s^V\leq Z_s^V \quad \forall V\in V,\forall s\in S \tag{26}$$

Where Z_s^V is a binary variable indicating the availability of a spare component V at time s.

Technician Availability: Scheduling must align with the availability of technicians, both in terms of numbers required and their specific skill sets. This constraint ensures that maintenance is only scheduled when the necessary technicians are available.

$$x_s^V\leq T_s^V \quad \forall V\in V,\forall s\in S \tag{27}$$

Where T_s^V is a binary variable representing the availability of technicians with the required skills to replace component V at time s.

By incorporating these additional constraints, the model will more accurately reflect the complexities of real-world offshore wind farm maintenance operations. The integration of these factors would enhance the model's capability to generate schedules that are not only cost-effective but also operationally viable.

The rolling horizon approach updates the scheduling decisions at regular intervals to reflect the current state of the farm and maintenance needs. As new information becomes available, the model recalibrates the schedule, ensuring that it remains responsive to the actual conditions and performance of the wind farm components. The maintenance planning window moves forward with each time step τ, allowing for the reevaluation of maintenance decisions based on the latest data and predictions.

The current day is updated according to:

$$k = k + \tau \tag{28}$$

where d_p is the present day and τ is the time step within the planning horizon L.

Maintenance activities planned until $k + \tau, \tau < L$ are executed according to the updated schedule.

A comprehensive overview of the methodology proposed is presented in 2.

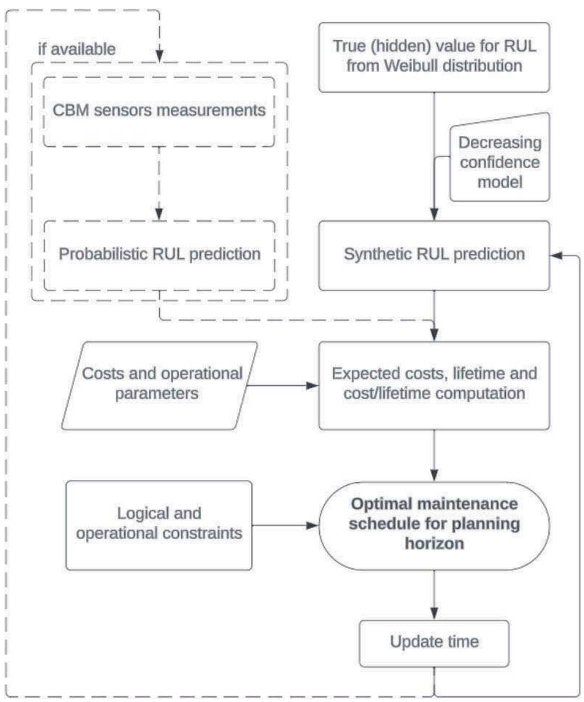

Figure 2. Flowchart of the proposed methodology.

4 CASE SCENARIO DESCRIPTION

In constructing the prognostic-driven optimization model, several assumptions were considered to reduce the complexity of the model.

The first assumption is that only replacement and preventive replacement are considered.

It is then assumed that the wind farm is always accessible and there are no delays or restrictions due to weather or other external factors, reflecting the ideal operational conditions where weather or other environmental factors do not impede maintenance activities. This could be applicable in regions with very stable and predictable weather conditions or where advanced forecasting allows for precise planning around weather constraints.

All necessary resources, including vessels, spare parts, and maintenance crews, are assumed to be available whenever required, aligning with situations where operations are well-funded, and resource management is efficient enough to maintain a surplus or quick availability of resources, possibly in smaller wind farms or farms close to supply bases.

Finally, only one maintenance activity can be performed at a time, precluding the possibility of simultaneous maintenance actions, which applies to a strategy that does not include opportunistic grouping of maintenance activities.

These assumptions could potentially lead to an underestimation of costs and scheduling times, as they do not account for delays and unavailability that often occur in real-world scenarios. While they allow for the development of an optimized maintenance schedule under ideal conditions, the actual implementation may require adjustments to account for the unpredictability of real-life operations and are left for further development of the model.

The proposed framework is applied to a single wind turbine located in an offshore wind farm characterized by specific environmental and operational conditions. Having assumed a strategy that does not capitalize on grouping maintenance tasks, addressing turbines individually becomes not just a simplification for modeling purposes, but a practical approach.

Cost data and failure rates for each component, as well as the duration of corrective and preventive replacements and the number of technicians required are presented in Table 6-8 and are taken or adjusted from (Li et al. 2022), (Golestani et al. 2023) and (Carroll et al. 2017), whereas other values are reasonably assumed and presented for the replicability of the model.

4.1 *Operational parameters*

A wind turbine consists of several critical components such as blades, bearings, gearbox, generator, and shaft. A detailed breakdown of these components includes their failure distribution parameters (shape and scale), material costs for preventive and corrective replacements, and the time required for each task type as presented in Table 6.

Table 6. Component maintenance and vessel assignments.

Component	Shape	Scale	Material Cost (*$*)	Time (*hrs*)	Assigned Vessel
Blades	3	3000	90,000	288	HLV
Bearings	2	3750	10,000	36	HLV
Gearbox	3	2400	230,000	231	HLV
Generator	2	3300	60,000	81	HLV
Shaft	1.5	7300	13,000	57	HLV

The key specifications of the wind turbine are included in Table 7.

Table 7. Turbine specifications.

Specification	Value
Rated Power Output (*MW*)	3
Cut-in wind speed (*m*/*s*)	3
Cut-out Wind Speed (*m*/*s*)	25
Rated Wind Speed (*m*/*s*)	12
Hub Height (*m*)	90

These specifications are used for determining the turbine's performance and for the computation of downtime losses. For the O&M environment, the operational parameters presented in Table 8 are considered:

The case scenario presented provides a comprehensive view of the operational, maintenance, and logistical aspects of O&M for an offshore wind turbine.

Table 8. Operational parameters.

Parameter	Value
Mean Wind Speed (*m*/*s*)	8.5
Cost of Electricity ($/*kWh*)	0.15
Distance from Shore (*km*)	25
Planning horizon L (*days*)	180
Time step τ (τ)	1
Technicians for Replacement	8
Hourly Rate for Technicians Hourly Rate for Technicians ($/*h*)	60
Vessel Day rate ($)	75000
Vessel mobilisation cost ($)	200000
Fuel consumption (*L*/*km*)	200
Vessel mean speed (*km*/*h*)	12

5 RESULTS

The implementation of MPC principles within our O&M scheduling optimization framework is illustrated in Figure 3 and 4, which display the updated results over successive weeks as the optimization model is rerun with new data inputs, simulating a rolling horizon approach characteristic of MPC strategies. These figures reveal the evolving decision-making process, where maintenance schedules are adaptively adjusted based on updated probabilistic RUL forecasts, reflecting MPC's inherent adaptivity and reactivity to system feedback.

On week 166, as seen in 3, the maintenance decision aligns with the initial prognosis, suggesting a conservative approach with an earlier maintenance day proposed relative to the MPC's rolling horizon forecast. As the weeks progress, on week

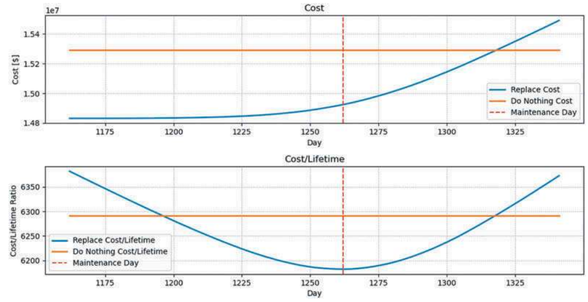

Figure 3. Optimization result on week 166, proposed replacement day: 1262.

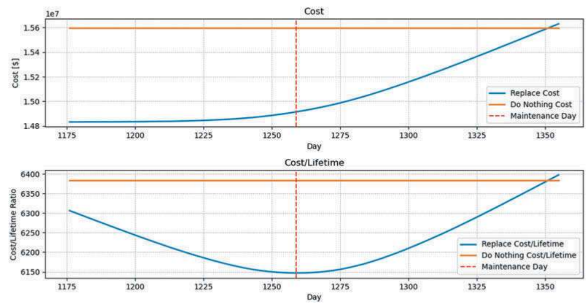

Figure 4. Optimization result on week 168, proposed replacement day: 1259.

168 a shift in the proposed maintenance day is noticed 4, illustrating the model's responsiveness to updated component health information. This dynamic adjustment exemplifies MPC's predictive control feature, which dictates that actions are based not only on the current state but also on predicted future states of the system.

The analysis of the expected costs and cost to lifetime ratios provides a clear indication that timely, preventive maintenance is financially prudent in the long run. The results of this model highlight the importance of scheduling maintenance before the probability of failure and the associated costs increase.

When compared to the cost of corrective maintenance, represented by the Expected cost of doing nothing, planning the replacement based on RUL prognosis can lead to a potential decrease in maintenance costs that ranges between 1 and 15%, depending on the component that requires maintenance and other operational parameters.

When focusing only on potential downtime losses the cost decrease becomes more significant, which is obvious given that other cost items in this study are assumed to be fixed and do not depend on the scheduling of maintenance activities, such as the cost of materials for replacements, the cost of technicians and the high mobilisation costs of the vessels.

The optimization results, therefore, confirm the suitability of incorporating MPC strategies within the O&M scheduling for offshore wind farms. By leveraging the predictive and adaptive capabilities of

MPC, our framework achieves a dynamic and cost-efficient schedule that minimizes the expected total O&M costs while maximizing the utilization rate of each component.

6 CONCLUSIONS

This study has provided a comprehensive analysis of an innovative prognostic-driven scheduling model for offshore wind farm operation and maintenance (O&M). The results demonstrate the model's potential to minimize O&M costs while maximizing equipment utilization rate. The integration of probabilistic remaining useful life (RUL) predictions within a mixed-integer linear programming (MILP) model underscores the practical utility of condition-based maintenance (CBM) strategies over traditional fixed interval maintenance schedules.

The strength of this model lies in its ability to use prognosis information about the RUL of critical components to optimize maintenance schedules accordingly. This adaptive scheduling approach mitigates the risk of unexpected failures, enhancing the overall reliability and efficiency of the system. By doing so, the model not only ensures the highest utilization rate of each component but also minimizes downtime, which is a significant cost driver in offshore wind farm operations.

The use of probabilistic methods to forecast component failure provides a more dynamic and responsive approach to maintenance scheduling, allowing for adjustments based on real-time data and predictions. The integration of MPC principles into the prognostic-driven scheduling model has been instrumental in demonstrating the model's capacity for adaptive and dynamic decision-making, critical for optimizing O&M. The rolling horizon approach, characteristic of MPC, has enabled the model to adjust maintenance schedules in response to continually updated RUL forecasts.

However, the model is not without its limitations. The assumption of constant accessibility and the availability of resources does not reflect the complex reality of offshore wind farm environments, where conditions are highly dynamic and often unpredictable. Weather conditions, logistical constraints, and limited resources can lead to significant deviations from the model's recommendations. Furthermore, the assumption of performing only one maintenance activity at the time does not reflect the most recent advancements in opportunistic maintenance strategies, whose advantages have been highlighted in studies such as (Li et al. 2021) and (Li et al. 2020). In the future, the integration of opportunistic maintenance strategies in the model might reveal additional benefits of a prognostic-driven strategy for O&M scheduling.

Another limitation is the model's reliance on synthetic data for RUL predictions, which, while useful in the absence of actual sensor data, may not fully capture the nuances of real-world operational conditions. The adaptation of the model to utilize real-life data from monitoring systems could enhance its accuracy and reliability. For future developments, research could focus on relaxing some of the model's simplifying assumptions to better reflect the operational challenges faced by offshore wind farms. Incorporating weather prediction models and stochastic resource availability could provide a more realistic maintenance scheduling framework. Additionally, exploring the potential for opportunistic maintenance where multiple maintenance activities are performed simultaneously could further optimize resource utilization and reduce operational costs.

In conclusion, the proposed prognostic-driven scheduling model serves as a starting point for further research on O&M scheduling for offshore wind farms. The model's integration of MPC principles, CBM strategies and probabilistic RUL predictions, make it a promising solution to the complex challenge of maintaining offshore wind farms. Future research should aim to build upon this foundation, refining the model to account for the full spectrum of real-world operational variables and constraints.

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REFERENCES

Ade Irawan, C., S. Starita, H. K. Chan, M. Eskandarpour, & M. Reihaneh (2023). Routing in offshore wind farms: A multi-period location and maintenance problem with joint use of a service operation vessel and a safe transfer boat. *European Journal of Operational Research 307*(1), 328–350.

Camci, F., K. Medjaher, V. Atamuradov, & A. Berdinyazov (2019, OCT 3). Integrated maintenance and mission planning using remaining useful life information. *Engineering Optimization 51*(10), 1794–1809.

Carroll, J., A. McDonald, I. Dinwoodie, D. McMillan, M. Revie, & I. Lazakis (2017, FEB). Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations. *Wind Energy 20*(2), 361–378.

Chen, C., C. Wang, N. Lu, B. Jiang, & Y. Xing (2021). A data-driven predictive maintenance strategy based on accurate failure prognostics. *Eksploatacja i Niezawodnosc-Maintenance and Reliability 23*(2), 387–394.

Dai, L., M. Stålhane, & I. B. Utne (2015). Routing and scheduling of maintenance fleet for offshore wind farms. *Wind Engineering 39*(1), 15–30.

Dawid, R., D. McMillan, & M. Revie (2018, SEP). Decision support tool for offshore wind farm vessel routing under uncertainty. *Energies 11*(9).

de Pater, I. & M. Mitici (2021, OCT). Predictive maintenance for multi-component systems of repairables with remaining-useful-life prognostics and a limited stock of spare components. *Reliability Engineering & System Safety* 214.

de Pater, I., A. Reijns, & M. Mitici (2022, MAY). Alarm-based predictive maintenance scheduling for aircraft engines with imperfect remaining useful life prognostics. *Reliability Engineering & System Safety* 221.

Fox, H., A. C. Pillai, D. Friedrich, M. Collu, T. Dawood, & L. Johanning (2022, JAN). A review of predictive and prescriptive offshore wind farm operation and maintenance. *Energies 15*(2).

Gogu, C. (2018). Prognostics and health management: current state-of-the-art for optimizing aircraft structural maintenance. In *2018 19th International conference on thermal, mechanical and multi-physics simulation and experiments in microelectronics and Microsystems (EUROSIME)*. 19th International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems (EuroSimE), Toulouse, FRANCE, APR 15–18, 2018.

Golestani, N., E. Arzaghi, R. Abbassi, V. Garaniya, & H. Meng (2023). A system dynamics model of offshore wind farm degradation: Enabling operation and maintenance planning under foreseen asset management impacts. *Applied Ocean Research 138*, 103685.

Irawan, C. A., D. Ouelhadj, D. Jones, M. Stalhane, & I. B. Sperstad (2017, JAN 1). Optimisation of maintenance routing and scheduling for offshore wind farms. *European Journal of Operational Research 256*(1), 76–89.

Kou, L., Y. Li, F. Zhang, X. Gong, Y. Hu, Q. Yuan, & W. Ke (2022, APR). Review on monitoring, operation and maintenance of smart offshore wind farms. *Sensors 22*(8).

Lazakis, I. & S. Khan (2021, APR 1). An optimization framework for daily route planning and scheduling of maintenance vessel activities in offshore wind farms. *Ocean engineering* 225.

Le, B. & J. Andrews (2016, APR). Modelling wind turbine degradation and maintenance. *Wind Energy 19*(4), 571–591.

Lee, J. & M. Mitici (2023, FEB). Deep reinforcement learning for predictive aircraft maintenance using probabilistic remaining-useful-life prognostics. *Reliability Engineering & System Safety* 230.

Li, M., X. Jiang, J. Carroll, & R. R. Negenborn (2022, SEP 1). A multi-objective maintenance strategy optimization framework for offshore wind farms considering uncertainty. *Applied Energy* 321.

Li, M., X. Jiang, & R. R. Negenborn (2021, JUL 1). Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch. *Ocean Engineering* 231.

Li, M., M. Wang, J. Kang, L. Sun, & P. Jin (2020, NOV 15). An opportunistic maintenance strategy for offshore wind turbine system considering optimal maintenance intervals of subsystems. *Ocean Engineering* 216.

Li, Z., J. Guo, & R. Zhou (2016). Maintenance scheduling optimization based on reliability and prognostics information. In *Annual reliability and maintainability symposium 2016 proceedings*, Reliability and Maintainability Symposium. Amer Inst Aeronaut & Astronaut; Amer Soc Qual Control Elect Div; IEEE; Ints Environm Sci & Technol; Inst Ind Engineers; SAE Int; SOLE; Soc Reliabil Engineers; Syst Safety Soc; American Society of Quality Control Reliabil Div. Annual Reliability and Maintainability Symposium, Tucson, AZ, Jan 25-28, 2016.

Liu, L., Y. Fu, S. Ma, L. Huang, S. Wei, & L. Pang (2019, OCT 28). Optimal scheduling strategy of o&m task for owf. *IET Renewable Power Generation 13*(14), 2580–2586.

May, A., D. McMillan, & S. Thons (2015, NOV). Economic analysis of condition monitoring systems for offshore wind turbine sub-systems. *IET Renewable Power Generation 9*(8, SI), 900–907. Annual Conference of the European-Wind-Energy-Association (EWEA), Barcelona, SPAIN, MAR, 2014.

Mayne, D., J. Rawlings, C. Rao, & P. Scokaert (2000). Constrained model predictive control: Stability and optimality. *Automatica 36*(6), 789–814.

Mazidi, P., Y. Tohidi, & M. A. Sanz-Bobi (2017, MAR). Strategic maintenance scheduling of an offshore wind farm in a deregulated power system. *Energies 10*(3).

Mitici, M., I. de Pater, A. Barros, & Z. Zeng (2023, JUN). Dynamic predictive maintenance for multiple components using data-driven probabilistic rul prognostics: The case of turbofan engines. *Reliability Engineering & System Safety* 234.

Nachimuthu, S., M. J. Zuo, & Y. Ding (2019, APR 2). A decision-making model for corrective maintenance of offshore wind turbines considering uncertainties. *Energies 12*(8).

National Renewable Energy Laboratory (2022). Offshore wind energy market assessment 2022. National Renewable Energy Laboratory.

NREL (2023). Annual technology baseline.

Pattison, D., M. S. Garcia, W. Xie, F. Quail, M. Revie, R. I. Whitfield, & I. Irvine (2016, MAR). Intelligent integrated maintenance for wind power generation. *Wind Energy 19*(3), 547–562.

Raknes, N. T., K. Odeskaug, M. Stalhane, & L. M. Hvattum (2017, MAR). Scheduling of maintenance tasks and routing of a joint vessel fleet for multiple offshore wind farms. *Journal of Marine Science and Engineering 5*(1).

Ren, Z., A. S. Verma, Y. Li, J. J. E. Teuwen, & Z. Jiang (2021, JUL). Offshore wind turbine operations and maintenance: A state-of-the-art review. *Renewable & Sustainable Energy Reviews* 144.

Rodrigues, L. R., J. P. P. Gomes, F. A. S. Ferri, I. P. Medeiros, R. K. H. Galvao, & C. L. Nascimento Junior (2015, DEC). Use of phm information and system architecture for optimized aircraft maintenance planning. *IEEE Systems Journal 9*(4), 1197–1207.

Safaei, F., E. Chatelet, & J. Ahmadi (2020, MAY). Optimal age replacement policy for parallel and series systems with dependent components. *Reliability Engineering & System Safety* 197.

Sarker, B. R. & T. Ibn Faiz (2016, JAN). Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy. *Renewable Energy 85*, 104–113.

Sinha, Y., J. A. Steel, J. A. Andrawus, & K. Gibson (2013, DEC). A smart software package for maintenance optimisation of offshore wind turbines. *Wind Engineering 37*(6), 569–577.

Stock-Williams, C. & S. K. Swamy (2019, APR). Automated daily maintenance planning for offshore wind farms. *Renewable Energy 133*, 1393–1403.

Tseremoglou, I., P. J. van Kessel, & B. F. Santos (2023, FEB). A comparative study of optimization models for condition-based maintenance scheduling of an aircraft fleet. *Aerospace 10*(2).

Turnbull, A. & J. Carroll (2021, AUG). Cost benefit of implementing advanced monitoring and predictive maintenance strategies for offshore wind farms. *energies 14*(16).

US Department of Energy (2022). Offshore wind market report: 2022 edition.

van Bussel, G. & C. Schöntag (1997). Operation and maintenance aspects of large offshore windfarms. In *Proceedings of the 1997 European Wind Energy Conference*, pp. 272–275.

Van Horenbeek, A. & L. Pintelon (2012a). A dynamic prognostic maintenance policy for multi-component systems. *IFAC proceedings* Volumes *45*(31), 115–120. 2nd IFAC Workshop on Advanced Maintenance Engineering, Services and Technology.

Van Horenbeek, A. & L. Pintelon (2012b). Optimal prognostic maintenance planning for multi-component systems. In C. Berenguer, A. Grall, and C. Soares (Eds.), *Advances in Safety, reliability and risk management*, pp. 910–917. Univ Technologie Troyes; European Safety & Reliabil Assoc; Reg Champagne Ardenne; Ville Troyes; Ctr Natl Rech Sci; Electricite France; GIS 3SGS; Det Norske Veritas; Grand Troyes; GDR MACS CNRS; MAIF. European Safety And Reliability Conference (ESREL), FRANCE, SEP 18-22, 2011.

Vianna, W. O. L. & T. Yoneyama (2018, JUN). Predictive maintenance optimization for aircraft redundant systems subjected to multiple wear profiles. *IEEE Systems Journal 12*(2), 1170–1181.

Zhuang, L., A. Xu, & X.-L. Wang (2023, JUN). A prognostic driven predictive maintenance framework based on bayesian deep learning. *Reliability Engineering & System Safety* 234.