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Research paper

Stochastic optimization of predictive maintenance scheduling for offshore wind farms

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ABSTRACT

This paper presents a stochastic optimization model for predictive maintenance scheduling in offshore wind farms. The proposed model integrates probabilistic Remaining Useful Life (RUL) prognosis with mathematical optimization and Model Predictive Control (MPC) techniques that updates RUL beliefs with new prognostic measurements at each epoch to dynamically adjust maintenance decisions. Unlike conventional scheduling methods that rely on static age thresholds, our approach uses real-time prognostics to improve cost efficiency and reduce downtime. A case study on 50 wind turbines demonstrates that dynamically adapting maintenance schedules using prognostics reduces O&M expenses by 8.7%, primarily through significant reductions in downtime, compared to traditional methods.

1. Introduction

Offshore wind energy is rapidly expanding, but operations and maintenance (O&M) remains a major challenge and cost driver. O&M activities for offshore turbines are significantly more expensive and complex than those onshore; for example, an average fixed-bottom offshore wind project incurs about 30.3 EUR/MWh in O&M costs, compared to roughly 12.1 EUR/MWh for onshore wind (Fox et al., 2022). In fact, O&M expenditures can comprise around one-third of an offshore wind farm's total lifetime costs. These high costs are driven by the harsh marine environment, accessibility constraints, and the scale of offshore equipment, making reliability and efficient maintenance crucial for reducing the levelized cost of energy. Improving maintenance strategies to curb unplanned downtime and optimize interventions is therefore essential to enhance the economic viability of offshore wind power.

Maintenance strategies in the wind industry range from reactive (run-to-failure) approaches to proactive schemes (Fox et al., 2022). Historically, many offshore wind operators relied on reactive or time-based periodic maintenance, either fixing components only after a breakdown or replacing them at fixed intervals, but these traditional approaches have clear drawbacks. Reactive maintenance can maximize component life utilization, yet it often leads to catastrophic failures with lengthy downtime and high repair costs, especially in offshore conditions where repairs are slow and weather-dependent. Strict periodic maintenance, on the other hand, may replace parts too early (wasting useful life) or too late (risking unexpected failure) if actual degradation deviates from assumed schedules. Opportunistic maintenance has emerged as an intermediate strategy: it seeks to perform preventive tasks whenever a convenient opportunity arises (e.g., grouping repairs during a scheduled vessel visit or favorable weather window) to reduce overall costs (Fox et al., 2022). While opportunistic scheduling mitigates some inefficiencies, it still does not fully account for the actual condition of each component.

With advances in turbine monitoring and prognostics, the industry is moving toward more condition-based and predictive maintenance approaches (Fox et al., 2022). In condition-based maintenance (CBM), real-time sensor data is continuously analyzed to assess equipment health; maintenance is triggered when measured parameters exceed certain thresholds or anomaly criteria. Predictive maintenance extends this by using operational data and analytics to forecast failures before they occur, enabling just-in-time interventions. The most recent evolution is prescriptive maintenance, which not only predicts impending failures but also recommends optimized O&M actions. These proactive strategies are particularly compelling for offshore wind, where unplanned failures are extremely costly and access is limited by weather and vessel availability.

Recent research efforts have started to integrate prognostic information into maintenance decision-making to capture the dynamic nature of component degradation. Traditionally, the tasks of predicting failures and planning maintenance were handled separately: many studies focused on RUL prognostics in isolation, while others optimized maintenance schedules assuming static failure distributions (Zhuang et al., 2023). To address this shortcoming, newer approaches aim to

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Table 1
Acronyms and nomenclature.

Symbol	Definition
BDL	Bayesian Deep Learning
CBM	Condition-Based Monitoring
CNN	Convolutional Neural Networks
CTV	Crew Transfer Vessel
HLV	Heavy Lift Vessel
LSTM	Long Short-Term Memory
MILP	Mixed-Integer Linear Programming
MPC	Model Predictive Control
O&M	Operation and Maintenance
RES	Renewable Energy Sources
RUL	Remaining Useful Life
SOV	Service Operation Vessel
VRP	Vehicle Routing Problem
α	Age-reduction coefficient
$c_{\text{corrective}}$	Corrective maintenance cost
c_{replace}	Replacement cost
C_{dt}	Downtime cost
C_{el}	Cost of electricity
C_{tech}	Cost of technicians
$C_{\text{mobil}}^{j(c,a)}$	Mobilization cost of vessel $j(c,a)$
$C_{\text{trans}}^{j(c,a)}$	Transportation cost for vessel $j(c,a)$ and activity a on component c
D_{travel}	Travel distance
DF	Discount factor
$\mathbb{E}[\text{Life}(k,d)]$	Expected lifetime
$F_{\text{cons}}^{j(c,a)}$	Fuel consumption rate of vessel $j(c,a)$
$f(d;\lambda,k)$	Probability density function of Weibull distribution
$j(c,a)$	Vessel type required for activity a on component c
k	Shape parameter of Weibull distribution
λ	Scale parameter of Weibull distribution
$M(k)$	Availability of technicians on day k
N_{tech}	Number of technicians
$P(v_{\text{mean}})$	Power output at average wind speed v_{mean}
$R_{\text{day}}^{j(c,a)}$	Daily rate of vessel $j(c,a)$
R_{hour}	Hourly rate of technicians
RUL_{pred}	Predicted remaining useful life
RUL_{true}	True remaining useful life
$S(k)$	Availability of spare parts on day k
$T(c,a)$	Hours required for maintenance activity a on component c
T_{dt}	Downtime (days)
T_{elapsed}	Time since beginning of operations (days)
$W(k)$	Availability of operational hours on day k
$x_{c,a}(k)$	Binary decision: perform activity a on component c at day k
η	Expected RUL (years)
ϕ^k	Probability distribution for RUL on day k

tightly couple prognostics with O&M planning so that maintenance can be dynamically adjusted as component health evolves (Vianna and Yoneyama, 2018; Lee and Mitici, 2023; Jain et al., 2021). This allows decisions to be made online using the latest available health data.

Several studies have demonstrated the potential benefits of such integration, confirming that maintenance planning is increasingly moving toward tighter integration with asset condition information and dynamic operational factors. For example, Ying et al. (2026b) highlight the value of coupling condition assessment with opportunistic maintenance planning while accounting for offshore operational drivers such as environmental conditions, electricity prices, resource constraints, and wind-farm layout. In parallel, Ying et al. (2025) explicitly frame opportunistic maintenance in terms of subsystem fault-chain relationships, highlighting that dependencies among subsystems can materially affect maintenance timing and grouping decisions. To address the dynamic update of maintenance timing and action selection as new prognostic information becomes available, Borsotti et al. (2024) present a predictive maintenance model that integrates probabilistic RUL forecasts into a rolling optimization framework, reducing O&M costs by 8.7% compared to age-based methods. Uncertainty in prognostic information is considered by He et al. (2025), addressing biased and incomplete prognostics using a Bayesian calibration strategy for offshore wind. Finally, Xie et al. (2020) propose a predictive-opportunistic maintenance approach that incorporates lead-time and task dependency, achieving cost savings of up to 39%. These examples underscore that integrating RUL information into maintenance planning can significantly reduce downtime and costs in offshore wind operations. This strengthens the case for moving beyond static or purely age-based maintenance logic.

However, several limitations remain in current work. Most existing models either assume simplified binary decisions (maintain or not) as in Zhuang et al. (2023), Lee and Mitici (2023), do not fully integrate with vessel logistics as in Raknes et al. (2017), or fail to update decisions dynamically as degradation evolves. Others focus solely on maintenance routing assuming fixed task lists, for example (Lazakis and Khan, 2021). A holistic framework that links RUL-based prognosis, dynamic optimization, and marine logistics is still lacking.

In this paper, we address this gap by proposing a tactical, closed-loop maintenance planning framework that integrates probabilistic RUL estimates with stochastic optimization to schedule opportunistic maintenance in offshore wind farms. We embed a probabilistic representation of the RUL within a receding-horizon MPC loop in which new prognostic measurements update the belief state and its uncertainty contracts over time, and the tactical plan is repeatedly re-optimized under these updated beliefs. Finally, we link offshore feasibility inputs to tactical decisions by incorporating weather-driven accessibility, enabling the planner to jointly select maintenance timing and action types under uncertainty. Overall, these elements establish a closed-loop prognostics-informed tactical planner that reduces downtime and total O&M cost under offshore operational constraints.

The list of acronyms and nomenclature can be found in Table 1, and the remainder of this paper is structured as follows: Section 2 reviews related literature. Section 3 details the proposed methodology. Section 4 describes the case study setup. Section 5 presents the results. Finally, Section 6 summarizes the conclusions and outlines future work.

2. Literature review

In this section, we first describe prognostic models, what kind of information they provide, their limitations, and how prognosis has been used to improve maintenance scheduling. To do that, we explore methodologies from various industries and highlight the gap in the integration of prognostic information into O&M models for offshore wind.

At the moment, much research is in progress to create models and develop tools to assess the current and future state of health of components. For example, sensor-based monitoring and the use of data-analytic techniques have improved failure prognosis (Bhuria et al., 2024) by collecting and analyzing real-time information from sensors and making predictions on the future state of health of the system, allowing for timely maintenance actions (Kou et al., 2022; Le and Andrews, 2016).

Incorporating Prognostics and Health Management (PHM) information into O&M planning models offers significant potential for improving maintenance strategies. Ideally, predictive models like CBM and data-driven prognostics should be integrated into scheduling decisions to enable timely and cost-effective interventions. However, their practical implementation faces substantial challenges. Across works that treat predictive maintenance, a clear theme is the coupling of prognostic outputs with maintenance decision, using prognostics to trigger or optimize maintenance timing rather than following fixed schedules. For instance, prognostic alerts or alarms are used by de Pater et al. (2022) and da Costa et al. (2023) to signal when an asset likely needs attention. Others feed continuous-valued RUL estimates into optimization algorithms (de Pater and Mitici, 2021; Zhuang et al., 2023) or into learned policies (Lee and Mitici, 2023).

The cost/benefit trade-off of acting on prognostics is a recurring consideration: (Chen et al., 2021) explicitly computes it via an online cost evaluation, Jain et al. (2021) incorporates it in their objective function, and Vianna and Yoneyama (2018) includes operational penalty costs in their optimization. All these studies find that using prognostic info yields significant improvements such as lower maintenance costs, fewer failures, or higher availability, validating the core premise of predictive maintenance.

In general, the information provided by prognostic models consists in an estimated time to failure and an associated confidence limit (Sikorska et al., 2011), although there are instances where only the point prediction is used to set a threshold for initiating a maintenance cycle as in J. He et al. (2023), where the net expected revenue is maximized for multi-component systems by optimizing the RUL percentage that triggers the replacement of the component.

One of the issues with integrating prognostic information in O&M models is the scarce availability of real-life prognostics data, which has been addressed in works such as (Borsotti et al., 2024) and R. He et al. (2023), by constructing a synthetic dataset of RUL prognostic data with a pre-generated prediction error, simulating an increasing confidence in the predictions as more Condition Monitoring (CM) data becomes available in time.

The presence of incomplete and uncertain prognostic information also poses a significant challenge, He et al. (2025) propose a probabilistic framework that compensates for it by calculating the expected cost of different maintenance actions based on the predicted RUL of components considering its related uncertainty.

Many authors acknowledge that prognostics are not perfect and have built-in ways to handle uncertainty. A common approach is to use probabilistic RUL predictions (distributions or confidence bounds) instead of single-point estimates. Lee and Mitici (2023) uses Convolutional Neural Networks (CNN), Zhuang et al. (2023) uses Bayesian Deep Learning (DL), and Jain et al. (2021) adopts Weibull Recurring Neural Networks (RNN), to output an entire RUL distribution. This allows decisions to be made with risk awareness, e.g. scheduling earlier if the risk of failure is high. Threshold-based policies with safety margins are another technique: (de Pater et al., 2022) triggers an alarm only when the predicted RUL falls below a conservative threshold, explicitly padding for error. Camci et al. (2019) and Vianna and Yoneyama (2018) embed reliability constraints (like *failure probability* $> X\%$) to ensure a conservative buffer against prognostic errors.

An insight from (Jain et al., 2021) is that the optimal maintenance timing itself should adapt as prognostic uncertainty evolves. Early on, when predictions are uncertain, a policy might schedule maintenance a bit early (to be safe), but as more data improves the prediction, the policy can afford to push maintenance closer to failure.

Optimization models such as (de Pater et al., 2022; de Pater and Mitici, 2021; Zhuang et al., 2023; Camci et al., 2019; Vianna and Yoneyama, 2018) typically use PHM inputs as fixed (sometimes stochastic) parameters, and solve over the long-term horizon for the maintenance plan that minimizes cost or maximizes availability. They guarantee optimality under the assumptions made, and can naturally handle constraints (spare inventory, maintenance crew availability, etc.) by inclusion in the optimization formulation.

In order to take into account new information about the failure dynamics of the critical components, O&M planning models should integrate new operational data to update the maintenance strategy, as seen in Li (2023). Approaches such as Model Predictive Control (MPC), for example, can enable dynamic scheduling by continuously updating maintenance plans based on real-time component degradation data, as in Borsotti et al. (2024), where probabilistic RUL predictions are used to evaluate the expected cost of performing different maintenance tasks. Similarly, in Kong and Liu (2025), a closed-loop MPC framework that accounts for probabilistic fatigue degradation and inspection outcomes is presented.

In recent offshore wind O&M optimization works, offshore operational mechanisms can be modeled explicitly, for example, Si et al. (2025b) propose a resource-centered maintenance strategy that leverages wind-wave information to estimate vessel accessibility and quantify maintenance opportunities linked to low-wind periods, while also accounting for key offshore resource drivers such as wave conditions, vessel fleet characteristics, and port-related limitations. In a different paper (Si et al., 2025a) the authors further develop a holistic opportunistic maintenance framework that distinguishes internal and external maintenance opportunities and explicitly links weather (wind speed and wave height) to access feasibility; they also frame offshore O&M decision-making as the combination of tactical decision support and operational maintenance strategy. Along the same line, recent work has also emphasized that environmental uncertainty itself deserves explicit treatment within offshore maintenance models. In particular, Ying et al. (2026a) show the relevance of representing uncertain environmental conditions as a dedicated input to maintenance planning. These contributions motivate representing (a) weather-driven accessibility and (b) seasonality in expected production loss when developing tactical, rolling-horizon maintenance planners for offshore wind farms. In the present study, this perspective is adopted through a decision-oriented representation of weather uncertainty, where offshore conditions are translated into accessibility information that can be embedded directly within a prognostics-informed rolling-horizon optimizer.

In reviewing the current state of predictive maintenance, it is evident that significant advancements have been made, although most research was developed within other industrial contexts and do not translate directly to the offshore wind sector, for example, the predictive scheduling approaches reviewed, such as (de Pater et al., 2022; de Pater and Mitici, 2021), only consider binary maintenance decisions of whether to maintain or not, neglecting diverse actions: minor, major repairs, and replacements.

On the other hand, current maintenance scheduling approaches for offshore wind farms remain fragmented, often separating strategical and tactical planning from short-term operational execution, relying on fixed thresholds or time intervals to trigger maintenance actions. Most existing models do not incorporate prognostic information and do not adapt maintenance plans in response to changes in the state of the system.

Therefore, there remains a gap in providing a dynamic, closed-loop framework that integrates real-time prognostic data to plan maintenance tasks for offshore wind farms, which we want to fill.

To tackle these challenges, we propose a closed-loop stochastic optimization model that integrates probabilistic RUL prognosis into tactical and operational maintenance planning. Using a MPC approach, our framework continuously updates component state observations, dynamically adapting maintenance decisions in response to evolving system conditions and uncertainties. Furthermore, our model explicitly incorporates offshore-specific logistical and weather constraints, diverse maintenance action options (minor repairs, major repairs, replacements), and is flexible enough to integrate prognostic information from generic models, synthetic datasets, or actual operational data.

In the following section we explain in detail the methodology implemented in the proposed model.

3. Methodology

In this section, we present a stochastic optimization framework for predictive maintenance scheduling in offshore wind farms, integrating probabilistic RUL prognostics with a closed-loop MPC strategy, dynamically updating maintenance schedules based on real-time prognostic data and operational constraints.

First, we describe our MPC-based rolling horizon approach, detailing how probabilistic RUL predictions inform both medium-term tactical decisions and short-term operational scheduling adjustments. Next, we explain the probabilistic modeling of RUL, including the generation of synthetic prognostic data and the incorporation of uncertainty. We also introduce an opportunistic maintenance strategy, demonstrating how the model effectively groups maintenance tasks to optimize resource utilization, particularly vessel selection. Then, we detail the maintenance model used, explaining how the state of each component is updated following different maintenance actions, the calculation of the expected lifetime of the components and the expected maintenance costs, considering material expenses, labor, downtime, and transportation. Finally, we present the mathematical formulation of our optimization model, incorporating constraints related to logistics, resource availability, and real-time prognostic updates, thus bridging tactical planning and short-term execution.

3.1. RUL prognostics modeling

The prognostic information used consists in a point prediction for the RUL (RUL_{pred}) of every critical component of the wind farm, and a measure of the uncertainty related to this prediction.

On the day of the observation k, we access the probability density function $\phi_k(d)$ which denotes the probability of the component failing at any given day d of the planning horizon, it indicates the belief at epoch k over failure day d:

$$RUL_{\text{pred}}(k) = RUL_{\text{true}}(k) + e(k) \tag{1}$$

$$e(k) \sim \mathcal{N}\big(0,\, std^2(k)\big) \tag{2}$$

$$\phi_k(d) = \mathcal{N}\big(RUL_{\text{pred}}(k),\, std^2(k)\big), \quad d \geq 0 \tag{3}$$

The distribution $\phi_k(\cdot)$ above is a continuous probability density over the (nonnegative) time-to-failure in days. However, the scheduling model is solved on a daily time grid. Therefore, we discretize the continuous belief into a probability mass function over day-bins. Let T_f denote the random time-to-failure (days) at epoch k with density $\phi_k(t)$ and cumulative distribution function $F_k(t) = \int_0^t \phi_k(\tau)\, d\tau$. For each integer day-bin $i \in \{0, \dots, H-1\}$ (with H the prediction horizon in days), we define the discrete failure probability as

$$p_k(i) \;=\; \mathbb{P}\big(T_f \in [i,\, i+1)\big) \;=\; \int_i^{i+1} \phi_k(t)\, dt \;=\; F_k(i+1) - F_k(i). \tag{4}$$

All summations over failure probabilities within the MILP (e.g., survival up to day d and expected downtime terms) use the discrete pmf $\tilde{p}_k(i)$, rather than the continuous density $\phi_k(\cdot)$, ensuring a consistent transition from continuous prognostic outputs to discrete-time decision-making.

The true value of RUL_{true} is sampled randomly from a Weibull distribution, defined in (5).

$$f(d; \lambda, \alpha) = \frac{\alpha}{\lambda}\Big(\frac{d}{\lambda}\Big)^{\alpha-1} e^{-(\frac{d}{\lambda})^{\alpha}} \tag{5}$$

where d is the time in days since the observation day, λ and α are the scale and shape parameter respectively. The sampling of RUL_{true} is done using the inverse transform method:

$$RUL_{\text{true}} = \lambda(-\ln(U))^{1/\alpha}, \quad U \sim \text{Unif}(0,1) \tag{6}$$

As the state of each component is updated at every timestep by reducing RUL_{true} and making new predictions, the closed loop MPC approach allows the model to update maintenance decision based on new information about the state of health of the system.

It should be noted that the Weibull distribution is not used here to represent the continuously updated health state of an individual component, but rather to sample the underlying “true” lifetime distribution in line with standard reliability engineering practice. The predicted RUL is then generated by adding stochastic error $e(k)$ to this true RUL and is updated at every decision step. This procedure, also followed in Borsotti et al. (2024), Li et al. (2021), enables reproducible benchmarking of predictive maintenance strategies under uncertainty in the absence of publicly available operational datasets.

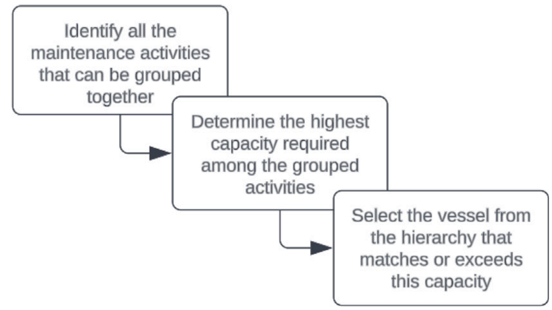


Fig. 1. Flowchart of vessel selection for grouped maintenance activities.

3.2. Opportunistic maintenance

In the proposed model, an opportunistic maintenance strategy is defined to save on the use of vessels by combining multiple tasks into a single maintenance cycle. The selection of vessels is based on their suitability for different tasks and the expected weather conditions (Li et al., 2024) and will influence the expected cost of the maintenance cycle.

A detailed approach to the selection of the appropriate vessel can be found in Dalgic et al. (2015) where SOVs and CTVs have been characterized based on their capacity and seakeeping abilities. Here, following a similar logic, vessels types are ranked from 1 to 4 based on their ability to carry out different maintenance tasks as shown in Table 2.

When maintenance activities are grouped, the vessel with the lowest rank that can perform all required tasks is chosen. This ensures that the chosen vessel has the necessary capacity to handle the combined workload.

The logic for selecting the appropriate vessel for grouped maintenance activities is summarized in Fig. 1.

For example, if minor and major maintenance activities are grouped together, the model would select a vessel that can handle both types of tasks. Although for a minor intervention a CTV (Rank 1) might be sufficient, if a SOV (Rank 2) is needed for the major maintenance, the model will choose the SOV to ensure all tasks are completed efficiently.

The optimizer evaluates the trade-off between deploying multiple vessels, which leads to higher mobilization costs but shorter rental durations, versus utilizing a single, higher-capacity vessel for an extended period, potentially resulting in lower mobilization costs but increased rental expenses due to longer sea time.

3.3. Maintenance model

As highlighted in Dalgic et al. (2015), different maintenance tasks are associated with different logistic requirements. Our model differentiates between minor, major repairs and replacements. To each maintenance type corresponds a certain lifetime extension, expressed as a percentage of the component's age at the time of repair. Let C be the set of components, A the set of actions [minor, major, replacement, Do Nothing], and T the planning-horizon length. To update the age of components that undergo maintenance, an age reduction coefficient is defined as follows:

$$\alpha_a = [0.3, 0.5], \forall a \in [\text{Minor, Major}] \tag{7}$$

So, the expected RUL of a component on which maintenance activity a is performed on day d can be computed as:

$$RUL_{\text{new}} = RUL_{\text{pred}} + d\alpha_a \tag{8}$$

In case of preventive or corrective replacements, a new component is installed in place of the old one, and its RUL predictions will not

Table 2
Vessel hierarchy for maintenance tasks.

Vessel Type	Rank	Description
CTV (Crew Transfer Vessel)	I	Suitable for most minor maintenance tasks.
SOV (Service Operation Vessel)	II	Capable of handling major maintenance activities and more extensive tasks compared to CTV.
Jack-up Vessel	III	Used for more intensive maintenance activities requiring significant equipment and stability.
Heavy Lift Vessel	IV	The vessel with the highest capacity to transport technicians, equipment, and spare parts, used for the most extensive maintenance and replacement tasks.

depend on the day on which maintenance is performed. The age reduction coefficients associated to different maintenance actions are taken from (Li et al., 2022).

The total cost of each maintenance activity includes material costs, labor costs, downtime costs, and transportation costs (Laura and Vicente, 2014).

We consider the cost of materials to be fixed and dependent only on the component and on the type of maintenance, thus, for any activity a performed on component c, there is an associated material cost $C_{\text{material}}(c, a)$.

Labor costs are calculated as follows:

$$C_{\text{tech}}(c, a) = N_{\text{tech}}(c, a) \times R_{\text{hour}} \times T(c, a) \tag{9}$$

where $N_{\text{tech}}(c, a)$ is the number of technicians needed for maintenance type a on component c, R_{hour} is the technicians cost per hour, and $T(c, a)$ is the number of hours required for the task.

Downtime cost estimates are based on the expected lost production due to the turbine being non-operational. Because the proposed model targets tactical planning, we approximate power loss using a seasonal expectation rather than an hourly wind profile. In particular, the mean wind speed is treated as month-dependent and computed from the metocean dataset described in the Case Study.

$$C_{\text{dt}}(T_{\text{dt}}, k) \;=\; P\big(\bar{v}_{m(k)}\big)\, C_{\text{el}}\, T_{\text{dt}}, \tag{10}$$

where $m(k) \in \{1, \dots, 12\}$ denotes the calendar month associated with day k, $\bar{v}_{m(k)}$ is the corresponding monthly average wind speed at the site, $P(\bar{v}_{m(k)})$ is the turbine power curve evaluated at that monthly average, C_{el} is the electricity price, and T_{dt} is the downtime duration (hours) during which the turbine is not producing energy due to failures or maintenance.

The cost related to the utilization of vessels is computed as the sum of mobilization cost, fuel consumption and daily rate:

$$C^{j}_{\text{trans}}(T(c, a)) = C^{j}_{\text{mobil}} + F^{j}_{\text{cons}} \cdot 2D_{\text{travel}} + R^{j}_{\text{day}} \cdot \frac{T(c, a)}{24} \tag{11}$$

where C^{j}_{mobil} is the mobilization cost of vessel j, F^{j}_{cons} is the fuel consumption rate of vessel j, $2D_{\text{travel}}$ is the round-trip sailing distance, R^{j}_{day} is the daily cost of vessel j, and $T(c, a)/24$ is the time (in days) required to perform maintenance activity a on component c.

Finally, the total cost of maintenance a on component c can be expressed as:

$$C(c, a) = C_{\text{material}} + C_{\text{tech}}(c, a) + C_{\text{dt}}(T) + C^{j}_{\text{trans}}(T(c, a)) \tag{12}$$

Now that the cost items have been described, the next paragraphs show how they are used to compute the expected cost of initiating any maintenance action a on any components c on any day d of the planning horizon.

The expected cost of each possible maintenance action is computed considering the cumulative probability of the component surviving until the day of predictive maintenance d or failing beforehand, incurring into corrective replacement and potential downtime costs.

$$\mathbb{E}_a[\text{Cost}(k, d)] = C(c, a) \sum_{i=0}^{d-1} \tilde{p}_k(i) + C(c, a_{\text{replacement}}) \left(1 - \sum_{i=0}^{d-1} \tilde{p}_k(i)\right)$$
$$+ C\left(\sum_{i=0}^{d-1} \tilde{p}_k(i)(d - i - 1)\right),$$
$$\forall a \in [\text{replacement, major, minor, Do Nothing}] \tag{13}$$

The expected cost includes the cost of the specific maintenance action $C(c, a)$, the cost of corrective replacement $C(c, a_{\text{replacement}})$ we would incur in if the component fails beforehand, and the downtime cost C_{dt}.

An additional cost is considered for minor and major repairs to acknowledge future expenses when the component will eventually be replaced. A discount factor (DF) is introduced to account for the time value of money considering that future costs are less valuable than current expenses due to potential interest earnings, as used by Sandborn et al. (2014) or by Ioannou et al. (2018) in their techno-economic model for offshore wind life-cycle.

Let η_a represent the expected RUL of the component in case of it undergoing maintenance a, converted into years:

$$\eta_a = \frac{\mathbb{E}_{\text{a}}[\text{Life}(k, d)] - T_{\text{elapsed}}}{365} \tag{14}$$

We can then use this value to calculate the discount factor at the time of the new expected failure for the component:

$$\text{DF}_a = (1 - \delta)^{\eta_a} \tag{15}$$

where δ is the discount rate.

In a similar fashion to how we calculated the expected cost, the expected lifetime of the components in case they undergo different maintenance tasks are computed using the cumulative probability of failure over the planning horizon. Maintenance activities impact the expected lifetime of components differently, this is characterized by the age reduction coefficient α.

For each maintenance type, the expected lifetime can be estimated as follows:

$$\mathbb{E}_{\text{a}}[\text{Life}(k, d)] = k + \sum_{i=0}^{d-1} i \cdot \tilde{p}_k(i)$$
$$+ d\left(1 - \sum_{i=0}^{d-1} \tilde{p}_k(i)\right) + \alpha_a(k + d)\left(1 - \sum_{i=0}^{d-1} \tilde{p}_k(i)\right), \forall a \in [\text{major, minor}] \tag{16}$$

Here, the expected lifetime is computed as the sum of the current day k and the remaining useful life distribution over the planning horizon. For major and minor activities, if the component survives until day d and undergoes maintenance, its lifetime is extended by a factor of α_a which is 0.3 for major maintenance and 0.5 for minor maintenance.

In case of replacements, the task effectively terminates the component's life and the equation can be simplified as:

$$\mathbb{E}_{\text{replacement}}[\text{Life}(k, d)] = k + \sum_{i=0}^{d-1} i\phi_k(i) + d\left(1 - \sum_{i=0}^{d-1} \tilde{p}_k(i)\right) \tag{17}$$

In case no maintenance is scheduled during the planning horizon ($a = Do\,Nothing$), the expected lifetime is computed simply as the elapsed time plus our prediction for the component's RUL:

$$\mathbb{E}_{\text{DN}}[\text{Life}(k)] = k + RUL_{\text{pred}}(k) \tag{18}$$

The expected cost/lifetime ratio is a key indicator of the O&M performance, representing the yearly cost of maintenance for a specific component. This metric allows for a direct comparison of the cost-effectiveness of different maintenance plans.

$$\mathbb{E}_{\text{a}}[\text{Ratio}(c, k)] = \frac{\mathbb{E}_{\text{a}}[\text{Cost}(k, d)]}{\mathbb{E}_{\text{a}}[\text{Life}(k, d)]/365}$$

$$\forall a \in [\text{replacement, major, minor, Do Nothing}] \tag{19}$$

3.4. Stochastic optimization formulation

The optimization model aims to identify the optimal scheduling of maintenance activities over a defined planning horizon that minimizes this cost/lifetime ratio.

The model uses a binary decision variable $x_{c,a}$ to indicate, for each component c, what maintenance activity a should be scheduled.

$$x_{c,a} = \begin{cases} 1 & \text{if maintenance activity } a \text{ is planned} \\ & \text{for component } c \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

Additionally, the binary variable $y(k)$ is introduced to define if a maintenance cycle should be initiated on day k of the planning horizon:

$$y(k) = \begin{cases} 1 & \text{if a maintenance cycle is to be initiated on day} k \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

The objective functions in scheduling models typically account for maintenance expenses and system utilization. For instance, Chen et al. (2021) seeks to minimize the expected cost over a component's projected lifespan, whereas other models concentrate exclusively on reducing maintenance costs as in Li et al. (2016). Considering the expected lifespan in the objective function allows the optimizer to penalize early interventions and over-maintenance; in other studies, such as (Jain et al., 2021), this is done by promoting a trade-off between corrective maintenance and lost RUL due to preventive maintenance.

In our case, the main goal of the model is to minimize the yearly maintenance cost and is formulated as follows:

$$\begin{aligned} min & \left[\sum_{c\in C} \sum_{k=0}^{T-1} \sum_{a\in A} (y(k) \cdot x_{c,a} \cdot \mathbb{E}_{\mathrm{a}}[\mathrm{Ratio}(c,k)]) \right. \\ & \left. + \sum_{c\in C} \sum_{k=0}^{T-1} \sum_{a\in A} ((1 - x_{c,a}) \cdot \mathbb{E}_{\mathrm{DN}}[\mathrm{Ratio}(c,k)]) \right] \end{aligned} \tag{22}$$

Where $\mathbb{E}_{\mathrm{a}}[\mathrm{Ratio}(c,k)]$ is the expected cost over lifetime ratio of performing maintenance activity a on component c on day k and $\mathbb{E}_{\mathrm{DN}}[\mathrm{Ratio}(c,k)]$ is the expected ratio in case no action is planned.

Logical and operational constraints are applied to ensure feasibility of the solutions generated by the model.

$$\sum_{a\in A} x_{c,a} \le 1 \quad \forall c \in C \tag{23}$$

$$\sum_{k=0}^{T-1} y(k) \le 1 \tag{24}$$

$$\sum_{a\in A} x_{c,a} \le \sum_{k=0}^{T-1} y(k) \tag{25}$$

$$M(k) = \begin{cases} 1 & \text{if technicians are available on day } k \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

$$S(k) = \begin{cases} 1 & \text{if spare parts are available on day } k \\ 0 & \text{otherwise} \end{cases} \tag{27}$$

$$W(k) = \begin{cases} 1 & \text{if enough operational hours on day } k \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

$$y(k) \le M(k) \quad \forall c \in C, \forall k \in \{0, \dots, T-1\}, \forall a \in A \tag{29}$$

$$y(k) \le S(k) \quad \forall c \in C, \forall k\ in \{0, \dots, T-1\}, \forall a \in A \tag{30}$$

$$y(k) \le W(k) \quad \forall c \in C, \forall k\ in \{0, \dots, T-1\}, \forall a \in A \tag{31}$$

$$\sum_{a\in A} x_{c,a} \ge f_c(d) \tag{32}$$

Each component can undergo at most one maintenance action within the planning horizon, this is taken into account in (23). Using (24), we can ensure that maintenance is initiated only once during the planning horizon. Additionally, (25) is used to ensure that a task is assigned to a component only if a maintenance cycle has been planned. Furthermore, maintenance can only be scheduled if there are enough technicians, spare parts, and if the weather conditions are favorable, considering the vessels' operational limits; the binary variables M_k, S_k, and W_k are thus defined in (26), (27) and (28) to indicate whether technicians, spare parts, and operational hours are available on day k respectively. Constraints (29), (30) and (31) ensure that maintenance is scheduled only if all necessary resources are available. Finally, statement (32) ensures that, if a component has already failed at the time of observation d, a maintenance cycle has to be initiated as soon as possible, here $f_c(d)$ is a binary variable indicating whether component c is failed on day d:

$$f_c(d) = \begin{cases} 1 & \text{if component } c \text{ is failed on day } d \\ 0 & \text{otherwise} \end{cases} \tag{33}$$

Various solution methods have been employed in the literature to optimize the expected cost of repair considering failure probability, For example, exhaustive search methods, despite their high computational demands, give exact solutions, as demonstrated in Vianna and Yoneyama (2018). These methods can be particularly useful for simpler systems to use as benchmarks for more complex models, as illustrated in Verleijsdonk et al. (2024).

In this paper, similarly to Zhuang et al. (2023), Chen et al. (2021) and Camci et al. (2019), we use Mixed Integer Linear Programming (MILP) with a rolling-horizon approach, as utilized in Mitici et al. (2023) and Zhuang et al. (2023) to revise decisions as new data becomes available, an essential feature given the continuous updates provided by prognostic information.

3.5. MPC formulation

We formulate maintenance scheduling as a receding-horizon control problem with partial observability of component health. At each decision epoch k, the controller observes an information state and computes a plan over a finite prediction horizon H (days), but only implements the first-step decision before re-optimizing.

Let the underlying (unobserved) physical state be $x_k = \{RUL_{\mathrm{true},c}(k)\}_{c\in C}$. The controller operates on the belief state

$$b_k = \{\mu_{c,k}, \sigma_{c,k}\}_{c\in C}, \tag{34}$$

where $(\mu_{c,k}, \sigma_{c,k})$ parameterize the probabilistic RUL belief for each component.

Given the current belief b_k, the optimizer predicts future beliefs by propagating: (i) component health forward in time (RUL decreases by one day if no intervention occurs), and (ii) uncertainty contraction according to (40). The resulting failure-time pmf $\tilde{p}_{c,k}(i)$ is computed via (4) and used inside the MILP objective.

At epoch k, we solve the MILP over days $k, \dots, k+H-1$ and apply the immediate decision of initiating a cycle or not. Then, at $k + \Delta k$ new prognostic measurements are assimilated, the belief is updated, and the MILP is re-solved. This repeated re-optimization constitutes the closed-loop MPC feedback mechanism.

If no maintenance is performed, the true RUL decreases deterministically:

$$RUL_{\mathrm{true}}(k + \Delta k) = RUL_{\mathrm{true}}(k) - \Delta k, \tag{35}$$

while if maintenance is carried out, RUL_{true} is increased according to (8). The predicted RUL is propagated in parallel, At epoch $k+\Delta k$, a new prognostic observation is generated:

$$RUL_{\mathrm{pred}}(k + \Delta k) = RUL_{\mathrm{true}}(k + \Delta k) + e(k + \Delta k). \tag{36}$$

Table 3
Turbine specifications.

Specification	Value
Rated Power Output (MW)	3
Rotor Diameter (m)	90
Hub Height (m)	80
Cut-in wind speed (m/s)	3
Cut-out Wind Speed (m/s)	25
Rated Wind Speed (m/s)	12

$$e(k+\Delta k) \sim \mathcal{N}(0, std^2(k+\Delta k)) \tag{37}$$

The range of possible standard deviations is defined, as in Borsotti et al. (2024), by:

$$std_{\max} = RUL_{\text{true}} \cdot \text{(large uncertainty)} \tag{38}$$

$$std_{\min} = RUL_{\text{true}} \cdot \text{(small uncertainty)}, \tag{39}$$

Where std_{max} represents the initial uncertainty in the RUL prediction and std_{min} the reduced uncertainty after new data has been accumulated. The confidence in the prediction increases with time, converging towards the lower bound of uncertainty. Here, large uncertainty denotes the conservative variance assumed when only limited condition data are available, while small uncertainty reflects the narrower variance achieved once more observations have refined the estimate. The specific values of *large* and *small uncertainty* can be chosen according to the quality of the prognostic system being simulated, allowing different levels of prediction accuracy to be represented. The transition in time from large to low uncertainty is modeled as:

$$std(k) = std_{\max} - (std_{\max} - std_{\min}) \left(\frac{1}{1 + \exp\left(-\frac{k - aRUL_{\text{true}}}{bRUL_{\text{true}}}\right)} \right) \tag{40}$$

where $std(k)$ is the time-dependent standard deviation of the prediction, and parameters a and b shape how quickly the uncertainty contracts.

The MILP then minimizes the expected cost/lifetime ratio using the new predicted RUL together with logistical constraints and the cycle repeats with the updated beliefs.

This iterative cycle of (i) propagating the prior, (ii) updating it with the new prognostic observation, and (iii) re-optimizing decisions constitutes the feedback mechanism that characterizes our closed-loop MPC formulation.

Fig. 2 summarizes the overall workflow of the proposed predictive maintenance approach, from prognostic inputs and offshore accessibility information to rolling-horizon optimization, execution, and feedback-based belief updates.

In the next section, we apply the proposed model to a case scenario and benchmark its results against an existing strategy.

4. Case study

The Case Study was chosen specifically to verify the results of the proposed methodology against the Multiple Age-Based Opportunity (MABO) strategy described in Li et al. (2021) so that the results could be compared and verified. We consider a generic Offshore Wind Farm in the North Sea, 25 km from the onshore base located in the Netherlands. The system includes 50 wind turbines with a rated power of 3MW, the characteristics of the wind turbine are shown in Table 3.

Each turbine is modeled as a series of 5 critical components, namely blades, bearings, gearbox, generator, and pitch system. Failure of any one of these components leads to the failure of the whole turbine. For each of these components we defined the failure distribution and cost parameters as presented in Table 4, collecting the values from (Li et al., 2021).

Table 4
Failure distribution and cost parameters for critical components.

Component	Shape	Scale	Failure replacement cost [kEUR]	Preventive replacement cost [kEUR]
Blades	3	1847	215	55
Bearings	2	1811	60	15
Gearbox	3	1477	260	65
Generator	2	1594	90	25
Pitch	3	1144	46	10

Table 5
Operational parameters.

Parameter	Value
Mean Wind Speed at 21 m (m/s)	8.58
Cost of Electricity (EUR/MWh)	150
Distance from Shore (km)	25
Hourly Rate for Technicians (EUR/h)	75
Mobilization cost (kEUR)	50
Vessel daily rate (kEUR)	10

Other operational parameters necessary for the model buildup are shown in Table 5.

Long-term weather measurements are essential to evaluate maintenance strategies under realistic variability in accessibility and waiting times. This paper uses the long-term hindcast database compiled by Li et al. (2015) for five European offshore sites. Their dataset is based on simultaneous hourly wind and wave hindcast data from 2001 to 2010 and provides joint information on mean wind speed at 10 m height and significant wave height, among other parameters. This multi-year coverage enables robust characterization of seasonal patterns and interannual variability, which is critical for benchmarking O&M decision models.

In the benchmark, only two parameters are retained as exogenous drivers of marine operability: significant wave height (H_s) and wind speed at 10 m (U_{10}), consistent with the key variables required to determine access feasibility and (where relevant) to approximate production conditions.

This study requires long time series of metocean conditions to benchmark maintenance decision policies under realistic access variability, including seasonal persistence of “good” and “bad” weather windows. We implemented a weather generator that preserves the empirical temporal structure of accessibility through a month-dependent Markov process.

Rather than generating continuous wind and wave time series, the generator produces vessel-specific hourly operability states (accessible vs. non-accessible) derived from historical wind speed and significant wave height records. This directly provides the binary accessibility indicators used in (31) as constraints for the optimization.

To obtain long accessibility time series while preserving realistic seasonal patterns, we generate synthetic vessel-specific operability sequences using a month-conditioned two-state Markov process calibrated from the hindcast-derived accessibility data. Concretely, the hourly hindcast observations are first thresholded using the vessel operability limits in Table 6, yielding an empirical binary sequence (accessible/non-accessible) for each vessel class. Then, for each vessel class, a separate two-state Markov model is estimated for each calendar month, so that the probability of remaining in (or switching between) accessible and non-accessible states reflects the observed persistence of weather windows in that month (e.g., longer storm regimes in winter versus more frequent short interruptions in summer). By simulating these month-dependent Markov models over multiple years with fixed random seeds, we produce long, reproducible accessibility series that retain the temporal structure of access constraints. The scheduling model uses these vessel-specific binary accessibility indicators (aggregated to the daily decision grid) as exogenous feasibility inputs for maintenance execution.

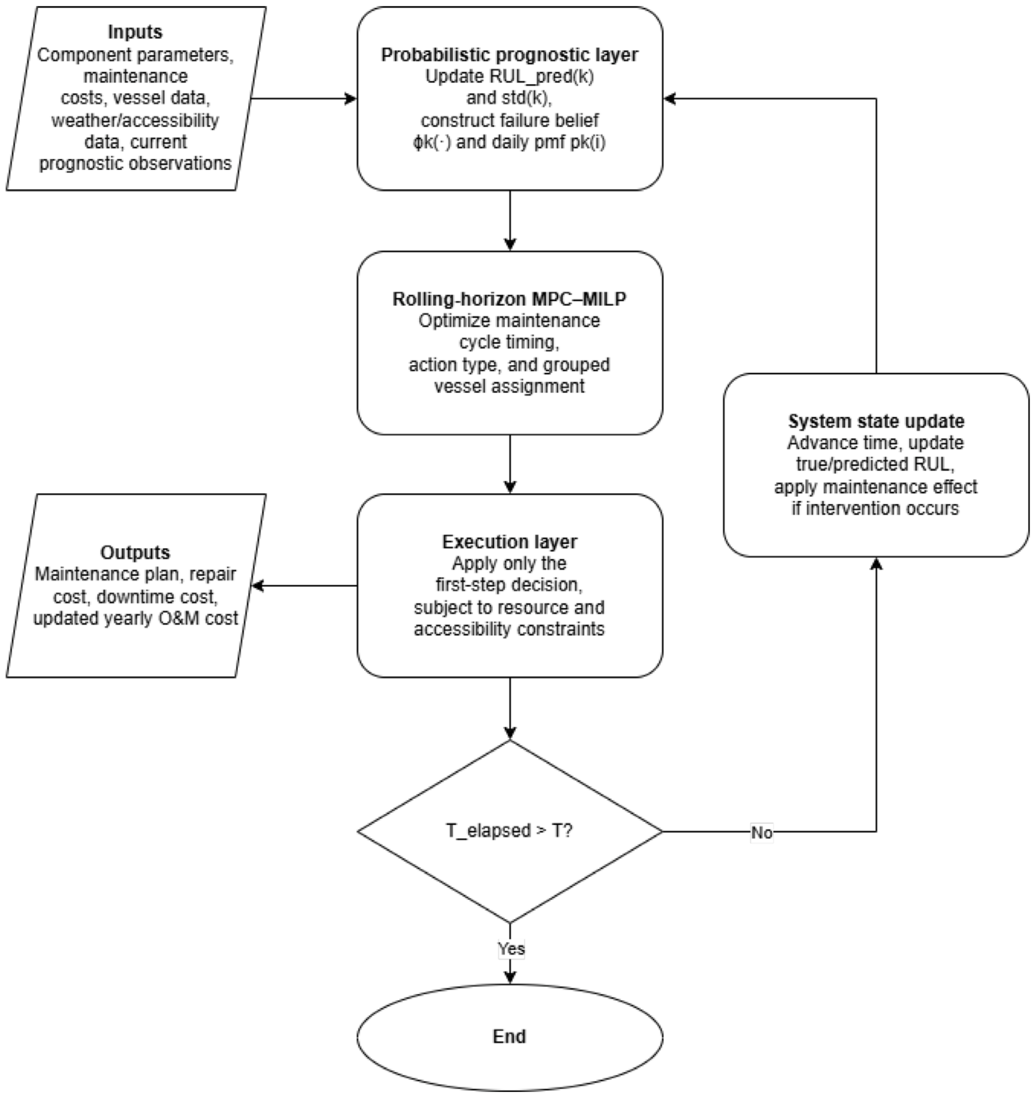


Fig. 2. Framework of the proposed prognostic-driven maintenance approach.

Table 6
Metocean operability limits for vessels.

Asset/vessel type	H_s limit (m)	U_{10} limit (m/s)	Notes (typical use)
CTV	1.5	12	Daily port-based technician transfer; boat landing; limited payload. (Saraswati et al., 2017)
SOV	3.0	20	Offshore accommodation; walk-to-work transfer; enables longer campaigns. (Saraswati et al., 2017)
Jack-up Vessel (heavy-lift)	2.0	10	Major component replacement; stability and crane operations typically wind- and wave-limited. (Dewan and Stehly, 2017)
Helicopter	–	20	Not directly constrained by H_s; primarily wind/visibility dependent; used for urgent transfer. (Saraswati et al., 2017)

The adopted approach is intentionally decision-centric: it generates the binary accessibility signal required by the O&M decision models, rather than aiming to reconstruct the full joint distribution of wind and wave processes.

Representative threshold values for each considered transportation mode $(\overline{U}_v, \overline{H}_{s,v})$ are reported in Table 6.

Once the case scenario is set, by adapting our model to utilize the same scheduling philosophy of Li et al. (2021), we can verify the results. A brief description of the age-based strategy proposed in the above-mentioned paper is thus due: in this case, maintenance cycles will be initiated once a component fails, at that moment, the age consumption of every other component will be computed as:

$$u_c(d) = \frac{d}{RUL_{\text{true}}} \tag{41}$$

Where u_c is the age consumption of component c, d is the elapsed time and RUL_{true} is the RUL of component c, randomly generated from the Weibull distribution. Therefore, having set age thresholds for preventive replacements, major and minor activities, every component whose age will have surpassed said thresholds will undergo the necessary action. This strategy, the selection of maintenance actions and its impact on the lifetime of the repaired component are summarized in Table 7.

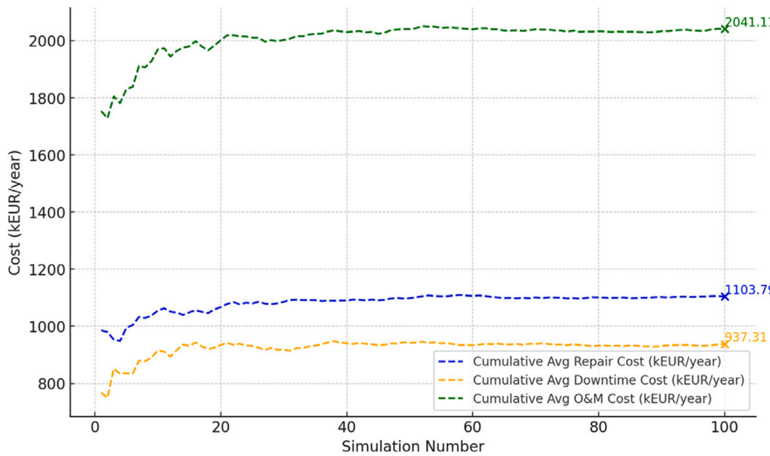


Fig. 3. Yearly maintenance cost of maintenance after 100 iterations.

Table 7
Age thresholds in MABO strategy.

Age consumption	Action	Age reduction
$u_c(d) >= 1$	Failure Replacement	1
$u_c(d) >= A_{max}$	Preventive Replacement	1
$A_{min} <= u_c(d) < A_{max}$	Repair	0.7

Table 8
Verification of the model.

	MABO (Li et al., 2021)	Verification using same age thresholds	Difference [%]
Yearly cost of maintenance [kEUR/year]	2116	2236	5.6%

Table 9
Sensitivity analysis with respect to the size of the Wind Farm.

Wind farm size	Strategy	Yearly cost of repairs $[\frac{\text{kEUR}}{\text{year}}]$	Yearly cost of downtime $[\frac{\text{kEUR}}{\text{year}}]$	Yearly cost of O&M $[\frac{\text{kEUR}}{\text{year}}]$
10 WT	PDS	231	201	432
	MABO	229	239	468
	Difference	1%	−16%	−7.7%
20 WT	PDS	459	336	795
	MABO	469	380	849
	Difference	−2%	−11.6%	−6.4%
50 WT	PDS	1103	937	2041
	MABO	1030	1205	2236
	Difference	+7%	−22%	−8.7%

Finally, in absence of real-life CM data, a synthetic dataset of probabilistic RUL prognosis was used, the model used to generate prognostic information is described in Borsotti et al. (2024).

By simulating this process over 15 years, we can take a look at the results of our model, focusing on the yearly cost of maintenance, averaged over 500 iterations. As shown in Table 8, the results of the two models differ by about 6%.

In the next section, we will compare the results obtained using the Multiple Age Based Opportunistic maintenance strategy against the prognostic-driven strategy proposed.

5. Results

In this section, we illustrate the results obtained using the prognostic-driven scheduling model, focusing on the yearly cost of maintenance. Firstly, we show how the proposed scheduling strategy outperforms age-based maintenance strategies, then, we analyze the sensitivity of our results with respect to the size of the wind farm.

To evaluate the impact of prognostic-driven scheduling on the overall lifetime costs of a wind farm, we analyzed the yearly cost of O&M by simulating the scheduling process over 15 years for the OWF described in Section 4.

The results indicated in this paper are averaged over 100 iterations in order to let the mean value converge and improve robustness with respect to uncertainties in the RUL predictions and in the random generation of the true RUL of the components. The convergence of the average value of the yearly cost of maintenance is shown in Fig. 3.

The proposed model results, thus, in a yearly cost of O&M of 2041kEUR, which represents a 8,72% reduction with respect to the MABO strategy. This reduction is better highlighted in Fig. 4.

The costs indicated in Fig. 4 have been categorized into repair costs, downtime costs and O&M costs which represent the sum of the first two. In order to test the sensitivity of our model with respect to the size of the Offshore Wind Farm, we have applied the proposed model to 10, 20, and 50 wind turbines, the results are presented in Table 9.

To address (a) the dependence of rolling-horizon maintenance planning on the prediction horizon length and (b) the sensitivity to dominant offshore O&M drivers, we performed three one-factor-at-a-time studies: prediction horizon H, prognostic uncertainty floor ($std_{\text{min}}/RUL_{\text{true}}$), and (c) distance to port. Each scenario was simulated over 15 years and repeated over multiple Monte Carlo iterations.

Fig. 5(a) shows that the chosen prediction horizon has a strong impact on both yearly downtime cost and total O&M cost. Longer look-ahead enables the planner to anticipate upcoming failures and schedule preventive actions earlier, which reduces exposure to costly corrective events and associated downtime.

We varied the minimum uncertainty floor used in the uncertainty-contraction model by setting $std_{\text{min}} = \{0.01, 0.05, 0.1\} \cdot RUL_{\text{true}}$. Fig. 5(b) shows that improved prognostic precision (smaller std_{min}) decreases both downtime cost and total O&M cost, supporting the premise that higher-quality prognostics enable better-timed interventions and lower downtime exposure.

To quantify the influence of a key offshore logistics driver, we varied the distance to the onshore base as $D_{\text{travel}} \in \{10, 25, 50\}$ km. Fig. 5(c) shows that increasing distance increases both the overall O&M cost and, more markedly, the downtime cost, consistent with longer travel times, higher transportation expenses, and delayed access.

6. Conclusions

This study introduces a stochastic optimization framework for predictive maintenance scheduling in offshore wind farms that explicitly

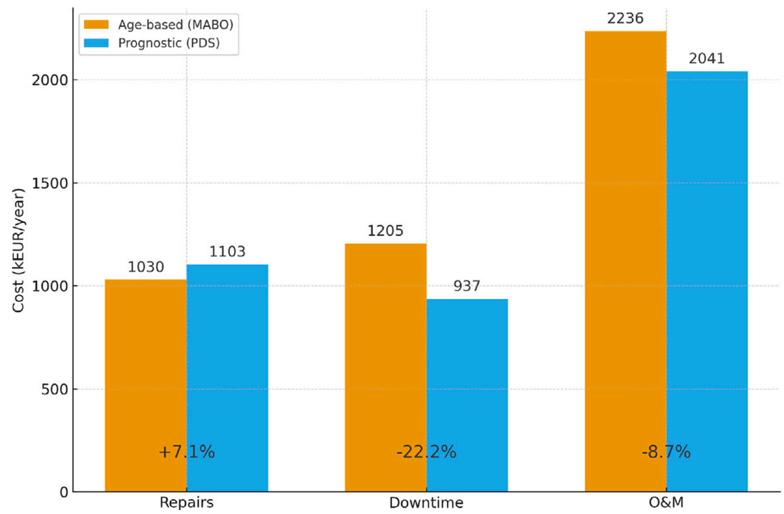
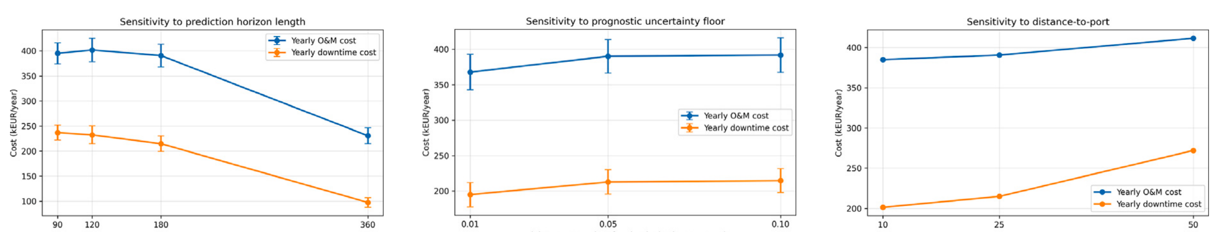


Fig. 4. Cost of repair, downtime and overall O&M cost using Prognostic-Driven Scheduling vs Age-Based strategy.



(a) Prediction horizon length. (b) Prognostic uncertainty floor. (c) Distance-to-port.

Fig. 5. Sensitivity analyses: yearly total O&M cost and yearly downtime cost for key tactical planning drivers.

considers domain-specific dynamics such as logistical and weather constraints, integrating probabilistic prognostic information to plan various types of maintenance tasks. The results of the proposed model have been benchmarked against an existing methodology that uses an age-based strategy to schedule maintenance activities. By using RUL predictions to inform the decision-making process, our method shows a considerable reduction in O&M costs, mainly driven by a higher responsiveness to incurring failures and a decrease of downtime costs.

The results demonstrate that our prognostic-driven scheduling strategy yields significant cost reductions compared to traditional age-based methods, achieving an 8.7% reduction in operational costs for an offshore wind farm consisting of 50 wind turbines. Importantly, this improvement is scalable and consistently observed across multiple wind farm sizes, confirming the robustness of the proposed approach with respect to the dimensions of the wind farm considered.

One limitation of the current approach is that it optimizes maintenance scheduling over a relatively short planning horizon. While this could overlook some long-term consequences of present decisions, the dynamic nature of our model helps mitigate this risk by continually adapting maintenance strategies to changing conditions. Moreover, although the model does not explicitly consider the finite operational lifespan of the wind farm, its predictive nature implicitly encourages timely maintenance interventions, thus mitigating potential large costs toward the system's end of life.

Additionally, the case study presented utilizes synthetic prognostic data due to the current scarcity of real-life condition monitoring datasets. The case relies on literature-based data and synthetic prognostics rather than proprietary SCADA/CMMS data. While this limits site-specific realism, it improves external reproducibility and lets us cleanly benchmark scheduling logics under controlled uncertainty. The framework is data-agnostic and can ingest site-specific prognostics when available. One of the key strengths of our proposed framework, in fact, lies in its flexibility, allowing the integration of various prognostic data sources, whether they originate from generic models, synthetic datasets, or actual operational data as they become available. This ensures that the proposed approach remains adaptable to future data improvements and availability.

Addressing these limitations requires further research into multi-horizon optimization approaches that evaluate the future impact of current decisions. Incorporating a finite operational lifespan into the model would also enable more realistic planning, aligning maintenance decisions with the wind farm's end-of-life considerations.

In conclusion, prognostic-driven scheduling promises potential to reduce O&M costs for offshore wind farms, contributing to their economic viability and sustainability. Future work should focus on extending the model to incorporate real prognostic data, long-term planning horizons, and finite lifespans, enhancing its applicability to real-world scenarios and maximizing its impact on the Offshore Wind sector.

CRediT authorship contribution statement

M. Borsotti: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **X. Jiang:** Writing – review & editing, Supervision. **R.R. Negenborn:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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