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A review of multi-horizon decision-making for operation and maintenance of fixed-bottom offshore wind farms

M. Borsotti*, R.R. Negenborn, X. Jiang

Department of Maritime & Transport Technology, Delft University of Technology, Delft, Netherlands

HIGHLIGHTS

- Organizes offshore wind O&M literature by strategic, tactical, and operational decision levels.
- Reviews simulation and optimization models used to support strategic decisions.
- Reviews fleet sizing, spare parts, and logistics models for tactical O&M planning.
- Reviews routing, scheduling, and short-term maintenance models for operational decision support.
- Identifies methodological gaps and emerging modeling directions for future research.

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Operation and maintenance
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Decision-making

ABSTRACT

Offshore Wind Farms (OWF) are expected to play a crucial role in mitigating climate change and promoting sustainable development, nevertheless, Operation and Maintenance (O&M) costs can reach 25–30 % of the total cost. Efficient O&M strategies reduce maintenance frequency, downtime, and improve overall performance. This paper reviews O&M decision-making for fixed-bottom OWFs according to a three-level decision-making hierarchy, strategic, tactical, and operational, reflecting how decisions vary by scope and time horizon of reference. Strategic decisions are typically focused on the overall maintenance strategy for the wind farm. Tactical decisions are focused on the selection of the fleet and the management of spare parts. Operational decisions are focused on the scheduling of individual maintenance tasks on a daily or weekly basis and the routing of the vessels. Exploring how the different decision-making layers have been addressed in the literature leads to valuable insights into open challenges and paves the way for the development of new decision-making methods. In this paper we highlight the untapped potential of prognostic-driven scheduling, we identify the lack of comprehensive models and methods that encompass all decision-making echelons holistically, and we emphasize the need for the integration of environmental considerations into the decision-making process.

1. Introduction

Offshore wind deployment is undergoing rapid expansion, with 6.3 GW of new capacity installed globally in 2023. This brought total operational capacity to 68.3 GW across 319 projects and over 13,000 turbines, marking a 10.2 % year-on-year increase [1]. Although a global offshore wind pipeline now exceeding 453 GW can support climate targets while significantly contributing to global electricity generation, high costs remain a barrier. As Fig. 1 illustrates, the Levelized Cost of Electricity (LCoE) for fixed bottom Offshore Wind in 2023 is estimated around 75 $/MWh, significantly higher than other common renewable energy technologies. Photovoltaic and Onshore Wind, by comparison, show a more economical LCoE for 2023, at 38 and 30 $/MWh respectively [2,3].

Operation and Maintenance (O&M) can account for 25 %–30 % of offshore wind project costs, significantly higher than the 10 %–15 % observed in onshore wind [4].

Fig. 2 shows that turbine sizes are increasing, with 17 MW units predicted by 2025 [5], which raises maintenance challenges. Larger

* Corresponding author.
Email address: m.borsotti@tudelft.nl (M. Borsotti).

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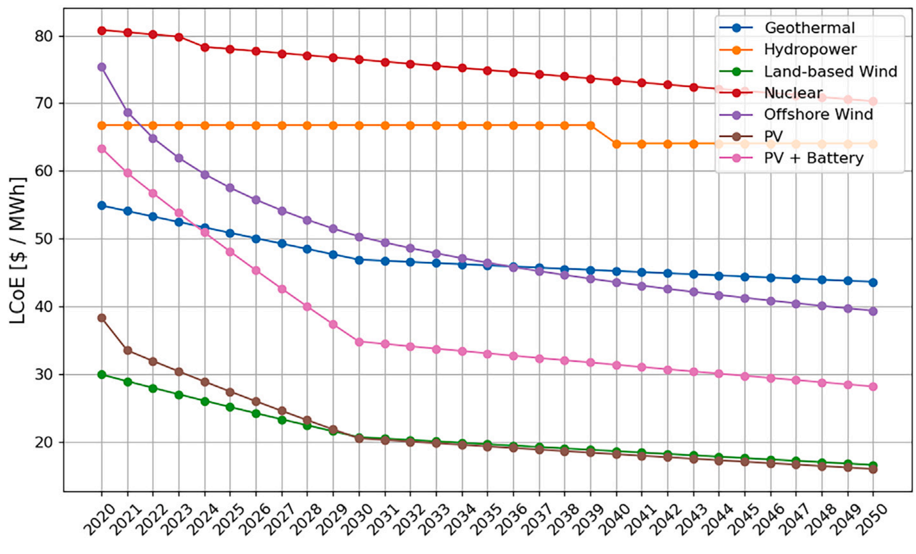

Fig. 1. LCoE prospect for renewable energy technologies [3].

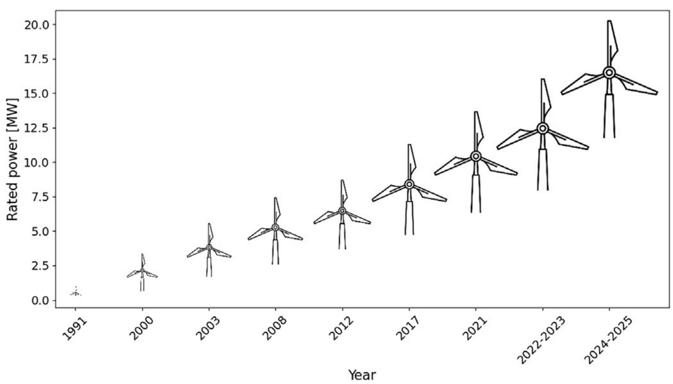

Fig. 2. Rotor size and power rating increase [5].

turbines demand specialized repair equipment and more careful maintenance, given the risk of high power losses and the increased complexity of certain operations, particularly heavy maintenance tasks.

Therefore, efficient O&M is crucial for reducing offshore wind LCoE. Optimized strategies can reduce maintenance frequency and downtime, thereby increasing turbine availability and performance.

1.1. Maintenance strategies

In this section, we will provide a concise overview of the main maintenance strategies utilized in the O&M of fixed-bottom OWFs. These strategies include corrective, preventive, condition-based, predictive, prescriptive, and opportunistic maintenance [6]. We will explore the fundamental principles and objectives of each strategy, highlighting their distinctive features, benefits and shortcomings.

Corrective maintenance: repairs or replaces components post-failure. Although reactive and potentially costly due to extended downtime, it effectively addresses unexpected failures [7].

Preventive maintenance: Schedules routine tasks (inspections, lubrication, cleaning, replacements) at fixed intervals to prevent failures and sustain performance, though it may lead to unnecessary maintenance and higher costs [8].

Condition-Based Maintenance (CBM): continuously monitors component conditions via sensors to detect deterioration, allowing maintenance to be performed only when necessary.

Predictive maintenance: uses sensor data and analytics to forecast failures and optimize scheduling [9]. It reduces unexpected failures by identifying trends and anomalies [10,11] but it requires a high initial investment in monitoring systems [8].

Prescriptive Maintenance: extends beyond predictive analytics by not only forecasting equipment failures but also prescribing specific maintenance actions to mitigate or completely avoid the issues [12].

Opportunistic maintenance: uses unplanned opportunities to group tasks, thereby optimizing resources, reducing downtime, and enhancing reliability [7].

The main goal is not to simply select one maintenance strategy over another, but rather to understand the optimal timing for employing different strategies.

Fig. 3 illustrates that as a component ages, there are specific points or thresholds where it is most effective to switch from one maintenance strategy to another.

To determine thresholds and make informed decisions, it is crucial to have a high level of confidence in knowing the state of health of the components. This is where health prognostic and diagnostic studies play a vital role. By utilizing condition monitoring data, advanced analytics, and predictive modeling techniques, health prognostic studies enable accurate assessments of the health and remaining useful life of components. This information enhances the effectiveness of maintenance strategies by allowing for timely interventions and proactive measures.

1.2. Decision-making framework for OWF o&M

In this review, we adopt a widely accepted decision-making classification that distinguishes between **strategic**, **tactical**, and **operational** levels [14]. This structure is commonly used in reliability engineering and operations management to differentiate decisions by scope, time scale, and level of detail.

- **Strategic decisions** focus on long-term planning (typically 10–25 years), such as selecting the O&M strategy, including activity types, frequency, and budgeting.
- **Tactical decisions** cover mid-term planning (months to several years), including spare parts logistics, vessel fleet selection, and maintenance resource allocation.
- **Operational decisions** address short-term execution (days to weeks), such as scheduling of maintenance tasks, routing of vessels, and responding to failures.

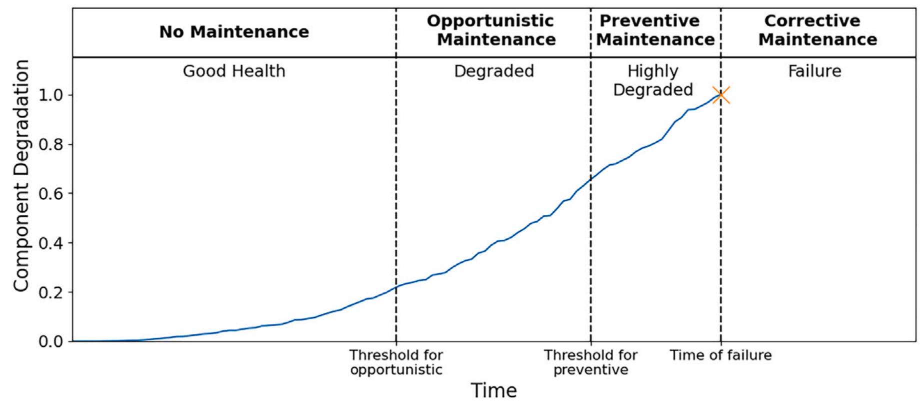

Fig. 3. Maintenance strategies, age thresholds and state of health of a component (adapted from [13]).

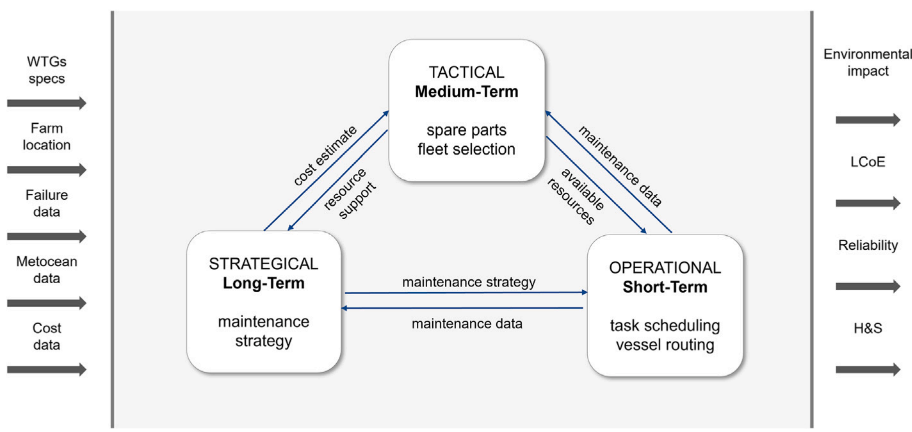

Fig. 4. Decision-making layers, scope, inputs and outputs.

The main scope of the three decision-making layers is summarized in Fig. 4, together with the most common input data and the typical outputs expected for their optimization. While Fig. 4 illustrates the main information flows and dependencies between the strategic, tactical, and operational layers, a more detailed breakdown of the specific inputs, outputs, and constraints associated with each decision-making level is provided later on in Table 10 from Section 6.2.

Overall, the state of the art in OWFs O&M is constantly evolving, with new technologies being developed and implemented all the time. In this paper we review the methodologies and approaches used to optimize the decision-making for O&M over these three layers and will point out the limitations of the existing models and the gaps in the literature. While prior reviews have provided valuable insights into specific aspects or decision-making layers, our work seeks to bridge these segmented understandings. Moreover, this review stands out by providing a detailed description of the tools, and methodologies that are used in different decision-making layers while providing a holistic critique of existing models. Throughout this review, we highlight how various modeling approaches support the development of decision support systems (DSS) for OWF O&M, which play a central role in assisting stakeholders across strategic, tactical, and operational levels.

1.3. Paper layout

The paper is organized as follows: Section 1 presents the background of the research, introducing the reader to the main O&M strategies and specifying the scope of the three decision-making layers used to organize the literature. Section 2 describes the methodology used for reviewing the literature. Section 3 focuses on strategic decisions, presenting an overview of the main O&M simulation models and explaining how O&M is optimized by identifying the optimal timing for maintenance activities based on the age of the components. Section 4 covers tactical decisions, discussing fleet selection and spare part management. Section 5 addresses operational decisions, providing an overview of the main diagnostic and prognostic methods and discussing the routing and scheduling of individual maintenance tasks. Section 6 explores the main gaps in the literature. Finally, Section 7 concludes the paper by highlighting its main contributions and providing suggestions for future research.

2. Review methodology

This review aims to provide a structured and critical assessment of the literature on OWF O&M, with a particular focus on optimization and decision support methods. The scope includes fixed-bottom OWFs unless stated otherwise. The methodology follows established systematic review principles, adapted to address the specific heterogeneity and multi-horizon nature of O&M models.

Database Search: The initial literature pool was built through searches in Web of Science, Scopus, ScienceDirect, and Google Scholar. We selected keywords aligned with the main decision layers and modeling approaches relevant to OWF O&M. These include technical, operational, and optimization-focused terms. Table 1 presents the keyword set used, always in combination with “offshore” and “offshore wind” to ensure domain specificity. The keyword list was refined iteratively based on preliminary search results and bibliometric keyword co-occurrence analysis.

Filtering and Inclusion Criteria: The initial search yielded 1645 documents. These were filtered in three stages:

Table 1
Keyword selection.

Operation and maintenance
Operation and maintenance optimization
Reliability
Availability
Condition based monitoring
Opportunistic maintenance
Spare parts management
Maintenance scheduling
Vessel routing
Fleet selection
Operation and maintenance simulation
Life cycle assessment

Title screening: articles were retained if they contained clear relevance to offshore wind O&M optimization, decision-making, simulation, or planning.

Abstract screening: documents were excluded if they addressed only general wind energy issues without a clear O&M focus or dealt solely with onshore systems.

Full-text filtering: the remaining set was assessed based on specificity (e.g., modeling depth), recency, citation impact, and diversity of methods or horizons considered.

After this multi-stage filtering, a final curated set of 100 papers was selected to ensure coverage across decision-making layers, methodological diversity, and citation impact. This set formed the basis of the critical review.

Classification: To structure the analysis, the selected documents were categorized along two axes:

Decision-making layer: strategic, tactical, and operational. Respectively, 57 %, 13 %, and 30 % of articles fall into these categories.

Topic of focus: this includes O&M Optimization, O&M Simulation, Routing and Scheduling, Fleet Selection and Spare Part Management (see Fig. 5).

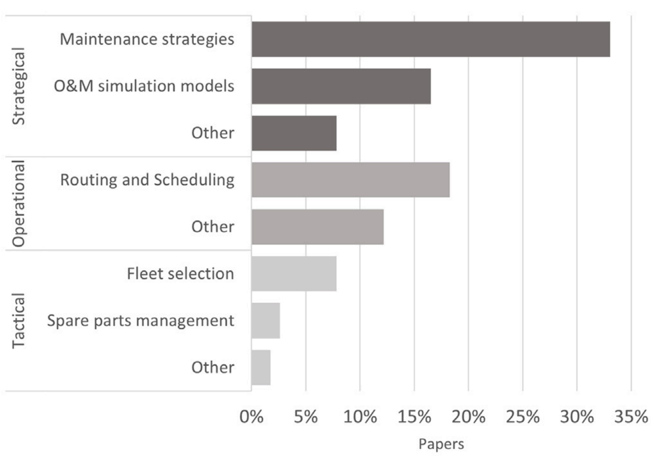

Fig. 5. Clustering by focus topic.

Bibliometric Analysis: To map research trends, a bibliometric analysis was performed using the Bibliometrix package in R [15]. Figs. 6–9 summarize the most cited sources, documents, and keywords, along with the annual scientific production in this domain.

Although this review does not claim to be exhaustive, we have aimed for breadth and representativeness by combining quantitative relevance (e.g., citations, coverage) with qualitative selection (e.g., methodological depth, diversity, and recency). The next sections are structured around the three decision-making layers and provide a critical analysis of the most relevant modeling contributions in each.

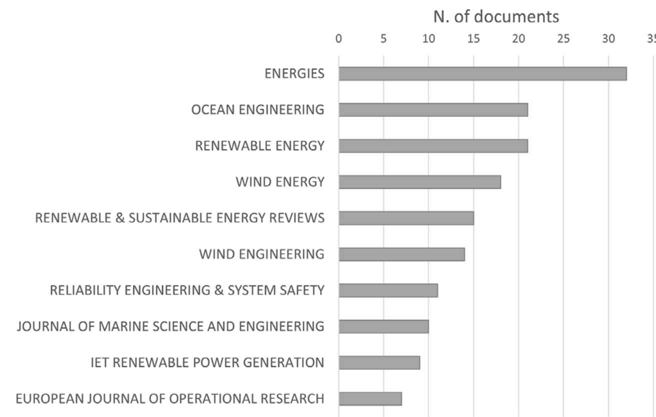

Fig. 6. Most relevant sources according to the bibliometric analysis.

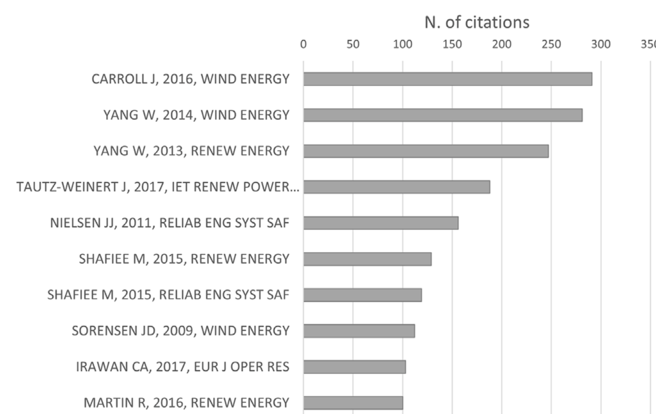

Fig. 7. Most relevant documents according to citation count.

Fig. 8. Most common keywords extracted from the reviewed literature.

3. Strategic decision-making

Strategic decision-making in OWF O&M involves high-level planning activities that shape the long-term performance and cost-effectiveness of assets. These decisions are typically made prior to or early in the operational phase and span the entire lifecycle of the wind farm. These decisions help define overarching maintenance strategies, guide long-term budgeting, and determine the key factors that will drive the initiation of maintenance cycles over time.

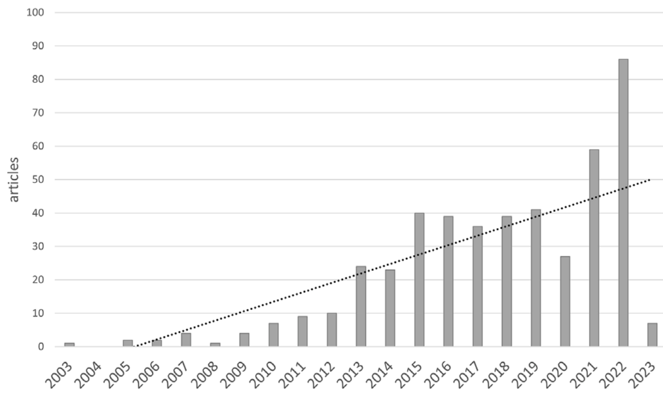

Fig. 9. Annual scientific production over time related to offshore wind O&M.

Given the scope and complexity of strategic O&M planning, this review distinguishes between two complementary modeling approaches: simulation models and optimization models. Simulation models are primarily used to evaluate the performance of predefined strategies under uncertainty and help explore the impact of logistical constraints, metocean conditions, and failure dynamics over time. Optimization models, in contrast, aim to determine the most cost-effective strategy by solving a mathematical formulation of the decision problem, often under simplifying assumptions. We separate these two families of models in our review to better reflect their distinct purposes, data requirements, and methodological approaches. The following subsections present simulation models used for strategy evaluation and optimization models used for long-term policy design, respectively.

3.1. Strategy evaluation

This section reviews O&M models by organizing the literature around key strategic planning objectives. We begin with scenario-based simulation tools used to evaluate cost, logistics, and reliability over the project lifecycle. Next, we cover analytical models designed for early-stage planning with reduced computational burden. We then review state-based formalisms that model degradation and maintenance dynamics. This is followed by a discussion on how financial impacts and uncertainty are handled. Finally, we examine how metocean and accessibility modeling support maintainability-aware site planning.

At the strategic level, it is important to assess the cost-effectiveness and technical feasibility of OWFs over their full lifecycle. As offshore turbines move further from shore, with increasingly complex configurations and harsh metocean conditions, accurate O&M modeling becomes central to reducing uncertainties in financial planning and strategic design decisions. A growing body of research has responded to this need with increasingly sophisticated simulation frameworks, capable of capturing not only turbine behavior and failure dynamics but also logistical constraints, weather-induced access limitations, and component-specific maintenance policies. This section reviews the most prominent O&M simulation models in the literature and highlights methodological innovations, data requirements, and the treatment of uncertainty.

A lot of effort has been put towards the development of such models, Rinaldi et al. [16] provide a comprehensive review of current O&M modeling practices for offshore wind, including traditional and emerging maintenance paradigms.

By simulating different operational scenarios, simulation tools can be used to predict the expected maintenance needs of a wind farm over the long term, and to identify potential bottlenecks and risks in the maintenance process. This approach involves modeling the behavior of the wind turbines, the impact of different types of maintenance activities, and the logistics of personnel and equipment required for maintenance.

In recent research on O&M simulation tools for OWFs, several distinct approaches have been proposed, for the purpose of this review, we have focused on presenting the primary and extensively referenced models. These tools aim to evaluate the costs, risks, and operational strategies associated with maintenance activities. The four main ones are summarized here and have been extensively compared and analyzed in [17]:

UiS [18]: adopts a multi-method simulation approach, combining agent-based and discrete event paradigms. The agent-based layer is used to model the individual attributes and behaviors of wind turbines, technicians, vessels, and maintenance managers, enabling decision-making at the agent level. In parallel, the discrete event paradigm models the time-driven execution of tasks within each agent. Specifically, it structures activities like travel, transfer, and repair as time-stamped events in a queue, processed sequentially based on resource availability and operational logic. This hybrid structure enhances the model's ability to capture the complexity and variability inherent in offshore O&M marine logistics.

ECUME [19]: is a comprehensive O&M simulation tool developed by EDF that assesses the average cost of operation for OWF projects. The tool is based on event modeling through Monte Carlo simulation and uses Hidden Markov Models for inaccessibility risk assessment. It considers both deterministic and probabilistic cash flows. Deterministic cash flows include capital costs and operational costs, while probabilistic cash flows account for corrective maintenance costs due to failures and condition-based maintenance costs.

NOWIcob [20,21]: uses a time-sequential Monte Carlo technique that incorporates weather uncertainties, different maintenance tasks and their associated costs. A key advantage of the model is the ability to represent various vessel concepts for wind farm access, as well as different maintenance regimes.

StrathOW [22,23]: combines a Multivariate Auto Regressive climate model with a Markov-Chain Monte Carlo approach. The strength of this tool lies in capturing the impact of climate, wind farm specifications, and operational strategies on O&M costs while maintaining computational simplicity. The outputs from this model, such as vessel costs and lost revenue, are used as inputs for decision support analysis through Bayesian Belief Networks and decision trees.

These tools collectively contribute to evaluating O&M strategies and improving the efficiency and profitability of OWF operations and are used in other works such as [24] where a comprehensive financial analysis model for OWFs is introduced, featuring stochastic time-series simulation modules that can be used to analyze technologies, strategies, and procedures throughout the wind farm's lifecycle. The model supports both fixed and floating turbines, multiple policies, and sites, while its O&M module calculates OPEX, energy production, and other critical performance indicators using NOWIcob.

In order to simulate the O&M activities of a wind farm over the long term, a discrete-event simulation approach is generally adopted. Fig. 10 presents a generalized step-by-step process for the O&M simulation of wind farms over the long term.

A key challenge of simulating the O&M of OWFs is the complexity of the models and the amount of data required to accurately simulate the behavior of an OWF. To address this issue, recent research has introduced more computationally efficient and analytically tractable models for long-term O&M decision-making. For instance, Centeno-Telleria et al. [25] propose a Markov chain-based analytical model that captures the key operational states of offshore renewable systems, enabling rapid long-term planning and extensive sensitivity analyzes. Compared to conventional simulation models, their approach reduces computational burden while retaining accuracy in capturing downtime patterns. This method is further applied by the same authors [26] to compare floating wind farms across the North Sea and Iberian Peninsula, linking maintenance-induced downtime with energy production to support strategic site-level planning. In a subsequent study [27], they assess heavy maintenance strategies, onsite versus towing, for floating wind turbines using a hybrid Markov framework, offering valuable insights for early-stage logistical and reliability planning. These analytical

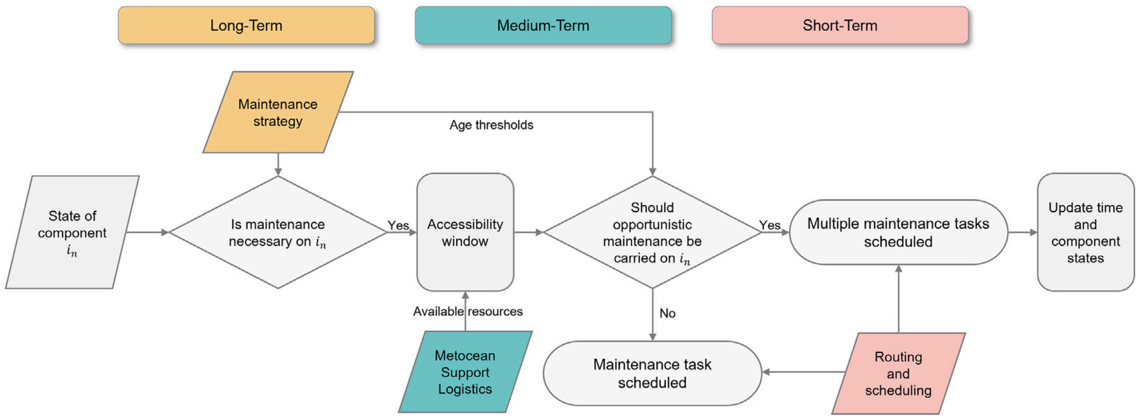

Fig. 10. Flowchart of common O&M simulation models.

approaches demonstrate that Markov-based models can deliver strategic insights comparable to Monte Carlo simulations, but with far lower computational requirements, making them well-suited for use in DSSs at the design or early operational stage.

In addition, several other notable contributions further extend the study and development of O&M simulation tools for OWFs. Three state-based formalisms are commonly used to model reliability and its financial consequences: Markov chains, Semi-Markov or Markov-reward processes and Petri Nets. Markov chains represent memory-less transitions between states with time-independent or time-dependent rates. They are often used to simulate turbine degradation and availability, as in [28,29]. Semi-Markov or Markov-reward processes combine probabilistic transitions with cost or reward structures assigned to each state. This is applied for example in [28]. Finally, Petri Nets, such as those employed by Elusakin et al. [30], provide a graphical framework for modeling concurrent activities, resource contention, and maintenance workflows, including crew and vessel constraints. For example, a reliability model for OWTs that includes degradation, inspection, and maintenance processes is introduced in [10]. This model employs a Petri net approach to capture the stochastic dynamics of these processes, integrating both degradation and maintenance operations, and yielding key results such as state probabilities, expected task counts, and the downtime impact of various maintenance strategies. A stochastic Petri network (SPN) model for O&M scheduling of floating turbines (FOWTs) and their supporting structures is presented in [30]. This model accounts for various factors, including component deterioration and renewal processes, and utilizes data from literature and wind energy industry databases. It was tested on a 5 MW wind turbine on a spar buoy platform.

The reviewed articles offer insights into asset modeling, integrated maintenance policies, financial analysis, reliability and maintenance management. Table 2 presents a typology of decision-making, failure, and metocean modeling approaches applied in O&M simulation models. This overview is intended for researchers building simulation frameworks and looking to identify which model combinations are commonly used or underexplored. It helps in selecting compatible methods for new modeling studies or comparative benchmarking.

Table 3 compares O&M simulation models based on how they address uncertainty and the types of maintenance strategies implemented. It is intended for researchers and practitioners seeking to identify existing models suitable for simulating different O&M strategies under uncertainty. The table allows a quick assessment of which studies consider logistics, repair types, and advanced strategies like CBM or opportunistic maintenance.

Table 2
Methods, failure models, and metocean models used in O&M simulation models.

	Simulation method							Failure model										Metocean model				
	Monte Carlo Simulation	Petri Net	Stochastic Petri Net	Fuzzy Logic	Numerical simulation	Bayesian Belief Network	Discrete event simulation	Exponential probability distribution	4-States Weibull distribution	3-States Weibull distribution	2-States Weibull distributions	Homogeneous Poisson Process	Non-Homogeneus Poisson Process	Stocastic Petri Net	Two-States Markov process	Time dependent failure rates	Constant failure rates	Average "Wait for good weather"	Markov Chain Model	Stocastic Petri Net	ARMA	MAR
[19]	✓										✓						✓		✓			
[20]	✓										✓					✓			✓			
[22]						✓				✓						✓						✓
[18]							✓						✓			✓						
[10]	✓	✓							✓								✓	✓				
[31]					✓					✓						✓	✓	✓				
[24]	✓											✓					✓		✓			
[32]				✓											✓		✓				✓	
[30]			✓						✓					✓			✓			✓		
[33]					✓			✓									✓		✓			

Table 3
Types of uncertainty, strategies, and repair types handled by O&M simulation models.

	Uncertainties							Strategies				Repair types										
	Costs	Failure rates	Prediction signals	Logistic time	Travel time	Repair time	Deterministic	Corrective	Scheduled	CBM	Opportunistic	Replacement	Major repair	Medium repair	Minor repair	Manual reset	Type 5[5]	Type 4[4]	Type 3[3]	Type 2[2]	Type 1[1]	Not specified
[19]	✓	✓		✓	✓	✓		✓	✓								✓		✓	✓	✓	
[20]			✓	✓		✓		✓	✓	✓												✓
[22]	✓							✓	✓													✓
[18]							✓	✓	✓													✓
[10]							✓	✓	✓	✓	✓						✓	✓	✓	✓	✓	
[31]			✓					✓	✓	✓	✓		✓		✓							
[24]							✓	✓	✓	✓		✓	✓		✓	✓						
[32]	✓	✓						✓														✓
[30]							✓	✓	✓	✓							✓	✓	✓	✓		
[33]							✓	✓	✓	✓				✓		✓						

[1]Heavy component, requires external crane, [2]Heavy component, requires internal/external crane ($> 800 - -1000\ kg$), [3]Small parts, requires internal crane ($< 800 - -1000\ kg$), [4]Small parts, inside nacelle, [5]Small parts, outside nacelle [10]

Table 4 identifies the turbine components most frequently modeled in O&M simulations. This can support practitioners in deciding which components to prioritize for predictive modeling, and researchers aiming to focus on underrepresented areas (e.g., yaw systems, cooling).

In the reviewed literature, two complementary approaches are used to represent the financial impact of O&M decisions. *Deterministic cash-flow* assumes a single expected value for certain cost or revenue terms. *Probabilistic cash-flow*, by contrast, incorporates uncertainty, e.g., failure rates, electricity prices, or weather-induced downtime, as random variables. The models that integrate this yield distributions for cost metrics, typically estimated through Monte Carlo simulation, as applied in Dinwoodie et al. [29] and Shafiee et al. [28], enable scenario-based analysis of lifetime costs. To mention another example, an analysis of the reliability and O&M management of OWTs is provided in [33], where various maintenance strategies are compared and optimized while evaluating their cost-benefit profiles using stochastic and probabilistic life cycle cost (LCC) models.

Uncertainty remains a key challenge in long-term O&M modeling, particularly in the estimation of failure probabilities and major component replacement rates for next-generation offshore turbines, for which field data are scarce. In fact, the results of O&M simulation models are highly dependent on the assumptions and parameters used in the model, which can be difficult to validate and adjust, given the scarcity of real-life data, for this reason many papers such as [31,32,34] focus on uncertainties and on evaluating their impact on the simulation results. Jenkins et al. [35] applied structured expert elicitation to estimate major replacement rates for future offshore wind technologies. Their approach helped quantify not only expected values but also credible bounds, which are essential for robust decision-making in early planning stages. More recently, Centeno-Telleria et al. [36] extended this work by performing a detailed sensitivity analysis on replacement cost and frequency assumptions for floating wind, showing that even small shifts in these parameters can significantly alter lifecycle cost projections and optimal maintenance strategies. These studies emphasize the importance of capturing uncertainty explicitly and demonstrate how expert-based methods can complement data-driven approaches when empirical evidence is limited. Furthermore, various sensitivity analyses have been carried out, demonstrating the use of simulation tools to investigate the effects of various inputs and uncertainties on O&M costs. For example, [37] identified 14 important inputs for calculating O&M costs, including failure rates, component costs, repair duration, and shift length. For availability, they considered factors like failure rates, duration of the shifts, and resource availability. The sensitivity analysis aimed to understand the impact of these inputs on O&M costs and availability. The impact of the chance of failure on asset performance evaluation is highlighted in [34]. They investigated the implications of different failure models and frequency on O&M models and simulation tools, comparing the resulting availability of assets and drawing conclusions about the effects on O&M strategies. A maintenance policy for wind turbines using a multi-component system approach is proposed in [31] where the authors analytically derive the system's lifecycle costs under the proposed policies using numerical simulations. Additionally, the study

Table 4
Components considered in O&M simulation models.

	Blades	Hub	Pitch system	Generator	Electrical system	Control system	Hydraulic system	Mechanical brakes	Yaw system	Converter	Transformer	Tower	Shaft	Bearings	Gearbox	Lubrication system	Cooling system	Mooring lines	Floating foundation
[19]	✓		✓	✓	✓	✓		✓	✓				✓	✓	✓				
[20]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
[22]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
[18]	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓			✓	✓		
[10]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				
[31]	✓	✓	✓	✓						✓		✓	✓						
[24]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				
[32]	✓		✓	✓	✓					✓			✓	✓	✓				
[30]	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
[33]	✓		✓	✓	✓	✓		✓	✓				✓	✓	✓				

factors in decision-making uncertainties by exploring how variations in prediction signal accuracy affect both the selection of decision criteria and the overall performance of the maintenance strategies. Finally, the effects of uncertainties related to weather, repair time, and the operational range of vessels on maintenance costs are examined in [38]. Using simulation tools, they analyzed the impact of these uncertainties on maintenance costs. The study aimed to quantify the influence of these factors and provide insights into optimizing maintenance strategies.

An essential aspect in long-term O&M modeling is the treatment of metocean conditions, which strongly influence site accessibility and thereby turbine availability. While traditional simulation models incorporate metocean effects through stochastic weather windows or time-sequential data (e.g., NOWIcob, StrathOW), recent analytical approaches have also begun to integrate these factors explicitly. Centeno-Telleria et al. [26] extend their Markov-based framework by incorporating high-resolution metocean datasets, such as significant wave height and wind speed, to compute site-specific accessibility profiles. This enables a more realistic estimation of downtime and its impact on energy yield. Rowell et al. [39] further demonstrate how floating wind sites differ markedly from fixed-bottom locations in terms of access windows, which has major implications for maintenance vessel strategies and service intervals. To support such evaluations at early planning stages, Konuk et al. [40] propose a technology-informed accessibility metric that combines metocean statistics with logistic feasibility, offering a standardized way to rank offshore renewable sites by maintainability. These studies highlight that modeling accessibility is not only critical for accurate O&M cost and performance prediction, but also increasingly feasible thanks to the growing availability of open metocean datasets.

Overall, O&M simulation models have evolved from basic cost estimators into multi-layered decision support tools that integrate failure dynamics, weather accessibility, vessel logistics, and financial forecasting. The continued development of probabilistic models, expert-informed uncertainty quantification, and hybrid analytical frameworks is expanding their applicability across design, planning, and operational stages. While simulation remains computationally demanding and data intensive, emerging approaches such as Markov-based models and structured expert elicitation offer scalable alternatives that retain critical realism. As offshore wind enters a new phase of deployment with larger, floating turbines in remote locations, the role of simulation in supporting robust, cost-effective O&M strategies will only become more pivotal.

3.2. Policy design

This subsection reviews optimization models developed to design cost-effective O&M policies at the strategic level. The primary objective of these models is to define the optimal timing to perform maintenance on the wind turbine components based on their age with respect to their expected lifetime. These models are increasingly integrated into DSSs, which combine data, modeling tools, and interfaces to assist planners in determining long-term strategies under uncertainty. The significant impact of age groups and age thresholds on the total cost of maintenance is highlighted in [41], where the authors propose a cost model for OWT maintenance based on opportunistic preventive maintenance.

Optimal age replacement policies for both parallel and series systems featuring dependent components are examined in [42]. The study employs a copula framework to model the interdependencies and to formulate the corresponding optimal decision problems. The results offer valuable insights to reduce costs or increase system availability, and the paper concludes with a discussion on applying these findings to OWT systems.

A maintenance strategy for OWFs that integrates degradation failures, incidents, and age-based opportunities is proposed in [43,44]. This strategy aims to reduce O&M costs, and its comparative analysis shows significant cost reductions with respect to traditional opportunistic maintenance strategies. Accessibility constraints are taken into account by modeling weather series using the Markov chain method, and the optimal preventive maintenance age along with the opportunistic maintenance age are evaluated through numerical optimization to minimize the total expected cost of maintenance.

The opportunistic maintenance strategy presented in [45] optimizes subsystem intervals by grouping tasks using a state transition degradation model. The results demonstrate the effectiveness of the proposed model in reducing the total maintenance cost compared to conventional preventive maintenance strategies.

A framework for optimizing maintenance strategies with multiple objectives is introduced in [46]. The study identifies three key uncertainties impacting the model: the random nature of failure times, discrepancies between actual and predicted failure occurrences, and the unpredictability of maintenance outcomes. To resolve conflicts among objectives, Monte Carlo simulation is employed along with the Non-dominated Sorting Genetic Algorithm (NSGA-II) to determine optimal maintenance decisions.

A single-component maintenance optimization model designed for OWT upkeep under time-varying cost conditions is presented in [47]. Building on existing policies, the study demonstrates that the optimal strategy in such a context is a time-dependent age replacement policy.

Table 5 summarizes key studies on age threshold optimization for O&M planning. It helps modelers compare how age-related decision variables, constraints (like accessibility), and optimization techniques are handled across different works. This table supports the understanding and practical design of age-based preventive maintenance policies.

Table 5
Optimization objectives, design variables, constraints, assumptions, and methods in studies using age-threshold-based maintenance policies.

	Objective Function				Design Variables			Constraints						Assumptions					Methodology						
	Yearly O&M Cost	Total O&M Cost	Availability	Downtime	Age Thresholds	Age Groups	Maintenance Intervals	Age groups of same lenght	Accessibility	Component Dependencies	Failure Replacement	Maintenance Interval	Safety	Same components WT	Weibull Failure Distribution	Fixed Maint. Time	Negligible Maint. time	Perfect Maintenance	Exhaustive Search	Markov Method	Simulation Analysis	Copula Framework	Monte Carlo	NSGA-II	LP/MILP
[41]	✓				✓	✓		✓						✓	✓		✓		✓						
[43]		✓			✓				✓						✓	✓				✓	✓				
[44]		✓			✓				✓						✓	✓				✓	✓				
[42]		✓	✓		✓					✓		✓			✓			✓				✓			
[45]		✓					✓			✓	✓				✓	✓				✓					
[46]		✓		✓	✓								✓	✓	✓	✓		✓					✓	✓	
[47]		✓			✓								✓			✓									✓

In conclusion, the reviewed literature provides insights into age threshold optimization for maintenance strategies in OWT systems. The studies emphasize the importance of determining the optimal number of age groups, considering risk-based planning methods, integrating multiple maintenance opportunities, and addressing time-varying costs.

In summary, strategic decision-making in OWF O&M relies on both simulation and optimization to explore and define long-term maintenance strategies. Simulation models support scenario-based evaluation of predefined strategies under uncertainty, helping assess cost and logistics trade-offs. Optimization models, by contrast, prescribe ideal policies based on simplified cost-reliability formulations. Together, these tools form the backbone of strategic decision support systems that inform early-stage investment, design, and planning decisions.

4. Tactical decision-making

Transitioning from the strategic overview, our focus shifts to the tactical echelon. In this section, we investigate the tactical perspective of O&M optimization for OWFs. We analyze the main factors and objectives in fleet selection and spare parts management for OWF O&M.

4.1. Fleet selection

The selection of the fleet for OWF O&M involves determining the optimal combination of vessels and resources needed to effectively and efficiently carry out maintenance activities. One of the primary goals is to minimize the overall O&M costs associated with the wind farm, considering factors such as vessel capabilities, seakeeping abilities, chartering costs, crew transfer costs, maintenance costs, and revenue loss due to downtime [23,48]. Additionally, different maintenance strategies have to be considered in fleet selection. The optimal fleet should be capable of supporting these strategies to ensure the reliability and availability of the wind turbines [49].

This literature review provides an overview of the current research on fleet selection for OWFs' O&M, highlighting significant findings and differences in approaches.

In [48], the authors compare six decision support tools for selecting optimal vessel fleets for O&M operations, including MAINTSYS, Shoreline [50,51], the MARINTEK fleet optimization model [52], and ECN's O&M Tool [53]. Notably, the comparison also includes ECUME and StrathOW, which were originally developed for strategic-level analysis (as reviewed in Section 3.1), but are here evaluated based on their ability to support medium-term decisions such as fleet composition. This reflects the cross-horizon applicability of certain tools when adapted to different planning contexts. The study assesses the robustness of these tools in minimizing O&M costs under varying weather conditions, vessel specifications, and failure scenarios.

Logistics planning for OWF operations is addressed in [54], where a Monte Carlo simulation approach is used to evaluate cost-effective allocation of O&M resources, considering different vessel types and weather conditions. The study emphasizes sustaining continuous power production by efficiently operating O&M fleets.

A mathematical model to optimize fleet selection, taking into account turbine availability, O&M costs, and revenue loss, is introduced in [55]. Factors such as weather conditions, vessel capabilities, and maintenance strategies are considered.

Uncertainty in weather conditions, travel times, and repair times is addressed in [52] through a mathematical model aimed at minimizing the expected total cost of the vessel fleet over the wind farm's lifetime while satisfying turbine availability requirements. A branch-and-cut algorithm is employed to solve this model.

A time-domain Monte Carlo approach for investigating the optimal chartering strategy for jack-up vessels is proposed in [56]. Additionally, the study highlights regional collaborations between different parties as an alternative solution for cost reduction, integrating climate parameters, failure characteristics, and vessel specifications to determine the best overall strategy.

The potential benefits of resource sharing among service providers for OWF maintenance are examined in [57]. Instead of each provider leasing its own Jack-Up vessel, the study proposes two alternatives: one where the vessel is purchased and shared, and another that combines vessel and harbor sharing. Simulation modeling is used to evaluate these scenarios, revealing significant cost benefits that vary with the number and distance of service providers involved.

Considering future major maintenance costs for OWFs is also a quite important challenge, as highlighted in [58], where a modeling framework assesses different operating strategies under various scenarios, incorporating offshore heavy lift vessel strategies. Four operational strategies are proposed: fix on fail, batch repair, annual charter and purchase based on different life failure distributions.

A mixed-integer linear programming (MILP) model for vessel fleet selection and maintenance scheduling is presented in [59]. The MILP model considers a priori information to optimize fleet composition and scheduling. A heuristic approach is introduced to assess the effect of a priori information on the MILP model's performance.

A two-stage stochastic programming model for fleet optimization in OWF maintenance is proposed in [60]. The model integrates preventive and corrective maintenance tasks, optimizing vessel fleet composition, and scheduling. The study considers uncertainty in maintenance needs and weather conditions.

Genetic algorithms are employed to optimize O&M asset configurations in [61], with the approach aimed at reducing operating costs while enhancing reliability and availability.

Finally, [62] presents a DSS designed to aid in fleet selection for OWF maintenance. They use a stochastic optimization model to determine the optimal configuration of vessels.

The selected literature describes simulation models, mathematical optimizations, and heuristic methods, to address the challenges associated with fleet selection.

Table 6 outlines the main modeling approaches for offshore maintenance fleet optimization. It is intended for researchers designing fleet selection models and for decision-makers comparing strategies such as purchasing vs chartering. The table can also guide tool developers in choosing appropriate constraints and objectives for real-world fleet planning tools.

4.2. Spare part management (SPM)

Spare part management in the O&M of OWFs involves effectively managing the availability, procurement, storage, and utilization of spare parts required for the maintenance and repair of wind turbines. It encompasses various activities and considerations to ensure uninterrupted operation, minimize downtime, and optimize costs. Efficient spare part management is crucial for the O&M of OWFs, impacting maintenance costs, downtime, and overall profitability. SPM aims to ensure that the right spare parts are available at the right time and place, minimizing the inventory holding costs and the downtime costs due to stockouts. However, determining the optimal inventory levels for spare parts is a complex and challenging task, as it involves multiple factors such as the failure characteristics of the components, the lead time and cost of procurement, the storage and handling costs, the maintenance policies and strategies, and the uncertainty and variability of demand.

Regardless of the specific methods applied, the optimization of inventory levels generally consists of the following steps:

1. System Analysis: Analyze historical failure data to identify patterns, frequencies, and severity. Categorize critical components by risk using methods such as FMEA [63] or Markov processes [64] to determine spare parts needs.
2. Demand Forecasting: Estimate future failure probabilities and timings, considering demand uncertainty and lead times, to predict spare parts consumption and replenishment requirements.
3. Cost Modeling: Develop a cost model that includes procurement, handling, stockout, and excess inventory costs.

Table 6
Fleet optimization approaches based on objective functions, constraints, and methods.

	Objective Function						Design Variables				Constraints			Assumptions			Methodology					
	Fixed Costs of vessels and base	Variable Cost of chartering	Downtime Cost	Total O&M Cost	Availability	Reliability	Vessels to Purchase	Vessels Chartering	Vessels-Task Assignment	Vessel-Technician Assignment	Budget	Seakeeping Ability / Capacity	Vessel Availability	Tasks are Pre-Determined	Deterministic	Fixed Inputs	MIP	Monte Carlo Simulation	Stochastic Prog.	Dantzig-Wolf Decomposition	Genetic Algorithms	Reliability Anal.
[52]	✓	✓	✓				✓		✓		✓	✓		✓		✓	✓					
[55]			✓	✓			✓	✓				✓	✓			✓		✓				
[56]				✓				✓				✓	✓	✓	✓			✓				
[60]				✓				✓	✓			✓	✓	✓		✓			✓	✓		
[57]		✓						✓	✓			✓	✓		✓	✓		✓				
[61]				✓	✓			✓	✓	✓		✓	✓			✓		✓			✓	✓

4. Inventory Optimization: Balance holding costs against benefits to determine optimal order quantity, reorder point, and safety stock based on criteria such as total cost minimization, service level, or risk reduction.

The above steps, summarized in Fig. 11, provide a general framework for SPM optimization; however, different methods and techniques may be applied within each step depending on the specific characteristics and requirements of each problem. In this paper, we review some of the most common approaches to SPM optimization, specifically in the context of OWFs.

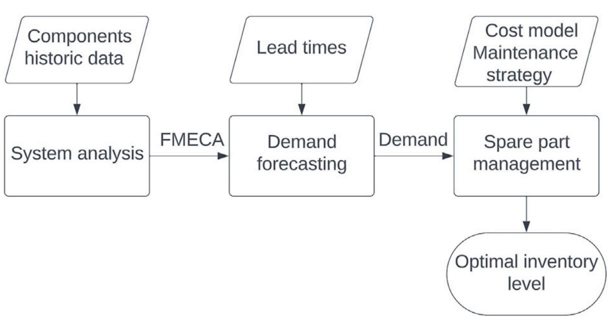

Fig. 11. Generic flowchart for Spare Part Management optimization, adapted by [65].

A critical review [65] compares various spare parts control strategies for OWFs. It systematically analyzes prominent models, highlighting significant contributions and claiming cost reductions of up to 51 % compared to traditional scheduling methods, while integrated approaches have demonstrated 27 % savings. This review provides valuable guidelines for effective and efficient spare parts management throughout the wind turbine's life cycle.

A model that integrates wind turbine accessibility and restrictive factors to minimize maintenance costs is proposed in [66]. Their findings reveal that restricted accessibility affects preventive maintenance scheduling and spare parts demand, suggesting the potential to reduce costs and enhance profitability by utilizing resources and technicians more efficiently.

Optimization schemes and component updating techniques have been explored to optimize spare parts quantity and reduce costs. An optimization scheme based on component updating and a Markov process is introduced in [64]. By considering availability as the optimization objective, they effectively reduce spare parts management costs. Simulation analysis demonstrates substantial cost savings compared to traditional methods. This approach presents a promising solution for spare parts quantity optimization.

A problem similar to SPM optimization has been tackled by [67], where a mixed-integer programming model for determining and validating repair kits under varying weather conditions is proposed. They emphasize the importance of adapting repair kits based on weather forecasts and demonstrate considerable downtime reductions through emergency resupplies. Their methodology comprises three phases, offering insights into the repair kit problem and aiding practitioners in defining repair kits under different conditions.

Table 7
Characteristics of main SPM methods proposed in the literature.

	Objective Function		Design Variables			Constraints			Methodology	
	Downtime Cost	O&M Cost	Spare Parts Inventory	Detection Time	Detection Frequency	Availability	Budget	Detection Cycle	FMEA	Markov Process
[63]	✓		✓			✓	✓		✓	
[64]		✓		✓	✓	✓		✓		✓

Table 7 synthesizes key characteristics of spare parts management (SPM) optimization methods in the context of offshore wind farms.

5. Operational decision-making

As we presented the medium-term considerations of fleet and inventory management, our attention turns to the short-term horizon. In this section, we explore the short-term perspective of O&M optimization for OWFs. This horizon is dedicated to the short-term scheduling of maintenance tasks, on a daily or weekly basis, where real-time factors like weather, component condition, and logistical constraints play a crucial role. Here, we present some of the latest developments in prognostic and diagnostic methods, which are used to inform decisions made at this horizon. We also present an overview of different techniques for optimizing routing and scheduling decisions.

5.1. Diagnostics and prognostics

This section reviews the importance of diagnostics and prognostics for OWTs and some of the methods and applications in this field. The ability to assess and predict component failures has a direct impact on optimizing the maintenance strategies employed over the wind farm's lifetime. By exploring CBM technologies in this section, we aim to underline their significance in influencing the broader decision-making process and highlight the synergy between technology and strategic planning.

Diagnostic means evaluating the current health or performance of a system based on its current state and past behavior, while prognostic means predicting the future health or performance of a system based on its current state and past behavior. Diagnostic and prognostic are essential for CBM because they provide information about the condition and the remaining useful life of the wind turbine components, which can be used to optimize the maintenance decisions [68]. For example, diagnostics can help identify the type, location and severity of a fault, while prognostics can estimate the time to failure or the probability of failure within a given time horizon.

There are several methods and techniques for the diagnostics and prognostics of offshore wind turbines (OWTs), which can be classified into data-driven, model-based, or hybrid approaches [69].

Data-driven methods use historical or real-time data from sensors or SCADA systems to extract features and patterns that indicate faults or degradation. One prominent area of research focuses on SCADA data analysis for CBM [70]. The importance of interpreting SCADA data to enable effective CBM is highlighted in [71]. These approaches enable researchers to extract valuable insights from operational data that are readily available to turbine operators without the need for potentially expensive sensors. Operational curve analysis, such as power curve, rotor speed curve, and blade pitch angle curve, is used to detect deviations from normal behavior, as shown in [72], aiding in early fault detection and proactive maintenance. Deep learning techniques also play a significant role in this domain. For instance, [73] presents a time-series fault detection method using convolutional neural networks (CNNs), capable of identifying anomalies from turbine operational data. A recent contribution to data-driven methods is the Gaussian mixture autoencoder developed by Fernández-Navamuel et al. [74], which enables uncertainty-aware damage identification in floating wind turbines by modeling complex, nonlinear data distributions. In addition, [75] introduces a probabilistic model to evaluate alarm counts for individual subassemblies and the entire wind farm. The model achieved 99.3 % accuracy for long-term forecasts and over 83 % accuracy for short-term predictions, using two years of met mast data. [76] combines statistical classification of SCADA data with event tree analysis to predict abnormal component behavior and assess predictive maintenance benefits, comparing Naïve Bayes and Neural Network classifiers.

Model-based methods rely on physical or mathematical representations of wind turbine components to simulate their behavior and compare predicted and observed responses. In [77], a high-fidelity gearbox model is used to estimate and detect wear in the main shaft bearing via statistical fault diagnostics. Similarly, [78] presents a CBM system analyzing power-dependent vibrations in the drivetrain to identify specific fault-related patterns. For floating offshore wind turbines, tailored architectures have been proposed. A mixed model and signal-based fault diagnosis architecture to detect and isolate faults specific to floating turbine dynamics is introduced in [79].

Hybrid approaches combine data-driven and model-based techniques to capitalize on their respective strengths. Bayesian methods are particularly well suited to this purpose. For example, [80] presents a generic diagnostic model that integrates outputs from multiple fault detection systems such as vibration, temperature, and oil particle sensors, using Bayesian updating to reduce uncertainty based on inspection outcomes.

Lastly, Digital Twin (DT) technologies are emerging as comprehensive hybrid solutions. A review of DT-based frameworks for OWFs [81] highlights their roles in failure monitoring, remaining useful life (RUL) prediction, safety and ecological management, O&M decision-making, and design optimization.

Table 8 provides a comparative summary of prominent health monitoring methods used for condition monitoring and prognostics in offshore wind turbines. It is intended for the reader to evaluate the relative strengths and scopes of different fault detection and prediction models. The table distinguishes between diagnostic and prognostic models, between SCADA-based and sensor-rich CBM methods, and lists typical analytical approaches. This overview supports informed decisions about the integration of health-monitoring technologies into predictive maintenance pipelines.

By using diagnostic and prognostic information, maintenance activities can be planned and scheduled according to the current and future condition of the wind turbine components. This can avoid unnecessary or premature maintenance actions, as well as prevent catastrophic failures or downtime due to undetected faults or degradation.

5.2. Routing and scheduling

The routing and scheduling problem in the O&M of OWFs involves determining the optimal routes and schedules for vessels, technicians and resources involved in maintenance activities. It aims to efficiently allocate resources, minimize travel time and costs, optimize task sequencing, and ensure timely completion of maintenance tasks. This

Table 8
Characteristics of main health diagnosis and prognosis methods proposed in the literature.

	Methodology										SCADA vs CBM		Prognostic vs Diagnostic	
	Gaussian process	Normal operational conditions	Convolutional Neural Network	FDAE	FIE	Statistical fault diagnosis	Naïve Bayes classifier	Neural Network	Bayesian update	Wind speed statistics	SCADA	CBM	Prognostic	Diagnostic
[71]		✓									✓			✓
[78]		✓										✓		✓
[72]	✓										✓			✓
[77]						✓						✓		✓
[80]									✓			✓		✓
[76]							✓	✓			✓		✓	
[75]										✓	✓			✓
[79]				✓	✓							✓		✓
[73]			✓								✓			✓

section reorganizes the reviewed literature into three modeling perspectives: fleet logistics, task sequencing and resource allocation, finally providing information on how weather, operational constraints and uncertainties have been incorporated into operational DSSs.

One of the primary goals of vessel routing is to optimize the paths taken by vessels to access and service the OWTs. This involves considering factors such as wind and wave conditions, vessel capabilities, and the location of the wind farm [82]. The objective is to minimize the cost by reducing travel time and distance, lowering fuel consumption, and ensuring safe and efficient transportation to and from the wind farm [83]. A mathematical model by [84] considers vessels capable of remaining offshore for several shifts while managing large repairs, the paper also presents a precise calculation of downtime costs. A simulation is employed to assess the model's performance, using a rolling horizon heuristic method to solve it. Moreover, the study demonstrates how coupling a mathematical model with simulation can help evaluate strategic decisions related to vessel fleet composition. Another mathematical model for planning and executing maintenance tasks is presented in [85]. The study also introduces a heuristic solution method based on a rolling-horizon approach and includes computational experiments to support strategic decisions on fleet composition. Docking operations have been studied in [86] which focuses on evaluating operational limits for different access systems. Their work introduced methodologies for numerical analysis of accessing techniques, such as active motion-compensated access devices and fenders. These methods can be utilized to assess docking operability, contributing to the safe and efficient transportation of technicians and materials. To improve the daily route planning of maintenance vessel operations, [87] developed an optimization framework known as OptiRoute. This framework employs heuristic and clustering techniques while taking into account weather, vessel characteristics and failure data. The experimental results showed that the operational windows were significantly extended, particularly when Service Operation Vessels (SOVs) and Crew Transfer Vessels (CTVs) were used in tandem. Additionally, [88] introduced a software tool named GESTIONE to optimize OWT maintenance. The package uses techniques such as Bayesian Networks, Artificial Neural Networks, and FMECA, utilizing condition monitoring data to predict component failures, thereby reducing O&M costs and providing insights into wind turbine operations. Furthermore, [89] introduced a decision support tool for OWF vessel routing under uncertainty. Their methodology incorporated uncertain maintenance action times into vessel routing, considering realistic OWF problems. The tool highlighted the importance of considering uncertainties in vessel routing decisions.

Efficient task sequencing is crucial to minimize downtime and maximize the utilization of resources. This includes determining the order in which maintenance tasks are performed, considering their dependencies, and assigning suitable time slots to each task. The aim is to minimize waiting times, avoid conflicts in resource allocation, and optimize the overall schedule for maintenance activities [54,90]. Contributing to the optimization of O&M scheduling, risk-based planning methods for wind turbines maintenance are discussed in [91] with the goal of evaluating the probability of failure based on inspections and finally minimizing the expected costs. They present various approaches, including decision rules based on crude Monte Carlo simulations, limited memory influence diagrams, Bayesian updating and Markov decision processes. The study concludes that decision rules based on the probability of failure yield lower costs compared to the methods based on Monte Carlo simulations. The integration of advanced mathematical techniques in maintenance management systems has been explored to improve the efficiency and cost-effectiveness of offshore wind power generation. A novel architecture and system for Reliability Centred Maintenance (RCM) was presented in [29]. Their integrated system demonstrated fault detection, reliability and maintenance modeling, and optimized maintenance scheduling, leading to maximized availability and revenue generation of turbines. A model that maximizes the profit of an OWF was developed in [92] by solving the Single-Level (SLP) and Bi-Level (BLP) optimization problems, considering various network and wind farm constraints. The model incorporates information from condition monitoring systems and provides a scalable solution for planning maintenance schedules in a deregulated power system. Lastly, [93] proposed an O&M scheduling strategy model for OWFs that aimed to minimize maintenance scheduling costs. By optimizing maintenance division, the number of model optimizations can be simplified, providing practical guidance for scheduling O&M tasks in OWFs. Alternative modeling techniques such as constraint programming also show promise. Froger et al. [94] developed a short-term scheduling model for offshore wind farms that simultaneously handles vessel routing, technician assignment, and turbine-specific fault types. Their framework flexibly incorporates spatial constraints (e.g., distance, location), temporal availability, technician skills, and weather-induced access windows. While not yet commonly integrated into prognostic-driven frameworks, such constraint-based models offer powerful tools for enhancing the realism and feasibility of short-term maintenance planning.

The routing and scheduling problem also involves allocating resources such as vessels, crew members, and equipment to different maintenance tasks [95]. It requires considering the availability and capabilities of resources, task requirements, and constraints. The objective is to optimize resource allocation to ensure efficient task execution and minimize idle time. An optimization model that considers multiple vessels, time periods, O&M bases, and wind farms was developed in [82]. The study aimed to minimize overall maintenance costs, including travel, technician, and penalty-related expenses. The results showed that using multiple vessels and O&M bases can significantly reduce maintenance costs, leading to improved cost-effectiveness. The model was later extended to include a service operation vessel (SOV) and a safe transfer boat (STB), enabling the transfer of technicians and equipment to turbines, as described in [83]. A mathematical formulation of this problem is presented in [95], where the authors focus on determining the cheapest assignments of turbines and routes to vessels. Resource-related decision-making in corrective maintenance has also been addressed through a mathematical model proposed in [96], which identifies cost-effective resource combinations and offers considerable cost savings. The model accounts for uncertainties in turbine failure information and supports stakeholders in making critical short-term decisions.

Decision support systems and optimization models play an important role in solving the routing and scheduling problem. These tools help evaluate different scenarios, incorporate real-time data, consider uncertainties in weather conditions and task duration, and optimize routing and scheduling decisions based on specific objectives, constraints, and performance metrics. Weather and operational constraints that affect vessel O&M activities have to be taken into account. This includes considering the effect of weather conditions on vessel operability, such as maximum wave height for safe access to turbines. Constraints related to vessel maintenance, crew shift schedules, and regulatory requirements may also be considered in the optimization process [97]. Historic wind farm data have also been used to evaluate maintenance planning methods and estimate their respective return on investment (ROI), as shown in [28]. Automated daily maintenance planning has been shown to bring significant financial benefits to the O&M of OWFs. Uncertainties in maintenance activities pose significant challenges in OWF maintenance. To address this, efficient solution methods for both deterministic and uncertain maintenance routing problems have been proposed in [84]. Their simulation-based optimization algorithm considers uncertain factors such as travel time, required maintenance time, transfer time for technicians and equipment, and unpredictable broken-down turbines. These methods provide valuable insights into handling uncertainties and optimizing maintenance strategies.

Table 9 presents an overview of key optimization and simulation methods used for routing and scheduling tasks in offshore wind farm maintenance. This table is intended to provide guidance in evaluating suitable methods for task sequencing, vessel routing, and scheduling under uncertainty. It allows comparisons across heuristic, exact, and machine learning-based approaches, providing a foundation for selecting a method based on computational requirements, uncertainty modeling, or solution precision.

In conclusion, the selected literature highlights representative optimization models, simulation-based algorithms, mathematical formulations, and decision support tools employed in the routing and scheduling of O&M activities in OWFs. The studies emphasize the importance of minimizing maintenance costs, considering uncertainties, and integrating advanced techniques for improved reliability, cost-effectiveness, and revenue generation.

6. Gaps and limitations

This section explores both the limitations of widely adopted modeling approaches and the underrepresented opportunities in the current offshore wind O&M literature. While our review has focused primarily on mainstream methods, such as stochastic modeling, optimization-based planning, and rule-based simulations, several promising alternatives remain relatively unexplored or fragmented across decision-making layers. We also highlight overlooked dimensions such as the limited integration of biodiversity considerations into decision frameworks. Addressing these gaps is essential for advancing more holistic, cost-effective, and environmentally conscious O&M solutions.

6.1. Prognostic-driven scheduling

The advent of advanced data analytics and predictive modeling has revolutionized short-term scheduling approaches. By integrating real-time data from sensors with prognostic models, it is now possible to predict component health and maintenance needs with greater accuracy [10]. This technological progression has facilitated the development of prognostic-driven approaches, which are known to be highly effective in optimizing short-term maintenance schedules [98].

A recent contribution by Frederiksen et al. [99] proposes a methodology to quantify the efficiency and economic benefit of predictive maintenance compared to preventive strategies.Their approach introduces separate indicators for predictive accuracy and realized maintenance efficiency, validated through a realistic OWF case study. The study finds that predictive maintenance can yield cost savings, but only if the model achieves high accuracy and the system responds efficiently. Otherwise, the economic advantage may be lost.

The selected literature outlines different strategies for optimizing both vessel routing and the timing of maintenance operations in OWFs. These approaches focus on reducing travel times, streamlining resource allocation, and ensuring transportation is conducted safely and efficiently to cut costs [82,83]. However, many of these methods have traditionally relied on fixed age thresholds for scheduling maintenance. Such thresholds are determined by models that base maintenance timing solely on a component's age rather than its real-time condition [41].

Age threshold optimization techniques have been extensively explored in Section 3. These techniques use stochastic models to determine the most cost-effective timing for maintenance actions [42]. Although effective, these traditional methods do not fully utilize the potential benefits of prognostic information, which could further enhance scheduling efficiency.

Recent advancements highlight a shift towards prognostic-driven scheduling models that utilize probabilistic RUL predictions to inform maintenance decisions [45]. Unlike traditional fixed age threshold models, these approaches assess the actual condition and anticipated future health of components, enabling a more adaptive and responsive maintenance strategy that may reduce costs and enhance system reliability [98].

The integration of prognostics for scheduling O&M marks a significant shift from reactive to proactive maintenance strategies. Advanced monitoring and prognostic strategies have shown potential for substantial cost savings and improved operational efficiency. For example, studies have indicated that employing prognostic-driven models can lead to a reduction in O&M costs of up to 8 %, and a reduction in lost production by up to 11 %, primarily through early intervention to prevent failures and major component replacements [100].

Recently, [101] presented a review of prognostic-driven scheduling models used in other fields where this approach is already commonly used, such as aircraft maintenance, identifying potential applications for OWFs. The model they then propose incorporates a Model Predictive Control (MPC) framework, which optimizes maintenance schedules based on probabilistic RUL predictions. This framework has shown promising results in dynamically adjusting maintenance plans to improve cost-effectiveness.

The adoption of predictive models must also consider the trade-off between their predictive performance and the practical cost-benefit of implementing them, as emphasized in recent techno-economic evaluations [102]. High-performance models often require substantial data acquisition and integration efforts, including real-time condition monitoring systems and tailored prognostic algorithms. These requirements can drive up operational costs and introduce complexity that may

Table 9
Methodologies used in the main Routing & Scheduling methods proposed in the literature.

	MILP	ILP	Branch and Bound	GA	Random Forests	Dynamic Bayesian Network	Memetic Algorithm	MIP	Rolling-Horizon Heuristics	Large Neighbourhood Search	Analytical model	Heuristic optimization	SLP/BLP	Bayesian Network	Artificial Neural Network	FMECA	Monte Carlo Simulation	Particle Swarm Optimization
[88]														✓	✓	✓		
[95]			✓															
[29]					✓	✓	✓					✓						
[85]								✓	✓			✓						
[82]	✓	✓						✓	✓	✓		✓						
[92]													✓					
[89]																	✓	
[93]												✓						✓
[28]				✓								✓						
[96]											✓							
[87]												✓						
[83]										✓		✓						

not yield proportional benefits unless carefully matched to the asset's criticality, degradation profile, and accessibility constraints.

Moreover, several studies highlight that the high upfront capital cost of condition monitoring sensors, remains a barrier to large-scale deployment. Dinwoodie et al. [14] argue that operators must weigh these sensor investments against expected gains in availability and maintenance efficiency.

In conclusion, while traditional age-threshold optimization has provided a useful foundation for medium- to long-term planning, such as selecting the strategy or initiating criteria for maintenance interventions, it is inherently limited by its reliance on static assumptions about failure rates and component aging. Prognostic-driven models, by contrast, enable more dynamic and responsive decision-making by leveraging condition-based information and probabilistic RUL estimates. These models allow maintenance schedules to adapt in real time to asset health, environmental conditions, and operational constraints, aligning short-term actions with evolving system risks. However, their implementation requires careful evaluation of predictive performance relative to the costs and logistical burden of data acquisition and system integration.

6.2. Considering the interconnections

The challenges related to strategic, tactical and operational decision-making in the O&M of OWFs have been addressed separately in the literature. However, it is important to note that many of the design variables, constraints, and optimization objectives that are used in these separate approaches are interconnected and affect each other across the different decision-making layers.

For example, strategic decisions can have a significant impact on the availability and readiness of resources for maintenance in the medium and short-term horizons. Similarly, operational decisions, such as the routing and scheduling of maintenance tasks, can impact the overall maintenance strategy and budget allocation in the long-term.

Considering these dependencies holistically can help resolve limitations faced when models operate in silos. For example, simulation tools like NOWIcob and StrathOW provide detailed short- and medium-term maintenance cost and accessibility estimates, but their outputs are rarely integrated into long-term strategic planning, potentially missing cumulative effects of climate or logistic constraints [20,22]. Similarly, analytical models such as those proposed by Centeno-Telleria et al. [25,26] offer fast long-term insights, but may oversimplify short-term scheduling constraints unless coupled with detailed operational models. Furthermore, insights from short-term condition monitoring, like those derived from SCADA-based fault diagnostics or CNN-based anomaly detection [70,73] are often underutilized when updating maintenance plans or long-term maintenance strategies, which normally make use of fixed failure rates to model degradation. These examples highlight how cross-horizon information flow could improve responsiveness, resource planning, and overall lifecycle cost-efficiency.

Therefore, it is crucial to consider the interdependencies and interactions between the different decision-making layers when addressing the O&M optimization problem.

Table 10 presents an interconnection matrix illustrating how core variables such as maintenance plans, personnel availability, or vessel capacity, interact with different offshore wind O&M sub-problems. The matrix highlights whether each variable acts as an input, constraint, or output within models for maintenance strategy, spare parts management, fleet selection, task scheduling, and vessel routing. This synthesis can be useful for researchers building O&M models, as it helps identify variable dependencies and coordination requirements across hierarchical decision layers.

Therefore, there is a pressing need to develop integrative frameworks that link decisions across horizons, facilitating feedback loops, information flow, and dynamic adaptation. This not only enables a system-level optimization of O&M but also helps align short-term operations with long-term goals. Decisions related to O&M are not isolated events but rather dynamic processes that evolve over the lifespan of a wind farm. The decisions made in one decision-making layer can significantly impact the effectiveness and outcomes of decisions made in other layers. The conditions, performance, and demands of OWFs are subject to continual changes and unforeseen circumstances [14].

To address these challenges, it is of utmost importance to develop a mechanism or framework that can integrate and fuse different algorithms and strategies for more effective decision-making [6]. Such mechanism would enable the seamless flow of information, insights, and data across different echelons, allowing for a holistic view of the O&M landscape. By integrating and fusing the various decision-making processes, operators can make more informed and comprehensive decisions that account for the interdependencies and interconnections between different aspects of O&M.

Developing such a mechanism or framework holds several key benefits. Firstly, it promotes synergy and coherence in decision-making, avoiding conflicts or suboptimal outcomes caused by isolated or disconnected strategies. Secondly, it facilitates knowledge sharing and cross-learning between different stakeholders and disciplines involved in O&M. This collaboration enhances the collective understanding and expertise in managing OWF O&M. Lastly, it enables the identification of potential trade-offs, synergies, and opportunities that may arise from integrating different algorithms and strategies.

To achieve this, future research efforts should focus on developing advanced decision support systems that can integrate different algorithms, models, and strategies. These systems should be adaptable and flexible to accommodate the dynamic nature of O&M requirements. Additionally, they should leverage emerging technologies such as artificial intelligence, machine learning, and big data analytics to maintain horizontal coherence (within one horizon) and vertical consistency (across horizons).

In conclusion, rather than viewing each decision horizon as isolated, we advocate for a holistic modeling approach. By accounting for cross-layer feedbacks, constraints, and dependencies, such integrated systems can significantly enhance the robustness, agility, and economic performance of offshore wind O&M strategies.

6.3. Environmentally-inclusive decision-making

In the realm of OWF O&M, there exists a growing interest in integrating environmental concerns into decision-making frameworks. However, different schools of thought must be distinguished. *Nature-Inclusive Design (NID)* refers to approaches that enhance positive environmental impacts, e.g., through habitat creation or biodiversity-friendly structures. In contrast, eco-conscious or techno-environomic frameworks aim to quantify and minimize environmental harm, often through metrics like lifecycle emissions or ecological cost functions.

Several studies have started incorporating environmental aspects into O&M-related decision support. For instance, [103] evaluates the Global Warming Potential (GWP) of floating OWFs and shows that the O&M phase can account for up to 49 % of lifecycle GHG emissions, depending on fleet composition and maintenance strategy. This demonstrates that O&M choices significantly influence environmental performance. Similarly, Canet et al. [102] propose a techno-environomic framework where wind turbine design and operation are optimized beyond purely economic metrics, incorporating carbon footprint explicitly into the objective function.

Despite this progress, these approaches still fall short of fully integrating ecological considerations or biodiversity objectives into maintenance planning. For example, vessel routing decisions or repair schedules rarely account for impacts on marine life or sensitive habitats. This is where the principles of Nature-Inclusive Design remain underexplored in the O&M domain.

A few studies hint at this potential. The work in [104] highlights how vessel type influences emissions, suggesting environmental

Table 10
Interconnection matrix.

Problem	Maintenance plan	Age thresholds	Personnel availability	Personnel skill set	Availability of spare parts	Critical components	Maintenance tasks	Task completion time	Availability of vessels	Fleet mix	Vessel speed	Vessel capacity
Maintenance strategy	O	O	I	I	C	O	O	I	I	C	I	I
Spare parts management	I	C			O	I	I					
Fleet selection	I	C	O	O			I	C	O	O	O	O
Task scheduling	I	I	C	C	I	I	I	O	I	C	I	C
Vessel routing	I		C	C	I		I	C	I	O	C	C

Note: I = Input; O = Output; C = Constraint. Each letter indicates whether a variable serves as an input, output, or constraint in the corresponding optimization sub-problem.

trade-offs in logistic planning. Similarly, the authors of [105] argue that Environmental Impact Assessment (EIA) should not be treated as a static regulatory requirement, but rather as a dynamic decision-support tool employed throughout the project lifecycle, including the O&M phase.

To bridge this gap, future efforts should develop hybrid frameworks that combine quantitative environmental assessment with ecological sensitivity mapping, integrating tools such as lifecycle assessment (LCA) and real-time monitoring of ecological indicators. These could help optimize O&M not only for cost and reliability but also for biodiversity and environmental preservation.

Such integration would yield multiple benefits, including compliance with increasingly stringent environmental regulations, minimized disruption to marine ecosystems and habitats, and improved public perception and stakeholder acceptance, particularly in ecologically sensitive regions.

Ultimately, aligning O&M decision-making with both sustainability and biodiversity goals can significantly enhance the long-term viability and social license of offshore wind developments.

6.4. Lack of real-life data

One of the challenges in the research of the O&M of OWFs is the availability of actual real-life data. This is due to the reluctance of turbine manufacturers and wind farm owners to share such information.

This obstacle has already been pointed out in articles such as [106] in the context of failure prognostics, [107] in their research regarding weather window prediction, and many others.

The reluctance to share data may stem from competitive reasons, as the performance and reliability of a wind farm can be key factors in attracting new customers and investors. Sharing this information may also expose potential vulnerabilities and weaknesses that could be exploited by competitors.

Moreover, the data collected by the turbine manufacturers and wind farm owners is often considered proprietary information and can be subject to intellectual property laws and contractual obligations. As such, the sharing of this data may require legal agreements and negotiations, which can be time-consuming and costly.

This lack of real-life data can limit the accuracy and validity of O&M simulations and modeling. Without access to actual data, researchers may have to rely on assumptions and estimations, which can introduce inaccuracies and biases into the analysis.

Therefore, researchers need to collaborate with turbine manufacturers, wind farm owners and other key players in the sector to obtain actual data and develop partnerships that can provide access to this data. This can involve building trust, addressing concerns around data privacy and security, and establishing clear benefits for all parties involved. By doing so, researchers can gain access to valuable information that can help to improve the O&M optimization of OWFs.

7. Conclusion

This review has examined the state of the art in OWF O&M modeling through the lens of strategic, tactical, and operational decision-making. For each decision level, we reviewed approaches that support: strategic evaluations of long-term costs, reliability, and logistical feasibility (Section 3); tactical planning of fleet composition and supply chain strategies (Section 4); and operational routing and short-term maintenance scheduling (Section 5). By organizing the literature around these three decision layers, the review offers a structured foundation for comparing methods, identifying common modeling practices, and highlighting gaps.

Our findings emphasize the growing relevance of prognostic-driven maintenance, particularly at the operational level, and the increasing sophistication of decision support systems that incorporate uncertainty, logistics, and cost modeling. We also identify a persistent lack of integration across decision levels, and note that few models explicitly consider the environmental impacts of O&M strategies, a gap that remains critical as the sector expands.

The main limitations and directions for future research are the following: the integration of prognostic-driven scheduling also requires more refined models that make use of real-time data to predict component failures accurately and optimize maintenance schedules dynamically. The accuracy and applicability of the models and methods discussed in this article depend on the quality and accessibility of data. Consequently, there is a need for greater efforts to collect, validate, and share data from real-life operations. In addition, such models often rely on simplifying assumptions and parameters that may not fully capture the complexity and dynamics of OWF systems. Thus, further research is necessary to develop more realistic and robust models that account for factors such as uncertainties and inter-dependencies. Furthermore, the models and methods discussed in this article frequently concentrate on one or two objectives such as cost minimization or availability maximization. Nevertheless, O&M optimization is a multi-objective and multi-constraint problem involving trade-offs between conflicting goals. Therefore, more research is required to establish models capable of providing a range of optimal solutions that satisfy diverse preferences and criteria. For example, current models often overlook the environmental impacts of O&M activities, such as emissions, noise, waste, and biodiversity loss. Nonetheless, OWFs are expected to play a crucial role in mitigating climate change and promoting sustainable development. Therefore, it is important to develop nature-inclusive models capable of quantifying and minimizing the environmental impacts of O&M activities.

To conclude, this article has delivered a critical review of current research on O&M optimization for OWFs across three distinct decision-making layers. It has also identified gaps in the literature and proposed directions for future research. By addressing these gaps and challenges, future research can contribute to the development of more effective and sustainable solutions for O&M optimization in OWFs.

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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Data availability

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