

Article

Strategic Deployment of Service Vessels for Improved Offshore Wind Farm Maintenance and Availability

Chenyu Zhao ¹, Adam Roberts ¹, Ying Cui ² and Lars Johanning ^{1,*}

¹ School of Engineering, Computing and Mathematics, University of Plymouth, Plymouth PL4 8AA, UK; chenyu.zhao@plymouth.ac.uk (C.Z.); adam.roberts@plymouth.ac.uk (A.R.)

² College of Electromechanical Engineering, Qingdao University of Science and Technology, Qingdao 266101, China; yingcui@qust.edu.cn (Y.C.)

* Corresponding author. E-mail: lars.johanning@plymouth.ac.uk (L.J.)

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ABSTRACT: This research explores the optimization of Operations and Maintenance (O&M) strategies for offshore wind farms using a sophisticated O&M simulator built on the Markov Chain Monte Carlo method. By integrating real-world constraints such as vessel availability and weather conditions, the study assesses O&M logistics' impacts on wind farm availability, energy production, and overall costs across different scenarios in the Celtic Sea. Through comparative analysis of eight case studies involving various combinations of Crew Transfer Vessels (CTV) and Service Operation Vessels (SOV), the research highlights the critical role of strategic vessel deployment and the potential of permanent SOV stationing to enhance operational efficiency, reduce downtime, and lower O&M costs. In this study, the permanent SOV can increase up to 20% availability of the whole wind farm. The findings underscore the importance of adaptive O&M planning in improving the sustainability and financial viability of offshore wind energy projects.

Keywords: Operations and Maintenance; Offshore wind farm; O&M logistics; Crew Transfer Vessels; Service Operation Vessels



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1. Introduction

The global wind energy sector has seen significant growth, with 2022 being the third-best year for new capacity additions at 78 GW globally. This expansion increased the total installed capacity to 906 GW, marking a 9% growth from the previous year. Predictions for 2023 suggest an unprecedented milestone, exceeding 100 GW of new capacity, indicating a robust year-on-year growth of 15%. The UK has been at the forefront of this shift, moving from onshore to offshore wind energy projects, taking advantage of stronger and more consistent offshore wind resources [1]. Despite these advantages, offshore wind energy comes with higher costs primarily due to the complex infrastructure required for its support. These costs are a result of the challenging conditions at sea, including higher wind speeds and wave forces, which complicate maintenance and repairs.

The Levelized Cost of Energy (LCOE) serves as a metric to compare the costs of wind energy, encapsulating the average cost per megawatt-hour of electricity produced throughout the lifecycle of the wind farm. It's commonly observed that the LCOE for offshore wind farms surpasses that of onshore wind projects, primarily due to the challenging environmental conditions faced offshore [2]. The LOCE comprises three main components: Capital Expenditure (CapEx), Operational Expenditure (OpEx), and Decommissioning Expenditure (DecEx). Within these categories, CapEx includes expenses related to both wind turbine components and those for power production infrastructure. Meanwhile, OpEx encompasses the costs of operation and maintenance activities [3,4]. OpEx significantly impacts the LCOE for offshore wind farms, accounting for up to 30% of the total investment cost; this number will go up with increasing offshore distances. However, O&M costs make up only 5% of the total investment for the onshore wind project [5,6]. As a result, reducing the OpEx could be an effective method to increase the cost-effectiveness of an offshore wind project, and this can generally be achieved by new O&M strategies that use novel techniques and applications. For

example, Ren et al. (2021) [7] offered a comprehensive review of the state-of-the-art in O&M for offshore wind farms, covering a range of aspects from maintenance strategies, schedule optimization, onsite operations, and environmental impacts. It emphasizes the critical role of maintenance in the lifecycle cost of offshore wind farms and discusses various maintenance strategies, including corrective, proactive (preventive and condition-based), and opportunistic maintenance. The review also explores optimization models for maintenance planning and highlights the environmental considerations associated with O&M activities. A similar review work also highlighted the shift from reactive to proactive maintenance strategies using operational data for decision-making [8]. Martin et al. (2016) [9] examined how different factors influence the O&M costs and availability of offshore wind farms. It uses sensitivity analysis to identify critical factors, including component failure rates, repair times, and the use of vessels for maintenance operations. The study emphasizes the importance of optimizing maintenance strategies to improve the reliability and efficiency of offshore wind farms, highlighting the significant impact of operational decisions on the overall cost and performance of these renewable energy projects. Another comprehensive O&M study evaluated different O&M logistics, including the towing of turbines to shore for major operations versus performing all operations on-site. The study reveals that the choice of O&M logistics and vessels significantly influences the Global Warming Potential (GWP) of offshore wind farms [10].

Regarding novel techniques, Yang et al. (2023) [11] gave a comprehensive survey on challenges and optimization strategies in O&M, emphasizing the need for technological innovations. Ambarita et al. (2023) [12] discussed the evolution towards autonomous operations in floating offshore wind farms, driven by the need for cost reduction and improved safety. It highlights the role of information and communication technology (ICT) and robotics in achieving autonomy, exploring technologies like digital twins (DTs), sensor systems, and offshore robotics. These advancements aim to address the challenges posed by harsh environments, accessibility, and high O&M costs, moving the offshore wind industry towards full autonomy for enhanced efficiency and sustainability. Kou et al. (2022) [13] introduced the transition towards digitization and intelligence in O&M to improve efficiency and reduce costs. Another paper introduced DT technology as a promising approach for enhancing O&M strategies by providing a comprehensive review of the latest research on DT applications in OWFs, including failure analysis, O&M optimization models, and the development of DT technology itself. A novel DT-based O&M optimization framework is proposed to improve the intelligence level of O&M, demonstrating the potential of DT technology to significantly contribute to O&M cost reduction [14].

Taking a different approach from most of these previous studies, this paper focuses on the strategic deployment of service vessels to examine the impact on offshore wind farm availability. It posits that selecting different vessels is a straightforward approach to altering O&M logistics and associated costs. Given the nascent stage of commercial offshore wind farms, failure data is of particular commercial sensitivity to existing wind developers and is often device and farm specific. To reduce the potential risk of data unavailability, this study evaluates typical corrective maintenance strategies, which involve assigning appropriate vessels based on specific turbine or farm component failures. Nevertheless, the methodologies and insights derived from this study will remain suitable for proactive O&M strategies. The implications of varying vessel combinations under the proactive or other advanced O&M strategies will be a significant area for future research, pending the collection of sufficient real-world data. The remainder of this paper is structured as follows: Section 2 introduces the O&M simulator utilized in this study. Section 3 outlines the case study configuration, including the specifics of the vessels, O&M tasks, and weather data. Section 4 presents the findings and discussions from the case study analysis. Finally, Section 5 draws the main findings of conclusions of this paper.

2. O&M Simulator

In this study, the simulation tool for O&M applies the Markov Chain Monte Carlo (MCMC) method, a widely recognized technique for predicting O&M costs, as detailed by [15,16]. The core principle of this approach involves assessing the operational state of wind turbines by comparing a randomly generated number to the reliability index, which reflects the failure rate of turbine components or the predicted frequency of maintenance activities. This method is integrated with Monte Carlo simulations, extensively used in reliability assessments as noted in [17]. The methodology is well-established and validated in other studies. The novelty of this paper lies in modeling various scenarios to quantify key factors that influence O&M costs and to offer new ideas for future cost reduction.

Figure 1 showcases the O&M simulator's workflow. The input of the simulator includes details on O&M tasks, vessels, wind turbines, weather data, and limitations within the industry, as elaborated in [18]. The main outputs describe the performance of the wind farm, such as energy output considering downtime, system availability, income, and total O&M expenses, which aid in identifying operational issues and devising potential corrective actions. Furthermore, it

utilizes statistical metrics like exceedance probabilities and cumulative averages throughout the simulation runs to assess the reliability of the outcomes. Extensive literature underscores the capabilities of this module through validation studies, case comparisons, and its proven accuracy in forecasting O&M expenditures, as observed [18–20]. Recent enhancements have refined the simulation’s code structure and incorporated new features to better support modern O&M tactics and adapt to the changing demands of offshore wind projects.

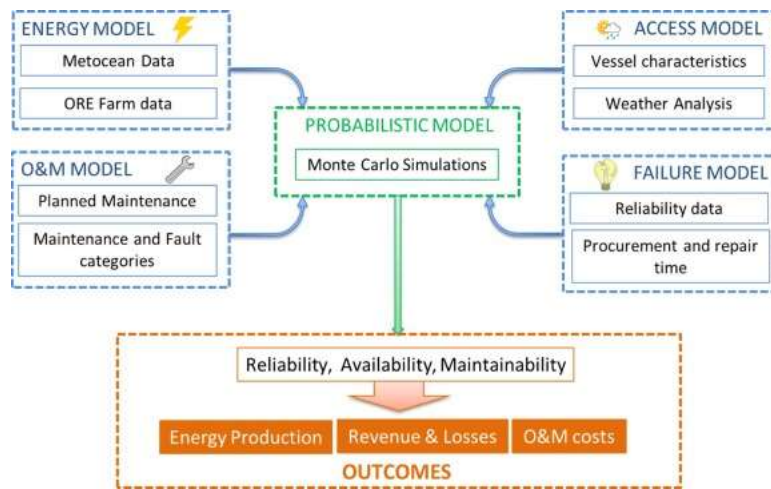


Figure 1. The workflow of the O&M module [18].

To broaden the O&M simulator’s capabilities, additional capabilities were added to an offshore wind farm simulator (Figure 2), such as those for design and installation [21]. The approach developed by [21] has been adapted and expanded, enabling assessing the overall performance of an offshore wind farm throughout its entire lifecycle.

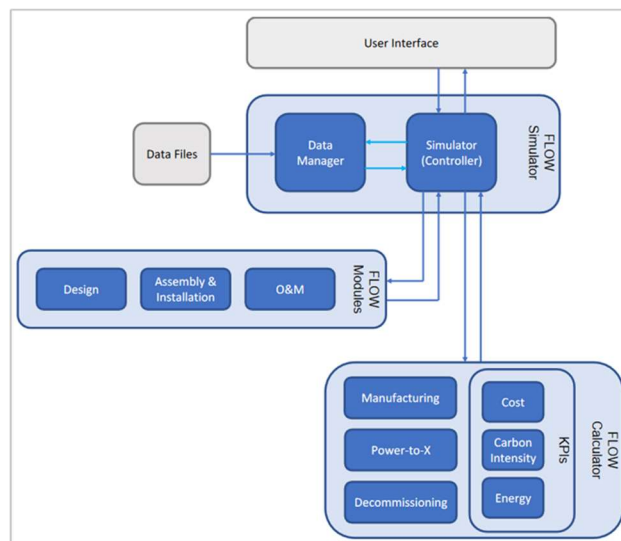


Figure 2. Workflow of the simulator of the whole life cycle of a wind farm [21].

To address the complexity of inputs required by the O&M simulator specifically, a user-friendly graphical user interface (GUI) was developed to assist users in defining specific O&M strategies for various wind farm projects. As shown in Figure 3, the GUI includes three distinct sub-windows designed to facilitate user input concerning vessels, O&M tasks, and comprehensive farm information. To begin, users are prompted to enter details regarding the vessel fleet, such as the number of vessels, fuel consumption rates, and other pertinent information. Subsequently, within the O&M task sub-window, users can allocate specific vessels to designated O&M tasks, tailoring the fleet’s operations to the requirements of the wind farm. It’s crucial to recognize that the module offers two different operation methodologies for addressing O&M tasks: on-site operations and tow-to-port operations. The latter method is generally preferred for significant repair or replacement O&M activities due to its cost-effectiveness. Moreover, the GUI is designed to account for O&M tasks that impact the entire farm, highlighting scenarios where such tasks could result in downtime across multiple turbines. An example of this is the failure of the farm’s main export cable, which could necessitate a complete

shutdown of the wind farm, underlining the importance of strategic planning and response in maintaining operational efficiency and minimizing downtime.

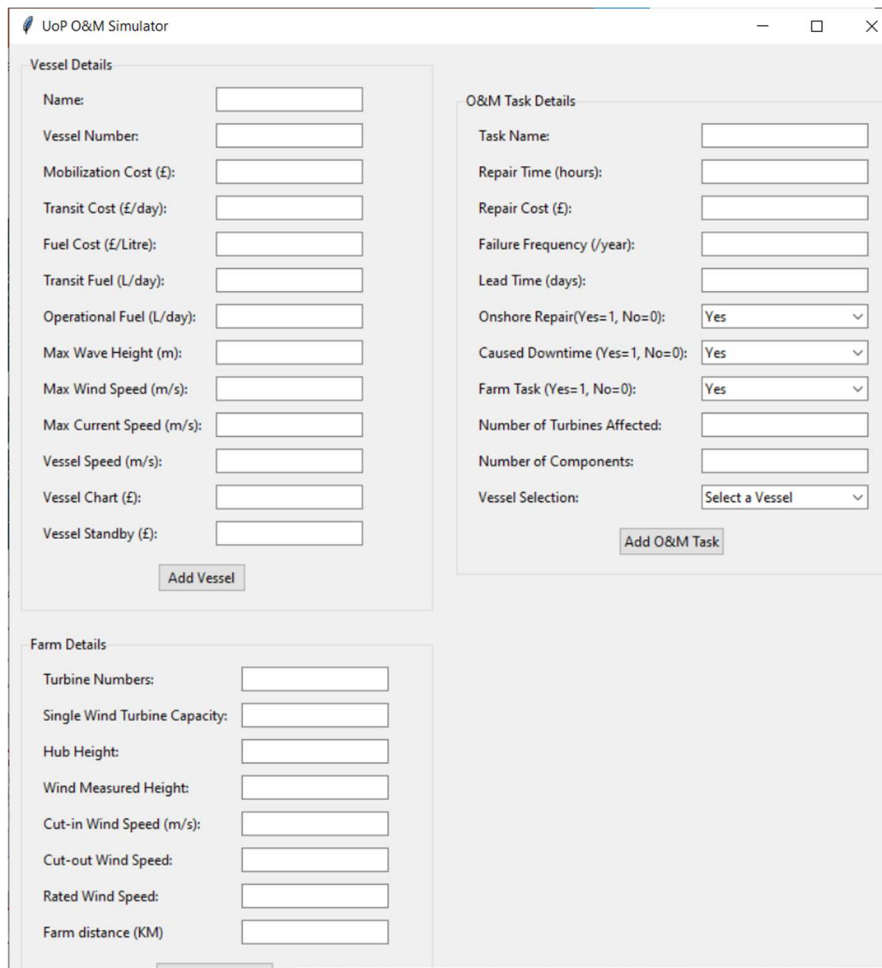


Figure 3. GUI of the O&M simulator.

3. Case Configuration

In this paper, the focus lies on examining the O&M costs for a 1 GW offshore wind farm located in two different areas of the Celtic Sea, using different O&M logistics strategies. This assessment is conducted through a series of eight cases that explore different aspects of O&M logistics, primarily centered on the use of Crew Transfer Vessels (CTV) and Service Operation Vessels (SOV). Note that the roles of other vessels such as Cable Laying Vessels (CLV) and Heavy Lift Vessels (HLV) are constant in all cases to make that variations cost derive from different use of CTVs and SOVs.

The first four cases are dedicated to Site 1 known for advantageous wind resources, but adverse wave conditions. Cases 5–8 investigate Site 2, where the focus is on understanding the impact of various weather conditions on O&M logistics (see Figure 4). These cases are systematically categorized based on the combination of the use of vessels (CTV and SOV), and the associated lead times for vessel deployment, which is a critical component in the analysis of the responsiveness and effectiveness of O&M operations. The specific cases are as follows and in the Table 1 practice.



Figure 4. General location of two sites within the Celtic Sea.

Both CTV and SOV Used, No Lead Time Considered: This case evaluates the impact on cost when both CTV and SOV are considered to understand the fundamental economic drivers of CTV and SOV usage.

Exclusive Utilization of SOV, Excluding Lead Time: This case evaluates the cost impact when SOVs completely replace CTVs, again without the incorporation of lead time.

Both CTV and SOV Used, Lead Time Considered: This case includes 10 days of lead time for larger vessels (SOV, CLV, HLV) and no lead time for CTV to study how delay of major vessels lead time impacts O&M cost.

SOV integrated with CTV Employed, with SOV Permanently Stationed at the Wind Farm: In this scenario, the SOV is constantly available at the wind farm, eliminating its deployment lead time. However, a 10-day lead time for other substantial vessels like HLV and CLV remains. The SOV charter cost will be replaced by a fixed fee.

Table 1. The cases configuration.

| Case Description | Site 1 | Site 2 |
|----------------------------------------------------------------------------------------------------------------|--------|--------|
| Both CTV and SOV used, excluding lead time | Case 1 | Case 5 |
| SOV replaces all CTV, excluding lead time | Case 2 | Case 6 |
| Both CTV and SOV used, 10 days lead time for large vessels, no lead time for CTV | Case 3 | Case 7 |
| CTV and SOV used, SOV permanently stationed at farm (no lead time), other large vessels with 10 days lead time | Case 4 | Case 8 |

3.1. Weather Conditions of Two Scenarios

Two potential wind farm sites are selected in this paper. The longitude and latitude coordinates for these sites are provided in Table 2. The weather data utilized spans the years 2000 to 2011, with updates every six hours.

Table 2. The two sites' location details.

| Parameter | Unit | Site 1 | Site 2 |
|----------------|-----------|---------------|---------------|
| Power Capacity | MW | 1000 | 1000 |
| Corner 1 | Longitude | 49.8240260° N | 51.6577176° N |
| | Latitude | 7.2731693° W | 6.2989939° W |
| Corner 2 | Longitude | 49.8641537° N | 51.6557592° N |
| | Latitude | 7.0755815° W | 6.0799149° W |
| Corner 3 | Longitude | 49.7355756° N | 51.5235705° N |
| | Latitude | 7.0137596° W | 6.0855971° W |
| Corner 4 | Longitude | 49.6950799° N | 51.5227848° N |
| | Latitude | 7.2113473° W | 6.3027820° W |

As shown by the environmental data from Site 1 and Site 2 (see Table 3), there are distinguishable characteristics between the locations that will impact the calculation and prediction of O&M costs of these wind farm sites. For example, both sites exhibit similar average wind speeds, which indicates comparable generation potential assuming the farm layouts and the wind direction relative to the layouts are also broadly equivalent. On the other hand, the wave conditions at Site 1 could pose greater operational challenges. During periods of high wave activity, maintenance tasks might need to be deferred due to safety concerns, potentially leading to increased downtime, and thus affecting the overall efficiency and profitability of the site. This scenario underscores the importance of predictive maintenance strategies, where maintenance activities are scheduled during periods of lower environmental stress to minimize downtime and optimize costs.

Since the wind speed of the two sides is basically the same, the wind turbines must likely undergo the same level of wear and tear from aerodynamic forces (assuming the same failure rate of wind turbines in all cases). However, the marginally higher average wind speed of Site 1 than that at Site 2 could lead to a tiny increase in generating energy output, which would somewhat offset increased O&M costs arising from wave conditions. But this factor alone is unlikely to entirely balance the greater expenses occasioned by a more severe wave environment. Financial planning for these sites must take into account these environmental differences, and accurately predicting and budgeting maintenance costs is crucial for long-term financial planning as it helps ensure both the sustainability and profitability of the wind farm projects. Additionally, understanding the specific environmental challenges of each site aids in risk management and operational planning. It allows for the implementation of tailored strategies that optimize performance while minimizing costs.

As summary, the distinct characteristics of each site, especially the difference in wave heights, play a significant role in shaping the O&M strategies and directly influence the associated costs. This analysis demonstrates the importance of a detailed understanding of site conditions in forecasting O&M requirements and ensuring the efficient and sustainable operation of wind farms.

Table 3. General Meteorological data information.

| Scenarios | O&M Port Distance (km) | Considered Time Length (Year) | Time Step (Hour) | Average Significant Wave Height (m) | Average Peak Period (s) | Average Wind Speed at 10 m (m/s) |
|-----------|------------------------|-------------------------------|------------------|-------------------------------------|-------------------------|----------------------------------|
| Site 1 | 270 | 11 | 6 | 2.48 | 10.40 | 8.20 |
| Site 2 | 91 | 11 | 6 | 1.88 | 8.82 | 8.17 |

3.2. Vessel and Task

The O&M tasks are designed around the parameters of an IEA 15 MW wind turbine and the semi-submersible UMaine VoltturnUS-S platform, as described in [22]. The parameters of this wind turbine used are summarised in Table 4. Each case includes 15 O&M tasks each encompassing various subsystems of the wind turbine, see Tables 5 and 6. It should be noted that each standard O&M task covers a single wind turbine, which maintains a one-to-one relationship between tasks and turbines and eliminates the complexity of concurrent tasks on multiple turbines. Additionally, each turbine can only be subject to a single O&M task at any one time, meaning there cannot be multiple concurrent failures in the same turbine. However, some tasks are defined as farm tasks, which will cause multiple turbines to experience downtime. For example, the failure of the export cable will cause the whole farm to shut down.

Table 4. Summary of wind turbine parameters. Data sourced from [22] for the IEA 15 MW RWT.

| Parameter | Unit | IEA 15 MW RWT |
|--------------------|------|---------------|
| Rated power | MW | 15.0 |
| Rated wind speed | m/s | 10.6 |
| Cut-in wind speed | m/s | 3.0 |
| Cut-out wind speed | m/s | 25 |
| Rotor diameter | m | 240 |
| Hub height | m | 150 |

Table 5. The O&M tasks-part I.

| | Floating Platform | Mooring Line Fatigue | Mooring Lines Breakage | Fairlead Failure | Anchors | Power Cable | Export Cable | Small Transformer Repair |
|----------------------------------|-------------------|----------------------|------------------------|------------------|---------|-------------|--------------|--------------------------|
| Repair time (hours) | 12 | 48 | 48 | 24 | 24 | 72 | 72 | 24 |
| Annual Failure rate (times/year) | 0.155 | 0.14892 | 0.0356532 | 0.1 | 0.15768 | 0.167 | 0.167 | 0.5 |
| Cost Replacement (£) | 147,221 | 200,000 | 1,500,000 | 200,000 | 109,348 | 444,267 | 6,587,914 | 50,000 |
| Vessel Selection | CTV/SOV | SOV | AHTS | SOV | AHTS | CLV | CLV | CTV/SOV |
| Farm task (Y/N) | N | N | N | N | N | Y | Y | Y |

Table 6. The O&M tasks-part II.

| | Large Transformer Repair | Manual Reset | Minor Repair | Medium Repair | Major Repair | Major Replacement | Annual Service |
|----------------------------------|--------------------------|--------------|--------------|---------------|--------------|-------------------|----------------|
| Repair time (hours) | 48 | 0.5 | 7.5 | 24 | 48 | 52 | 24 |
| Annual Failure rate (times/year) | 0.05 | 7.5 | 3 | 0.275 | 0.04 | 0.04 | 1 |
| Cost Replacement (£) | 4,000,000 | 1000 | 10,000 | 185,000 | 735,000 | 5,000,000 | 10,000 |
| Vessel Selection | SOV | CTV/SOV | CTV/SOV | SOV | HLV | HLV | CTV/SOV |
| Farm task (Y/N) | Y | N | N | N | N | N | N |

Based on the requirements of O&M tasks, five types of vessels/vessel combinations are selected, detailed in Table 7. For this study, turbines will need to be towed back to the O&M port for some major repair tasks. The disconnect/connect time of the wind turbine is assumed to be 24 h. The fuel consumption rate and vessel speed are assumed to remain constant across various weather conditions, despite the potential for weather to influence these factors. The O&M simulator is equipped to account for weather-related variations in speed and fuel consumption. However, the time step for weather data is set at 6 h, which is sufficiently large to justify using average values for both speed and fuel consumption rates. Moreover, employing constant values for speed and fuel consumption significantly accelerates the simulation process. It should be noted that the details of the vessels and O&M tasks come from a range of public literatures which may be stratified with the latest developments of the offshore wind energy industry [23–25]. However, the simulator in this paper allows the users to fully customize the O&M and vessel information.

Table 7. The O&M vessel information.

| Name of the Vessel | CTV | SOV | HLV | AHTS | CLV |
|-----------------------------------|------|--------|---------|---------|---------|
| Vessel speed (km/h) | 43 | 35 | 20 | 18.5 | 22.7 |
| Day rate (£) | 0 | 0 | 150,000 | 187,350 | 150,000 |
| Mobilisation cost (£) | 1000 | 9500 | 270,000 | 250,000 | 300,000 |
| Transit fuel cost (£) | 3600 | 27,000 | 27,000 | 36,000 | 36,000 |
| Operation fuel burn (litres/hour) | 20 | 150 | 300 | 300 | 300 |
| Wave height limitations (m) | 1.75 | 5 | 5 | 5 | 5 |
| Wind limitations (m/s) | 20 | 20 | 15 | 15 | 20 |

4. Results and Discussions

This section analyses the outcomes of the previously discussed cases, focusing on farm availability, failure occurrence and downtime, vessel fuel consumption, and O&M cost. The findings aim to quantify the impact of varying O&M logistics strategies on maintenance efficiency, offering a comparative perspective on operational effectiveness under different management approaches.

4.1. Farm Energy-Based Availability

Energy-based availability means how much electricity can be created in practice as a percentage of its theoretical maximum potential output for some given period. This factor is an important measure that highlights how well a wind farm operates overall, and average reliability is critical for investors who will determine a project’s life expectancy based upon this figure. It also gives a way to measure the actual real-world efficiency of a particular wind farm, taking into account its environmental conditions.

$$A_{energy} = \frac{Energy_{produced}}{Energy_{theoretical}}$$

where the $Energy_{theoretical}$ is calculated by the power curve of wind turbine and metocean data.

As previously mentioned, the difference in the ideal energy output between the two sites under review, over the given duration of weather data, is anticipated to be minimal due to the similarity in their wind resources. The energy outputs are calculated to be 54,595.3 GWh and 54,573.7 GWh, respectively. Given the similar energy output, the energy-based availability can serve as a reliable basis for comparing and analysing the delivered energy or power across both locations. This approach allows for a focused assessment of how each site’s operational efficiencies and energy delivery capabilities stand in comparison, underpinning strategic decisions and optimizations in energy production and site management.

Figure 5 depicts the availability percentages of the entire wind farm for the eight evaluated cases. For Site 1, Case 2 registers the highest availability. This suggests that employing SOVs may offer operational benefits, particularly in harsh sea conditions, if vessels are available immediately and there is no lead time required following a failure. However, before the cost data discussion, it is impossible to determine the cost-effectiveness of this increase in availability. When comparing Case 2 with Case 1, there is an observable improvement in availability, although this increase is less pronounced than the improvement observed at Site 2. Case 3 at Site 1 shows the lowest availability, potentially due to the added lead times for large vessels such as SOVs, CLVs, and HLVs, which could result in delayed maintenance responses and extended downtime. At Site 2, with gentler sea conditions, Case 6 demonstrates the highest availability, where the direct replacement of CTVs with SOVs, without the constraint of lead time, again suggests that CTVs’ limited weather operability is a significant factor in downtime. The lowest availability observed in Case 7 for Site 2 underscores the considerable impact that vessel lead times have on maintenance scheduling and the consequent availability of the wind farm.

It also highlights the necessity to align O&M strategies with realistic operational capabilities, acknowledging that while immediate vessel deployment is ideal (like Cases 2 and 6), it is not always feasible. The results from Case 4 and Case 8, which involve stationing a SOV at the wind farm, offer a pragmatic approach towards maintenance logistics. This strategy addresses the impracticality of having no lead time for vessel deployment by providing an on-site SOV, which can significantly reduce response times for maintenance tasks. The stationed SOV serves as a middle ground, offering improved availability as shown in the results for Site 1 and Site 2.

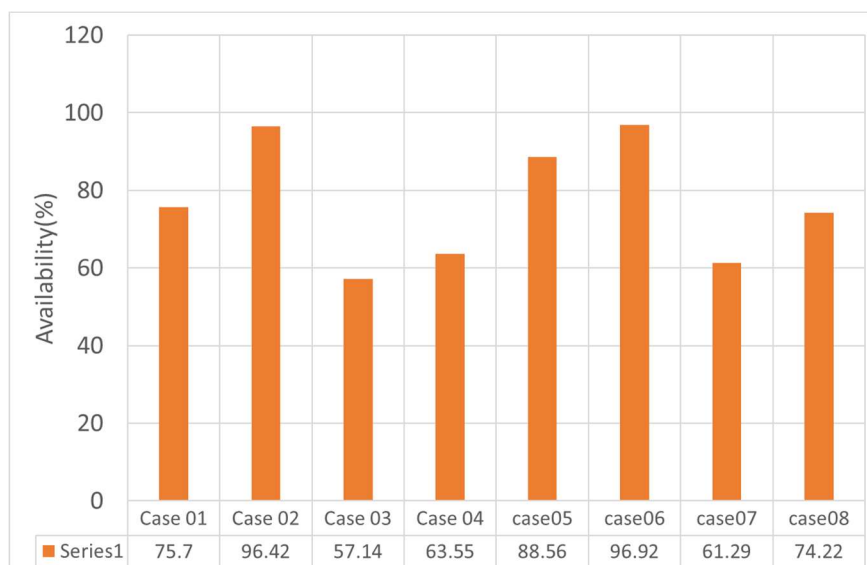


Figure 5. The time availability of all cases.

4.2. Failure Occurrences and Downtime

Figure 6 illustrates the total failure numbers for the offshore wind farm across the eight cases, reflecting the influence of each case’s O&M strategy on handling the logistical intricacies of vessel deployment, site-specific environmental conditions, and general operational efficiency. In this paper, it is presumed that all O&M tasks lead to wind turbine downtime, despite the possibility that some turbines could continue to operate at a reduced capacity, during some minor repairs. The primary focus of this study centers on vessel deployment, and the impact of tasks that do not result in downtime is considered negligible. to the assumption regarding wind turbine failure occurrence, where the chance of additional failures occurring during a non-operational period caused by an initial failure is deemed so low as to be negligible, increased farm time availability inherently allows for more opportunities for component failures, thus potentially leading to a higher failure number. This correlation suggests that the primary contributors to downtime are factors other than component repair or replacement—specifically, vessel lead times and weather suitability, as inferred from the availability analysis.

In Cases 1 and 5, the simultaneous utilization of CTVs and SOVs without accounting for lead times may mask the real-world operational delays, particularly due to the CTVs’ lower tolerance for harsh weather. This could necessitate extended periods of waiting for appropriate weather windows, resulting in increased downtime (fewer failure numbers). In contrast, SOVs, which can endure harsher conditions, are solely deployed in Cases 2 and 6, potentially diminishing downtime by reducing the dependency on favourable weather windows, which could explain fewer failure numbers in Cases 1 and 5.

Incorporating vessel lead times, as observed in Cases 3 and 7, introduces other expected delays in vessel availability, specifically for larger vessels like SOVs, CLVs, HLVs, and AHTSs. This may initially heighten the number of failures as maintenance is deferred. Nevertheless, the presence of a vessel, especially once an SOV is stationed on-site as in Cases 4 and 8, can increase repair efficacy and thus improve availability.

Considering the environmental factors, failure numbers in Cases 5 to 8, corresponding to Site 2, are anticipated to be lower than those at Site 1 due to milder wave conditions that enable more consistent vessel operations. Despite these gentler conditions, the strategic decision to employ CTVs alongside SOVs, or to exclusively use SOVs as in Case 6, significantly influences failure numbers. SOVs’ higher operational capability in harsh weather conditions may lead to reduced weather-induced downtime, resulting in increasing failure numbers.

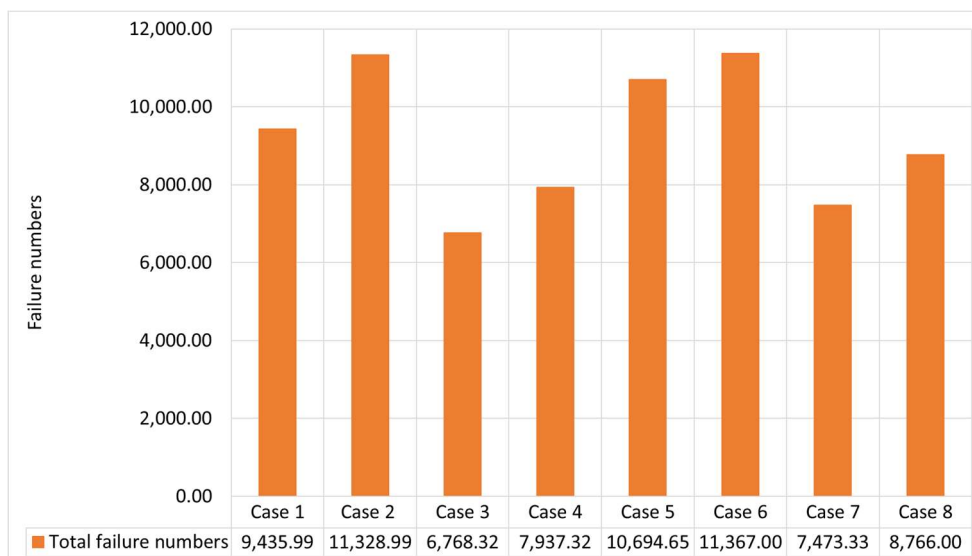


Figure 6. The total failure numbers of the wind farm.

The effect of lead time becomes clearly visible when the total downtime is compared for the various cases (as shown in Figure 7). Cases that include lead times for large vessels, like Cases 3 and 7, show significantly more downtime than those without such lead times, like Cases 1 and 5. This shows there is a significantly large operational delay due to the waiting time while a vessel and crew are prepared for deployment. Conversely, when SOVs are stationed at the farm permanently (as in Cases 4 and 8), the downtime is reduced significantly from that of Cases 3 and 7. This suggests that having SOVs on-site at all times can balance out the negative impact of having lead times for large vessels. With the removal of downtime of the vessel for deployment, small maintenance jobs can occur more regularly thus, reducing downtime overall and maintaining the energy provision of the wind farm.

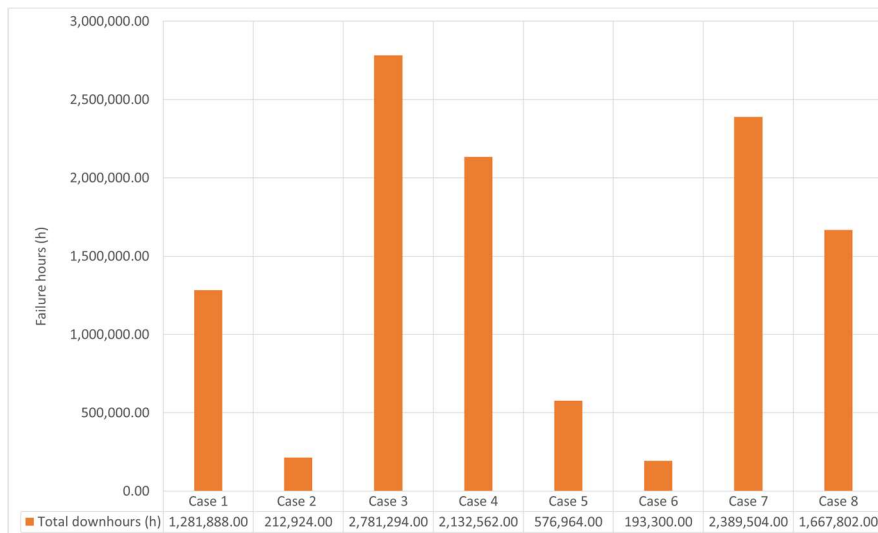


Figure 7. The total down hours of the wind farm’s downtime are calculated across 67 turbines.

To illustrate directly the impact of vessel capacity on downtime, Figure 8 shows the downtime and failure numbers with “Manual Reset”, “Minor Repair” and “Annual Service” in Cases 1/2 and 5/6. This comparison clearly demonstrates the flexible effects of using both CTV and SOV in varying weather, and also the robustness of substituting the CTVs entirely with SOVs, without additional concern for lead time involved in acquiring such substitute capacity. This approach yields insights into how decisions in vessel selection, conditioned to their operational weather capacity, result in expected downtime across different site conditions in maintenance operations.

Across these cases, the failure numbers do not vary significantly (shown in Figure 8a), suggesting that the type of vessel (CTV vs. SOV) does not drastically influence the frequency of failures. This indicates that operational challenges, such as manual resets, minor repairs, and annual services, occur with relatively consistent frequency regardless of the maintenance strategy employed. However, there’s a stark contrast in downtime hours (Figure 8b), particularly when comparing CTV-utilized cases to those where SOVs are employed. For instance, in Case 1 (CTVs and SOVs at Site 1 with adverse weather) versus Case 2 (SOVs replace CTVs at the same site), the reduction in downtime is substantial. The large differences in downtime can primarily be attributed to the limited weather capacity of CTVs. CTVs, with their lower threshold for operational weather conditions, are less capable of performing maintenance tasks during adverse weather, leading to increased downtime. In contrast, SOVs, designed to operate in rougher conditions, can continue maintenance operations, thereby reducing downtime.

In comparing Site 1 Case 1/2 with Site 2 Case 5/6, the principal observations are the impact of different environmental conditions on downtime, despite a similar decline in the number of failures. Site 1 (harsher wave conditions) shows that Case 1 (CTV utilized) sees significantly greater downtime when compared to Case 2 (SOVs utilized). This again illustrates the effect of the more limited weather capacity of CTVs in more challenging conditions. Site 2 (milder weather) on the other hand still shows that the SOV utilized cases (Case 6) have a lower downtime compared to CTV cases (Case 5), but the variance is not as significant as was the case at Site 1. This comparison emphasizes that the environmental conditions at each site only serve to amplify the limitations of CTVs and that vessel selection is critical in order maximize for site-specific weather challenges.

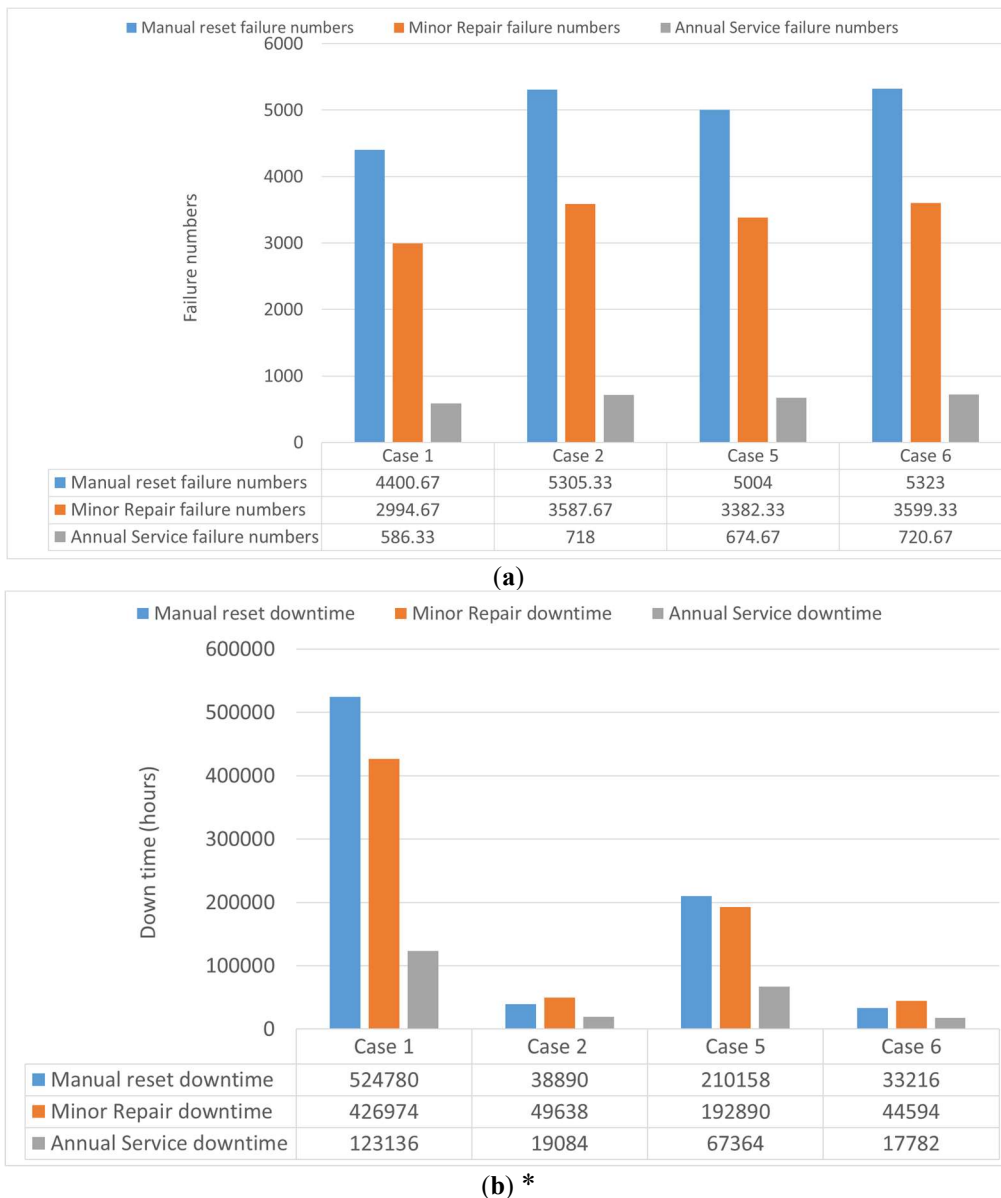


Figure 8. The CTV vs SOV cases: **(a)** Failure numbers, **(b)** Downtime, * The downtime is calculated by across 67 turbines.

4.3. Vessel Fuel Consumption

The analysis of fuel consumption across the eight cases (see Figure 9), particularly focusing on the impact of vessel type and deployment strategies, reveals distinct patterns. Cases 2 and 6, where SOVs are exclusively used, show the highest total fuel consumption. This is primarily attributed to the extensive transit required for SOVs to travel between the port and the wind farm. In contrast, Crew CTVs, which are not used in these cases, typically have lower fuel consumption due to their smaller size and limited operational range.

A comparison of cases where SOVs are used exclusively (Cases 2 and 6) against cases where a combination of CTVs and SOVs are used (Cases 1 and 5) shows a notable increase in fuel usage when SOVs replace CTVs. Despite having larger capacities for cargo and crew, which allow them to operate in harsher conditions, the greater fuel usage of a larger vessel combined with the penalty of having to repeatedly travel to and from the site for transit operations results in very large increases in fuel consumption.

However, significant total fuel consumption reductions are observed in Cases 4 and 8, where SOVs are stationed at the wind farm. This reduction underscores the impact of transit operations on fuel use, highlighting that the major portion of fuel consumption for SOVs is attributed to traveling to and from the site. By having SOVs permanently stationed at the farm, the need for regular transit is eliminated, resulting in substantial fuel savings. The efficiency of stationed SOVs is further evidenced by the lower fuel usage in Cases 4 and 8, suggesting that when SOVs are not engaged in transit operations, their total fuel consumption can be significantly reduced. This points to the conclusion that most of the fuel consumed by SOVs in the higher usage cases is due to transit rather than on-site operations.

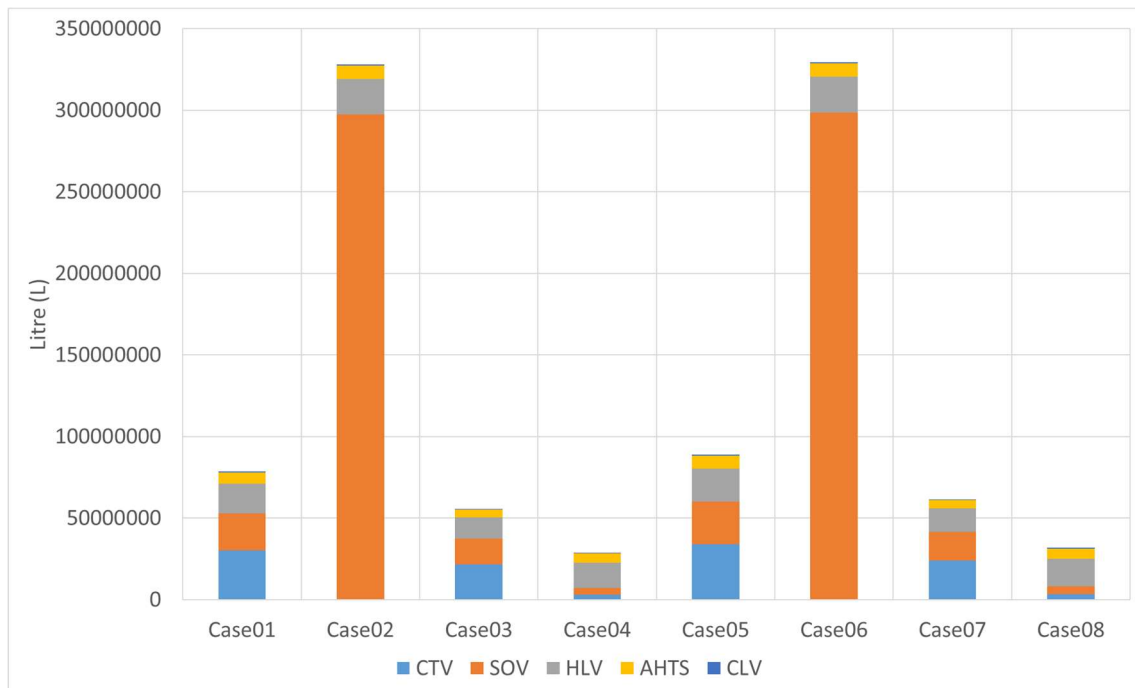


Figure 9. Vessel total fuel consumption.

4.4. O&M Cost

The calculation of O&M costs includes both direct and total O&M costs. Direct O&M Costs are those directly related to the O&M of the wind farm, including routine maintenance, repairs, parts replacement, labour, and the operation of service vessels, which involve charges like chart and mobilization fees and fuel costs. Total O&M costs, meanwhile, include the economic implications of lost income resulting from O&M activities. This broader perspective is necessary to fairly and accurately grasp the full economic impact of O&M on an offshore wind farm's profitability and financial health. Lost income is regarded as a reflection of the energy production lost as a result of O&M activities, which is calculated by energy lost production multiplied by the strike price. The strike price in this study was assumed to be £100 per MWh. The inclusion of lost income in the total O&M cost calculation thus provides a more comprehensive understanding of the O&M cost of offshore wind farms.

Additionally, both types of O&M costs are normalized by the energy delivered, which aims to provide a more accurate, fair, and standardized metric for evaluating and comparing the O&M logistics. It aligns the costs directly with the revenue-generating aspect of the operation, for a clear understanding of the relationship between maintenance efforts and energy production efficiency.

Figure 10 presents the normalized direct O&M cost. Typically, Site 1 (Cases 1–4) shows higher O&M costs than Site 2 (Cases 5–8), due to the more challenging weather conditions at Site 1, which could increase maintenance complexity and cost. It also can be observed that Case 2 and Case 6 have the lowest O&M costs, which align with the cases where SOVs are exclusively used without considering lead times. Even though SOVs have higher fuel consumption during transit, their ability to operate in harsher weather conditions might contribute to lower total O&M costs due to reduced downtime and more efficient maintenance operations.

Conversely, Case 3 and Case 7 show higher O&M costs, which could be due to the incorporation of lead times for larger vessels. The delay in deploying SOVs could lead to increased downtime and consequently higher O&M costs. In a strategic pivot, Cases 4 and 8 where SOVs are permanently stationed at the wind farm, show a mid-range O&M cost. While the fuel costs are reduced due to the lack of transit, the fixed presence of SOVs might entail higher standby charges which are reflected in the O&M costs.

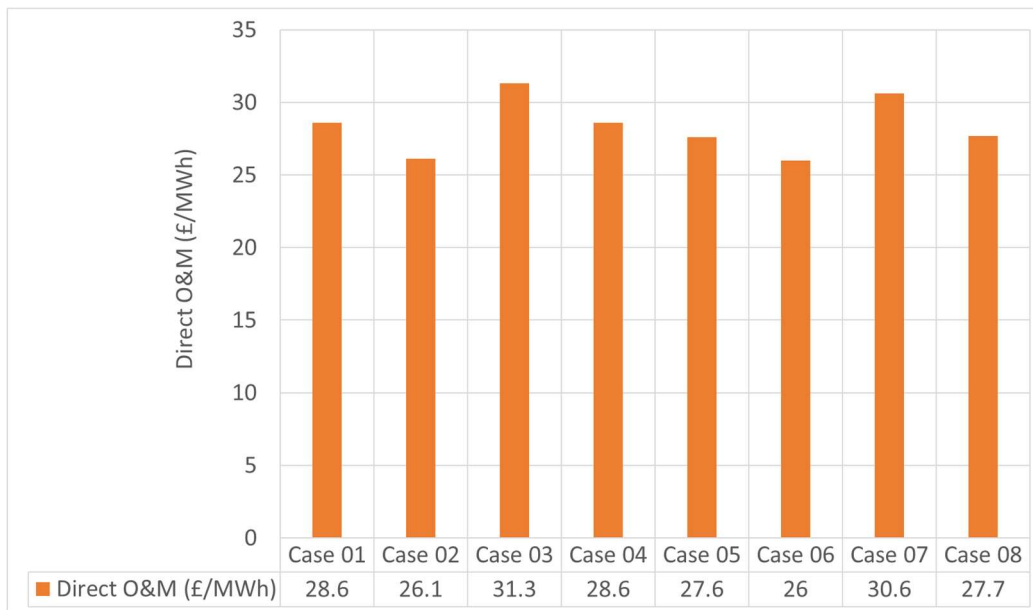


Figure 10. Direct O&M cost of all cases.

It should be noted that variations in direct O&M costs are relatively small across all cases, which could imply that the majority of the O&M costs are likely driven by parts repair and replacement rather than by the logistics of vessel deployment.

As shown by Figure 11, the tasks associated with power cable, mooring lines breakage, major repairs, and major replacements are consistently the most expensive across all cases. This aligns with the expectation that maintenance of such critical components, due to their essential nature and the complexity of repairs or replacements, would lead to higher costs. Cases where SOVs are permanently stationed at the farm (Cases 4 and 8) show a more even distribution of costs across tasks, possibly indicating that the immediate availability of SOVs can lead to more efficient execution of repairs and replacements. However, the data suggests that the use of SOVs, whether exclusively or in combination with CTVs, does not significantly change the repair and replacement cost structure. In light of these observations, it is clear that the key to optimizing O&M strategies lies in addressing the most expensive maintenance tasks. Targeting efficiency improvements in these areas, whether through technological innovation, process optimization, or enhanced logistics planning, could yield significant cost savings.

It’s important to highlight that in Cases 4 and 8, the fixed costs associated with stationed SOVs are not taken into account due to the lack of comprehensive data collection, though mobilization costs are still included, with charter costs excluded. These fixed costs could encompass regular monthly crew changes and additional supplies for the SOVs, which are considered service platforms when there is no failure occurs. The findings of the direct O&M cost suggest that repair and replacement expenses significantly outweigh the costs related to the vessel itself. Moreover, it is implied that the fixed costs for stationed SOVs are not expected to exceed the variable costs found in scenarios involving non-stationed SOVs. Consequently, the minor nature of these fixed costs does not justify the benefits provided by the stationed SOVs.

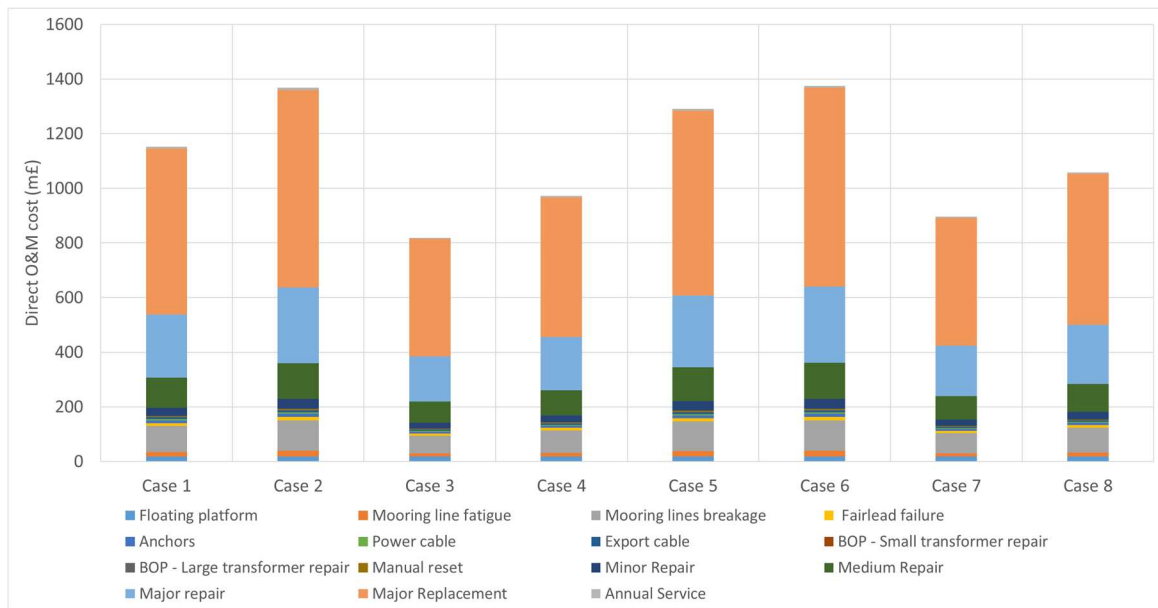


Figure 11. Repair and Replacement cost of each task.

The total O&M costs per MWh, including lost income due to downtime over the eight cases, are shown in Figure 12. In the realistic operational context where vessel lead times are unavoidable, the data from these cases offer a stark representation of the financial implications. Cases 3 and 7, which take these lead times into account, show significantly higher total O&M costs. This suggests that the delay in deploying large vessels such as HLV, SOV, not only increases the downtime, but also amplifies the lost income, and thereby greatly increasing the O&M costs. The lower costs incurred in Cases 2 and 6, although both cases represent unrealistic scenarios in which there are no lead times, help to demonstrate the potential cost savings. These cases illustrate a what-if scenario where immediate vessel availability could significantly reduce O&M costs.

By focusing on the SOV stationing strategy, Case 4 and Case 8 show an intermediate cost level compared to when SOVs are constantly at the wind farm. This strategy brings the lead time almost to zero, which makes reactive maintenance response nearly immediate, substantially reducing lost income, and is more cost-effective relative to cases with significant lead times. As a final point, while examining the total O&M costs across site-specific differences, the harsher conditions at Site 1 produce a higher set of costs compared to Site 2, reflecting the increased frequency and complexity of needed maintenance under the more challenging environmental conditions.

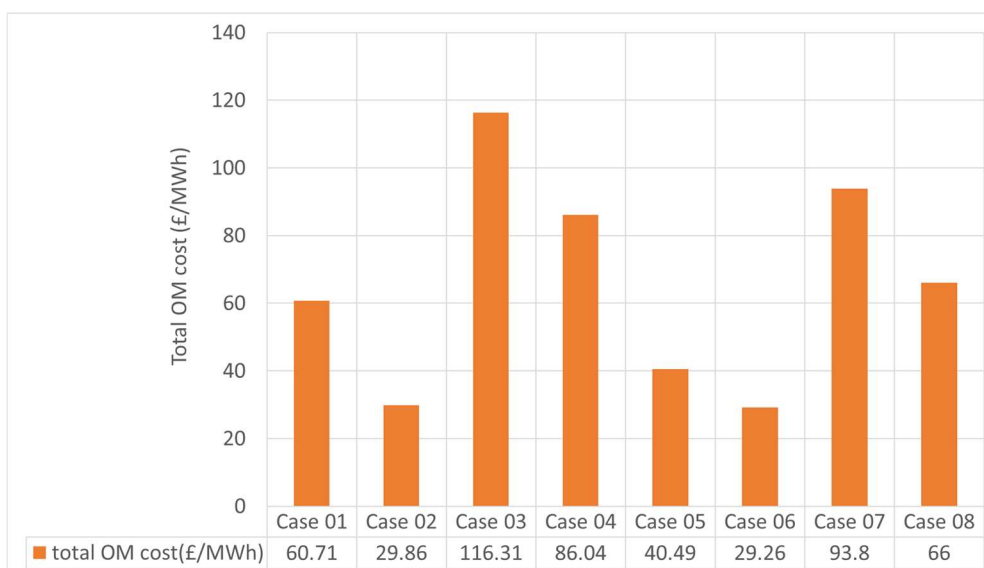


Figure 12. Total O&M cost.

In summary, the narrative woven by these case studies advocates for a strategic re-evaluation of O&M logistics. It becomes clear that mitigating vessel lead times through solutions such as SOV stationing can play a pivotal role in reducing total O&M costs. While not the lowest cost solution, the presence of SOVs on-site represents a balanced

approach, blending increased readiness with a more favourable cost profile, which could be instrumental in driving down the expenses associated with offshore wind farm maintenance.

4.5. Discussions

This analysis of the O&M strategies for 1 GW offshore wind farms, particularly through the lens of SOV deployment and the consideration of large vessel lead times, reveals significant operational efficiencies and cost benefits. The main findings underscore the strategic advantage of SOV utilization, especially when permanently stationed at the wind farm, in mitigating the adverse effects of challenging sea conditions and unpredictable weather patterns.

Exclusively and in combination with CTVs, the deployment strategy of SOVs has produced marked operational efficiency. Stationing SOVs on a permanent basis has a direct impact, not only on the rapidity and efficacy of maintenance response—and a consequent, significant reduction in downtime and associated costs—but also on a critical environmental advantage: very substantial fuel savings. This finding is pivotal, as it directly contributes to reducing the carbon footprint of wind farm maintenance operations, aligning with the global push towards more sustainable energy production methods.

To contextualize the importance of these findings, consider the broader impact of fuel consumption on carbon emissions in the maritime sector. Maritime transportation is one of the most significant contributors of CO₂ to the global effort to reduce emissions, and reductions in fuel use can have the biggest absolute effect on reducing emissions. For example, there are ambitious targets to reduce greenhouse gas (GHG) emissions from shipping by at least 50% by 2050 compared to 2008 levels, as set out by the International Maritime Organization (IMO) [26]. The operational efficiencies and fuel savings that strategic placement of SOVs into offshore wind farm operations have the potential to make a truly meaningful contribution towards the achievement of these global environmental outcomes.

Furthermore, the incorporation of vessel leading times, as part of a contingency analysis, into the O&M strategy further highlights the necessity for logistical planning that is pre-emptive. In addressing the influence of vessel lead times, findings surmise that such an inevitable lag in deploying vessels is one that significantly affects operational efficiency and the scheduling of maintenance activities. However, insight from Cases 4 and 8, where SOVs are permanently stationed and effectively integrate CTV capabilities, highlights a practical approach to counter the challenges imposed by vessel lead times. This strategy improvement with maintenance response times and thus reduce downtime, underpins the criticality of pre-emptively planning strategies to overcome operational disruption.

Among all cases, major repairs and replacements emerge as the most cost-intensive; O&M tasks necessitating the use of HLVs represent the most cost-intensive aspects of wind farm maintenance. This insight underscores the critical need for a strategic approach to O&M tasks, one that leverages the robust capabilities of SOV and the specialized functionalities of HLVs. The strategic employment of SOVs, especially those that integrate HLV capabilities, presents a novel solution to the challenges posed by these high-cost maintenance tasks. By enabling SOVs to perform or support tasks traditionally requiring HLVs, wind farms can achieve a higher level of operational flexibility and efficiency. This integration not only streamlines the maintenance process but also significantly reduces the logistic complexities and costs associated with deploying multiple specialized vessels.

The comparative analysis across different sites (with different weather conditions) further illustrates the cost-effectiveness of SOV employment under varied environmental conditions. The adaptability of SOVs to harsher weather, coupled with their operational readiness through reduced lead times, emerges as a pivotal factor in enhancing the sustainability and profitability of offshore wind farms.

In summary, the strategic deployment of SOVs, particularly with reduced lead times, emerges as a critical factor in the operational success of offshore wind farms. These findings call for a re-evaluation of current O&M logistics strategies, with vessel availability and response time emerging as prominent factors for optimizing wind farm operations. Although the model has been validated in prior research, some constraints need clarification. Certain data, such as failure rates, are highly sensitive and challenging to obtain from commercial companies. The data in this paper, sourced from open databases, may not reflect the most recent developments in the offshore wind industry. Furthermore, the failure data were considered constant, although they may vary over time. Future model enhancements should incorporate temporal variations. Other research can expand on these insights, focusing on the potential that integration of advanced technologies such as digital twins and AI-driven predictive analytics into O&M operations holds in revolutionizing maintenance strategies. Such insights are vital to the continued development of offshore wind energy and align with broader efforts to more effectively incorporate renewable energy in the global energy mix.

5. Conclusions

This paper concludes that the benefits of SOVs, particularly when stationed permanently at wind farms, alongside the identification of key factors impacting wind farm availability and O&M costs, underscore the necessity for strategic planning and execution of maintenance operations in offshore wind energy projects. The findings reveal several critical insights and recommendations for optimizing O&M strategies:

The adoption of SOVs, especially when these vessels are permanently stationed at the wind farm, brings forth substantial benefits in terms of O&M efficiency. The permanent stationing of SOVs reduces the critical challenge of vessel deployment lead times, ensuring immediate availability for maintenance tasks. This approach significantly enhances wind farm availability by reducing the downtime associated with waiting for vessel arrival and deployment.

By stationing SOVs permanently at the site, significant fuel savings are realized due to the elimination of repeated transit between the port and the wind farm. This not only reduces operational costs but also contributes to lower carbon emissions, aligning with the sustainability requirement of the offshore wind farm.

The small weather capacity of CTVs poses a significant challenge, as it limits their ability to operate under adverse weather conditions, leading to increased downtime and reduced wind farm availability. This advantage performs more significantly under the harsher weather conditions. In this paper, the farm availability can be reduced by up to 20% on the site.

The lead time associated with deploying large vessels, including SOVs and HLVs, for maintenance tasks introduces delays that directly impact the availability and operational efficiency of the wind farm. In this study, in the cases with smaller wave conditions where the vessel weather limitations effects are not significant, the vessel lead time can reduce farm availability by up to 30%.

In conclusion, the strategic employment and permanent stationing of SOVs at offshore wind farms present a compelling solution to the challenges of maintenance efficiency, operational downtime, and O&M cost optimization. Addressing the factors that reduce wind farm availability and focusing on the most cost-sensitive maintenance tasks are crucial for enhancing the performance and financial viability of offshore wind energy projects. These strategies, coupled with ongoing advancements in maintenance technologies and practices, pave the way for more sustainable, reliable, and cost-effective offshore wind energy production.

Author Contributions

Writing—Original Draft Preparation, C.Z.; Writing—Review & Editing, L.J.; Visualization, A.R. and Y.C.

Ethics Statement

“Not applicable” for studies not involving humans or animals.

Informed Consent Statement

Not applicable, for studies not involving humans.

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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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