Ocean Engineering 330 (2025) 121190

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Research paper

The silver lining: Utilising curtailment in offshore wind as an opportunity for operation and maintenance

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ARTICLE INFO

Keywords:
Opportunistic maintenance
Curtailment
O&M modelling
Operational costs
Availability

ABSTRACT

Opportunistic maintenance strategies for offshore wind may provide significant reductions in operational costs and downtime for turbines. The utilisation of favourable periods to complete maintenance in past literature has often focused on internal factors, where the replacement of components allows preventive maintenance to be completed on other components that are approaching failure, in order to extend useful remaining life. In this paper, an offshore wind opportunistic maintenance model is created, that simulates the operations of a wind farm over it's lifetime. The research conducted produces a model that utilises both internal opportunity and also external opportunity by incorporating periods of curtailment as opportunities to complete maintenance. By completing preventive maintenance during periods of curtailment, in which the wind farm is being paid to switch off turbines, the lost production costs often associated with other maintenance periods are nullified. A cost benefit analysis is utilised to determine if completing maintenance during curtailment is financially beneficial to the wind farm. Other constraints within the model include vessel accessibility limits, resource limitations, preventive maintenance thresholds and weather windows for repair. Outputs for the model include a breakdown of the repair, transport, lost revenue and staff costs, as well as other key metrics such as availability and energy production. A case study for an offshore wind farm was conducted to validate the model considering both internal and external opportunities for maintenance against two other maintenance strategies; a corrective strategy and an opportunistic strategy that considers only internal opportunity for maintenance. Operational costs are reduced by 50 % using the curtailment opportunistic strategy in comparison to the corrective strategy, whereas using only the internal opportunistic strategy has 20 % reduction in costs compared to the corrective strategy. Sensitivity analyses are conducted for three of the model inputs namely, number of technicians, distance from shore and failure distribution values, to determine the impact and importance of the various inputs into the model.

1. Introduction

One of the commitments made at COP26, by 133 global leaders, to address the climate crisis, was an instalment of 494 GW of offshore wind worldwide by 2030 (IRENA, 2023). The success of offshore wind in the energy market is reliant on its ability to provide competitive electricity prices and maintain a low Levelised Cost of Energy (LCOE). To ensure a low LCOE, the operation and maintenance (O&M) cost, which accounts for up to 30 % of the total cost of a wind farm, must be reduced (Li et al., 2024). It can prove challenging for wind farms to attain low O&M costs, as wind farms are being built further from shore and wind turbines are growing in size. Transport costs, supply chain bottlenecks, and large component repairs are all growing concerns for the industry. To counteract these changes, maintenance strategies are developed to optimise the practices of the wind farm and keep unexpected costs at a minimal level. These strategies have developed over the years as technology has matured. Table 1 gives a summary of the most commonly used offshore wind maintenance strategies. One of the earliest and simplest strategies is a corrective approach, sometimes termed reactive, where a component runs until its failure and then is fixed or replaced. Although this requires little to no upfront cost and is a simple operational strategy, it becomes costly and has the added risk of a component failure damaging other components in the process. Preventive maintenance is often scheduled maintenance, where maintenance is performed at regular time-based intervals to extend the lifetime of the components. Preventive maintenance can be beneficial as it reduces unplanned downtime, but the downside of this strategy is the potential waste of remaining useful life in the components if they are replaced too early. Condition-based maintenance is a more advanced approach, involving the continuous monitoring of a wind turbine component's health, and if it falls below a predetermined threshold then maintenance will take place. Condition-based maintenance reduces downtime significantly whilst also avoiding

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https://doi.org/10.1016/j.oceaneng.2025.121190
Received 3 February 2025; Received in revised form 27 March 2025; Accepted 6 April 2025
Available online 15 April 2025

Nomenclature

$\%_{curtail}$	% Active installed capacity to be curtailed
α	Roughness Index
β	Shape Parameter
ϵ	Travel hours
λ	Scale Parameter
ρ	Fuel Consumption
A_E	Energy Based Availability
A_t	Time Based Availability
C_{CTV}	CTV Daily Charter Rate
C_{elec}	Electricity Price
C_{JackUp}	Jack Up Charter Rate
$C_{lostrevenue}$	Lost revenue cost
$C_{maintenance}$	Cost of maintenance trip
C_{mob}	Jack Up Mobilisation Rate
C_{repair}	Repair Cost
$C_{replace}$	Replacement Cost
C_{SOV}	SOV Daily Charter Rate
C_{staff}	Staff Cost
$C_{technician}$	Technician Salary
$C_{transport}$	Transport Cost
E_{prod}	Actual energy produced by the wind farm
E_{total}	Total energy that can potentially be produced by the wind farm
G	Energy generation
$G_{curtail}$	Lost generation due to curtailment
G_{down}	Lost generation due to downtime
H_{CTV}	CTV Significant Wave Height Limit
H_{SOV}	SOV Significant Wave Limit
h_{swh}	Significant Wave Height
I	Number of Turbines
i	Index for turbine
J	Number of Components
j	Index for component
K	Status of turbine
L	Lifetime of Wind farm
N_{tech}	Technician Pool
P_{rating}	Wind Turbine Rating
q	Maintenance quality ratio
$R_{curtail}$	Curtailment reimbursement
T	Total Number of time steps in a simulation
t_a	Start of maintenance trip
t_b	End of maintenance trip
t_{mob}	Jack Up Mobilisation Duration
t_{repair}	Repair Time
$t_{replace}$	Replacement Time
$TA_{new,ij}$	New component age
$TA_{old,ij}$	Old component age
u_{cut-in}	Cut in speed
$u_{cut-out}$	Cut out Speed
u_{rated}	Rated Speed
u_r	Measured Wind Speed
v_{CTV}	CTV Average Speed
w_{CTV}	CTV Wind Speed Limit
w_{SOV}	SOV Wind Speed Limit
z_{nac}	Nacelle Height
z_r	Measurement Height

replacing components too early. The downside of condition-based monitoring is often related to the set up, instrumentation and computational cost being much higher. Opportunistic maintenance is a relatively recent strategy that has been adopted in offshore wind and has a broad definition. It aims to carry out maintenance when there is a predefined

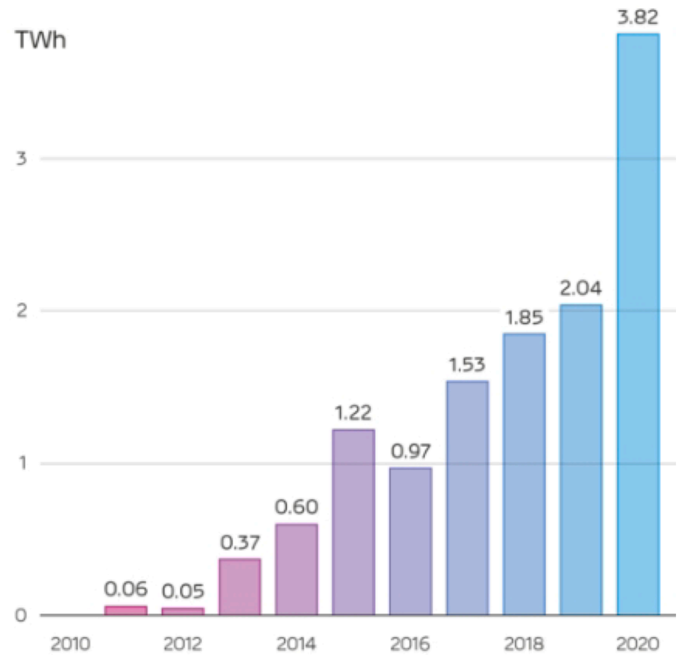

Fig. 1. Annual curtailment for wind energy in TWh for the UK between 2010 to 2020. Figure sourced from Staffell et al. (2020).

opportunity, in order to reduce costs, this is further explained in Section 1.1. There are multiple opportunistic maintenance models that have been developed over recent years, that investigate different factors and outline new opportunities, but, to the author's knowledge, the research has not yet considered all external factors.

In this paper, the novelty stems from using an external factor, curtailment, as an opportunity to complete maintenance at the wind farm. Fig. 1 shows the annual curtailment amounts for the UK between 2010 to 2020. With the target to install 494 GW of offshore wind globally in the next 6 years, there undoubtedly will be increased penetration of wind energy to national grids, which, if not managed correctly will lead to high levels of curtailment. Curtailment is outlined in further detail in Section 1.2.

1.1. Opportunistic maintenance

The strategy of opportunistic maintenance was first developed in 1963 for maintaining a single component in a multi component system, with the simple strategy of performing maintenance on other components while repairing a down component (McCall, 1963). The use of opportunistic maintenance in wind energy was first proposed by Besnard et al. (2009). Over the last 50 years, the definition of an 'opportunity' has been unclear, with opportunistic maintenance strategies involving both internal factors such as component corrective replacements and external factors such as weather conditions (Erguido et al., 2018). In this study, we use the definition that 'an opportunity is a pre-determined event which triggers a decision to perform a predefined set of tasks', which follows the definition used in the work of McMorland et al. (2023).

Early implementations of opportunistic maintenance strategies in wind energy, seen in Ding and Tian (2011), take advantage of corrective maintenance trips to also perform preventive maintenance on other components within the wind turbine. In Tian et al. (2011), this approach is expanded so that a corrective replacement triggers the opportunity for preventive maintenance across any of the wind turbines. The triggers for opportunistic maintenance can vary. In literature, often thresholds are set as the levels of accepted component degradation before a degree of maintenance needs to be performed. If a component reaches the preventive threshold set by the model, maintenance can be carried

Table 1
Overview of the most common maintenance strategies for offshore wind and some of their associated characteristics.

Maintenance Type	Maintenance Trigger	Frequency	Initial Cost	Risk	Planning Required
Corrective	Fix on fail	Unpredictable	Low	High	Minimal
Preventive	Time based intervals	Regular	Moderate	Low	Moderate
Predictive/CBM	Data driven	As needed	High	Low	Moderate
Opportunistic	Opportunity dependent	As needed	Moderate	Low	Moderate

Table 2
Literature for offshore wind opportunistic maintenance strategies.

Authors	Thresholds	External Triggers	Met-ocean limits
Sarker and Faiz (2016)	Age Based	No	No
Kennedy et al. (2016)	No Threshold	Weather Conditions	Yes
Erguido et al. (2017)	Reliability Based	Weather Conditions	No
Lu et al. (2018)	Condition Based	No	No
Zhang et al. (2019)	Reliability Based	Weather Conditions	Yes
Zhou and Yin (2019)	Condition Based	No	No
Li et al. (2020)	Cost Based	No	No
Kang and Guedes Soares (2020)	Location Based	Weather Conditions	Yes
Papadopoulos et al. (2022)	Time Based*	Weather Conditions	Yes
Papadopoulos et al. (2024)	Time Based*	No**	Yes
Jinhe Wang and Zhang (2024)	Condition Based	Weather Conditions	No
Tao et al. (2024)	Reliability Based	Joint Wind Farm	No
Si et al. (2025)	Reliability Based	Weather Conditions	Yes
This Study	Age/Cost Based	Curtailment	Yes

out. Multiple thresholds may be defined, as demonstrated in Sarker and Faiz (2016): the older the component, the more extensive the preventive repair, resulting in a greater reduction in the component's effective age. Components meeting the lower threshold undergo only minor repairs, leading to a smaller reduction in their component age compared to larger repairs. In these studies, the act of repairing a component and returning it back to the condition it was when it was new is called perfect maintenance. Imperfect maintenance repairs the component by a certain degree but not back to its initial condition.

Thresholds are not always based on the age of the components. In more advanced models, that utilise condition base monitoring, thresholds are based on probability of failure (Lu et al., 2018). Thresholds also do not need to be set at a fixed value, with dynamic thresholds being utilised in recent studies. A number of papers look at wind speeds to determine these dynamic thresholds (Zhang et al., 2019; Erguido et al., 2017). A higher threshold is set during high wind speeds, as it is less favourable to perform maintenance when energy production of the turbines is high. At lower wind speeds, these thresholds are lowered allowing more maintenance to occur during periods of lower production, thereby reducing the lost revenue costs. Table 2 outlines recent opportunistic maintenance models specific to offshore wind, the type of thresholds utilised in the model, if the opportunity is based on external triggers and if there are met-ocean limits implemented. In terms of thresholds, Li et al. (2020) is the only paper that considers the cost benefit of the maintenance trip and Kang and Guedes Soares (2020) considers the locations of the turbines when implementing thresholds. The most widely used thresholds in literature use the reliability, condition or age of the components to determine if maintenance should occur.

External maintenance opportunities are less frequently utilised than internal opportunities in the literature. As seen in Table 2, if external triggers are implemented in the maintenance strategy it is often related to weather conditions. Weather conditions is a blanket term used for where the literature has either defined maintenance as occurring during favourable weather or during periods of low energy production for the turbine, both of which involve low wind speeds and/or low wave heights. For example, Jinhe Wang and Zhang (2024) creates an opportunistic model that takes advantage of periods of time when there are intermittent wind speeds, that fall below the cut in speed of the turbine, to complete maintenance actions. Tao et al. (2024) uses a joint wind farm maintenance strategy in their study, the two wind farms influence the maintenance opportunities of the other, so this has been categorised as an external trigger. Papadopoulos et al. (2024) and Papadopoulos et al. (2022) considers curtailment and market prices as external factors in their models but do not class them an opportunity to complete maintenance. Similarly, Erguido et al. (2017) considers external market factors but does not class them as an opportunity for maintenance action. Recent opportunistic literature focuses on optimisation of resource allocation and route scheduling for wind farms. Si et al. (2025) considers accessibility to the wind farm by looking at maintenance windows and grouping component maintenance.

Met-ocean limits are the accessibility limits in place at a wind farm, specific to the type of vessel, that determine if a vessel can access the wind farm to complete maintenance. Although accessibility limits are considered in some of the literature, it is not common practice and the papers that do refer to accessibility limits (Zhang et al., 2019; Kang and Guedes Soares, 2020; Papadopoulos et al., 2022; Kennedy et al., 2016; Papadopoulos et al., 2024; Si et al., 2025) do not have specific inputs for different vessel types.

In this study, periods of curtailment are used as an external opportunity to complete maintenance. Curtailment periods could offer more frequent opportunity for maintenance action in comparison to waiting for the wind turbine to drop below cut in speed, as seen in previous literature, as often wind farms can be asked to shut off when they are within these operational limits. The thresholds set in the model are age based but also rely on a cost benefit analysis to determine if the maintenance trip is beneficial to the overall wind farm operation. All maintenance actions abide by accessibility limits that are applied to each specific vessel and resource limitation in terms of vessels and personnel available. The model utilises a traditional preventive maintenance strategy seen frequently in previous literature, where there is an opportunity to complete preventive maintenance on other components during the replacement of the broken component.

1.2. Curtailment

Curtailment in this study refers to the process of a generator reducing their energy output to an amount less than their actual energy production, usually at the request or benefit of the electricity grid

(Bird et al., 2016; Yasuda et al., 2022). There are several reasons curtailment may occur, such as operational constraints, weak transmission infrastructure or system balancing challenges. The increase in renewable energy sources means a higher penetration of wind energy into the grid, that can cause issues if the grid is structurally weak. With the rate of new wind farm developments, many transmission networks have not been improved or expanded at a fast enough rate to handle the energy production increase. Grid instability can be partially solved by curtailment, as high levels of energy production may not match the demand from the end user and issues can arise with voltage control. Due to the non-synchronous nature of wind energy generation, there can be problems with frequency control and system stability. High penetrations of non-synchronous generation can cause issues if the non-synchronous generators are unable to provide fast frequency response and synthetic inertia. As a preventive measure, non-synchronous generation can be curtailed or constrained by the required amount. The levels of curtailment for wind energy are increasing as a result, in particular for offshore wind. Curtailment is becoming a concern for national grids that have not got the necessary mechanisms to handle the increased energy production. From 2011 to 2021, the UK has experienced increased levels of curtailment, rising to around 4 % of the total electricity generated in 2020, which is predicted to rise in future (Giampieri et al., 2024). Public acceptance of wind energy is key in the approval of future developments and curtailment is seen as a drawback of renewable energy generation. Carbon Tracker, a UK based think tank, non-profit organisation, has predicted that wind curtailment may cost households an additional £150 onto their annual energy bills in 2026, if electrical infrastructure does not improve (Carbon Tracker Initiative, 2024).

For wind farm operators, curtailment may not be favourable either. Despite the compensation provided by the national grid to curtail the turbines, there may still be disadvantages. The switching off of the turbines involves transitioning between the operational conditions. If this is done frequently, as a result of curtailment, the wind turbine may experience high fatigue loads on the tower and foundations (Robbelein et al., 2023). Economically, curtailment is not always favourable for wind farm owners, with high penetrations of wind energy at the risk of causing cannibalisation and driving down market prices, thereby reducing the compensation received by the wind farms (Atherton et al., 2023).

There are several solutions to reduce curtailment being explored, and noticeable improvements have been made in China over the last number of years (Chen et al., 2022). The solution has not been a one fits all approach with different areas of China tackling the problem differently, for example, the north west of China have focused on power transmission, whereas the north east is implementing a peak shaving auxiliary service market. Solutions to curtailment can include grid improvements, more interconnectors, storage solutions, or looking at hydrogen or heat as an alternative energy vector to use the curtailed energy. Regardless of the solutions, it is clear that curtailment will be an issue that wind farms will face in the current landscape. Utilising these periods of downtime, when the wind farm still receives financial compensation as an opportunity to complete maintenance may prove beneficial for wind farm operators.

1.3. Motivation

There is a gap in the current literature for opportunistic maintenance strategies that utilise external factors, other than low wind speeds, as opportunities to complete maintenance. This research aims to close that gap by introducing a model that simulates the lifetime operations of an offshore wind farm and implements an opportunistic maintenance strategy that utilises curtailment periods alongside a traditional internal maintenance trigger to perform preventive maintenance when an opportunity arises. The model considers accessibility limits, vessel selection, resource limitations, different repair types along with multiple thresholds, transit times, energy production of the wind farm, overall operational costs and the lost revenue of the wind farm. Each maintenance trip triggered by a curtailment period involves a decision making process that weighs the cost benefit of completing the trip. The aim of the research is to determine if any significant savings can be made by completing maintenance in periods of curtailment. In this research, a holistic approach is used by combining the traditional structure of an operation and maintenance model, like the model developed in Dinwoodie et al. (2013), that simulates the operations throughout the wind farm lifetime, along with the structure of an opportunistic maintenance model, similar to the one used in Li et al. (2020). The model is simulated for a Scottish offshore wind farm, using historical climate and curtailment data, followed by a comparison to an opportunistic maintenance strategy that does not consider curtailment as an opportunity for maintenance, as well as a simple corrective strategy.

Globally, there has been a significant increase in the levels of curtailment and studies indicate that this increase is due to continue unless grid improvements are implemented. This paper looks to find a silver lining, where curtailment can be used as an advantage, for the offshore wind operators. The model acts as starting point for using curtailment as a maintenance opportunity, that can be built upon in future work to include more external factors such as market electricity prices. The author is unaware of any opportunistic maintenance models in current literature that utilise periods of curtailment as opportunities to complete maintenance on a wind farm.

To summarise, this paper contributes novelty to the field by doing the following:

- developing a unique operations and maintenance model for offshore wind that aims to explore new maintenance strategies
- creating an opportunistic maintenance strategy that utilises curtailment as an opportunity to complete maintenance on an offshore wind farm
- including a cost benefit decision for the opportunistic maintenance strategy to reduce the number of unnecessary maintenance trips being completed.
- determining the total operational costs of using an opportunistic strategy for an offshore wind farm including the total lost revenue, transport, repair and staff costs as well as the energy production and revenue generated.

2. Methodology

In this section, an opportunistic maintenance strategy for an offshore wind farm is proposed, and a model to simulate the operations of the wind farm utilising this strategy is developed. Fig. 2 gives an overview of the model. The model is set up as a Matlab live script to allow the user to alter any of the inputs for the model and obtain outputs regarding cost, energy production and availability without a requirement to understand the operations simulation itself. The model uses a Monte Carlo simulation and simulates the entire lifetime of the wind farm in hourly intervals. The maintenance strategy encompasses both preventive maintenance action and corrective maintenance action. Any maintenance that occurs at the wind farm must abide to the accessibility limits of the vessels. If the climate conditions exceed the accessibility limits, maintenance is delayed until a suitable weather window appears. Maintenance can only occur if there are sufficient repair vessels and technicians available to complete the repair. If a component within the wind farm fails, a corrective maintenance strategy is implemented and the component is replaced at the earliest opportunity, with the turbine out of operation until replacement is complete. Preventive repair can occur in two scenarios:

1. During a corrective replacement, other components within the turbine can have preventive repair take place if the component age falls between predetermined preventive thresholds.
2. During a period of curtailment, components in the wind farm that are closest to their predetermined failure age can be repaired subject to a cost benefit analysis and vessel availability.

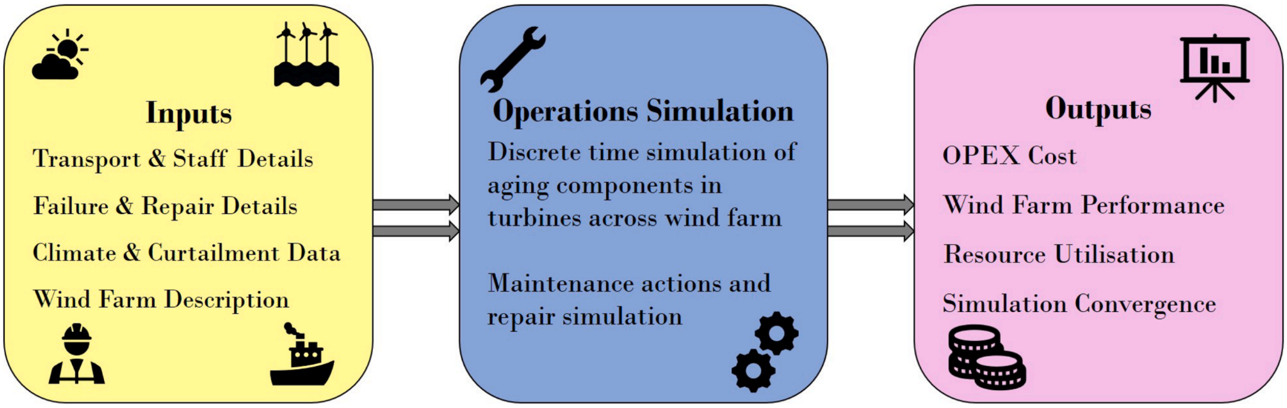

Fig. 2. Overview of the model outlining the main inputs, the operations simulation and outputs.

2.1. Inputs

The model requires the user to input a general description of the offshore wind farm. A wind farm contains I turbines, with J components in each turbine, that are identical throughout the wind farm. It is assumed that a component of the same type, for example a gearbox, has equal repair time and cost as other gearboxes within the wind farm. All component lifetimes, or mean time to failure (MTTF), are modelled with two parameter Weibull distribution with scale and shape parameters β and λ. Each component has an associated repair time and repair cost as well as a replacement time and cost. The probability density function for a component in the wind farm is given as :

$$f_{ij}(t) = \frac{\beta_{ij}}{\lambda_{ij}} \left(\frac{t}{\lambda_{ij}} \right)^{\beta_{ij}-1} e^{(-t/\lambda_{ij})^{\beta_{ij}}} \tag{1}$$

and the MTTF for each component can be found using :

$$MTTF_{ij} = \int_0^{\infty} t f_{ij}(t) \tag{2}$$

The degradation of each component will increase as the component ages until it reaches its failure age, at which point it requires replacement. The failure ages for each component are generated randomly by sampling the Weibull distribution based on the scale and shape parameters provided by the user.

In parallel to the hourly lifetime operations, wind speed, wave height and curtailment time series are simulated. Using the input climate data, a time series is generated for the lifetime of the wind farm. The model requires at least one year of hourly wind speed measurements, u_r, and one year of significant wave height, h_{swh}, measurements. If the input data spans only one year but L is greater than a year, it is repeated L times to generate climate for the duration of the wind farm operations. For an input of 2 years and over, if the input data is shorter than L, the model randomly selects years from the input to construct the extended time series. This process ensures that the generated series reflects the variability of the input data while fulfilling the required time span. Wind speed and wave height are used to determine accessibility to the offshore wind site. Wind speed is also required to calculate energy production from the turbines. Using the wind power law as shown in Eq. (3), with z and z_r as user inputs, a time series is created for the wind speed at sea level and the wind speed at the turbine nacelle. The model assumes that the two wind speed time series are uniform across the whole wind farm.

$$U(t) = u_r(t) \left(\frac{z}{z_r} \right)^{\alpha} \tag{3}$$

Similarly, the curtailment data is in a time series format. The user can input curtailment data in a hourly or half hourly format. The half hourly format is added as extra functionality for curtailment due to the structure of the electricity market in the UK, where data is provided in half hour measurements known as settlement periods. If the data is given in a half hourly format the model will average the two values within that hour period to allow an hourly time series to run concurrently with the wind speed and wave height. The maintenance strategy requires both of the values within the hour period to have curtailment for maintenance to occur. If only one settlement period has curtailment within the hour then the value assigned to that hour will indicate no maintenance can occur. If both half hour settlement periods have curtailment then the value assigned indicates that maintenance can occur. If the user does not have real curtailment data they can enter the time series as one's or zero's for every hour, where one indicates the wind farm is required to curtail and zero indicates operation as usual with no curtailment. Real curtailment data in the form $\%_{curtail}$ allows the model to estimate the number of turbines that are being switched off during a time period based on the total number of turbines in the farm and the rated power of the turbines. Using this information, more insight can be given regarding Key Performance Indicators (KPI's) such as energy production and availability. The user can decide the P_{rating} and enter a specific power curve for the model. The power curve must include a power output, $p(u)$, for each wind speed from u_{cut-in} to $u_{cut-out}$, as well as stating the u_{rated}. The calculation for the power produced at time t, $P(t)$, is shown in Eq. (4). Eq. (4) is then used to determine an estimate for the energy produced in the total wind farm and to determine lost generation caused by downtime.

$$P(t) = \begin{cases} 0, & u_{cut-in} \le U(t) \\ U(t)p(u), & u_{cut-in} < U(t) \le u_{cut-out} \\ 0, & U(t) > u_{cut-out} \end{cases} \tag{4}$$

In order to carry out any of the repairs or replacements on the turbines, vessels for transporting the maintenance staff and spare parts to the wind farm are required. The location from the nearest port to the offshore wind farm is needed to determine the transit time for the vessels, with the assumption that the port and wind farm are two points and a chosen vessel is travelling at a constant speed between the two points. The three vessel types that can be selected for repairs and replacements are: Crew Transfer Vessel (CTV), Service Operating Vessel (SOV) and Jack-Up vessel. Accessibility limits for each of the vessels need to be specified: a maximum allowable significant wave height and maximum allowable wind speed. The average speed of the vessel is used to estimate the total amount of time spent travelling to and from the wind farm. The vessel fuel consumption and cost of the fuel is also required to calculate the total cost of fuel for each vessel as shown in Eq. (5). All of the vessel costs are assumed to be one off costs which are totalled at the end of the wind farm lifetime. If a vessel is utilised for a maintenance trip they have an associated daily charter cost, C_{CTV}, C_{SOV} and C_{JackUp}. For the Jack Up vessel, a mobilisation period, t_{mob}, is included, due to the variability of the availability of these vessels. There is an

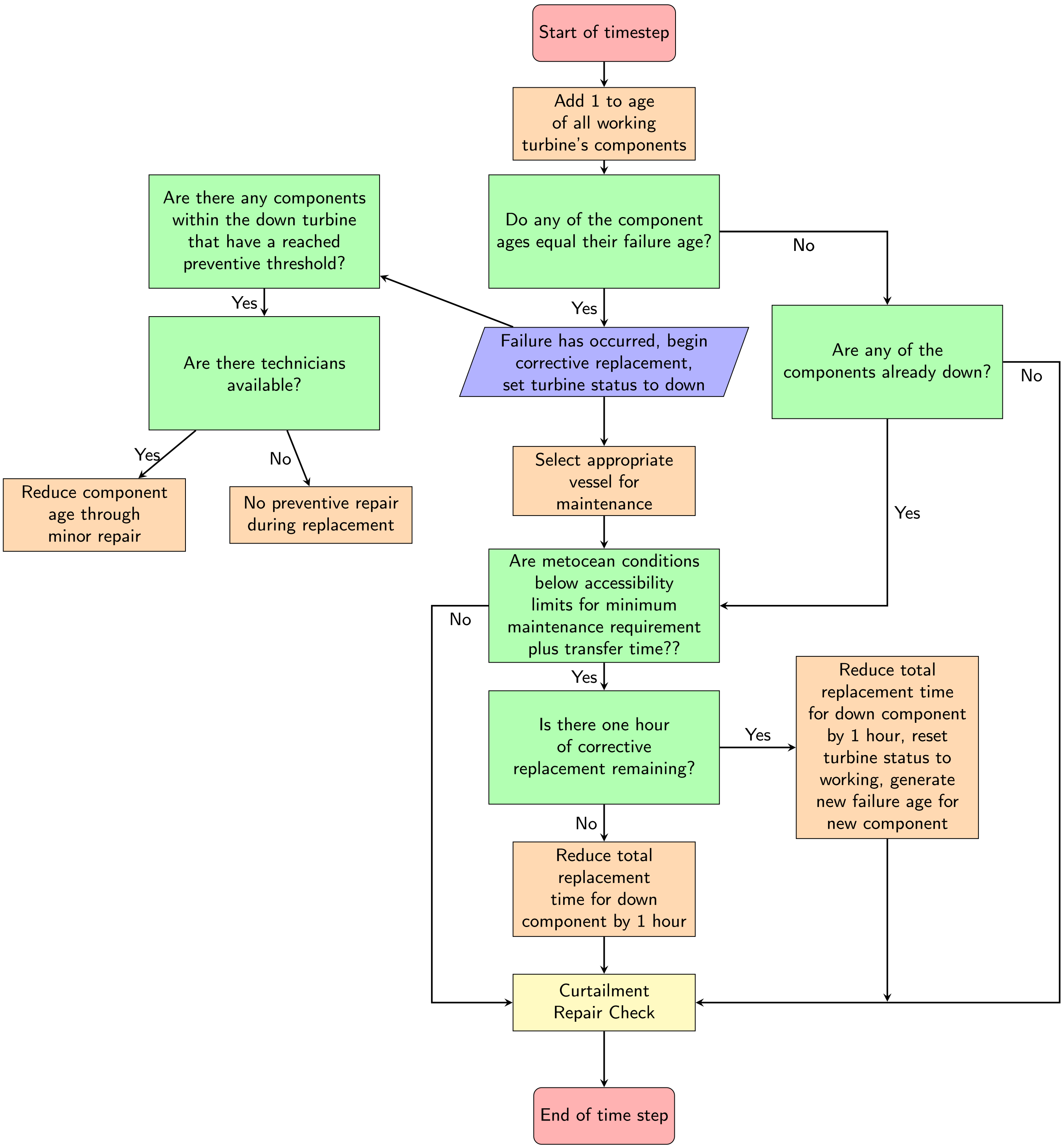

Fig. 3. Decision flow chart for corrective replacement induced opportunistic maintenance at each timestep in the model simulation.

associated mobilisation cost for this period, C_{mob}. The number of vessels in the CTV fleet needs to be specified by the user along with the number of technicians working for the wind farm. It is assumed that for specialist replacements, personnel will be hired external to the wind farm to work on heavy lift operations on the Jack Up vessel.

$$C_{\text{fuel}} = \sum_{q=\text{CTV, SOV, JackUp}} C_{f,q}\,\rho_q\,\epsilon_q \tag{5}$$

Simulation time for the model is dependent on the number of iterations chosen by the user. The higher the number of simulations the greater the convergence achieved in the outputs.

2.2. Operations simulation

Figs. 3 and 4 represent the decision process for maintenance at the wind farm. Fig. 3 illustrates each time step within the simulation, focusing on the corrective replacement element of the maintenance strategy. The step 'Curtailment Repair Check' is then expanded upon in Fig. 4. Similarly, in Fig. 4, the first step is 'Corrective Repair Check' which represents all of the previous steps that have been shown in Fig. 3. Initially, component lifetimes are generated for each component in the wind farm. The component lifetime is equal to the failure age of the component. During each time step, the age of a component increases

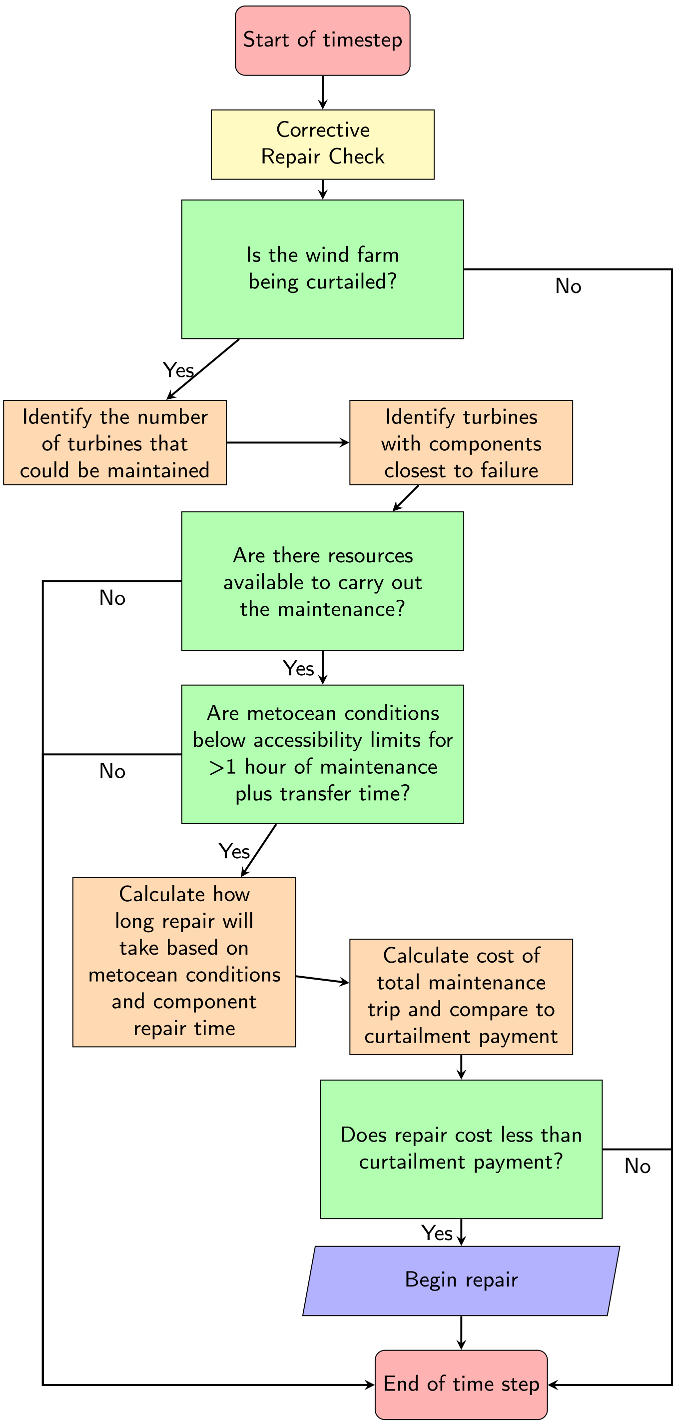

Fig. 4. Decision flow chart for curtailment induced opportunistic maintenance at each timestep in the model simulation.

only if the turbine is operational. If there is component failure, it is assumed that the turbine of the failed component does not age during the period of repair or replacement, as the turbine is shut down during maintenance activities. The model continually monitors component ages, checking whether any component's age reaches any the predetermined failure age, indicating the need for replacement. If a corrective replacement is required, an appropriate vessel is allocated for the replacement and the total time for the replacement is set based on the user inputs. Simultaneously, the components in the turbine containing the down component are surveyed to see if any meet the predetermined preventive thresholds. The thresholds are a fraction of the component's failure age and will determine the level of maintenance that will be required. If a component age falls within the range p_1 and p_2 then minor repair will take place. A component age that is above p_1 but below the components failure age will undergo major repair. The categorisation of minor repair, major repair and replacement is based on the costs of each maintenance action, following the work in Donnelly et al. (2024). The preventive maintenance carried out results in a reduction of the component's age by a ratio of q $(0 \leq q \leq 1)$ as shown in Eq. (6). The value of q is dependent on the quality of the maintenance, the more effective the maintenance the larger the reduction of the components age. If the maintenance is a perfect action, q is set to 1, thereby resetting the component's age to 0 or 'good as new'. The values of the thresholds and the ratio of the quality of maintenance carried out is up to the user. The assumption is that the preventive repair times are always shorter than the replacement times and that the preventive threshold for major repair is always a higher threshold than the preventive threshold for minor repair. In order to determine whether preventive repair can be carried out, the model also will check if there are enough technicians left in the technician pool to carry out the repair. Each type of component repair has an associated number of technicians required for maintenance. If there are not enough technicians, the repair is not carried out. Both corrective and preventive maintenance only occur if there is a sufficient weather window that allows the vessel to access to the turbine and complete transit to and from the port. If there is a mobilisation period associated with the vessel, maintenance can only be completed once mobilisation has ended. After replacement is complete, the model generates a new failure age for the component and sets the turbine status to working.

$$TA_{new,ij} = \begin{cases} TA_{old,ij}(1-q_1), & p_1 \leq TA_{old,ij} < F_{ij} \\ TA_{old,ij}(1-q_2), & p_2 < TA_{old,ij} < p_1 \end{cases} \tag{6}$$

During each time step, a curtailment maintenance check also takes place after the corrective check, as seen in Fig. 4. If there is no curtailment the model moves onto the next time step. If there is curtailment, the model identifies the number of turbines that are required to shut down based on the amount of power being curtailed. The number of available vessels to carry out turbine repairs is checked. Based on the vessels available and the number of turbines being switched off, the model identifies a number of components in the wind farm that are closest to their failure age. The repair can only be carried out if there are enough technicians in the technician pool left over to complete the task. For each repair, the model will check the weather window and if the window is sufficient for a repair it will calculate the total time the repair will take based on the component repair time and the met-ocean conditions. A cost benefit analysis of the maintenance trip is required to determine if the cost of sending the vessel out to repair the component is larger than the benefit of reducing the turbine downtime. The cost of the trip is shown in Eq. (7).

$$C_{maintenance_{ij}} = \sum_{t=t_a}^{t_b} C(t)_{transport_{ij}} + C_{repair_{ij}} + C_{elec} \sum_{t=t_a}^{t_b} G(t)_{ij} \tag{7}$$

The calculated maintenance cost is the sum of the transport costs for the trip, the cost of repair for the trip and the lost production cost for the duration of the maintenance action, which uses the potential energy generation multiplied by the electricity price. Eq. (7) is compared against the total reimbursement payment given by the grid operator to the wind farm, as shown in Eq. (8). It is assumed that the price of electricity is fixed and that the compensation given to the wind farm is equal to the amount of revenue that would have been generated in regular operation. During the maintenance trip, if the grid does not require the turbines to be curtailed then the turbines will not be operational as they are undergoing repair and are assumed to be shut down until repair is complete. The reimbursement payment only takes into account the time during the repair when curtailment is requested and similarly, the lost generation in Eq. (7) does not include curtailment. The remaining time is classified as downtime.

$$R_{curtail} = C_{elec} \sum_{t=t_a}^{t_b} G(t)_{curtail} \tag{8}$$

If the maintenance trip costs more than the compensation that is received by the wind farm for curtailment during the period of the maintenance trip then the trip will not occur. If the compensation is more than the cost of the trip, the trip is deemed beneficial and the maintenance action begins. The cost benefit analysis is a simple approach, used as an example, and can be modified and extended in further work but this framework acts as a starting point for research to start introducing more cost focused decisions in opportunistic maintenance.

The degree of repair that the component undergoes during periods of curtailment follows the same methodology as the preventive repair that takes place during corrective action. The thresholds for repair are the same and the reduction in component age remains the same throughout the model.

2.3. Outputs

The wind farm's key performance indicators are it's energy production, time based availability and energy based availability. KPI's are output for each simulation and, in post process, displayed as yearly averages and total life time averages. Eq. (9) shows the total energy produced in a wind farm in its lifetime.

$$E_{prod} = I \sum_{t=0}^{T} \left(G(t)_{ij} - G(t)_{down,ij} \right) \tag{9}$$

The energy based availability of the wind farm is calculated using Eq. (10):

$$A_E = \frac{E_{prod}}{E_{total}} \times 100 \tag{10}$$

where the total energy produced in the wind farm is divided by the total potential energy if there was no downtime during the lifetime. The calculation does not consider curtailment as an outage. The time based availability of the wind farm, as seen in Eq. (11), is time the turbines were available over the total time of the wind farm lifetime. Curtailment is also not included in this calculation, downtime only considers forced outages. Although time based availability is easier to determine as it does not require a calculation of the energy generated at each hour it does have some shortcomings. If a turbine is experiencing downtime, it is considered unavailable, however, the wind speed at that instance in time could be above or below cut in speed, meaning that if the turbine was operational it would not be generating electricity. In that respect, energy based availability can often be a favourable metric if wind speeds and expected generation is known.

$$A_t = \frac{T - \sum_{t=0}^{T} K(t)_{down}}{T} \times 100 \tag{11}$$

The OPEX outputs from the model contain a breakdown of the four main cost contributors: $C_{lostrevenue}$, $C_{transport}$, C_{staff} and C_{repair}. The lost revenue cost is the amount of money that could have been made if the turbines had been operational at all times but due to downtime that potential revenue was lost.

$$C_{lostrevenue} = C_{elec} \sum_{t=0}^{T} G(t)_{down} \tag{12}$$

The transport costs for the wind farm are the charter rates and mobilisation costs of the different vessels for the life time of the wind farm. Fuel costs are also summed for each vessel and added to the total transport cost.

$$C_{transport} = C_{CTV} + C_{SOV} + C_{Jackup} + C_{mob} + C_{fuel} \tag{13}$$

The repair cost is made up of two main costs, the cost of a new component due to a replacement and the cost of repairing a component preventively either during corrective periods or during a curtailment period.

$$C_{repair} = C_{replace} + C_{prevent} \tag{14}$$

The staff costs are calculated by multiplying the number of technicians employed by the wind farm by the salary of the technicians by the number of years in the wind farm lifetime. The staff costs are rough estimates and the assumption is that every technician will have the same salary which is often not the case as different maintenance tasks require a varying level of skill and expertise.

$$C_{staff} = C_{tech} \times L \times N_{tech} \tag{15}$$

The total OPEX costs encompass all the above components. The model normalises the costs and outputs an average OPEX cost in a £/MWh format to allow for an easy comparison with other literature. The direct OPEX cost differs from the total, as it does not consider lost revenue costs, this is also normalised in a £/MWh format.

$$OPEX_{total} = C_{lostrevenue} + C_{transport} + C_{repair} + C_{staff} \tag{16}$$

$$OPEX_{direct} = C_{transport} + C_{repair} + C_{staff} \tag{17}$$

Finally, to ensure the model outputs are not random and variable, Eq. (18) determines the relative standard error of any chosen key performance indicator in the model. Relative standard error is used in statistics to determine the precision of an estimate by dividing the standard error by the mean of the value. In the model, this will act as a measure of convergence in the results with the theory that more simulations runs will reduce the relative standard error. It is up to the user to determine the level of desired convergence they require for the results which may differ depending on the KPI and the user requirement.

$$X_{KPI} = \frac{\sigma_{KPI}}{\sqrt{N} \times \overline{KPI}} \tag{18}$$

3. Modelling assumptions

Perfect modelling for operations and maintenance is rarely possible and often incurs heavy computational costs. The model presented opts for quicker simulation time but results in some limitations. As previously mentioned, electricity prices remain constant throughout the simulation. The reality is that market prices are dynamic and impact the amount of curtailment reimbursement received by the wind farm. Obtaining a time series of market prices proved difficult but is an area of future work to implement into the model. There is also an assumption that when a boat arrives at the turbine, the maintenance will occur instantaneously and for the full hour. In terms of the maintenance staff, the assumption currently is that there are day technicians and night technicians who instantaneously switch to allow for 24 h maintenance on the wind farm but additional functionality in the model could allow for only day or night operations to occur rather than both.

4. Results and discussion

4.1. Comparative study

To understand the effectiveness of the curtailment strategy it must be compared against strategies that do not use curtailment as an opportunity. Therefore, the curtailment model (V) was altered to make two separate versions; the first version (V1) has only a corrective maintenance strategy, where a component is only fixed once it has broken. The second version (V2) carries out maintenance so that during a corrective repair, other components within the turbine can have preventive repair take place if the component age falls between predetermined preventive thresholds. V encompasses both V1 and V2 along with the opportunity to complete maintenance during periods of curtailment. Aside from maintenance strategy, every other aspect of the models are kept consistent

Table 3
Repair inputs for Beatrice Case Study.

Component	$C_{prevent}$	t_{repair}	$C_{replace}$	$t_{replace}$	β	λ
Gearbox	2697	4	1218000	231	2400	3
Control System	6525	7	435000	10	1750	2
Blades	1357	9	12516	21	3000	2
Generator	2697	6	1740000	81	2400	3
Pitch System	2610	9	174000	25	1500	2
Yaw System	3313	5	295800	49	1800	3

Table 4
Transport inputs for Beatrice Case Study.

Vessel	Input	Value
CTV	ω_{CTV}	15
	H_{CTV}	1.5
	C_{CTV}	1530
	ρ	0.4
SOV	ω_{SOV}	12
	H_{SOV}	3
	C_{SOV}	10000
	ρ	0.7
Jack Up	t_{mob}	60
	C_{mob}	252000
	C_{JackUp}	190000
	ρ	1.2

in terms of inputs, outputs and general structure to ensure the fairest comparison.

The case study used for this research is Beatrice wind farm, located on the North East coast of Scotland, chosen due to the availability of curtailment data for an input to the model. Curtailment data comes from an open source data set on the Elexon webpage, providing settlement period readings for all energy generators in the UK (Elexon, 2024). The climate data selected comes from the FINO dataset based on the North Sea (Bundesamt für Seeschifffahrt und Hydrographie, 2024). The wind farm lifetime is set at 20 years. Beatrice contains 84 turbines, with a 7 MW rating, at a distance 13 km from shore. Power curve data comes from the NREL database and a 7 MW reference turbine is used (NREL, 2025). Each turbine is assumed to have only six components; gearbox, control system, blades, generator, pitch system and yaw system. More components can be included in future studies but lack of failure distribution data has limited this study to only six components per turbine. The failure distributions of these components can be seen in Table 3 and are taken from the work by Ma et al. (2022). The failure distribution data is not specific to Beatrice wind farm and may affect the reliability of the results, so to counteract this, Section 4.3 conducts sensitivity analysis of the scale parameter values. Repair and replacement times along with their associated costs are also included in Table 3. Inputs regarding transport are found in Table 4. All inputs for times, costs and transport are sourced from the previous studies carried out in Donnelly et al. (2024), Dinwoodie et al. (2013), Dalgic et al. (2015). Other costs that are fixed throughout the study are electricity price, set at £50 /MWhr and the technician salary, set at £40,000. Preventive maintenance thresholds are set for V and V2 are held constant throughout the simulations to allow for fair comparison. T_1 is the set threshold that indicates major repair can occur if an opportunity arises when a component has reached 90 % of it's predicted failure age and q_1 is set at 0.25. Similarly, T_2 triggers a minor repair if an opportunity arises when a component has reached 85 % of it's predicted failure age and q_2 is set at 0.15. These values are selected arbitraily but kept constant throughout simulations to allow for comparison.

The overall operational costs for each version of the model are calculated and displayed in Fig. 5. The $OPEX_{direct}$ and $OPEX_{total}$ are the average lifetime operational costs from 100 simulations of each model. V1, the corrective strategy has the highest overall costs, followed by V2 and then V, which has the lowest operational costs. The opportunistic maintenance strategy in both V2 and V resulted in lower overall operational costs due to the reduction in replacements occurring by completing more frequent repairs on components compared to the corrective strategy. The difference in operational costs between V2 and V, results from the added level of maintenance occurring during periods of curtailment in the V model alongside the repairs occurring during corrective replacement. $OPEX_{total}$ is expected to be higher than $OPEX_{direct}$ as it is factoring in the lost revenue costs on top of repair, staff and transport costs. To further understand the difference between the models, in terms of costs, Fig. 6 gives a breakdown of the $OPEX_{total}$ into the average transport, repair, staff and lost revenue costs for the lifetime of the wind farm across the 100 simulations. Noticeably, the highest contributions to the cost are repairs and transport. The reduction in overall component replacements occurring due to preventive maintenance in V and V2 lowers the overall lost revenue costs.

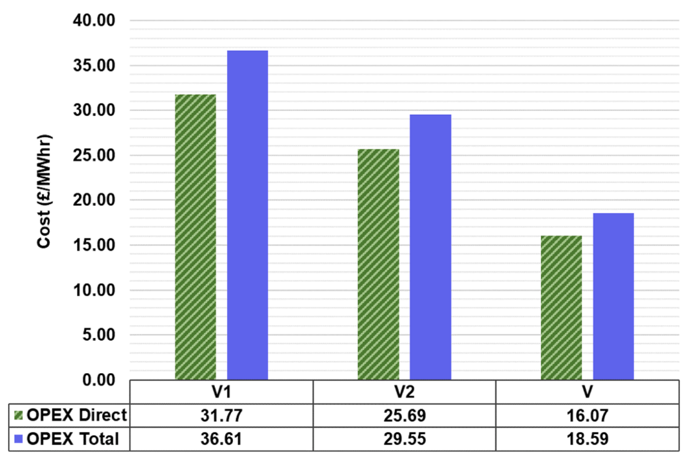

Fig. 5. Cost comparison of the original model V with V1 and V2 looking at the average OPEX direct and total costs across 100 simulations.

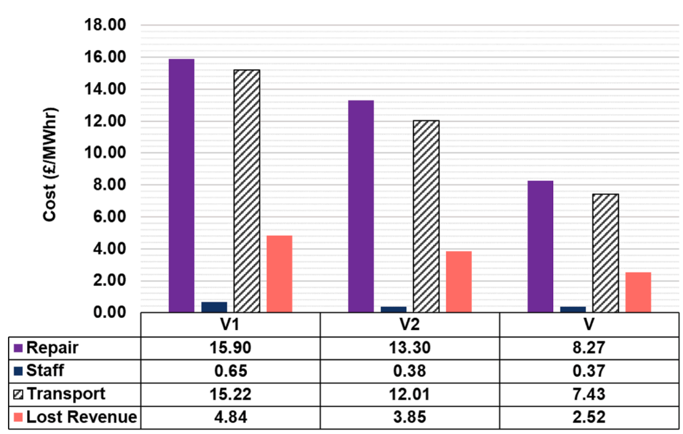

Fig. 6. Breakdown of the average total and direct OPEX costs for each model, V, V1 and V2, highlighting transport, repair, staff and lost revenue costs.

Fig. 7 compares the energy based and time based availability across the models for Beatrice wind farm. The energy based availability is around 5 % lower than the time-based availability across all three versions of the model. Lower energy based availability is due to the metric accounting for the total amount of energy lost during periods of downtimes whereas time based availability accounts for the total amount of time the turbine is out of operation. For example, if downtime takes place during periods of high wind speed, the energy availability is going to be lower than the time based availability and if downtime took place during low wind speeds then the time based availability would be lower, as explained in Conroy et al. (2011). In the case of Beatrice wind

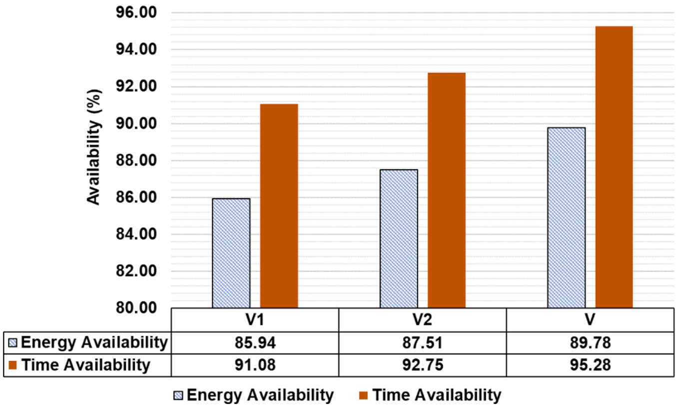

Fig. 7. Time based and energy based availability values for the three models; V1, V2 and V.

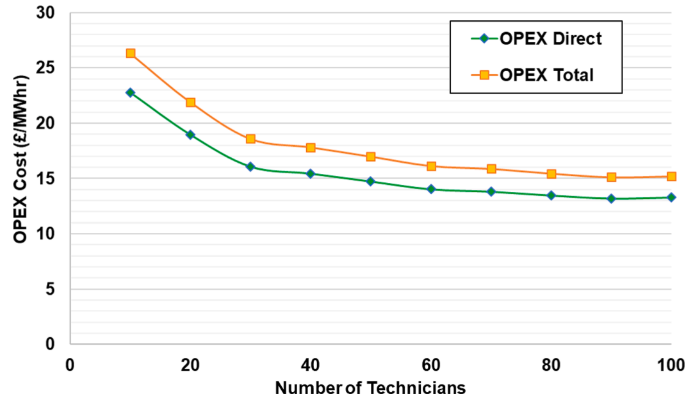

Fig. 9. Operational expenditures for simulated wind farm with varying number of technicians.

farm, downtimes occurred more frequently during high wind speeds and due to the accessibility limits imposed during high wind speeds, maintenance is delayed. The delay in component repairs or replacements means the downtime during high wind speeds would last for a longer period of time, thereby reducing the overall energy availability. Comparing the different models, the lowest time and energy based availability is in V1, followed by V2 and then the highest availabilities are found in V. Lower availability for the corrective version of the model, V1, stems from an increased amount of broken components due to the absence of preventative maintenance. More components breaking results in long replacement times which will cause the downtime of the turbines to increase. As expected, the introduction of preventively maintaining the components to increase their useful lifetime, means a reduction in the downtime of the turbines and an increase in the availability of the turbines. V has the highest availabilities as it offers extra maintenance opportunities during curtailment periods on top of the strategy in V2, allowing a further reduction in the downtime however, the difference between these two strategies is around 1 % and is not as significant as the difference between V2 and V1. Fig. 8 shows the convergence of the average time based availability value over 100 simulations, reaching a relative standard error of 0.0005.

In summation, the comparison of maintenance strategies, using the Beatrice case study, has revealed an OPEX cost reduction and increase availability of the wind farm when employing the opportunistic maintenance strategy in model V. The opportunity to complete maintenance during periods of curtailment and during corrective replacement under the constraints of the specific wind farm chosen is proven to be beneficial to the wind farm owners. By employing the additional curtailment strategy in comparison to only utilising the simple preventive maintenance strategy seen in previous literature, further cost reductions are realised in this case study. To explore how advantageous this strategy is, the following sections alter different inputs, namely turbine size, distance from shore and failure distributions, to see their impact on the output from the model.

4.2. Number of technicians

The number of available technicians was set to 30, with a fleet comprising of five CTVs. To assess the impact of resource constraints, a sensitivity analysis was conducted on the number of technicians. The model does not permit repairs at the wind farm if an insufficient number of technicians is available. However, replacements can still be performed under the assumption that external personnel are hired for large scale replacements.

The simulation was executed for 10 cases, varying the number of technicians from 10 to 100, with the results presented in Figs. 9 and 10. The operational costs, depicted in Fig. 9, are highest when the technician pool is limited to 10 personnel, as the lack of workers restricts preventive maintenance, leading to an increased reliance on costly replacements. As the number of technicians increases, operational costs decrease; however, the marginal benefit diminishes, as indicated by the plateau in OPEX.

Similarly, the availability of the wind farm, shown in Fig. 10, improves with a larger technician workforce, as more repairs can be

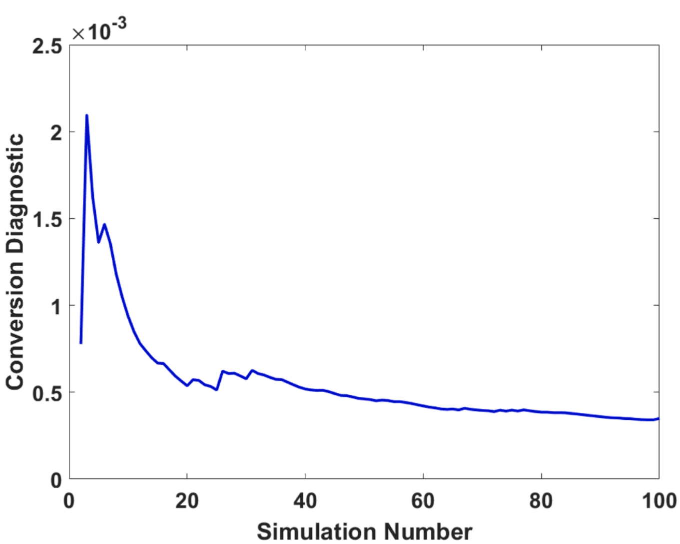

Fig. 8. The convergence of time based availability results after 100 simulations of the model.

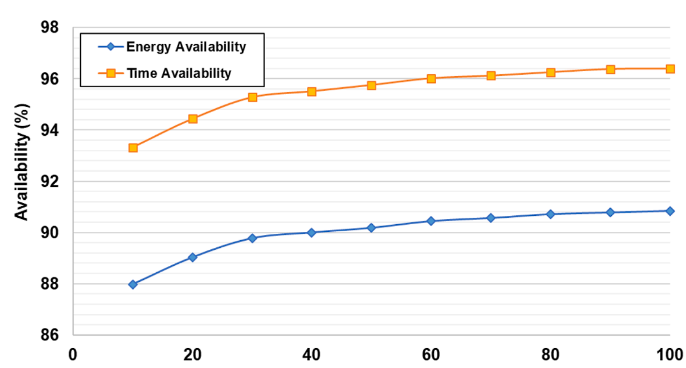

Fig. 10. Availability for simulated wind farm with varying number of technicians.

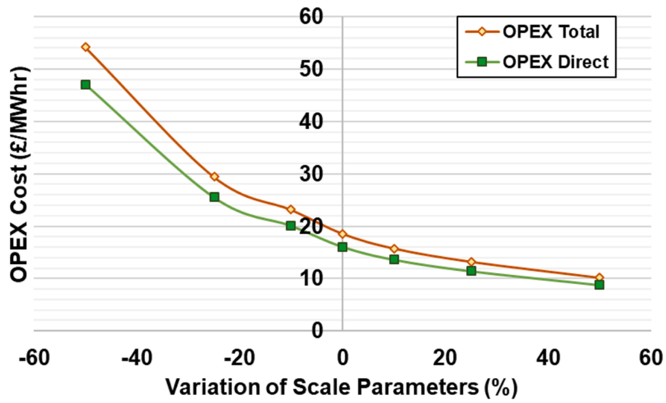

Fig. 11. Operational expenditures for Beatrice wind farm with varying scale parameter values.

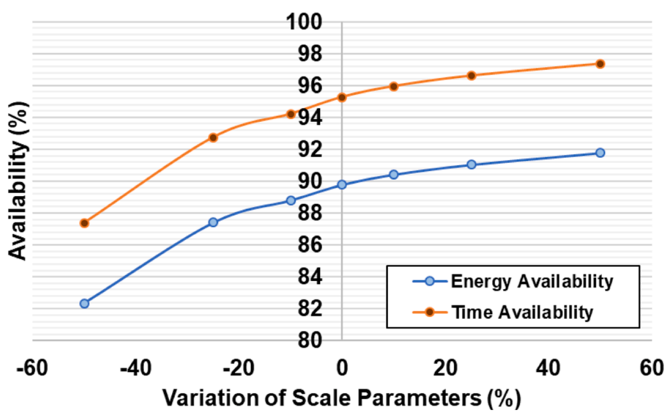

Fig. 12. Availability of the Beatrice wind farm with varying scale parameter values.

undertaken. A greater number of technicians allows for an increased number of preventive maintenance tasks to be performed, thereby reducing overall turbine downtime. A plateau effect is evident for both energy and time based availability, suggesting that beyond a certain threshold, further increases in maintenance capacity provide diminishing returns. At this point, the improvements in availability are counterbalanced by the additional staffing costs.

4.3. Failure distributions

Due to the lack of publicly available failure distribution data for component lifetimes, the failure distribution is one of the biggest areas for uncertainty in the inputs of the model. The sensitivity analysis carried out in this section uses the original scale parameter values for the six components in Table 3 and varies them from −50 % to +50 % of their original value. All components are varied the same amount for each simulation to allow for fair comparison. Smaller scale parameter values should result in more frequent repairs of the components resulting in higher O&M costs and the larger scale parameter values indicate less frequent repairs resulting in lower costs. The shape parameter was kept the same to allow for consistency and a clear conclusion to be drawn. The operational costs, shown in Fig. 11, follow a similar trend for both direct and total costs. For scale parameters at 50 % of the original value, the operational costs are the highest, with total operational costs at £54 /MWhr. Whereas, increasing the scale parameters by 50 % of the original value, results in the lowest operational costs at roughly £10 /MWhr. The significant decrease in costs stems from the less frequent failures in the components resulting in less downtime, less repairs and less requirement for transport vessels. The reduction in costs begins to plateau as the energy production begins to reach it's maximum capabilities due to the reduction in downtime experienced by the turbines. Hypothetically, if failure distributions of the components were set such that failures only occur after the end of the wind farm lifetime, the energy production would be at a maximum and the costs would keep reducing until the only remaining costs would be the staff costs, causing another dip for the shape of the graph. Similarly, in Fig. 12, the availability of the wind farm increases as the scale parameter increases because the failures in the wind farm are less frequent thereby reducing the downtime.

Overall, it is clear that the failure distributions have a large effect on the outputs of the wind farm. Further analysis could also investigate the individual components being changed while others remain constant or changing the value of the shape parameter also.

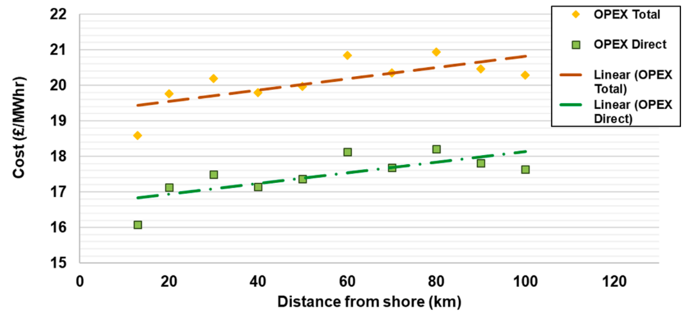

Fig. 13. Operational costs using the curtailment model for the Beatrice case study with varying distances from shore.

4.4. Distance from shore

In keeping with other simulations, the Beatrice case study uses the exact same inputs, while the distance from the wind farm to the shore changes. Fig. 13 outlines the cost outputs from the simulations that were ran from 10 to 100 km. For both the $OPEX_{direct}$ and $OPEX_{total}$, the linear trend shows increasing costs as the distance from shore increases. The increased costs as distance increases predominately stem from the increased transport costs and increased lost revenue costs. The transport costs increase with distance from shore as the journey to site is longer and therefore fuel consumption for vessels is higher. Another reason for transport costs to increase is that the longer transit time may result in less time during a weather window to complete a repair. If a repair is not completed within a day it results in an extra day of work along with an additional charter cost for the vessel. The lost revenue costs increase for a similar reason. If the turbine is broken and the site is further from shore, a longer weather window is required to account for longer transit times. The longer weather windows increases the chance of repairs not being completed as quickly, resulting in an increased amount of downtime and consequent increased lost revenue costs. In comparison to the turbine size and failure distributions, the distance to shore appears less significant to the overall costs of the windfarm when looking at 10 km to 100 km and may require a much larger distance before a stark increase in the OPEX is produced.

5. Future work and conclusion

The research produces an opportunistic maintenance model that utilises periods of curtailment for the wind farm as an opportunity to complete maintenance on wind farm turbine components. The model simulates the whole lifetime of the wind farm and produces output metrics such as OPEX, power production and availability. To assess the effectiveness of this maintenance strategy, preventative thresholds relating to the components lifetime are used, similar to previous research. A cost benefit analysis is introduced that determines if the cost of carrying out a maintenance trip is more than the cost incentive given to the wind farm during curtailment, in which case the decision is made not to carry out maintenance and vice versa. The model also utilises traditional opportunistic maintenance strategies, wherein components can be preventatively maintained if a component within the same turbine requires replacement, provided they meet the maintenance thresholds. The model was compared to two less complex maintenance strategies, a corrective strategy and a simple opportunistic strategy. Using Beatrice offshore wind farm as a case study, simulations showed 50 % decrease in operational costs when utilising the curtailment strategy in comparison to the corrective strategy. The simple opportunistic strategy has a 20 % reduction in costs compared to the corrective strategy. Time based availability and energy based availability were also compared across the three models with curtailment strategy providing optimal time based availability and energy based availability at 95 % and 90 % respectively, 2 % higher than the basic opportunistic strategy for both time and energy based availability.

Due to the sensitivity of the model to various inputs, multiple sensitivity analyses were performed. The three inputs focused on were number of technicians, failure distribution values and distance from shore. The model showed a decrease in costs as number of technicians increased, due to the increased number of opportunities to carry out preventive maintenance tasks. The scale parameter for all components was varied and found that smaller values for scale factor increased costs due to the increased repairs required. Similarly, the distance from shore analysis revealed that an increased distance from shore increases the operational costs due to increased transport costs and longer periods of downtime. Although, validation has been performed on the model through comparison of various models and investigating the sensitivity of inputs, further analyses and case studies should be carried out to allow for a fuller picture to be developed.

Future work for this model would look at a more comprehensive cost benefit analysis to see how much is gained from preventatively maintaining a component in terms of it's life extension and the extra production gain from that extension. To more accurately replicate the offshore wind market, the introduction of dynamic electricity prices would benefit the model in future iterations. The validating of this model is only completed for one case study, to ensure there is generalisability of the results, further case studies in different locations need to be carried out.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Orla Donnelly reports financial support was provided by Engineering and Physical Sciences Research Council. James Carroll reports financial support was provided by Engineering and Physical Sciences Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Orla Donnelly: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **James Carroll:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

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