Sensitivity analysis of offshore wind farm operation and maintenance cost and availability

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ABSTRACT

Operation and Maintenance (O&M) costs are estimated to account for 14%—30% of total Offshore Wind Farm (OWF) project lifecycle expenditure according to a range of studies. In this respect, identifying factors affecting operational costs and availability are vital for wind farm operators to achieve the most profitable decisions. Many OWFs are built in stages and the important factors may not be consistent for the different phases. To address this issue, three OWF case studies are defined to represent two phases and a complete project. An initial qualitative screening sensitivity analysis was conducted to identify the most important factors of O&M affecting operating cost and availability. The study concluded that the important factors for total O&M cost were access and repair costs along with failure rates for both minor and major repairs. For time-based availability, the important factors identified were those related to the length of time conducting the maintenance tasks, i.e. the operation duration and the working day length. It was found that the two stages had similar results, but these were different compared to the complete project. In this case, the results provide valuable information to OWF operators during the project development and decision making process.

1. Introduction

Offshore wind is a burgeoning industry for electrical generation in Europe. The rapid growth of turbine size, capacity, increased number of turbines within projects, coupled with working in dynamic offshore environments, leads to challenges through the project lifecycle. Operation and Maintenance (O&M) is estimated to account for 14%—30% of total offshore wind farm (OWF) project lifecycle costs [1,2]. Identifying factors affecting operational expenditure and availability are vital for an operator to tackle main issues and reduce cost. However, some elements are uncertain and difficult to predict, such as meteorological conditions and turbine reliability.

Aspects that an operations team may encounter during the O&M phase are turbine and support structure (such as a transition piece) reliability; accessibility via vessels; transfer of technicians and components to the turbine; meteorological conditions and condition monitoring. The offshore environment presents challenges that make OWF operation different to an onshore wind farm. Also unlike onshore wind farms, large OWFs are often built in different stages or extended. Sections of projects are completed and move into the operations stage before installation of another section. Examples in the UK are Walney, Gunfleet Sands and the planned Dogger Bank project.

Computer models inform project developers and operators of

likely costs and performance. Sophisticated models that incorporate a level of uncertainty to emulate stochastic elements from the weather and reliability, help to reduce the cost of energy. This can be achieved through identification of the level of risk of operational expenditure by providing a distribution of costs rather than single mean values. It also provides guidance on areas in uncertainty reduction. Potential cost reduction can be achieved through identification of optimal maintenance strategies and demonstrating the benefits when moving from time-based to condition-based maintenance.

There are a number of wind farm O&M models currently under development incorporating turbine reliability and meteorological conditions both for the onshore [3,4,5] and offshore [6,7,8,9] wind sectors. The majority of models estimate O&M cost, while some consider wind turbine/farm availability. Models can assess a range of options of how to manage an OWF to maximize profitability [7]. A thorough overview of O&M tools for onshore and offshore wind can be found in Dinwoodie et al. and Hofmann [6,7]. At the core of most offshore wind O&M models is a stochastic approach for representative failure event generation based on wind turbine reliability analysis. Approaches are based on either statistical distributions (using Weibull distributions or Poisson processes), Markovian or Structural Load elaboration [10]. All O&M models include a meteorological module employed to provide weather windows relevant to planned maintenance intervals of turbines. Uncertainty is introduced by using Markov chains or similar approaches. The models investigated in Dinwoodie et al. [6] do not couple the meteorological simulation with the reliability model. It has been found that there is a weak correlation between periodicity of wind turbine failure rates and wind speed [11,12] but this aspect has yet to be included in models and the effect on O&M is yet to be studied.

Sensitivity Analysis (SA) methodologies measure a computer model output variance against the variance in model inputs, resulting in identification of inputs that have the largest influence on outputs. Application of SA methods can be found where there is use of a model to simulate a natural system; be it biological, chemical, operational, mechanical or a more abstract process like economics and statistics [13]. It can be used to understand the uncertainty associated with each input factor as well as to identify variables to create a metamodel [14]. A variety of different methods exist to explore the sensitivity of inputs factors to model outputs, each with their own strengths and weaknesses. Reviews exist to compare different methods, often through the prism of the research field; nuclear, medical or biological [15,16,17]. A thorough introduction of all SA types is provided by Saltelli et al. [14]. There are some examples of application of SA to OWF O&M models.

Hofmann and Sperstad [18] have conducted a one-at-a-time (OAT) SA on O&M cost using the NOWIcob simulation model. Main findings included high sensitivity to vessel operational wave limits, failure rates and maintenance task duration. Moreover, O&M cost was not sensitive to fuel cost or inter turbine distance. A limitation is that it only investigates local points in the global region of investigation. A simple method was opted for in this case as a more complex method requires restrictions, such as wind farm size and capacity within the region of interest.

The analysis applied in this investigation provides a qualitative way to screen out unimportant factors in a computationally efficient manner. While, if additional analysis is needed, a more sophisticated analysis can be conducted on those remaining to quantify their effect on the model outputs. This paper presents how the important factors contributing to O&M cost and availability change when building OWF projects in phases using the application of the well-known Morris method for sensitivity analysis [19]. The first half of the methodology section defines the OWF O&M model,

outlines the fixed and variable inputs used (Sections 2.1 And 2.2). The second half (Section 2.3) introduces a general framework for conducting SA and the approach used is outlined in Section 2.3.2. The case studies are introduced in Section 3 along with details of the analysis execution. The results and discussion of the analysis follow in Section 4 along with concluding remarks in Section 5.

2. Methodology

This section describes the overall methodology, including presentation of the Offshore Wind O&M tool on which the work performed. Then, details on the variable inputs are provided such as wind farm site, fixed costs, technicians used, vessels and helicopters employed in the O&M activities together with the wind turbine component reliability features. Furthermore, details on the SA performed and selection of appropriate SA method are presented.

2.1. Offshore wind model

The offshore wind O&M tool used for the analysis is described by Douard [20]. The tool evaluates the annual and total O&M cost and the cost of wind farm unavailability. Fig. 1 shows a schematic of the different modules of the tool.

The *wind farm technology* block in Fig. 1 provides project information, such as turbine number, monthly capacity factors and components. Failure rates, repair times and costs are inputs for each component. *Strategy and resources* provides details of technicians and vessels available to conduct maintenance. The *site meteorological condition* data is provided as a time series of wind speed and wave height data which is used to determine length of access windows for maintenance operations for a given site. Within the *meteorological simulation* the time series data is randomised. A probabilistic *failure event model* is used to simulate failure occurrences using an inverse transformation sampling algorithm. It formulates dates according to distributions based on the lifecycle of the component related to the bathtub curve [20], as shown in Fig. 2 [21]. The model is capable of simulating corrective and time-based, but not condition-based, maintenance. After a corrective maintenance action occurs, the component is returned to an "as bad as old" state, a conservative assumption. Other information sources
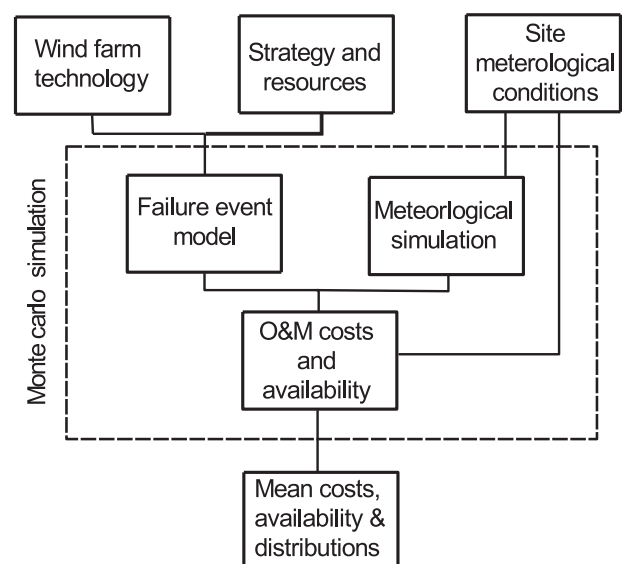

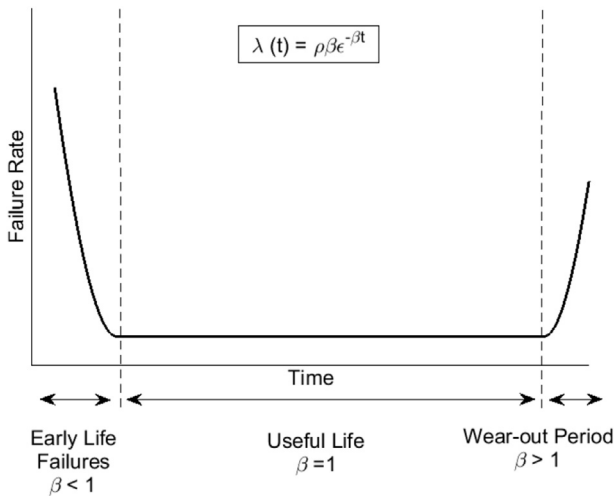**Fig. 1.** Diagram of the Offshore Wind O&M tool [20].

Fig. 2. Diagram of a theoretical bath tub curve for a repairable system [21], λ(t) is the failure rate as function of time, β is a shape parameter and ρ is a scale parameter.

used in the model are deterministic costs and strategy chosen by the user. The mean cost and exceedance probabilities are calculated using Monte Carlo simulation [20]. The results from the tool are used to assess the estimated cost of a particular strategy based on best available data and compared with other possible maintenance strategy solutions.

The model is treated as a black box for the SA, meaning that the experimenter does not have information on the model's internal parameters and algorithms other than the inputs and resulting outputs.

2.2. Variable inputs

The values of the total set of variable inputs are found from industrial experience, operational research, scientific literature and analysis. An important part is to provide the right distribution to reflect reality as close as possible. With a nascent industry like offshore wind it is a challenge to identify the full spectrum of possible values. Additionally, turbine manufacturers and operators are reluctant to distribute information related to reliability and cost due to intellectual property agreements. With models that require hundreds of input factors, assigning accurate distribution factors incur a lot of effort if the factor effect is deemed to be negligible. Therefore, uniform and log-uniform distributions can be used initially. When the important factors have been identified a more complex distribution is used [14]. With this in mind, an attempt was made to identify possible minimum and maximum values and affix a uniform distribution. Where this was unobtainable, due to lack of published data or commercial sensitivity, a single value is identified and uncertainty envelope of ± 10% or 20% was applied. This was performed in order to input a known value of uncertainty proportional to the estimated value but is simplistic. Ten percent was been used when a variety of sources was available, whereas 20% was used where only a single value was found therefore has a greater uncertainty attached to the value. This approach in assigning uncertainty to unknown parameters has been adopted by other SA practitioners and model developers [3,6,22]. Once the number of factors under investigation has been reduced then effort can be awarded to attributing more accurate uncertainty distributions for further analysis.

In this section, a subset of the variable inputs is described. In order to identify inputs in the results, abbreviations have been used.

The mean inter-turbine distance [WFint] is the mean value of the distance between all turbines from every other turbine. This was calculated from a sample of several operating and planned wind farm layouts. It indicates turbine geographical spread ensuring that, over the course of the project lifetime, cost and time taken to travel between turbines is accounted for. This can be site-specific but the values used in this analysis are indicative as there are two likely forces governing this value. The first is the desire for a developer to maximise the number of turbines in a licenced area and the second is that a minimum distance between each turbine needs to be kept for wake loss and toppling distances.

An average capacity factor for each month [WFjan − Wfdec] is found from multiplying an approximation of three turbine manufacturers published power curves [23,24,25] with 5 years' worth of modelled wind speed data from an existing OWF [26] in increments of 1 m/s over 1 h averages. A spread of 10% was found and inputted at a uniform distribution.

Balance of plant (BoP) availability [WFbop] includes downtime for the OWF not due to turbines such as cables, substation and grid issues. Information in the public domain on BoP availability is minimal but it is known to be quite high, between 98% and 99% [27], so a conservative margin of between 90% and 100% was chosen.

The wind speed was inputted in the time series from ground level and extrapolated to hub height using the wind shear law [20]. This allows the wind speed to be affected in the SA through changing the wind speed at hub height by varying the alpha value between 0.06 and 0.27 [28,29].

The fixed onshore costs for the O&M site infrastructure such as office and staff will depend on the base location and the wind farm size. As they are foreseen to have an additive effect on OWF cost, a mean value is found based on scaling existing OWF costs according to turbine number.

$$C_{st_{x(i)}} = C_{st_{x(0)}} \times \frac{N_{t_{x(i)}}}{N_{t_{x(0)}}} \tag{1}$$

In Equation (1), $x_{(i)}$ is the new cases, $x_{(0)}$ is an existing wind farm, C_{st} is the staff cost and N_t is the turbine number.

One key input is the technician number available to keep the turbines operable. Information on the technician number for current OWFs is limited. Details of the technician number and total staff are available from six wind farms; Teesside, Robin Rigg, Greater Gabbard, Sheringham Shoal, Dudgeon, Lynn, Lyncs and Inner Dowsing from personal communication with operators and promotional literature [30,31,32]. For these OWFs, the total staff number, including onshore staff, ranges from 0.37 to 0.75 persons per turbine. For Teesside and Robin Rigg, the proportion of turbine technicians to other operational staff is approximately 60% [32]. From the trend found in Fig. 3, the total staff number for the three cases can be estimated. The 60% factor from Robin Rigg and Teesside is applied to find an approximate technician number.

The working day length [MEend] varies between 10 and 12 h per day as a typical one shift per day strategy.

The vessel inputs are based on a typical Crew Transfer Vessel (CTV), from the Ocean Wind series, aluminium catamarans with ± 10% uncertainty to account for fleet variation. Workboats in the UK fleet attending offshore wind O&M are similar with regards to maximum vessel speed and operational limitation. The vessel number for each case was based on a survey of CTVs working at 19 UK OWFs taken on 5th March 2014 using the Marine Traffic website [33]. The survey criterion was to count the number of CTVs and workboats visiting OWFs within a 24 h period (Fig. 4).

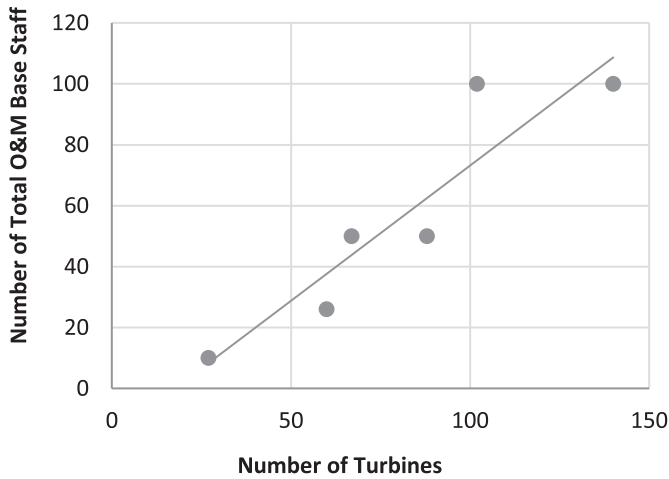The Heavy Lift Vessels (HLV) used are based on a self-propelled

Fig. 3. Number of total O&M based staff from 6 UK OWF based on number of turbines.
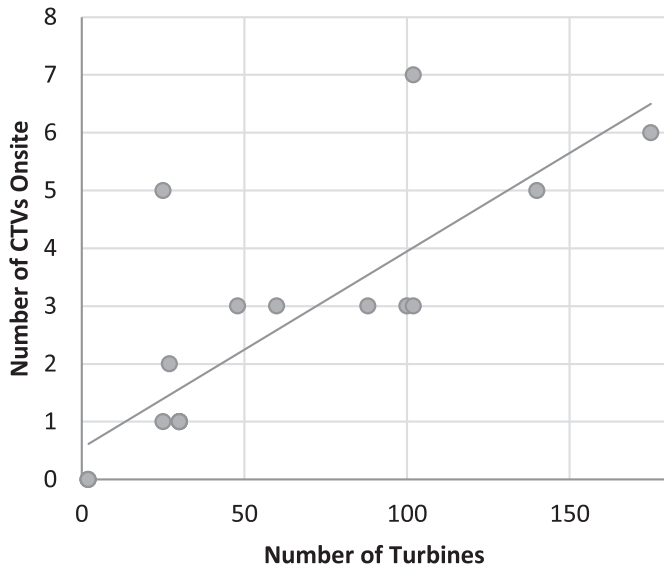

Fig. 4. Number of CTVs and workboats used per turbine.

jack up barge and values for operational limits based on a survey of eligible vessels from the 4C Offshore vessel database [34]. The mean maximum significant wave height from the database was 1.83 m.

Information on helicopters is based on the Eurocopter ECN 135, used at Greater Gabbard OWF. A ± 10% uncertainty envelope was applied as this helicopter model represents the majority of those used on OWFs currently.

The reliability and maintenance of seven major components of a generic turbine with a gearbox have been considered in this

Table 1
WTG components and corresponding label.

Component	Label
Blades/Pitch system	a
Generator	b
Electrical system	c
Control system	d
Mechanical brakes	e
Yaw system	f
Gearbox	g

analysis. Table 1 lists the components along with a label used to identify in the analysis.

Failure rate and associated downtime information of modern components is a significant gap in offshore wind turbine performance modelling. The most complete information source in the public domain stems from reliability data in the Scientific Measurement and Evaluation Programme (WMEP) and Landwirtschaftskammer (LWK) databases from Germany [35]. Although failure rates may differ for larger turbines placed offshore [36], onshore values are commonly used. To reflect this large uncertainty, an envelope of ± 20% was applied. It is assumed that the turbines remain within the useful life region of the bathtub curve shown in Fig. 2 and so have a constant failure rate. The failure rates in Ref. [35] are based on databases that do not distinguish between failures requiring CTVs and those that require large, specialist vessels. Therefore it was assumed that the rate of failure type 2 for each component is lower than failure type 1, but the proportion of components is consistent. As this information was not available, industry experts were asked for how many failures they expect over the course of the project lifetime and the mean failure rates tuned to that value.

It was assumed that component repair costs will be similar to onshore costs and have been taken from a database of component costs collated by National Renewable Energy Laboratory [37].

2.3. Sensitivity analysis methodology

The suggested framework of conducting SA on a given model includes: identifying the input factors' distributions of values which best represent the input uncertainty in the real system then to decide on the SA method, which will, to some degree, dictate the design of experiment to test the model. Finally, calculate the SA indices according the method chosen.

In many of the more complex, global SA methods the required model evaluation number can become untenable depending on the input factor number k, model run time length, and number of replicates chosen. For example, using the Fourier Amplitude Sensitivity Testing method (FAST), the model evaluation number is $k \times N$, where N is the size of the sample and should be greater than 500 [17], therefore if there are 100 input factors the model evaluation number can be 50,000. When the number of input factors is high and a single simulation is more than a few seconds then the run time for such analysis becomes unfeasible without the use of advance computational capability [14]. The more simplistic designs require a lower number of simulations or replicates.

2.3.1. Choice of SA method

Methods can range from simple to complex. They can be classed into two groups; local and global [14,16,38]. 'Local methods' assess the impact at the point of measurement, whereas 'global methods' consider the impact across the entire region of investigation. The method choice largely depends on the computational size of the analysis with regards to time, which will be influenced by the number of the input factors k, number of replications necessary r and length of time it takes to complete one model execution. The choice of method will also depend on the desired assessment requirements. For example, screening methods can provide a ranking of the factor influence but without quantification of how much more important these are with respect to other input factors. Some models can handle interactions between factors better which may also influence the method choice [14].

The OWF O&M model computational execution time can be between one and 30 min long for each model execution. The number of inputs factors for this analysis was 115. For these reasons a screening design was chosen as this approach allows for the most

important factors to be found with a reasonable amount of computational efficiency, i.e. the information obtained for the least computational effort. There are several different approaches available for factor screening. The easiest to understand are OAT and factorial designs. The more complex are the Morris method, Cotter, iterated fractional factorial design and sequential bifurcation [39]. Again, screening design choice depends on the type of model subject to the study (inputs complexity, output type) and the type of information required from the study (first order, linear, non-linear or higher order effect).

An OAT SA of 12 different factors in the model was conducted and compared with four other O&M models in Ref. [6]. The results provided valuable insight into the effect of internal model parameters on cost and availability of OWFs, but did not go further than the OAT analysis. Key factors, such as failure rates and number of technicians, were raised and lowered around a base case of inputs. The variation between outputs and the variation between the sensitivity of the outputs to the changes in inputs between different models were discussed and internal model parameters that caused the difference in sensitivity identified. The OAT method was suitable for this application as the objective was to compare the main effects from a limited subset of inputs. The study was conducted under the assumption that failure rates, technician number and vessel number were of the most important to the model outputs. The effect of interaction between input factors on the outputs could not be investigated as the factors of interest were not changed simultaneously. Any factor that exhibited significance through interaction with others may be over looked using the OAT method. The results from an OAT study are dependent on the mean values from which the input factor values are increased and decreased. This aspect is ideal for creating a reference case to compare different O&M models but serves as a weak point for single model factor screening.

For this paper the objective was to consider the main and possible interactive or non-linear effects of 115 inputs within a reasonable amount of model executions. This is achieved through using the Morris method for factor screening. Furthermore, the Morris method is often presented as best practice for factor screening because, firstly of its applicability to most models, secondly, that it is computationally inexpensive and, thirdly, provides information on the influential factors beyond the first order [40].

2.3.2. Morris method for factor screening

This approach is a type of local SA but allows changing of the input factors, x_i, throughout the region of study. The number of runs required by following Morris' design described by Morris [19] is $n = r(k + 1)$. The r value is the number of replicates and is chosen by the experimenter. Practitioners have suggested that $r = 4$ is the minimum and $r = 10$ is satisfactory [13,41].

The original author of the Morris method provides a sampling design matrix to explore the region of study for least computation cost. A full description of the method is available in Morris and Saltelli et al. [13,19].

As mentioned above, it is a type of local sensitivity method but the effect of changing the input factors, x_i, throughout the study region. Morris offers a design of experimentation which changes the values of x_i throughout the region of investigation [19]. The first column of the design matrix is an initialising vector of x_i, the values of which are randomly chosen and is not used in the analysis but is a starting point for translating x_i to a predetermined distance away Δ. The distance Δ is found from a predetermined multiple of $1/(p-1)$ where p is a value of discretization of the input factor distribution. The effect of the change of the output due to the input is found through, what Morris calls, the Elementary Effect (EE). The EEs are determined from each trajectory for each input factor using:

$$EE(\boldsymbol{x}) = \frac{[y(x_1, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_k) - y(\boldsymbol{x})]}{\Delta} \tag{2}$$

Where if Δ is increased:

$$EE(\boldsymbol{x}^l) = \frac{\left[y\left(\boldsymbol{x}^{(l+1)}\right) - y\left(\boldsymbol{x}^{(l)}\right) \right]}{\Delta} \tag{3}$$

And if Δ is decreased:

$$EE(\boldsymbol{x}^l) = \frac{\left[y\left(\boldsymbol{x}^{(l)}\right) - y\left(\boldsymbol{x}^{(l+1)}\right) \right]}{\Delta} \tag{4}$$

Where y is the output of the model l and $l + 1$ denote the perturbed points [19]. If using the design matrix by Morris, then for each input x_i there are r EEs from which a distribution is sampled.

After executing the model according to the sampling design matrix, the relative importance of input factor to each other is ascertained with two sensitivity indices. The first is calculated from a distribution of sampled EEs in the results [19]. It indicates the main or first order effects of the input factor [40]:

$$\mu^*_{\ i} = \frac{\sum_{i=1}^r |EE_i|}{r} \tag{5}$$

Higher μ^* means more influence on the model output. Note, μ^* is used here as opposed to μ to differentiate between the original calculation [19] and a later improvement [41]. The second index is an indicator of the interaction or non-linear effects of an input factor or a combination of the two but cannot be distinguished from each other. It is calculated from the standard deviation of the EE distribution [40]:

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^r (EE_i - \mu_i)^2}{r}} \tag{6}$$

The μ^* and σ indicate the mean and standard deviation of the change in output over the change in the input. They should not be considered as a measure of uncertainty but as an indication of the effect of the input on the output. They can be compared for the same output, for example $\mu^*_{availability}$ and $\sigma_{availability}$, and μ^*_{costs} and σ_{costs}, but not $\mu^*_{availability}$ and μ^*_{costs}.

There has been criticism of the method's ability to truly identify the most important effects adequately when compared to the results of a more sophisticated design. Additionally, an investigation into the number of replications required indicates that r may need to be much greater than 10 suggested by other authors. It may need to be of the order of hundreds instead [17].

3. Case study

In this section of the paper the application of the above presented methodology will be demonstrated. In this case, in order to investigate how the costs and availability affect different stages of a built OWF project, three separate case studies were identified and considered as independent OWFs. Fixed inputs were defined and the uncertainty ranges of the variable inputs determined based on literature and industry knowledge, as detailed in Section 2.2. An SA approach was used on these three cases studies and the results were then compared with each other.

3.1. Case study description

The cases, labelled 1A, 1B and 1C were potential phases of a pre-consent OWF in the south of the UK. The best opportunity for

conducting this type of analysis is before decisions pertaining to the O&M have been made. Discovering key factors at an early stage allows sufficient time to inform decisions and manage the operation stage, resulting in lower cost and higher availability. The OWF could be built in two stages. The two halves with regards to geographical extent (north and south) are labelled 1A and 1B and the entire project is labelled 1C. Fig. 5 shows an illustration of the cases.

The cases modelled in this investigation are moderately complex, with seven components with independent failure rates; representing the major sub-assemblies found in wind turbines. The turbines are maintained through both condition based maintenance and timed-based maintenance. Each component could fail in two ways, requiring corrective maintenance action. The first requires minor repairs and the second requires major repairs. Minor repairs, called failure type 1, includes all failures that can be tended to by corrective technicians to restore the turbine to an operative state, who access the turbine with a CTV. A CTV is used to take personnel to and from the turbines as well as small components and have very limited lifting capability on board. A major failure, failure type 2, requires specialist contractors and charter of a HLV. A HLV has a large capacity for lifting heavy components, typically a crane. Here HLV is used to describe a self-propelled vessel or jack up barge.

The turbines are also subject to an annual servicing visit to simulate preventative maintenance (although the model does not change the potential for failure after the preventative maintenance visit, it serves for unavailability and costs calculation purposes only). The parameters related to the strategy vary in terms of number of technicians, teams, number of vessels needed and costs.

In order to investigate the sensitivities within the three cases, the number of turbines and the capacity was fixed as per Table 2. These cases are based on a possible option for an OWF but do not represent a particular plan for a real wind farm.

The meteorological time series is comprised of four years of hourly data from a wave buoy near the site and the corresponding wind speed at 10 m above sea level from modelled data from the
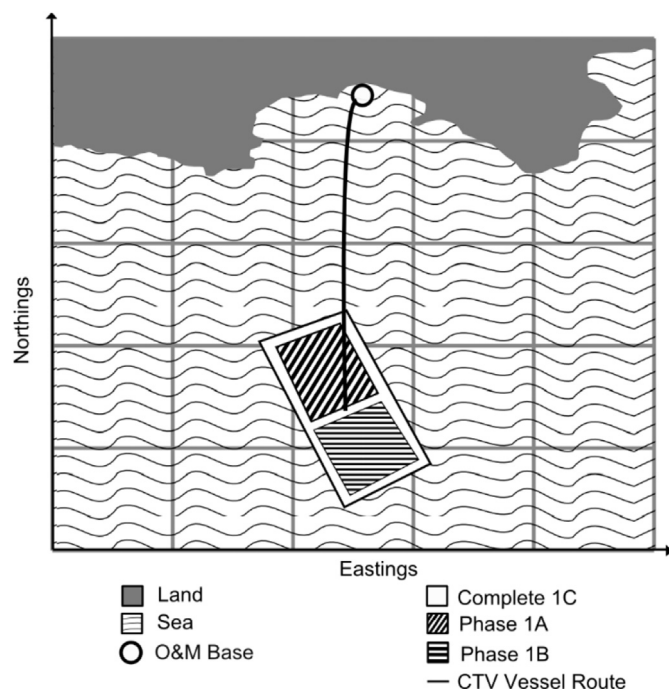
Table 2
Fixed inputs used in the three case studies modelled in SA.

Case studies	1A	1B	1C
Number of turbines	62	59	121
Capacity of one turbine (MW)	8	8	8
Total capacity (MW)	496	472	968

site. The mean wind speed of the dataset is 7.15 m/s and the mean annual wave height is 1.02 m. The mean annual wind speed is approximately 0.5 m/s lower than compared to other UK OWF sites of equivalent development stage. Likewise, when comparing the annual wave height of other UK OWFs from the Atlas of UK Marine Renewables [42], the site is lower than the mean by 0.47 m.

Other than the fixed inputs shown in Table 2, all 115 inputs in the study are varied. The majority of input minimum and maximum values are the same across all cases. Five of the inputs factors, the minimum and maximum values of inputs are different between the cases. This avoids the model simulating maintenance strategies that would not occur in real life, for example 10 maintenance teams but only 1 CTV, The factors where the distribution of limits vary between cases are:

- MEnve: Number of CTV chartered to the site
- MEptm: Number of preventative maintenance technicians teams available
- MEcmt: Number of corrective maintenance teams available
- WFinf: Mean inter-turbine distance
- WFdis: Distance from the centre of the wind farm to the O&M base

For this study, the sensitivity of the O&M costs and the time-based availability to the change in inputs are considered. The cost is the average annual cost of operations and performing maintenance and is not discounted. It is a summation of the costs of repair, the cost of technicians' salaries, vessels daily rates and fuel costs as well as costs for extra costs for subcontractors. The direct O&M costs do not include the cost of lost production. The availability is the time based as a proportion of the time the turbines are in a ready state to the total time.

3.2. SA execution

Having described the inputs in the previous section, the SA framework software SimLab [43] was used to create the samples according to the Morris design and to calculate the sensitivity indices. MATLAB was used to write the input file to the offshore wind O&M tool according to the sample, execute it, provide the results and save them to an output file for SimLab to read. The time to complete a simulation is dependent on turbine number.

The flowchart in Fig. 6 shows how the SA of the model was implemented using MATLAB and SimLab. For the three cases 1A, 1B and 1C, k was 115, discretization level p was 8 and the number of replications r was 10. The number of model executions is therefore $N = 1160$ for each case. The number of p and r are chosen to provide the highest number of model executions whilst remaining within the limits of SimLab software, which allows a maximum r value of 10.

The computational time is dependent on the number of turbines in the OWF. For case 1A and 1B the analysis took several days to complete on an HP EliteBook with Intel® Core™ i5 processor. However Case 1C, with 150 turbines, required use of the parallel computing toolbox in MATLAB and an 8 processor desktop computer to reduce the computational time down from weeks to days.
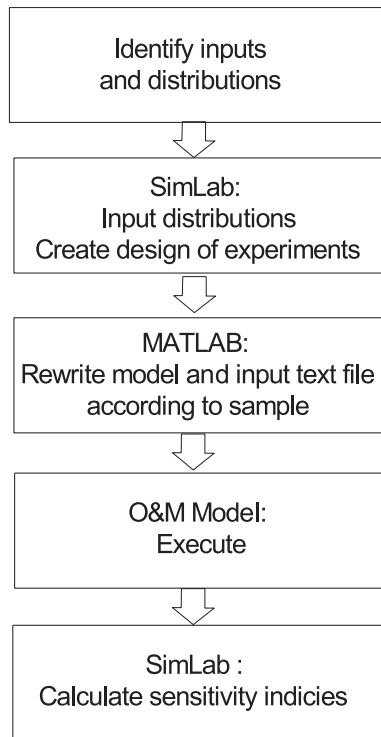

Fig. 5. Illustration of OWF of project phasing, each grid length is 20 km.

Fig. 6. Flow chart of SA used with computational software in bold.

If a global SA method such as FAST was used, then the required number of simulations suggested in literature would be of the order $k \times 500 \rightarrow 1000$ [17], between 57,500 and 115,000 model executions resulting in computational time of several months to complete.

4. Results

The results from two OWF cases are shown in Figs. 7 and 9 along with histograms of sample results in Figs. 8 and 10. The results from case 1A and 1B were indistinguishable. Therefore results from 1A to 1C are shown in Table 3 and Table 4 and the implications for operators discussed. The factors identified are provided in the Appendix along with a full description and the sensitivity indices results.

Each point in Figs. 7 and 9 represents an input factor with the coordinates provided from the μ^* and σ indices. The location of the points in relation to each other provides information on the input factor importance in the model. Factors with a negligible effect on the model have low indices values and are located in the lower left of the graph. The more important factors will have higher indices and appear depending on the strength of main or interactive/non-linear effect. The majority of factors are a mixture of the two and occasionally there will be factors with a primarily strong main or interactive/non-linear effect. A factor was classified as either a) main effect, b) interactive/non-linear or c) a mixture of the two by calculating the ratio of difference between μ^* and σ and the mean value. If this value is less than 10%, the factor is considered mixed, a negative value greater than 10% is interactive/non-linear and a positive value greater than 10%, a main effect.

4.1. Operational expenditure

The results for the O&M costs are shown in Figs. 7a and 9a. A list of the important factors is seen in Table 3 along with the effect. From these graphs it can be argued that the high rate of component failures for both small and large repairs is important as these factors in Table 3 are prominent.

For both the first phase, case 1A, and the complete project, case 1C, the component failure rates for the electrical system and the gearbox are important. The electrical system is susceptible to high rate of small failures but has the lowest component cost. The gearbox, on the other hand has a low failure rate for repairs requiring a HLV, but has a high component cost. This demonstrates to operators that they have to consider the frequent, low cost component failures as well as the high cost, low probability failures and take steps to reduce the failure rate and cost of both. Other important factors for cost in both 1A and 1C are the cost for HLVs and helicopters [MEjdr and MEhco, respectively].

For case 1C the duration of smaller repairs [DE1od] and interaction with shift length [MEend] are other important factors. Shown by DE1od and MEend in Fig. 9a on the left hand side of the group, indicating high interaction.

Component cost and failure rates are assumed to be the same as those for onshore wind farms. Therefore it can be concluded that the influence of those constituents would also be non-negligible for onshore wind. Especially as the same conclusion cannot be made for the access vehicles for onshore wind projects, where helicopters are not used and the cost implications of lifting heavy components is much larger in an offshore context. The length of shift and operation duration would similarly affect costs for onshore wind farms as offshore. However, they are unlikely to be the same magnitude. Fixed costs associated with each visit to the turbine, if the operation was more than one shift length, would be higher offshore as vessel daily rates are greater than vehicles used to
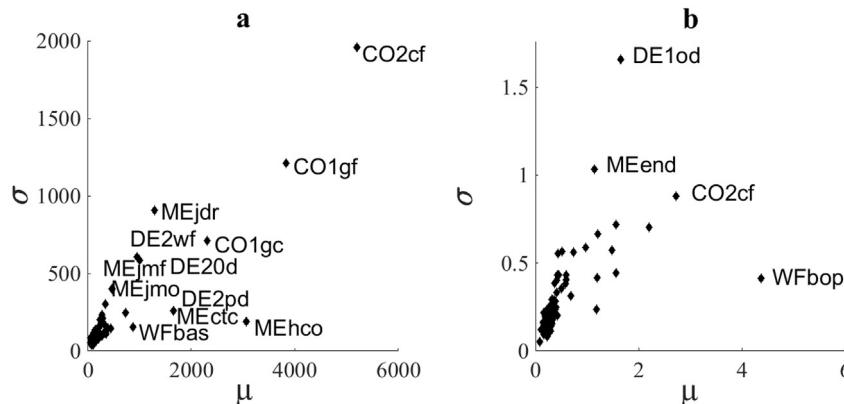

Fig. 7. Sensitivity results for case 1A a) costs and b) availability of the OWF.
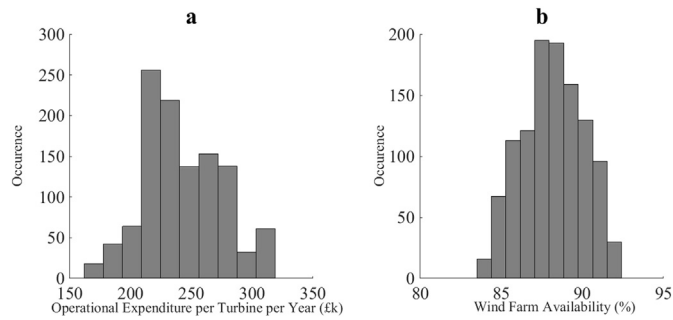
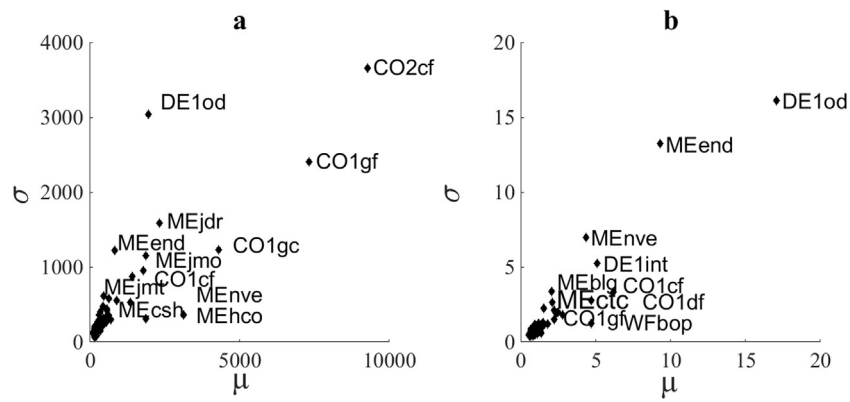**Fig. 8.** Histograms of sample results from a) costs and b) availability for Case 1A.

Fig. 9. Sensitivity results for case 1C a) costs and b) availability of the OWF.
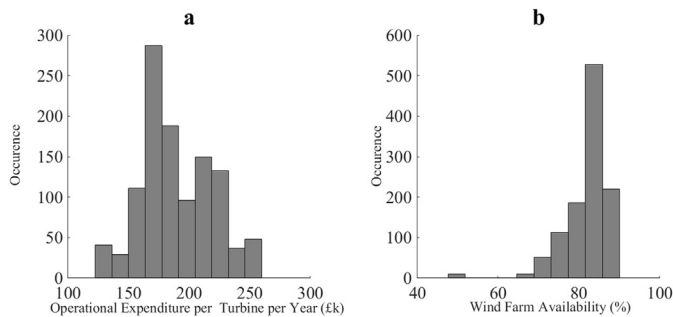

Fig. 10. Histogram of sample results for a) costs and b) availability for Case 1C.

Table 3
Important factors for costs in both cases in alphabetical order with description and type of influence (main effect, interactive/non-linear or mixed).

Code	Description	Type of influence
CO1gc	Repair cost for gearbox for failure type 1	Main
CO1gf	Failure rate of gearbox for failure type 1	Main
CO2cf	Failure rate of electrical system for failure type 2	Main
DE1od	Operation duration of repair for failure type 1	Interactive/Non-linear
DE2od	Operation duration of repair for failure type 2	Main
DE2pd	Planning delay to conduct failure type 2 repair	Main
DE2wf	Cost of subcontracted workforce to conduct failure type 2 repair	Interactive/Non-linear
MEctc	Number of technicians per corrective maintenance team	Main
MEend	Work end time	Interactive/Non-linear
MEhco	Annual fixed cost of helicopter	Main
MEjdr	Day rate of HLV	Main
MEjmf	Maximum number of failures before mobilization of jack up vessel	Main
MEjmo	Time to mobilize HLV	Main
WFbas	Distance to O&M base from OWF centre	Main

Table 4
Important Factors for availability in alphabetical order with description and type of influence (main effect, interactive/non-linear or mixed).

Code	Description	Type of influence
CO1df	Failure rate of control system for failure type 1	Main
CO2cf	Failure rate of electrical system for failure type 2	Main
DE1int	Number of teams required to repair failure type 1	Mixed
DE1od	Operation duration of repair for failure type 1	Mixed
MEend	Work end time	Mixed
MEnve	Number of type CTV	Interactive/Non-linear
WFbop	Average BoP availability	Main

access onshore farms.

The results demonstrate that the access strategy may need to look beyond just CTVs and helicopters to provide enough time to conduct necessary repairs. This analysis shows that, other than the access and duration of small repairs, the important factors related to costs are the same for the first phase and complete project.

4.2. Availability

For case 1A the most important factors are the small repair duration [DE1od], working day length [MEend], failure rate of the components requiring a HLV [CO2cf], BoP availability [WFbop] and personnel transfer time from vessel to turbine [MEblg].

For the complete OWF project 1C, the top factors are the same as for case 1A. Additional factors are the vessel number [MEnve] and number of teams required in order to complete small repairs [DE1int].

The histograms in Figs. 8 and 10 show the results from the samples. The range of availability generated for the first case is between 84% and 92%, with an average of 89%. With case 1C, there is a dramatic reduction in project availability which sometimes can be as low as 50% and an average of 82%. The maintenance strategy was limited to only an onshore O&M base, with transfer via either CTVs or helicopter and a single 12 h shift. In this case, this is the limiting factor of the availability. Employing an offshore base in a mothership or permanent structure might lead to increased availability for case 1C.

5. Discussion

5.1. Case comparison

The factors that affect costs are similar for different phases of the same OWF. The exceptions are failure rates and repair costs. Therefore plant reliability becomes more important with larger OWFs.

For the first construction phase, 1A, it is turbine reliability and speed of which repairs can take place that primarily affects farm availability. This is true for the complete farm, 1C, but the repair strategy also becomes more prevalent.

5.2. Input factor limitations

There is minimal information available in the public domain on the frequency of major component failures. The input distribution of failure rate is taken from onshore reliability databases from smaller turbines a decade ago.

The OWF performance in case 1C was limited having by only an onshore O&M base strategy, where as other options include using offshore bases such as motherships or fixed platforms to reduce CTV travel time. In the same manner, a single shift per day scenario was modelled, which can be extended to consider 2 or 3 shifts per day as well.

5.3. Future work

Once the screening process has been completed, the next stage is to look at those factors that have been identified in Tables 3 and 4, improve the input distributions, and then perform a more sophisticated global SA in order to quantify the amount of sensitivity. The model does not yet directly capture the effect of conditional monitoring systems or structural health monitoring on the operations of OWFs. As such, the contribution of such systems to the sensitivity of costs and availability of OWF projects is not considered but could be subject for further study.

6. Conclusion

In this paper, an SA approach was applied to an offshore wind O&M model to discover which factors are most important for both cost and availability. The novelty lies in using SA to identify the most significant factors affecting O&M cost and availability, what type of effect they have and if they change for different projects phases. A general SA framework was introduced. The process to identify distributions of some inputs was outlined. The approach itself was introduced and the results discussed. It was found that the results from the northern half of the project was identical to the southern half however a difference in results was found between the smaller phases and the complete project.

Fourteen inputs were found to be important in calculating O&M cost; including failure rates, component cost, repair duration interacting with the shift length. For availability, seven important factors were found, components with both low and high failure rates, the maintenance resources availability and shift length. In a comparison of two cases of a single OWF, it was found that the larger OWF had the same important input factors as the smaller phases plus additions. This indicates to operators considering a multi-phase project that the priorities for making the most profitable decisions may change with OWF extensions.

Appendix

List of identified important factors for cost and availability divided into the case 1A and 1C along with the input ranges and sensitivity indices μ^* and σ.

Case		Factor code	Factor description	Min Value	Max Value	μ^*	σ
1A	Availability	DE1od	Operation duration of repair for failure type 1	3 h	14 h	1.649	1.658
		MEend	Work end time	17:00	20:00	1.139	1.033
		CO2cf	Failure rate of electrical system for failure type 2	0.005	0.02	2.722	0.8794
		WFbop	Average BoP availability	90%	100%	4.378	0.4109
	Cost	CO2cf	Failure rate of electrical system for failure type 2	0.005	0.02	5200	1960
		CO1gf	Failure rate of gearbox for failure type 1	0.19	0.65	3840	1210
		MEjdr	Day rate of HLV	£50k	£125k	1290	908.6
		CO1gc	Repair cost for gearbox for failure type 1	£101k	£187k	2310	711.7
		DE2wf	Cost of subcontracted workforce to conduct failure type 2 repair	£20k	£100k	947.7	607.5
		DE2Od	Operation hours to conduct failure type 2 repair	1 h	20 h	1010	584.2
		MEctc	Number of technicians per corrective maintenance team	2	3	1660	258.5
		MEhco	Annual fixed cost of helicopter	£2,000k	£6,000k	3070	190.4
		MEjmo	Time to mobilize HLV	5 h	24 h	473.3	401.3
		MEjmf	Maximum number of failures before mobilization of HLV	1	5	471	398.6
		DE2pd	Planning delay to conduct failure type 2 repair	18 h	47 h	334.9	301.2
		WFbas	Distance to O&M base from the OWF centre	30 km	50 km	880	154.4
1C	Availability	DE1od	Operation duration of repair for failure type 1	3 h	14 h	17.08	16.12
		MEend	Work end time	17:00	20:00	9.308	13.23
		MEnve	Number of type CTV	4	6	4.328	6.981
		DE1int	Number of teams required to repair failure type 1	2	3	5.107	5.241
	Cost	CO2cf	Failure rate of electrical system for failure type 2	0.005	0.02	9290	3660
		DE1od	Operation duration of repair for failure type 1	3 h	14 h	1950	3040
		CO1gf	Failure rate of gearbox for failure type 1	0.19	0.65	7320	2400
		MEjdr	Day rate of HLV	£50k	£125k	2320	1590
		CO1gc	Repair cost for gearbox for failure type 1	£101k	£187k	4310	1230
		MEend	Work end time	17:00	20:00	825	1220
		MEjmo	Time to mobilize HLV	5 h	24 h	1780	948.1
		MEhco	Annual fixed cost of helicopter	£2,000k	£6,000k	3130	357.7

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