Ocean Engineering 145 (2017) 334–343

Contents lists available at ScienceDirect

Ocean Engineering

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

Testing the robustness of optimal access vessel fleet selection for operation and maintenance of offshore wind farms

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ARTICLE INFO

Keywords:
Offshore wind
O&M
Logistics
Optimisation
Simulation
Sensitivity analysis

ABSTRACT

Optimising the operation and maintenance (O&M) and logistics strategy of offshore wind farms implies the decision problem of selecting the vessel fleet for O&M. Different strategic decision support tools can be applied to this problem, but much uncertainty remains regarding both input data and modelling assumptions. This paper aims to investigate and ultimately reduce this uncertainty by comparing four simulation tools, one mathematical optimisation tool and one analytic spreadsheet-based tool applied to select the O&M access vessel fleet that minimizes the total O&M cost of a reference wind farm. The comparison shows that the tools generally agree on the optimal vessel fleet, but only partially agree on the relative ranking of the different vessel fleets in terms of total O&M cost. The robustness of the vessel fleet selection to various input data assumptions was tested, and the ranking was found to be particularly sensitive to the vessels' limiting significant wave height for turbine access. This is also the parameter with the greatest discrepancy between the tools, implying that accurate quantification and modelling of this parameter is crucial. The ranking is moderately sensitive to turbine failure rates and vessel day rates but less sensitive to electricity price and vessel transit speed.

1. Introduction

With more than 3200 offshore wind turbines connected to the European grid at the start of 2016 (EWEA, 2016), operation and maintenance (O&M) of these assets is a key challenge to achieve commercially viable projects. The estimated contribution of O&M to the life cycle cost of an offshore wind farm varies significantly, accounting from 15 to 30% (Musial and Ram, 2010; Wiser et al., 2016). Offshore logistics and vessels are major contributors to the O&M costs, estimated to account for almost 45% (GL Garrad Hassan, 2013; Smart et al., 2016), and are decisive factors in ensuring high availability of the wind turbines and hence high electric power production. As offshore wind farms are remote, unmanned and often difficult to access due to weather restrictions, the offshore logistics related to O&M becomes a highly complex task. Since most offshore wind farms have been in operation for only a few years, there is a general lack of O&M industry experience. Developers, original equipment manufacturers (OEM), operators, and financial institutions are looking for tools to guide decision making when deciding on maintenance strategies, vessels, manning, and investments. The problem is exacerbated for non-OEMs, since much of the existing operating experience has been gained during the initial warranty period. This increases the uncertainty for non-OEMs around future operations.

This paper focuses on decision support tools applied to the selection of the O&M vessel fleet, i.e. the crew transfer vessels or other logistics solutions for accessing the wind turbines to conduct maintenance. This is an example of a decision problem in offshore wind O&M that has received much attention both in the research literature and in the industry. For instance, optimising the offshore logistics solution and investigating its robustness to assumptions are often done as a part of due diligence in preparation for the investment decision for offshore wind

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http://dx.doi.org/10.1016/j.oceaneng.2017.09.009
Received 29 July 2016; Received in revised form 15 August 2017; Accepted 8 September 2017
Available online 23 September 2017

projects. In practice, a number of aspects must be considered in the selection of O&M vessels, such as the technical, hydrodynamic evaluation of the accessibility of the turbines by the vessels (Wu, 2014; Guanche et al., 2016). However, this paper takes a higher-level, strategic perspective and considers the economic evaluation of the vessels as part of the overall logistics system of the wind farm. The research literature reports a number of tools for such economic evaluation that have been applied to the problem of selecting the O&M vessel fleet, including analytic cost tools (Besnard et al., 2013), simulation tools (Dalgic et al., 2014, 2015a, 2015b; Endrerud et al., 2015; Sperstad et al., 2016) and mathematical optimisation tools (Halvorsen-Weare et al., 2013; Gundegjerde et al., 2015). For comprehensive reviews of strategic decision support tools for offshore wind O&M and logistics more generally, see Hofmann (2011) and Shafiee (2015).

As a large number of strategic decision support tools have already been developed, the purpose of this paper is emphatically not to present yet another new or improved tool. The work is rather motivated by the need to reduce the uncertainties that still remain related to both modelling assumptions and input data for such tools. Uncertainties related to input data assumptions have been studied in some of the works cited above using sensitivity analysis. Sensitivity analysis for offshore wind O&M is also treated more generally in Martin et al. (2016). However, the insights from previous sensitivity studies may have restricted generality as they depend on the modelling assumptions implemented in the particular decision support tool considered in each study. Uncertainties related to modelling assumptions intrinsic to the tools were previously addressed in Dinwoodie et al. (2015) by comparing four different simulation tools for calculating O&M costs and wind farm availability. In that study, a reference wind farm case with relevant input data was defined, and baseline results were reported for the different tools. The comparison revealed how different tools can produce significantly different results because of dissimilar modelling assumptions. However, Dinwoodie et al. (2015) considered only simulation tools for O&M, and the study did not consider the application of the tools as decision support tools for optimising the O&M strategy.

In this paper, four simulation tools, one mathematical optimisation tool and one analytic spreadsheet-based tool have been tested on the reference case from Dinwoodie et al. (2015) to compare how they rank a predefined set of vessel fleets. The objectives of this work is to answer the following research questions: a) How robust is the ranking of vessel fleets to the kind of decision support tool that is used? Even if different decision support tools disagree on the absolute performance measures of different vessel fleets for offshore wind O&M, do they still agree on the relative ranking of the vessel fleets? b) How robust is the ranking of the vessel fleets given by each tool to the assumptions made for different key input parameters?

Although previous work has compared different offshore wind O&M decision support tools qualitatively (Hofmann, 2011), this is the first time the robustness of offshore wind O&M decision support has been investigated quantitatively, using more than one tool. Furthermore, it is the first study to consider sensitivities in the ranking of different vessel fleets. Addressing these research questions through a comparison of different tools can identify the direction for further model validation and development work, reducing the uncertainty associated with decision support for offshore wind O&M and logistics. Furthermore, model comparison and sensitivity studies can identify which uncertainties in the input data are most important to consider and may also provide other recommendations for using advanced tools to support offshore wind O&M and logistics decisions.

The rest of the paper is organized as follows. Section 2 explains the proposed methodology for O&M vessel fleet optimisation and sensitivity analysis. The reference wind farm, vessel alternatives and decision support tools used are also introduced in this section. Section 3 presents the results for the vessel fleet ranking and sensitivity analysis. The results are discussed in Section 4, after which the paper is concluded in Section 5 by summarizing key findings and suggesting implications for the use of strategic decision support tools for selecting the O&M vessel fleet.

2. Methodology

This section describes the proposed methodology for O&M vessel fleet optimisation and sensitivity analysis. The focus is on the selection of the *access vessel* fleet, i.e. the fleet of crew transfer vessels (CTV) and/or other vessel concepts for transferring and allowing technicians access to the turbines. The section first defines the optimisation problem and then introduces the decision support tools used for evaluating different vessel fleets. This is followed by a description of the base case specifications for the reference wind farm and the different vessel types and the vessel fleet alternatives that are considered. Finally, the methodology and cases for the sensitivity analysis are described.

2.1. Vessel fleet ranking

In this section an optimisation problem for the selection of a vessel fleet for O&M of an offshore wind farm is formulated. A solution space of possible vessel fleet alternatives is defined, and for all alternatives in the solution space, the performance of the vessel fleets are evaluated and ranked according to the value of the objective function f. The optimal vessel fleet is the one with the lowest value of f. For this optimisation problem, a simple objective function, referred to as the *total O&M cost*, is defined to capture the trade-off between O&M costs and wind farm availability:

$$\begin{aligned} f &= \text{Total O\&M cost} \\ &= \text{Direct O\&M cost} + \text{Lost revenue due to downtime} \end{aligned} \tag{1}$$

Lost revenue due to downtime, or lost production or downtime costs, is the difference between theoretical revenue for the ideal case of no wind turbine downtime and actual revenue. This can be expressed mathematically as follows:

$$\text{Lost revenue due to downtime} = P_{\text{el}} \sum_{t=1}^{N_{\text{hours}}} \sum_{j=1}^{N_{\text{turbines}}} E_{\text{theor},j,t} \times \left(1 - A_{j,t}\right) \tag{2}$$

Here, P_{el} is the electricity price, i.e. the revenue generated per MWh, measured in £. The analysis considers a period of N_{years} with a number of hours $N_{\text{hours}} = N_{\text{years}} \times 365 \times 24$. $E_{\text{theor},j,t}$ is the electricity production in units MWh of turbine j in hour t, given the wind speed and turbine power curve and given that the turbine is available to generate electric power. The availability $A_{j,t}$ of wind turbine j in hour t is 0 during downtime and 1 when the turbine is available to generate electric power.

Direct O&M cost is here composed by the following cost components:

$$\text{Direct O\&M cost} = \text{Vessel cost} + \text{Personnel cost} + \text{Total repair cost} \tag{3}$$

In reality, there are also a number of other direct O&M cost components that are not included in this equation (GL Garrad Hassan, 2013; Smart et al., 2016), but this simplification is made to focus on the key cost elements that may vary between different O&M vessel fleets. Cost elements that do not vary between different vessel fleets are constant terms in the optimisation problem and do not impact the optimal vessel fleet selection.

The vessel cost is the sum of day rates (i.e. charter costs per day) for all vessels in the O&M vessel fleet:

$$\text{Vessel cost} = N_{\text{years}} \times 365 \times \sum_{v} (\text{Day rate})_v \tag{4}$$

The personnel cost is the sum of annual salaries for all N_{tech} maintenance technicians working in the wind farm:

$$\text{Personnel cost} = N_{\text{years}} \times N_{\text{tech}} \times \text{Annual technician salary} \tag{5}$$

Total repair cost is the sum of all repair costs (including costs of spare parts and consumables but excluding vessel and personnel cost) for all maintenance tasks considered in the problem:

$$\text{Total repair cost} = \sum_i N_{\text{task},\,i} \times (\text{Repair cost})_i \tag{6}$$

Here, $N_{\text{task},\,i}$ is the number of maintenance tasks completed for failure category i. All cost variables are calculated for the same period of N_{years} of the operational phase of the wind farm.

In the case of corrective maintenance at a turbine, downtime is incurred from the time of occurrence of a turbine failure and until the maintenance task is completed. In the case of pre-determined, preventive maintenance (PM) of a turbine, downtime is only incurred while technicians are carrying out the PM task at the turbine or accessing the turbine. Including lost revenue due to downtime in the objective function ensures that a possible vessel fleet solution is penalised for not having the capacity to perform corrective maintenance in a timely manner. It does not, on the other hand, ensure that the vessel fleet is also capable of completing the pre-determined, preventive maintenance that is scheduled for the wind turbines. The tools that are considered will typically give corrective maintenance tasks priority over preventive maintenance tasks. This may result in vessel fleet solutions where the total O&M cost is low, but where not all the preventive maintenance tasks are completed. This is important to take into account in the vessel fleet ranking, since delaying preventive maintenance beyond the recommended maintenance intervals may adversely affect wind turbine reliability in the long run. Precisely how reliability is affected by maintenance is very difficult to quantify until sufficient operating experience is obtained, and none of the tools in this paper attempts to capture this relationship explicitly. In these analyses, vessel fleets that are unable to complete all PM are always considered inferior to vessel fleets that are able to complete all PM. Therefore, the vessel rankings are performed based on two decision rules applied in a hierarchical fashion: First, the vessel fleets are ranked according to the percentage of the planned PM tasks they have performed. Second, all vessel fleets that have completed the same percentage of PM tasks (±0.1%) are ranked according to their total O&M cost.

2.2. Description of the decision support tools

Six different strategic decision support tools with different modelling methodologies have been applied for the work reported in this paper. Four of the tools are simulation tools: 1) The NOWIcob tool developed by SINTEF Energy Research (Hofmann and Sperstad, 2013, 2014), 2) MAINTSYS developed by the University of Stavanger and Shoreline (Endrerud et al., 2014, 2015) 3) the ECUME model developed by EDF R&D (Douard et al., 2012) and 4) the Strathclyde University offshore wind OPEX model (StrathOW-OM) (Dalgic et al., 2015a). These simulation tools were also presented and compared in Dinwoodie et al. (2015). In this paper, also 5) the MARINTEK vessel fleet optimisation model (Stålhane et al., 2016) and 6) the Energy Research Centre of the Netherland's (ECN) O&M Tool (Obdam et al., 2011) are included. Except from the MARINTEK vessel fleet optimisation model, these tools can be viewed as long-term cost estimation tools that can be applied for planning purposes and strategic decision support. Although all the decision support tools have been developed independently, they are all considered applicable to the problem of selecting O&M vessel fleets and are hence comparable for the purposes of this paper. All the tools are developed in cooperation with the industry (offshore wind farm developers/owners/operators) and have been applied to provide decision support for actual wind farm projects. It could be noted that, being designed for strategic applications, the tools are not applicable to operational (short-term) decision support.

The four simulation tools are based on a discrete-event time-sequential Monte Carlo simulation modelling approach. They produce estimates of performance parameters such as wind farm availability and O&M costs as output parameters. Applying the simulation tools to an optimisation problem, the tools must evaluate each of the alternative solutions of the problem and estimate its objective value based on these output parameters. By using a mathematical optimisation tool such as the MARINTEK tool, on the other hand, all alternatives may be evaluated implicitly through the optimisation procedure, which then only returns the solution with the lowest objective value. However, for this work the MARINTEK optimisation tool has also been set to consider only one vessel fleet at a time to allow for comparison with the simulation tools. In the optimisation tool, a penalty term is included in the objective function to explicitly penalize vessel fleets for each PM task that they are not, according to the tool, able to complete. Both the simulation tools and the optimisation tool are dynamic in the sense that they capture the time dependence resulting from metocean conditions and stochastic wind turbine failures.

The ECN O&M Tool is a commercially available Microsoft Excel tool developed to estimate long-term annual average O&M costs and other outputs. As such it is not dynamic in the sense described above for the simulation and optimisation tools but treats several aspects of O&M in a more simplified manner. However, it allows significant user control over inputs and for this work was modified by analysts at the National Renewable Energy Laboratory (NREL) to represent specific vessel capabilities, costs, and metocean conditions as detailed as for the other tools. The ECN O&M Tool includes a set of macros for post-processing of results that optimise the use of resources. In contrast to the simulation tools, the ECN O&M Tool hence automatically estimates the number of technicians and vessels needed to fully complete repairs for each season for an average year.

2.3. Description of reference case

For the computational study, the performance of 10 alternative vessel fleets used for the O&M of a reference offshore wind farm have been compared. The reference wind farm is based on Dinwoodie et al. (2015), which defined a number of reference cases designed for comparing O&M simulation tools. These reference cases specify representative values for the minimal set of input parameters needed to run such tools in a meaningful manner. The base case from Dinwoodie et al. (2015), including wind turbine data, metocean data, failure data and vessel data, is henceforth simply referred to as the reference case. The reference wind farm consists of 80 Vestas V90 3.0 MW wind turbines located 50 km from an onshore maintenance base.

The failure data for the reference case are given in Table 1. The failure data used in Dinwoodie et al. (2015) are assumed but the present study does not include the failure categories of major repair and major replacement. The reason for leaving out these failure categories is that they require that specialist vessels (referred to as Field Support Vessels and Heavy Lift Vessels in the reference case) are chartered. The results from optimal vessel fleet selection are not significantly affected by the presence or absence of other failure categories requiring specialist vessels (Sperstad et al., 2016). The reason is that the interactions between maintenance tasks performed by access vessels and maintenance tasks performed by specialist vessels are negligible. Thus, the decision of when, and for how long, to charter specialist vessels to perform these maintenance tasks, and as an extension their contribution to the objective

Table 1
Base case failure data for the reference case (from Dinwoodie et al. (2015)).

Failure category	Manual reset	Minor repair	Medium repair	Annual service
Active maintenance time (hours)	3	7.5	22	60
Required technicians	2	2	3	3
Failure rate (per turbine per year)	7.5	3.0	0.275	n/a
Repair cost (£)	0	1000	18 500	18 500

Table 2
Base case parameter values specifying the vessel types.

Vessels	Hs limit (m)	Vessel speed (knots)	Day rate (£)	Technician capacity	Access time (min)
Crew transfer vessel (CTV)	1.5	20	1750	12	15
Surface effect ship (SES)	2.0	35	5000	12	15
Small accommodation vessel (SAV)	2.0	20	12 500	12	15
Mini mother vessel (MM)	2.5	14	25 000	16	30
Daughter vessel	1.2	16	n/a	6	15

function, can be seen as independent of the fleet of access vessels. However, such failure categories can contribute substantially to the statistical uncertainty in simulation results (Sperstad et al., 2016), which makes a statistically significant comparison of different vessel fleets more computationally demanding. Furthermore, the modelling of the charter of Heavy Lift Vessels (or jack-up vessels) has previously been identified as a major source of discrepancies between different tools (Dinwoodie et al., 2015). Therefore, only maintenance categories where only crew transfer vessels are required for the maintenance are considered: three corrective maintenance categories (manual reset, minor repair and medium repair) and one preventive maintenance task (annual service). For more information on these maintenance categories and the failure data set, we refer to Smart et al. (2016). A corrective maintenance strategy as in the reference case is assumed, and it is assumed that corrective maintenance tasks are always given priority over preventive maintenance tasks.

As in the reference case, the metocean data used in this study come from the FINO 1 offshore research platform (BSH, 2012). However, for the present study, the same historical 8-year wind and wave time series are used for all decision support tools. In other words, those tools that have the functionality for generating synthetic metocean time series do not employ this functionality. The reason for this choice is to ensure that the comparison is not biased by any differences in the generation of synthetic metocean time series, as such modelling differences were found for the reference case to be a source of discrepancies between results from different tools (Dinwoodie et al., 2015).

2.4. Description of vessel fleet alternatives

In addition to a standard CTV based on the specifications in the reference case, three other access vessel concepts are considered. A surface effect ship (SES) is an advanced crew transfer vessel with higher service speed and higher limiting significant wave height (Hs) for technician access/transfer to the turbine. Both CTV and SES need to return to the onshore maintenance base at the end of each shift. A small accommodation vessel (SAV) is an access vessel that also offers offshore accommodation for the technicians. A mini mother vessel (MM) is a somewhat larger vessel offering offshore accommodation and hosts two small daughter vessels. Technicians can be transferred from the MM to the turbines both via the daughter vessels and directly via a gangway or similar access system. The SAV and the MM vessel types are assumed to stay offshore for 14 days before they have to spend 1 day travelling back to shore to resupply.

The specifications of the vessel types are given in Table 2 and are, in part, based on experience from research projects with offshore wind farm developers/owners/operators. In addition to the input parameters used in the reference case to describe the CTV, the *access time* of the vessels has been introduced. This parameter describes the time it takes from when the vessel is in the vicinity of the turbine to when the last technician is on the turbine, with the equipment needed to start working. This parameter is introduced to model the crew transfer capabilities of the vessels more accurately for the vessel fleet comparison. The same time is assumed to be required for picking up the technicians as for deploying them to the turbine. Internal travel distances within the wind farm are neglected in the tools which have this as an input parameter, but the time spent travelling within the wind farm can be regarded as included in the access time.

Technicians operating from the onshore maintenance base, and transported by CTVs or SESs, work 1 × 12 h shifts each day, and technicians operating from a SAV or a MM work 2 × 12 h shifts per day. It is assumed that the number of technicians available for working from the vessels each shift equals the maximal number the vessels have capacity for transporting or accommodating (the *technician capacity*). Since the SAV and MM vessels operate with two shifts per day, these vessels accommodate twice the number of technicians available to work each shift: For the MM vessel, e.g., there are 8 technicians working day shifts and 8 technicians working night shifts. Although two working shifts for access vessel operations may not be common industry practice today, it is likely to be relevant for mother vessels and similar access vessel concepts in the future.

The composition of the 10 vessel fleet alternatives considered in the computational study is given in Table 3. This defines the solution space considered for the optimisation problem. The ECN O&M Tool is only able to produce results for a subset of these fleet compositions. Since the tool's post-processing of results estimates the number of vessels required to fully complete repairs, the number of vessels is not specified by the user. For example, the ECN results for the vessel fleet "2 CTV" indicates that two CTVs are needed in three seasons and three CTVs are needed in one season; hence the vessel fleet "3 CTV" is not represented in the results for the ECN O&M Tool. Furthermore, the MAINTSYS model is not able to represent the MM.

2.5. Sensitivity analysis

From the procedure described in Section 2.1, it is possible to obtain the ranking of the n alternative vessel fleets; the rank of vessel fleet i is denoted by r_i. Changing the assumptions of the input data may change how a tool assesses the performance of a vessel fleet and thus how well the decision support tool ranks it compared to the alternatives. To assess the robustness of the results from a tool, the sensitivity index of the objective function has been considered. The total O&M cost is denoted $f(x)$ as a function of an input parameter x, where x for instance could be the service speed of a given vessel. The following sensitivity index is then defined:

Table 3
Definition of the vessel fleets considered.

Vessels	Fleet 1	Fleet 2	Fleet 3	Fleet 4	Fleet 5	Fleet 6	Fleet 7	Fleet 8	Fleet 9	Fleet 10
Crew transfer vessel (CTV)	2	3	1	2	0	1	0	1	0	0
Surface effect ship (SES)	0	0	1	1	2	2	0	0	3	0
Small accommodation vessel (SAV)	0	0	0	0	0	0	1	1	0	0
Mini mother vessel (MM)	0	0	0	0	0	0	0	0	0	1

$$c_f = \frac{[|f(x_0+\Delta x)| + |f(x_0-\Delta x)|]/2}{\Delta x} \cdot \frac{x_0}{f(x_0)}. \tag{7}$$

This sensitivity index measures the changes in the performance (i.e. objective value) of a vessel fleet, as assessed by one of the tools, when an input parameter x is changed by $\pm\Delta x$. As it measures the sensitivity to changes around a base case value $x = x_0$, it is a local sensitivity index. A two-sided sensitivity index is chosen to average over the effect of increasing and decreasing the input parameter. For instance, if changing x by increasing or decreasing x_0 by 20% also changes $f(x_0)$ by 20%, the sensitivity index is $c_f = 1$.

However, if the performance estimate for a vessel fleet changes for changing assumptions, this does not necessarily mean that the rank of the vessel fleet when compared to the alternatives also changes. For each input parameter x, the ranking of vessel fleet i can be expressed as a function of that parameter as $r_i(x)$. The overall ranking of the vessel fleets can be expressed as the sequence $\{r_i(x)\}_{i=1}^{n}$. To investigate how robust the ranking of the vessel fleets is, a measure of the ranking's sensitivity to changes in different input parameters is needed. The Spearman's rank correlation coefficient ρ, has been introduced as a measure of how much the ranking of the vessel fleets $\{r_i(x)\}_{i=1}^{n}$ for one value of x differs from the ranking for another value of x (Walpole et al., 1993). Denoting the base case value of x as x_0, the Spearman's rank correlation coefficient can be expressed as follows:

$$\rho(x) = 1 - \frac{6\sum_{i=1}^{n}[r_i(x) - r_i(x_0)]^2}{n(n^2-1)} \tag{8}$$

This correlation coefficient by definition equals one for the base case, $\rho(x = x_0) = 1$, and it decreases if the ranking of the vessel fleets changes as one is moving away from the base case, as $\rho(x) \leq 1$.

To measure how much a ranking changes when changing parameter x by Δx, a sensitivity index c_x for the rank correlation is defined as follows:

$$c_x = \frac{1 - [\rho(x_0+\Delta x) + \rho(x_0-\Delta x)]/2}{\Delta x / x_0} \tag{9}$$

If neither increasing nor decreasing x by Δx changes the ranking of the vessel fleets, the Spearman's rank correlation coefficients will equal one and the rank sensitivity index c_x will be zero. If changing the parameter value changes the value, however, $c_x > 0$, and the magnitude of c_x increases as the correlation coefficient $\rho(x)$ decreases.

For sensitivity analysis, a number of input parameters have been considered that are assumed to influence the ranking of the vessel fleet alternatives: 1) Expected average failure rates are generally uncertain and may depend on a number of factors. The number of failures also greatly impacts the maintenance requirements of the wind farm that the vessel fleet needs to serve. 2) The expected revenue generated by the wind farm project per MWh of electric energy that is produced (the electricity price): The future values of this parameter may be certain or uncertain depending on the electricity market and what support scheme is in place, if any. Changes in this parameter can also be taken to represent changes in the assumptions about wind power production depending on turbine performance or wind speeds. 3) Vessel day rates are generally uncertain for the wind farm owner/operator in the development and planning phase and they constitute an appreciable part of the direct O&M cost. 4) The average limiting significant wave height (Hs) for technicians to access the turbines should be understood as an effective limit for Hs when averaging over sea states (characterised by wave direction, wave period, etc. in addition to Hs) where the operation is possible and safe. Hence, the actual value of this parameter depends on the metocean conditions at the wind farm site and is generally uncertain (Sperstad et al., 2014). 5) The service speed of a vessel is typically stated by the vessel provider. However, there is uncertainty associated with the actual average vessel speed, which may depend on e.g. sea states or the maintenance strategy.

Sensitivity cases for each of the vessel fleets are defined by changing the assumptions for each of these input parameters to a higher and lower level around the assumptions of the base case. The base case values x_0 are defined in Table 1 for the failure rate assumptions and in Table 2 for the vessel assumptions, and the base case electricity price is 90 £/MWh. The sensitivity cases considered are listed in Table 4, which also shows which vessels a parameter changes for each of the cases. New simulations need to be carried out for the parameters failure rate, Hs limit and vessel speed, whereas sensitivity analyses can be performed for vessel day rates and the electricity price simply by post-processing simulation results from the base case.

3. Computational study

This section presents the results of the computational study using six different decision support tools for O&M vessel fleet selection. Results for the objective value for different vessel fleet alternatives and the sensitivity of these results are presented in Section 3.1. Section 3.2 presents the resulting ranking of the vessel fleets, and in Section 3.3 the sensitivity of this ranking to changes in input data assumptions is considered.

3.1. Objective function sensitivity analysis

Each of the tools described in Section 2.2 has been used to evaluate the objective function as described by Eqs. (1) and (2) for each of the 10 vessel fleet cases described in Section 2.3. For each of the simulation tools, the number of Monte Carlo iterations was chosen so that the statistical uncertainty in the objective value was sufficiently low for comparing the different vessel fleets with that tool. The exact number of iterations was not equal for all tools because different tools have levels of statistical variability in the Monte Carlo results and different procedures for selecting the number of iterations.

A comparison of the performance of the different vessel fleets as evaluated by the different decision support tools is shown in Fig. 1. To allow a clearer comparison of the relative performance of the different vessel fleets across different tools, the objective value estimates for each tool have been scaled to the value of the vessel fleet with the lowest objective value according to that tool. In other words, for each tool, the vessel fleet with the lowest objective value is shown with objective value 100%. In the previous study conducted with many of the same tools by Dinwoodie et al. (2015), it was observed that the absolute value of the total O&M cost varied significantly between different tools. For the present study, the primary interest is rather on the differences between the tools in how they rank different vessel fleets. Therefore, relative total O&M cost values, rather than absolute values, are considered.

The results in Fig. 1 are shown with vessel fleets ordered from the lowest to the highest charter cost of the vessel fleet (left to right). In general, the following trend can be expected for the total O&M cost as a

Table 4
Definition of sensitivity cases considered.

Sensitivity case label	Change for CTV	Change for SES	Change for SAV	Change for MM
Failure rate	X	X	X	X
Electricity price	X	X	X	X
Day rate all vessels	X	X	X	X
CTV day rate	X			
SES day rate		X		
SAV day rate			X	
MM day rate				X
Hs all vessels	X	X	X	X
Hs CTV	X			
Hs SES		X		
Hs SAV			X	
Hs MM				X
Speed all vessels	X	X	X	X
Speed CTV	X			
Speed SES		X		

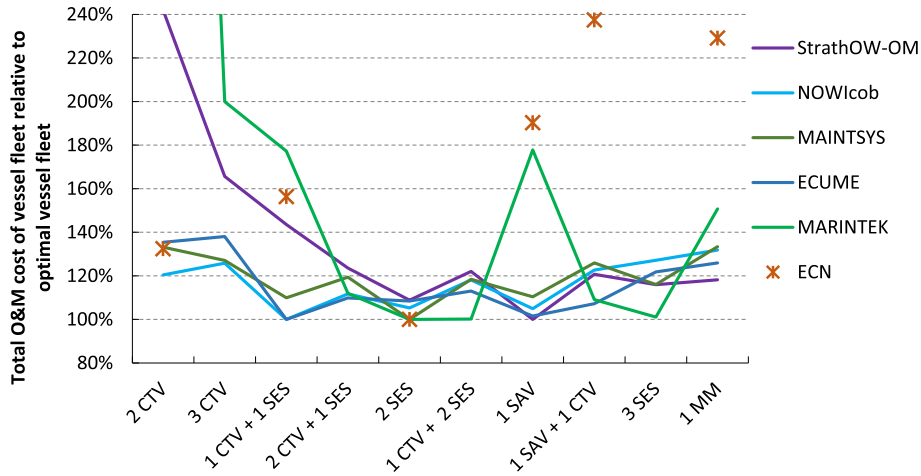

Fig. 1. Total O&M cost for the vessel fleets for each decision support tool relative to the vessel fleet found to be optimal for that tool.

function of the charter cost of the vessel fleet: The total O&M cost is high for the least expensive fleets since they have insufficient capacity to perform all of the corrective O&M tasks at the wind farm and therefore result in a high revenue lost due to downtime. Increasing the vessel cost, the total O&M cost then decreases towards a minimum as a trade-off is being made between vessel cost and downtime costs. For the most expensive fleets, the total O&M cost then increases again since the increase in vessel costs are larger than the reduction in revenue lost due to downtime for these vessel fleets. This general trend can be seen in Fig. 1 for most of the tools. However, Fig. 1 also shows several differences between the results from different tools, and these differences will be investigated in more detail below.

It is important to keep in mind that the objective values shown in Fig. 1 alone do not identify whether or not the vessel fleet is able to complete all annual services. Therefore, the fraction of annual services completed is presented in Table 5. The MARINTEK tool does not give the exact percentage of annual services completed so "<99.90%" means that not all of them were performed.

Fig. 1 shows a similarity in how the tools evaluate the differences in performance between the vessel fleets for the base case. For instance, all tools agree that the least expensive alternatives, "2 CTV" and "3 CTV", are insufficient for the maintenance requirements of the reference case. However, the tools disagree strongly on the relative performance difference between these fleets and the better performing ones. For the MARINTEK tool, the explanation is that the objective function for this optimisation tool explicitly includes a penalty cost for not completing all maintenance activities. For the StrathOW-OM model, the low relative performance of "2 CTV" and "3 CTV" can be explained by this tool having in general less optimistic modelling assumptions than the other tools. This leads to overall lower availability estimates, and the effect is aggravated for cases with insufficient maintenance resources. These results are in line with the findings in Dinwoodie et al. (2015), which concluded that differences between tools are most pronounced for cases where maintenance resources are heavily constrained.

The tools also disagree strongly on the performance of the "SAV" vessel fleet. All simulation tools agree that a single SAV is unable to complete all the required annual services due to its small capacity for technicians. In the MARINTEK tool this again results in large penalty costs being added to the total O&M cost. Only the ECN O&M Tool is able to complete all annual services with using 1.25 SAVs annually (i.e., two SAVs were required for a single season of the year). However, the ECN O&M Tool's estimate of the objective function is far above that of most vessel fleets. The ECN O&M Tool is incentivized to complete annual services in a different manner than in the other tools. Annual services are completed, but the SAVs are operating nearly continuously throughout the year in order minimize turbine downtime. The results presented in Fig. 1 highlight the importance of taking into account the completion of preventive maintenance in assessing the performance of access vessels. They also illustrate the importance of how preventive and corrective maintenance is prioritised in O&M tools. Separate tests also showed that changing these priorities gave substantial differences in results for some of the tools.

To investigate how strongly the objective value is affected by different input parameters, the sensitivity index of the total O&M cost as defined in Eq. (7) has been calculated. The results for relative changes of $\Delta x/x_0 = \pm 20$ % to the values all the considered parameters are given in Fig. 2. Here the results for each parameter are averaged over all vessel fleets for which the parameter is relevant. The normalization of the sensitivity index is such that a value of 1 means that increasing the input parameter by 20% gives a 20% increase in the total O&M cost. As can be seen by the figure, there is only partial agreement between the tools as to which parameters affect the total O&M cost the most. The day rates and the speed of the vessels seem to have little effect on the total O&M cost, while the objective function on average is most sensitive to changes in the wave height limits of the vessels. There is also a considerable sensitivity to changes in the price of electricity and the failure rates. Both of these influence the total downtime cost of the wind farm, which is one of the major cost components. For some wave height limit parameters, the results for the sensitivity index for MARINTEK and StrathOW-OM are outside the range chosen for Fig. 2.

For electricity price and vessel day rates, a linear relationship between the value of the parameter and the objective value of a given vessel

Table 5
Fraction of annual services completed for each vessel fleet for each of the decision support tools.

	2 CTV	3 CTV	1 CTV +1 SES	2 CTV +1 SES	2 SES	1 CTV +2 SES	1 SAV	1 SAV +1 CTV	3 SES	1 MM
ECUME	95.39%	99.98%	98.94%	100.00%	100.00%	100.00%	84.67%	100.00%	100.00%	100.00%
NOWIcob	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	71.47%	100.00%	100.00%	100.00%
StrathOW-OM	73.69%	100.00%	97.85%	100.00%	100.00%	100.00%	90.38%	100.00%	100.00%	100.00%
MARINTEK	<99.90%	<99.90%	100.00%	100.00%	100.00%	100.00%	<99.90%	100.00%	100.00%	100.00%
MAINTSYS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	98.00%	100.00%	100.00%	n/a
ECN	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

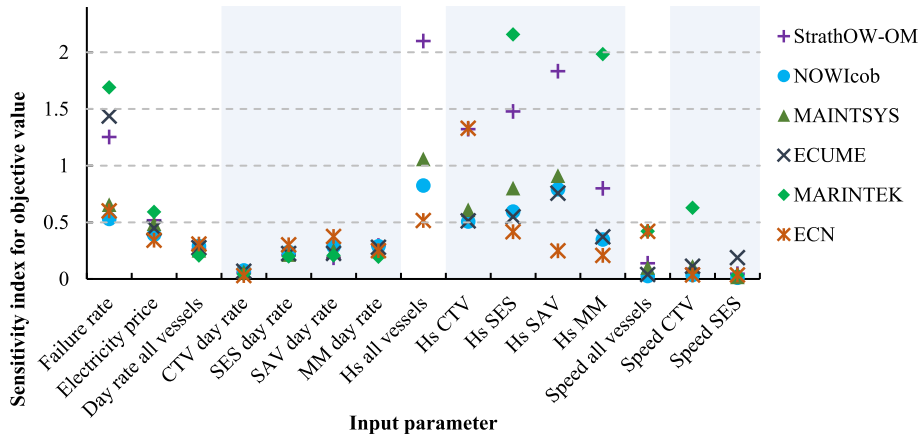

Fig. 2. Sensitivity of the objective value averaged over all vessel fleets.

fleet would be expected. This trend is evident in Fig. 2 where the sensitivity of all tools to changes in these parameters is more or less the same. The effect of changing the limiting wave height parameter has a great impact on the objective value of all tools; however, the magnitude of the impact varies to a large extent. Finally, changing the speed of the vessels seems to have little effect on the objective value of all tools. An explanation for this may be that the objective value as a function of the speed is more similar to a step function where there are only small changes in the objective value until the speed reaches a given threshold value, at which point it will increase/decrease drastically. Increasing the speed of a vessel will only improve the objective value significantly if the additional time available at a wind farm can be used to perform additional maintenance tasks. Thus, this parameter is likely to have a greater impact if the wind farm is located further offshore than in our tests, or if the parameters are changed by considerably more than 20%.

3.2. Vessel fleet ranking

Table 6 shows the vessel fleet ranking for all tools for the reference case when it is also required that the vessel fleets be capable of completing all preventive maintenance as explained in Section 2.1. For this reference case, it is clear that there are some fleets that all tools find to be good and some fleets that all tools agree are bad. However, for many of the fleets, the tools disagree on the actual ranking, just as they disagree on the relative performance as shown in Fig. 1. The fact that the relative performance curves in Fig. 1 are so different for different tools also makes it less likely that different tools in general would agree on the optimal solution to the vessel fleet optimisation problem.

In Table 7, the Spearman's rank correlation between each pair of tools is presented, as defined in Eq. (8). The ECUME, StrathOW-OM, and MARINTEK tools seem to agree fairly well on the vessel ranking; the same goes for NOWIcob and MAINTSYS. However, between many pairs of tools there is virtually no correlation of the fleet rankings. Some pairs of tools even have a slightly negative correlation, meaning that fleets ranked high by one tool are generally ranked low by the other tool and vice versa.

3.3. Vessel fleet ranking sensitivity analysis

Having found that there are differences in how different tools rank different vessel fleets, also when one takes into account whether preventive maintenance is completed, an investigation into how sensitive the rankings themselves are to changes in the inputs was carried out. Changes in the correlation coefficients for the ranking are considered as a measure of how robust the results for the vessel fleet ranking are. To be able to compare the sensitivity of the vessel fleet ranking to changes in

Table 6
The vessel fleet ranking for each of the decision support tools according to the total O&M cost, taking also into account that all annual services should be completed. A darker shade of grey indicates a higher ranking of a vessel fleet for a tool.

	ECUME	NOWIcob	StrathOW-OM	MARINTEK	MAINTSYS	ECN
2 CTV	10	5	10	10	8	2
3 CTV	7	7	7	9	7	
2 CTV + 1 SES	3	3	6	5	5	
1 CTV + 1 SES	8	1	9	7	2	3
2 SES	2	2	1	1	1	1
3 SES	5	8	2	3	3	
1 SAV + 1 CTV	1	6	4	4	6	6
1 SAV	9	10	8	8	9	4
1 MM	6	9	3	6	10	5
1 CTV + 2 SES	4	4	5	2	4	

Table 7
The Spearman's rank correlation coefficient between the vessel fleet ranking for the different decision support tools.

	ECUME	NOWIcob	StrathOW-OM	MARINTEK	MAINTSYS	ECN
ECUME	1.00	0.28	0.76	0.83	0.45	−0.23
NOWIcob	0.28	1.00	−0.09	0.30	0.75	0.61
StrathOW-OM	0.76	−0.09	1.00	0.83	0.33	−0.10
MARINTEK	0.83	0.30	0.83	1.00	0.65	0.07
MAINTSYS	0.45	0.75	0.33	0.65	1.00	0.54
ECN	−0.23	0.61	−0.10	0.07	0.54	1.00

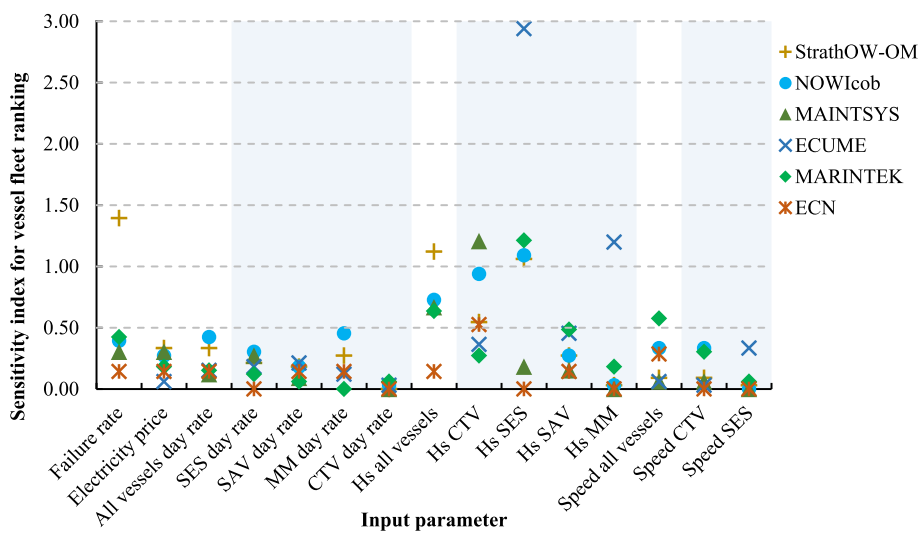

Fig. 3. Sensitivity index as a measure of the sensitivity of the vessel fleet ranking to different input parameters.

different parameters, the sensitivity index defined in Eq. (9) is considered. The results are shown in Fig. 3 for relative changes of $\Delta x/x_0 = \pm 20$ % to all the considered parameter values. The normalization of the sensitivity index is such that a value of 1 means that changing the input parameter by 20% gives a 20% decrease in the Spearman's rank correlation function. The figure shows that the findings for the objective function value sensitivities are also broadly valid for the ranking of the vessel fleets: The ranking of different vessels is strongly dependent on the Hs assumptions and appreciably less dependent on the vessel speed assumptions. Simply put, the implication is that when ranking which vessel fleets perform best, the ranking is robust to the uncertainty in the actual speed of a vessel, but making inaccurate estimates for the accessibility of a vessel could result in a completely different ranking. However, the Hs limit could be a less important parameter for wind farms in milder metocean conditions, as the metocean conditions of the reference case are relatively harsh (Dinwoodie et al., 2015). It should also be pointed out that the sensitivity to vessel speed would be stronger had a reference wind farm with a greater distance to shore been chosen. Fig. 3 also shows that different tools disagree strongly on the extent to which the vessel fleet ranking is affected by changes in the different parameters. Most importantly, there is a wide span between the tools in the sensitivity of the ranking to changes in Hs and in the failure rate.

The sensitivity case "Hs all vessels" can also be interpreted as investigating sensitivity to changes in the metocean data, since decreasing the Hs limit of all vessels by 20% has the same effect as increasing the wave height of all metocean states in the input data by 20%, and vice versa. As can be seen in Fig. 3, this is one of the changes to which the tools are the most sensitive. This indicates that representing the metocean data correctly will also have a great impact on the vessel fleet ranking.

4. Discussion of the results

As shown in the comparison of the vessel fleet rankings and sensitivities in the preceding section, there are discrepancies between the results from different decision support tools. One possible explanation for the discrepancies is that tools assuming more efficient utilization of small weather windows will favour less capable and less costly vessels. Tools that do not allow maintenance tasks to be split over multiple shifts or that have pessimistic failure modelling may on the other hand favour vessel fleets with higher capacity. For instance, the MARINTEK optimisation tool has a time resolution of 6 h in considering weather windows, using the worst-case metocean conditions during each 6-h period. In contrast, the simulation tools consider metocean conditions with a time resolution of 1 h. Some discrepancies for specific vessel fleets (e.g. for the SAV) were also explained in Section 3.1 to be due to how the completion of preventive maintenance is taken into account in different tools. Apart from this, it has proven challenging to pinpoint the modelling assumptions that cause the discrepancies between different tools.

From this it may be concluded that what constitutes the best fleet to perform maintenance at an offshore wind farm depends heavily on the actual assumptions made in developing each decision support tool. Since the tools compared in this paper were developed independently of each other, and developed in cooperation with the industry, it is likely that the differences in assumptions stem from the fact that different wind farm owners/operators plan and perform their maintenance differently. Consequently, it is important to ensure that the assumptions in the tool reflect the operational strategy of the wind farm owner/operator. One implication is that wind farm operators or other stakeholders may want to use different and possibly complementary tools and estimation techniques if it is uncertain what decision support tool has the overall most representative assumptions for a particular wind farm project.

The reference wind farm considered is relatively close to shore. Therefore, accommodation vessels and mother vessel concepts would probably have been ranked higher for wind farms farther from shore than in the results shown here. The small accommodation vessel and the mini mother vessel included among the vessel fleets considered are examples

of such vessel concepts. However, even for this reference case, different tools disagreed strongly on the ranking of the small accommodation vessel. Therefore, more work may be necessary to represent such vessel alternatives in a way that is more realistic for a more accurate comparison with conventional logistics strategies. For instance, as our results showed, a small accommodation vessel with only six technicians available to do maintenance each shift does not have sufficient capacity to handle the maintenance requirements of this reference wind farm. Additional modelling considerations may also be required when using shore-based maintenance logistics approaches for wind farms farther offshore. For instance, it could be more important to capture the effect of sea sickness, the effect of wave state-dependent vessel speeds and how increased transit times might change task priorities and vessel utilization.

The solution space of possible combinations of the different vessels is much larger than the 10 vessel fleets considered in this study. This means that the optimal vessel fleet could, in principle, be in a part of the solution space that has not been considered. When faced with a large solution space, using mathematical optimisation rather than simulation may be particularly advantageous. In fact, when the MARINTEK optimisation tool was used to consider all possible combinations, i.e. not restricting the solution space to the 10 combinations considered above, it was demonstrated that "2 SES" remains the optimal solution according to that tool. Although they are simplified representations, the vessel types included in this study are believed to be representative of the kinds of alternatives decision makers have to choose from. Furthermore, possible biases due to the characteristics of any of the chosen vessel types are reduced by considering the combined results for all the vessel fleet alternatives. In this way, it the sensitivity trends exhibited by the results can be assumed to be fairly general.

Due to the number of vessel fleet alternatives, the number of input parameters varied in the sensitivity analysis, and the number of different tools, a large total number of cases was considered for this work. For practical reasons, compromises were necessary and a number of potential cases and analyses omitted. For instance, a local sensitivity analysis was performed, with parameter value changes restricted to ± 20 %. Hence it would not be possible to identify any nonlinear effects for the different parameters. Furthermore, in restricting the analysis to a one-at-a-time approach it is not possible to identify any significant interactions between the different parameters. However, it is possible to argue intuitively for what the implications of such interactions are likely to be. For example, when assuming a higher base electricity price than the base case value, downtime costs would become higher relative to direct O&M costs, and the sensitivities for e.g. Hs limits would be relatively stronger than sensitivities for vessel day rates. See also Martin et al. (2016) for other sensitivity analysis methods applied to offshore wind O&M.

5. Conclusions

In this study, six different strategic decision support tools for offshore wind farm O&M and logistics were applied to the problem of selecting the best O&M vessel fleet for a reference wind farm. It has been established that the decision support tools show general agreement on which vessel fleet is the best, but they agree only partially on the overall ranking of the different vessel fleets. The tools agree only partially on how sensitive the performance of each vessel fleet alternative (the objective value) is to different input assumptions. However, they generally agree on how sensitive the ranking of the vessel fleet alternatives is to different input assumptions. The ranking of different vessel fleets is i) strongly dependent on the assumption for the limiting significant wave height for access, ii) appreciably less dependent on the vessel speed assumptions, and iii) moderately dependent on assumptions for failure rates and vessel day rates. Different tools disagree on precisely how sensitive the results are to changes in these parameters, especially for failure rates and the limiting significant wave height. The disagreements do not appear to be due to differences intrinsic in the type of tool (e.g. based on simulation or on mathematical optimisation) as such, but rather due to how optimistic or pessimistic the modelling assumptions are.

The work reported in this paper suggests some recommendations for optimising the O&M and logistics strategies for offshore wind farms: First, it is crucial to take into account the completion of preventive maintenance (e.g. annual services) when evaluating the performance of vessel fleets for O&M. The sum of direct O&M costs and lost revenue due to downtime appears to be an appropriate objective function for making the trade-off between availability and O&M costs but does not by itself consider whether or not preventive maintenance is completed. In an optimisation tool, non-completion of preventive maintenance can be taken into account explicitly in the form of penalty terms in the objective function or as constraints. When using a simulation tool for optimisation, it may be necessary to take this into account separately. Furthermore, results from our sensitivity analyses confirm that it is important to be aware of and, if possible, to try to reduce uncertainties in input data, particularly in the significant wave height limit. This also implies that it is important to consider how metocean conditions and accessibility of the turbines are modelled in the tool. Finally, since different tools provide somewhat different results for the same input data, decision makers need to ensure that the modelling assumptions are representative of the wind farm project in question and might also consider using several tools to support their decisions.

Acknowledgements

For data from the FINO project, the authors thank the BMU (Bundesministerium fuer Umwelt, Federal Ministry for the Environment, Nature Conservation and Nuclear Safety) and the PTJ (Projekttraeger Juelich, project executing organisation). The authors thank Lars Magne Nonås and Thomas Welte for useful discussions in the initial phases of the study, Shuangwen Sheng for discussions regarding the presentation of the results, and Nancy Lea Eik-Nes for language help and proofreading. The authors also thank three anonymous reviewers for thorough feedback that greatly helped to improve the precision and clarity of the paper. The contributions of I. B. Sperstad are co-funded under the research programme NOWITECH (193823). The contribution of I. Dinwoodie was generated under the University of Strathclyde Low Carbon Power and Energy AM02 research programme (EPSRC Grant No. EP/G037728/1, Centre for Doctoral Training in Wind Energy Systems), the authors wish to recognize the contributions of Dr Yalcin Dalgic, Dr David McMillan, Dr Iraklis Lazakis and Dr Matthew Revie to the development of this project. The contribution of O.E. Endrerud is supported by the research program NORCOWE (193821). The contribution of R. Martin is supported through the Industrial Doctorate Centre for Offshore Renewable Energy (IDCORE), funded by the Energy Technology partnership and the RCUK Energy Programme Grant number EP/J500847/1. The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under the agreement SCP2-GA-2013-614020 (LEANWIND).

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