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Vessel fleet optimization for maintenance operations at offshore wind farms under uncertainty

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Abstract

In this paper we consider the problem of determining the optimal fleet size and mix of vessels to support maintenance activities at offshore wind farms. A two-stage stochastic programming model is proposed where uncertainty in demand and weather conditions are taken into account. The model aims to consider the whole life span of an offshore wind farm, and should at the same time remain solvable for realistically sized problem instances. The results from a computational study based on realistic data is provided.

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1. Introduction

Today, the offshore wind energy industry needs financial support to be profitable, and producers in the United Kingdom receive a subsidy of approximately EUR 100 per produced MWh [1]. Following the initial investment, the largest cost component is the cost of operations and maintenance (O&M) activities, which may constitute between 20–25 % of the life-cycle costs of an offshore wind turbine [2]. The yearly cost of O&M activities at offshore wind farms could be anywhere between GBP 50 000 and GBP 100 000 per turbine [3]. The sum depends on a range of factors including location, machine size, and how well the O&M activities are organized. A significant reduction in these costs is needed to make offshore wind farms a competitive alternative to other energy sources. Therefore it is of importance to select a cost-effective fleet size and mix of vessels to support the O&M activities.

This paper presents a new mathematical programming model that determines the optimal fleet of maintenance vessels to support the O&M activities at one or more offshore wind farms. The problem modeled is faced by offshore wind farm operators which operate one or more wind farms that are expanded over time. As the wind farms grow both

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in covered area and in number of turbines, the fleet of maintenance vessels must be adapted to handle an increased demand for O&M activities, greater distances, and more volatile weather conditions.

The remainder of this paper is structured as follows. Section 2 provides a description of the problem. A mathematical formulation of the problem is given in Section 3. A computational study follows in Section 4, and concluding remarks are found in Section 5.

2. Problem description

The cost of vessels, helicopters and infrastructure used to support O&M activities is one of the largest cost elements during the operational phase of an offshore wind farm. The vessel fleet size and mix is determined from a heterogeneous set of vessels and helicopters that can be purchased, or chartered for shorter periods of time. Purchased vessels may be chartered out in time periods where they are not used. Large wind farms will be developed in several building steps, and the requirements of the vessel fleet to support O&M activities will increase as more turbines become available in each new building step. Hence, the optimal vessel fleet may change over time.

The vessels in the fleet can operate from onshore or offshore bases. An onshore base can be any given port, and offshore bases can be, for example, artificial islands or mother vessels. The number of vessels that can operate from a base is limited. Offshore bases can be advantageous for wind farms far offshore where the travel time to onshore ports make it hard for vessels to do a return trip from shore to the wind farm during a normal work shift. The offshore bases will have large investment costs and are unlikely to be profitable for single, small wind farms. Knowledge about development of future wind farms, with which an offshore base can be shared, can make it profitable to invest in one at an early stage. Thus, the planning horizon needs to cover the entire life span of an offshore wind farm to properly evaluate such opportunities.

All vessels cannot be used to support all types of O&M activities. Supply vessels can be used to transport maintenance personnel and small equipment. If large components need to be changed, a crane vessel or jack-up vessel is required. Helicopters and smaller vessels can only transport maintenance personnel, but can do so at a higher speed.

The distance between a vessel's base and the wind farm affects the transfer time, which again affects the time a vessel can be used to support O&M activities at the wind farm before returning to its base. Vessels with high transfer speed are valuable if this distance is great. Also, increased distance between an offshore wind farm and the shore will make an investment in an offshore base more profitable.

A long term plan for purchasing vessels is important as there is usually a time delay between entering a contract to purchase a vessel and its delivery. Some vessel types will be available for charter at a daily rate. The demand for vessels may, however, exceed the supply for such vessels, especially during times of the year when weather conditions are expected to be good. For this reason, an offshore wind operator will seek to enter into charter contracts well ahead of the start of the charter period. Hence, the timing for purchasing or chartering vessels is of importance.

There are two main types of O&M activities that must be supported by the vessel fleet: preventive and corrective. The preventive type consists of planned activities that intend to guard against component failures. Typical examples are visual inspection, changing of consumables, oil sampling, and tightening of bolts [4]. These activities can be postponed, but should be performed regularly to reduce the risk of future failures. The cost of preventive maintenance activities is the sum of transportation cost, personnel cost, equipment cost and the cost of lost production due to turbine shut-down when the activity is being performed. Corrective maintenance activities occur when there is a component failure followed by a production stop. There will be an immediate loss of income due to the production stop, and this loss will continue to grow until the corrective maintenance activity has been performed and production can restart. The total cost of corrective maintenance activities is the sum of transportation cost, personnel cost, equipment cost and the loss in revenue due to the production stop.

There are many uncertain parameters affecting the execution of O&M activities at offshore wind farms. Today, the industry is immature and expensive, and any new wind farm developments depend on government subsidies to make it a viable investment. The industry actors are concerned with the accessibility (access to) and availability (produced electricity vs. theoretical potential for electricity production) of a wind farm. The former is highly related to weather conditions, and the vessels and access system used, while the latter is related to both the time it takes to repair a failure and the number of failures. Hence, the focus in this paper is on uncertainty in weather conditions, and the occurrence of turbine failures that result in corrective maintenance activities. There are several weather parameters

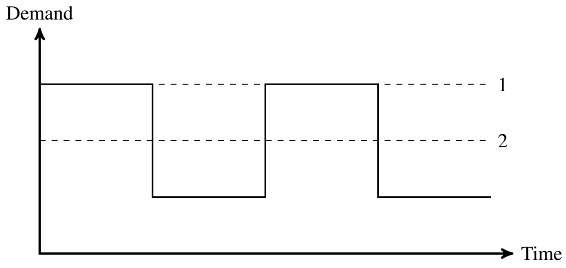

Fig. 1. Demand for maintenance activities as a function of time, within a single time period. Dashed line 1 is the capacity of a vessel fleet giving the minimum downtime cost. Dashed line 2 is the minimum capacity of the fleet.

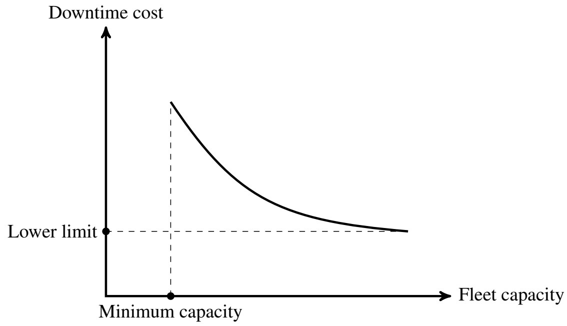

Fig. 2. Downtime cost as a function of vessel fleet capacity.

that affect the operability of the vessels, such as wind speed and direction, wave height, period and direction, and current speed and direction. We only consider wave height and wind speed parameters as it was shown in [5] that these were sufficient to provide reasonable results for strategic O&M models. Seasonal variations in weather are taken into consideration. Preventive maintenance activities will normally be performed only in the summer season, due to better weather conditions. Corrective maintenance activities need to be performed during the whole year, depending on when failures occur.

3. Mathematical model

In this section we present a two-stage stochastic programming model to determine a suitable fleet size and mix for supporting O&M activities at offshore wind farms. Two main types of decisions are considered: Which types of vessels to use, and how and when to acquire them. The model is divided into time periods that can be of varying length. We assume that for a given time period all O&M activities that are planned need to be performed and all failures that occur need to be corrected.

A vessel type's capacity to support O&M activities during a time period is given by the total amount of time the vessel type can operate during the time period and how many hours it will need to support an O&M activity of a given type at a given wind farm. The transfer time (the time a vessel uses from its onshore or offshore base to the wind farm) is included in the latter time parameter. We assume that a vessel only operates at one wind farm on each trip and that the distances between the wind turbines within the same wind farm are negligible. Such internal travel time at a wind farm can, however, be included in the time it takes to support an O&M activity. The actual routing of the vessels within a wind farm is not modeled.

Decisions regarding purchasing, selling, chartering in, and chartering out vessels are made at the start of each time period. Decisions regarding which vessels to charter in and charter out are made for an entire time period. There is no functional spot-market for O&M vessels for the offshore wind market today, and this assumption is made based on feedback from industry indicating that 3-months charter contracts are plausible for such a market.

The objective function is to minimize the net present value of the total costs of the vessel fleet to support O&M activities. The total costs can be divided into vessel costs and downtime costs. Downtime costs are losses in revenue due to production stops. As illustrated in Figure 1, unforeseen failures do not necessarily occur evenly throughout a period. If the vessel fleet capacity only just covers the total demand for O&M activities from unforeseen failures, the fleet has minimum capacity. An increased fleet capacity will reduce the losses in revenue from production stops in peak maintenance periods, but increasing the fleet capacity above the demand in peak periods, will have no effect. The curve illustrated in Figure 2 shows how the total downtime costs may depend on the vessel fleet capacity. To model this curve in a mixed integer linear problem it is divided in k line segments, with a decreasing slope for each line segment.

The mathematical model formulation contains parameters that represent the uncertain number of failures and the weather conditions. The number of failures affects the demand for vessels, and the weather conditions affects the number of hours that a vessel can operate in a given time period. Under the assumption that each time period is relatively long (3 months or more) the weather conditions and the number of failures in one period may be treated as independent of the realizations in the previous periods. The weather conditions are auto-correlated over short periods of time, but this auto-correlation disappears when considering longer time periods. Thus, the weather in different time periods are considered to be independent of each other, while the short-term correlation of the weather parameters within one time period is handled in the scenario generation process. The scenario generation process also accommodates the fact that the weather conditions change with the different seasons. Failure rates are also somewhat correlated across time, as typically there will be more failures during the first few years of a wind turbine, and then again more at the end of the lifetime with a somewhat less probability of failure in the time between. There may also be some correlation between weather conditions and failures, but data regarding this is unavailable to us, and as we are only considering which failures that occur within a fairly long time period, this is expected to level out.

This makes a two-stage stochastic programming model suitable: In the first stage decisions on how many vessels should enter and leave the vessel fleet and how many offshore bases should be built in each time period are made. The demand for O&M activities, and the time available for each vessel type then becomes known before stage 2. Based on the realization of the uncertain parameters, decisions regarding which vessels to charter in and charter out can be made, as well as decisions regarding which vessels should be used for which O&M activities.

The mathematical notation and the complete mathematical model are presented below.

Indices

f	Wind farm.
i	Type of maintenance activity.
p	Time period.
v	Vessel type.
w	Type of offshore base.
k	Line segment (to calculate downtime costs).
s	Scenario.

Sets

F	Set of wind farms.
P	Set of time periods in the planning horizon.
V	Set of vessel types.
W	Set of offshore bases.
A	Set of O&M activities.
V_w^W	Set of vessel types that can be associated with offshore base w, $V_w^W \subseteq V$.
V_i	Set of vessel types that can support O&M activity of type i, $V_i \subseteq V$.
A_v	Set of O&M activities that can be supported by vessel of type v, $A_v \subseteq A$.
K_i	Set of line segments to calculate downtime costs for O&M activity i.
S	Set of scenarios.

Parameters

C_{pv}^I	Investment cost of purchasing a vessel of type v in time period p.
C_{pv}^F	Fixed cost of a vessel of type v in time period p.
C_{pv}^V	Variable cost of a vessel of type v per operational hour in time period p.
C_{pv}^R	Cost of chartering in a vessel of type v in time period p.
C_{pw}^I	Cost of purchasing an offshore base of type w in time period p.
C_{pw}^F	Fixed cost for offshore base of type w in time period p.
C_{fikp}^D	Reduction in downtime cost due to additional fleet capacity.
C_p^B	Investment budget for vessels and offshore bases in time period p.

R^S_{pv}	Revenue from selling a vessel of type v in time period p.
R^H_{pv}	Revenue from chartering out a vessel of type v in time period p.
T^O_{pvs}	Maximum operational time in hours for a vessel of type v in time period p in scenario s.
T^M_{fipv}	Number of hours that a vessel of type v needs to support an O&M activity of type i at wind farm f in time period p.
N_{fips}	Number of O&M activities of type i to be performed in time period p at wind farm f in scenario s.
M_w	Maximum vessel capacity at an offshore base of type w.
G_{vw}	Capacity a vessel of type v will need on an offshore base of type w.
E_{fikps}	Length of line segment k used to calculate downtime costs for activity of type i at wind farm f in period p in scenario s.
R^V_v	Residual value of a vessel of type v in the end of the planning horizon.
Pr_s	Probability of scenario s.

Decision Variables

x_{pv}	Number of vessels of type v in the fleet in time period p.
x^J_{pv}	Number of new vessels of type v joining the fleet in time period p.
x^L_{pv}	Number of vessels of type v leaving the fleet in time period p.
y^R_{pvs}	Number of vessels of type v chartered-in in time period p in scenario s.
y^H_{pvs}	Number of vessels of type v chartered-out in time period p in scenario s.
z_{pw}	Number of offshore bases of type w in time period p.
z^J_{pw}	Number of offshore bases of type w acquired in time period p.
t_{fipvs}	Number of hours a vessel of type v operate on wind farm f in time period p supporting O&M activities of type i in scenario s.
u_{fikps}	The excess capacity of the vessel fleet used to reduce downtime cost in time period p on wind farm f for O&M activities of type i in scenario s.

Using the notation described above the mathamtical model can be formulated as follows:

$$\min Z = \sum_{p\in P}\sum_{v\in V} C^I_{pv} x^J_{pv} + \sum_{p\in P}\sum_{v\in V} C^F_{pv} x_{pv} \tag{1a}$$

$$+ \sum_{p\in P}\sum_{w\in W} C^I_{pw} z^J_{pw} + \sum_{p\in P}\sum_{w\in W} C^F_{pw} z_{pw} \tag{1b}$$

$$- \sum_{v\in V} R^V_v x_{|P|v} - \sum_{p\in P}\sum_{v\in V} R^S_{pv} x^L_{pv} \tag{1c}$$

$$+ \sum_{s\in S} Pr_s \Bigg[\sum_{p\in P}\sum_{v\in V} C^R_{pv} y^R_{pvs} - \sum_{p\in P}\sum_{v\in V} R^H_{pv} y^H_{pvs} \tag{1d}$$

$$+ \sum_{f\in F}\sum_{i\in A}\sum_{p\in P}\sum_{v\in V} C^V_{pv} t_{fipvs} - \sum_{f\in F}\sum_{i\in A}\sum_{k\in K_i}\sum_{p\in P} C^D_{fikp} u_{fikps} \Bigg]. \tag{1e}$$

The objective function describes the expected total costs, which should be minimized. The first two terms in the objective function (1a) is the sum of the investment cost and the fixed costs of the vessels in the fleet. The first term of (1b) is the investment costs of offshore bases and the second term is the fixed costs of them. The value of the vessel fleet at the end of the planning horizon is included in the objective function as the first term of (1c). The second term of (1c) is the revenue for selling vessels. The first term of (1d) is the sum of all costs for chartering in vessels, and the second term is the revenue from chartering out vessels. The first term of (1e) gives the variable costs, such as fuel costs, for both chartering in vessels and purchased vessels. The last part of (1e) is the reduction in revenue loss due to production stops, resulting from increasing the capacity of the vessel fleet. This is a linearization of the downtime cost as a function of the fleet capacity, as illustrated in Figure 2. The terms in (1d) and (1e) are calculated for each scenario s, and the expected value is obtained by multiplying with the corresponding probabilities, Pr_s.

The following constraints contain only first stage variables:

$$x_{pv} = x^J_{pv}, \qquad p = 1, \qquad v \in V, \tag{2}$$

$$x_{pv} - x_{p-1,v} = x^J_{pv} - x^L_{pv}, \qquad p \in P \setminus \{1\}, \qquad v \in V, \tag{3}$$

$$z_{pw} = z^J_{pw}, \qquad p = 1, \qquad w \in W, \tag{4}$$

$$z_{pw} = z_{p-1,w} + z^J_{pw}, \qquad p \in P \setminus \{1\}, \qquad w \in W, \tag{5}$$

$$\sum_{p=1}^{p'} \sum_{v \in V} C^I_{pv} x^J_{pv} + \sum_{p=1}^{p'} \sum_{w \in W} C^I_{pw} z^J_{pw} - \sum_{p=1}^{p'} \sum_{v \in V} C^S_{pv} x^L_{pv} \leq C^B_p, \qquad p' \in P, \tag{6}$$

$$x_{pv}, x^J_{pv}, x^L_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{7}$$

$$z_{pw}, z^J_{pw} \in \mathbb{Z}^+, \qquad p \in P, \quad w \in W. \tag{8}$$

Constraints (2) ensure that the number of vessels in the fleet in the first period is equal to the number of vessels purchased at the start of the planning horizon. Then constraints (3) ensure that the number of vessels in the fleet at the start of each subsequent time period is equal to the number of vessels in the previous time period plus the change in vessel fleet due to purchasing or selling vessels. Constraints (4) and (5) are similar constraints for offshore bases, except that such bases cannot be sold. The total investment in bases and vessels is limited by the investment budget in constraint (6). Finally, constraints (7)–(8) set the integer requirements for the first stage variables.

The following constraints contain some second stage variables, that is, variables representing decisions that may vary depending on the realization of the uncertain parameters:

$$M_w z_{pw} \geq \sum_{v \in V^W_w} G_{vw} \left(x_{pv} + y^R_{pvs} \right), \qquad p \in P, \quad w \in W, \quad s \in S, \tag{9}$$

$$\sum_{v \in V_i} \frac{t_{fipvs}}{T^M_{fipv}} \geq N_{fips} + \sum_{k \in K_i} u_{fikps}, \qquad f \in F, \quad i \in A, \quad p \in P, \quad s \in S, \tag{10}$$

$$\sum_{f \in F} \sum_{i \in A_v} t_{fipvs} \leq T^O_{pvs} \left(x_{pv} + y^R_{pvs} - y^H_{pvs} \right), \qquad p \in P, \quad v \in V, \quad s \in S, \tag{11}$$

$$u_{fikps} \leq E_{fikps}, \qquad f \in F, \quad i \in A, \quad k \in K, \quad p \in P, \quad s \in S, \tag{12}$$

$$y^R_{pvs}, y^H_{pvs} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \quad s \in S, \tag{13}$$

$$t_{fipvs} \geq 0, \qquad f \in F, \quad i \in A, \quad p \in P, \quad v \in V, \quad s \in S, \tag{14}$$

$$u_{fikps} \geq 0, \qquad f \in F, \quad i \in A, \quad k \in K, \quad p \in P, \quad s \in S. \tag{15}$$

Constraints (9) ensure that the number of vessels assigned to an offshore base is less than the capacity at the base and that the base has to be built if any vessels are assigned to it. If it is not possible to charter vessels that use an offshore base, these constraints will not be scenario dependent and the variable y^R_{pvs} can be removed. Constraints (10) ensure that the time used to support O&M activities in a given time period at least cover the number of O&M activities that must be performed within that time period. If the allotted time is greater than the minimum requirement, there is some extra capacity in the vessel fleet that potentially can be used to reduce the total downtime costs when failures occur that results in corrective maintenance activities. Hence the u_{fikps} variables on the right hand side may be increased to allow for reduced downtime costs. The total time spent on O&M activities is limited by the number of vessels in the fleet, captured by constraints (11). Constraints (12) set upper limits for the decision variables u_{fikps}, and non-negativity and integer requirements on the variables are imposed by constraints (13)–(15).

4. Computational study

In our test instances, we consider a potential offshore wind farm located in the North Sea. There is a number of vessel types, helicopters and offshore bases that can be included in the optimal fleet size and mix. Input data are based on information from [6–8]. The charter cost and revenue for a vessel during a period is higher than the fixed period cost of owning a vessel of the same type. Since it is expected that most preventive maintenance activities will be performed when weather conditions are more stable during the summer months, the demand is expected to be higher in this period. Hence we use a higher charter price during the summer than in the winter.

Operational costs are calculated per hour and are the same for both purchased and chartered vessels of the same type. The residual value of a vessel in the last time period is equal to the sales price of that vessel in the previous time period. The vessel types included in the computational study and some of their characteristics are listed in Table 1.

Table 1. Vessel and helicopter characteristics. Number of personnel refers to the maximum number of technicians that the vessel can transfer to the wind farm. Max wave height is the maximum significant wave height at which the vessel can operate.

Vessel number	Vessel type	Number of personnel	Max wave height [m]	Lift capacity [Metric tons]
1	CTV(small)	12	1.5	0
2	CTV(large)	24	2.0	0
3	Supply vessel (small)	40	2.5	0
4	Supply vessel (large)	70	2.5	0
5	Helicopter 1	7	-	0
6	Helicopter 2	9	-	0
7	Multi-purpose vessel	100	2.0	250
8	Jack-up rig	150	2.5	400

Two options for offshore bases have been included in this study: A mother vessel concept with capacity for four small CTVs and two Helicopters of type 2, and an artificial island with capacity for eight small CTVs and four Helicopters of type 2. Both these offshore base concepts are new concepts that have not yet been built and tested in real scale; the data regarding the offshore bases are based solely on expert opinions.

Preventive maintenance activities are performed twice a year on each wind turbine. Due to rough weather conditions in the North Sea during the winter season, these maintenance activities will be performed during the summer season. Random failures that result in need for corrective maintenance activities are divided into four groups, shown in Table 2.

Each maintenance activity type requires a specific number of personnel and lifting capacity. For corrective maintenance activities human interaction, lifting capacity, and transport activity restrict which vessel types can be used. Only gearbox failures will require lifting capacity. All vessels can be used to support preventive maintenance activities as

Table 2. Overview of maintenance activity types.

Type of maintenance	Operation type	Failure rate [per turbine per year]
Preventive	General maintenance	1.00
Corrective	Gearbox	0.13
Corrective	Hydraulic	0.27
Corrective	Electric	0.55
Corrective	Brakes	0.20

these types of activities only require personnel resources. When vessels that can transport more personnel than needed for a preventive maintenance activity are used the time used on the activity is reduced as a consequence of personnel working in parallel on several turbines simultaneously. There is an upper limit on the number of teams that can work in parallel due to safety regulations.

In this study, time periods are fixed to three months. Hence, a year consists of four time periods, and wind farms with an expected lifetime of 25 years thus have a planning horizon of 100 periods. Time value of money need to be considered in strategic planning models with long planning horizons. The costs will be depreciated at a yearly rate of 3 %. In the computational study there is no investment budget limit. The number of wind farms varies for the different problem instances.

The uncertain parameters in the stochastic model represent weather conditions and number of corrective maintenance activities. Weather data are used to calculate the number of hours a vessel can operate in each time period. The wave height is crucial for vessels' accessibility to wind turbines, and the wind speed has a large effect on the accessibility of helicopters and lifting capability of cranes. The wind speed also determines the production of electricity, thereby directly affecting the profit from a wind farm. Wind speed is modelled by a two-parameter Weibull distribution [9], with parameters based on studies in [10–12]. The correlation between wind speed and wave height is set to 1, based on historical wind speed and wave height data from the Ekofisk field in the North Sea. The conversion from wind speed to wave heights is based on the historical data.

For each time period we generate a time series of wind speeds and wave heights on an hourly basis, thus capturing the short term statistical correlation between the weather conditions in two consecutive hours. Based on these time series we calculate how many hours each vessel can perform maintenance tasks at the wind farm, for this given time series. The data from Table 2 are used to generate sets of failures at each wind farm in each time period. It is normal that the failure rate for a given wind turbine varies somewhat during its lifetime. However, as the proposed model considers wind farms that are developed over time, a fixed failure rate is nevertheless used, taking into consideration that, at any point in time, the turbines will be in different life-stages.

Results

The mathematical model has been implemented in the MOSEL language and the solver package used is FICO™ Xpress Optimization Suite by Dash Optimization. All tests are performed on a computer with an Intel Xeon QuadCore E5472 3.0 GHz processor, 16 GB of RAM and running on a Linux operating system. Fr all problem instances the maximum computational time was set to one hour (3600 seconds), and the optimality gap tolerance was set to 1 %.

We test how the mathematical model behaves when changing the number of turbines, time periods and wind farms in the input data. Initial tests revealed that 50 scenarios is sufficient to reach a good level of in-sample stability, whereas out-of-sample stability requires fewer scenarios. The results are shown in Tables 3–5. We report the expected value of perfect information (EVPI), the value of the stochastic solution (VSS), the computational time (CPU), and the optimality gap (Gap). The optimality gap is calculated as the difference between the best primal and dual solutions found by the branch-and-bound search, divided by the best primal solution.

EVPI is calculated as the difference between the objective value of the stochastic programming model given in Section 3, and the average objective value obtained by solving the same model for one scenario at a time, known as the wait-and-see solution. The EVPI thus gives the difference in objective value between the proposed model, and the best decisions that could have been made given that we have perfect information regarding the future. It is obviously not possible to know the future, so a more accurate interpretation of the EVPI may be as the potential for improving the decisions taken by investing in equipment or expertise to better predict future events. For this particular problem it may indicate whether it is worthwhile to invest in more expensive condition monitoring equipment on the turbines and develop more complex weather forcasting models to obtain better estimates of the exact realisations of failures and weather conditions in coming months, or if knowing the statistical properties of these uncertain parameters is sufficient.

VSS is calculated as the difference between the objective value of the stochastic model, and the value obtained by first solving the expected value problem (EVP) where all uncertain parameters are set to their expected value, and then solving the stochastic model with the first stage solution fixed to correspond with the solution of the EVP. The VSS thus gives a measure of how much the solution may improve by using a stochastic optimization approach, compared to just using the average values of the uncertain parameters in a deterministic optimization model. If the value of the

VSS is low, this indicates that there is little to be gained by using a stochastic programming model compared with a deterministic model using average values of the uncertain parameters. Conversly, a large value of the VSS indicates that the stochastic model gives an added value to the solution process.

Table 3. Computational results for problem instances with 25 time periods, 50 scenarios, and one wind farm. For each number of turbines 10 instances has been randomly generated and solved. The values reported are the average of those 10 instances.

# of turbines	VSS [%]	EVPI [%]	CPU [secs.]	Gap [%]
20	48.53	−0.03	1428	0.01
30	27.68	−0.02	83	0.00
40	16.12	0.00	322	0.01
60	4.95	0.33	3601	0.27
80	−0.29	1.59	3605	2.12
100	0.09	0.50	3601	5.43
150	−0.13	0.19	3602	4.97
200	0.17	0.08	3602	1.95
300	−0.24	0.30	3602	3.04

Table 4. Computational results for problem instances with 40 turbines, 50 scenarios, and one wind farm. For each number of turbines 10 instances has been randomly generated and solved. The values reported are the average of those 10 instances.

# of periods	VSS	EVPI	CPU [secs.]	Gap [%]
5	0.00 %	−0.01 %	1	0.00 %
10	0.00 %	−0.01 %	3	0.00 %
15	0.00 %	−0.01 %	5	0.00 %
20	0.00 %	−0.01 %	57	0.00 %
25	16.12 %	0.00 %	322	0.00 %
30	4.00 %	0.94 %	2078	0.03 %

Table 3 reports the results for problem instances with a varying number of wind turbines. EVPI is low, below 1.6 % for all instances, while the VSS is decreasing with the number of wind turbines, reaching a negligible level when there are 80 or more turbines in one wind farm. These results indicate that when a wind farm grows, the uncertainty in the number of failures and the available time for vessels per 3-month period becomes less important, and the value of a stochastic model diminishes. This result can be partly explained by less variation in the number of corrective maintenance activities when there is an increasing number of turbines. The negative values for VSS in some instances can be explained by the optimality gap settings used when solving the stochastic model.

Results for problem instances with a varying number of time periods is shown in Table 4. EVPI is low and less than 1 % for all problem instance. VSS is low except for certain lengths of the planning horizon. Finally, Table 5 shows results for problem instances with a varying number of wind farms. Again, we see that EVPI is low. We observe that VSS decreases as the number of wind farms increases. This is in line with the results from Table 3, as VSS decreases with an increasing number of turbines.

Table 5. Computational results for problem instances with 40 turbines per wind farm, 25 time periods, and 10 scenarios.

Number of wind farms	EVPI [EUR]	EVPI [%]	VSS [EUR]	VSS [%]	CPU [secs.]
1	96025	0.1	7450520	11.4	3
2	206626	0.3	6026756	7.3	13
3	157027	0.2	5119201	5.4	6
4	185194	0.2	3576172	3.6	99
5	253613	0.2	3168340	3.1	867

The computational experiments show that the mathematical model presented in this paper provide close to optimal fleet size and mix decisions within short CPU times. The model provides significant added value compared with the deterministic counterpart in some instances. Closer inspection reveals that much of the VSS comes from the costly investments in a jack-up rig. The stochastic model is more reluctant to purchase such a rig, preferring to charter in whenever needed for small wind farms. The deterministic expected value problem is eager to invest in a rig, not being able to see that the special demand for the rig will be irregularly distributed.

5. Concluding remarks

The offshore wind industry is relatively young and in a development stage, and it is essential to find methods to reduce costs. The offshore element makes operation and maintenance (O&M) activities expensive, and an important means to reduce the costs are to keep a suitable fleet of vessels and helicopters with a suitable infrastructure of onshore and offshore bases.

We have presented a two-stage stochastic programming model to determine a cost-optimal fleet size and mix for O&M activities at offshore wind farms for long planning horizons. This is an important addition to the literature, as previous stochastic models have only considered planning for a single year [7]. Emphasis has been put on developing a model that can be solved for realistically sized problem instances. The computational study showed that for some instances it is valuable to take uncertainty in demand and weather conditions into account. However, it is surprising that the value decreases for larger wind farms, and it is possible that for this particular problem the details of the tactical planning cannot be simplified as much as commonly believed [13]. With a more detailed representation of the tactical planning, the model will quickly become impractical to solve, and this appears to be a challenging prospect for future research.

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