A Decision Support System for Vessel Fleet Analysis for Maintenance Operations at Offshore Wind Farms

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December 2016

Abstract:

This paper presents a decision support system (DSS) for determining the optimal fleet of vessels and helicopters to support maintenance operations at offshore wind farms. This vessel fleet is used to transport maintenance technicians and spare parts to and from the wind farm, and to execute lifts of heavy parts onto the turbines. The cost of the vessel fleet constitutes a major part of the maintenance cost for an offshore wind farm and hence having a cost efficient fleet is essential to reduce the cost of energy. The DSS uses a stochastic optimization model to solve the vessel fleet size and mix problem, and returns the optimal fleet of vessels and other relevant problem output to the decision maker. To test the performance of the DSS, a computational study in three parts is conducted. First, we perform a verification of the underlying mathematical model by comparing results to leading work from the literature, before conducting both in-sample and out-of-sample stability testing to verify that our stochastic modelling approach give stable results that capture the uncertainty of the problem. Finally, we demonstrate how the DSS can help offshore wind farm operators and vessel developers to improve their decision making.

Keywords: Offshore Wind; Operations Research; Decision Support; Fleet Size and Mix; Maintenance

1 Introduction

The offshore wind industry is young and rapidly growing: The installed capacity of offshore wind in Europe has increased from less than 40 MW in 2000 to 8 GW by the end of 2014, and currently, 12 new projects are under construction with a planned total installed capacity of 2.9 GW (1). However, a major challenge for the industry is that the operating costs are high, making it difficult to operate profitably without government subsidies. The cost of energy needs to be reduced, and it is therefore essential to consider cost reductions in all parts of the value chain to make offshore wind a competitive alternative to other energy sources. One of the major cost components of operating an offshore wind farm are the cost of executing maintenance activities, which is expected to account for up to 25% of the total life-cycle cost for an offshore wind farm (2). The maintenance activities needed to be executed at offshore wind farms during the operational phase are more challenging than their onshore counterpart due to the rougher environment to which the turbines are exposed. Compared to onshore wind turbines, the turbines at offshore wind farms are more prone to breakdowns and the accessibility to the wind farm sites are limited and uncertain due to unpredictable weather conditions. At the same time, as the offshore wind industry grows, the wind farms are moving further offshore, limiting the access to the wind farm site and increasing the costs of the maintenance activities.

To minimize the maintenance costs it is important to ensure that the resources available to support and execute the maintenance activities are employed efficiently, and that the right resources are procured. The most expensive resources in the operation and maintenance (O&M) phase of an offshore wind farm are the vessels and helicopters used to support the maintenance activities. As offshore wind is a relative new industry, new and innovative vessel concepts are being designed, and it is expected that many more will be launched to the market in the near future. With many concepts to choose from, all with their strengths and weaknesses, it is difficult for the wind farm operators to select a fleet of vessels that will minimize the total O&M costs of their wind farm. The best vessel fleet to support maintenance activities at an offshore wind farm depend on many factors such as the size of the wind farm, the weather conditions at the site, and the distance to shore. Combining this with the fact that the number of possible fleets grows exponentially as the number of vessel types increase, it becomes evident that a decision maker needs help determining the best fleet of vessels for a given offshore wind farm. Similarily vessel designers and developers needs to be able to analyze what type of wind farms their vessels are suited for, to quantify the economic advantages to the offshore wind supply chain that comes from procuring their vessels.

This paper presents a decision support system (DSS) for vessel fleet analysis for maintenance activities at offshore wind farms. The DSS can be used by wind farm operators both when planning for the operational phase to decide on the optimal fleet of maintenance vessels and helicopters, and during the operational phase when it is necessary to make updates to the existing maintenance fleet. It can also be used by other actors in the offshore wind industry, e.g. by vessel design companies to evaluate new vessel concepts, or to analyze at what charter rates a given vessel concept is competitive. The DSS has been developed in cooperation with the Norwegian energy companies Statkraft and Statoil who both have a lot of experience from owning and operating offshore wind farms in Europe. Both companies have been active participants in the development of the DSS, and have given invaluable feedback throughout the development process.

Only a few optimization based approaches for analyzing vessel fleets for maintenance activities at offshore wind farms have been studied previously. In (3) and (4) a deterministic and a stochastic mathematical programming formulation for the problem are presented, and (5) demonstrates the effects of single- and multi-parameter wave criteria in simulation and optimization models for strategic maintenance and logistic problems for offshore wind farms. Other than these studies, there has been little work that involves the use of optimization models for solving the fleet size and mix problem for offshore wind farms. For an overview of related fleet size and mix problems, we refer the reader to the survey conducted by (6).

Some other examples, not directly related to the problem studied in this paper, are (7) that presents a deterministic optimization model for the routing and scheduling problem for a maintenance fleet, and (8)-(9) that present a deterministic and stochastic optimization model for opportunistic maintenance at offshore wind farms. A review of DSS for offshore wind farms with emphasis on O&M strategies is provided in (10), where a total of 49 models were reviewed, most of them being simulation models. Two examples of simulation models are presented in (11) and (12).

The problem with the optimization models presented in (3) and (4) is that they use the simplification that each vessel has a number of units of time available each day, and these time units are assigned to maintenance activities. Though this may make sense in a vessel fleet size and mix model, it may produce results that a user of a DSS finds nonintuitive, and thus not thrustworthy. E.g. it may result in a vessel spending its shift doing two hours of repair on six different maintenance tasks that each takes four hours to complete, instead of completing three of those maintenance tasks. Additionally, it may overestimate the number of maintenance activities each vessel is capable of performing in each shift. Thus, one major objection to the two models above from wind farm operators was that the actual shift plans generated by the model were infeasible or unreasonable. In this work we remedy this by generating sets of actual feasible shift plans for each vessel as input to a stochastic optimization model to determine the optimal vessel fleet size and mix for a given offshore wind farm.

The contributions of this paper include a demonstration of a decision support system that can be used by both wind farm operators to analyse their need for maintenance vessel fleet, and other actors in the offshore wind industry that are developing new concepts and tools for the operational phase at offshore wind farms. A new pattern-based stochastic mathematical model formulation for the fleet size and mix problem for maintenance activities at offshore wind farms forms the basis of the DSS, and solves the underlying optimization problem of determining a cost-effective vessel fleet size and mix. A computational study demonstrates the strengths and flexibility of the DSS and part of the broad range of analysis it can be used to support.

The remainder of this paper is organized as follows: Section 2 provides an overview of the fleet size and mix problem for maintenance activities at offshore wind farms, while Section 3 presents a mathematical formulation of the problem. An overview of the decision support system, including a detailed description of all its main components, is provided in Section 4. The computational study is presented in Section 5, before the paper is concluded in Section 6.

2 Problem Description

The fleet size and mix problem for maintenance activities at offshore wind farms consists of determining an optimal fleet of vessels and helicopters, and their corresponding infrastructure that can be used to support all, or most of, the maintenance activities during a given planning horizon. To determine this optimal fleet, we need to describe the logistic challenges of using the fleet to support maintenance activities. In the remainder of this paper we will use the collective terms *vessel* and *vessel fleet* to describe the maintenance fleet resources that may consist of both vessels and helicopters.

The maintenance activities that need to be executed can be divided in two main categories: Preventive and corrective. Preventive, or scheduled, activities are executed with the aim of prolonging the lifetime of a wind turbine or other wind farm components, and to keep the number of breakdowns at a reasonable level. When and how often such activities are to be executed depend on the type of turbines and components, and the wind farm operator's maintenance strategy. Typical frequency is suggested to 1-2 turbine visits every year with a major overhaul every 5 years (13). Component failures that results in system breakdowns and the need for repair and/or replacement result in corrective maintenance activities. These are distinctively different from preventive activities as they are unforeseen and result in an immediate loss of production that will continue until the necessary activity has been executed. Hence, it is beneficial to execute these types of activities as quickly as possible to minimize revenue losses.

Each activity type, both preventive and corrective, are associated with an estimated duration, a required number of maintenance technicians to execute the activity, a set of required spare parts, and an estimated cost. Preventive maintenance activities are divided into types, and there is a number of required preventive activities of each type. Corrective maintenance activities are divided into both types and individual activities as the demand for each such activity appears when a failure occurs. There is downtime costs associated with the activities due to lost electricity production. For preventive activities, this downtime cost will only be related to the time it takes to execute the activity, i.e. when the turbines need to be temporarily shut-down due to maintenance work. Hence, these types of activities may be beneficial to execute when the wind speed is expected to be low, i.e. when the loss in electricity production is low. The downtime cost for corrective maintenance activities are related to when a breakdown occur: There will be lost electricity production that accumulates from the time the breakdown occurs and until the corrective maintenance activity has been executed.

A fleet of vessels is needed to support the maintenance activities. All vessels need to be associated with a base that can be an onshore port, an offshore base, e.g. an offshore station or a mother vessel, or an airfield for helicopters. A mother vessel is a new concept developed for the offshore wind industry consisting of a large vessel that function as a base for both smaller daughter vessels and/or helicopters and provides accommodation for maintenance technicians. In addition, the mother vessel may support maintenance activities, and have crane capacity that enables support to activities that require heavy lift operations.

The vessels travel between their base and the offshore wind farm site. Vessels are divided into types, where each type have different characteristics such as sailing speed, lifting capacity, maintenance technician transfer capacity, access system, weather limitations for when technicians may be safely transferred from the vessel to a given wind turbine, and weather limitations for when the vessels cannot stay offshore and need to return to a safe haven. The characteristics of the vessel types determine which maintenance activities they can support. A vessel may be used to support one single activity at a time, or it may support several activities in parallel, i.e. drop of a team of technicians at one turbine before moving to another turbine to drop of another team. How many activities that can be supported in parallel are restricted by the vessel capacity, the activity type and health, safety and environment (HSE) requirements.

Vessels have both variable and fixed costs. Variable costs are all costs associated with using the vessels, and will be accumulated depending on how much the vessel is in operation during the planning horizon. Fixed cost will in most cases be the time charter costs for the vessels, as vessels are likely to be time chartered on either a long- or a short term basis. For vessels that are time chartered for a longer period than the planning horizon, the fixed costs will be the time charter costs associated with the planning horizon. For vessels that are not time chartered but rather purchased by the offshore wind farm operator, the fixed costs will be the depreciated investment costs for the vessel over the planning horizon.

All vessel bases, e.g. ports, offshore stations and mother vessels, have a given distance from the offshore wind farm site, a given vessel capacity, and a given maintenance technician capacity. They may also be given a cost that can correspond to e.g. the depreciated investment costs for the base over the planning horizon or fixed and variable cost associated with using a specific base.

Some assumptions are made with regards to the operational phase of standard offshore wind farms:

- All vessels are associated with exactly one base
- All vessel trips begin at and return to the vessel's base
- Vessels that are short term time chartered must be chartered for a given number of time periods, and the set of possible time charter periods are not overlapping
- Vessels operate in shifts that are a time frame set by the number of consecutive hours the maintenance technicians may be working
- Each shift starts when a vessel leave its base and ends when it returns to the same base

Some vessel types can operate offshore for several shifts before returning to base, and these are given an artificial base located at the wind farm. A special case is jack-up type vessels and other vessel types that are used to support maintenance activities that may take several days, and hence, does not return to base until the activity is finished. Some vessel types, e.g. mother vessels, have properties of both a base and a vessel.

3 Mathematical model

To find the optimal fleet of vessels to support maintenance activities at an offshore wind farm we have developed a two stage stochastic optimization model. The first stage decisions are which bases to use, and which vessels to charter both on long term and short term contracts. For short term contracts we also need to select the month to charter the vessels. The second stage decisions are to determine which maintenance activities to support by which vessel on each day of the planning horizon for each scenario. The scenarios consist of realizations of weather conditions and failures that require corrective maintenance activities. We have chosen a model formulation where all possible *maintenance patterns* that each vessel type may execute during a shift are generated, and the model chooses a combination of these to satisfy the demand for O&M activities during the planning horizon for each scenario.

In this section we present the stochastic optimization model as its scenario-tree deterministic equivalent. We start by introducing all sets, parameters and variables before we present the mathematical model.

Sets used in the model are as follows:

K Set of potential bases

K^C Set of pairs of bases where at most one may be used

V Set of available vessel types including helicopters

V_k Set of available vessel types that can operate from base k, $k \in K$, $V_k \subseteq V$

W_{kv} Set of all possible maintenance patterns that may be executed by a vessel of type v operating from base k, $k \in K$, $v \in V_k$

N Set of all types of maintenance activities

N_v Set of maintenance activity types that can be supported by vessels of type v, $v \in V$, $N_v \subseteq N$

V_i Set of available vessel types that can support maintenance activities of type i, $i \in N$, $V_i \subseteq V$

N^P Set of preventive maintenance activity types, $N^P \subset N$

N^C Set of corrective maintenance activity types, $N^C \subset N$

N^C_{is} Set of corrective maintenance activities of type i in scenario s, $i \in N^C, s \in \mathcal{S}$

P Set of time periods in the planning horizon

P_v Set of time periods where vessels of type v can operate, $v \in V$, $P_v \subseteq P$

P_{vijs} Set of time periods where vessels of type v can support corrective maintenance activity j of type i in scenario s, $v \in V$, $i \in N^C \cap N_v$, $s \in \mathcal{S}$, $j \in N^C_{is}$, $P_{vijs} \subseteq P_v$

P_{kvws} Set of time periods where vessels of type v operating from base k can execute maintenance pattern w in scenario s, $k \in K$, $v \in V_k$, $w \in W_{kv}$, $s \in \mathcal{S}$, $P_{kvws} \subseteq P_v$

P^T Set of sets of time periods for short term charter of vessels, $P^T \subset P$

$\mathcal{S}$ Set of scenarios

Parameters are:

C^F_k Fixed yearly cost of operating base k, $k \in K$

C^F_v Yearly time charter cost or depreciation cost for vessels of type v, $v \in V$

C^F_{vt} Time charter cost for vessels of type v for the set of time periods t, $v \in V$, $t \in P^T$

C^D_{ips} Downtime cost when executing preventive maintenance activity i in period p in scenario s, $i \in N^P$, $p \in P, s \in \mathcal{S}$

C^D_{ijps} Downtime cost when executing corrective maintenance activity j of type i in period p in scenario s, $i \in N^C$, $j \in N^C_i$ $v \in V_i, s \in \mathcal{S}, p \in P_{vijs}$

C_{kvwps} Cost of a vessel of type v operating from base k executing shift pattern w in time period p in scenario s, $k \in K$, $v \in V_k$, $w \in W_{kv}, s \in \mathcal{S}, p \in P_{kvws}$

C_i^P Penalty cost associated with not executing a maintenance activity of type i during the planning horizon, $i \in N$

A_i Number of preventive maintenance activities of type i that may be executed during the planning horizon, $i \in N^P$

A_{iw} Number of maintenance activities of type i that is executed in shift pattern w, $i \in N$, $v \in V_i$, $w \in W_{kv}$

M_k Maintenance technicians available per shift at base k, $k \in K$

M_v Capacity for transportation of maintenance technicians at vessels of type v, $v \in V$

E_k Equal to 1 if base k must be used, 0 otherwise, $k \in K$

E_{kv} Number of vessels of type v at base k that must be used, $k \in K$, $v \in V_k$

Q_{vt}^{MX} Maximum number of vessel of type v available for time charter in the set of time periods t, $v \in V$, $t \in P^T$

Q_{kv} Maximum number of vessels of type v that can operate from base k, $v \in V$, $k \in K$

P_s Probability of scenario $s \in \mathcal{S}$

The variables are the following:

$$\delta_k = \begin{cases} 1, & \text{if base } k \text{ is used, } k \in K \\ 0, & \text{otherwise} \end{cases}$$

$$y_{vijps} = \begin{cases} 1, & \text{if corrective maintenance activity number } j \text{ of type } i \text{ is supported by a} \\ & \text{vessel of type } v \text{ in period } p \text{ in scenario } s,\ v \in V,\ i \in N^C \cap N_v,\ j \in N_{is}^C,\ s \in \mathcal{S},\ p \in P_{vijs} \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ijs} = \begin{cases} 1, & \text{if corrective maintenance activity number } j \text{ of type } i \text{ is not executed in scenario } s \\ & \text{during the planning period, } i \in N^C,\ s \in \mathcal{S},\ j \in N_{is}^C \\ 0, & \text{otherwise} \end{cases}$$

x_{kv}^L Number of vessels of type v operating from base k that are available for the entire planning horizon, $k \in K$, $v \in V_k$

x_{kvt}^S Number of vessels of type v operating from base k on time charter in the set of time periods t, $k \in K$, $v \in V_k$, $t \in P^T$

λ_{kvwps} Number of vessels of type v operating from base k that are executing maintenance pattern w in time period p in scenario s, $k \in K$, $v \in V_k$, $w \in W_{kv}$, $s \in \mathcal{S}$, $p \in P_{kvws}$

z_{is} Number of preventive maintenance activities of type i that has not been executed during the planning horizon in scenario s, $i \in N^P$, $s \in \mathcal{S}$

3.1 Objective function

The objective function minimizes the fixed costs of vessels and their corresponding bases, the variable costs of vessels executing maintenance patterns, the downtime costs associated with when the maintenance activities are executed, and the penalty costs of any maintenance activities that is not executed within the planning horizon. It is modeled as follows:

$$\min \sum_{k \in K} C_k^F \delta_k + \sum_{k \in K} \sum_{v \in V_k} C_v^F x_{kv}^L + \sum_{k \in K} \sum_{v \in V_k} \sum_{t \in P^T} C_{vl}^F x_{kvt}^S + \sum_{s \in \mathcal{S}} P_s \Bigg[\sum_{v \in V} \sum_{i \in N^C \cap N_v} \sum_{j \in N_{is}^C} \sum_{p \in P_{vijs}} C_{ijps}^D y_{vijps} + \sum_{k \in K} \sum_{v \in V_k} \sum_{w \in W_{kv}} \sum_{i \in N^P \cap N_v} \sum_{p \in P_{kvws}} C_{ips}^D A_{iw} \lambda_{kvwps} + \sum_{k \in K} \sum_{v \in V_k} \sum_{w \in W_{kv}} \sum_{p \in P_{kvws}} C_{kvwps} \lambda_{kvwps} + \sum_{i \in N^P} C_i^P z_{is} + \sum_{i \in N^C} \sum_{j \in N_{is}^C} C_i^P z_{ijs} \Bigg]. \tag{1}$$

The first three terms of the objective functions include the first stage decisions of the model. The first term of the objective function is the total cost of operating the bases, including capital and operational costs. The second and third term are the time charter costs, or capital costs, associated with vessels that are in the fleet the whole planning horizon and that are time chartered for shorter parts of the planning horizon, respectively.

Term four to eight cover the second stage decisions of the model, and are multiplied with the probability of each scenario. The fourth and fifth terms are the downtime costs for corrective and preventive maintenance activities, respectively. The sixth term is the variable cost of vessels executing maintenance patterns. Finally, the seventh and eight terms add penalty costs to preventive and corrective maintenance activities that are not executed within the planning horizon.

3.2 First stage constraints

The first stage constraints in the mathematical model are the following:

$$x_{kv}^L + x_{kvt}^S \leq Q_{kv} \delta_k, \qquad k \in K, v \in V_k, t \in P^T, \tag{2}$$

$$\delta_{k1} + \delta_{k2} \leq 1, \qquad (k1, k2) \in K^C, \tag{3}$$

$$\delta_k \geq E_k, \qquad k \in K, \tag{4}$$

$$x_{kv}^L \geq E_{kv}, \qquad k \in K, v \in V_k, \tag{5}$$

$$\sum_{k \in K} x_{kvt}^S \leq Q_{vt}^{MX}, \qquad v \in V, t \in P^T, \tag{6}$$

$$\delta_k \in \{0, 1\}, \qquad k \in K, \tag{7}$$

$$x_{kv}^L \in Z^+, \qquad k \in K, v \in V_k, \tag{8}$$

$$x_{kvt}^S \in Z^+, \qquad k \in K, v \in V_k, t \in P^T. \tag{9}$$

Constraints (2) state that the total number of vessels operating from a base in any given short term time charter period cannot exceed the capacity at that base, while constraints (3) ensure that at most one of two non-compatible bases are used. Then constraints (4) and (5) ensure that existing bases and vessels are included in the optimal solution, and constraints (6) limit the number of vessels time chartered per charter period to the maximum number available. Finally constraints (7) – (9) put binary and integral requirements on the variables.

3.3 Second stage constraints

The second stage constraints of the mathematical model are the following:

$$\sum_{k \in K} \sum_{v \in V_k \cap V_i} \sum_{w \in W_{kv}} \sum_{p \in P_{kvws}} A_{iw} \lambda_{kvwps} + z_{is} = A_i, \qquad i \in N^P, s \in \mathcal{S}, \tag{10}$$

$$\sum_{v \in V_i} \sum_{p \in P_{vijs}} y_{vijps} + z_{ijs} = 1, \qquad i \in N^C, s \in \mathcal{S}, j \in N_{is}^C, \tag{11}$$

$$\sum_{k \in K} \sum_{w \in W_{kv}} A_{iw} \lambda_{kvwps} - \sum_{j \in N_{is}^C} y_{vijps} = 0, \qquad v \in V, i \in N^C \cap N_v, p \in P_v, s \in \mathcal{S}, \tag{12}$$

$$\sum_{w \in W_{kv}} \lambda_{kvwps} \leq x_{kv}^L + x_{kvt}^S, \qquad k \in K, v \in V_k, p \in P_v, t \in P^T | p \in t, s \in \mathcal{S}, \tag{13}$$

$$\sum_{v \in V} \sum_{w \in W_{kv}} M_v \lambda_{kvwps} \leq M_k \delta_k, \qquad k \in K, p \in P, s \in \mathcal{S}, \tag{14}$$

$$\lambda_{kvwps} \in Z^+, \qquad k \in K, v \in V_k, w \in W_{kv}, s \in \mathcal{S}, p \in P_{kvws}, \tag{15}$$

$$y_{vijps} \in \{0,1\}, \qquad v \in V, i \in N^C \cap N_v, s \in \mathcal{S}, j \in N^C_{is}, p \in P_{vijs}, \tag{16}$$

$$z_{is} \in Z^+, \qquad i \in N^P, s \in \mathcal{S}, \tag{17}$$

$$z_{ijs} \in \{0,1\}, \qquad i \in N^C, s \in \mathcal{S}, j \in N^C_{is}. \tag{18}$$

Constraints (10) and (11) ensure that all preventive and corrective maintenance activities are executed during the planning horizon or given a penalty in the objective function, while constraints (12) maps each corrective maintenance activity to a specific time period and vessel. Then, constraints (13) make sure that there are sufficient vessels available to execute all the vessel maintenance patterns that are used in any given time period, and constraints (14) state that vessels can only operate out of a base that is used during the planning horizon, and ensure that the maximum number of available maintenance technicians at that base is not exceeded. Finally constraints (15) – (18) put binary and integral requirements on the variables.

4 Decision support system

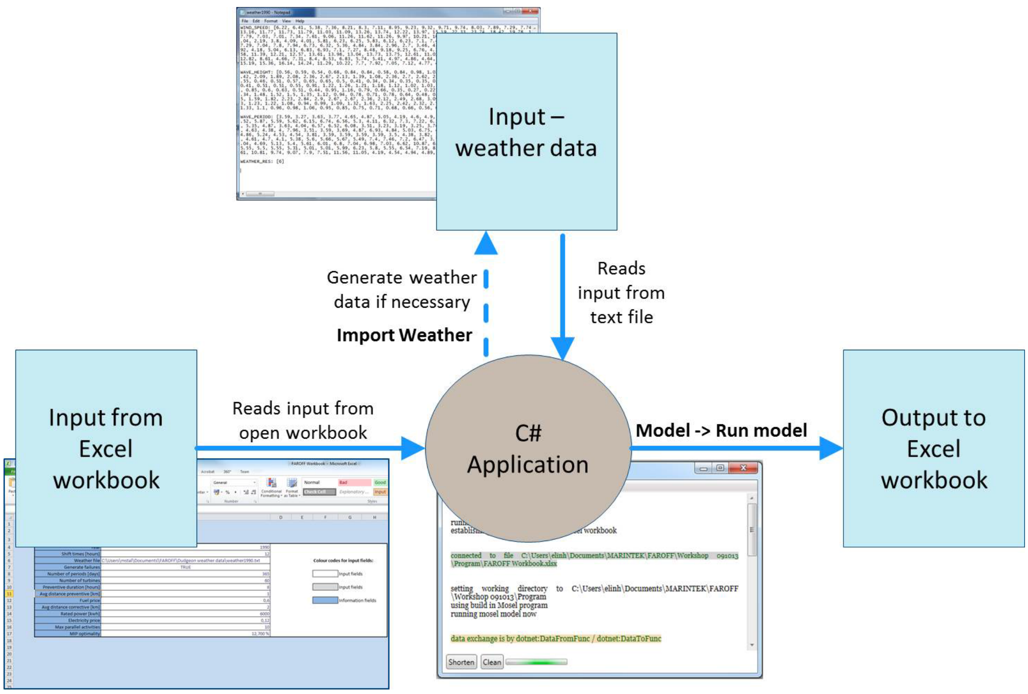

Figure 1: Overview of decision support system

In this section we provide an overview of the DSS created for finding the optimal fleet of vessels to perform maintenance at an offshore wind farm, and describe in detail how the stocastic optimization model from Section 3 is solved. An overview of the DSS is shown in Figure 1. The decision support system has a Microsoft Excel user interface, and a C# application that transfer data, set up, and run the underlying stochastic optimization model. The input data is used to assign values to the sets and parameters described in Section 3, or in some cases data needed to calculate the given parameters. The DSS then reads this data from the spreadsheet and sets up and runs the stochastic optimization model using the commercial software FICO Xpress. Once the optimal solution to the stochastic optimization model is found, the results are transferred back to the spreadsheet. The DSS does not only present the optimal fleet of vessels, but also additional information regarding the solution. This includes a break down of the cost structure of the solution, and information regarding the usage of the fleet both in terms of number of shifts per month, and monthly usage as a percentage of the availability of the fleet. It is also possible to go into greater detail and see what each vessel is doing on a given day in a given scenario. This last part is important to ensure that the user trusts the DSS by enabling him to verify that the underlying operational plans are reasonable. A screenshot of some of the output charts from the DSS, together with the application itself, is shown in Figure 2.

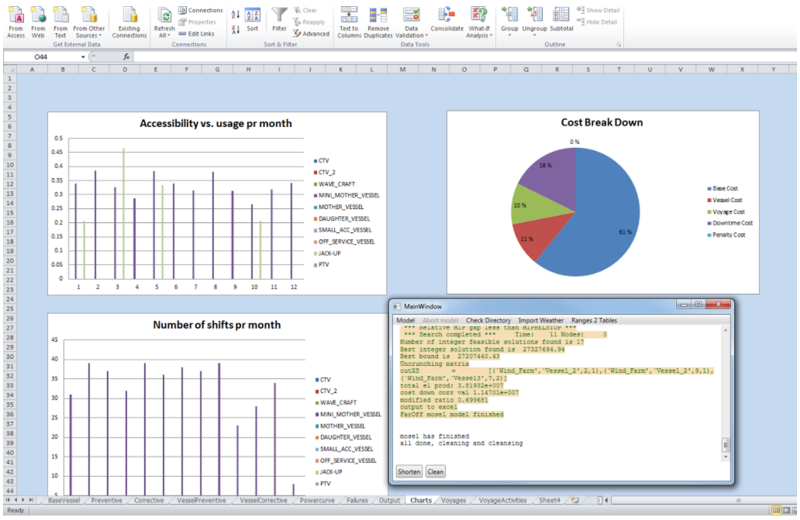

Figure 2: Screenshot of the charts sheet in the Excel workbook, and the C# application.

In the remainder of this section we describe in detail the solution process used by the DSS to find the optimal vessel fleet based on the stochastic optimization model presented in Section 3. The process is divided into three steps, where the first one is to generate a set of scenarios $\mathcal{S}$ for the model. The second step is to generate all possible working shifts (or patterns) for each vessel. Once step one and two is completed, the mathematical model presented in Section 3 can be solved. In the following we go through each step in detail.

4.1 Generate new set of scenarios

Each scenario represents one possible planning problem for one year of O&M activities and consists of two types of uncertainty: weather data and realization of corrective maintenance activities. Given that the weather conditions is one of the key aspects when choosing the site of an offshore wind farms, operators usually have detailed historical weather data and/or a good weather model for the site in question. Thus, rather than implementing a separate weather model for the DSS, it take weather files as input and formats them to fit with the stochastic model. If the granularity of the historical weather data is smaller than the weather resolution of the model, the weather generation procedure uses the maximum wave height and wind speed from each time interval defined by the weather resolution. I.e., if the weather data is provided on an hourly basis, and the weather resolution is 6 hours, the weather generation procedure will return the highest wave height and wind speed from each 6 hour interval. For the purpose of scenario generation we choose one year of weather data randomly for each scenario, producing the sets H_{ps}^{WA} and H_{ps}^{WI} which are the significant wave height and wind speed in period p in scenario s, respectively.

The corrective maintenance activities that need to be executed at the offshore wind farm during the planning horizon are results of failures at individual wind turbines. The optimization model treats the realization of future failures as known at the planning stage. The failure set N_{is}^{C} must be generated for each scenario s and corrective maintenance type i before the optimization model can find the best vessel fleet.

Failures are binary events: either a failure occurs at a certain time or it does not. The failure rates are given in the input data as the expected number, x_i, of failures per turbine per year for each maintenance type i. Assuming that failures are uniformly distributed over the planning horizon, the expected number of failures per time step and turbine is therefore the same for all time periods and equal to $p_i = x_i/N$, where N is the number of time periods. This number should be within $[0, 1]$, since it represents an individual probability of one turbine failing within one time period. The number of failures of n

turbines, all of the same type, is distributed according to a binomial distribution. The function $f(k, n, p)$ describes the probability that exactly k out of n turbine will fail, if the individual probability is equal to p:

$$f(k, n, p) = \binom{n}{k} p^k (1-p)^{n-k}.$$

The binomial coefficient is part of a Pascal diagram, which is the base of an efficient calculation of the probability mass function and then the cumulative density function. The generation of a new set of failures is based on the well-known method of first generating uniform distributed values and then using the inverse of the cumulative density function. This is carried out for each step of the planning horizon.

4.2 Generate all feasible maintenance patterns for vessels

The mathematical model presented in Section 3 relies on the generation of all possible maintenance patterns for all the vessel types for all time periods of the planning horizon. In this section we will describe the overall methodology on how the maintenance patterns are generated. Sets and parameters used in this section have the same definition as in Section 3. All new sets and parameters are introduced as they appear in the text.

Each maintenance pattern describes the potential maintenance activities a given vessel type can support during a work shift. These shifts cannot be longer than the maximum number of hours maintenance technicians can work during a work-day. This is typically 12 hours. For vessel types that can stay offshore for several shifts before returning to their associated base, we still define patterns the same way, and give the vessel types an artificial base at the offshore wind farm, that is, a base with zero travel distance to the wind farm. Jack-up type vessels and other vessel types that are used for heavy lifting operations, e.g. changing turbine blades and generators, will stay at the turbine for several shifts until the O&M activity it supports has been executed, and are treated as a special case.

A maintenance pattern will then consist of bundles of O&M activities that can be executed in parallel, i.e. where the vessel may drop off a team of maintenance technicians at one turbine before proceeding to another turbine dropping of another team, and activities that require the vessel to be present at the turbine, or at stand-by close to the turbine.

Bundles are characterized by the total execution time including time to drop of and pick up teams of maintenance technicians, the total cost of executing the activities in the bundle, the total required number of maintenance technicians, and a set of O&M activities. Bundles are generated according to Algorithms 1 and 2. Starting with an empty bundle for each vessel type, B_v, the procedure generates new bundles using a dynamic programming approach in a depth first manner.

Let b.Time, b.Cost, b.Tech, and b.List be the time used, cost, number of maintenance technicians, and list of activities executed in bundle b, respectively. bMax is the maximum number of O&M activities that can be executed in parallel. T_{vi}^{V} is the estimated time it takes for a vessel of type v to dock to a turbine and transfer the required number of maintenance technicians and spare parts as required of maintenance activity i. T_{vi} is the time it takes to execute O&M activity i if supported by a vessel of type v, and T_{v}^{MX} is the length of a work shift. C_{vi} is the total cost for executing O&M activity i if supported by a vessel of type v, and C_{vi}^{V} is the vessel cost, e.g. fuel consumption cost of using a vessel of type v to support activity i.

When all bundles for a given vessel type are generated, there will be many symmetric bundles, i.e. bundles that include the same O&M activities only listed in a different order. Hence, a *dominance procedure* is enforced that limit the number of bundles.

Let H_R be the chosen resolution for the weather input data. A bundle b_1 dominates b_2 if the following two criteria hold:

1. $\lfloor \frac{b_1.\text{Time}}{\text{H\_R}} \rfloor \leq \lfloor \frac{b_2.\text{Time}}{\text{H\_R}} \rfloor$

2. $b_1.\text{List} \supseteq b_2.\text{List}$

Note that these criteria do not imply exact dominance: We ignore cost as an extra O&M activity is always worth the additional fuel cost. We are also applying a somewhat simplified view on time: The chosen weather resolution determines how many parts each shift are divided into. Hence, there exists no shifts where b_2 can be used and b_1 cannot be used, given that criterion 1 holds.

When Algorithm 1 is finalized, it returns a set of non-dominated bundles for each vessel type. These bundles are then used to generate maintenance patterns. Maintenance patterns are generated for each base and vessel type combination and is characterized by the total execution time (w.Time), total cost of executing the maintenance pattern (w.Cost), and a set of O&M activities (w.List). For each feasible base and vessel type combination, we start by adding the time and cost of a return trip from base to the offshore

Algorithm 1 Generate bundles

```
for v ∈ V do
    initiate BundleSet B_v
    initiate Bundle b
    Build_Bundles(B_v, b)
    perform dominance procedure on B_v
    return B_v
end for
```

Algorithm 2 Build_Bundles(BundleSet B_v, Bundle b)

```
for i ∈ N_v do
    if v not needed at turbine then
        temp_time = max {b.Time + T^V_vi × 2, T^V_vi × 2 + T_vi}
        temp_cost = b.Cost + C^V_vi × 2 + C_vi
        temp_list = b.List ∪{i}
        temp_tech = b.Tech + M_i
        if temp_time ≤ T^MX_v and temp_tech ≤ M_v then
            create new bundle b' = (temp_time, temp_cost, temp_list, temp_tech)
            B_v = B_v ∪ {b'}
            if |b'.List| ≤ bMax then
                Build_Bundles(B_v, b')
            end if
        end if
    end if
end for
```

wind farm site. The remaining time can then be used to schedule bundles of parallel activities and non-parallel activities. We do this by applying a dynamic programming approach based on the recursive algorithm presented by Algorithms 3 and 4. In the algorithms, T^T_{kv} is the transit time of a return trip from base k to the wind farm site by a vessel of type v, and C^T_{kv} is the cost, i.e. fuel cost, of a return trip from base k to the wind farm site by a vessel of type v.

When all feasible maintenance patterns for all base and vessel type combinations, W_{vk}, have been generated, we need to find the feasible time periods during the planning horizon for each scenario s, P_{kvws}, where the maintenance patterns may be executed. These sets and parameters are created as shown in Algorithm 5. In the algorithm, H^{WAW}_v and H^{WIW}_v

Algorithm 3 Generate maintenance patterns

for $k \in K, v \in V_k$ **do**

  initiate PatternSet W_{vk}

  initiate Pattern w

  w.Time = T^T_{kv}

  w.Cost = C^T_{kv}

  w.List = { }

  Build_Patterns(W_{kv}, w)

  return W_{kv}

end for

are the significant wave height and wind speed limits for when vessels of type v can safely transfer maintenance technicians to the wind turbines.

4.3 Solve the optimization model

When all input data are available, including weather data and corrective O&M activities, and maintenance patterns are generated as described in Section 4.2, the mathematical model described in Section 3 may be solved. The mathematical model is solved using the commercial optimization software Xpress that can be used to solve e.g. mixed integer linear programs. To reduce the computational complexity, we relax the integer requirements on the λ-variables. In addition, the required optimality gap is a user input so the optimization algorithm terminates when the difference between the primal and dual bound is less than the input value.

5 Computational Study

The computational study presented in this Section is divided into four parts. The first part provides a brief overview of the test instances used when testing the DSS. Then the second part verifies that the DSS gives reasonable output, and the third part tests the underlying stochastic optimization model. Finally, the fourth part provides some example cases as to how the DSS may provide valuable decision support to a user. All tests have been run on a HP bl68c G7 computer, with four 2.2 GHz AMD Opteron 6274 16 core processors and 128 GB of RAM, and the optimality gap was set at 1 %.

Algorithm 4 Build_Patterns(PatternSet W_{kv}, Pattern w)

```
for i ∈ N_v do
  if v needed at turbine then
    temp_time = w.Time + T^V_vi × 2 + T_vi
    temp_cost = w.Cost + C^V_vi × 2 + C_vi
    temp_list = w.List ∪{i}
    if temp_time ≤ T^MX_v then
      create new pattern w′ = (temp_time, temp_cost, temp_list)
      W_vk = W_vk ∪ {w′}
      Build_Patterns(W_wk, w′)
    end if
  end if
end for
for b ∈ B_v do
  temp_time = w.Time + b.Time
  temp_cost = w.Cost + b.Cost
  temp_list = w.List ∪ b.List
  if temp_time ≤ T^MX_v then
    create new pattern w′ = (temp_time, temp_cost, temp_list)
    W_vk = W_vk ∪ {w′}
    Build_Patterns(W_wk, w′)
  end if
end for
```

5.1 Test instances

To test the DSS we have used the reference wind farm presented in (14). The main input data from their reference case can be found in Tables 1 – 3, and these will be used for the verification part of the model testing. However, to make the tests interesting when selecting a fleet size and mix we introduce some additional vessel types. The additional vessels are presented in Table 4. We have a fast, but expensive surface effect ship, one accommodation vessel that can stay offshore for multiple periods, and a mother vessel concept that includes two daughter vessels. We assume that all the additional vessel types can support the same set of maintenance activities as a CTV from the reference case.

Algorithm 5 Find_Periods(Base k, Vessel type v, Pattern w, Scenario s)

for $p \in P_v$ **do**
  temp_time = 0
  nr_periods = 0
  for $i = p$ to $\lceil \frac{T_v^{MX}}{24} \rceil$ **do**
    nr_periods = nr_periods + 1
    if $i \in P_v$ **then**
      for $j = 1$ to $\frac{w.Time}{H\_R}$ **do**
        $k = (p-1) * \frac{24}{H\_R} + j$
        if $H_{ks}^{WA} \leq H_v^{WAW}$ **and** $H_{ks}^{WI} \leq H_v^{WIW}$ **then**
          temp_time = temp_time + H_R
          if temp_time $\geq$ w.Time **then**
            $P_{kvws} = P_{kvws} \cup \{p\}$
            break to *end*
          end if
        end if
      end for
    end if
  end for
  end
end for

5.2 Verification of the model

To verify the model we have tested it on some of the reference cases for operation and maintenance at wind farms suggested by (14). We have chosen to use the following cases: *More CTVs, More Technicians, Failure rates up, No HLVs, Historical weather data*, and *Major replacements only.* The reason why we have not tested the *Base case* from (14) is that we have tested the model on historical weather data, which makes the case named *Historical weather data* a better comparison, since it removes one source of discrepancy: The weather generation procedures in the simulation models. It should be mentioned that since the tests in this verification work is on a fixed fleet, we had to fix the fleet in our DSS, so it does not do any optimization on the number of vessels that are long term chartered. However, it does optimize when, and for how long, jack-up and other heavy lifting vessels are chartered.

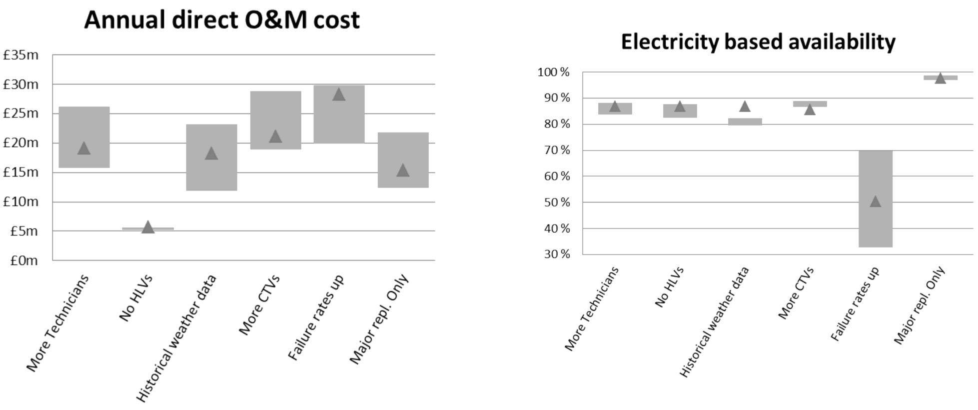

Figure 3: Comparison of the DSS and the simulation models presented by (14) when it comes to average annual direct O&M cost and electricity based availability. The triangle represents the value obtained by the DSS, while the grey area represents the range of values obtained by the simulation models.

The comparison of our model to the results presented by (14) related to direct O&M costs and electricity based availability can be seen in Figure 3. For all test cases the results are well within the range of results obtained by the four simulation models tested in (14) when it comes to total O&M costs, while we are a off by a few percent in two of the cases when comparing the electricity based availability. These results are likely to be related to the DSS' weather resolution that has a lower granularity than the simulation models, and picks the worst weather state within each time interval. Thus, the DSS slightly overestimate the downtime costs.

The most valuable comparison with the models presented in (14) is when comparing the total annual costs (including downtime costs) since it is this value that the DSS aims to minimize. This comparison is presented in Figure 4. As can be seen in the figure, the results are well within the range provided by the simulation models, and also in the lower end of the range for all cases except *Failure rates up*. For this case, the reason is that the simulation models are unable to execute all the preventive maintenance activities within a year, in contrast to our optimization model. As a consequence the total costs of repairs increase, even though the other costs are comparable.

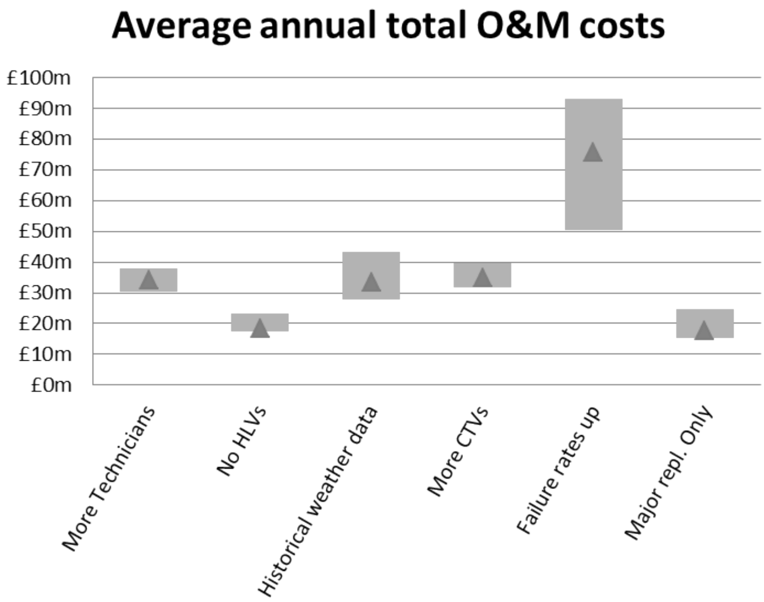

Figure 4: Comparison of the DSS and the simulation models presented by (14) when it comes to average annual total cost including downtime costs. The triangle represents the value obtained by the DSS, while the gray area represents the range of values obtained by the simulation models.

5.3 Testing the stochastic optimization model

Having confirmed that the DSS give reliable output for a fixed fleet of vessels, we next need to verify that the results of the stochastic optimization model are not just dependent on the generated scenarios, but on the actual uncertainty of the problem. To achieve this we have adopted an approach from (15) which suggests two procedures: In-sample and out-of-sample stability tests. These tests also give good indications as to how many scenarios are needed in the DSS to get good, stable results. All the following test have been done with the *No HLVs* test case from (14), but with the additional vessels from Table 4.

The in-sample stability tests show to what degree the optimal objective value of the mathematical model varies for different sets of scenarios. Let the optimal objective value of instance i with solution $\hat{x}_i$ and scenario-tree $\mathcal{T}_i$ be denoted as $f(\hat{x}_i, \mathcal{T}_i)$. The in-sample stability test can then be seen as verifying that:

$$f(\hat{x}_i, \mathcal{T}_i) \approx f(\hat{x}_j, \mathcal{T}_j) \tag{19}$$

holds for all pairs of test instances i and j.

To test the in-sample stability, we created 50 scenario-trees with 1-8 scenarios each, and solved all the resulting instances. Within each of the 50 instances with equally many scenarios, we calculated the average objective function value, and the standard deviation. Based on these values we created a 95 % confidence interval for the optimal objective value. A narrow interval indicates good in-sample stability.

Figure 5 shows the development in the 95 % confidence interval for the optimal objective value as the number of scenarios increases. We observe that the average objective function value increases with an increase in the number of scenarios. This occurs as the solutions become less tailored to the specific realization of the uncertain parameters of a given scenario. Further, the width of the confidence interval narrows with the increase in number of scenarios, indicating that the results stabilize. The confidence interval is quite narrow for these instances, deviating by less than 0.5 % from the average value.

Out-of-sample stability is checked by taking the optimal solutions from tests with different scenario-trees and then calculate the solutions' true objective value. Let $\mathcal{E}$ be the true distribution of the uncertainty in the model. The out-of-sample stability can then be

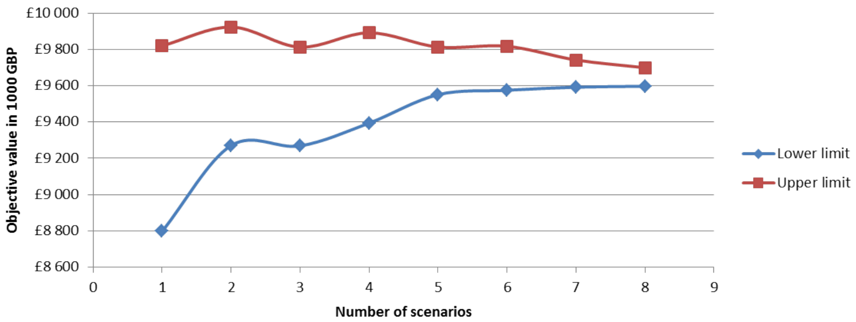

Figure 5: Figure showing how the 95 % confidence interval for the in-sample stability tests changes as a function of the number of scenarios in the scenario-tree.

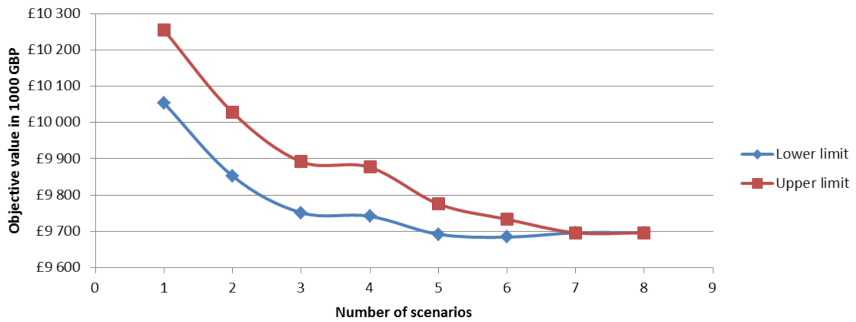

Figure 6: Figure showing how the 95 % confidence interval for the out-of-sample stability tests changes as a function of the number of scenarios in the scenario-tree.

expressed as verifying that:

$$f(\hat{x}_i, \mathcal{E}) \approx f(\hat{x}_j, \mathcal{E}) \tag{20}$$

holds for all pairs of test instances i and j.

Since $\mathcal{E}$ in this problem is a continuous distribution we approximate it by sampling. For our computational tests, we consider 200 scenarios to estimate $f(\hat{x}_i, \mathcal{E})$ for each of the solutions $\hat{x}_i$ obtained during the in-sample tests. Thus, for each solution $\hat{x}_i$ obtained by the in-sample tests, we have run the stochastic program 200 times with the first stage decisions fixed. In addition, we have for these tests re-introduced integral requirements of the λ-variables. Thus, we also get to test the impact of the relaxation in the stochastic model.

Figure 6 presents the results from the out-of-sample stability tests. We have, as for the in-sample tests, calculated the average and the standard deviation of $f(\hat{x}_i, \mathcal{E})$ over all test instances i with the same number of scenarios, and presents the graph showing a 95 % confidence interval. We observe a decrease in the average objective value when the number of scenarios increases. This is expected since the stochastic model will find fewer solutions that are tailored to a specific scenario's realization of uncertain parameters. Also, there is a decrease in the width of the confidence interval, and once we pass 7 scenarios, all scenario-trees give the same first stage solution to the problem, i.e. the same vessel fleet.

The objective of the in-sample and out-of-sample stability tests was to check that the solutions produced by our mathematical model, come from the behaviour of the model itself, and not from the scenario generation. The tests show that once the number of scenarios exceeds 5 we get relatively stable results in terms of low variance in the objective values. Further, we see from the out-of-sample tests, that once we exceed 7 scenarios we get the exact same objective value for all test instances, when the solution is re-evaluated over 200 scenarios. The out-of-sample stability tests converge on approximately 9.7 million GBP, while the in-sample stability tests converges towards approximately 9.65 million GBP. This indicates that we lose little in terms of estimating the correct cost and fleet, by relaxing the λ-variables in the stochastic model.

We also need to consider the computing time of the optimization model in a DSS. For a stochastic program, the computing time varies with the size of the scenario-tree. We have therefore calculated a 95 % confidence interval for the computing time for each set of tests having the same number of scenarios. The results are presented in Figure 7. When comparing the results of the in-sample and out-of-sample tests, with the computing times, we suggest that 5 scenarios give a good balance between quality and time. However, the user is free to adjust this number based on their preferences.

5.4 Example cases of the use of the DSS

Having confirmed that the stochastic model behaves correctly, and is capable of capturing the uncertainty of the problem, we now show some examples of problems that may be solved using the DSS. Below we present a set of examples. We have used the same test case as in Section 5.3, except for some features unique to each case. Each test have been run with a scenario-tree consisting of 5 scenarios. The detailed results of each test are summarized in Table 1.

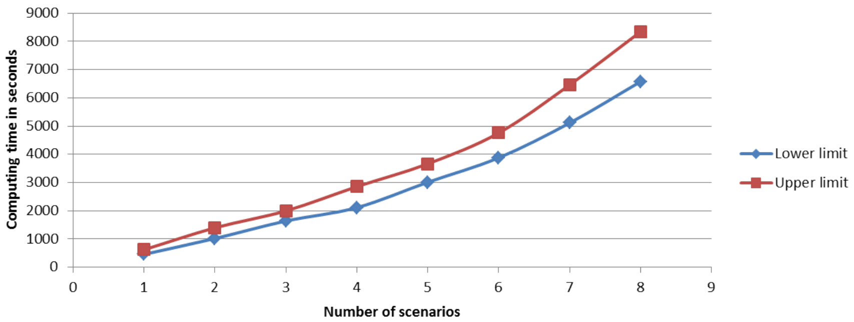

Figure 7: Figure showing how the 95 % confidence interval for how the computing time changes as a function of the number of scenarios in the scenario-tree.

5.4.1 Finding the optimal fleet

This is what we did in Section 5.3 and we just summarize the results here. The optimal vessel fleet for this instance is to long term charter two *Surface Effect ships* (SES).

5.4.2 Updating an existing vessel fleet

Assume that the wind farm operator has a current fleet of two CTVs. Even though we know that the optimal fleet is to long term charter two SES, the operator may want to keep the two CTVs currently in the fleet. Assuming that their cost is sunk, it may be better to keep them in the fleet and potentially charter one or more complementary vessel. Thus we solve the same case as before, but give the stochastic model an existing fleet of 2 CTVs.

The optimal fleet, according to the DSS in this case, is to long term charter one SES, to complement the two CTVs.

5.4.3 Planning a maintenance campaign

Assume the wind farm operator with a fleet of two SES is planning a maintenance campaign one summer in addition to the regular yearly maintenance. This maintenance campaign consists of one maintenance activity per turbine that takes 4 technicians 50 hours to perform, and should be done between May and August the coming year. To facilitate this, the operator may want to short term charter some additional CTVs. We assume that the charter rate for a CTV is 2000 GBP pr. day (rather than the 1750 we assume for long term charter).

Using the DSS we are told that chartering two CTVs for one month (or one CTV for two months) is sufficient for the maintenance campaign. In addition, the two SES are also used to support the maintenance activities in the campaign.

5.4.4 Distance to shore

Assume that the ship designer that has created the *Small Accomodation Vessel* (SAV) described in Section 5.1 wants to know how far away from shore a wind farm must be before the design is superior to a fleet operating from a shore base. To do this, we have run the DSS with distances of 100 km and 150 km from the onshore base to the wind farm. The results show that extending the range to 100 km gives the same optimal fleet as for the 50 km case, while at 150 km the SAV was chosen. This indicate that for a wind farm of this size the distance to the closest onshore base should be 100 km or more for the SAV to be competitive with the other vessel types at the given time charter rates.

5.4.5 Cost of a vessel

Assume that the ship designer that has created the *Small Accommodation Vessel* (SAV) described in Section 5.1 wants to know at what price the SAV is competitive with the other fleets for the wind farm in question. We first solve the model to optimality without the SAV, and then we solve the model with the SAV fixed to the fleet with a cost of 0. We may then look at the difference between the objective values, to get an upper limit on when the SAV is competitive for this wind farm. In our case, the solution without the SAV was $\approx$ 9.70 million GBP while the optimal solution with the SAV at cost 0 was $\approx$ 6.51 million GBP. Thus, we may conclude that the SAV should be priced in the region of 3.2 million GBP pr year, or 8700 GBP pr day to be a competitive alternative. This is significantly lower than the 12500 GBP pr. day we have used in the earlier tests.

6 Conclusions

In this paper we have presented a decision support system for the vessel fleet size and mix problem for O&M activities at offshore wind farms. This is a fairly new and relevant industry problem, where it is essential to find good or optimal solutions that will help reduce the cost of energy from offshore wind farms. To determine the optimal vessel fleet

Table 1: Detailed results from the tests presented to demonstrate how the DSS can be used.

	Base case	2 CTV in fleet	Campaign	100 km to shore	150 km to shore	SAV cost test
Availability - energy based	95.00 %	94.60 %	94.00 %	93.81 %	94.04 %	94.54 %
O&M cost (in GBP)	9 696 380	9 569 655	11 342 194	11 000 293	11 696 490	6 513 477
Loss of production (in GBP)	5 400 635	5 830 955	6 168 244	6 724 093	6 464 480	5 835 682
Vessel cost (in GBP)	3 650 000	3 102 500	4 528 750	3 650 000	4 562 500	0
Spare part costs (in GBP)	645 745	636 200	645 200	626 200	669 510	677 795
Optimal Fleet	2 SES	2 CTV + 1 SES	2 SES + 1 CTV for 2 months	2 SES	SAV	SAV

size and mix we need to also consider the deployment of the fleet, hence the DSS both determines the optimal fleet and the optimal deployment of the fleet over a given planning horizon. For this purpose we have developed a new two-stage stochastic mathematical model where all feasible maintenance patterns for all potential vessel types are generated and used as input. Uncertainty in weather data and the occurrence of corrective O&M activities is included.

The performance of the DSS and its underlying optimization model has been tested and verified in a computational study. We find that the DSS provides results that are comparable with existing simulation models for O&M activities at offshore wind farms, and the stochastic optimization model is shown to give stable results within reasonable computational time. Finally, we have demonstrated how the DSS can be used for several types of valuable analysis for decision makers such as wind farm operators and vessel developers. These types of analysis include determining an optimal vessel fleet, advising on vessel fleet renewal, planning maintenance campaign and assessing and pricing new vessel concepts.

Acknowledgements

This work was supported by the projects NOWITECH and FAROFF, partly funded by the Norwegian Research Council.

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A Input data for the computational study

Table 1: Overview of the failure types and failure rates from the reference case presented by (14).

FAILURE INPUT	Manual reset	Minor repair	Medium repair	Major repair	Major replacement	Annual service
Repair time	3 hours	7.5 hours	22 hours	26 hours	52 hours	60 hours
Required technicians	2	2	3	4	5	3
Vessel type	CTV	CTV	CTV	FSV	HLV	CTV
Failure rate	7.5	3	0.275	0.04	0.08	1
Repair cost	0	1000	18 500	73 500	334 500	18 500

Table 2: Overview of the vessel types from the reference case presented by (14).

VESSEL INPUT	Crew Transfer Vessel (CTV)	Field Support Vessel (FSV)	Heavy-Lift Vessel (HLV)
Number of vessels	3	1	1
Governing weather criteria	Wave	Wave	Wave / Wind
Weather criteria	1.5 m	1.5 m	2.0 m / 10.0 m/s
Speed of vessel	20 knots	12 knots	11 knots
Technician capacity	12	60	100
Day rate	1750	9500	150 000
Maximum offshore time	1 shift	4 weeks	No limit

Table 3: Overview of the main data related to the the wind farm, working shifts, and power production from the reference case presented by (14).

Other test data	**Value**
Number of turbines	80
Distance maintenance base to wind farm	50 km
Wind and wave weather data	FINO [16]
Technician cost	80 000 /year
Number of technicians available	20
Working shift	12 hours
Number of daily shifts	1
Price of electricity	90 /MWh
Wind turbine power curve	Based on V90 power curve
Cut-in and cut-out speeds	3 m/s, 25 m/s

Table 4: Overview of the vessel types used when testing the DSS.

Vessel Input	Surface Effect Ship (SES)	Small Accommodation Vessel	Mini mother vessel	Daughter vessel
Governing weather criteria	Wave	Wave	Wave	Wave
Weather criteria	2.0 m	2.0 m	2.5 m	1.2 m
Speed of vessel	35 knots	20 knots	14 knots	16 knots
Technicians available pr. shift	12	12	16	6
Number of shifts pr. day	1	2	2	2
Day rate	5000	12500	25000	0
Maximum offshore time	1 shift	2 weeks	2 weeks	1 shift