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Abstract. For offshore wind farms, a move from a preventive and corrective maintenance regime to a predictive maintenance regime requires new methods for modelling approaches for maritime logistics planning. This paper presents an overview of the maritime logistics planning problem for a predictive maintenance regime and introduces the current state-of-the-art for operational research in the field of operation and maintenance at offshore wind farms. Findings are that a combination of the vessel resource scheduling problem for operation and maintenance at offshore wind farms with predictive analysis and digital twins is a promising future research step. A framework for a decision support tool is presented that will help bridge the gap, both with respect to the academic path, and the gap between academic research and industry.

1. Introduction

Traditionally, maintenance operations at offshore wind farms are performed in a preventive, scheduled manner. In a preventive maintenance regime, the components are maintained or replaced according to certain intervals given by the turbine producer. In addition, there will be corrective maintenance when unscheduled maintenance needs appear due to component failures requiring repair or replacement.

The cost of operation and maintenance (O&M) accounts for a large amount of the total expenses of an offshore wind farm, up to 30% [1] of the total lifetime cost. This paper aims at investigating a predictive maintenance regime for optimisation of the maritime logistics related to O&M where the conditions and estimated end-of-life of the wind turbine components determine when maintenance should be executed. The move from a preventive and corrective maintenance regime to predictive maintenance has a potential to reduce the operating costs substantially, increasing the value of an offshore wind farm by up to 12%, and extending the useful asset life by 25% [2]. Hence, a predictive regime will lower the cost of energy and encourage further investment in offshore wind.

The purpose of this paper is threefold: Firstly, to introduce the maritime logistic challenges related to predictive maintenance at offshore wind farms. Secondly, to give a representative selection of the current state-of-the-art within the field of operational research on O&M at offshore wind farms. Finally, to identify and propose the future path to bridge the gaps found in the state-of-the-art. Part of the work has been introduced in [3].

The remainder of this paper is structured as follows: A problem overview of the maritime logistics planning problem for predictive maintenance at offshore wind farms is given in Section 2. Current state-of-the-art within operational research for maritime logistics planning for O&M at offshore wind farms is presented in Section 3. Then, a framework for a new innovative maritime logistic optimisation tool for predictive maintenance at offshore wind farms – SmartMOW – is presented in Section 4. Finally, some overall conclusions are provided in Section 5.

2. Maritime logistics for predictive maintenance at offshore wind farms

In a predictive maintenance regime, fixed scheduled maintenance tasks that need to be executed based on given maintenance intervals are replaced by maintenance tasks that are to be executed based on the condition of the components and the prediction of how they are expected to degrade. This means that maintenance tasks may be executed both before or after they would be according to a preventive maintenance regime. The predictive maintenance regime requires good reliable data on the current conditions and the prediction of future conditions for the components. For the maritime logistics planning problem for predictive maintenance at offshore wind farms, it is assumed that such data exists, and these data can, e.g., be provided by digital twins, using sensor data from the wind turbine components combined with degradation models to estimate the needs for repair or replacement of components. Digital twins can be created on a turbine basis and at a wind farm basis.

[4] categorises the predictive maintenance strategy as a subcategory of condition-based maintenance. A condition-based maintenance strategy is characterised by components being continuously monitored and that maintenance actions are executed according to the condition. The predictive maintenance strategy is then, according to [4], described as the aim to predict failures before occurrence and that real-time data and predictive analytics are used, leading to a prescriptive maintenance strategy where recommended actions are provided based on the predictions.

The maritime logistics planning problem for predictive maintenance at offshore wind farms consists of determining which vessel resources that should be used to support which maintenance tasks and when. This includes optimising the use of vessel resources and corresponding logistics: Maintenance ports and inventory levels of spare parts and maintenance technicians available, prioritisation of maintenance tasks and routing and scheduling of the vessels. In the following, the elements of the maritime logistics planning problem are detailed. It is distinguished between static and dynamic data: Static data are those that do not change on a short-term basis, while dynamic data are the real-time system data.

There may be several ports from which spare parts and maintenance technicians are available. Figure 1 shows an illustration of an offshore wind farm surrounded by three ports: A, B and C. All these ports can be used as maintenance bases for the offshore wind farm. A maintenance base/port is recognised by its location (longitude and latitude) and daily costs. These are considered static port data. There are also dynamic port data. These relate to the port's inventory of spare parts and availability of maintenance technicians. Maintenance technicians are again divided into different skill levels based on the requirements for the maintenance tasks. A maintenance base can also be located at the wind farm if there are, e.g., offshore installations or larger vessels that are used for spare part inventory and accommodation for maintenance technicians.

Maintenance tasks are generic and describes an activity that need to be executed at the offshore wind farm, e.g., *change a blade*. They are recognised by static data. These include expected time to execute the task, expected costs of executing the tasks, required number and skill level(s) of maintenance technicians, required number and type(s) of spare parts and whether a vessel is required to support the maintenance task, e.g., if there are heavy lift activities involved. The time to execute a maintenance task may vary depending on the effectiveness of the resource used, e.g., if lifting activities are done more efficiently by one vessel over another.

The wind farm has both static and dynamic data. The static data relate to turbines (and other wind farm components) and their location (latitude and longitude), and the power curves

Figure 1. Three potential maintenance ports surrounding an offshore wind farm

for the turbines. Dynamic data relate to the conditions of the offshore wind farm components and are based on data from sensors monitoring the components on the wind turbines. The conditions of the components are translated into an estimated remaining useful lifetime based on degradation analysis. These estimates are then used to evaluate the need for maintenance, and the urgency of the maintenance can be categorised, e.g., in an interval from 1-4 where 1 is given the highest priority.

Vessels are needed in the logistics system to bring maintenance technicians and spare parts to the offshore wind turbines. These are recognised by static data which are service speed, maximum number of maintenance technicians they can transport and limits of spare parts they can carry, time charter costs and operational criteria consisting of, e.g., fuel consumption rates and weather criteria for different operation modes. Dynamic data for a vessel consist of current position of the vessel (latitude and longitude), where it is headed (to wind farm, between turbines or to port), the number and skill level of technicians on board and spare part inventory on board the vessel. It is assumed that a vessel can drop off a team of technicians at one wind turbine and continue to the next and drop of a new team of technicians and so on, and then pick up the teams once they have finished the maintenance tasks. Vessels are also given compatibilities and incompatibilities with maintenance tasks they can and cannot help executing, and ports they can and cannot visit.

Given these data, the routing and scheduling of vessel resources for the next few days can be determined. This can be called the smart maintenance logistic problem for offshore wind farms. A weather forecast will be taken as input, and this can be static or stochastic. Based on the overall data describing the current scenario, the next maintenance tasks to be executed will be determined and which vessel that will accommodate which maintenance task. The objective will be to reduce costs, where these consist of cost of executing maintenance tasks (personnel costs, spare part costs, etc.), time charter costs of vessels, voyage cost of vessels (fuel costs) and downtime costs (lost income due to downtime) for the turbines at the wind farm.

3. State-of-the-art: Relevant literature

This section presents the current state-of-the-art for optimisation and simulation of the maritime logistics planning problem for maintenance operations at offshore wind farms. The main focus is on mathematical programming models and operational research, although other approaches are also considered, e.g., pure simulation models.

There exist commercially available software products aiming at optimising the maritime logistics operations for maintenance operations at offshore wind farms. However, most of the solutions offered are simulation based where the user needs to define the resources to use and the sequence of operations to execute. One is Shoreline [5], a company offering a solution based on a simulation model presented in a PhD thesis [6]. NOWIcob [7], is another example of a simulation model for optimising maintenance activities and related logistics for offshore wind farms. It is not a commercially available product, but it is possible to get access to a version for testing purposes. In the DTOcean+ project [8], open-source design tools were developed for selection, development and deployment of ocean energy systems, including offshore wind. The methods implemented contain a simplified procedure for optimising the infrastructure solutions where the costs of all options are calculated and the one found to be the most promising is selected [9].

To the best of the authors' knowledge, there does not exist any commercially available software products that offer a solution based on mathematical programming models. However, HOWLOG [10] is an example of a tool based on solution methods for mathematical programming models. However, this tool is not developed to a viable product and is only available for testing purposes. In addition, the tool's main purpose is to determine the optimal vessel fleet for O&M at offshore wind farms, and while it does consider the underlying problem of scheduling the maintenance operations, it does not focus on the more detailed shorter-term scheduling of the maritime resources to support maintenance operations.

There exist several review papers on maintenance optimisation [11][12][13][1], and one was found on predictive maintenance [4] at offshore wind farms. An early review of decision support models for offshore wind farms is provided in [14]. A review on new tendencies in wind energy operation and maintenance [15] found that research into wind farm maintenance increased by 87% between 2007 and 2019. Hence, it is clear that there is a large increase in research interest in the field of onshore and offshore wind farm maintenance, associated with the increased focus on green energy sources where wind power, and offshore wind power in particular, is expected to play a major role. Further, [15] concludes that it is important to limit the maximum faults for offshore wind turbines, something that can be achieved through predictive O&M. [12] conclude that there remains a big gap between academic models and application in practice, and hence a shift from theoretical research to applied research is required.

The problem of determining optimal vessel fleet composition for O&M at offshore wind farms has been explored in several research papers [16][17][18][10][19][20][21][22]. These research papers all explore mathematical optimisation models and solution methods. A comparison of six decision support tools, five based on simulation models and one on a mathematical optimisation model, related to optimal access vessel fleet selection for O&M at offshore wind farms is presented in [23].

An overview of the results from the EU project LEANWIND [24] on logistic optimisation and full life cycle simulation model for offshore wind farms is given in [25]. These include studies on vessel fleet optimisation (HOWLOG [10]), routing and scheduling [26] and a simulation model for life cycle cost estimation (NOWIcob [7]) that are related to the O&M phase at offshore wind farms. The routing and scheduling model proposed in [26] is an exact optimisation model based on the Dantzig-Wolfe decomposition method [27], solving a mixed integer linear program. It considers multiple vessels, multiple time periods (days), multiple O&M bases and multiple wind farms. It finds the optimal schedule for maintaining the wind turbines and optimal routes for the crew transfer vessels, including the number of technicians required per vessel.

The routing and scheduling problem for O&M at offshore wind farms is highly relevant for the smart maintenance logistic problem for offshore wind farms presented in Section 2. To the best of the authors' knowledge, it was first introduced in [28] that presents a method called duo ant colony optimisation to improve the utilization of the maintenance fleet and reduce O&M costs.

Then, [29] presents a mathematical model for the problem considering optimal assignments of turbines and routes for vessels in terms of cost. [30] presents both an arc-flow and a path-flow mathematical model for the problem. A heuristic solution procedure was implemented for the path-flow model. [31] studies a similar problem and proposes a mathematical model formulation but does not consider the routing of the vessel resources. [32] studies the routing and scheduling problem for multiple wind farms modelling several work shifts and considering vessels that can stay offshore for several shifts. A mathematical model and a rolling horizon heuristic for the problem is proposed. [33] presents the problem of sharing of technicians between wind farms over multiple periods and determining per period the vessel routes for pick-up and delivery of technicians. An adaptive large neighbourhood search heuristic is proposed as solution method. [34] studies the daily maintenance planning problem for offshore wind farms and proposes a metaheuristic optimisation model. [35] proposes an optimisation framework called OptiRoute for daily (or short-term) maintenance operations. The paper considers route planning and scheduling for offshore wind farms far from shore where larger service operation vessels are combined with smaller crew transfer vessels. A similar problem is considered in [36] where an optimisation model is presented, and a novel metaheuristic procedure is proposed to solve the problem efficiently. [37] proposes a scheduling and routing framework for maintenance at offshore wind farms on a tactical-operational level, and propose a matheuristic as solution method.

Uncertainty, especially regarding weather conditions, is relevant for the routing and scheduling problem for O&M at offshore wind farms. It has been considered in, e.g., [38] that considers uncertainty in travel time, maintenance time and transfer time from vessel to turbine. [39] considers uncertainty in weather conditions and maintenance tasks for a tactical maintenance planning problem. [40] proposes a simulation optimisation approach to determine the impact of opportunistic maintenance. An ant colony system approach is suggested for optimising the vessel routing problem, and a multi agent model to represent the behaviour of the system.

The above-mentioned research papers study vessel fleet size and mix for O&M at offshore wind farms and/or the corresponding short-term routing and scheduling problem for the O&M resources. Several levels of details are considered: Some propose exact mathematical models for simplified problem formulations while others consider levels of detail only suitable for simulation models due to the increased computational time for exact and heuristic optimisation procedures. However, none of them consider predictive maintenance regimes. Some authors have addressed opportunistic maintenance strategies with predictive analysis and degradation models, see e.g., [41] and [42], whereas none of these have a focus on the maritime logistics value chain for the maintenance operations. The success of a model for the smart maintenance logistic problem for offshore wind farms is reliant on the implementation of advanced monitoring systems and good models for estimating remaining useful life of components and hence form the basis for the predictive maintenance strategy. [43] presents a cost benefit analysis of implementing advanced monitoring and predictive maintenance strategies for offshore wind farms and concludes that a potential cost reduction of up to 8% could be achieved in direct O&M costs and up to 11% reduction in lost production. Digital twins [44] combined with the offshore wind turbines control and monitoring systems can be used in combination with a smart maintenance logistics optimisation model to achieve a high potential O&M cost reduction, and increased power production from the wind turbines. Some recent studies have considered digital twins for estimating remaining useful life and predictive maintenance for components at offshore wind farms [45][46][47][48]. To the best of the authors' knowledge, there does not exist any research that combines predictions from digital twins with maritime logistics optimisation for O&M at offshore wind farms.

The state-of-the-art review shows that the vessel fleet optimisation problem for O&M at offshore wind farms has to a large extent been explored in the literature. There are also several studies on different variants of the routing and scheduling problem. Predictive maintenance

Figure 2. SmartMOW framework - Conceptual overview

strategies and the use of digital twins for O&M at offshore wind farms has received increased interest during the last few years, but there is currently a great gap between academic and applied research that needs to be bridged. Combining the vessel resource scheduling problem for O&M at offshore wind farms with predictive analysis and digital twins is a promising future research step, and applied research and development of decision support tools for use by the industry would help bridge the acknowledged current gap.

4. SmartMOW - Smart Maintenance logistics for Offshore Wind farms

SmartMOW – Smart Maintenance logistics for Offshore Wind farms – is a framework for an innovation that considers the short-term routing and scheduling problem for vessels supporting the offshore operations in a predictive maintenance regime for offshore wind farms.

The aim of SmartMOW is to quickly generate one, or several, solutions to the problem described in Section 2. Plans will be generated based on the current status at the offshore wind farm and expectations about the future, as depicted in Figure 2. Data may be provided by, e.g., digital twins. This enables an offshore wind farm operator to evaluate options and optimise the use of logistics resources on a day-to-day basis. With the use of digital twins and data management, updates to the logistics plan can be sent to all involved personnel, as for example maintenance technicians and captains, efficiently.

The problem described in Section 2 is a version of a vehicle routing problem (VRP), see, e.g., [49]. It is a capacitated VRP with pick-up and deliveries (of spare parts and technicians), and inventory control as technicians and spare parts need to be available at the node, i.e., port or offshore base, where they are being picked-up. Another addition to the traditional VRP with pickup and deliveries is that technicians need to be delivered to the same port/offshore base as they are picked-up. In addition, vessels can have multiple trips during the planning horizon, typically one per day.

The VRP and its variants have been widely studied in the existing academic literature on operational research and models that capture some of the aspects that are to be considered by SmartMOW have been proposed. There are, however, new combinations of the problem aspects in the SmartMOW problem definition that has not been captured by the literature to the best of the authors' knowledge. The problem to be solved is complex, and stochastic data will be relevant, e.g., related to weather forecasts and imperfect data from degradation models resulting in unscheduled maintenance tasks. Hence, the underlying model in SmartMOW should be of a stochastic and dynamic nature. To include all these problem aspects, and to be able to solve potentially large problem instances, it will be necessary to develop a heuristic solution methodology to obtain good quality solutions within reasonable computational time. As solution methodology, a Genetic Algorithm (GA, see, e.g., [50]), is proposed. To analyse the effects of the stochastic parameters and to get risk profiles, a simulation model can be applied to evaluate solutions in the GA, an approach used in [51].

Figure 3 illustrates the input data to SmartMOW, as described in Section 2, with dynamic and static data. The weather forecast may be static, assumed "perfect" weather forecast for the planning horizon, or stochastic, with increased uncertainty in the forecast as a function of time.

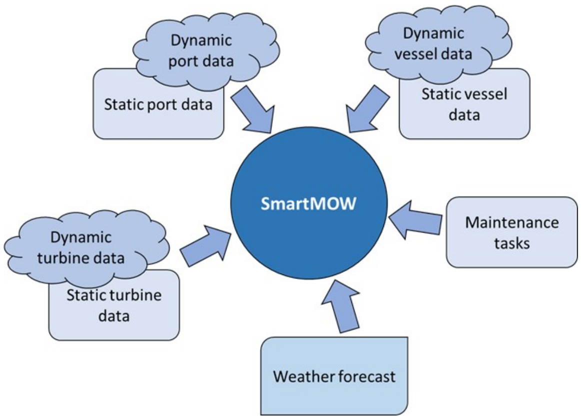

Figure 3. Input overview - SmartMOW.

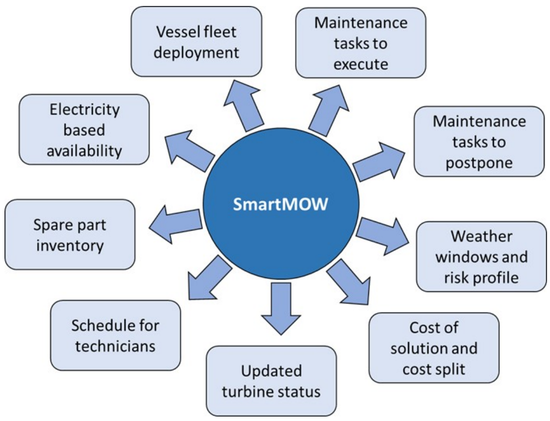

Figure 4. Output overview - SmartMOW.

Algorithm 1 describes the basis of the optimisation procedure of SmartMOW. It starts by initialising the problem, retrieving input data from the necessary sources and creating an empty set of final solutions in the Pareto front. Then some construction algorithms will be used to create an initial pool of solutions. Each of the solutions will be simulated under weather conditions to determine feasibility, costs, and other indicators, as, e.g., number of executed maintenance tasks. Local search procedure(s) will be implemented to explore neighbouring solutions. After this initial evaluation of solutions, the Pareto front will be populated with solutions. Objectives to consider will be to minimize costs and maximize the number of executed maintenance tasks with given priorities. Then the optimisation procedure will, while some stopping criteria are not met, update (delete a number of solutions) and rank (based on objective values and diversification from other solutions) the solutions in the solution pool and generate a set of new solutions (by, e.g., using cross-over operators on two solutions from the solution pool, and generating new solutions by construction algorithms as in [51]). Each of the new solution will undergo the same procedures as the initial solutions; simulation and local search, before the Pareto front is updated. Stopping criteria can be, e.g., maximum runtime, maximum number of total iterations, maximum number of iterations with no improvement to the Pareto front. Finally, the algorithm will return the Pareto front, consisting of the best solutions found during the optimisation procedure.

Figure 4 shows the output data from SmartMOW. These consist of:

– Vessel fleet deployment: Which vessels should sail which routes when.
– Maintenance tasks to execute: Schedule for when to execute the maintenance tasks, will also include information on spare part utilisation and technicians that execute the tasks.
– Maintenance tasks to postpone: Maintenance tasks that cannot be executed during the planning horizon due to, e.g., not enough available resources or weather conditions.
– Weather windows and risk profile: Information on available weather windows for executing maintenance tasks, and risk profile if stochastic weather input data is used. This output can also be used to show weather windows not utilized by the solution.
– Cost of solution and cost split: The total cost of the planned maintenance schedule, and the cost split into, e.g., cost of vessels used (time charter cost, fuel cost etc.), technicians, spare parts, downtime cost.
– Updated turbine status: The new status of the turbine after maintenance has been performed, i.e., updated remaining useful life of components.

Algorithm 1 SmartMOW optimisation procedure

```
initialise problem; ParetoFront = ∅
construct SolutionPool
for each solution in SolutionPool do
    simulate solution under weather conditions
    execute local search procedure
end for
generate ParetoFront
while StoppingCriteria not met do
    update and rank solutions in SolutionPool
    generate new solutions
    for each new solution do
        simulate solution under weather conditions
        execute local search procedure
    end for
    update ParetoFront
end while
return ParetoFront
```

– Schedule for technicians: When to be picked up at port/offshore base, when to execute given maintenance tasks, and when to return at port/offshore base.
– Spare part inventory: Inventory levels for spare parts at the ports/offshore bases.
– Electricity based availability: Uptime of turbines at the offshore wind farm during the planning horizon.

Use of a tool as the one represented by SmartMOW, has a potential to significantly reduce the cost of O&M as well as lost income from offshore wind farms: *Lost income* can be reduced as SmartMOW minimises the unexpected downtime time by evaluating risk of failures (component degradation) and resource (vessel, equipment, personnel) availability and dynamically plans for efficient maintenance operation to avoid failures. Optimal use of logistic resources, e.g., vessels, maintenance technicians, spare parts inventory, will reduce the *logistic costs*. The *cost of wind turbine components* can be reduced as components will be used until they need to be replaced or maintained. Finally, SmartMOW may be used to select the most *cost-efficient vessel fleet* and support the development of the most *cost-efficient vessel resources* for an offshore wind farm.

5. Concluding remarks

This paper has considered the maritime maintenance logistics problem for offshore wind farms when moving from a preventive and corrective maintenance regime to a predictive maintenance regime. A predictive maintenance regime has the potential to greatly reduce costs of offshore wind farm maintenance by prolonging remaining useful life of assets at the wind farm, and by executing maintenance tasks not at given intervals or when failures occur, but at the time estimated to be optimal for maintenance depending on the state of the turbine components.

A problem description for the maritime predictive maintenance logistics problem at offshore wind farms together with a state-of-the-art literature review show that there is a gap in state-of-the-art for offshore logistics connected to predictive maintenance of offshore wind turbines. In addition, a great gap between academic and applied research has been identified. The proposed framework, SmartMOW, will help bridge these gaps. SmartMOW aims at utilizing data from digital twins, combining probability distributions on failures, data on vessel capabilities and logistics planning to minimize the O&M costs at offshore wind farms.

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