Report

Predictive maintenance logistics for offshore wind farms

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Report

Predictive maintenance logistics for offshore wind farms

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SUMMARY
This report contains a summary of state-of-the-art for maritime logistics planning of maintenance activities at offshore wind farms within mathematical programming and simulation. It presents a description of a shift from a preventive and corrective maintenance paradigm to a predictive planning regime and its effect on the modelling approaches for maritime logistics planning. A planned innovation in NorthWind: SmartMOW is presented where the plan is to integrate information on degradation of components from digital twins.
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Table of contents

1 Introduction

Traditionally, most maintenance on offshore wind farms is conducted on 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 is *corrective* maintenance when unscheduled maintenance needs appear because components fail and need repair/replacement.

The cost of operation and maintenance (O&M) at offshore wind farms accounts for a large amount of the total expenses of the wind farm, up to 30% [1] of the total lifetime cost of an offshore wind farm. This report describes a *predictive* maintenance regime for optimisation of the 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 wind farm by up to 12%, and extending the useful asset life by 25% [2]. Hence, the predictive regime will lower the cost of energy and encourage further investment in offshore wind.

In previous projects, a decision support tool (DST) for optimising the vessel fleet for preventive and corrective maintenance tasks at offshore wind farms has been developed. This tool also considers the underlying problem of assigning maintenance tasks to the vessels. The DST is described in Chapter 2, and may form a basis for future work on developing an optimisation model for predictive maintenance operations.

A short problem description of the predictive maintenance logistics problem for offshore wind farms is given in Chapter 3. Current state-of-the-art is presented in Chapter 4, with an overview of relevant literature for predictive maintenance optimisation for offshore wind farms. Then the underlying idea behind a planned new innovative logistic optimisation tool for predictive maintenance at offshore wind farms – SmartMOW – is provided in Chapter 5. The way forward – planned work in NorthWind on predictive logistic maintenance planning – is presented in Chapter 6, before some overall conclusions from the report are given in Chapter 7.

2 Background

In the LEANWIND[1] and NOWITECH[2] projects, a tool to determine optimal vessel fleet for offshore wind operation and maintenance (O&M) was developed. In this tool a metaheuristic solution method [3] is implemented, consisting of two steps:

1. A quick construction heuristic to generate a feasible starting solution
2. A local search improvement algorithm to evaluate the neighbourhood solutions of the starting solution

The methodology considers two stochastic parameters: Weather conditions and turbine failures resulting in corrective maintenance tasks. Each candidate solution (starting solution or solution found during the local search improvement algorithm) is evaluated by a simulation program.

[1] LEANWIND – Logistic Efficiencies and Naval architecture for Wind Installations with Novel Developments, EU FP7 project (2013-2017) – http://www.leanwind.eu/

[2] FME NOWITECH – funded by the Research Council of Norway and NOWITECH partners (2009-2017) – now continued as a research network – https://www.sintef.no/projectweb/nowitech/

The methodology has been implemented in a DST named HOWLOG [4]. HOWLOG can be used by actors in the offshore wind industry to find and evaluate optimal vessel resources for the O&M phase for offshore wind farms.

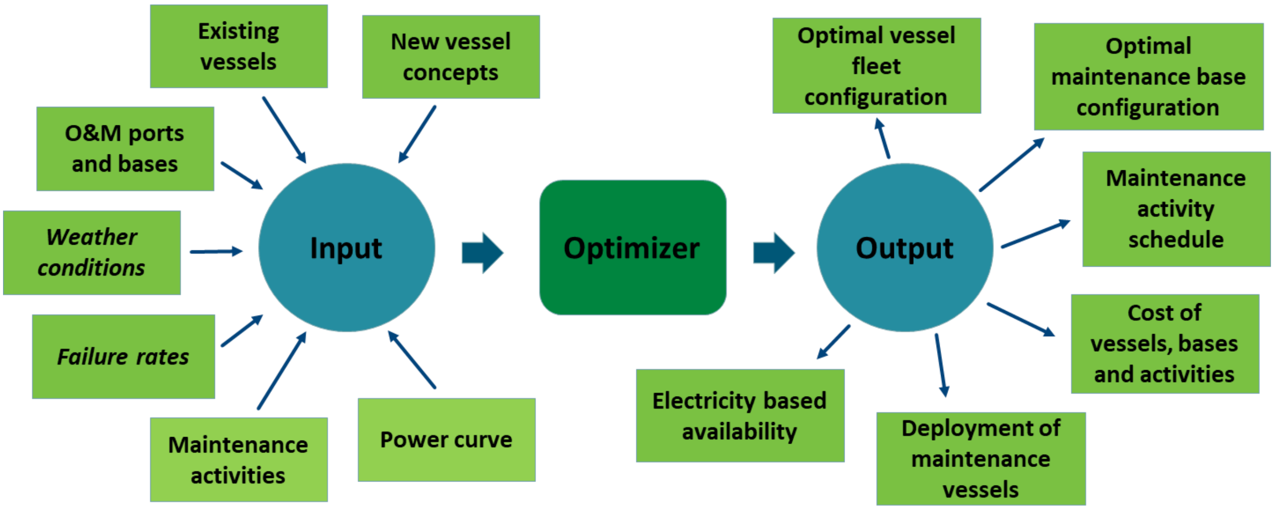

Figure 1: Input and output overview, HOWLOG

Figure 1 shows an overview of the input and output to the HOWLOG DST, while Figure 2 shows the configuration of the tool. An Excel workbook is used for input and output, and HOWLOG is a Java desktop application that reads in data from the Excel workbook and writes out the results to the workbook. In addition to the input from Excel, historical weather data is read from a separate weather data file.

HOWLOG considers two types of maintenance tasks: Preventive and corrective. The preventive tasks are planned activities, while the corrective tasks are a result of failures resulting in shut-down of turbines and require maintenance actions for the production to start. Failures, and hence corrective maintenance tasks, are treated as stochastic input parameters in HOWLOG.

The main intention of HOWLOG is to determine the optimal type and number of vessel resources and maintenance base configurations needed to execute the maintenance tasks at the offshore wind farm. To determine this, the scheduling of the resources also need to be examined, and hence results from the model will also include the deployment of the maintenance vessels: which maintenance activities that are scheduled to be executed when.

An overview of the solution methodology in HOWLOG is shown in Figure 3. It consists of a version of a greedy randomized adaptive search procedure – GRASP [5]. First, initial feasible solutions to the problem are constructed by the GRASP algorithm. Such a solution consists of a feasible fleet of maintenance vessels and the corresponding maintenance bases/ports. After constructing feasible solutions, these are improved by a local search procedure, a Tabu Search algorithm [6], to construct *neighbourhood solutions.* All the solutions generated are then evaluated by a simulation procedure that consists of a scenario generator and a calculator. The scenario generator generates several weather data sets and corrective maintenance tasks sets, and the calculator calculates the objective function value of the solutions for a given weather data set and corrective maintenance task set. The evaluation of a solution will then be the average sum of the objective function values over all scenarios.

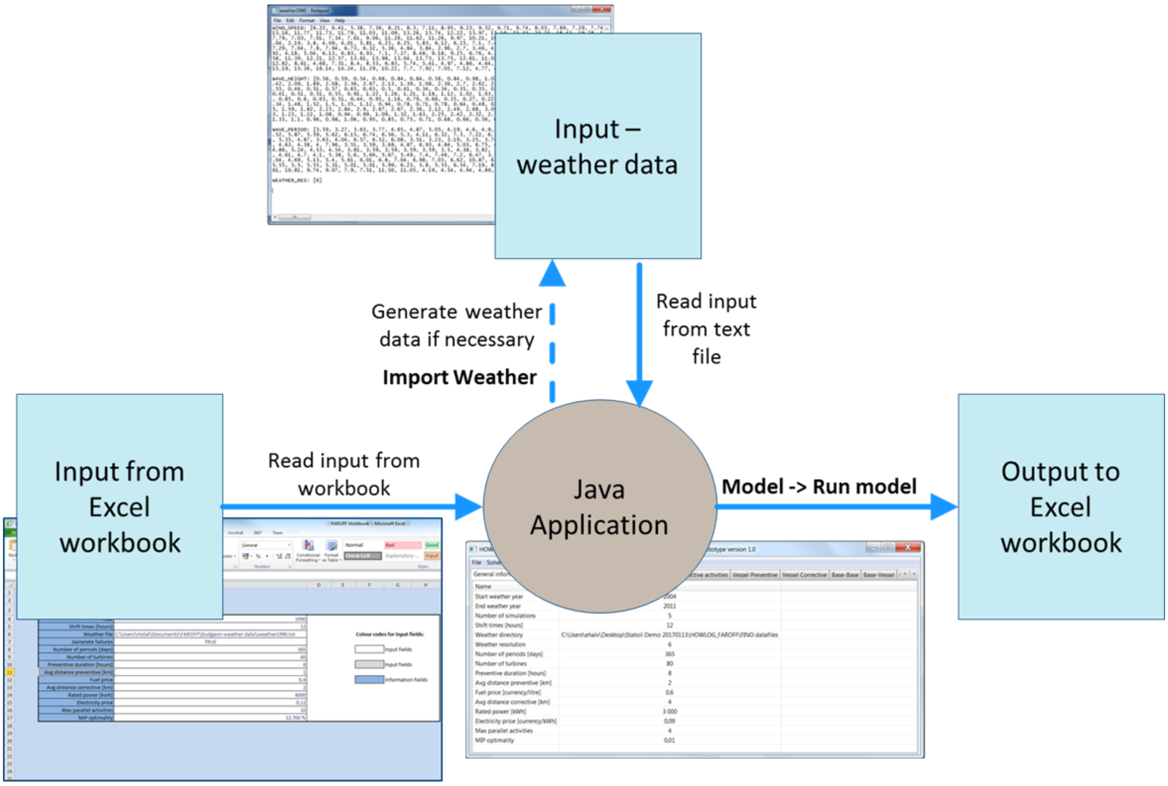

Figure 2: Configuration of the HOWLOG vessel fleet optimisation tool.

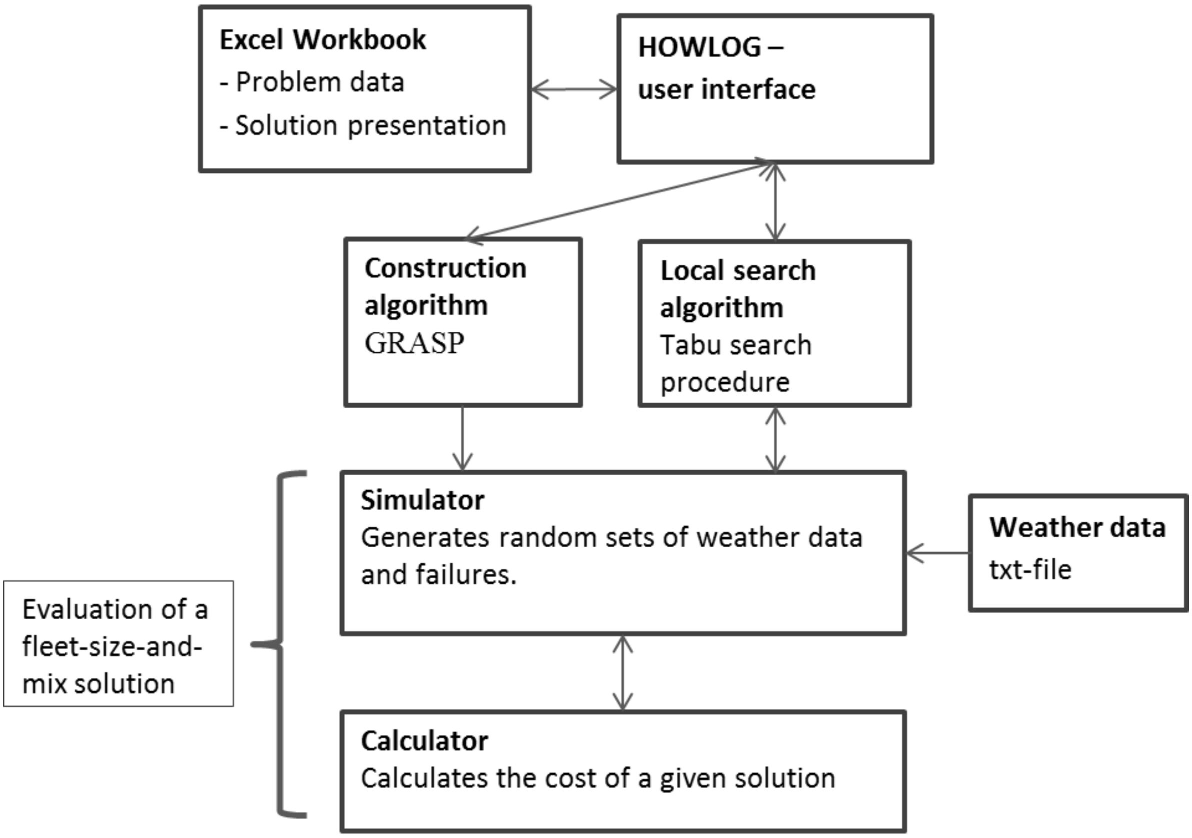

Figure 3: Overview of solution methodology implemented in HOWLOG

The problem considered by HOWLOG differs to some extent from the predictive maintenance logistics problem at offshore wind farms: The maintenance task data are either static (preventive maintenance tasks) or purely stochastic (corrective maintenance tasks) and does not rely on predictions. At the same time, the overall focus of the DST is to determine optimal composition of vessel fleet and maintenance bases, while for the predictive maintenance logistics problem the main focus will be on the vessels' schedule and which maintenance tasks to execute and which to postpone in a given (short) time horizon. However, much of the tool structure and methodology can be adapted to accommodate for predictive maintenance logistics optimisation.

3 Predictive maintenance logistics 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 at the wind farm based on the condition of the wind turbine components and the prediction of how the components 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 wind farm components. For the predictive maintenance logistics optimisation problem 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 and/or replacement of components. Digital twins can be created on a turbine basis and at a wind farm basis.

Fox et al. (2022) [7] categorize 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, by Fox et al., described as the aim to predict failures before occurrence and that real-time data and predictive analytics is used, leading to a prescriptive maintenance strategy where recommended actions are provided based on the predictions. Figure 4 shows an overview of the turbine condition development depending on different maintenance strategies.

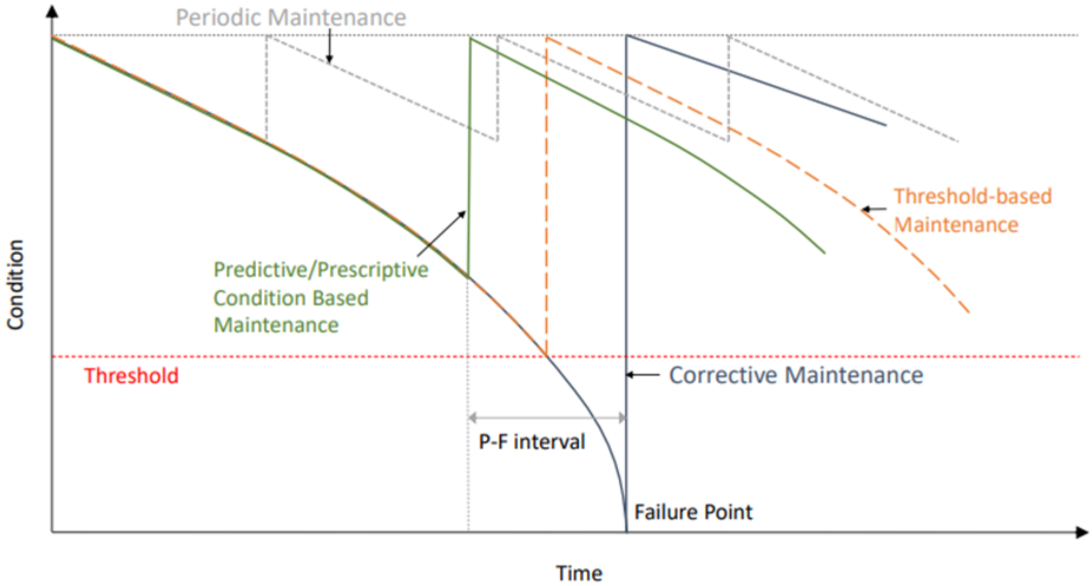

Figure 4: Overview of turbine condition development for different types of maintenance strategies. Figure from Fox et al. (2022) [7], adapted from Wu et al. (2013) [8]

In the predictive maintenance logistics problem, there may be several ports from where spare parts and technicians are available for execution of maintenance tasks. Figure 5 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 recognized by its location (longitude and latitude) and daily port costs. These are considered *static port data*. There are also *dynamic port data*. These relate to the ports' inventory of spare parts and maintenance technicians. Maintenance technicians are again divided into different skill levels based on the requirements for the *maintenance tasks*. A base can also be located at the wind farm if there are, e.g., offshore installations or vessels that are used for spare part inventory and accommodation for maintenance technicians.

Figure 5: Three ports surrounding an offshore wind farm

Maintenance tasks are recognized 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 get the maintenance task executed, e.g., if there are heavy lift activities involved.

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 curve 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 (RUL) based on degradation analysis. These estimates are then used to evaluate the need for maintenance, and the urgency of the maintenance need can be categorized, e.g., in an interval from 1-4 where 1 is given the highest priority.

Vessels (or helicopters) are needed in the logistics system to bring maintenance technicians and spare parts to the offshore wind turbines. These are recognized 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 the teams up 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 vessels for the next few days can be determined. We call this the smart maintenance logistic problem for offshore wind farms. A weather forecast will be 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.

4 State-of-the-art: Relevant literature

This chapter considers 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 operations research, although also other approaches are 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 [9], a company offering a solution based on the simulation model developed by Endrerud in his PhD thesis [10]. NOWIcob [11] [12], 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 [13], 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 all options are calculated and the one calculated to be most promising is selected [14].

As far as we know, there does not exist any commercially available software products that offer a solution based on mathematical programming models. The DST presented in Chapter 2, HOWLOG, is another 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, this tool's main purpose is to determine the optimal vessel fleet for O&M does not focus on the short-term scheduling of the maritime resources to support maintenance operations.

There exist several review papers on maintenance optimisation [15] [16] [17] [1], and one was found on predictive maintenance [7] at offshore wind farms. An early review of decision support models for offshore wind farms was provided by Hofmann (2011) [18]. A review on new tendencies in wind energy operation and maintenance [19] 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, [19] concludes that it is important to limit the maximum faults for offshore wind turbines, something that can be achieved through predictive O&M. Shafiee and Sørensen (2019) [16] 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 through several research papers [20] [21] [22] [23] [4] [24] [25] [26]. 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 mathematical optimisation model, related to optimal access vessel fleet selection for O&M at offshore wind farms was given by Sperstad et al. (2017) [27].

An overview of the LEANWIND results on logistic optimisation and full life cycle simulation model for offshore wind farms is given in [28]. These include studies on vessel fleet optimisation (HOWLOG [4]), routing and scheduling [29] and a simulation model for life cycle cost estimation (NOWIcob [12]) that are related to the O&M phase at offshore wind farms. The routing and scheduling model proposed in [29] is an exact optimisation model based on the Dantzig-Wolfe decomposition method [30], 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 Chapter 3. As far as we know, it was first introduced by Zhang (2014) [31] who proposed a method called duo ant colony optimization to improve the utilization of the maintenance fleet and reduce O&M costs. Then Dai et al. (2015) [32] presented a mathematical model for the problem considering optimal assignments of turbines and routes for vessels in terms of cost. Stålhane et al. (2015) [33] presented both an arc-flow and a path-flow mathematical model for the problem. A heuristic solution procedure was implemented for the path-flow model. Besnard et al. (2013) [34] studied a similar problem and proposed a mathematical model formulation but did not consider the routing of the vessel (and/or helicopter) resources. Raknes et al. (2017) [35] studied the routing and scheduling problem for multiple wind farms modelling several work shifts and considering vessels that can stay offshore for several shifts. They proposed a mathematical model and a rolling horizon heuristic for the problem. Schrotenboer et al. (2018) [36] studied 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 was proposed as solution method. Stock-Williams and Swamy [37] studied the daily maintenance planning problem for offshore wind farms and proposed a metaheuristic optimisation model. Lazakis and Khan (2021) proposed an optimization framework they call OptiRoute for daily (or short-term) maintenance operations. They consider 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 was considered by Irawan et al. (2022) [38] where an optimisation model was presented, and a novel metaheuristic procedure was proposed to solve the problem efficiently.

Uncertainty, especially regarding weather conditions, is relevant for the routing and scheduling problem for O&M at offshore wind farms. It has been considered by, e.g., Irawan et al. (2021) [39] that considered uncertainty in travel time, maintenance time and transfer time from vessel to turbine. Schrotenboer et al. (2020) [40] considered uncertainty in weather conditions and maintenance tasks for a tactical maintenance planning problem.

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., Li et al. (2021) [41] and Zhou and Yin (2019) [42], whereas none of these have a focus on the maritime logistics value chain for the maintenance execution. 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. Turnbull and Carroll (2021) [43] conducted a cost benefit analysis of implementing advanced monitoring and predictive maintenance strategies for offshore wind farms and concluded 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 by utilising advanced monitoring strategies. 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 our knowledge, there does not exist any research that combines predictions from digital twins with maritime logistics optimisation for offshore wind O&M.

The state-of-the-art review presented here 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 the routing and scheduling problem. Predictive maintenance 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.

5 SmartMOW – Smart Maintenance logistics for Offshore Wind farms

SmartMOW – Smart Maintenance logistics for Offshore Wind farms – is a planned 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 problem to consider is a version of a vehicle routing problem, see, e.g., Toth and Vigo (2014) [49]. It is a capacitated version with pickup and deliveries (of spare parts and technicians), and inventory control since technicians and spare parts need to be available at the node (port/offshore base) where they are being picked-up. Another complication to the traditional vehicle routing problem 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 vehicle routing problem and its variants have been widely studied in the existing academic literature on operations 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 as far as we know. It is therefore suggested that a mathematical model presentation of the problem is made as a starting point. Such a model can be implemented and solved by commercially available software.

However, the SmartMOW problem is quite complex, and stochastic input data may be relevant, e.g., related to weather forecasts and imperfect data from degradation models resulting in unscheduled maintenance tasks. Hence, the model should be of a stochastic and dynamic nature. Including these problem aspects, and also to be able to solve potentially large problem instances, it will be necessary to develop a heuristic solution methodology to achieve good quality solutions within reasonable computational time. As solution methodology, a Genetic Algorithm (GA, see, e.g., Whitley (1994) [50]), may be implemented. 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 Halvorsen-Weare et al. (2021) [51].

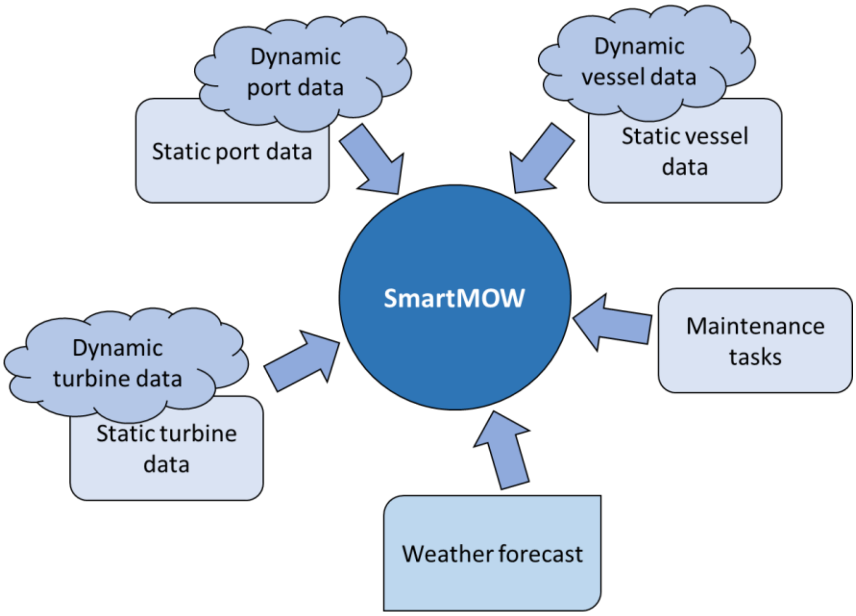

Figure 6: Planned input data to SmartMOW

Figure 6 illustrates the planned input data to SmartMOW, as described in Chapter 3, with dynamic and static data. The weather forecast may be static (assumed "perfect" weather forecast for the next few days), or stochastic, typically with more uncertainty regarding the weather the longer into the planning horizon. In the first version of SmartMOW, the weather forecast is likely to be assumed static, while future versions may include uncertainty. Weather conditions that may be considered are typically significant wave height (Hs), wind speed, and peak wave period (Tp). It is likely that the first version of SmartMOW will include only one weather point, assuming that the weather is the same everywhere in the offshore wind farm, including the distance travelled between port/offshore base and wind farm. Future versions may then include several weather points and other weather conditions, for example wave and wind direction.

Figure 7 shows the planned 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 utilization 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.
- 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.

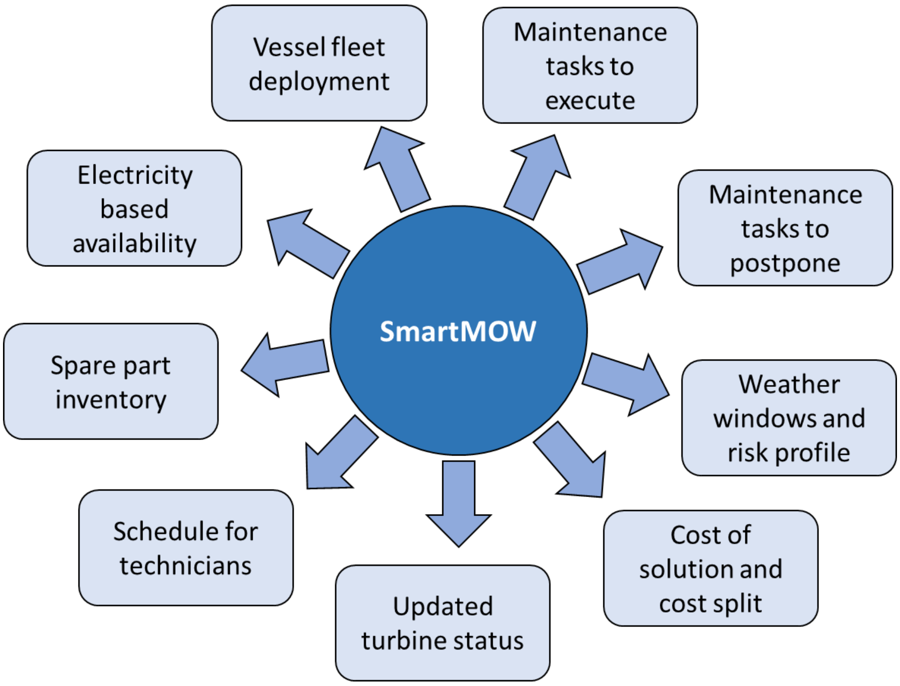

Figure 7: Planned output data from SmartMOW

The aim of SmartMOW is to quickly generate one, or several, solutions to the problem described in Chapter 3 given the current situation at the offshore wind farm, information 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 technicians and captains, efficiently.

6 The way forward

In NorthWind's work package (WP) 2.3 (Offshore wind farm logistics) a decision support system for predictive planning of maintenance operations is to be developed. It should combine probability distributions on failures, data on vessel capabilities and logistics planning to minimize the downtime costs. It is planned to use component predictions from the predictive maintenance digital twin in NorthWind's WP4.3 and vessel operability data from WP2.2.

In this report, a planned NorthWind innovation that fulfils the requirements of the decision support system – SmartMOW – has been described. Next step will be to verify that the understanding of SmartMOW's planned functionalities, input and output data, are realistic and in line with the needs of the industry. This will include coordination with WPs 2.2 (service operation vessel for offshore wind turbines) and 4.3 (asset management) and discussions with relevant NorthWind partners.

Further, when the problem description for SmartMOW has been adjusted according to input received, from industry partners and WPs 2.2 and 4.3, the next steps will be the planning of developing a SmartMOW prototype version. For a prototype version an Excel-based input/output format could be used. The main focus for the prototype version will be on developing a functional solution algorithm. Future work, within or outside of NorthWind, would be to develop a first version of the tool, that may, e.g., be a web-based solution where the solution algorithm is improved to accommodate a high solution quality while at the same time meeting the users' required maximum computational time.

7 Conclusions

This report has considered the maintenance logistics problems for offshore wind farms when moving from a preventive/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.

The report has presented a decision support tool, HOWLOG, that has been developed in previous projects and that may form a basis for, or serve as inspiration to, the development of a new innovative decision support tool – Smart Maintenance logistics for Offshore Wind farms – SmartMOW. A problem description for the 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 that will be filled by the SmartMOW model.

To achieve the potential cost reduction under a predictive maintenance regime, it is essential to have access to good data on the current state of the turbine components and degradation models and at the same time ensure that the maritime logistics operations are executed as efficiently as possible. The proposed innovation, SmartMOW, relies on good data from, e.g., digital twins, on the current state of turbine components and hence the need for maintenance tasks, and will suggest optimal solutions to the maritime logistics problem of executing the maintenance tasks given the forecasted weather conditions at the offshore wind farm site.

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