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Highlights

- Mixed integer linear programming model for offshore wind farm maintenance
- Deterministic scenario based model supporting decisions on vessel fleet composition
- Derives a practical decision rule to schedule maintenance operations
- Illustrates the underestimation of the cost by a complete information model
- Applies the procedure to a practical case

On offshore wind farm maintenance scheduling for decision support on vessel fleet composition

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Abstract

Maintenance costs account for a large part of the total cost of an offshore wind farm. Several models have been presented in the literature to optimize the fleet composition of the required vessels to support maintenance tasks. We provide a mixed integer linear programming (MILP) description of such a model, where on the higher level, the fleet composition is decided and on the lower level the maintenance operations are scheduled for a set of weather and breakdown scenarios. A drawback of deciding an a priori information schedule for the coming year is that, the weather outcomes and breakdowns are not known in advance. Consequently, given a fleet composition, its corresponding maintenance costs are underestimated compared to what can be realised in practice under incomplete information. Therefore, we present a heuristic that simulates the practical scheduling and may provide a better cost estimate. The latter method is used to evaluate a fleet composition based on available information and it is compared with the MILP solution based on a priori information.

Keywords: Scheduling, Offshore Wind Farm, Heuristic, Fleet composition, Maintenance planning

1. Introduction

The offshore wind energy industry is expected to continue its growth tendency in the near future. The European Wind Energy Association expects in its Central Scenario by 2030 a total installed capacity of 66 GW of offshore wind in the EU [4]. Offshore wind farms (OWFs) are large scale infrastructures, requiring a large fleet of vessels able to perform operations and maintenance (O&M) tasks on the installed turbines and therefore relying on non-renewable

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energy resources to be operative. Operation and maintenance constitute up to as much as one third of the running costs of OWF installations [14]. Therefore, optimising the efficiency of resources used for O&M tasks of an OWF becomes extremely important in order to make them economically viable and to reduce CO2 emissions.

Recent deterministic and stochastic formulations for fleet composition and optimisation of maintenance operations at OWF's can be found in [5] and [7]. A recent literature review on decision support systems (DSS) for OWF's is given by [8].

In [10], a mathematical model for maintenance operations for onshore wind farms is introduced. It determines the best time for maintenance operations considering the performance of the turbines and the resources that are available. A stochastic optimization model for opportunistic maintenance of offshore wind farms is presented by Besnard et al. [2]. Opportunistic maintenance is a term used in literature to express that sending out maintenance teams is based on forecasts of generation data. Their model is based on a rolling horizon, updating the maintenance plan daily, according to production and wind forecast data. Another opportunistic maintenance method is presented in [11], scheduling preventive operations when a component reaches its calculated reliability threshold. Reference [13] presented a mathematical model and a rolling horizon heuristic for scheduling maintenance operations at multiple OWF.

In [3, 9] and [16], a model for maintenance routing and scheduling at offshore wind farms based on the Dantzig-Wolfe decomposition method has been implemented. In fact, [9] extends and combines the models in [3] and [16]. In that work, a mixed integer linear model is solved for each subset of turbines to generate all feasible routes and maintenance schedules for the vessels for each period. The routes take several constraints into account, such as weather conditions, the availability of vessels and the number of technicians available at the operation and maintenance base. In [17], a two-stage stochastic model is presented to determine a cost-optimal fleet size and mix for O&M tasks at offshore wind farms for the total expected lifetime of the OWF. For that, the study considers time periods fixed to three months.

In the current work, we make the following contribution to the literature on decision support systems for O&M tasks at OWFs: (1) We present a MILP model to select a fleet of vessels to perform O&M tasks at OWFs, based on a priori information. (2) We introduce a heuristic for scheduling O&M tasks using a set of available vessels. (3) We conduct a numerical study comparing the MILP model solution with the heuristic, illustrating the effect of a priori information for this type of MILP models.

The basis of our investigation is a scenario based MILP model, which like the models in [7] and [17], decides on the vessel fleet composition. It is based on a more extensive model on fleet size and mix decisions in [15]. Such models use a priori information to perform the scheduling and use that to evaluate the vessel fleet composition and base selection, i.e. the weather conditions (wind speed and wave height) and breakdowns happening during a scenario of a year are known beforehand. The research question in the current paper is whether the vessel fleet composition may be affected when maintenance scheduling is done in a heuristic way following a practical decision rule given the available information at the time of maintenance scheduling.

We investigate this question in the following way. Section 2 describes the practical decision problem of operating an OWF and selecting a fleet to support its maintenance tasks. Section 3 describes an MILP model, which simultaneously determines the maintenance scheduling as well as the fleet composition. In Section 4, a heuristic for the operational stage of the model is presented. Section 5 presents a computational study used to compare the outcomes of both procedures. Finally, Section 6 summarises our findings.

2. Problem definition

This section describes the maintenance planning problem related to a fleet of vessels for an offshore wind farm during a planning horizon, based on a more extensive model of fleet size and mix decisions in [15]. The aim is to find an optimal fleet of vessels and a collection of maintenance tasks to be performed on the wind turbines. That model contains a detailed description of the operational scheduling dealing with each individual action, i.e. breakdown. Our vision also distinguishes periods (shifts) of 12 hours, but aggregates the scheduling of individual breakdowns into a group that still requires repair.

Two types of maintenance tasks are considered. *Preventive* maintenance tasks are meant to prevent failures and prolong the lifetime of wind turbines. Examples include visual inspection, changing of consumables, oil sampling, and tightening of bolts [12]. *Corrective* maintenance tasks are needed to repair broken down wind turbines. There is a one-to-one correspondence between failure type and corrective task type.

The number of necessary preventive tasks of each type to be performed is predefined at the beginning of the year. Corrective tasks are only needed after a specific failure occurs in a wind turbine. The planner is confronted in each scenario with failures occurring dynamically and weather conditions, including wind speed and wave height. For each shift, the scenario events consist of weather condition data and a turbine failure list with a specification of the type of required (repair) tasks. There is a downtime cost associated to the lack of electricity production in turbines during the execution of a maintenance task. Downtime costs are also considered for broken down turbines, incurred for the shifts from diagnose until reparation.

To perform maintenance tasks, a fleet of vessels is needed. A vessel type has properties such as the type of maintenance tasks it can perform, capacity for transferring technicians, a depreciation cost over the planning horizon, a sailing speed, and a threshold for wind speed and wave height above which it cannot sail and transfer technicians to the turbines. Every vessel is associated to a base, from which it travels to the wind farm to perform maintenance tasks. Each base has a certain vessel capacity, a capacity to accommodate technicians, an associated cost and coordinates which provide its distance to the wind farm.

The decision problem includes a number of candidate bases that can be used and a number of vessel types associated to them. Each vessel type is able to support a particular set of patterns, from the base they are associated with. A pattern consists of one or several maintenance tasks to be performed at the OWF that fits in a shift, including the time it takes the vessel type to perform a round trip visiting the OWF from their base. For each shift the available vessels are able to perform a single pattern of the possible ones that are associated to their type and their base. Some patterns from different vessel types and associated to different bases might be virtually the same, containing the same list of tasks to be performed during the shift. Their cost and time required may vary, considering the speed of the vessel or the distance from their base to the OWF. Some task types do not require the vessel to be present at the turbine. This facilitates performing several tasks in parallel in a single time shift. It is irrelevant whether a pattern contains tasks that run in parallel or sequentially, as long as they meet the time constraints of a shift and the vessel type can accommodate enough technicians to perform the tasks. Moreover, some task types take longer than the time available in a single shift. Each pattern includes the time dedicated to each task in order to keep track of how many tasks have been finished. If a long task is initiated in one shift, it does not necessarily have to be continued in the following. However, for corrective tasks, downtime costs are incurred for all shifts until the task is finished and the failure in the turbine has been repaired. In summary, a pattern is associated to a vessel type and a base and consists of a list of tasks and associated dedication time and costs. Section 3.3 describes the process to generate the possible patterns and their costs.

Decisions actually take place on two levels: the first (tactical) level decides which bases to use and which vessels should be available during the planning horizon period under consideration. The second (operational) level schedules operations including which patterns to support by which available vessel in every shift of the planning horizon. The random events the planner is confronted with consist of weather conditions preventing use of vessels for maintenance and the possible failures of turbines that require corrective maintenance tasks.

3. MILP model description

Like in the models of [7] and [17], the tactical level decisions are evaluated based on a scenario approach, where the planner has a priori information to schedule the operational maintenance tasks. Our model keeps track of the number of tasks rather than considering each task individually. The following symbols are used to describe the mathematical optimisation model.

Sets

$\mathcal{K}$	Set of bases
$\mathcal{V}$	Set of vessel types
$\mathcal{V}_k$	Set of vessel types that can operate from base k, $\mathcal{V}_k \subseteq \mathcal{V}$
$\mathcal{S}$	Set of scenarios of weather and breakdown outcomes
$\mathcal{T}_{vs}$	Set of shifts during which weather in scenario s allows vessel v to sail
Γ	Set of maintenance task types
$\mathcal{NP}$	Set of planned preventive maintenance task types, $\mathcal{NP} \subseteq \Gamma$
$\mathcal{NC}$	Set of corrective maintenance task types, $\mathcal{NC} \subseteq \Gamma$
$\mathcal{P}$	Set of all possible patterns
$\mathcal{P}_{kv}$	Set of possible patterns for vessel of type v operating from base k

Parameters

T	Number of shifts in the planning horizon
F_k	Fixed cost per year of operating base k
G_v	Charter cost for using a vessel of type $v \in \mathcal{V}$ over the complete planning horizon
D_{ts}	Downtime income loss of performing a task in scenario s in shift t
H_{ts}	Hourly downtime cost in shift t of scenario s
C_p	Cost of executing pattern $p \in \mathcal{P}_{kv}$ from base k with vessel type v
CP_i	Penalty cost for not executing a maintenance task of type $i \in \Gamma$
N_i	Time (hours) required to finish a maintenance task of type $i \in \Gamma$
PP_i	Number of planned preventive maintenance tasks of type $i \in \mathcal{NP}$
M_k	Number of technicians available at base $k \in K$ in each shift
MP_p	Required personnel (number of technicians) to execute pattern p
Q_{kv}	Maximum number of vessels of type v that can operate from base k
B_i	Time (hours) one can spend on a task of type i in one shift
A_{ip}	Number of tasks of type i worked on in pattern p
P_s	Probability of scenario s
Y_{its}	Number of failures of type $i \in \mathcal{NC}$ accumulated in shifts $1, \ldots, t$. in scenario s

Tactical decision variables

$y_k \in \{0, 1\}$	Equal to 1 if base k is used, 0 otherwise
$x_{kv} \in \{0, \ldots, Q_{kv}\}$	Number of vessels of type v operated from base k

Operational decision variables

$w_{its} \in \mathbb{Z}^+$	Number of corrective maintenance tasks of type $i \in \mathcal{NC}$ worked on during shift t in scenario s
$q_{its} \in \mathbb{Z}^+$	Number of preventive maintenance tasks of type $i \in \mathcal{NP}$ worked on during shift t in scenario s
$u_{pts} \in \mathbb{Z}^+$	Number of vessels executing pattern p during shift t in scenario s
$\bar{w}_{its} \in \mathbb{Z}^+$	Number of turbines down during scenario s in shift t requiring finishing a corrective maintenance task of type $i \in \mathcal{NC}$
$\bar{q}_{is} \in \mathbb{Z}^+$	Number of preventive maintenance tasks of type $i \in \mathcal{NP}$ not completed in scenario s at the end of the planning horizon

In order to solve the model, the bounds on the variables should be set as sharp as possible to facilitate pre-solving operations of an LP solver that filters out those variables with a value of zero and nonbinding constraints. The parameter Q_{kv} is an upper bound on the number of vessels that can be used from each base. Therefore, the number of patterns that can be performed in a shift for a particular scenario is bounded by the total capacity of vessels for the considered bases. The sum of the vessel capacity of each base and the maximum number of tasks for each type that can be performed in a single pattern is an upper bound on the number of each preventive and corrective task that can be performed in a certain shift. The number of broken down turbines at a certain shift is smaller than or equal to the total number of occurrences of failures Y_{its} thus far. The number of preventive tasks not performed at the end of the horizon is bounded by the number of planned preventive tasks PP_i. We define the following bounds:

$$0 \leq x_{kv} \leq Q_{kv}, \quad k \in \mathcal{K}, v \in \mathcal{V} \tag{1}$$

$$0 \leq u_{pts} \leq \sum_{k\in\mathcal{K}} \sum_{v\in\mathcal{V}_k} Q_{kv} \quad p \in \mathcal{P}, s \in \mathcal{S}, t \in \{1,\dots,T\} \tag{2}$$

$$0 \leq w_{its} \leq \sum_{k\in\mathcal{K}} \sum_{v\in\mathcal{V}_k} Q_{kv} \max_{p\in\mathcal{P}_{kv}} A_{ip} \quad i \in \mathcal{NP}, s \in \mathcal{S}, t \in \{1,\dots,T\} \tag{3}$$

$$0 \leq q_{its} \leq \sum_{k\in\mathcal{K}} \sum_{v\in\mathcal{V}_k} Q_{kv} \max_{p\in\mathcal{P}_{kv}} A_{ip} \quad i \in \mathcal{NC}, s \in \mathcal{S}, t \in \{1,\dots,T\} \tag{4}$$

$$0 \leq \bar{w}_{its} \leq Y_{its} \quad i \in \mathcal{NC}, s \in \mathcal{S}, t \in \{1,\dots,T\} \tag{5}$$

$$0 \leq \bar{q}is \leq PP_i \quad i \in \mathcal{NP}, s \in \mathcal{S} \tag{6}$$

3.1. Objective function

The objective is to minimise the fixed costs of operating the bases and the charter cost of the selected vessels, the costs of all performed patterns throughout the planning horizon, the downtime costs associated with the running maintenance tasks or persistent failures and the penalty costs of preventive and corrective task types that are not finished within the planning horizon:

$$\min \sum_{k\in\mathcal{K}} F_k y_k + \sum_{k\in\mathcal{K}}\sum_{v\in\mathcal{V}_k} G_v x_{kv} + \sum_{s\in\mathcal{S}} P_s \left(\sum_{k\in\mathcal{K}}\sum_{v\in\mathcal{V}_k}\sum_{p\in\mathcal{P}_{kv}}\sum_{t=1}^{T} C_p u_{pts} \right) + \tag{7}$$

$$\sum_{s\in\mathcal{S}} P_s \left(\sum_{i\in\mathcal{NP}}\sum_{t=1}^{T} H_{ts} B_i q_{its} + \sum_{i\in\mathcal{NC}}\sum_{t=1}^{T} D_{ts}\bar{w}_{its} + \sum_{i\in\mathcal{NP}} CP_i \bar{q}_{is} + \sum_{i\in\mathcal{NC}} CP_i \bar{w}_{iTs} \right)$$

The first two terms of the objective function (7) cover the costs for the tactical decisions: cost of bases and vessels. The first term refers to the fixed costs for operating the chosen base(s) during the planning horizon. The second defines the charter costs for the available fleet of vessels during the planning horizon.

The following terms cover the expected operational costs of the model, where the cost of each scenario is multiplied by its probability. The third term of the objective function (7) determines the cost of operating the patterns during the planning horizon. Terms four and five describe the downtime costs of preventive and corrective task types, respectively. While the downtime costs for preventive task types are only incurred while a task is taking place on a turbine, downtime for a corrective task starts from the moment the breakdown occurs and continues until the shift in which it has been repaired. The last two terms are related to penalty costs. Term six is the penalty incurred for the preventive maintenance task types that are not performed within the planning horizon while term seven is the penalty for not finishing all corrective tasks.

3.2. Constraints for tactical and operational decisions

There is only one constraint on the tactical level describing the usual relation that base k should be in use, if one wants to station vessels there, and set the bounds of the maximum number of each vessel type for each base.

$$x_{kv} \leq Q_{kv} y_k \qquad k \in \mathcal{K}, v \in \mathcal{V} \tag{8}$$

The tactical decision directly influences the possibilities of the operational planning. A larger fleet allows to perform more patterns each shift. Constraints on the operational level are given by the following inequalities:

$$\sum_{p\in\mathcal{P}_{kv}} u_{pts} \leq x_{kv}, \quad k\in\mathcal{K}, v\in\mathcal{V}, s\in\mathcal{S}, t\in\{1,\ldots,T\} \tag{9}$$

$$\sum_{v\in V_k}\sum_{p\in\mathcal{P}_{kv}} MP_p u_{pts} \leq M_k y_k, \quad k\in\mathcal{K}, s\in\mathcal{S}, t\in\{1,\ldots,T\} \tag{10}$$

$$\sum_{k\in\mathcal{K}}\sum_{v\in V_k}\sum_{p\in\mathcal{P}_{kv}} A_{ip} u_{pts} - q_{its} \geq 0, \quad i\in\mathcal{NP}, s\in\mathcal{S}, t\in\{1,\ldots,T\} \tag{11}$$

$$\sum_{k\in\mathcal{K}}\sum_{v\in V_k}\sum_{p\in\mathcal{P}_{kv}} A_{ip} u_{pts} - w_{its} \geq 0, \quad i\in\mathcal{NC}, s\in\mathcal{S}, t\in\{1,\ldots,T\} \tag{12}$$

$$\bar{w}_{its} \geq Y_{its} - \frac{B_i}{N_i}\sum_{\tau=1}^{t} w_{i\tau s}, \quad i\in\mathcal{NC}, s\in\mathcal{S}, t\in\{1,\ldots,T\} \tag{13}$$

$$\sum_{\tau=1}^{t} w_{i\tau s} \leq \left\lceil \frac{N_i}{B_i} Y_{its} \right\rceil, \quad i\in\mathcal{NC}, s\in\mathcal{S}, t\in\{1,\ldots,T\} \tag{14}$$

$$\bar{q}_{is} \geq PP_i - \frac{B_i}{N_i}\sum_{t=1}^{T} q_{its}, \quad i\in\mathcal{NP}, s\in\mathcal{S} \tag{15}$$

$$u_{pts} = 0, \quad p\in\mathcal{P}, t\in\{1,\ldots,T\}\setminus\mathcal{T}_{vs} \tag{16}$$

Constraint (9) bounds operations on the availability of sufficient vessels at each base. Each available vessel has the potential to contribute by performing one of its possible patterns each shift. Constraint (10) limits operations due to available personnel at the bases. Constraints (11) and (12) link the assignment of individual tasks to planned patterns and availability of vessels, for preventive and corrective types respectively.

The model keeps track of the number of broken down turbines $\bar{w}_{its}$ requiring to finish a corrective task of type i, as the affected turbines incur downtime costs. To repair a breakdown of type $i \in \mathcal{NC}$ requires $\frac{N_i}{B_i}$ shifts to be worked on. If $B_i = N_i$, sum $\sum_{\tau=1}^{t} w_{i\tau s}$ gives the number of completed tasks type i from shift 1 up to shift t. If $N_i > B_i$ the sum is larger than the number of repairs. Assuming a FIFO assignement of tasks (first to break down, first to be repaired), the number of repaired turbines cannot be bigger than this sum divided by $\frac{N_i}{B_i}$. Constraint (13) states that the number of breakdowns $\bar{w}_{its}$ that have not been repaired at shift t cannot be smaller than the cumulative number of breakdowns minus the number of repairs. Constraint (14) ensures that the number of times work took place on tasks of type i cannot be bigger than that required by broken down turbines up to shift t, i.e. at shift t, you cannot repair turbines that have not been broken down yet up to moment t. For preventive tasks it is only necessary to check the number of not performed tasks at the end of the time horizon. Constraint (15) keeps track of that. The number of preventive tasks type i not finalized in scenario s is the number to be done minus the number of hours spent on the task divided by the necessary hours to finish it.

Implicitly, constraints (13),(14) and (15) imply that the individual task schedule follows from a FIFO approach for preventive and corrective task types, where the first task that has been started is the first to be ended. Such an assumption is needed: if each task was treated as an individual task, the model would become intractable for small instances. Finally, constraint (16) prevents patterns to be performed during shifts in which the weather conditions exceed the threshold of wind speed or wave height for the vessel type used to execute the pattern.

3.3. Generating columns (bundles and patterns) for the model

The basic decisions of the scheduler relate to the number u_{pts} of vessels sent out (number of trips) to perform maintenance tasks. The data A_{ip} that specifies the number of tasks of type i to be worked on for B_i hours during a trip are based on feasible patterns, previously crafted by the decision maker. This section describes an automatic procedure to generate the feasible maintenance patterns $p \in \mathcal{P}_{kv}$ for every base and vessel type combination to compute the data A_{ip}.

Table 1 illustrates the idea of the outcome of the procedure. For each base-vessel combination, we would like to know which activities i can be worked on during one trip to the wind farm. One row-vector in $\mathcal{P}_{kv}$ describes A_{ip}. The specific data is based on the case described in 5.1 with 4 different task types i.

Table 1: Possible efficient patterns that can be performed from each base-vessel combination with 4 task types. Data for base set $\mathcal{K} = \{K_1, K_2, K_3\}$ and vessel set $\mathcal{V} = \{V_1, V_2, V_3, V_4\}$ as outlined in Section 5.1

k	v	$\mathcal{P}$
K_1	V_1	$\{(0,0,4,0)\}$
K_1	V_2	$\{(0,0,4,0)\}$
K_1	V_3	$\{(3,0,0,0),(0,2,0,0),(0,0,4,0),(0,0,0,1)\}$
K_1	V_4	$\{(6,0,0,0),(3,3,0,0),(2,2,2,0),(3,0,3,0),(0,3,3,0),(0,0,6,0),(0,0,0,1)\}$
K_2	V_1	$\{(3,0,0,0),(0,2,0,0),(0,0,4,0),(0,0,0,1)\}$
K_2	V_2	$\{(3,0,0,0),(0,2,0,0),(0,0,4,0),(0,0,0,1)\}$
K_2	V_3	$\{(3,0,0,0),(0,2,0,0),(0,0,4,0),(0,0,0,1)\}$
K_2	V_4	$\{(6,0,0,0),(3,3,0,0),(0,6,0,0),(2,2,2,0),(3,0,3,0),(0,3,3,0),(0,0,6,0),(0,0,0,1)\}$
K_3	V_1	$\{(3,0,0,0),(0,0,4,0),(0,0,0,1)\}$
K_3	V_2	$\{(3,0,0,0),(0,0,4,0),(0,0,0,1)\}$
K_3	V_3	$\{(3,0,0,0),(0,2,0,0),(0,0,4,0),(0,0,0,1)\}$
K_3	V_4	$\{(6,0,0,0),(3,3,0,0),(2,2,2,0),(3,0,3,0),(0,3,3,0),(0,0,6,0),(0,0,0,1)\}$

As sketched in Section 2, some task types do not require the vessel to be present at the turbine during the operation such that these types can be run in parallel and they are denoted by the set Γp_v. We first pack those tasks in what we will call a *bundle* of parallel tasks and in a second stage, we will add a task that requires the vessel to be present in what will be called a *pattern*. As can be observed in Algorithm 1, the first step is the generation of bundles and after that these bundles are used to generate the patterns adding non-parallel tasks.

In fact, we want to generate all possible combinations of tasks that fit in the time frame and do not exceed the number of technicians that can come along on the trip. This is done by a recursive algorithm, Algorithm 2, that generates all combinations of task types from Γp_v that can be run in parallel.

A bundle b is defined as a quadruple (List, Time, Cost, Tech) specifying the list of tasks, the time needed to execute the tasks, the cost and the number of technicians required, respectively. Each task in List is performed at a different turbine and they are run in parallel. During the execution of a bundle, the vessel docks to the first turbine, offloads the task materials and technicians required and then moves to another turbine until all the tasks are started. When finished, the vessel recollects the technicians and returns to base. The duration (Time) of a bundle consists of the set up time (setupTime_i) for its tasks and the docking time (docktime_v) at each turbine when dropping off and when picking up the technicians. With respect to the time B_i spent on a single task, we have to keep in mind they are run in parallel. The procedure has to take into account the number of technicians Tech_v allowed on vessel v and the number of hours TMX_{kv} it may stay at the Offshore wind farm. TMX_{kv} follows from the travel time to and from the wind farm to be subtracted from the time of a shift.

Algorithm 1 Generate set of patterns for a base-vessel combination

Require: base k, vessel $v \in \mathcal{V}_k$, Tech_v, docktime_v, distance to OWF, vessel speed of v, fuel costs per km of v
  Global: sets $\mathcal{B}_{kv}$ and $\mathcal{P}_{kv}$

  Determine TMX_{kv} from the travel time, compute travel cost and Tech_v
  $b = (\emptyset, 0,\text{travel cost},0)$ ▷ Define empty bundle
  $\mathcal{B}_{kv}$ = build_bundle(b, k, v) ▷ Alg. 2
  $\mathcal{P}_{kv}$=build_pattern($\mathcal{B}_{kv}$,k, v) ▷ Alg. 3
  return $\mathcal{P}_{kv}$

Algorithm 2 build_bundle

Require: bundle b=(List,Time,Cost,Time), base k, vessel $v \in \mathcal{V}_k$
  Global: Tech_v, TMX_{kv}, docktime_v, setupTime_i, B_i, $i \in \Gamma p_v$

  for all $i \in \Gamma p_v$ **do** ▷ For all the task types that can be executed in parallel
    Add i to List and update Cost, Tech, Time
    if this fits, i.e. Time $\leq \text{TMX}_{kv}$ and Tech $\leq \text{Tech}_v$ **then**
      Define new bundle $\hat{b}$=(List,Time,Cost,Tech)
      $\mathcal{B}_{kv} = \mathcal{B}_{kv} \cup \{\hat{b}\}$ ▷ add $\hat{b}$ to set of bundles
      Recursive call to build_bundle($\hat{b}$,k, v)
  return $\mathcal{B}_{kv}$ ▷ Set of bundles of tasks for k, v

The procedure determines the initial travel cost of the trip from the distance from k to the wind farm. Then, starting with $b = (\emptyset, 0, travelcost, 0)$ builds a set $\mathcal{B}_{kv}$ of bundles of tasks for each vessel using the set of tasks Γ specified for each vessel Γ_v. The lists of the bundles are unordered with repetitions of the same task types.

Algorithm 3 build_pattern

Require: $\mathcal{B}_{kv}$, base k, vessel $v \in \mathcal{V}_k$
  Global: Tech_v, TMX_{kv}, sets $\mathcal{P}_{kv}$ and Γn_v: set of tasks requiring vessel to be present

  $\mathcal{P}_{kv} = \mathcal{B}_{kv}$ ▷ Copy the set of bundles into the set of tasks for k, v
  for all $i \in \Gamma n_v$ **do** ▷ For the non-parallel task types
    for all $b \in \mathcal{B}_{kv}$ **do** For all bundles k, v
      Add i to List and update Cost, Tech, Time of b
      if this fits, i.e. Time $\leq \text{TMX}_{kv}$ and Tech $\leq \text{Tech}_v$ **then**
        Define new pattern $\hat{p}$=(List,Time,Cost,Tech)
        $\mathcal{P}_{kv} = \mathcal{P}_{kv} \cup \{\hat{p}\}$ ▷ add $\hat{p}$ to set of patterns
  return $\mathcal{P}_{kv}$ ▷ Set of possible patterns for base-vessel combination k, v

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Algorithm 3 then uses the bundles to combine them with the task types that require the vessel to be present the so-called non-parallel task types in Γn_v to derive the pattern sets $\mathcal{P}_{kv}$. To create a sharp set description, a dominance procedure is run over the pattern sets. Let List_1 and List_2 be such that $\text{List}_1 \subseteq \text{List}_2$, then the pattern with List_1 is removed.

4. Operational scheduling based on available information

In this section, we discuss a scheduler (decision rule) for the operational part of the model. In each shift t, a plan is made for the next shift given the information. In contrast to the MILP approach, no anticipation of weather conditions and failures in the turbines is taken into account. In the notation, we will use similar symbols without the scenario index. Available information consists on one hand of the state of the system depending on earlier decisions and on the other hand on weather circumstances for the coming shift and the average situation compared to the rest of the year.

The stochastic events consist of 1) the observation of a breakdowns Y_{it}, 2) the next shift prediction of the wave height identifying the set $\mathcal{T}_v$ defining possible patterns p that can be selected with vessel v (if wave height is too high, vessel v cannot sail out), and 3) the next shift prediction of hourly loss of energy production due to downtime of a turbine. The current repair state is given by the number of broken down turbines still requiring tasks of type i. However, the observed state is more refined: The number of additional hours to be spent on broken down turbines requiring task i such that the turbines are operational again. For a corrective task $i \in \mathcal{NC}$ this is described by

$$RmainHour_{it} = N_i Y_{it} - B_i \sum_{z=1}^{t-1} q_{iz}, i \in \mathcal{NC}. \tag{17}$$

Moreover, the planner keeps track of the number of preventive tasks of type i that still have to be done from shift t up to end of horizon T. For preventive tasks $i \in \mathcal{NP}$, we also translate that to the number of required hours

$$RmainHour_{it} = N_i PP_i - B_i \sum_{z=1}^{t-1} q_{iz}, i \in \mathcal{NP}. \tag{18}$$

In terms of the symbols of the MILP model, in each shift a plan is made that consists of deciding on u_{pt}, i.e. which trips to carry out next shift given the limitation of the weather $\mathcal{T}$. The relative profit of this selection can be called a fitness function f_p for each pattern p to be scheduled. The focus of the scheduler is rather pattern oriented instead of vessel oriented. Given the current weather situation, it determines which vessels can sail and from that derives the complete set of possible patterns to be carried out. The selection of the following pattern has a greedy heuristic character, choosing the one with the largest fitness and recalculating the fitness of the remaining trips. Notice, that the gain of performing a trip may be lower than the cost of performing it, which represents the situation that the fitness is smaller than zero and correspondingly there may be available vessels that are not selected to perform a pattern. The success of the scheduler depends of course on the used fitness calculation. The cost of performing a pattern is relatively easy to estimate. On one hand we have the trip cost C_p and on the other hand the downtime cost $H_t \sum_{i \in \mathcal{NP}} B_i A_{ip}$ of the preventive tasks to be performed. The fitness of a pattern is given by

$$f_p = E_p + S_p - C_p - H_t \sum_{i \in \mathcal{NP}} B_i A_{ip} \tag{19}$$

confronting the relative gains of performing pattern p expressed by the gain E_p in electricity production of repaired turbines and the potential gain S_p of avoiding end of horizon penalties. Let the average hourly energy production for month m be $h_m, m = 1, \ldots, 12$. For the benefit of repairing a broken down turbine we roughly take the average advantage $R = \sum_{m=1}^{12} h_m$ for generating energy during one hour. The contribution of performing pattern p to the energy production due to repairs is estimated as

$$E_p = R(T - t) \sum_{i \in \mathcal{NC}} \frac{\min\{RmainHour_{it}, A_{ip} B_i}{N_i}\}. \tag{20}$$

Notice that this advantage depends on the number of broken down turbines via the number of hours still needed for corrective task type i to repair turbines.

To determine the advantage with respect to end of horizon penalties, the planner keeps track of the number of preventive tasks type i that have been

Algorithm 4 OWFscheduler

Require: shift t to be planned, broken down turbines Y_{it}, vessel plan x, information vessel v may sail out $\mathcal{T}_v$
  Global: N_i, PP_i, $\mathcal{P}_{kv}$, C_p, B_i and H_t

  Update $RmainHour_{it} = N_i Y_{it} - B_i \sum_{z=1}^{t-1} q_{iz}$, $i \in \mathcal{NC}$
  Update $RmainHour_{it} = N_i PP_i - B_i \sum_{z=1}^{t-1} q_{iz}$, $i \in \mathcal{NP}$
  $U = \emptyset$ ▷ U: Set of feasible patterns
  for all k, v with $x_{kv} > 0$ **do**
    if $t \in \mathcal{T}_v$ **then**
      $U = U \cup \mathcal{P}_{kv}$
  Determine fitness f_p for each pattern $p \in U$ according to (19)
  Find $r = \mathrm{argmax}_{p \in U} f_p$ ▷ Greedy heuristic choice
  while $f_r > 0$ and there exist vessels without assigned pattern **do**
    for Chosen pattern r and all tasks i with $A_{ir} > 0$ **do**
      $RmainHour_{it} = \max\{RmainHour_{it} - B_i A_{ir}, 0\}$
      Remove the used vessel and update U correspondingly
      Update fitness f_p for each pattern $p \in U$ according to (19)
      Find $r = \mathrm{argmax}_{p \in U} f_p$ ▷ Greedy heuristic choice
  return Which vessel is going to perform which pattern next shift t

carried out so far. The planner could aim at distributing the preventive tasks evenly over the horizon as depicted by the blue line in Figure 1. However, there is global information on monthly averages of wind speed, based on historic weather data which translates to the average hourly electricity production averaged of a month h_m. The planner aims at carrying out more tasks in the month where $\gamma_m = \frac{1}{h_m}$ is high. We assume he aims at having carried out a fraction

$$\varphi_m = \frac{\sum_{z=1}^{m} \gamma_z}{\frac{1}{12}\sum_{z=1}^{12} \gamma_z} \tag{21}$$

of preventive tasks during month m as sketched by the green line in Figure 1. Let φ_t be the interpolated value for shift t. The planner perceives to be behind schedule with the performance indicator

$$I_{it} = \max\{0, (1 - \varphi_t) PP_i - \left\lceil \frac{RmainHour_{it}}{N_i} \right\rceil\}, i \in \mathcal{NP} \tag{22}$$

For the broken down turbines, this indicator could be perceived as the number of turbines that are still not repaired

$$I_{it} = \left\lceil \frac{RmainHour_{it}}{N_i} \right\rceil, i \in \mathcal{NC}. \tag{23}$$

(15) The perception on potential saving S_p of performing pattern p on the end of horizon penalties can be taken as

$$\frac{t}{T} \sum_{i \in \Gamma} \frac{A_{ipB_i}}{N_i} I_{it} CP_i \tag{24}$$

such that this valuation increases linearly towards the end of horizon. The evaluation of the operational cost of a certain vessel plan defined by x_{kv} can be done by simulating the decision rule in Algorithm 4 over the complete time horizon for a number of scenarios keeping track of the costs.

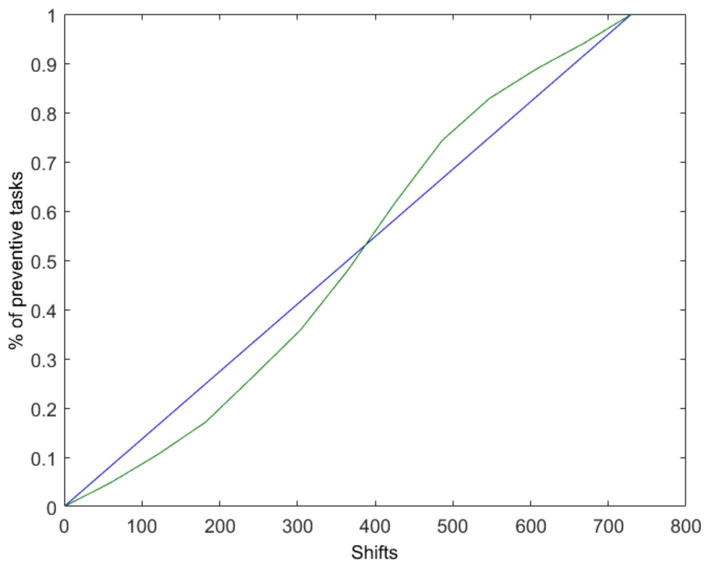

Figure 1: Linear and monthly average approaches to guide scheduling preventive tasks

5. Computational illustration

In the MILP model, the lower level operational planning cost provides a lower bound for the incurred cost due to failures and downtime. By formulating the operational tasks in a one-shot model, in principle all the scenario is known beforehand and earlier tasks can be planned based on a priori knowledge of failures that will occur later, i.e. anticipation is allowed. This makes the planning in principle cheaper than what is possible in reality. On the other hand, due to the nature of the variable $\bar{w}_{its}$, there is a tension in the optimal outcome to start repairing a failure as soon as possible by a corrective task.

In this section, we discuss the amount of underestimation for specific realistic data confronting the optimal MILP outcome of the lower level for scenarios with the heuristic decision rule defined in Section 4. The model and the heuristic have been compared for an instance similar to the one published in [6].

The MILP has been implemented for the bi-level model using GAMS interface [1], and solved using the CPLEX solver, setting the optimality gap at 1%.

5.1. A case study

We consider an OWF consisting of 125 turbines. The planning horizon is one year and the periods represent 12 hour shifts and include a return trip from the base the vessel is located to the OWF and a bundle of tasks. In practical terms there are 730 periods. There are three available bases $\mathcal{K} = \{K_1, K_2, K_3\}$ around the OWF, each of which can accommodate up to 48 technicians and they are located at 110, 61 and 86 kilometers respectively from the OWF. The cost of using each of them, for the entire time horizon is $F_k = 2, 6$ and 7 million monetary units (mu) respectively.

Four types of vessels are considered: $\mathcal{V} = \{V_1, V_2, V_3, V_4\}$. Each base has space to allow two vessels of type V_1, two of type V_2, four of type V_3 and one of type V_4. Vessel type V_4 is able to accommodate up to 30 technicians, while the rest has space for only 12. The cost of having a vessel during the whole planning horizon for vessel types V_1, V_2, V_3 and V_4 is, respectively, $G_v = 1224, 2500, 750$ and 7200 thousand mu. Vessel types V_1 and V_2 can travel at a speed of 20 knots, while vessel types V_3 and V_4 can travel at 40 knots. In practical terms this means that vessel types V_1 and V_2 require about 5.94, 3.3 and 4.64 hours to perform a return trip between bases K_1, K_2 and K_3 respectively while vessel types V_3 and V_4 require half of that time, allowing more time to perform tasks in each shift.

There are two preventive task types γ_1, γ_2 and two corrective task types γ_3, γ_4. All vessel types are able to perform all the task types considered, i.e. $\Gamma = \{\gamma_1, \gamma_2, \gamma_3, \gamma_4\}$. Task type γ_4 requires the vessel supporting the operation to be present at the turbine while the task is performed, whereas task types $\gamma_1, \gamma_2, \gamma_3$ can be run in parallel. The vessel drops a group of technicians at each turbine that is going to be supported during the shift. The time required to perform task types γ_1, γ_2, γ_3 and γ_4 is $N_i = 60, 100, 3$ and 7.5 hours respectively. The maximum time per period and turbine that a group of technicians can support a task type is $B_i = 6$ hours. Consequently, only tasks of type γ_3 can be performed in a single shift. The penalty cost for not executing a preventive task type is $CP_i = 10$ million mu. For corrective tasks of type γ_3, the cost is $CP_{\gamma_3} = 50,000$ mu, and for type γ_4, the penalty cost rises to $CP_{\gamma_4} = 50,0000$ mu. The patterns for each combination of base and vessel type are generated following the procedure described in Algorithms 2 and 3.

For our case study, the number of planned preventive tasks is $PP_{\gamma_1} = 125$ and $PP_{\gamma_1} = 60$. The number of corrective task types corresponds to the number of failures of the turbines and depends on the scenario. A scenario consists of the events of the failures of the turbines and the weather conditions for every period. Failures that require corrective task types γ_3 and γ_4 follow a binomial distribution. The rate of failures for a corrective task of type γ_3 is 5 times per turbine per year, and 3 times per turbine a year for failures that require a task of type γ_4. Weather conditions are taken from historical weather data. For each scenario, a report file containing a year of wind speed and wave height data of the OWF area is picked.

5.2. Discussion of results

Table 2: Associated costs for the MILP optimal solution and the heuristic in thousands mu for vessel plans X1 and X2. The columns represent the total costs (Total), pattern costs (Pattern), preventive downtime costs (P.D.), corrective downtime costs (C.D.), the operational costs (Operational) as a sum of pattern P.D. and C.D. costs and the tactical costs (Tactical), as the costs of chartering vessels and using the bases selected.

	Total	Pattern	P. D.	C. D.	Operational	Tactical
MILP X1	10986	5060	1118	558	6736	4250
MILP X2	11472	5127	1028	315	6470	5000
HEUR. X1	13402	5346	2296	1510	9152	4250
HEUR. X2	12959	5436	1235	1288	7959	5000

For comparing the performance of the heuristic for the operational stage with the optimal solution of the MILP problem, two vessel plans are considered. The first one is the optimal solution for the MILP, (X1), which consists of using three vessels of type V_3 from base K_1. The second vessel plan (X2) consists of a more expensive plan using four vessels of type V_3 from base K_1 in order to provide more slack for the operational planning.

A set of 20 scenarios of weather data and failures has been generated. For each scenario, the heuristic has been run and the MILP problem has been solved for vessel plans (X1) and (X2). Table 2 presents the average value of the 20 scenarios for the total cost, executing patterns cost, preventive and corrective downtime costs and operational stage costs for vessel plans X1 and X2, running the heuristic and solving the MILP problem. Preventive and corrective penalty costs are not included in Table 2, since they result to be zero for the generated scenarios.

The MILP a priori information solution for X1 has a total cost of nearly 11 million mu, while the heuristic for X1 has a cost of 13.4 million mu. Considering only the costs of the operational stage, the MILP a priori information solution is 6.73 million mu, while the heuristic reaches 9.15 million mu. Downtime costs for corrective tasks is about 2.7 times higher than the MILP cost. For preventive tasks the cost doubles that of the MILP solutions. This shows that the heuristic does not perform well for X1 with the optimal MILP a priori information setting. In a real setting, when failures and weather conditions are not known in advance, that tactical plan might not be optimal, as the evaluation of the relaxed vessel plan X2 shows.

For X2, the deviation between the two solutions is quite different. The MILP a priori information solution for the operational stage is 6.47 million mu, reducing only slightly the costs of X1. However, the heuristic reduces that cost to 7.95 million mu, and this reduction comes mostly by handling preventive tasks much better, reducing the cost by half compared to vessel plan X1. It can be observed that the downtime cost for corrective tasks, incurred by broken down turbines until they are repaired, is the only cost significantly higher for the heuristic compared to the MILP solution costs, for both plans X1 and X2. This can be explained considering that the MILP model has a priori information for when the failures occur for all the periods of the problem, being able to anticipate corrective tasks early in time. In contrast, the cost of performing the patterns, which constitutes the major cost of operating the OWF and is not related with uncertain events, is only 6% above the one provided by the MILP. So for the heuristic simulating the situation when no a priori information is available, the relaxed vessel plan X2 is optimal, despite the higher tactical cost. This means, what an a priori MILP solution does not show is that using more investment in additional material, may in practice work out better due to the ability to react on uncertain events.

6. Conclusion

Models in the literature on selecting an optimal vessel fleet composition for operations and maintenance tasks at OWFs during a planning horizon typically follow a deterministic approach using a priori information. The models are confronted with weather conditions and turbine failures. Weather conditions may prevent vessels sailing and execute tasks at the OWF, while turbine failures result in new corrective maintenance tasks. However, weather conditions and failures are unknown in practice. Therefore, a deterministic approach using a priori information to find the optimal solution for the operational stage only provides a lower bound on the maintenance costs in the operational stage. In the current paper, a MILP model for the fleet composition using a priori information is presented. The question is: What are the costs if the scheduler applies a heuristic rule based on the information available in practice? This means, the heuristic is not based on a priori information, only having knowledge of weather and failure events at the beginning of each shift. The results show that the heuristic performs well when the tactical vessel plans include enough vessels to cover the demand of O&M tasks at the OWF and allows for slack in the scheduling compared to the optimal MILP solution. Although the performance costs of the heuristic for the chosen scheduling are only 6% above the optimal lower bound, for the corrective tasks, where (stochastic) failures have to be repaired, the cost is about four times higher than that given by the MILP. This illustrates the effect of anticipation in an a priori information situation. The value of evaluating the fleet composition in a realistic setting is that probably the best vessel plan contains more vessels in practice than that predicted by an a priori information model, as the additional investment facilitates recourse actions on random events.

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