Modelling vessel fleet composition for maintenance operations at offshore wind farms

Alejandro Gutiérrez. Alcoba, Gloria Ortega, Eligius M.T. Hendrix and Inmaculada García

Paper presented at the conference ECOS 2018, an extended version has been submitted to an international journal.

Modelling vessel fleet composition for maintenance operations at offshore wind farms

A. Gutierrez-Alcoba, G. Ortega, E.M.T. Hendrix and I. García[a]

[a] *Universidad de Málaga, Málaga, Spain, gutialco@gmail.com;{gloriaortega,eligius,igarciaf}@uma.es*

Abstract:
Chartering a vessel fleet to support maintenance operations at offshore wind farms (OWF's) constitutes one of the major costs of maintaining this type of installations. Literature describes deterministic optimization models based on complete information within scenarios to schedule the maintenance and support decisions on the vessel fleet composition. The operations to be carried out can be classified as preventive and corrective tasks. The first type aims at reducing the likelihood of breakdowns and to prolong the life of turbine components. Corrective tasks are needed to repair breakdowns in turbines when they occur. Our research question is how to generate a vessel fleet composition, where the evaluation is based on scheduling without complete information. Such a model is a bi-level decision problem. On the first (tactical) level, decisions are made on the fleet composition for a certain time horizon. On the second (operational) level, the fleet is used to schedule the operations needed at the OWF, given random events of failures and weather conditions. A scenario based approach allows evaluation by parallel operational scheduling for each scenario.

Keywords:

Offshore wind farms, scheduling, maintenance.

1. Introduction

Offshore wind energy is expected to increase contributing to European energy supply; the European Wind Energy Association aims in its Central Scenario by 2030 at a total installed capacity of 66 GW. Offshore wind farms (OWFs) require a vessel fleet to perform operations and maintenance (O&M) tasks on the installed turbines. O&M constitutes up to one third of the OWF costs [4]. Well scheduled maintenance operations aid in requiring a smaller fleet size.

Models in literature, see e.g. the overview in [2], typically base the decision on the fleet size by scheduling several scenarios of weather conditions and breakdowns in a deterministic way with perfect information about the future. We argue that when using scenarios of stochastic outcomes, it would be better to base the required vessel fleet on realistic scheduling of the maintenance operations. The next question is how to generate an optimal composition based on its evaluation by a scheduler.

We investigate this question as follows. Section 2 describes the practical scheduling of maintenance operations at an OWF. Section 3 provides a typical MILP model, where simultaneously the maintenance is scheduled as well as the fleet composition is decided. Section 4 describes a practical way to schedule the operations based on the available information. Section 5 provides an illustration based on a real case and compares outcomes. Section 6 summarises our findings.

2. The OWF maintenance scheduling

The aim is to find an optimal vessel fleet and to perform required maintenance tasks on the wind turbines. We distinguish periods (shifts) of 12 hours in which a trip of a vessel can be planned to perform various preventive and corrective maintenance tasks. A preventive maintenance task is meant to prevent failures and prolong the lifetime of wind turbines [3]. Corrective maintenance tasks aim at repairing broken down wind turbines.

The number of preventive tasks of each type to be performed is determined at the beginning of the year, whereas the corrective tasks depend on the stochastic occurrence of wind turbine failure. The planner has to react on the failures dynamically. A maintenance task implies a downtime cost due to the lack of electricity production in the turbine. If a turbine is broken, downtime cost is incurred during the complete period from diagnose up to reparation took place.

In the vessel fleet, each vessel type has specific maintenance tasks it can do, a capacity for transferring technicians, a depreciation cost over the planning horizon, a sailing speed and a threshold for wind speed and wave height which defines the weather situations under which it can sail. Each base has a certain vessel capacity, a capacity to accommodate technicians, an associated cost and coordinates which define its distance to the OWF. The long tasks types are divided in smaller sub-operations to be performed during a shift and the planner should monitor when they are finished. Some tasks do not require the vessel to be located at the turbine, which facilitates performing several tasks in parallel in a single shift.

To evaluate a vessel fleet composition, which types of vessels are rented and located at which base, we should know how well this composition fits the maintenance scheduling requirement. Of course, the challenge is that the schedule in practice depends on random events; weather conditions preventing use of vessels for maintenance and occurrence of failures of turbines. Here is where our research question comes in. Most models presented in literature take a perfect information approach to schedule the trips, evaluating a number of weather and failure scenarios. We will present such a model in Section 3. However, the model can also be used to schedule the maintenance trips in a more realistic way based on a decision rule that takes the available information into account, as we will outline in Section 4. The next question is how to generate and select the vessel composition that provides the best performance.

3. A perfect information MILP model

We sketch the ingredients of a deterministic MILP model in Section 3.1 and the generation of data for the scheduling problem in Section 3.2.

3.1. MILP model

The following symbols are used. Typical indices are i for task, b for base, b=1,..,n, p for trip, v for vessel type, s for scenario, s=1,..,S and t for shift with the horizon T.

Sets

V_b : Possible vessel types at base b

W_{vs} : Shifts during which weather in scenario s allows vessel v to sail

P_{bv} : Possible trips for vessel v from base b

I : Preventive task types

J : Corrective task types

Parameters

F_b : Yearly fixed cost for using base b

G_v : Charter cost for vessel v

D_{st} : Hourly downtime cost for a turbine during shift t in scenario s

C_p : Cost trip $p \in P_{bv}$ for a vessel type v from base b

K_i : Penalty for not finishing a maintenance task type i at the end of horizon

N_i : Number of required hours to finish task type i

B_i : Number of hours spent on task type i in one shift

R_i : Number of planned preventive tasks of type $i \in I$ during the horizon

Y_{its} : Cumulative number of failures that require corrective task $i \in J$ at shift t scenario s

A_{ip} : Number of tasks type i in trip p

M_b : Number of maintenance technicians at base b

Mp_p : Number of required maintenance technicians for trip p

Q_{bv} : Maximum number of vessels type v at base b

Tactical decision variables

$y_b \in \{0,1\}$ Base b in use

$x_{bv} \in \{0,.., Q_{bv}\}$ Number of vessels type v at base b

Scheduling variable

$u_{pts} \in \{0,.., Q_{bv}\}$ Number of trips type $p \in P_{bv}$ from base b vessel v in shift t scenario s

Notice, this only can take place if $t \in W_{vs}$

Dependent variables

q_{its} Number of maintenance tasks type i in shift t scenario s

c_{its} Number of corrective tasks type $i \in J$ not finished in shift t scenario s

d_{is} Number of preventive tasks type $i \in I$ not finished at end of horizon T in scenario s

Objective function

$$\mathrm{Min}\frac{1}{S}\sum_{s=1}^{S}\left(\sum_{i\in I}K_i d_{is}+\sum_{i\in J}K_i c_{iTs}+\sum_{t=1}^{T}(\sum_{b=1}^{n}\sum_{v\in Vb}\sum_{p\in Pbv}C_p u_{pts}+\sum_{i\in I}D_{st}B_i q_{its}+\sum_{i\in J}12D_{st}q_{its})\right)+\sum_{b=1}^{n}\left(F_b y_b+\sum_{v\in Vb}G_v x_{bv}\right) \quad (1)$$

The first term evaluates the vessel composition plan based on a number of scenarios. It includes the penalty costs, the cost of performing trips and the downtime loss of energy production. The second term consists of the direct cost of the vessel fleet composition plan for using bases and vessels.

The composition plan variables, besides upper bounds are interrelated by equation (2). No vessel is stationed at a base, which is not in use.

$$x_{bv}\le y_b \forall b,v\,. \quad (2)$$

The other constraints limit the trips to be performed and relate the trips to the dependent variables.

A trip can only be performed if there are vessels at a base for it:

$$\sum_{p\in Pbv}u_{pts}\le x_{bv}\;\forall b,v,s,t\in W_{vs}\,. \quad (3)$$

There should be enough technicians to perform a trip:

$$\sum_{v\in Vb}\sum_{p\in Pbv}Mp_p u_{pts}\le M_b\;\forall b,s,t\in W_{vs}\,. \quad (4)$$

The number of tasks during a shift is limited by the trips:

$$\sum_{b=1}^{n}\sum_{v\in Vb,t\in W_{vs}}\sum_{p\in Pbv}A_{ip}u_{pts}\ge q_{its}\;\forall i,s,t\,. \quad (5)$$

Equation (6) keeps track of the number of breakdowns c_{its} that have not been repaired at shift t:

$$B_i\sum_{z=1}^{t}q_{izs}\ge N_i(Y_{its}-c_{its})\forall s,t,i\in J\,. \quad (6)$$

The number of corrective tasks type i is bounded by the number of broken down turbines up to moment t. You cannot repair turbines that have not been broken down yet:

$$\sum_{z=1}^{t} q_{izs} \leq \left\lceil \frac{N_i}{B_i} Y_{its} \right\rceil \forall s, t, i \in J \,. \tag{7}$$

Equation (8) counts the number of not finished preventive tasks d_{is} for scenario s at the end of the horizon:

$$B_i \sum_{t=1}^{T} q_{its} \geq N_i (R_i - d_{is}) \forall s, i \in I \,. \tag{8}$$

For the operational scheduling, (6) and (8) implicitly imply a FIFO approach where the oldest breakdown or preventive task of a type is finished first.

3.2. Generation of data

The technical data to evaluate a vessel composition is defined by accounting for the cost of the various ingredients of the model. The most elaborative part is to generate the bundles of tasks A_{ip} that go into one trip. Given the shift of 12 hours and the sailing time (depending on speed of the vessel and location of the base), time is left over to perform tasks that sometimes can be done in parallel for those activities that do not require the vessel to be present.

The generation of trips p thus requires enumerating all possibilities of packing tasks into the shift. The result is a trip p which is characterised by its costs C_p, the number of required technicians M_p, and the column A_{ip}, that tells us how many tasks of type i are planned in trip p. The generation of trips requires a pre-processing of technical data, which forms the core of the data generation for the model.

Besides the enumeration of technical possibilities, the scenarios have to be generated with respect to the failures (breakdowns) that occur during the year (parameter Y_{ist}) and the weather circumstances (defining set W_{vs}). For the second part, historical patterns can be used. For the first, a sample can be generated from a probability distribution.

In [1], the model has been illustrated from generating an MILP solution for a realistic case. For only 3 scenarios the model has about 300,000 variables and 50,000 constraints and requires quite some computational time and memory (to store the search tree) to be solved to optimality.

As argued, the optimal solution of the MILP model scheduling implies complete information of what is going to happen during the year for each scenario. This means that the planner in April already has knowledge about the breakdowns and weather circumstances in November and can anticipate on that to prevent downtime of the turbines when the weather is profitable for generating energy. This is not only not very realistic, but also provides an underestimation of the operational cost of a given vessel fleet composition plan. Therefore, we will have a look at the consequences of scheduling the trips and tasks given the information available to the planner.

4. Scheduling maintenance based on available information

In this section, we discuss a scheduler (decision rule) for the operational part of the model. In each period 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 W_v defining possible trips 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 D_t of a turbine.

The repair state is given by the number of broken down turbines still requiring tasks of type i. However, the observed state is more refined: How many additional hours should be spent on broken down turbines requiring task i such that the turbines are operational again. We will use the symbol $RmainHour_{it}$ for that

$$RmainHour_{it} = N_i Y_{it} - B_i \sum_{z=1}^{t} q_{iz}, i \in J . \tag{9}$$

Moreover, the planner keeps track of the number of preventive tasks of type i that still have to be done from shift t+1 up to end of horizon T following the dynamics as expressed in (8) in an iterative way. We also translate that to the number of required hours $RmainHour_{it}$

$$RmainHour_{it} = N_i R_i - B_i \sum_{z=1}^{t} q_{iz}, i \in I . \tag{10}$$

Algorithm 1: OWFscheduler

Require: t, W_v, Y_{it} (broken down turbines), $\sum_{z=1}^{t-1} q_{iz}$

1: **Update** $RmainHour_{it} = N_i Y_{it} - B_i \sum_{z=1}^{t-1} q_{iz}, i \in J$

$RmainHour_{it} = N_i R_i - B_i \sum_{z=1}^{t-1} q_{iz}, i \in I$

2: $U=\emptyset$ #U: Set of Feasible trips
3: **for all** v, b with $x_{bv}>0$ **do**
4: **if** $t \in W_v$ **then** $U = U \cup P_{bv}$
5: **end for**
6: Determine fitness f_p for each trip $p \in U$
7: Find $r = \arg\max_{p \in U} f_p$ #Greedy heuristic choice
8: **while** $f_r>0$ **and** there exist vessels without trips **do**
9: **for** Chosen trip r and all tasks i with $A_{ir}>0$ **do**
10: $RmainHour_{it} = \max\{ RmainHour_{it} - B_i A_{ir}, 0\}$
11: Remove the used vessel and update U correspondingly
12: Update f_p for each trip $p \in U$ and r
13: **end for**
14: **end while**

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 W_v. The relative profit of this selection can be called a fitness function f_p for each trip p to be scheduled.

The focus of the scheduler is rather trip 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 trips. The selection of the following trip has a greedy heuristic character, choosing the one with the largest fitness. Now the result of the chosen trip is elaborated in steps 10 and 11 of Algorithm 1 and the fitness of the remaining trips is re-evaluated in step 12. 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 trip. The success of the scheduler depends of course on the used fitness calculation.

The cost of performing a trip is relatively easy to estimate. On one hand we have the trip cost C_p and on the other hand the downtime cost for the preventive tasks, $D_t \sum_{i \in I} B_i A_{ip}$.

The fitness of a trip as used in this paper is given by

$$f_p = E_p + S_p - C_p - D_t \sum_{i \in I} B_i A_{ip} \,, \qquad (11)$$

where the costs are confronted by the relative gains of performing trip p expressed by the gain E_p in electricity production of repaired turbines and the potential gain S_p of avoiding penalties at the end of the horizon.

Let the average hourly energy production for month m be D_m, m=1,..,12. For the benefit of repairing a broken down turbine we roughly take the average advantage for generating energy during one shift

$$\Delta = \frac{1}{T}\sum_{m=1}^{12} D_m \;.$$

The contribution of a trip to the energy production due to repairs is estimated as

$$E_p = \Delta(T-t)\sum_{i \in J} \frac{\min\{RmainHour_{it}, A_{ip}B_i\}}{N_i} \quad . \qquad (12)$$

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.

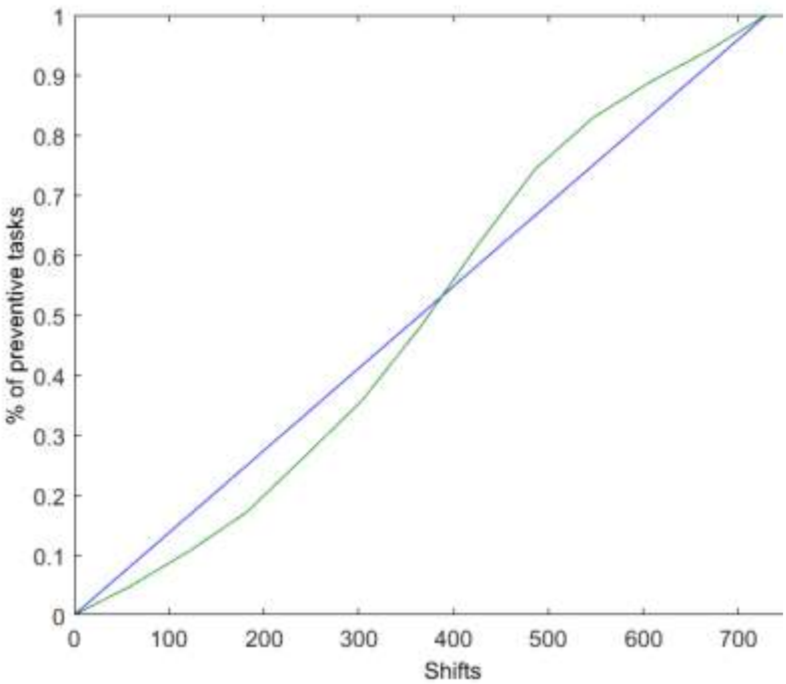

Fig. 1. Accumulative distribution of planned preventive tasks according to equal over the horizon (blue) or aiming at more tasks when energy production is low (green).

With respect to the penalties, the planner keeps track of the number of preventive tasks type i that have been 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 D_m. The planner aims at carrying out more tasks when $\delta_m = 1/D_m$ is high. We assume he aims at carrying out a fraction

$$\varphi_m = \delta_m \frac{1}{12}\sum_{z=1}^{12} \delta_z \qquad (13)$$

of preventive tasks during month m according to the green line in Figure 1, where φ_t represents the interpolated value for shift t. The planner perceives to be behind schedule with the performance indicator

$$H_{it} = \max\{0, (1-\varphi_t) R_i - \left\lceil \frac{RmainHour_{it}}{N_i} \right\rceil\}, i \in I. \quad (14)$$

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

$$H_{it} = \left\lceil \frac{RmainHour_{it}}{N_i} \right\rceil, i \in J. \quad (15)$$

The perception on potential saving S_p of a trip p on the penalties at the end of horizon will be taken as

$$S_p = \frac{t}{T} \sum_i \frac{A_{ip} B_i}{N_i} K_i H_{it} \,, \quad (16)$$

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_{bv} can be done by simulating the decision rule in Algorithm 1 over the complete time horizon for a number of scenarios keeping track of the costs.

5. Computational illustration

The optimum lower level operational planning cost of the MILP model provides a lower bound for the incurred cost due to failures and downtime which can be reached in practice. In fact, all the events of the scenario are known beforehand and earlier tasks can be planned based on knowledge of failures that will occur later, i.e. anticipation is possible. This makes the planning in principle cheaper than what is possible in reality.

In this section, we discuss the amount of underestimation for specific realistic data comparing the optimal MILP outcome of the lower level for scenarios with the decision rule in Algorithm 1. The data of an instance similar to that in [1] has been used to compare outcomes for the MILP model with anticipation and the decision rule. For the solution of the MILP model, the GAMS interface has been used and solutions are generated by CPLEX with an optimality gap of 1%.

The considered OWF has 125 turbines and the planning horizon is one year, where periods are 12 hour shifts. This means that a trip from the base the vessel is stationed to the OWF includes the return trip and the scheduled tasks in the trip. Three bases, B1; B2 and B3 are relevant located at 110, 61 and 86 kilometers respectively from the OWF. The cost of using them for the entire time horizon is 2, 6 and 7 million monetary units (MU) respectively. Each of them can accommodate up to 48 technicians. Four types of vessels are considered: V1; V2; V3 and V4 with a renting cost for the whole horizon of 1,224,000, 2,500,000, 750,000 and 7,200,000 MU respectively. At a base, two vessels of type V1, two of type V2, four of type V3 and one of type V4 can be handled. Vessel type V4 can accommodate up to 30 technicians, while the rest has space for only 12. Vessel types V1 and V2 can travel at a speed of 20 knots, while vessel types V3 and V4 can travel at 40 knots. In practical terms this means that vessel types V1 and V2 require about 5.94, 3.3 and 4.64 hours to perform a return trip between bases B1, B2 and B3 respectively, while vessel types V3 and V4 would require half of that time, leaving more time to perform tasks in each shift.

Two preventive task types A1; A2 and two corrective tasks A3; A4 are considered. All vessel types are able to perform all the task types. Task A4 requires a vessel supporting the operation at the turbine, while tasks A1; A2; A3 can be done in parallel. A vessel drops a group of technicians at each turbine that is going to be supported by the trip. The time required to perform task types A1, A2, A3 and A4 is 60, 100, 3 and 7.5 hours respectively. The maximum time per period and turbine that a group of technicians can support a task is 6 hours. Consequently, only tasks of type A3 can be performed in a single shift. The penalty cost for not finishing a preventive task is 10 million MU. For corrective tasks, the penalty is set at 50,000 MU for type A3 and 500,000 MU for type A4. The trips for each base-vessel combination are generated following the procedure described in Section 3.2.

In this study, 125 tasks have been planned of type A1 and 60 of type A2. The number of corrective takes depends on the number of turbine failures. A scenario consists of a list in time of turbine failure events and the weather conditions for each period. The random failures follow a binomial distribution. The failure rate is 5 per year per turbine for break-downs that require task type A3 and 3 times per turbine a year for a break-down requiring a repair task of type A4. We assume that failures are observed at the beginning of the day, i.e. every two shifts. Weather conditions are taken from historical weather data. For each scenario, a year of wind speed and wave height data of the OWF area is picked for generating the corresponding parameters.

To compare the scheduling in the operational stage of the decision rule of Algorithm 1 with the optimal MILP solution, two vessel plans are considered. The first one is the optimal solution for the MILP, (3V31), which consists of using three vessels of type V3 from base B1. The second instance (4V31) consists of widening the scheduling opportunities by using one vessel more (four vessels) of type V3 from base B1. Notice that this is not optimal according to the MILP model.

A set of 20 scenarios have been generated. For each scenario, the decision rule of Algorithm 1 has been run and the scheduling part of the MILP model has been solved for 3V31 as well as 4V31. Table 1 presents the average cost values over the 20 scenarios specifying the total cost, trip costs, downtime cost of the performed preventive tasks and electricity loss due to downtime of broken down turbines. The penalties are not included in the table, because they are zero for the 20 scenarios as the vessel plan is wide enough to handle all preventive tasks and repair all broken down turbines.

Table 1. Operational costs in thousands MU for MILP solution and rule, vessel plans 3V31, 4V31

			Downtime		*Total*	*Total*
plan	scheduling	Trips	Preventive tasks	Broken down	Operational	Oper+Tact
3V31	MILP	5,060	1,118	558	6,736	10,986
	Dec rule	5,346	2,296	1,510	9,152	13,402
4V31	MILP	5,127	1,028	315	6,470	11,472
	Dec rule	5,436	1,235	1,288	7,959	12,959

The MILP complete information solution for 3V31 an operational stage cost of 6.73 million MU, while the decision rule reaches 9.15 million MU. The downtime cost for broken down turbines is about 2.7 times higher than the MILP cost. For preventive tasks, the downtime cost doubles that of the MILP solutions. This shows that anticipation mainly makes use of the hourly downtime information D_t in the future and can handle with the small fleet of 3 vessels of plan 3V31. In a real setting, when failures and weather conditions are uncertain, 3V31 might not be optimal.

Therefore, we evaluated the wider plan 4V31. It is interesting to observe, that despite the big relaxation for the scheduling, the MILP complete information solution reduces the cost of the operational planning only slightly, from 6.74 to 6.47 million MU. However, the more realistic decision rule reduces operational cost drastically, from 9.15 to 7.95 million. This reduction is mainly caused by being able to handle preventive tasks better. The unpredictability of future failures causes the big difference between the MILP solution (knowing the future) and the decision rule, which has to react on the observations of failures up to day.

The largest part of the operational cost consists of the cost of operating the trips. The difference between the MILP solution and decision rule, is only 6%. This difference is caused by the number of trips, where again, the MILP solution knows it should work ahead in preventive tasks knowing that in the future some break-downs are going to occur. The MILP solution shows that the total cost of tactical and operational level is lower for vessel plan 3V31 than for plan 4V31. In the realistic setting of the decision rule 3V31 cannot be optimal; there exists a better vessel plan, i.e. 4V31.

6. Conclusions

To evaluate the fleet composition during a planning horizon, models in literature on operations and maintenance tasks at OWFs typically apply a complete information MILP approach. The models include weather conditions and turbine failures. Weather conditions may prevent vessels to sail and perform tasks at the OWF, while turbine failures result in new corrective maintenance tasks. However, weather conditions and failures are unknown beforehand in practice. Therefore, a complete information approach to determine the OWF schedule underestimates the maintenance costs and downtime of turbines. This paper presents a similar MILP model for the fleet. The question is: What are the costs if the scheduler applies a decision rule based on the information available in practice? This means, the rule is not based on perfect information, realising the weather and failure events at the beginning of each shift. The results show that the rule performs well when the tactical decisions 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 complete information plan. Although the maintenance costs of the rule for the chosen scheduling are only 6% above the optimal lower bound, the downtime of turbines due to (stochastic) failures may provide a loss in electricity production up to four times higher than that given by the complete information MILP schedule. This illustrates the effect of anticipation in a perfect information situation. The value of evaluating the fleet composition in a realistic setting is that probably the chosen vessel plan will contain more vessels, as this facilitates recourse actions on random events.

Acknowledgments

This work has been funded by a grant from the Spanish Ministry (TIN2015-66680) and Junta de Andalucía under contract P11-TIC7176 in part financed by the European Regional Development Fund (ERDF). G. Ortega is a fellow of the Spanish 'Juan de la Cierva' Postdoc program.

Nomenclature

MILP: Mixed Integer Linear Programming

MU: monetary units

T: Time horizon (number of 12 hour shifts)

F_b : Yearly fixed cost for using base b (MU)

G_v : Charter cost for vessel v (MU)

D_{st} : Hourly downtime cost for a turbine during shift t in scenario s (MU)

C_p : Cost trip $p \in P_{bv}$ for a vessel type v from base b (MU)

K_i : Penalty for not finishing a maintenance task type i at the end of horizon (MU)

N_i : Number of required hours to finish task type i (hours)

B_i : Number of hours spent on task type i in one shift (hours)

R_i : Number of planned preventive tasks of type $i \in I$ during the horizon

Y_{its} : Cumulative number of failures that require corrective task $i \in J$ at shift t scenario s

A_{ip} : Number of tasks type i in trip p

M_b : Number of maintenance technicians at base b

Mp_p : Number of required maintenance technicians for trip p

Q_{bv} : Maximum number of vessels type v at base b

E_p : Estimate of financial contribution due to energy production of trip p (MU)

S_p: Estimate contribution to penalty savings of a trip p (MU)

φ_t: Aimed at fraction of total preventive maintenance at shift t

$RmainHour_{it}$: Number of hours should to spent on broken down turbines requiring task i (hours)

3V31: Vessel plan with 3 vessels of type 3 stationed at base number 1

4V31: Vessel plan with 4 vessels of type 3 stationed at base number 1

decision variables

$y_b \in \{0,1\}$: Base b in use

$x_{bv} \in \{0,.., Q_{bv}\}$: Number of vessels type v at base b

$u_{pts} \in \{0,.., Q_{bv}\}$ Number of trips type p from base b vessel v in shift t scenario s

q_{its}: Number of maintenance tasks type i in shift t scenario s

c_{its}: Number of corrective tasks type $i \in J$ not finished in shift t scenario s

d_{is}: Number of preventive tasks type $i \in I$ not finished at end of horizon T in scenario s

References

[1] Gutierrez-Alcoba A., Ortega G., Hendrix E.M.T., Halvorsen-Weare E.E., Haugland D., A model for optimal fleet composition of vessels for offshore wind farm maintenance. Procedia Computer Science 2017; 108:1512-1521.

[2] Hofmann M., A review of Decision Support Models for offshore wind farms with an Emphasis on Operation and Maintenance Strategies. Wind Engineering 2011; 35:1-16.

[3] Obdam T., Braam H., Rademakers L., Eecen P., Estimating costs of operation & maintenance for offshore wind farms. In Proceedings of the European Offshore Wind Energy Conference; 2007, 4-6.

[4] Snyder B., Kaiser M.J., Ecological and economic cost-benefit analysis of offshore wind energy. Renewable Energy 2009; 34: 1567-1578.