Development of an O&M tool for short term decision making applied to offshore wind farms

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Introduction

Every day, wind farm operators have to make difficult logistical decisions, which require them to efficiently use resources to maximise wind turbine availability. Deciding which turbines to maintain and how to do it is challenging due to multiple constraints such as the weather, type of failure that occurred, vessels and technicians available.

A recent report by Catapult (Newman, 2015) stated that improvement of asset management strategies through the use of decision making tools is one of the priorities for offshore wind O&M industry. The research community is starting to propose solutions to the problem. Zhang (2014) applied a Duo Ant Colony Optimization approach, which suggests the optimal routing of vessels to wind turbines, taking into account a penalty cost for delayed service. Stalhane et al. (2015) explored the difference between solving a vessel routing problem optimally and sub-optimally, suggesting that the sub-optimal result obtained using a path-flow model is far more computationally effective than the optimal result obtained using an arc flow model. Dai et al. (2015) described an approach based on maintenance grouping, which allows to schedule different types of maintenance action during the same period or even visit.

The model proposed in this article is designed to identify a cost-optimal policy, which specifies which turbines should be repaired using which vessels, while taking numerous constraints into account. Unlike the models discussed above, it allows considering unsuccessful repairs and takes into account the transfer time from the vessel to turbine. Furthermore, the model does not require significant amounts of data and the optimal policy obtained here is visualised to the user using easily understandable graphics.

Approach

Firstly the problem is defined; the following values are specified:

- Types of failure that can occur: the probability of successful repair, cost of repair, technicians and time required to fix the issue
- Vessels available: type of vessel, day-rate, speed, fuel consumption, capacity to carry technicians
- Number of failed wind turbines: their distance from shore, type of failure that occurred
- Expected weather window on the day
- Technicians available on the day

To ensure no logistical possibilities are missed out, all possible combinations of dispatching each vessel to each turbine are generated (including the option not to service a failed turbine). Obviously, due to various constraints, many of those mathematically possible policies will not be feasible. The following filters are used to remove the policies which are impossible to conduct:

- Return travel time, transfer time from vessel to turbine and waiting time exceed the weather window
- Insufficient vessel capacity to carry technicians required for repairs
- Wave height is higher than the limit for a given vessel
- Incorrect type of vessel for the job
- Policy requires more technicians than the number available on the day

Then, all the remaining polices are ranked according to the sum of all the costs associated with each policy:

- Vessel hire cost
- Cost of transportation (fuel cost)
- The reward for fixing the turbine

In the end, the policy with the lowest cost is displayed to the user. The maintenance scheduler can then evaluate the model's suggestion and use it to aid his/her decision.

Main body

To illustrate the outputs of the model, the following case study is proposed. Consider a wind farm with 8 turbines failed at the start of the day. The distance from base to turbine i is denoted as D_i, which ranges from 50 to 54km. The failed turbines require different types of repair, which are specified in Table 1. Unsuccessful repairs are implemented through the use of repair probability, reflecting the fact that the technicians won't always be able to successfully repair the turbine that day, for example due to incorrect diagnosis of the problem. The time window for repairs that day is 10 hours. The number of technicians available on the day is 21. The operator has 5 vessels available on the day; their properties are shown in Table 2. The significant wave height on the day was assumed to be 1.2m.

Table 1. Types of failure (CTV stands for Crew Transfer Vessel).

Type of failure	Technicians required	Time required	Repair cost	Repair probability	Vessel required
Manual reset	2	2	£5,000	1	CTV
Lubricant top-up	2	3	£10,000	1	CTV
Minor repair	4	5	£100,000	0.8	CTV
Medium repair	5	6	£200,000	0.7	CTV
Major replacement	6	8	£400,000	0.8	Jack-up

Table 2. Available vessels and their properties.

Vessel	Capacity	Wave height limit (m)	Hire cost (£)	Fuel consumption (£/km)	Speed (km/h)
CTV1	8	1.5	£0	40	25
CTV 2	8	1.5	£0	40	25
CTV 3	10	1.75	£5,000	80	40
CTV 4	10	1.75	£5,000	80	40
Jack-up vessel	30	2	£40,000	80	40

It was assumed that in addition to the travel time, each transfer from a vessel to a turbine and vice versa will take 15 minutes. The question arises: given the types of failure, location of the turbines, time window and number of technicians available, how to decide which vessels to dispatch and which turbines to repair? The model described in the previous section is run and the resulting actions are shown in Figure 1. In this particular case, the model considers 1,679,616 unique policies, running the simulation on a standard desktop computer took 260 seconds.

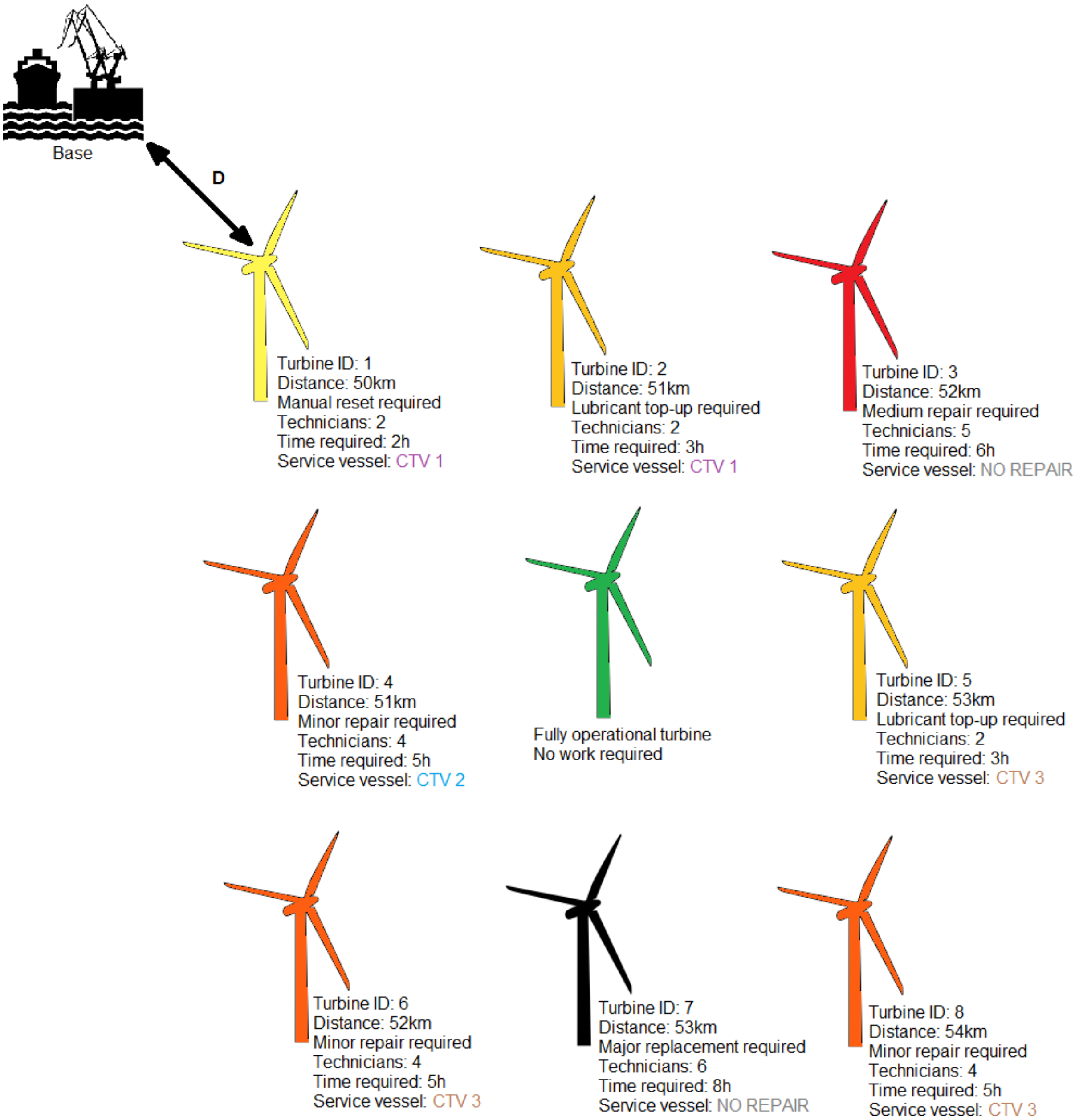

Figure 1. Illustration of the optimal policy. Note: colour of the wind turbine icon indicates the severity of failure.

The optimal policy recommends using CTVs 1, 2 and 3 to repair all turbines except numbers 3 and 7, which exhibit the most serious failures. The reason for not repairing these turbines is the shortage of technicians: to repair all turbines 29 technicians would be required. It can be seen that CTVs 1 and 2 will carry less technicians than their capacity (4 technicians on each vessel, capacity of 8). This is due to the fact that although either vessel has enough capacity to carry enough technicians to repair turbines 1, 2 and 4, the transfer time to and from the turbines eliminates that possibility, as such policy would take longer than the permitted time window of 10 hours (it was assumed that in one day, one team of technicians can only carry out repairs on one turbine). CTV 3 is carrying the maximum number of technicians permitted; due to the faster cruise speed compared to CTVs 1 and 2, it can service all 3 turbines within the time window. An alternative policy could be to repair turbines 1, 2 and 4 using CTV 4, however, the cost of hiring this vessel and its travel cost exceeds the travel cost of both CTV 1 and 2, which incur no hire fee. From Figure 1, it can be seen how the use of fuel consumption parameter forces the optimal policy to use vessels to repair turbines located close to each other.

Time is one of the key practical constraints, as wind farm operators will usually have less than an hour to decide the dispatch policy for the day. The model presented here requires minimal data input and is computationally effective, making it a useful decision support tool for wind farm operators.

Possible methods of validation of this model would include a blind test with an industrial partner who would provide a case study; the results of the model would then be compared to the decisions that were made on the day. Alternatively, cross comparison of results with other models in the field could be conducted.

Conclusions

The model described here allows effective planning of resources by automating the process of logistical decision making of maintenance action for offshore wind farms. In many cases, maintenance decisions are still made without the help of mathematical models and it is possible that operators may miss a certain policy that allows repairing an additional wind turbine. This would be particularly important if a period of rough sea is expected in near future, meaning no possible repairs for a certain period of time. Furthermore, automating the decision making process by using the model described here would likely save time and resources, while extending the effective repair window.

Future work would include considering other maintenance actions such as annual service and inspections, servicing multiple wind farms with multiple maintenance bases and extending the planning horizon beyond one day.

Learning objectives

Understanding how to prioritise repairs and optimally dispatch vessels under multiple constraints.

References

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