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Optimizing Jack-up vessel strategies for maintaining offshore wind farms

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Abstract

In this paper we present a new two-stage stochastic mathematical programming model that determines the optimal jack-up vessel strategy for an offshore wind farm. Given an offshore wind farm site, and distance to shore the model decides when, and for how long, a jack-up vessel should be chartered in order to minimize the total expected cost. The model considers both chartering and operational costs of the jack-up vessels, and the downtime costs of the wind farm which occurs when the wind turbines are not producing electricity. The model considers uncertainty both in the weather conditions and in when and how many components fail each year at the wind farm.

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1. Introduction

Between 2000 and 2012, the world's electricity consumption increased by about 48% [1], and it is projected that the consumption will continue to grow in the future. Currently, fossil fuels constitute about 67% of electricity generated worldwide [2], with approximately the same numbers emerging in Europe [3]. The EU goals for 2020 state that 20% of the energy consumption in EU countries should come from renewables [4], and this will further increase the focus on green energy in the coming years. One of the most popular sources of renewable energy to be exploited in recent decades is wind energy. Traditionally, wind energy has been produced by wind turbines placed on land, but in the past decade there has been an increase in electricity delivered to the European market by offshore wind farms. In 2015, 419 new offshore wind turbines were installed in Europe and six new projects were under construction. Total grid-connected capacity at year end was about 11.0 GW. When completed, the six projects expand the capacity further by 1.9 GW [5].

There are several reasons for wind turbines to be installed offshore rather than onshore, the most important being space. Offshore installation allows for wind farms with both more and larger turbines being located where wind conditions are more stable and favorable, thus increasing production. Furthermore, noise and visual effects are minimized.

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However, currently, offshore wind is not financially competitive with lifetime levelized costs being 59% higher than onshore wind and about 127% higher than fossil fuels [6]. The elevated costs of offshore wind energy are caused by significant installation as well as operations and maintenance (O&M), costs. Currently, O&M costs constitute about one-third of lifetime costs [7]. This includes spare parts, transportation, technician salaries and costs of repair actions as well as lost revenue due to turbines not producing electricity (hence forward referred to as *downtime cost*). In addition, the harsher weather conditions offshore increase the failure rate, and decrease accessibility, with the availability of the turbines being significantly lower than for those located onshore [8]. Thus, the opportunities for conducting maintenance are limited and expensive as extended periods of favorable weather are required. This is especially true in winter, when weather conditions become worse and downtime for turbines can be extensive.

One way to make offshore wind more financially competitive, is to reduce O&M costs. Vessel chartering constitutes around 70% of lifetime O&M costs [9], and decision supporting tools for this problem are limited. The single most expensive O&M cost is that of chartering jack-up vessels, which can have charter rates as high as GBP 287 000 per day [9]. Jack-up vessels use a number of extendable legs that elevates the hull above the sea surface for stabilization purposes and are equipped with a crane capable of lifting heavy components. In an O&M setting they are used when replacing major components on a wind turbine such as blades, gearboxes, transformers, and generators, which are too heavy for regular maintenance vessels.

Breakdown and replacement of such heavy components are rare events, and are difficult to predict. Therefore one ideally would like to charter a jack-up vessel after a breakdown has occurred. However, this is a difficult strategy for several reasons. First, there is a limited market for jack-up vessels, and there is often a mobilization time of several months between a vessel is chartered and it is available to the charterer. Second, chartering a jack-up vessel is expensive, and the charter rate is higher the shorter the mobilization time. Third, due to the high costs of chartering jack-up vessels it is (in most cases) not profitable to charter a jack-up vessel to replace a single component, but rather to wait until a given number of replacements are needed. However, due to the mobilization time there is still significant uncertainty in the number of additional breakdowns that require replacement between the time the jack-up vessel is chartered and the time it is available. Finally, since both the jacking operations and lifting operations performed during a replacement is restricted by the weather conditions, it is not possible to know at the time of chartering the jack-up vessel, how long the replacements will take.

Jack-up vessel chartering strategies for offshore wind farms have previously been studied by [9], where a simulation model is used to compare a set of different strategies. However, they only conduct a sensitivity study by simulating a small subset of the possible chartering strategies. In addition, they do not decide when the Jack-up vessel is chartered, and do not consider the option of chartering a vessel in several shorter intervals each year. Related fleet size and mix problems for offshore wind farms that focus primarily on crew transfer vessels have previously been studied by [10] and [11]. In [10] a deterministic optimization model of the problem is presented, while [11] studies a three-stage stochastic optimization model to determine the optimal fleet of vessels to perform maintenance at offshore wind farms. Both these papers consider a planning horizon of one year that represents a typical year of maintenance of the offshore wind farm. [12] include long-term uncertainty in the development of the wind farm over time. The decisions include not only which vessels to invest in, but also how long to charter each vessel for, with an opportunity to replace vessels later on, as the wind farm evolves. However, even though [10–12] all include the opportunity to add jack-up vessels, neither of them focus on modelling jack-up operations in detail, something which is done in this work.

In this paper we present a two-stage stochastic programming model that finds the optimal jack-up chartering strategy for a given offshore wind farm. The aim is to decide when, and for how long, to charter jack-up vessels, based on probabilistic information regarding the weather conditions at the offshore wind farm and the failure rates of components requiring jack-up vessels to replace. The advantage of using this type of model is that the wind farm operator can decide well in advance, when to charter a jack-up vessel, thus get lower mobilization costs, and enable better planning of its O&M activities.

In Section 2 we give a formal description of the optimal jack-up chartering strategy problem, together with a stochastic programming model of the problem. In Section 3 we discuss how the model may be solved, before finally, giving some concluding remarks in Section 4.

2. Problem description and mathematical model

The problem studied in this paper is to find the optimal chartering strategy for a given planning horizon, which is divided into a set of discrete time periods $\mathcal{T}$. Within this planning horizon we need to decide when, and for how long, a jack-up vessel should be chartered in order to minimize the sum of the charter costs and the downtime costs.

We consider a set of components, $\mathcal{C}$, that require a jack-up vessel to replace, if broken, and a set $\mathcal{V}$ of jack-up vessels available for charter. Let C_{vt}^M and C_{vt}^P be the fixed cost and the day rate of chartering jack-up vessel v in time period t, respectively. Typically, charter rates are higher in the summer months when the weather conditions are better, and the vessel can perform more maintenance in a given time interval, thus the need for time period dependent cost parameters. In addition, we assume $\underline{T}^L$ state the minimum number of days a jack-up vessel can be chartered, and that the operator plans charter schedules sufficiently early so that a vessel can be chartered at any time during the planning horizon and is unaffected by mobilization times.

In this problem we consider uncertainty both in the weather conditions at the offshore wind farm, the electricity price, and in the occurance of failures that requires a jack-up vessel to replace. All uncertain parameters are dependent on a random process $\omega_1, \ldots, \omega_{|\mathcal{T}|}$ defined on some probability space. Let $\xi_{ct}^F(\omega_t)$ be the number of failures of component type c in time period t, and let $\xi_t^E(\omega_t)$, $\xi_t^{HS}(\omega_t)$ and $\xi_t^W(\omega_t)$ be the electricity price, significant wave height, and wind speed in time period t, respectively. For simplicity we denote $\xi = (\xi_{ct}^F(\omega_t), \xi_t^E(\omega_t), \xi_t^{HS}(\omega_t), \xi_t^W(\omega_t))_{c\in\mathcal{C},t\in\mathcal{T}}$. We assume that the probability distributions of $\xi_{ct}^F(\omega_t)$, $\xi_t^E(\omega_t)$, $\xi_t^{HS}(\omega_t)$, and $\xi_t^W(\omega_t)$ are known. To simplify the notation further we denote $\mathcal{F}_{ct}(\xi) = \{(1,t), \ldots, (\xi_{ct}^F, t)\}$, and $\mathcal{F}_c(\xi) = \bigcup_{t\in\mathcal{T}} \mathcal{F}_{ct}(\xi)$ as the set of failures of component type c.

Further, let $T_{vct}(\xi)$ be the time needed by vessel v to replace component of type c, if the repair begins in time period t. This parameter is dependent on the realisation of the weather, as the significant wave height limits when the vessel can jack up and down, and the wind speed restricts when lifting operations can be performed. It is assumed that all vessels require an integral number of time periods to finish a maintenance operation, and that this number is not affected by the weather. We do however, allow temporary stops in the maintenance operations, both between jacking operations and lifing, and during lifting operations, due to bad weather, so the total replacement time, $T_{vct}(\xi)$, is still dependent on both weather parameters (significant wave height and wind speed).

If a component fails, we assume that the wind turbine is shut down, and therefore does not produce any electricity from the time period in which the failure occurs until the replacement of the failed component is completed. An implication of this is that all failures occur at different wind turbines, which is a reasonable assumption since the failure rates of components that require a jack-up vessel to repair them are close to zero (typically below 0.1 failures per year [9], [13]). If a replacement of component type c to fix failure $(n, t_1) \in \mathcal{F}_c(\xi)$ is started on day t_2 we can calculate the downtime cost $C_{vct_1t_2}^D(\xi)$ as follows:

$$C_{vct_1t_2}^D(\xi) = \sum_{t=t_1}^{t_2+T_{vct}(\xi)} \xi_t^E(\omega_t) \times power(\xi_t^W(\omega_t)),$$

where $power()$ is a function giving the turbine power production for a time period at a given wind speed. An illustration of the downtime costs can be seen in Figure 1, where a component fails in period 2, maintenance starts in period 13 and is completed in time period 19. In this case the downtime cost is the accumulated value of the production lost due to the failure.

2.1. Mathematical model

To solve the problem described above we propose a two stage stochastic programming model, where the first stage decisions are when, and for how long, to charter a Jack-up vessel, while the second stage decisions are how to deploy the vessel(s). It is assumed in the model that the realisation of failures and weather conditions for the entire planning horizon become known, before the deployment of the jack-up vessels are decided. This is obviously not the case, but the impact of this assumption on the decisions made in the second stage is minimal. First, it will always be beneficial to fix the failures as quickly as possible due to the downtime costs. Thus, there is no benefit to knowing that other failures occur later, or that the weather will be better in the near future. Further, it can be assumed that fairly

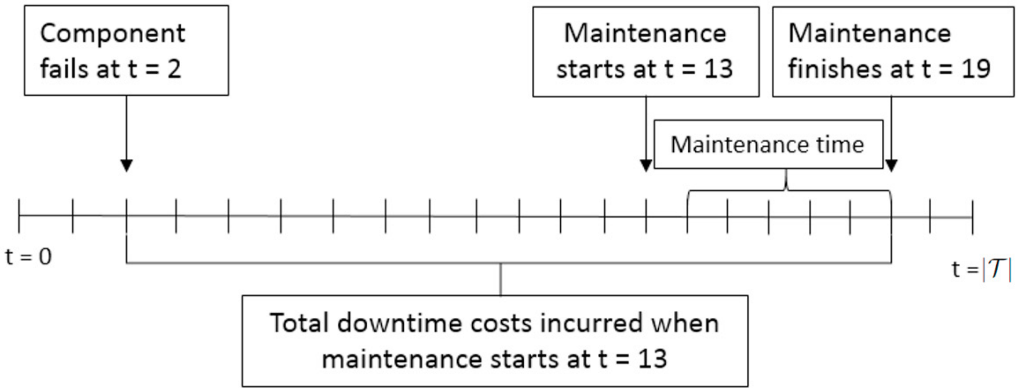

Fig. 1. Illustration of how the downtime costs are calculated. A failure occuring in time period 2, with the replacement starting in time period 13 and taking 6 time periods. The first time period is used to position and jack-up the vessel, and the remaining 5 time periods are used for the maintenance itself. The turbine is then operational again in time period 19, which means that the downtime cost can be calculated as the accumulated value of the lost energy production between time period 2 and 19.

good weather forecasts can be obtained within a horizon of at least one week. Therefore, planning whether or not to perform replacement of an already failed component, given that the jack-up vessel has already been chartered, should be realistically modelled. Second, the model does not contain any possibility of extending or shortening the duration of a charter period in the second stage, and thus there is no way the model can improve the first stage solution by having this information available in the second stage.

To avoid end effects in the model the last and the first time period are connected. As a result, failures occurring in the last time periods that are not repaired before the end of the planning horizon, are considered to be in a failed state at the start of the planning horizon. This approach avoids results that compensate for the fact that failures occurring in late time periods might be best left in a failed state for the remaining time periods giving the model both an incentive and an opportunity to repair these failures. This can be interpreted as failures happening late in the planning horizon get replaced early in the next planning horizon, and/or failures that happened late in the previous planning horizon get replaced early in the current planning horizon. Given that this is a problem that will repeat for many consecutive planning horizons during the life time of the wind farm, this should be a realistic assumption.

Before presenting the mathematical model, some additional notation is needed. Let $A_{vct\tau}(\xi)$ be equal to one if $t \leq \tau \leq t + T_{vct}(\xi)$, and zero otherwise. This means that the parameter is one if replacement of component c starting in time period t is still ongoing in time period τ. For simplicity we also let the function $t(f)$ denote the time period in which failure $f \in \mathcal{F}_c(\xi)$ occur. Further, we have the first stage decision variable v_{vt} which is equal to one if vessel v begins a charter period in time period t, and zero otherwise, and y_{vt} which is equal to one if vessel v is chartered in time period t and zero otherwise. Further, the second stage variables x_{vft} is equal to one if vessel v begins repair on failure f in time period t, and zero otherwise, and z_f is equal to one if failure f is not repaired during the planning horizon, and zero otherwise. This variable is associated with an artificial penalty C^P for each component that is not repaired at all during the planning horizon in order to ensure that we have full recourse in our stochastic program. Using this notation we can formulate the two-stage stochastic program as follows:

2.2. First stage problem

$$\min \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} C^P_{vt} y_{vt} + \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} C^M_{vt} v_{vt} + E_{\xi}[Q(y, \xi)] \tag{1}$$

$$y_{vt} - y_{v(t-1)} \leq v_{vt}, \quad v \in \mathcal{V}, t \in \mathcal{T} \setminus \{1\}, \tag{2}$$

$$y_{v1} - y_{|\mathcal{T}|} \leq v_{vt}, \quad v \in \mathcal{V}, \tag{3}$$

$$\sum_{\tau=t}^{t+\underline{T}^L-1} y_{\tau} \geq \underline{T}^L v_t, \quad v \in \mathcal{V}, t \in \mathcal{T} : t \leq |\mathcal{T}| - \underline{T}^L + 1, \tag{4}$$

$$\sum_{\tau=t}^{|\mathcal{T}|} y_{\tau} + \sum_{\tau=1}^{t+\underline{T}^L-|\mathcal{T}|-1} y_{\tau} \geq \underline{T}^L v_t, \quad v \in \mathcal{V}, t \in \mathcal{T} : t \geq |\mathcal{T}| - \underline{T}^L, \tag{5}$$

$$y_{vt} \in \{0, 1\}, \quad v \in \mathcal{V}, t \in \mathcal{T}, \tag{6}$$

$$v_{vt} \in \{0, 1\}, \quad v \in \mathcal{V}, t \in \mathcal{T}. \tag{7}$$

The objective function (1) minimizes the total chartering costs and the expected value of the function $Q(y, \xi)$ representing the total downtime cost for a given set of first stage decisions and a realisation of the uncertain parameters. Constraints (2) and (3) fixes the start of the charter period, while constraints (4) and (5) ensure that the jack-up vessel is chartered for at least the minimum number of time periods. Finally, constraints (6) and (7) define the domain of the first stage variables.

2.3. Second stage problem

Let y^* be the optimal values of the y-variables in the first stage problem, and let ξ be a realisation of the uncertain parameters. The second stage problem can then be formulated as follows:

$$Q(y^*, \xi) = \min \sum_{v \in \mathcal{V}} \sum_{c \in \mathcal{C}} \sum_{f \in \mathcal{F}_c(\xi)} \sum_{t_2 \in \mathcal{T}} C^D_{vct(f)t_2}(\xi) x_{vft_2} + \sum_{c \in \mathcal{C}} \sum_{f \in \mathcal{F}_c(\xi)} C^P z_f, \tag{8}$$

$$\sum_{c \in \mathcal{C}} \sum_{f \in \mathcal{F}_c(\xi)} \sum_{t \in \mathcal{T}} A_{vct\tau}(\xi) x_{vft} \leq y^*_{v\tau}, \quad v \in \mathcal{V}, \tau \in \mathcal{T}, \tag{9}$$

$$\sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} x_{vft} + z_f = 1, \quad c \in \mathcal{C}, f \in \mathcal{F}_c(\xi), \tag{10}$$

$$x_{vft} \in \{0, 1\}, \quad v \in \mathcal{V}, c \in \mathcal{C}, f \in \mathcal{F}_c(\xi), t \in \mathcal{T}, \tag{11}$$

$$z_f \in \{0, 1\}, \quad c \in \mathcal{C}, f \in \mathcal{F}_c(\xi). \tag{12}$$

The second stage objective function minimizes the total downtime costs of all turbines with a failed component accummulated from the time the failure occurs and until it is repaired and the penalty cost of not performing all repairs during the planning horizon. Constraints (9) state that the repair of a failure can only be conducted on day t if the jack-up vessel is chartered from day t and until the end of the repair, and constraints (10) ensure that all failures are either repaired of penalized in the objective funtion. Finally, constraints (11) and (12) define the domain of the second stage variables.

2.4. Calculating the $T_{vct}(\xi)$ parameter

It is stated above that $T_{vct}(\xi)$ is the time needed by vessel v to replace component of type c, if the repair begins in time period t. However, the time it takes to complete a replacement of a component in given weather conditions, is dependent on some assumptions regarding how the actual replacement is performed. E.g. if a replacement is estimated to take 4 days, does this mean that it requires 4 consecutive days where the weather conditions continously stay below the vessel's wind and wave limits, or is it possible to do it over 6 days, given that the weather is below the limits on 4 out of those 6 days.

The first alternative may be too pessimistic compared with reality as a replacement consists of several lifts with the possibility of a break in-between, while the second alternative may be overly optimistic if one of the lifts take more than one time period. A third alternative for calculating the $T_{vct}(\xi)$ parameter could be to divide the replacement of component c into a set of sub-tasks, each taking a given number of time periods, and then requiring that the weather stay below the vessel's limits for the number of time periods each sub-task take, with breaks allowed in-between each sub-task. It should be noted that exactly how the value of $T_{vct}(\xi)$ is calculated does not affect the correctness of the model itself, but may affect the solution obtained from the model.

3. Solution method

Two stage stochastic programs, like the model presented in Section 2.1 are usually solved by generating scenarios and then solving what is known as the *deterministic equivalent* of the scenario based formulation. Below we discuss briefly how these scenarios may be generated, and how we can use a well-known method known as *Sample Average Approximation* to solve the problem.

3.1. Scenario generation

Let $\mathcal{S}$ denote the set of scenarios, with each scenario $s \in \mathcal{S}$ representing one realisation of each of the uncertain variables in ξ, i.e the number of failures of each component (ξ^F_{ct}), the electricity price (ξ^E_t), the significant wave height (ξ^{HS}_t), and the wind speed (ξ^W_t), for each time period in the planning horizon. We denote this realisation ξ_s.

The value of ξ^F_{ct} may be calculated by using the probability of a component failing in any given time period. This probability may either be static, i.e. a constant probability per time unit, or it may be dynamically depending on the realisation of the weather conditions in the previous time periods. A random number generator may be used to obtain a uniformly generated random number for each turbine in the wind farm, and for each of these numbers whose value is lower than its corresponding failure probability, the value of ξ^F_{ct} is increased by 1. This procedure should be repeated for all components, time periods and scenarios.

The values of ξ^E_t could be generated based on historical electricity price data, where the seasonal variations of the price is taken into account. The values of ξ^{HS}_t and ξ^W_t should be based on the weather data, originating either from historical measurements, or based on simulation of the weather conditions, at the wind farm site. Since the resolution of such weather data is usually finer than the time periods used in this model, the weather data must be adjusted to the desired time resolution using extreme values, i.e. the highest wind speed and wave height observed in the time period.

3.2. Sample Average Approximation Algorithm

The combined uncertainty of the parameters present in ξ is expected to require a high number of scenarios to represent properly, making the determinstic equivalent problem difficult to solve. To circumvent this we propose applying a method known as *Sample Average Approximation* (SAA).

SAA is a solution method for stochastic optimization problems. Generally, the method utilizes statistical properties and solves many smaller problems to represent a larger problem. It was introduced by [14], where a Monte Carlo simulation-based approach to stochastic discrete optimization problems is proposed. A random sample of N scenarios is generated and the expected value function is approximated using the corresponding sample average function. A solution is found for the sample average optimization problem and the procedure is repeated a number of times until a stopping criteria is satisfied. The method allows for solution of stochastic problems where the feasible region is very large, for example when the probability distribution is continuous [14].

The first step is to convert the objective function (1) into a sample average function. The sample size N denotes the number of scenarios considered, with $N \ll |\mathcal{S}|$. We can then re-write the objective function as:

$$\min \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} C^P_{vt} y_{vt} + \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} C^M_v v_{vt} + \frac{1}{N}\sum_{n=1}^{N} Q(y,\xi_n) \tag{13}$$

ξ_n is the nth realization of the random vector ξ. The steps of the algorithm are as follows:

1. Generate M independent samples of N scenarios and solve the SAA problem in (13).
2. Compute the average of all optimal objective function values from the SAA problems, and the variance of the sampling distribution of objective values. As the sample size and/or number of samples grow, the properties approach the population properties and the variance of the sampling distribution of objective values decreases. The average objective function value provides an optimistic bound on the optimal objective function value for the original problem.
3. Pick a feasible first stage solution (y^*, v^*) for the original problem. This solution is used to estimate the objective function value of the original problem using a reference sample of size N' as

$$\min \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} C^P_{vt} y^*_{vt} + \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} C^M_v v^*_{vt} + \frac{1}{N'}\sum_{n=1}^{N'} Q(y,\xi_n) \tag{14}$$

4. This estimator serves as a pessimistic bound on the optimal function value. The reference sample of size N' must be generated independently of the other M samples and since the first stage solution is fixed, N' can be greater than N. This step requires solving N' independent second stage problems.
5. Compute the estimators for the optimality gap and its variance. Using the estimators calculated in steps 2 and 3, one gets a gap estimator and an estimation of the gap variance of the sampling distribution of the objective values Using this information a confidence interval for the optimality gap may be obtained with $z_\alpha := \Phi^{-1}(1-\alpha)$, where $\Phi(z)$ is the cumulative distribution function of the standard normal distribution.

Determining M is not straightforward. Suppose that M samples of size N have been solved so far. If the distribution of the SAA problem is continuous, the probability that the $(M+1)^{th}$ SAA sample of size N will produce a better solution than all preceding solutions, is equal to $\frac{1}{(M+1)}$. In the case of discrete distributions, the probability is less than or equal to $\frac{1}{(M+1)}$. Thus, as $\frac{1}{(M+1)}$ becomes sufficiently small, the additional SAA sample will provide little value and the procedure should be stopped or the sample size N increased [14].

4. Concluding remarks

In this paper we have presented a two-stage stochastic programming model of the optimal jack-up chartering problem. In addition, we have outlined how the problem may be solved by generating scenarios based on the uncertain parameters, and then using the sample average approximation algorithm to solve the problem. By using such a model for decision support a wind farm operator may reduce the total O&M cost by improving its jack-up chartering strategy. The benefits of this model are two-fold. First, by minimizing the sum of the downtime costs and the chartering costs, the operator avoids chartering in the jack-up vessel too often, leading to high chartering costs. Second, since this model tells the operator when to charter in jack-up vessels, regardless of the realisation of failures, chartering contracts can be entered into earlier, thus lowering the mobilisation costs paid to the vessel owner.

The next steps in this research is to test the model on realistic test cases from the industry. This includes wind farms of different sizes, and located in areas with different weather conditions. Further, we want to test the effect of the proposed strategies in a O&M simulation model, such as the Nowicob model [15], to verify that the solutions given by the model actually improves the total O&M costs. It would also be interesting to compare the results of this model to a *batch-repair* strategy where a jack-up vessels charter is triggered by the number of replacements needing a jack-up vessel reaching a given threshold.

Further developments of the model, could include looking at degradation of components and strategies that include the possibility of replacing components before they fail, or to combine replacements of failed components with replacements of other components on the same turbine.

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