Quantifying the Potential Logistic Benefits of a Predictive Maintenance Strategy in Offshore Wind Farms

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December 2021

Abstract

The present work aims to quantify the potential benefits of a predictive maintenance strategy in offshore wind farms, benchmarking these benefits against corrective maintenance. The predictive maintenance is also tested for five different predictive periods, here referring to how many days ahead a failure can be predicted. To quantify these benefits, two analyses are performed based on a computational model developed in Python for this purpose, built with a module-based structure. Firstly, a wind farm analysis assesses the potential benefits that predictive maintenance can bring to a wind farm. Then, a component-level analysis aims to statistically quantify total failure costs variability throughout the year, for each maintenance strategy and subassembly. Statistical logistic benefits in the total failure costs are also found. In general, major cost decreases are found in a 5-day predictive period. Wind farm results show that the lowest total wind farm costs, and highest energetic availability, were found for a 20-day predictive period. However, these total cost results are close to the results from the 10-day predictive period. The component level results show that different subassemblies have different logistic benefits, but similar benefits are found for the same maintenance type. The total failure cost benefits of the subassemblies' replacements vary from 1.4% to 3.2%, major repairs from 13.3% to 19.6%, and minor repairs from 56.4% to 60.5%.

Keywords: offshore wind farm, operation and maintenance, predictive maintenance, logistic benefits.

1. Introduction

Wind energy is one of the most promising sources of renewable energy. Despite recent technological advancements in the offshore wind sector, in the last decade, its cost of energy is still significant [1].

Operation and maintenance (O&M) is a big contributor to these costs, representing about 23% of the total investment costs of an offshore wind project (OWP) [2]. Offshore wind farms are deployed in harsh environmental conditions, which affects component reliability and maintenance requirements. Also, due to the high distance from shore, weather conditions and operational constraints, there are only some weather windows, that are long enough, where vessels are allowed to be deployed to perform the maintenance actions. Therefore, operations may be delayed, leading to an increase in operational costs (namely due to vessel hiring) but also in the downtime of the wind turbines which may lead to significant revenue losses [3].

The maintenance philosophy adopted in an OWP has an impact on O&M costs, downtime, and in turbine availability. Therefore, wind farm maintenance must be adequate, given the highly complex relationships between component repair schedules, maintenance crew logistics, and revenue opportunities [4]. Currently, the most adopted maintenance strategy consists in a combination of preventive maintenance (PM) and CM [4].

Recently, research efforts have been directed towards PdM. In this maintenance strategy, prognostics-based methods are used to predict future component degradation, allowing to schedule the maintenance operations [5], in times with low energy production, and times with higher site accessibility, where environmental conditions are better suitable for the maintenance operations [4].

Given the technological advancements (e.g., with machine learning [6] [7]) in PdM, the present work aims to quantify the potential logistic benefits of PdM strategy in offshore wind farms, benchmarking these benefits against CM. For this, two analyses were carried out supported by a model developed for this purpose. The model is module-based and is integrating the DTO+LMO tool from DTOceanPlus project [8]. Firstly, a wind farm analysis is performed to understand what are the potential logistic benefits that a PdM can bring to a wind farm. Then, a component-focused analysis was performed, estimating the operational durations and costs that are resulting from pure CM and PdM strategies.

2. Methodology

Both analysis, that are carried out, are supported by the developed model that is using a module-based structure.

2.1. Reliability Module

The reliability is responsible for generating component failure events throughout the project lifetime based on failure rates reported in literature (e.g., Carroll [9]) and typical failure probability distributions, commonly used in reliability theory. Failure events are distributed in the time-series by generating different time to failures (TTF). The TTFs are generated assuming a constant failure rate, leading to the usage of the exponential distribution. The cumulative distribution function for the exponential distribution is given by Equation 1,

$$F(t) = 1 - e^{-\lambda_k t}, \qquad (1)$$

where, λ_k is the component's failure rate, and t the TTF, in years.

2.2. Power Module

The power module objective is to compute the energy produced by in each hour of its lifetime. To do this, three main steps are performed. Firstly, the mean hourly wind speed is extrapolated from reference height to turbine hub height [10]. Then, the power available is found in the turbine's power curve for that wind speed. Finally, the energy production is computed for that hour.

2.3. DTO+LMO Module

This module contains the results from the DTO+LMO tool developed by WavEC – Offshore Renewables within the DTOceanPlus project [8]. This tool computes the operation durations that maintenance operations have if started in each hour of the components' lifetime. These include the mobilization, waiting times, transit times, and the duration on site, which account the vessel positioning time, and repair time.

2.4. Corrective Maintenance Module

In a CM strategy the maintenance interventions are scheduled after failure occurrence. Thus, downtime will start immediately after the failure occurs, and last until the maintenance has been successfully completed on site (and thus not considering transit from site to port).

2.5. Predictive Maintenance Module

Different predictive periods were considered in the analysis to estimate their impacts on the maintenance scheduling and costs. In the present work, the predictive period refers to how many days in advance a potential failure can be detected with certainty. Each predictive period is used to model an independent, and purely, PdM strategy, only distinct by this feature.

There are two scenarios when computing the downtime. Figure 1 shows the scenario 1.

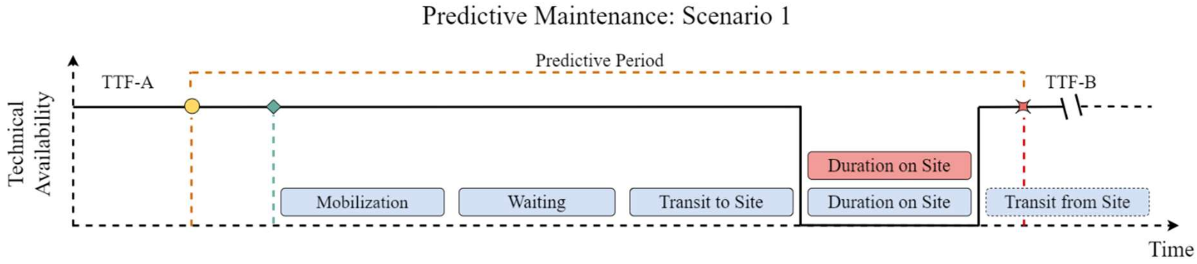

Figure 1. Predictive maintenance downtime computation in scenario 1.

The scenario 1 occurs when the predictive period is long enough to fit the total operation duration (minus the transit from site and repair time), and also the selected time to start the maintenance operation (green marker) is far enough from the predicted failure (red marker) so that the technicians can get to site before the predicted failure occurs. The downtime in scenario 1 will always be the duration on site. In Figures 1 and 2, the output durations from the DTO+LMO module are represented in blue, and the computed PdM downtime, in red. The yellow marker represents when the failure is predicted, and from that to the predicted failure, is the predictive period of that failure.

The scenario 2 is modeling an exception. The predictive period may not be long enough to fit the total operation duration (minus the transit from site and repair time) or the selected time to start the maintenance operation (green marker) is too close to the predicted failure (red marker) thus, technicians don't have time to get to the wind turbine before the predicted failure occurs. The downtime will now vary according to the selected starting scheduling of the maintenance operation. The downtime will start immediately after the predicted failure until the failure is repaired (after duration on site). Figure 2 shows the computation of downtime for scenario 2.

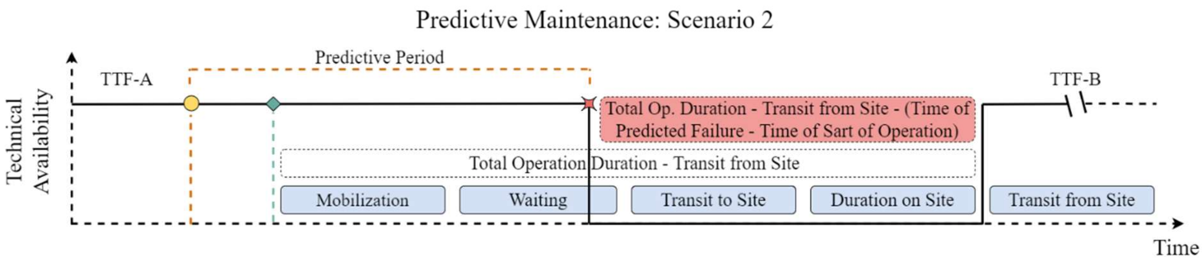

Figure 2. Predictive maintenance downtime computation in scenario 2.

The main goal of the PdM module is to reduce costs. The module will analyze every hour of the predictive period and compute the total costs. The analysis is conducted by computing the downtime, and total costs by simulating the start the maintenance operation in that hour. After it analyzes all the hourly time steps in the predictive period, it selects the hour with minimum total costs. The optimized schedule is then found.

Both maintenance modules are computing the costs of each failure in the same way, even though the PdM performs an optimization. The total costs include the operation costs, and the energy loss costs. The total operations costs consider the vessel, and component costs, and technician costs. The vessel costs are computed based on [8], where a self-propelled crane vessel is used for major replacement, a service operation vessel for major repairs, and a crew transfer vessel for minor repairs. The cost of technicians were computed based on the average number of technicians.

The revenue generated by a wind turbine comes from the sale of the energy that it produces. If a wind turbine is down, due to a failure, and if there is wind resource available, there are energy losses, that imply loss of revenue, associated with that downtime. This, from the point of view of O&M, can be seen as an opportunity cost that must be reduced. The indirect costs related to revenue losses were computed multiplying the energy losses, caused by downtime, with the price that the energy could eventually be sold, if it were produced.

2.6. Availability Module

To compute the turbine availability, this module includes a time-series builder that aims to build operation time-series of each turbine along their whole lifetime, that are used to compute three availabilities. First, the technical availability, that includes only the downtimes caused by component failures. Then, the operational availability includes the downtimes caused by component failures, and times where the wind speed is out of the power curve. Finally, the energetic availability is based on the energy produced by the wind turbine during its lifetime, divided by the potential energy that could be produced in that same lifetime.

2.7. Base Case Study

Both analyses use the base case inputs. The DTU 10 MW reference wind turbine was used, with a turbine hub height of 119 m and power curve found in [11]. Turbine breakdown was taken from [9], along with the subassemblies' failure rates, used by the reliability module, and the average number of technicians. Also, the component costs for minor and major repair costs are assumed to be the same as in [9], but the replacement costs were adapted with [12] for a 10MW turbine. Table 1 shows how these costs were adapted.

Table 1. Average repair costs of each subassembly adapted from [5].

	Major Replacement [€]			**Major Repair [€] [9]**	**Minor Repair [€] [9]**
	Carroll [9]	**Used**	**Info.**		
Pitch / Hyd	14000	696150	Sum of Blade pitch system and cooling and Hydraulic system costs in [12].	1900	210
Other Components	10000	10000	Assumed same as [9].	2400	110
Generator	60000	676685	Taken from [12].	3500	160
Gearbox	230000	1772250	Taken from [12].	2500	125
Blade	90000	701222	Taken from [12].	1500	170
Grease / Oil / Cooling Liq.	-	-	Failure rate is zero.	2000	160
Electrical Components	12000	12000	Assumed same as [9].	2000	100
Contactor / Circuit / Breaker / Relay	3500	13500	Assumed same as [9].	2300	260
Controls	13000	13000	Assumed same as [9].	2000	200
Safety	-	-	Failure rate is zero.	2400	130
Sensors	-	-	Failure rate is zero.	2500	150
Pumps / Motors	-	-	Failure rate is zero.	2000	330
Hub	95000	275570	Taken from [12].	1500	160
Heaters / Coolers	-	-	Failure rate is zero.	1300	465
Yaw System	12500	383520	Taken from [12].	3000	140
Tower / Foundation	-	-	Failure rate is zero.	1100	140
Power Supply / Converter	13000	668440	Cost of Power Electronics in [12].	5300	240
Service Items	-	-	Failure rate is zero.	1200	80
Transformer	70000	525045	Cost of Electrical Connections in [12].	2300	95

The predictive periods considered in the PdM module are 5, 10, 20, 40, and 80 days. These are based on literature, where it was found that generator faults can be predicted 18 days ahead of time [7], and in another work, the degradation of a wind turbine was successfully detected 44 days prior to failure [13].

2.8. Wind Farm Analysis

For the wind farm analysis, the objective is to quantify the benefits of a PdM strategy where a wind farm that composed of 20 equal wind turbines, is simulated. The model simulates all wind turbines, and all their components' maintenance types. Figure 3 shows the diagram of the wind farm analysis. The reliability module simulates the component's failures by generating TTFs that are based on its failure rates. Once a TTF is generated, it is sent to the availability module where the turbine operation time-series is being created. With this, the time of failure is determined. The corrective and predictive modules are supported by the power, and DTO+LMO modules to compute their results. The maintenance strategy modules use the time of failure to compute that failure's results. In the CM module computes the total costs, and downtime that is returned to the availability module to be added to the operation time-series by the time-series builder. The PdM module, apart from downtime, also returns the optimized scheduling, that is based on minimum total costs, for the maintenance of the failure. This is considered by the time-series builder. The process continues until it simulates all failures, of all subassemblies and their maintenance types, for all turbines. Finally, the turbine availability can be computed through the time-series.

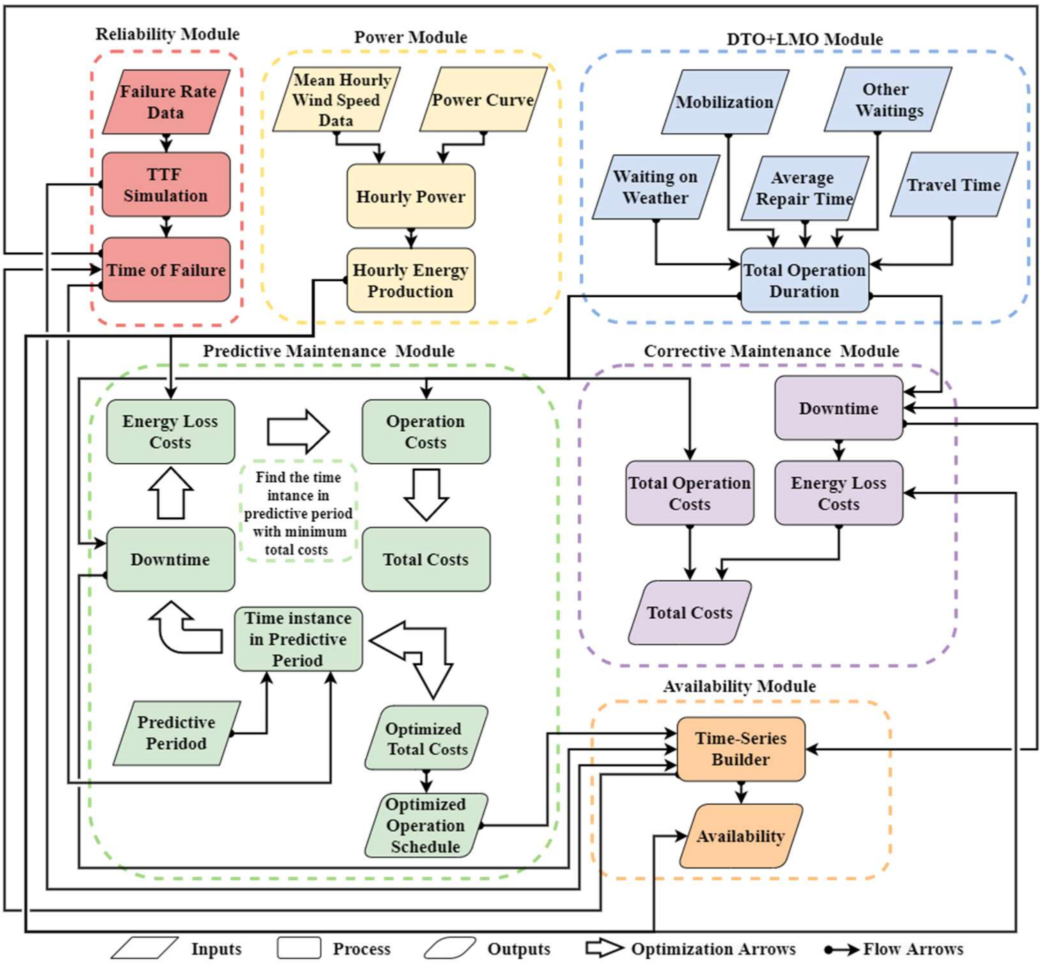

Figure 3. Wind farm analysis diagram.

2.9. Component Level Analysis

For the second analysis, the main objective is to understand the potential logistic benefits of a PdM strategy at a component level. The component level analysis uses the same four core modules used in wind farm analysis showed in Figure 3, namely the power, DTO+LMO operation, corrective, and predictive modules. In this analysis, 10500 failures are distributed, for each component and its different maintenance types, instead of being simulated by the reliability module. In this case, the availability module is also not used. Each failure is analyzed with the CM module, followed by the PdM module for the 5 different predictive periods.

3. Results & Discussion

3.1. Wind Farm Analysis

The wind farm model is computing the three average lifetime availabilities. Figure 5 shows how the availabilities vary with the predictive period.

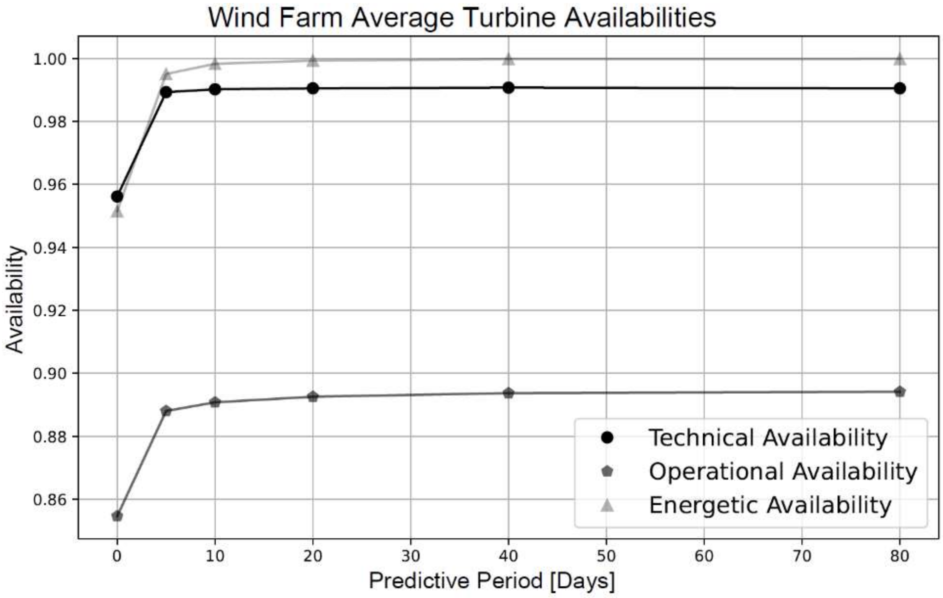

Figure 4. Wind farm average turbine availabilities.

All the three availabilities have their lowest value for a CM strategy (where predictive period is 0). In general, for a PdM strategy with 5 days predictive period, there is a significative increase in the availabilities. This increase represents the highest variation of availability between maintenance strategies. The technical availability for CM has a value of about 0.956. There is a big increase to 0.989, in the 5-day predictive period, and hits a practically constant value of about 0.99 in a 10-day predictive period. The operational availability follows a similar tendency as the technical availability. This is, explained because the only difference between the two availabilities is that the technical availability doesn't consider the downtime caused by the hourly mean wind speed being outside of the power curve, but the operational availability does consider it. The energetic availability is practically maximized for a predictive period of 20 days. The increase in energetic availability proves that the modeled PdM strategy is optimizing the scheduling of maintenance actions for times with low or zero energy production.

Figure 6 shows the wind farm results of the total present value costs for different predictive periods. Each failure costs are depreciated from the failure time to the commissioning date. The total costs presented in the Figure 6 are the total of all components of all simulated turbines.

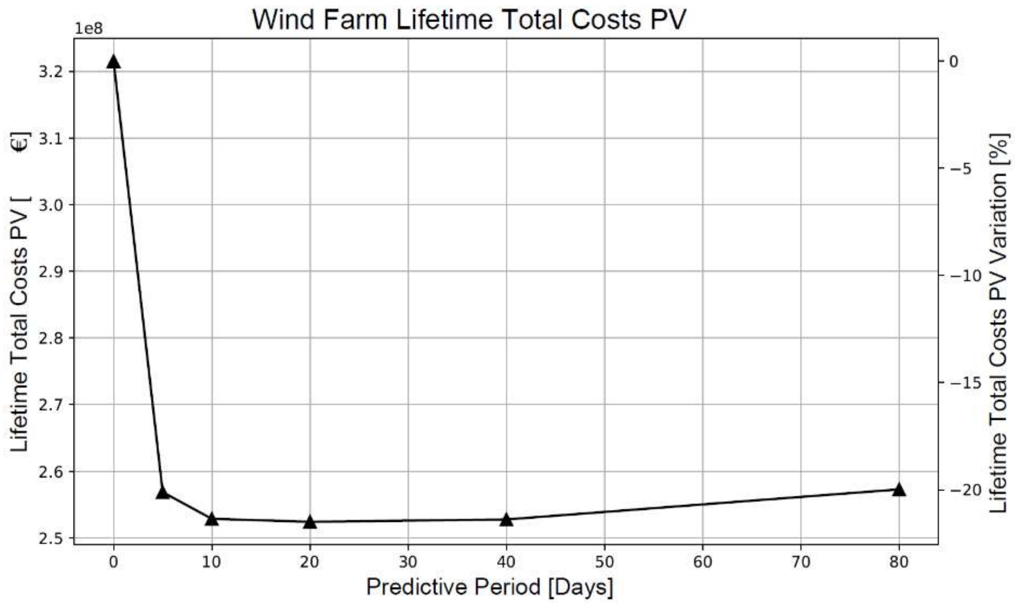

Figure 5. Total costs present value (PV) variation with predictive period.

In general, the total costs variation, along the predictive periods, show a decreasing trend from 0 to 20 days. The biggest cost variation happens from a predictive period of 0 to 5 days. This variation decreases with the predictive period and arrives to the lowest total costs in the predictive period of 20 days. From 20 to 80 days, the trend shows an increase in total costs.

The increase in total lifetime costs for higher predictive periods can be explained by the extra generated failures resultant of the way that the PdM is modeled. PdM is shortening the remaining useful life (RUL) of a component by maintaining the component before it can fully utilize it. This enhanced for longer predictive periods and is causing extra failures to be generated at the end of the component's lifetime. Higher failure rates can generate more extra generated failures due more RUL shortening. The higher the number of failures, the higher the total lifetime costs.

3.2. Component Level Analysis

The main objective of this analysis was to quantify the economic and logistic benefits of knowing in advance future component failures in order to react proactively. For each component's maintenance type, a Monte Carlo simulation is used to compute statistical results of total costs, distributing in time 10500 failures for each subassembly and maintenance type, which was restricted from going higher due to computational limitations. The PdM benefits in median total costs were computed benchmarked against their CM results. With this, the median percentual decrease in total costs was found. Results show that the median benefits of the total costs can vary greatly between different maintenance types, thus maintenance types are presented separately. Table 2 summarizes the found median cost variation in the total costs of the replacement maintenance type. In the major replacement maintenance types, it can be seen a small percentual decrease in the total costs. These vary with a PdM strategy from 1.4% to 3.2%. Even though the percentual decrease is small, these results present high-cost savings because the replacement of components is associated with high total costs than the other maintenance types.

Table 2. Median logistic total costs benefits of a predictive maintenance strategy for each subassembly's replacement.

Subassemblies' Replacement	Variation in Total Costs [%]				
	PdM1	**PdM2**	**PdM3**	**PdM4**	**PdM5**
Blade	-1.9	-1.9	-2.0	-2.0	-2.0
Contactor/Circuit Breaker/Relay	-2.6	-2.8	-2.8	-2.9	-2.9
Controls	-3.0	-3.1	-3.2	-3.2	-3.2
Electrical Components	-2.5	-2.7	-2.7	-2.7	-2.7
Gearbox	-1.4	-1.5	-1.5	-1.5	-1.5
Generator	-1.9	-2.0	-2.0	-2.1	-2.1
Hub	-2.3	-2.5	-2.5	-2.5	-2.5
Other Components	-2.6	-2.8	-2.9	-2.9	-2.9
Pitch/Hyd	-1.9	-2.1	-2.1	-2.1	-2.1
Power Supply/Converter	-1.9	-2.1	-2.1	-2.2	-2.2
Transformer	-2.1	-2.2	-2.3	-2.3	-2.3
Yaw System	-2.2	-2.4	-2.4	-2.4	-2.4

Table 3 summarizes the median cost variation in the total costs for the major repairs.

Table 3. Median logistic total costs benefit of a predictive maintenance strategy for each subassembly's major repair.

Subassemblies' Major Repair	Variation in Total Costs [%]				
	PdM1	**PdM2**	**PdM3**	**PdM4**	**PdM5**
Blade	-14.9	-15.8	-16.2	-16.2	-16.2
Contactor/Circuit Breaker/Relay	-14.5	-15.3	-15.6	-15.6	-15.6
Controls Major Repair	-18.8	-19.5	-19.6	-19.6	-19.6
Electrical Components	-18.8	-19.5	-19.6	-19.6	-19.6
Gearbox	-15.1	-16.0	-16.4	-16.5	-16.5
Generator	-15.3	-16.4	-16.8	-17.0	-17.0
Grease/Oil/Cooling Liq.	-14.4	-15.1	-15.3	-15.3	-15.3
Heaters/Coolers	-18.9	-19.6	-19.7	-19.7	-19.7
Hub	-13.3	-15.1	-15.9	-16.5	-16.8
Other Components	-14.9	-15.8	-16.1	-16.2	-16.2
Pitch/Hyd	-14.6	-15.4	-15.6	-15.7	-15.7
Power Supply/Converter	-18.4	-19.1	-19.2	-19.2	-19.2
Pumps/Motors	-17.9	-18.3	-18.3	-18.3	-18.3
Safety	-16.8	-16.9	-16.9	-16.9	-16.9
Sensors	-16.6	-16.6	-16.6	-16.6	-16.6
Tower/Foundation	-15.4	-15.4	-15.4	-15.4	-15.4
Yaw System	-14.7	-15.5	-15.8	-15.9	-15.9

The results of major repair maintenance type include total cost benefits from 13.3% to 19.6%. Using a PdM strategy seems more advantageous for major repair than for the replacements, when looking at the percentual total cost decrease. Although, the total cost decrease in the replacement is higher, in euro, because these represent much higher costs. Table 4 summarizes the median cost variation in the total costs of the minor repair maintenance type.

Table 4. Median total costs benefits of a predictive maintenance for each subassembly's minor repair strategy.

Subassemblies' Minor Repair	**Variation in Total Costs [%]**				
	PdM1	**PdM2**	**PdM3**	**PdM4**	**PdM5**
Blade	-59.3	-60.3	-60.3	-60.3	-60.3
Contactor/Circuit Breaker/Relay	-56.7	-56.8	-56.8	-56.8	-56.8
Controls	-58.7	-59.4	-59.4	-59.4	-59.4
Electrical Components	-57.5	-57.7	-57.7	-57.7	-57.7
Gearbox	-58.8	-59.6	-59.6	-59.6	-59.6
Generator	-58.3	-58.9	-58.9	-58.9	-58.9
Grease/Oil/Cooling Liq.	-57.2	-57.3	-57.3	-57.3	-57.3
Heaters/Coolers	-56.7	-56.9	-56.9	-56.9	-56.9
Hub	-59.3	-60.5	-60.5	-60.5	-60.5
Other Components	-57.9	-58.1	-58.1	-58.1	-58.1
Pitch/Hyd Minor Repair	-58.9	-59.8	-59.8	-59.8	-59.8
Power Supply/Converter	-58.2	-58.7	-58.7	-58.7	-58.7
Pumps/Motors	-57.1	-57.2	-57.2	-57.2	-57.2
Safety	-56.4	-56.4	-56.4	-56.4	-56.4
Sensors	-58.6	-59.3	-59.3	-59.3	-59.3
Service Items	-58.5	-59.0	-59.0	-59.0	-59.0
Tower/Foundation	-56.7	-56.9	-56.9	-56.9	-56.9
Transformer	-57.9	-58.4	-58.4	-58.4	-58.4
Yaw System	-57.4	-57.6	-57.6	-57.6	-57.6

The minor repairs can have the greatest benefits when compared to their total cost for a CM. Implementing a PdM strategy results in a drop in costs ranging from 56.4% to 60.5%, depending on the predictive period. Noting that these costs, in euro, are much lower than for other maintenance types.

Results show that the biggest decrease in total costs is for the maintenance strategy with a predictive period 5 days. Even though this may seem a small window to perform PdM, it is already of great advantage to use this strategy. This is seen throughout all component's maintenance types. The total costs still decrease with higher predictive periods, but not in such degree as from the corrective to the first PdM strategy.

4. Conclusions

At wind farm level, it was found that implementing PdM strategies led to a slight increase in the total number of failures, due to RUL shortening. This is a resultant of how the PdM was modeled where it's purely minimizing the total costs and is not maximizing the RUL, in its optimization. Thus, this is enhanced for higher predictive periods where there is higher flexibility to schedule maintenances. Results show that the three lifetime availabilities can be greatly increased. The biggest increase occurs from CM to PdM1. The lowest total costs, and highest energetic availability, are found for a 20-day predictive period. Although, these results are very similar to the results of the 10-day predictive period. On the other hand, there are already major benefits of using a 5-day predictive period.

At component level, a PdM strategy is optimizing the total costs. These costs are greatly optimized for longer predictive periods because there is more flexibility to schedule maintenance actions in times where the energy loss and waiting's are lower. This is consequently translated in lower energy loss, vessel, and technician costs. Component level results show that different components, and their maintenance types, have different logistic benefits. Major differences were found between different maintenance types, where the total costs of the replacements vary from 1.4% to 3.2%, major repairs from 13.3% to 19.6%, and minor repairs from 56.4% to 60.5%. In percentage, the total cost benefits are increasing from replacement to minor repair maintenance types. When the total cost benefits are translated to euro, the replacement of components has much higher costs savings than the major repair and these are even higher than minor repairs.

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