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

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Dedicatory

To my beloved grandmother, Camila Constança Pedroso.
You never got to see me go to college. This is for you.

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Resumo

O presente trabalho visa quantificar os benefícios potenciais de uma estratégia de manutenção preditiva em parques eólicos offshore, comparando com a manutenção corretiva. A manutenção preditiva também é testada para cinco períodos preditivos diferentes, referindo-se este com quantos dias de antecedência uma falha pode ser prevista. Para quantificar estes benefícios, são realizadas duas análises baseadas num modelo computacional desenvolvido em Python para este fim, construído com uma estrutura baseada em módulos. Em primeiro lugar, uma análise do parque eólico avalia os potenciais benefícios logísticos que a manutenção preditiva pode trazer a um parque eólico. Depois, uma análise a nível de componentes visa quantificar estatisticamente a variabilidade dos custos totais das falhas ao longo do ano, para cada estratégia e subconjunto de manutenção. São também encontrados benefícios logísticos estatísticos nos custos totais das falhas. De um modo geral, verificam-se grandes diminuições de custos num período preditivo de 5 dias. Os resultados dos parques eólicos mostram que os custos totais mais baixos dos parques eólicos, e a maior disponibilidade energética, foram encontrados para um período preditivo de 20 dias. Contudo, estes resultados de custos totais estão próximos dos resultados do período preditivo de 10 dias. Os resultados a nível de componentes mostram que diferentes subconjuntos têm benefícios logísticos diferentes, mas benefícios semelhantes são encontrados para o mesmo tipo de manutenção. Os benefícios do custo total das substituições dos subconjuntos variam de 1,4% a 3,2%, das grandes reparações de 13,3% a 19,6%, e das pequenas reparações de 56,4% a 60,5%.

Palavras-chave

Energia Eólica Offshore, Parque Eólico Offshore, Operação & Manutenção, Manutenção Preditiva, Benefícios Logísticos.

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%.

Key Words

Offshore Wind Energy, Offshore Wind Farm, Operation and Maintenance, Predictive Maintenance, Logistic Benefits.

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List of Abbreviations

ALF	Average Load Factor
CBM	Condition-based Maintenance
CDF	Cumulative Distribution Function
CM	Corrective Maintenance
CMSs	Condition Monitoring Systems
CTV	Crew Transfer Vessel
FR	Failure Rate
FV	Future Value
GRS	Global Renewable Shipbrokers
LCOE	Levelized Costs of Energy
LMO	Logistics and Marine Operations
MTTF	Mean Time to Failure
O&M	Operation and Maintenance
OM	Opportunistic Maintenance
PCV	Self-Propelled Crane Vessel
PDF	Probability Density Function
PdM	Predictive Maintenance
PM	Preventive Maintenance
PPA	Power Purchase Agreement
PV	Present Value
RAMS	Reliability Availability Maintainability Survivability
ROVs	Remotely Operation Vehicles
RUL	Remaining Useful Live
SCADA	Supervisory Control and Data Acquisition
SFOC	Specific Fuel Oil Consumption
SOV	Service Operation Vessel
TIP	Total Installed Power
TTF	Time to Failure
WACC	Weighted Average Cost of Capital
WUL	Wasted Useful Life

Chapter 1: Introduction

1.1 Motivation and Objectives

Wind energy is one of the most promising sources of renewable energy. Being a clean, renewable, and highly abundant energy resource, onshore wind capacity has been steadily increasing in Europe since the 90's [1] [2]. With this, and the total number of deployments in the onshore wind sector, sharp cost-reductions have been observed. Since 1991, with the first offshore wind farm, installed in Denmark, the wind sector has been expanding into other offshore environments, namely, Sweden, the Netherlands, and the UK [2]. In 2010, Europe's offshore wind energy was representing about 3.5% of total installed wind capacity, growing to about 11.4%, in 2020 [3]. This expansion has been motivated by the several economic advantages such as higher and more consistent wind speeds, lower environmental and social impacts (visual, noise, competition for space), and the opportunity to deploy larger turbines to produce more electricity and reduce generation costs [4]. Such advantages have attracted the attention of political decision-makers, investors, and project developers in the renewable energy sector [5]. More recently, as offshore wind farms inevitably progressed into further offshore and deeper waters, pre-commercial floating wind projects such as Windfloat Atlantic [6] [7], Hywind Scotland [4] [6] [7] and Kincardine [7] have been making the news due to their achievements [8].

Despite technological advancements in the offshore wind sector in the last decade, the cost of energy is still significant, frequently requiring public funding, tariffs, and other support mechanisms [9]. The global levelized costs of electricity (LCOE) of offshore wind declined by 21% from 2010 to 2018, in about USD 0.16/kWh to USD 0.13/kWh [10]. Still, to boost competitiveness and mass adoption, the reduction of project costs is the current priority in the sector.

Operation and maintenance (O&M) is one of the most researched topics in the offshore wind sector, contributing greatly to the LCOE. It's estimated that O&M costs represent about 23% of the total investment costs of an offshore wind project [11]. This is mostly due to the high challenges of maintaining wind farm assets in offshore environments. Offshore wind farms are deployed in harsh environmental conditions, which affect component reliability and maintenance requirements. Most offshore wind farms are typically deployed within 10-40km off the coast [5], although their distance to the O&M port may be greater. Due to 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 [5].

The maintenance philosophy adopted in an offshore wind project has a strong impact on O&M costs, downtime duration, and consequently, on wind farm availability [11]. Wind farm maintenance must therefore be adequate, given the high complexity of relationships between component repair schedules, maintenance crew logistics and, revenue opportunities thus, the scheduling of the maintenance is fundamental for wind farm operations [12]. Therefore, it's necessary to find methods to improve wind farm maintenance strategies to mitigate O&M costs [12].

Currently, the most adopted maintenance strategy used in wind farms consists in a combination of preventive maintenance (PM) and corrective maintenance (CM) [12]. CM consists of scheduling maintenance operations as a reaction to component failure. In PM, maintenance is performed at fixed time intervals in the attempt to prevent future failure occurrences [12].

However, research efforts have been directed towards predictive maintenance (PdM) due to its potential. In this maintenance strategy, prognostics-based methods use current and prognostic information of the wind turbines to predict their future component degradation. With this, the aim is to optimally schedule maintenance operations [13]. These are scheduled in times with low wind speed, where energy production is low, and times with higher site accessibility where environmental conditions are more suitable for the maintenance operation and thus, reducing delays without having the risk of an imminent failure [12]. Benefits from this strategy may include improvement of availability, reductions in O&M costs, and downtime. There's also the chance to reduce the probability of more significative damage, due to maintenance being performed before the failure occurs, avoiding further damage.

The present work aims to quantify the potential logistic benefits of PdM strategy in offshore wind farms, when benchmarked against CM strategy. To quantify these benefits, two analyses were carried out, leveraging on the computational model developed for this purpose. Firstly, a wind farm analysis is used to understand what are the potential logistic benefits that a PdM can bring to a wind farm. Then, a component-level analysis was performed, statistically quantifying total failure cost variability for each maintenance strategy, and subassembly.

1.2 Structure of Dissertation

This master's dissertation is divided into five fundamental parts. Firstly, an introduction to the subject matter is provided in Chapter 1. Chapter 2 describes the state-of-the-art of O&M in offshore wind projects. A brief description of existing logistic modelling tools applicable to offshore wind projects is provided in Chapter 3. The underlying methodology of the analysis carried out in this work is presented in Chapter 4, describing the developed modules and their functionalities. Results are presented and discussed in parallel, in Chapter 5. Finally, the conclusions, and future work, are presented in Chapter 6.

Chapter 2: Offshore Operation and Maintenance

O&M is one of the five lifecycle stages in offshore wind projects. After commissioning, the O&M phase lasts throughout the entire project's lifetime, being responsible for a significant fraction of the project costs [8]. These costs are estimated to represent about 23% of the total investment costs of an offshore wind project [11]. The lifecycle of offshore wind projects is shown in Figure 2.1 and can be broken down into five main phases. The O&M phase is highlighted in the figure.

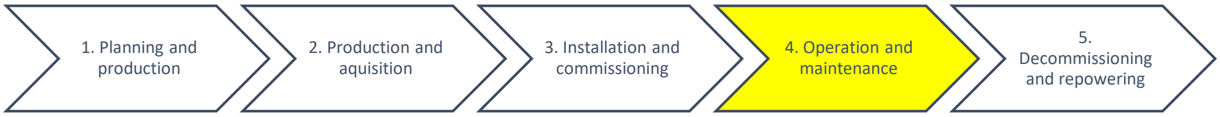


Figure 2.1. Five stages of an offshore wind farm. Source: [8].

The O&M of offshore wind farms is facing decision optimization and engineering challenges. These challenges include the large scale of turbines that imply large components, long logistic delays, expensive setup costs, restricted and random maintenance operation windows due to weather conditions, and limited reliability-oriented field data [1]. To overcome the challenges mentioned before, it is important to use appropriate maintenance strategies to restore the wind turbines back to "full health", which includes decision support systems used to plan maintenance operations [13]. A maintenance operation is a follow-up of procedures that are needed to take place to complete a specific offshore task. Several maintenance operations are performed on a daily basis in an offshore wind farm; thus, it is important to perform them in an effective and reliable way [11]. Maintenance operations are ideally scheduled during periods with low wind speeds and when vessels are available [13]. For health and safety reasons, offshore maintenance operations are limited under specific environmental conditions [1]. The use of vessels in these operations can only be carried out during sufficiently long periods of suitable weather conditions. For this reason, it is important to note that weather windows for maintenance operations are limited and random [1]. Weather window analysis is of great importance to strategic planning of maintenance operations, to estimate potential weather delays. Usually, historical met-ocean is used to simulate the weather windows of a project throughout its lifetime. An analysis performed based on historical met-ocean data is defined as hindcast analysis [14].

There has been an increasing focus, from both wind farm owners and operators, on reducing O&M costs. The impact of these costs on the total cost of energy is significant, and this has been recently approached as a decision-making problem. These costs become even more critical nowadays, as not only the distance to shore increases, but also when the rated capacity increases. An increase in rated capacity of offshore wind turbines will increase the generated energy, but in counterpart, it's downtime will cause greater energy losses [13]. The aspects considered in the offshore O&M costs can be differentiated in two major groups, all the activities related to the maintenance operations and repair of the failures (total operation costs), and the energy loss costs caused by downtime of the wind turbine [15], that would otherwise be revenue if the turbine wasn't down. This revenue can be considered as an opportunity cost. This is the reason that "cost-effective" O&M strategies and "well-planned" inspections have a major importance for current and future offshore wind farms [13].

2.1 Maintenance Strategies

An overview of maintenance strategies is performed. There are several strategies that can be applied to a wind farm during its lifetime, but wind farm operators must choose the maintenance strategy that better suits their needs and priorities. Normally, the aim is to extend components lifespans, reduce the number of emergency repairs, and decrease overtime labor costs [11]. A cost-effective O&M strategy consists in reducing the number of maintenance tasks while maintaining good reliability of the wind turbine. If a low number of maintenances is performed, the wind turbine can have an increase of failures that will result in an increase of repair costs and downtime, which ultimately causes energy generation loss [13]. It is a balance that needs to be optimized. This optimization contains a high degree of uncertainty due to the variety of wind turbine designs used in industry, their components, and failure modes. The weather conditions also influence wind turbine reliability itself and site accessibility. The spare parts availability, the vessels' availability and other limited resources also play their part into this uncertainty [13]. With this optimization, wind turbine availability and economic benefits are maximized.

In literature, there are several ways to categorize the different maintenance strategies. In [11], several classes of maintenance strategies are identified. Figure 2.2 shows an overview on the classification of these maintenance strategies used, adapted from [11].

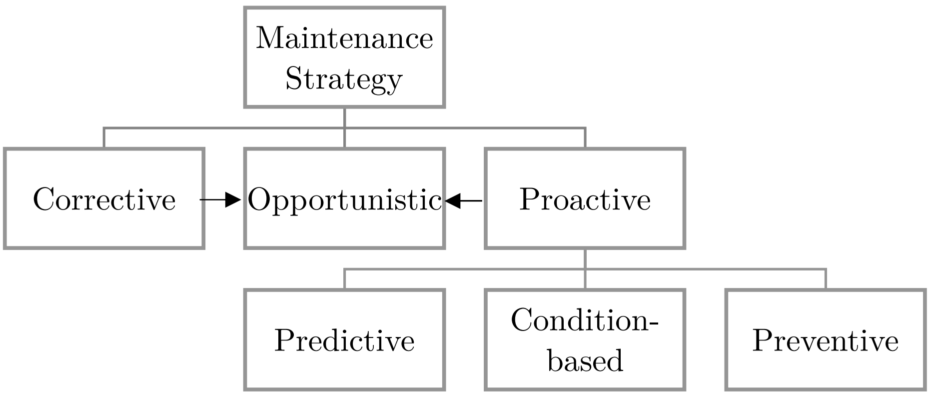


Figure 2.2. Classification of maintenance strategies. Adapted from [11].

2.1.1 Preventive Maintenance

As the name suggests, the objective of PM is to perform maintenance on an asset before a failure can occur. As such, PM must be performed regularly based on time intervals or operational thresholds (e.g., number of operating hours). However, PM can be unnecessarily expensive if done too frequently, due to the costs associated with maintenance vessels and personnel. On the other hand, unsuitably low PM frequency may lead to increased component degradation, resulting in higher failure rates, and consequently, higher downtimes and project costs. It follows that planning PM consists of a trade-off between failure risks and operational costs [11].

PM interventions include visual inspections of specific components to detect typical problems such as leakage and corrosion. Other routine inspections can take place in bigger time intervals and at bigger detail to detect other types of problems. Non-destructive testing is an inspection method that takes use of techniques like acoustic emission, ultrasonic, radiography, thermographic, and electromagnetic to assess the wind turbine condition [13]. Performance-based PM activities can also take place on specific dates that are calendar-based, component age-based, or energy production-based to prevent future failures and wind turbine degradation. Calendar-based maintenance can be of two types, the PM1, and PM2. PM1 maintenance takes place one time per operation year, usually in July, and the PM2 takes place two times a year, usually in May and October. To perform the component age-based and the energy production-based maintenance, a time interval or energy interval needs to be defined. It can be difficult task to find the optimum interval to replace critical assets that maximizes system reliability [13].

2.1.2 Corrective Maintenance

In the CM strategy, also known as breakdown or reactive maintenance, the maintenance action is scheduled as a reaction to component failure. Component failure can result in partial or total shutdown of the wind turbine's energy generation. While this type of maintenance avoids unnecessary maintenance interventions, it may lead to high costs and revenue losses, especially for offshore wind farms that are deployed far from shore and with low accessibility [13], [16]. Whenever downtime occurs, a quick maintenance response is fundamental to avoid significant economic losses [16]. The greatest advantage of this maintenance strategy is that the remaining useful life of the asset is always fully utilized, which means that there is no waste of resources by replacing parts before they become non-functional. This ultimately means that a certain asset will fail the least it can, along its lifetime [16] thus, a lower number of failures implies a lower number of maintenance operations. On the other hand, CM can cause more damage to components when a failure occurs, which can increase costs [16]. If a failure occurs during a time of high wind speed resource, the revenue loss can be very high. This revenue loss is augmented by high downtime consequent of the usage of this strategy itself or if the failure occurs on a month of harsh weather causing low site accessibility.

Opportunistic maintenance (OM) can be used on top of CM. It takes place when an unscheduled maintenance task is undergoing repair or replacement of a component in a wind turbine. It consists in taking the opportunity of this maintenance task to perform other PM tasks on other components or wind turbines [13] to reduce crew visits, production losses, traveling and setup expenses [12].

2.1.3 Condition-based Maintenance

Condition-based maintenance (CBM) is a more sophisticated maintenance approach, where the diagnosis of the health condition of a wind turbine is performed. The health of the wind turbine components is assessed through continuous monitoring and inspections, and whenever the condition reaches a certain threshold, maintenance interventions, either component repair or replacement, are scheduled [13].

Condition monitoring systems (CMSs) are sensors used in CBM. CMSs have high installation and maintenance costs. These costs can go up to 13,000€ per turbine [17]. Thus, adoption of CMSs has been low in current wind farms [18]. The Supervisory Control and Data Acquisition (SCADA) system is also a data collection system that is considered a standard and is largely installed on existing wind farms. SCADA monitors the run-time operation condition of a wind turbine by collecting data at low sample rate, generally once per 10 minutes [17]. The types of data collected by the system are, for example, temperature, speed, and power [18].

2.1.4 Predictive Maintenance

The PdM strategy uses current, and old data of the system obtained through sensor measurements and signal processing methods. This information is used to predict the failure of the system during operation to optimally schedule maintenance operations [13]. Maintenance operations are performed only when its necessary, so that the system is not over-maintained, since that may lead to unnecessary costs [16]. The PdM strategy can also take advantage of SCADA systems to perform fault prognostic functions, without the need for installation of additional CMSs equipment that can lead to higher costs [17] [18] [19].

In the last few years, research has been published on the topic of PdM in offshore wind applications. Some studies use machine learning algorithms to predict wind turbine failures. Some examples of machine learning publications were found. Predictions can be made in short-term or long-term, depending on the algorithm.

Elmar et al. [20] and Leahy et al. [17] are two examples of short-term prediction models. Elmar et al. [20] reports using machine learning techniques for fault prediction in generators. The methodology used in this paper takes into account data limitations, performs statistical tests on time series, selects the features with the most predictive power, and applies machine learning models to predict a fault in the next 1 hour [20]. Leahy et al. [17] presents a new method for automatically identifying historical stoppages on wind turbines using SCADA and alarms data. Each time that the turbine stops operating, that stoppage is associated with a turbine fault, a routine maintenance activity, a grid-related event, or several other categories. This is then checked against maintenance logs to find the accuracy of the label. The labeled data is then fed into a classifier to predict when stoppages will occur. Maintenance activities were predicted with fault prediction windows of 2, 4, 8, 12, 24, and 48 hours, where 92% of unplanned maintenance activities, and 100% of planned maintenance activities were correctly predicted [17].

Zhao et al. in [19] and [18] gives examples of long-term predictions. Zhao et al. [19] reports the prediction of wind turbine generator failures using data-driven methods. It is also stated, that for generators, 10 to 30 days is sufficient lead time to schedule maintenance activities before a generator failure occurs. The purchase of the generator usually takes about 20 to 30 days, and the replacement and debugging can take 1 or 2 days. Apart from this, it is also stated that wind turbine performance degradation can be seen for about 44 days before failure occurs [19]. Zhao et al. [18] is able to predict the remaining useful life (RUL) of wind turbine generators 18 days ahead before a fault occurs with 80% accuracy. Besides that, the model is able to diagnose the state of the wind turbine generator when the fault occurs [18].

2.2 Offshore Logistic Infrastructure

The selection of appropriate logistic infrastructure, namely vessels, ports, and support equipment, is a fundamental step in planning O&M operations in offshore wind projects due to its impact on project costs. Considerations about these support infrastructures are provided in the next subsections.

2.2.1 Vessels

Vessels are used mainly in the transport of personnel, transport of equipment, and transport and installation of components. In the O&M phase, the type of vessel used depends on the maintenance operation and its maintenance requirements to repair or replace a certain component. Examples of types of vessels are given below, from Figure 2.3 to Figure 2.7.

Firstly, crew transfer vessels (CTV) in Figure 2.3, are small vessels mainly designed to quickly transport offshore personnel, and smaller cargo to the offshore wind site. Personnel are often technicians that transit to the site with the aim of performing small repairs that don’t require large equipment or components. CTVs typically have short-range capabilities (about 75 km [21]).

Figure 2.3. Crew Transfer Vessel. Source: [22].

Figure 2.4. Service Operation Vessel. Source: [23].

Service operation vessels (SOV), shown in Figure 2.4, are vessels with high transit ranges (about 150 km [21]) and excellent station-keeping capabilities, being capable of operating in offshore environments for weeks [21]. They are frequently equipped with wave motion-compensated gangways that are used to ensure safe and more comfortable personnel transfers under more energetic sea states. They are typically used to carry out a wide range of functions, and as such can be included in several vessel categories such as construction support vessels, installation support vessels and walk-to-work vessels [24].

Figure 2.5. Self-Propelled Crave Vessel. Source: [25].

Figure 2.6. Jack-up Vessel. Source: [26].

A self-propelled crane vessel (PCV), shown in Figure 2.5, is a vessel used to lift large and heavy parts. The jack-up vessel is used for station keeping using self-elevating legs to stabilize itself on the bottom of the sea, as can be seen in Figure 2.6 [24].

In Figure 2.7, it is shown the transport barge that is commonly used to transport large or heavy components to a site [24]. Other vessel types are also used in offshore wind projects. These include tugs, multicats, anchor-handling tug supply vessels, cable laying vessels, diving support vessels, guard vessels, non-propelled barge, non-propelled crane vessels, platform supply vessels, rock dumper, SOV with gangway, and survey vessels [14].


Figure 2.7. Non-propelled Transport Barge. Source: [27].

2.2.2 Ports

In the context of offshore wind energy, ports can be classified into three categories. The first category is O&M port, the second category is the assembly port, and the third category, the manufacturing port [21]. The O&M Port is the port where activities associated with O&M of an offshore wind farm are performed, during its design lifetime. The facilities contained at an O&M port are specific to the O&M strategy used in the wind farm project. An example of this is the type of vessels used by the maintenance strategy [21].

O&M ports may have two main sub-distinctions: CTV-based, and SOV-based. Northern European projects have typically adopted a CTV-based O&M strategy, where the vessels and technicians only stay at sea for a single shift. SOV-based O&M strategies have been used in fewer projects but are more likely to be used more in future projects deployed further offshore, it can be advantageous to use the greater distance range, and the higher time of service of the SOVs, for greater cost savings. It is also feasible for projects to adopt mixed CTV and SOV-based O&M strategies. O&M ports are not suitable for the replacement of major components like a blade, in that case, it is required a port accessible to larger vessels such as assembly or manufacturing ports [21].

An example of an O&M port can be seen in Figure 2.8 and Figure 2.9. Mukran port is located in the Baltic Sea, on the island of Rügen, in Germany. This port is serves as a base for offshore installations and a service hub for operations and maintenance. Its water dept of 11.5 m is perfect for specialized offshore vessels such as jack-up barges, floating cranes, and cable-laying vessels. The service hub is situated within the boundaries of the port area and offers sufficient facilities for CTVs, tugs, and other types of smaller vessels [28].

Figure 2.8. Mukran port in Baltic Sea, Rügen, Germany. Source: [29].

Figure 2.9. Mukran port in Baltic Sea, Rügen, Germany. Source: [29].

2.2.3 Equipment

To fulfill maintenance operations, extra equipment may be required. This equipment is usually rented, which implies additional costs for the operation. There is a variety of equipment's that support the maintenance operations. Examples of equipment are given from Figure 2.10 and Figure 2.11.

Figure 2.10. Motion Compensating Crane. Source: [30].

Figure 2.11. Remotely Operated Vehicle. Source: [31].

Figure 2.10 shows a 3-axis motion-compensating crane that allows extremely accurate load positioning during offshore wind turbine, rig supply and maintenance operations to fixed or floating offshore installations. Remotely operated vehicles (ROVs) are underwater vehicles that can be used, for example, for underwater inspections [24], as shown in Figure 2.11.

2.3 Wind Turbine Reliability

The reliability of an asset denotes its ability to fulfill the specified requirements for which it was designed, during its lifetime [32] or, the ability of an item to perform a required function under given conditions for a given time interval. Reliability of an offshore wind farm depends on several factors, one of these being the individual reliability of every single wind turbine that comprises the wind farm, that itself is tied to their component's reliability. To express reliability, the failure rate (FR) [33] or mean time to failure can be used (MTTF).

Reliability is part of the acronym RAMS for reliability (R), availability (A), maintainability (M), and survivability (S) [32]. This method is often used to evaluate the performance of a wind farm and its maintenance strategy.

Availability can be divided into three types. Technical availability, or just availability, can be defined as the fraction of time that a wind turbine is operating according to its design specifications during a specific time interval [34] [16]. Normally, this time interval is the turbine lifetime. The operational availability considers only full and partial performance, the amount of time that the wind turbine is operating or can operate during its lifetime. The last type of availability is the energetic availability that is a fraction of energies. It considers the amount of energy produced by the wind turbine divided by the energy that could be produced if there was 100% availability. A turbine with poor availability will have significant losses in energy production and therefore maximizing it is a top priority for wind farm operators [16]. Availability is an important performance index when assessing a maintenance strategy for a wind farm.

The other two remaining items of the RAMS acronym are maintainability and survivability. Maintainability is the ability of a system or component to be repaired and restored to service. Maintenance is performed by trained personnel with the proper skill set, specific procedures, and resources. It can be assessed through mean time to repair [32]. The survivability of an item can be defined as the probability of an item still being functional, at a certain time [33].

2.3.1 Wind Turbine Failure Rate

Like any mechanical system, wind turbines occasionally fail throughout their lifetimes, although the definition of failure may vary. In [35], a failure is interpreted as "a visit to a turbine, outside of a scheduled operation, in which material is consumed", and in [16] it is interpreted as the "inability of a system or component to perform its required functions within specified performance requirements".

The failure rate is a common term used to express the reliability of an item, as mentioned. In general, it is expressed as the number of failures per unit of time. In [35], the failure rate of a wind turbine can also be expressed per turbine per year and is computed, as Equation 2.1 shows,

$$\lambda = \frac{\sum_{i=1}^{I}\sum_{k=1}^{K} n_{i,k}/N_i}{\sum_{i=1}^{I} T_i/8760}, \tag{2.1}$$

where, λ is the failure rate per turbine per year, I is the number of samples for which data are collected, K is the number of sub-assemblies, $n_{i,k}$ is the number of failures, N_i is the number of turbines and, T_i is the total time period, in hours. In Equation 2.1, the numerator is the sum of the number of failures in all periods per turbine. The denominator is the sum of all time periods in hours divided by 8760, which is the total number of hours in a year. Even though the failure rate denotes an average number of failures per time period, the failure rate itself typically varies along the lifetime of any given asset. Experience shows that these variations frequently follow the trend in the shape of a "bathtub" curve [33]. Figure 2.12 shows an example of the variations in failure rate, in the shape of the bathtub curve.

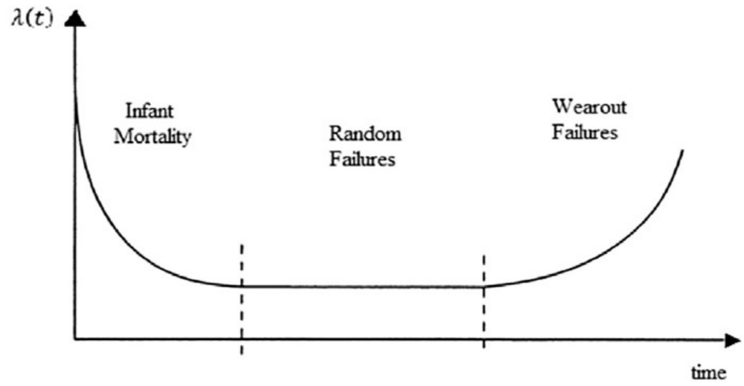


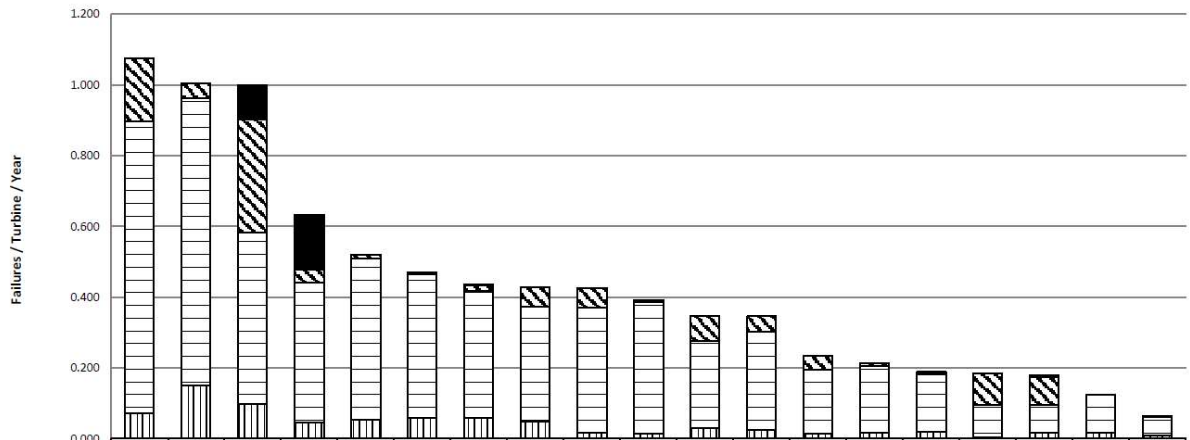
Figure 2.12. Bathtub curve, generic representation of failure rate with time. Source: [36].

In reliability engineering, it is observed that the failure rate of an item, throughout its lifetime, will go over three types of periods, composing the bathtub curve. The first period is called "Infant Mortality", where the failure rate is decreasing over time. The second period is called "Random failure" or "useful life", where the failure rate is constant over time. Finally, the third period is called "Wear out" where the failure rate increases over time. These three periods imply that there are two points where distributions change. In [35] it was observed a decreasing trend in the failure rates for components with higher failure rates, such as the converter/electrical component, that may point to the beginning of the bathtub curve. However, these results are outnumbered by components where the curve is not observed, resulting in no evidence of a bathtub curve in the overall turbine failure rates. Also, the value of the bathtub in characterizing infant mortality is still questionable as seen in [36].

2.3.2 Offshore Reliability Data

As previously mentioned, a conventional way to express wind turbine reliability is through the concept of failure rates. In [35], an analysis to determine the failure rates, average repair time, average repair cost and average number of technicians was conducted with approximately offshore 350 turbines, and their sub-assemblies, over a five year period. The turbines are from sites distributed throughout Europe and owned by anonymous leading manufacturers. All the turbines included are geared turbines with an induction machine where their nominal power goes from 2 to 4MW, and the rotor diameter goes from 80 to 120m (exact values not disclosed). The turbines were maintained using CM and PM but the used data does not consider all scheduled operations such as scheduled services or inspections, though it is unclear if or how much OM was used [35]. In this paper, failures are categorized into three categories, divided per component, and the respective failure rates computed. The total failure rate of the component is the sum of all the categories. The categories were defined by type of maintenance and classified by material costs. Each failure was categorized by analyzing the material costs of repairing that failure. Categories include firstly, major replacement, where all the failures considered in this category have costs greater than 10000€. Secondly, the major repair, where the costs go from a range of 1000 to 10000€. Finally, the minor repair, where the costs must be under 1000€. There is an extra category, called no cost data, that represents the failures that did not have a material cost in the work order database, which is a database where every work carried out in the turbine is recorded [35].

Figure 2.13 shows the failure rates per turbine per year for the subassemblies and cost category.



	Pitch / Hyd	Other Components	Generator	Gearbox	Blades	Grease / Oil / Cooling Liq.	Electrical Components	Contactor / Circuit Breaker / Relay	Controls	Safety	Sensors	Pumps/ Motors	Hub	Heaters / Coolers	Yaw System	Tower / Foundation	Power Supply / Converter	Service Items	Transformer
Major Replacement	0.001	0.001	0.095	0.154	0.001	0.000	0.002	0.002	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.005	0.000	0.001
Major Repair	0.179	0.042	0.321	0.038	0.010	0.006	0.016	0.054	0.054	0.004	0.070	0.043	0.038	0.007	0.006	0.089	0.081	0.001	0.003
Minor Repair	0.824	0.812	0.485	0.395	0.456	0.407	0.358	0.326	0.355	0.373	0.247	0.278	0.182	0.190	0.162	0.092	0.076	0.108	0.052
No Cost Data	0.072	0.150	0.098	0.046	0.053	0.058	0.059	0.048	0.018	0.015	0.029	0.025	0.014	0.016	0.020	0.004	0.018	0.016	0.009

Figure 2.13. Failure rates for subassembly and cost category. Source: [35].

With this category definition, costs are not dependent on distance to shore because only material costs are considered, which brings great advantage when using them as inputs of O&M models. Carroll et al. [35] provides additional data on the average repair time, average number of technicians, and average repair costs for each type of maintenance.

In a data review conducted by Dao et al. [37], 18 wind turbine reliability data sources were used, containing more than 18000 wind turbines. In the data sources, 4 are European offshore sites, corresponding to 1551 offshore wind turbines and, the remaining are onshore. All the turbines have a nominal power greater than 2MW. Dao et al. [37] identifies the differences between the population of onshore and offshore wind turbines. Additionally, an analysis is performed on failure rates and downtimes of the wind turbine subassemblies. The latest found data review was conducted by Cervasco et al. [34], where a systematic review of the reliability, availability and maintainability data for on- and offshore wind turbines is performed. In this review, the data was collected from 24 repositories at system and subsystem level. Operational availabilities were estimated for several data repositories using the openO&M tool [38]. Carroll et al.'s [35] work is included in many of these reviews, such as in [37], [34], [39], [40].

Chapter 3: Modeling Logistic Support Tools

To compute the eventual logistic benefits that a PdM strategy might bring to offshore wind projects, an offshore logistic support tool needed to be developed to aid in the computations. One important aspect of an offshore logistic support tool is how it models wind turbine reliability, which is reviewed in the following section. Then, a review of offshore logistic support tools is performed in a table, and the two last tools are presented in more detail. These last two tools served as inspiration for some features of the developed model.

3.1 Modeling Reliability

The simulation of failures on a wind turbine or component is an important feature of an O&M tool. The simulation of failures aims to model failure events throughout a wind farm's lifetime, as an approximation to reality, and the time of failure serves as an input to other O&M tool functionalities, for example, to compute maintenance costs, and perform other analyses. The simulation of failures can be done based on reliability theory, used on reliability engineering.

3.1.1 Weibull distribution

The Weibull distribution is normally used in reliability engineering due to its versatility to characterize the bathtub curve, even though there are other distributions that can be used [33]. The Weibull distribution can contain three parameters and its probability density function (PDF) is given below in Equation 3.1,

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}}, \tag{3.1}$$

where, γ is the offset from zero, β is the shape parameter, and η is the scale parameter. To find the probability of failure within the time interval (0, t) [41], the cumulative distribution function (CDF) in Equation 3.2 is used,

$$F(t) = P(T \leq t) = \int_0^t f(u)du = 1 - e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}}. \tag{3.2}$$

Equation 3.2 sums all the area below $f(t)$, from 0 until t. T denotes the stochastic variable of time to failure.

To describe the survivability of an item, in this case a wind turbine, normally the reliability function $R(t)$ is used, also called the survival function [41]. It is used to describe the probability of an item still being functional, at a certain time [33] or the probability that no failure occurred prior to the time step t. For the three-parameter Weibull distribution, the reliability function is shown below in Equation 3.3,

$$R(t) = P(T > t) = 1 - \int_0^t f(u)du = \int_t^\infty f(u)du = e^{-\left(\frac{t-\gamma}{\eta}\right)^\beta}, \tag{3.3}$$

where it uses the same parameters as the PDF (Equation 3.1). With this, as time passes, $F(t)$ grows, and $R(t)$ decreases.

As seen in [41], the time dependent failure rate function for the Weibull distribution is defined as the probability that an item will fail in the time interval $(t,\ t + \Delta\mathrm{t})$ when its known that the item is functioning at time interval t [41], given in Equation 3.4,

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{\frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^\beta}}{e^{-\left(\frac{t-\gamma}{\eta}\right)^\beta}} = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1}. \tag{3.4}$$

Figure 3.1 shows how the shape parameter (β) of the Weibull distribution can influence the failure rate function (also called hazard function, $h(t)$) [42].

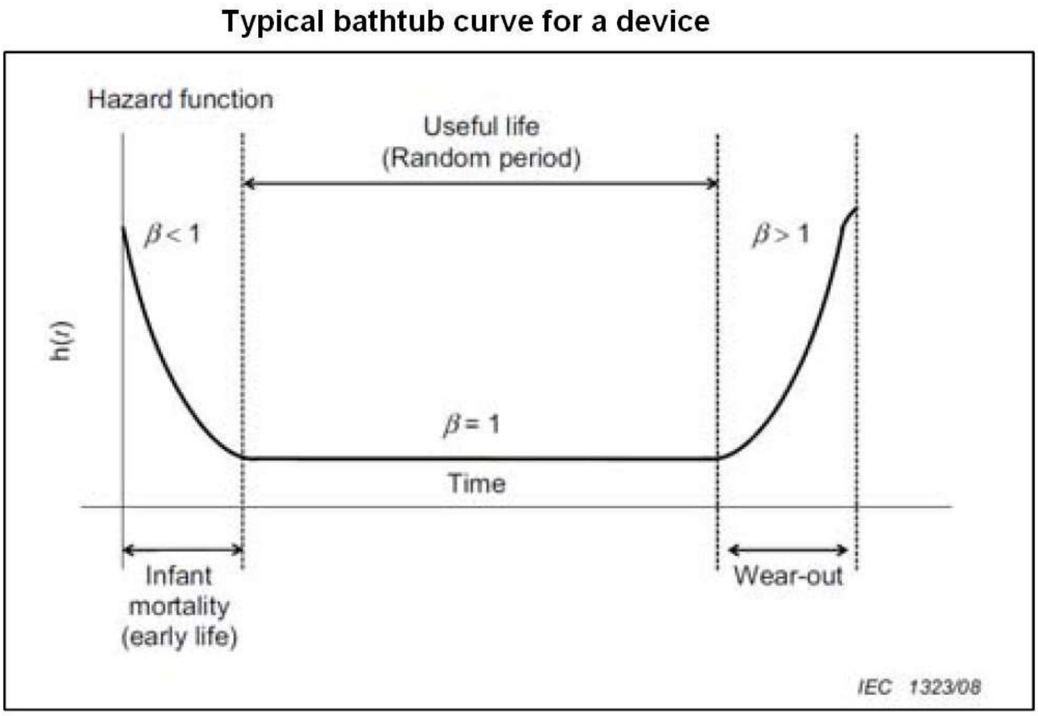


Figure 3.1. Influence of the shape parameter (β) in the failure rate function. Source: [42].

A shape parameter smaller than one will translate into a decreasing failure rate function, a shape parameter of one will translate into a constant failure rate function, and a shape parameter higher than one will translate into an increasing failure rate function.

3.1.2 Exponential Distribution

In the case where shape parameter (β) of one, the failure rate in Equation 3.4 is constant, and not time dependent. This represents the random failure period in the bathtub curve,

$$\lambda = \frac{1}{\eta}. \tag{3.5}$$

Even though failure rates may vary over time, most studies rely on the simplification of the failure rate as a constant [33]. If one already has a failure rate from given data repository, to find the distribution for constant failure rate (where β equals to 1), one can find the scale parameter (η) with Equation 3.6,

$$\eta = \frac{1}{\lambda}. \tag{3.6}$$

Moving forward, replacing Equation 3.6 in the Weibull distribution PDF (Equation 3.1), taking the offset (γ) of zero, and a shape parameter (β) of one, the PDF of the Weibull distribution is equal to the PDF of the exponential distribution [33], [41], [34], setting this as a special case of the Weibull distribution, when $\eta = 1/\lambda$, with constant failure rate (λ). The PDF of the exponential distribution can then be seen in Equation 3.7,

$$f(t) = \lambda\, e^{-\lambda t}. \tag{3.7}$$

The reliability function of the exponential distribution is given by Equation 3.8 [41],

$$R(t) = P(T > t) = \int_{t}^{\infty} f(u)du = e^{-\lambda t}. \tag{3.8}$$

The CDF for the exponential distribution is given by Equation 3.9, as also stated in [41], and [32].

$$F(t) = P(T \leq t) = \int_{0}^{t} f(u)du = 1 - e^{-\lambda t}. \tag{3.9}$$

3.1.3 Time to Failure

With the CDF of the exponential distribution, the time to failure (TTF) can be found. The TTF is defined as the time that it takes for an item to fail, and it can be found, in this case, through Equation 3.10 [32],

$$t = -\frac{1}{\lambda_k}\ln[1 - \hat{F}(t)], \tag{3.10}$$

where, λ_k is the component failure rate, t is the TTF, and $\hat{F}(t)$ is a value that is found by uniformly sample (between 0 and 1) the CDF in Equation 3.9 [32].

The theoretical mean time to failure can be approximated to Equation 3.11, from [32],

$$MTTF_k = \frac{1}{\lambda_k}, \tag{3.11}$$

where λ_k is the component failure rate. Using Equation 3.11 to find the TTF could also be possible, though it is a very large approximation because it is only true after an infinite number of failures. This ultimately would mean that the simulated failures would be separated in time by fixed intervals. In reality, there is always randomness that needs to be considered in the process.

3.2 Offshore Logistic Support Tools

An overview of available tools for offshore projects is performed. There are several logistic support tools developed for offshore projects. Table 3.1 presents a review of these main tools and their functionalities [14] such as the weather window analysis, referred to as hindcast, where historical met-ocean data is used, or referred to as forecast, where met-ocean data is estimated.

Table 3.1. Main logistic support tools for offshore wind projects and their functionalities. Color scheme: red–worse scenario, orange–in between scenario and, green–best scenario. Infrastructure selection label: P–ports. V–vessels and, E–equipment. Adapted from [14].

Product Name	Open source	Applicable to Ocean Energy	Weather window analysis	Infrastructure selection	Optimal operation plan	Inst.	O&M	Decom.
O2M	No	No	Hindcast	No	No	No	Yes	No
OMCAM	No	No	Hindcast	No	No	No	Yes	No
ECN O&M Access	No	No	Forecast	No	No	No	Yes	No
DTO Logistics module [43]	Yes	Yes	Hindcast	P, V, E	Yes	Yes	Yes	No
DTO+LMO module [14]	Yes	Yes	Hindcast	P, V, E	Yes	Yes	Yes	Yes
ECN O&M Calculator (OMCE) [44]	No	No	Hindcast	No	No	No	Yes	No
Multi-Agent-System	No	No	Hindcast	No	No	No	Yes	No
ROMEO O&M Tool [45]	N/A	No	Forecast	No	No	No	Yes	No
NoWIcob [46]	No	No	Hindcast	V	No	No	Yes	No
Vessel fleet optimization models [47]	No	No	Hindcast	V	No	No	Yes	No
Shoreline Design [48]	No	No	Hindcast	No	No	Yes	Yes	No
StrathOW-OM [49]	No	No	Hindcast	No	No	No	Yes	No
WES O&M Tool [50]	Yes	Yes	Hindcast	No	No	No	Yes	No
Mermaid [51]	No	Partially	Hindcast	No	No	-	-	-
ForeCoast Marine [52]	No	Partially	Hindcast	No	No	-	-	-
StormGEO S-Planner [53]	No	Partially	Forecast	No	No	-	-	-
OpenO&M Tool [38]	Yes	N/A	Hindcast	No	N/A	No	Yes	No
O&M simulation tool [33]	N/A	N/A	Hindcast	No	N/A	No	Yes	No

These tools can be compared with respect to their main functionalities. Most of the reviewed tools use a hindcast weather window analysis. Only three tools are open source, the DTO Logistics module, the DTO+LMO module, and the WES O&M Tool. O&M tools can deliver several advantages to offshore projects, such as the identification of critical components in terms of performance and costs, the estimation of availability, revenue and operational expenditure (OPEX) and planning and optimization of logistical strategies [54]. The DTO+LMO module tool, from DTOceanPlus, is the more complete tool with the advantage of being open source. In Table 3.1, there are only four tools that consider infrastructure selection. The DTO Logistics module and the DTO+LMO module contain port, vessel, and equipment selection. The NoWIcob and the Vessel fleet optimization model only consider vessel selection, and the other models exclude this functionality completely.

The OpenO&M [38] and O&M simulation tools [33] in Table 3.1 are presented in more detail in the following sections. These served as the main inspiration for some features of the developed model for this dissertation.

3.2.1 OpenO&M Tool

Details about the development on an O&M tool were found in [38], referring to the OpenO&M. The OpenO&M tool is an open access tool, developed in Matlab®, for the simulation of O&M activities. The tool is composed of a reliability module, power module, weather module, and maintenance module. It uses as inputs user-defined failure rates of various subsystems alongside maintenance, repair policies, and simulated weather conditions to simulate long-term availability and power production. Stochastic simulations in the time domain are made to simulate the failure modes of the wind turbines, by using failure rates to simulate time to failures, based on an exponential distribution [38]. Figure 3.2 shows the structure of the OpenO&M tool.

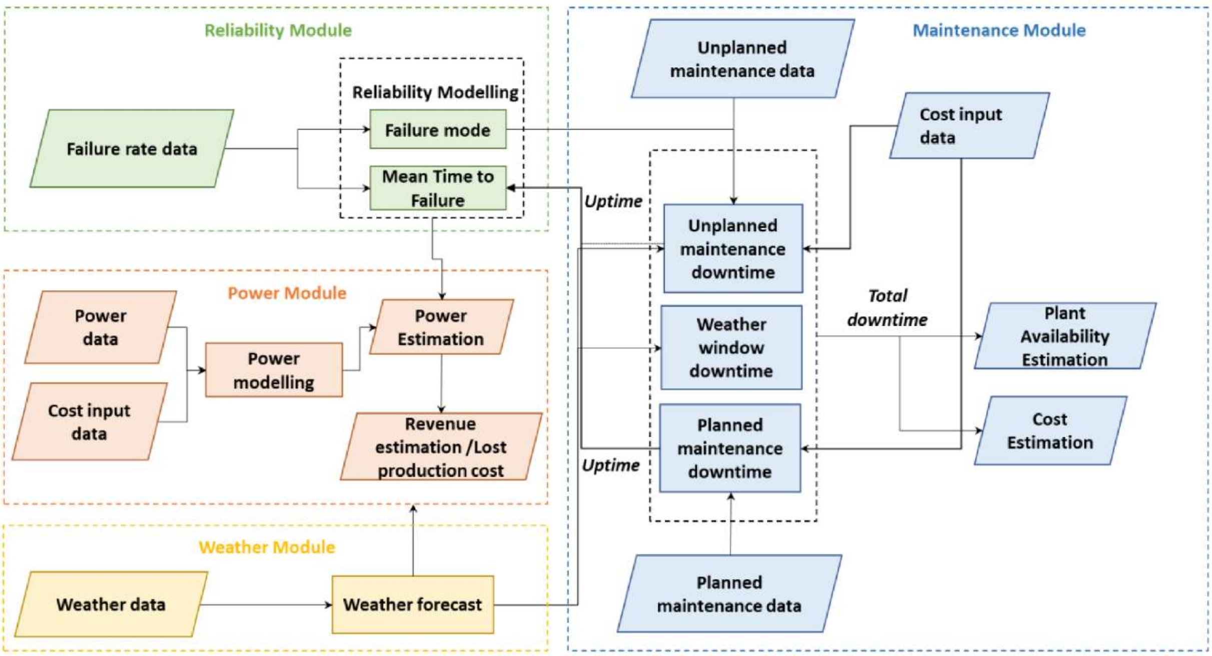


Figure 3.2. Structure of OpenO&M simulation tool. Source: [16] and [34].

The reliability module simulates the occurrence and severity of the different failure types of the subsystems of the turbine. The maintenance types are divided in three categories, minor failure, major failure, and replacement, similarly to what was done in Carroll et al. [35]. Each type of failure has different consequences for the turbine's availability. Minor failure considers that the wind turbine continues operational after the failure and thus, the downtime associated with that failure is only the repair time. In this case, the maintenance is scheduled after the failure and the turbine continues operational until then. For the major failure, the turbine immediately stops operating at failure and maintenance operation must take place to restore it back to "full health". Finally, the replacement failure type also causes immediate downtime, maintenance operation must happen to replace the failed subsystem and that may imply greater downtime than major failures. There is a failure rate used for each maintenance type of the subsystems, and with the sum of all those three failure rates, the failure rate of a given subassembly can be obtained as seen in Figure 2.13 from [35]. The same applies to the wind turbine, where the sum of all failure rates of the subsystems of the turbine originates the turbine failure rate. References [16] and [34] are also based in the OpenO&M tool.

3.2.2 O&M Simulation Tool

In reference [33] it is proposed a version of an O&M simulation tool where a failure simulation model is integrated with an O&M simulation model to assess the wind farm availability. Figure 3.3 shows the flowchart with the main functionalities of the tool.

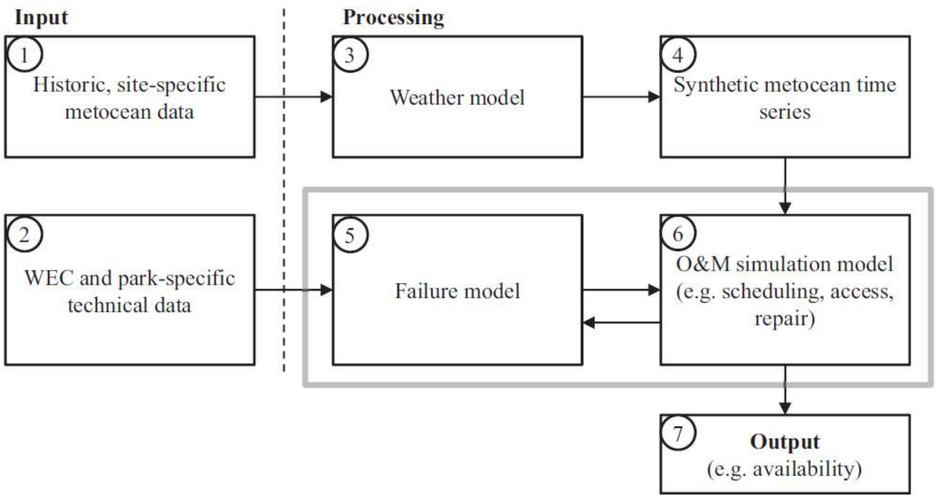


Figure 3.3. O&M simulation tool - main functionalities. Source: [33].

The tool in [33] is divided into several modules from 1 to 7. Module 1 contains the historic and site-specific met-ocean data (e.g., wind speed and wave height). Module 2 contains the wind turbine (referred as wind energy converter (WEC) in Figure 3.3), and park-specific technical data (e.g., failure rates, lifetime, and rated power). Modules 1 and 2 are for defined inputs, and the remaining are processing modules. Module 3 is where the weather data from module 1 is processed by using a Markovian process to generate discrete wind speed and wave height time series for the duration of the simulation. A more detailed description can be found in [33]. Module 4 represents the output from module 3, the discrete time series for wind speed and wave height along the simulation duration. Module 5 contains the failure model. The failure model processes the failure rates of the turbine components to generate turbine failure events [33]. The focus of this module itself is to generate time to failures. The TTF is determined by the generation of a random number in a selected statistical distribution function around the failure. Reference [33] aims to test different distributions functions for this TTF generation to assess the influence of statistical uncertainty on component reliability estimations.

One of the most important modules in reference [33] is module 6. It is composed of an O&M simulation tool which represents the chosen O&M strategy. The objective of this module is to compute the total downtime for each failure, that is composed of several sums of time intervals, the mobilization & logistics, the waiting for weather window, the transportation time, and the repair time. The interactions between modules 5 and 6 is shown in Figure 3.4. The circled numbers (5 and 6) in Figure 3.4 refer to the modules previously shown in Figure 3.3.

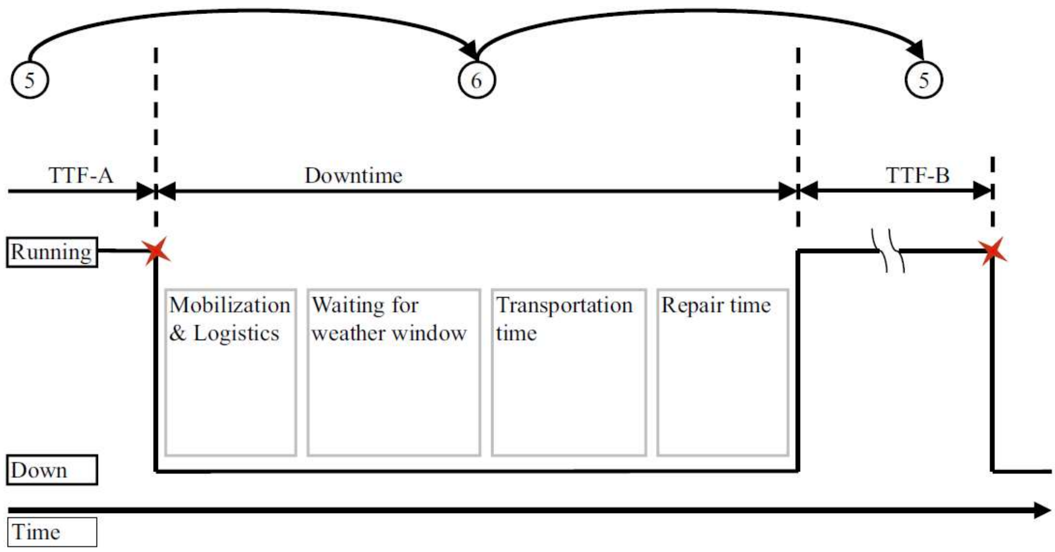


Figure 3.4. Failure module and O&M simulation interaction. Source: [33].

Initially, for a component, a first TTF ("TTF-A") is generated by the failure simulation model (module 5). During this "TTF-A" the turbine is running and, at the end of this time to failure interval, the failure happens, represented by a red "X" in Figure 3.4, that will cause downtime. Then the O&M simulation model (module 6) generates the total downtime for a failure that happens at that time. Afterwards, the component is back to "full health" because it was repaired or replaced. With the component at full health, another TTF ("TTF-B") is generated again by the failure model (module 5) and the process repeats until the end of the simulation duration, represented in the time axis. Component failures are assumed to be uncorrelated nor dependent on external conditions [33].

The validation of this O&M simulation tool [33] is made by the number of expected failures. Assuming that constant failure rates are obtained from a wind farm with the same O&M strategy used in the tool, the expected number of failures of the wind farm is given by Equation 3.12 from [33],

$$No.\,Expected\ Failures = Total\ Annual\ FR \times\ No.\,Turbines\ \times Simulation\ years. \tag{3.12}$$

Chapter 4: Methodology

To quantify the potential logistic benefits of a PdM strategy in comparison with a CM strategy, two separate but complementary analysis are carried out, based on the developed Python model for this dissertation. The wind farm analysis focuses on simulating the impacts of CM and PdM interventions in the context of an offshore wind project, taking into consideration the subassemblies' reliability. In this analysis, turbine operation time-series are created to simulate the turbines' lifetime. The main benefits computed in the wind farm analysis include variations in total lifetime costs, and lifetime availabilities. It is important to note that, in this analysis despite PdM being the focus of this work, failures are not predicted by the model, failures are instead simulated. The present study is assuming that these failure simulations are failure predictions made by a sensor-based predictive algorithm. The objective of the developed model is to compute the benefits as if it were known, with full certainty, when the failures would happen, and not to predict the actual failures.

The component level analysis focuses on evaluating the impact that failures distributed throughout different months can have on total costs. For each subassembly, failure events are distributed throughout the year in order to assess the annual variability and the consequences of having maintenance interventions during "good" and "bad" weather months for a given site. Benefits related to the total costs of all distributed failures for each subassembly and maintenance type are computed. In response to failure events, CM and PdM operations are scheduled after or before failure occurrence and compared based on total costs. This analysis is decoupled from subassembly reliability.

Firstly, in this chapter, general inputs for a base case are presented. Afterwards, the methods used to develop the modules, that build the model, are presented with their specific base case inputs. Finally, both analyses are explained in a more integrated way.

4.1 Base Case General Inputs

4.1.1 Wind Farm Characteristics

The wind speed data obtained was collected from an offshore site in Ireland. This data is historical data on mean wind speed, in an hourly time step for 20 years, starting from 1st of January 1994 at 02h00, here set as the commissioning date. The lifetime considered for the analysis was thus 20 years, and the site located somewhere offshore of Ireland, assuming 100 km of distance from the O&M port. There are 20 wind turbines used in the wind farm analysis, and it is assumed that all turbines have the same specifications.

4.1.2 Wind Turbine Characteristics

For both analyses, the DTU 10MW reference wind turbine is used. It is a three-bladed upwind wind turbine with a multi-stage gearbox, 119 m of hub height, and 178.3 m of rotor diameter.

The wind turbine composition used in this dissertation is from Carroll et al. [35], reviewed previously. In reference [35], different subassemblies have three different maintenance types, the replacement, the major repair, and minor repair. These maintenance types are modeled for each subassembly, where each requires its own specific maintenance operation.

4.2 Model Structure

To conduct the two analyses, a model was developed in python. This model employs a module-based structure. The methodology used to develop the modules is explained in the following sections. In each module, the used base case inputs are given in parallel and explained.

4.3 Reliability Module

The reliability module is based on reliability theory, reviewed in the literature. The failures events are generated from the failure rates, from [35]. Table 4.1 shows the failure rates of each subassembly and maintenance type.

Table 4.1. Failure rates of each subassembly maintenance type. Source: [35].

Subassembly	**Major Replacement [Failures /turbine/year]**	**Major Repair [Failures /turbine/year]**	**Minor Repair [Failures /turbine/year]**
Pitch / Hyd	0.001	0.179	0.896
Other Components	0.001	0.042	0.962
Generator	0.095	0.321	0.583
Gearbox	0.154	0.038	0.441
Blade	0.001	0.01	0.509
Grease / Oil / Cooling Liq.	0	0.006	0.465
Electrical Components	0.002	0.016	0.417
Contactor / Circuit / Breaker / Relay	0.002	0.054	0.374
Controls	0.001	0.054	0.373
Safety	0	0.004	0.388
Sensors	0	0.07	0.276
Pumps / Motors	0	0.043	0.303
Hub	0.001	0.038	0.196
Heaters / Coolers	0	0.007	0.206
Yaw System	0.001	0.006	0.182
Tower / Foundation	0	0.089	0.096
Power Supply / Converter	0.005	0.081	0.094
Service Items	0	0.001	0.124
Transformer	0.001	0.003	0.061

To model the failures of the category "No Cost Data", it was assumed that these failures belong to the minor repair category, by doing the sum, because these had no cost data associated.

It is assumed that failure events of different subassemblies are independent of each other. Therefore, a failure that happens in a certain subassembly does not affect another subassembly's reliability. Maintenance types with a failure rate of zero are not modeled because there are no failures, in that case. Those include the grease/oil/cooling liq. major replacement, the heaters/coolers major replacement, the pumps/motors major replacement, the safety major replacement, the sensors major replacement, the service items major repair, the service items major replacement, and finally the tower/foundation major replacement.

4.3.1 Failure Events

Failure events are distributed in the time-series by generating different TTFs. The TTFs are generated assuming a constant failure rate, leading to the usage of the exponential distribution, as seen in literature. The cumulative distribution function (CDF) for the exponential distribution is given by Equation 4.1,

$$F(t) = 1 - e^{-\lambda_k t}, \tag{4.1}$$

where, λ_k is the subassembly's maintenance failure rate, and t is the TTF. The TTFs for each subassembly and maintenance types are found through Equation 4.2,

$$t = -\frac{1}{\lambda_k} \ln\left[1 - \hat{F}(t)\right], \tag{4.2}$$

where, $\hat{F}(t)$ is a value that is found by uniformly sample (between 0 and 1) the CDF in Equation 4.1 [32]. The TTF is then converted into hours.

All TTF's, that generate each failure, are the same for all maintenance strategies modeled for a given subassembly's maintenance type, except when there are extra failures generated caused by wasted useful life (WUL) in the PdM strategy. In this case, extra TTFs are generated if needed. More on this in the Wind Farm Analysis results.

4.4 Power Module

The power module objective is to compute the energy produced in each hour of the turbine's lifetime. To do this, three main steps are performed for each hour, the wind speed is extrapolated from reference height to turbine height, then power is found for that wind speed, and finally the energy production is computed.

4.4.1 Wind Speed at Hub Height

The wind speed varies between different sites depending on the climate of the region, the surface roughness conditions, and the topography. The lowest region of the atmosphere is known as the atmospheric boundary layer that goes from the surface to between 300 m and 2000 m [55]. The met mast, which measures wind speed, is not placed at hub height but at a much lower height, to save costs, before even any turbine is installed on site. To use the power curve of a wind turbine, the wind speed at hub height is needed. Thus, reference [55] shows how to extrapolate the mean wind speed at reference height to hub height using the Prandtl logarithmic law, in Equation 4.3,

$$\overline{U}_H = \overline{U}_h \left(\frac{\ln(H/Z_0)}{\ln(h/Z_0)} \right) \qquad [m/s], \tag{4.3}$$

where, $\overline{U}_H$ is the mean wind speed at hub height, $\overline{U}_h$ is the mean wind speed at reference height measured at the met mast, H is the height of the hub of the turbine, 119 m, and h is the height where the data was measured by the met mast, in this case 10 m. Z_0 is the surface roughness height equal to 0.0002 m [56]. With this, every hour of mean wind speed in the site wind speed data is extrapolated to the turbine height.

4.4.2 Power Curve

With the mean wind speed at hub height, the power curve can be utilized. The power curve of a wind turbine is composed of four major regions. These regions are defined by three wind speeds in the curve, the cut-in wind speed, the rated wind speed, and the cut-out wind speed, meaning the wind speed where the turbine starts producing energy, the wind speed that obtains maximum power, and the wind speed where the turbine stops producing energy, respectively [38]. For the 10MW wind turbine considered in the base case, the cut-in wind speed is 4 m/s, the rated wind speed 11.4 m/s, and the cut-out is 25 m/s. Figure 4.1 shows the power curve of DTU 10 MW reference wind turbine from [57].

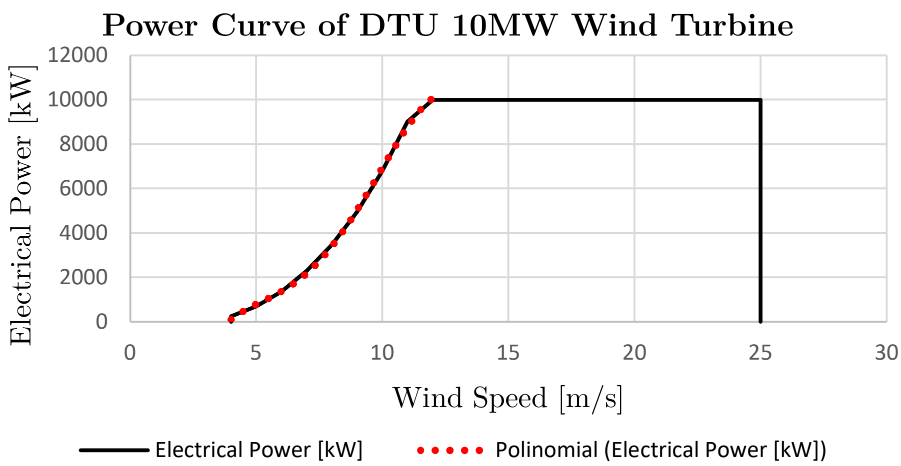


Figure 4.1. DTU 10 MW reference wind turbine power curve. Source: [57].

The first part of the power curve is approximated to a polynomial to grant flexibility to find the power for any given mean hourly wind speed in the data. Equation 4.4 shows the polynomial equation that includes the peak shaving until 12 m/s,

$$P_{elec} = -6.908 \cdot w^4 + 208.73 \cdot w^3 - 2141.1 \cdot w^2 + 9773.4 \cdot w - 16331 \qquad [kW], \tag{4.4}$$

where, P_{elec} is the electrical power, in kW, and w is the mean hourly wind speed, in m/s. The squared error (R^2) of the polynomial is equal to 0.9987, which assesses the trendline with a very good approximation. Therefore, for each hour from the mean hourly wind speed at turbine height, the power that can be extracted is computed for the whole turbine's lifetime.

4.4.3 Energy production

The energy produced ($E_{production}$) by the wind turbine, assuming the wind turbine yaw controller perfectly aligns the wind turbine rotor with the wind direction, can be computed using Equation 4.5,

$$E_{production} = P_{elec} \cdot t \qquad [kWh], \tag{4.5}$$

where, P_{elec} is the current power, in kW, and t is the time that the turbine is running with the current power, in hours [38]. In this case, power is computed for each hour of the turbine's lifetime, hence t is 1 hour. Thus, the energy produced during each hour of the turbine's lifetime is computed. With this, it is possible to compute the energy produced by the turbine in any given time interval of the turbine's lifetime by summing the energy produced during the hours that compose that time interval. This way is more useful to the model so it can compute of energy losses in each hour, during downtimes that can happen in any given time.

4.5 DTO+LMO Module

The DTO+LMO module refers to the Logistics and Marine Operations (LMO) module of the DTOceanPlus software [58], developed by WavEC Offshore Renewables [59] within the DTOceanPlus H2020 project [60]. One of the functionalities of this open-source tool is to compute the total durations, including weather delays, of specific installation and maintenance operations based on predefined operation plans. In this dissertation, the LMO module is used to compute mobilization times, expected waiting times caused by weather delays, transit durations, and durations on site, based on specified operation plans. To compute the durations, this tool uses the same mean hourly wind speed and wave height data from the site considered in the base case.

4.5.1 Mobilization

Mobilization is the time needed to prepare for the maintenance operation. This time may include time to rally the technicians and time to setup the vessel with the necessary parts and equipment.

4.5.2 Waiting Times

The waiting times are essentially the weather delays, in hours, that each operation has if it starts at a particular time. It depends on the weather conditions and on the size of the weather window needed to perform a certain maintenance task. As discussed previously, each vessel has its own weather conditions limiting its operation. These weather conditions are used as inputs for the DTO+LMO tool.

4.5.3 Transit Time

The transit time is computed with the vessel transit speed and distance from port. Assuming a 20 km/h vessel transit speed and a distance to port of 100 km, the transit time 10 hours in total, 5 hours to site and another 5 hours from site.

4.5.4 Duration on Site

The duration on site includes the time for vessel positioning and the average repair time. The average repair times used are from Carroll et al. [35] but some values for major replacement maintenance type are adapted. Table 4.2 shows the adapted average repair times for major replacement of each sub-assembly, in hours.

Table 4.2. Average repair times for each sub-assembly. Adapted from [35].

Subassembly	Major Replacement [h]			Major Repair [h] [35]	Minor Repair [h] [35]
	Carroll [35]	Used	Info.		
Pitch / Hyd	25	24	WavEC internal report.	19	9
Other Components	36	24	WavEC internal report.	21	5
Generator	81	20	WavEC internal report.	24	7
Gearbox	231	24	WavEC internal report.	22	8
Blade	288	16	WavEC internal report.	21	9
Grease / Oil / Cooling Liq.	-	-	Failure rate is zero.	18	4
Electrical Components	18	18	Same as [35].	14	5
Contactor / Circuit / Breaker / Relay	150	24	WavEC internal report.	19	4
Controls	12	12	Same as [35].	14	8
Safety	-	-	Failure rate is zero.	7	2
Sensors	-	-	Failure rate is zero.	6	8
Pumps / Motors	-	-	Failure rate is zero.	10	4
Hub	298	24	WavEC internal report.	40	10
Heaters / Coolers	-	-	Failure rate is zero.	14	5
Yaw System	49	24	WavEC internal report.	20	5
Tower / Foundation	-	-	Failure rate is zero.	2	5
Power Supply / Converter	57	24	WavEC internal report.	14	7
Service Items	-	-	Failure rate is zero.	-	7
Transformer	1	24	WavEC internal report.	26	7

The average repair time is constant throughout corrective and PdMs. The average repair time is defined as the amount of time, on average, that technicians spend repairing the turbine [35].

4.6 Maintenance Strategy Modules

Both component level analysis and wind farm analysis use the same CM and PdM strategies. Although, the PdM strategy considers a slight exception in the predictive period, for the wind farm analysis to grant a more realistic approach. This exception will further be explored in the Overlapping Maintenance Exception 4.8.1 subsection, discussed further along this chapter.

4.6.1 Corrective Maintenance Module

In a CM strategy, as seen, maintenance actions are performed always after failure occurrence. It follows that, as a result, downtime will occur immediately after the failure. In the current analysis, once a failure has been identified, wind farm operators schedule corrective actions as soon as possible. It is thus considered that failure detection is perfect and immediate. It is considered that there are no other operations taking place at the site that could perform maintenance or inspections when that failure occurs. Finally, it is also considered that once the maintenance intervention at the turbine is completed, the turbine is immediately restored back to “full health”. Therefore, the downtime caused by failure occurrence will be equal to the total duration of the maintenance operation (including mobilization, preparation at port, waiting on weather, transit, and work at the turbine) but excludes the last transit back to port. In this case, the computation of downtime is given by Equation 4.6,

$$Downtime = Total\ Duration - Transit\ from\ Site \qquad [h]. \tag{4.6}$$

The total duration of the maintenance operation and transit from site are time durations taken from DTO+LMO module, from the specific maintenance operation. The total duration is the total maintenance operation duration, which is the sum of all durations, waiting’s, transit, and mobilization time of a certain subassembly at a given hour time-instance where failure occurred.

Figure 4.2 shows how downtime can be visualized in the wind turbine operation time series. In Figure 4.2, the TTF-A is the generated TTF used to determine at what time the failure will happen (time of failure). Then, the downtime of that failure is computed and a new TTF, TTF-B, is used to determine when the next failure will happen (in the case of the wind farm analysis). The durations from the DTO+LMO module are represented in blue and how the downtime is computed, in red. The failure is represented by a red marker after TTF-A, and before the downtime.

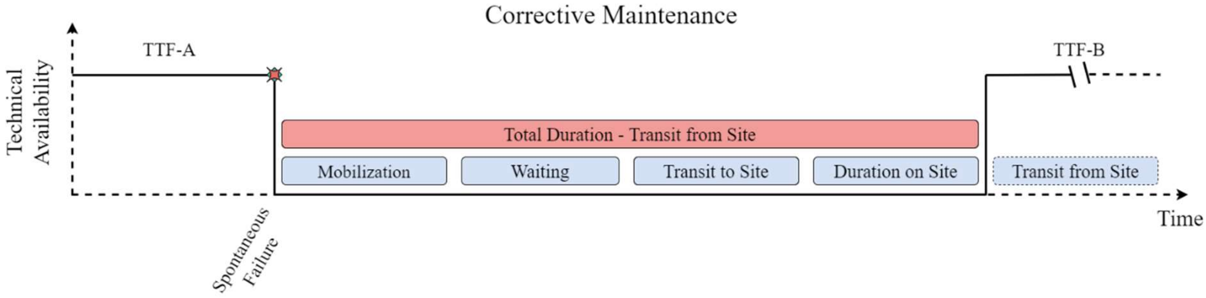


Figure 4.2. Corrective maintenance downtime.

The CM module returns the downtime, energy loss costs, maintenance operation costs, and the present value of those costs associated with each failure.

4.6.2 Predictive Maintenance Module

Different predictive periods were considered in the analysis to estimate their impacts on maintenance scheduling and costs. In the context of the present work, the predictive period refers to how many days ahead a potential failure can be detected. This is a sensor-based detection and is the output of a given fictitious predictive model, or algorithm, that would be able to know "x" days in advance when a failure will occur (failure prediction). In this work, it is assumed that failures are predicted with full certainty. Each predictive period is used to model an independent, and purely, PdM strategy, distinct only by this feature. All failures inside a PdM strategy use the same predictive period. Table 4.3 shows the five PdM strategies analyzed and their predictive periods.

Table 4.3. Predictive periods considered.

Maintenance Strategy	Predictive Period
PdM1	5 Days
PdM2	10 Days
PdM3	20 Days
PdM4	40 Days
PdM5	80 Days

One of the objectives of the present dissertation is to estimate the sensitivity of offshore wind maintenance economics with different predictive periods. As such, the selected predictive periods are defined, regardless of whether current technology is capable of supporting such strategies. Still, recent research shows that generator faults can be predicted 18 days ahead of time [18]. In another work, degradation of a wind turbine was successfully detected 44 days prior to failure [19]. Based on this, five different predictive periods were considered: 5, 10, 20, 40, and 80 days.

With a PdM strategy, the failures are now predicted thus, the downtime caused by each failure can be reduced because it is already known in advance when the failure will occur, and wind farm operators can plan when the maintenance actions will take place.

Although, as seen, this may not be an easy task and simulation tools are used for logistic support.

There are two scenarios when computing the downtime in the PdM module. In general, the downtime caused by a failure, with this maintenance strategy, will always be the duration on site (vessel positioning plus repair time), but there is an exception. Figure 4.3 shows scenario 1 of the computation of downtime.

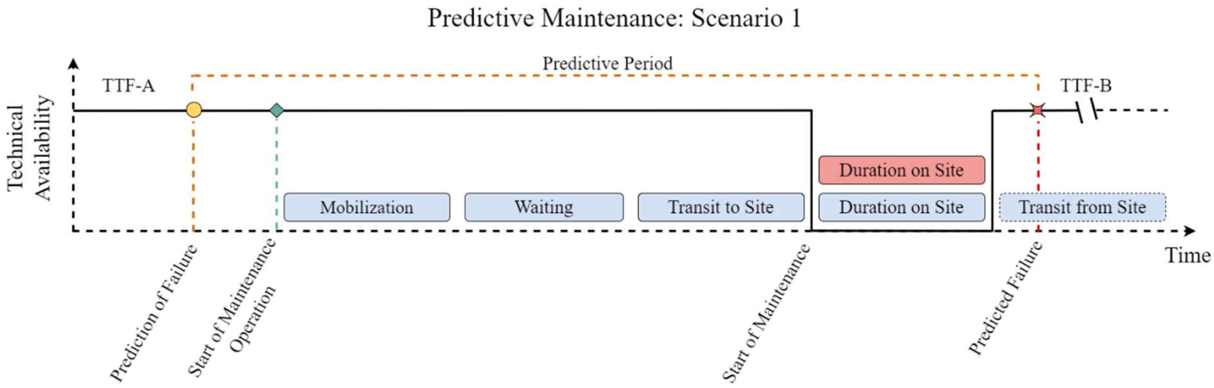


Figure 4.3. Predictive maintenance downtime computation in scenario 1.

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 in Figure 4.3) 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, composed by the repair time plus the vessel positioning time. In Figure 4.3, the durations from the DTO+LMO module are represented in blue, and how the downtime is computed, in red. The yellow marker represents when the failure is predicted. From the failure prediction to the predicted failure, it is considered the predictive period of that failure. Equation 4.7 shows the computation of downtime in scenario 1, simply given by,

$$Downtime = Duration\ on\ Site \qquad [h]. \tag{4.7}$$

The scenario 2 is modeling an exception that is slightly different. 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 is too close to the predicted failure thus, technicians don't have time to get to the wind turbine before the predicted failure happens. The downtime will, in this case, 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 4.4 shows scenario 2 of the computation of downtime. In Figure 4.4, the durations computed by the DTO+LMO module are represented in blue, while the calculated downtime is depicted in red. In this scenario, as the technicians cannot get to the turbine before failure occurs, it is considered that the turbine fails at the predicted failure and therefore there is higher downtime than in scenario 1.

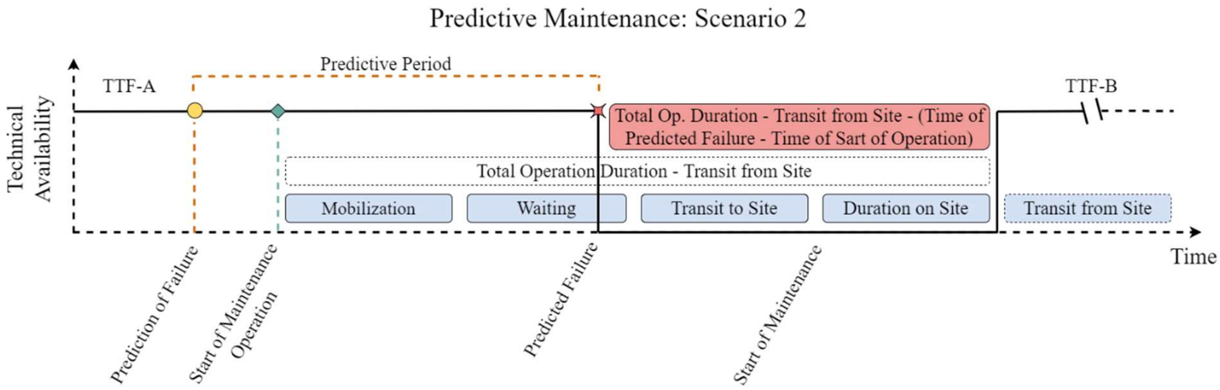


Figure 4.4. Predictive maintenance downtime computation in scenario 2.

Equation 4.8 shows the computation of downtime in scenario 2.

$$\begin{aligned} Downtime = Total\ Op.Duration - Transit\ from\ Site \\ - (Time\ of\ Predicted\ Failure - Time\ of\ Start\ of\ Maint.Op.) \quad [h]. \end{aligned} \tag{4.8}$$

As downtime varies according to the time of start of maintenance operation and the time of predicted failure, there was a need to find an equation that would consider this. The Equation 4.8 computes the downtime by checking how much of the maintenance operation time was undertaken before the predicted failure to compute the remaining (minus transit from site) as downtime.

The main goal of the PdM module is to reduce total costs. The total costs include the operation costs, and the energy loss 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 of the maintenance operation in that hour. After it analyzes all the hourly time instances in the predictive period, it selects the hour with the minimum total costs. When the minimum total costs are found, the optimized schedule is also found. It is at what time should the maintenance operation be initiated and consequently when the repair or replacement starts.

4.6.3 Total Costs

To compare the CM and PdM strategies, total costs are one of the key indicators used to see what benefits the latter might bring to the table. The total costs are computed the same way in both corrective and predictive strategies and computed for each failure. The total costs of each maintenance are a resultant of operation costs plus the energy loss costs, as presented in Equation 4.9.

$$C_{total} = C_{op} + C_{energy} \qquad [€]. \tag{4.9}$$

4.6.3.1 Operation Costs

For each time that maintenance is needed on a wind turbine, there are operation costs associated with that maintenance that are highly correlated with the duration of the operation itself. Equation 4.10 shows how to compute the costs of that maintenance operation (C_{op}), adapted from [14],

$$C_{op} = (d_{op} \cdot C_{vessel}) + C_{technicians} + C_{spare\,parts} \qquad [€], \tag{4.10}$$

where, d_{op} refers to the maintenance operation duration, in days, C_{vessel} to the vessel costs, in $[€/day]$, $C_{spare\,parts}$ to the repair or replacement costs, in [€], and $C_{technicians}$ represent the costs related to the work of the technicians, in $[€/day]$. For each subassembly's failure where a maintenance task takes place, a specific spare part is consumed, technicians to perform that maintenance task are needed, and there is a selection of the vessel, port, and equipment. All these topics have associated costs.

4.6.3.2 Vessel costs

The vessel costs are included in the operation costs, as seen in Equation 4.10 and are dependent on the maintenance operation duration. The daily vessel costs themselves include the daily vessel charter costs and daily fuel costs.

To estimate the daily vessel costs (C_{vessel}) of each maintenance operation, Equation 4.11 is used from [14],

$$C_{vessel} = C_{charter} + C_{fuel} \qquad [€/day], \tag{4.11}$$

where, $C_{charter}$, refers to the daily vessel charter rates and, C_{fuel} to the daily fuel costs.

Depending on, not only the vessel type needed for the operation, but also the vessel characteristics and capabilities and site market conditions, daily vessel charter rates ($C_{charter}$ in $[€/day]$) may vary. Contract duration and contract set-ups can also influence charter rates. The industry way of chartering the rates may be different for different types of vessels. For example, CTVs are usually charted based on duration of usage, but cranes usually are contracted in comprehensive service agreements.

Table 4.4 summarizes the daily chart rate regressions' functions of the used vessels considering the different input parameters that were identified for each type of vessel, based on Global Renewable Shipbrokers (GRS). The different types of maintenance require different types of vessels. The functions Table 4.4 were estimated based on real databases and excluded fuel and port costs [14]. Each function contains a mean squared error of the trendline, represented in Table 4.4 by R^2. The error varies from 0.26059 to almost 1, giving a notion on how accurate these estimates are. In Table 4.4, LOA represents the vessel length overall.

Table 4.4. Daily charter rate regression curves of different vessel types. Source: [14].

Vessel Type	Input Parameter	Domain Validity	Cost Function [€]	R^2
CTV	LOA (m)	$15 \leq x \leq 33$	$C_{charter} = -1.26x^2 + 179.16x - 85.57$	0.4729
SOV with gangway	No. passengers	$x < 60$ $x \geq 60$	$C_{charter} = 24000$ $C_{charter} = 50000$	$N.D.$
SOV gangway relevant	No. passengers	$x < 60$ $x \geq 60$	$C_{charter} = 24000$ $C_{charter} = 42000$	$N.D.$
Propelled Crane Vessel	Crane lift capacity (tons)	$4 \leq x \leq 3300$	$C_{charter} = -5.44 \cdot 10^{-3}x^2 + 88.91x + 12714.58$	0.9955

In the analysis, one type of vessel was assigned to each type of maintenance. The CTVs were assigned to the minor repairs, SOV were assigned to major repairs and PCV to the major replacements. These types of vessels can easily be changed by the user in the input excel sheets. Table 4.5 shows the resultant inputs for each type of maintenance. Vessels are assumed to be always available when needed.

Table 4.5. Vessel charter rates of each type of maintenance.

Maintenance Type	Vessel	Input Parameter	$C_{charter}$ [€/day]
Major Replacement	PCV	x = 10999 tons (Crane lift capacity)	332515
Major Repair	SOV	x < 60 (No. passengers)	24000
Minor Repair	CTV	x = 21.79 m (LOA)	3220

The daily fuel costs are composed of two elements, as can be seen in Equation 4.12,

$$C_{fuel} = f_{Consumption} \cdot p_{fuel} \qquad [€/day], \tag{4.12}$$

where, $f_{Consumption}$ is the fuel consumption of the vessel, p_{fuel} is the price of the fuel. Vessel consumption can depend on distance to shore, and vessel speed, but in [14] an estimation is made in its computation, seen in Equation 4.13,

$$f_{Consumption} = TIP \cdot ALF \cdot SFOC \cdot 24 \cdot \frac{1}{1000^2} \qquad [ton/day], \tag{4.13}$$

where, TIP is the total installed power of the vessel in kW, ALF is average load factor, assumed 80% as default as in [14], $SFOC$ is the specific fuel oil consumption, assumed 210 g/kWh as recommended by the Global Renewable Shipbrokers (GRS) [14].

The fuel price (p_{fuel}) may vary with the oil market, but in [14] a reference value of 515 €/ton was taken from the marine diesel oil in the port of Rotterdam.

Table 4.6 summarizes the result parameters to estimate the vessel fuel costs for each type of maintenance. The total installed power of the vessels (TIP) is based on a report by WavEC [61].

Table 4.6. Vessel fuel cost parameters.

Maintenance Type	Vessel	TIP [kW]	$f_{Consumption}$ [ton/day]	C_{fuel} [k€/day]
Major Replacement	PCV	21125	8518	4387
Major Repair	SOV	9505	3832	1974
Minor Repair	CTV	1066	430	221

4.6.3.3 Port Terminal Costs

Each specific port around the world has its own costs and they can vary greatly with the type of contract established, contract duration, leased storage area and equipment. It is stated in [14], that port costs only represent about 0.5% of total operation costs on average for offshore wind projects. Thus, these costs were neglected.

4.6.3.4 Equipment Costs

The offshore operations are specialized work that may require specific equipment to undertake different types of repairs or replacement at component level. This equipment's can be rented thus may have associated costs. However the maintenance types defined in [35] did not specify exactly what kind of maintenance tasks were included in each type of maintenance, due to its classification being defined only through material costs. In the analyses, equipment costs are then neglected to reduce noise and uncertainty that would be created by assigning equipment's to the maintenance types.

4.6.3.5 Spare parts Costs

The spare parts costs, in Euros, are shown in Table 4.7.

Table 4.7. Average repair costs of each subassembly. Adapted from [35].

Subassembly	Major Replacement [€]			Major Repair [€] [35]	Minor Repair [€] [35]
	Carroll [35]	Used	Info.		
Pitch / Hyd	14000	696150	Sum of Blade pitch and cooling and Hydraulic costs in [62].	1900	210
Other Components	10000	10000	Assumed same as [35].	2400	110
Generator	60000	676685	Taken from [62].	3500	160
Gearbox	230000	1772250	Taken from [62].	2500	125
Blade	90000	701222	Taken from [62].	1500	170
Grease / Oil / Cooling Liq.	-	-	Failure rate is zero.	2000	160
Electrical Components	12000	12000	Assumed same as [35].	2000	100
Contactor / Circuit / Breaker / Relay	3500	13500	Assumed same as [35].	2300	260
Controls	13000	13000	Assumed same as [35].	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 [62].	1500	160
Heaters / Coolers	-	-	Failure rate is zero.	1300	465
Yaw System	12500	383520	Taken from [62].	3000	140
Tower / Foundation	-	-	Failure rate is zero.	1100	140
Power Supply / Converter	13000	668440	Cost of Power Electronics [62].	5300	240
Service Items	-	-	Failure rate is zero.	1200	80
Transformer	70000	525045	Cost of Electrical Connections [62].	2300	95

Spare part costs ($C_{spare\,parts}$), that are also called component repair costs, are different for each subassembly and for maintenance types, and must be considered in the total operation costs. The average repair costs from [35], are for a 2 to 4 MW wind turbine. The turbine used in the Power Module has a rated power of 10 MW, thus it is necessary to adjust the major replacement costs. The minor and major repair costs are assumed to be the same as in [35]. Cost breakdown for a 10 MW wind turbine were found in [62]. Table 4.7 also shows how costs were adapted for major replacements.

The costs presented in [35] only include the costs of the materials used during maintenance of a turbine, on average. Labor costs or compensation costs are not included. In [62], the costs are for factory new components. In the analysis, it is assumed that spare parts are always in stock.

4.6.3.6 Technician Costs

The number of technicians needed to repair different subsystems can vary, which leads to different technician costs. As seen in [35], the average number of technicians can vary from 1 to 10 technicians. The cost of technicians ($C_{technicians}$) are then computed by Equation 4.14,

$$C_{technicians} = n_{technicians} \cdot p_{technicians} \cdot d_{op} \qquad [€/h], \tag{4.14}$$

where, $n_{technician}$ is the number of technicians, $p_{technician}$ is the tariff charged by the technicians, and d_{op} refers to the maintenance operation duration, in hours. Table 4.8 contains the average number of technicians ($n_{technician}$) taken from reference [35].

Table 4.8. Average number of technicians. Source: [35].

	Major Replacement [Technicians]	**Major Repair [Technicians]**	**Minor Repair [Technicians]**	**No Cost Data**
Pitch / Hyd	4.0	2.9	2.3	2.8
Other Components	5.0	3.2	2.0	2.3
Generator	7.9	2.7	2.2	2.4
Gearbox	17.2	3.2	2.2	2.2
Blade	21.0	3.3	2.1	2.6
Grease / Oil / Cooling Liq.	0	3.2	2.0	2.0
Electrical Components	3.5	2.9	2.2	2.4
Contactor / Circuit / Breaker / Relay	8.3	3.0	2.2	2.0
Controls	2.0	3.1	2.2	3.2
Safety	0	3.3	1.8	2.0
Sensors	0	2.2	2.3	2.7
Pumps / Motors	0	2.5	1.9	2.5
Hub	10.0	4.2	2.3	2.4
Heaters / Coolers	0	3.0	2.3	2.7
Yaw System	5.0	2.6	2.2	2.4
Tower / Foundation	0	1.4	2.6	2.3
Power Supply / Converter	5.9	2.3	2.2	2.7
Service Items	0	0	2.2	2.2
Transformer	1.0	3.4	2.5	2.8

The average number of technicians refers to the number of technicians required to perform the maintenance on the turbine, on average.

The average salary for a wind turbine technician is 82 886 €/year, taken from [63]. With 261 working days in a year, a rough estimation was performed resulting in 317.57 €/day. Assuming 12h shifts, the $p_{technicians}$ is 26.46 €/h.

4.6.3.7 Energy Loss Costs

The revenue generated by a wind turbine comes from the sale of the energy that it produces. The greater the production, the greater the revenue. If a wind turbine does not produce energy, due to a failure, and if there is wind resource available to do so, 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 just like the usual costs. Therefore, downtime reduction or availability maximization, is very important for O&M.

The cost of energy (C_{energy}) can then be computed with Equation 4.15,

$$C_{energy} = E_{production} \cdot p_{energy} \qquad [€], \tag{4.15}$$

where, $E_{production}$ is the energy loss caused by downtime, and p_{energy} is the price that the energy could eventually be sold at if it were produced. The electricity price considered was 0.1062 €/kWh.

4.6.3.8 Depreciating Costs

Each maintenance strategy module returns the total costs and the total costs in present value. The total costs are depreciated to the commissioning date after they are simulated for each failure. Equation 4.16 shows how total costs are depreciated,

$$PV = \frac{FV}{(1+r)^n}, \tag{4.16}$$

where, PV is the present value (PV), in this case the total depreciated costs at the time of commissioning, FV the future value (FV), that is the total costs of a certain failure at the time of that failure. r is the discount rate used, in this case the weighted average cost of capital (WACC), with value of 6% taken from a similar project [64], and n is the number of periods between the time of the failure and the commissioning date.

4.7 Availability Module

The availability module was only used in the wind farm analysis to grant a higher approach to reality. The wind farm analysis is a simulation performed in the time domain thus the time-series builder creates time-series for each subassembly and maintenance type using TTFs and downtimes. The TTFs are used to find the time of failures and the downtimes are a consequence of those failures.

4.7.1 Time-Series Builder

The time-series builder runs integrated in the code, failure-by-failure, even though it is represented as a separate module for clarity reasons. This means that it starts from the turbine commissioning time and keeps building the subassembly's operation time-series after getting the results of each failure from the maintenance strategies modules until the turbine's lifetime is over. After a TTF is generated in the reliability module, the time-series builder adds this time period to the end of the current time instance in the operation time-series of the current subassembly's maintenance type. It sets a value of one where the TTF is added in the operation time-series. In the case of the CM strategy, the number of hours of downtime caused by that failure is added right after the TTF and the next TTF of the next failure generated is added after the downtime of the previous failure. In the case of the PdM strategy, it is a bit more complex. The TTF of the generated failure is added, then, when the PdM module assesses the failure, it returns the time when the downtime will happen. This downtime is always before, or at the end, of the TTF added. Thus, the TTF previously added is "clipped" to fit the scheduling set by the PdM module output and the downtime for that failure is added afterwards. Downtimes are represented in the operation time-series by zeros. Ultimately, after all subassemblies are simulated, the turbine operation time-series can be found by multiplying all the subassemblies operation time-series.

4.7.2 Availability

After the turbine operation time-series is created, to assess availability, one must count the number of ones and zeros in the operational time-series. Ones will represent the number of available hours and zeros the number of unavailable hours, for that turbine, in the turbine's lifetime. In Equation 4.17 from [34], it is shown how to compute availability in general,

$$Availability = \frac{t_{available}}{\mathrm{t}_{available} + t_{unavailable}}. \tag{4.17}$$

To compute the technical availability, the $t_{available}$ considered includes only the time that the turbine is operational according their design specifications, and $t_{unavailable}$ includes only the time that the turbine/ subassembly is being maintained and the time when is down due to subassembly failure [34].

In the operational availability, $t_{available}$ includes the time that the turbine is operating according to design specifications, and $t_{unavailable}$ includes the turbine maintenance and failure but also the downtime caused by the lack of energy output due to too low or too high wind speed conditions out of the power curve [34].

The energetic availability is computed differently than the two previous availabilities. It simply considers the amount of energy produced over the potential energy produced, given by Equation 4.18 from [34],

$$Energetic\ Availability = \frac{P_{actual}}{P_{potential}}, \tag{4.18}$$

where, P_{actual} is the actual energy produced by the wind turbine in its lifetime, and $P_{potential}$ is the potential energy that could be produced by the wind turbine during its lifetime with an availability of 100% [34].

4.8 Wind Farm Analysis

The main objective of this analysis is to quantify the benefits that a PdM strategy can bring at the wind farm level. This wind farm is composed of 20 turbines, as mentioned, with the same characteristics. Wind farm layout, moorings and cables are not considered. Figure 4.5 shows the diagram of the wind farm analysis.

The diagram in Figure 4.5 shows how the model simulates a given wind turbine subassembly's maintenance type. The reliability module simulates the subassembly's maintenance type failures events by generating TTFs that are based on 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 placed in the time-series. If a failure rate of a certain subassembly is very low (or even zero) the subassembly might never fail during the whole turbine's lifetime.

The power and DTO+LMO Operations modules provide inputs for the CM and PdM modules. The power module provides the energy produced during every hour, of the whole turbine's lifetime. The DTO+LMO module contains the operation durations of time that the maintenance activities would take if it was performed in that hour, for all hours in the turbine's lifetime. With these inputs, and time of failure, the CM strategy module can compute the downtime and total costs associated with each failure of a subassembly. The downtime is then returned to the availability module to be added to the operation time-series by the time-series builder. The PdM module, apart from downtime and costs, also returns the optimized scheduling for the maintenance of the failure. That aspect is considered by the time-series builder. Once the time-series builder finishes a subassembly's lifetime operation time-series, the next subassembly starts being simulated. The process continues until it simulates all subassemblies of all the turbines. The time-series builder builds the time-series by associating the value of one, when the subassembly is operational and zero, when is not. Then, turbine availability can be computed. For the turbine availability, when a failure occurs in a certain subassembly, it is assumed that it causes the failure of the entire wind turbine.

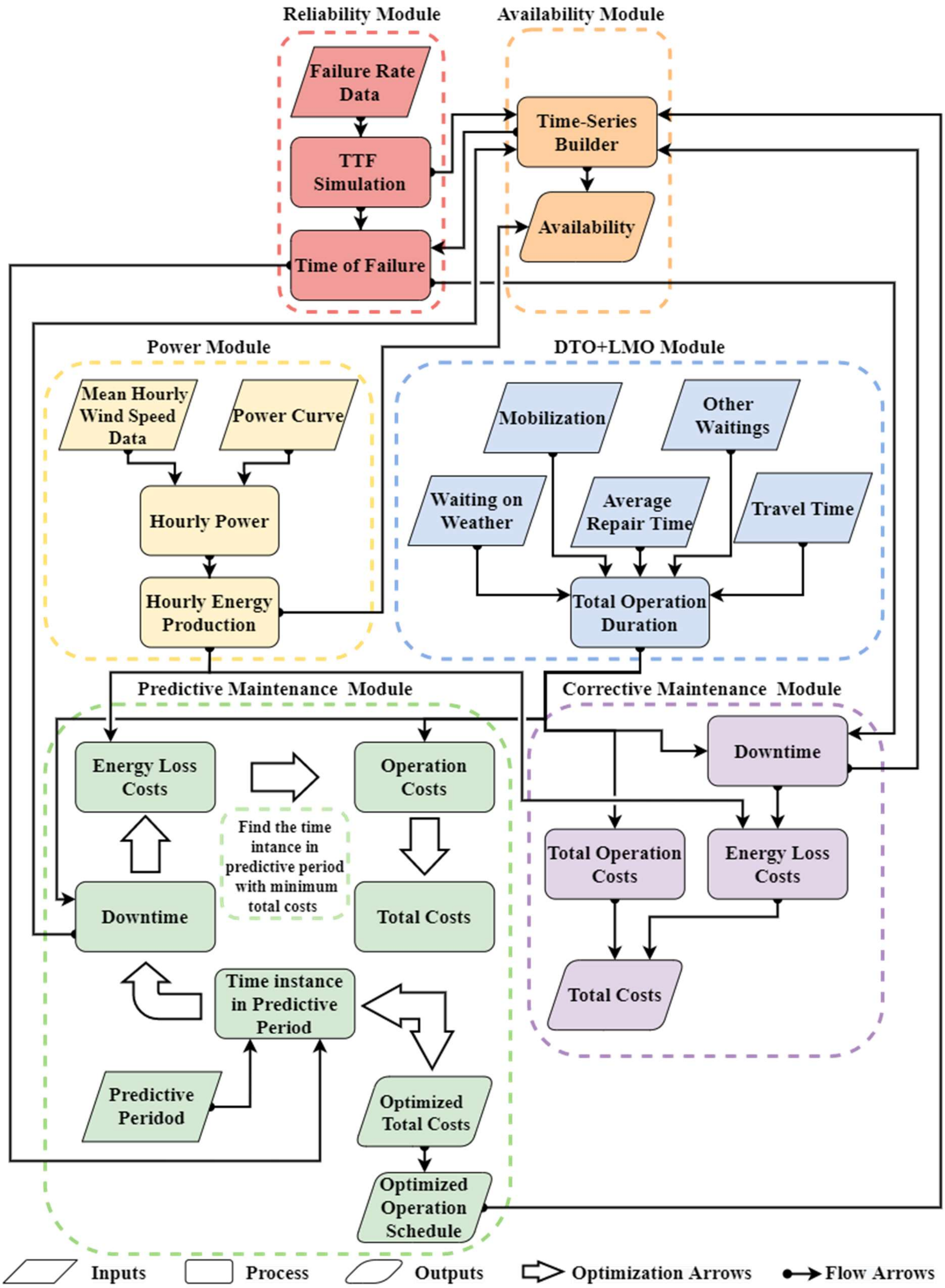


Figure 4.5. Wind farm analysis diagram.

4.8.1 Overlapping Maintenance Exception

In the case of the wind farm analysis, the PdM module was slightly refined. As the wind farm analysis is a simulation performed in the time domain, when considering the PdM, the predictive periods of two nearby failures may overlap. This can happen if the time interval between two failures is very short (small TTF) or if the predictive period for that maintenance strategy is very long. With a very short time interval between two failures, the model would look for the minimum total costs in overlapping predictive periods, which could result in the scheduling of two maintenance actions at the same time, for a given subassembly. In that case, the model is finding the same schedule when minimizing the total costs in the predictive period. Having two maintenances of the same subassembly at the same time is not a realistic modeling thus, an exception in the code was made. When the predictive period of a current failure overlaps the predictive period of the previous failure, the current failure's predictive period is shortened from the end of the previous failure's downtime to the current failure. This means that the predictive period of the current failure is equal to the TTF that generated it.

4.9 Component Level Analysis

The main objective of the component level analysis is to statistically quantify the variability of the total costs, when failures are scheduled at different times of the year, for each subassembly and maintenance type. On top of this, the analysis is also able to find statistically relevant results in the total cost breakdown of all scheduled failures of each subassembly's maintenance types. Statistical benefits are then found in the total failure costs median results, of all failures. This analysis uses four of the same modules as the wind farm analysis, the power, DTO+LMO operation, the CM, and PdM modules. Figure 4.6 shows the diagram for the component level analysis.

In a hypothetical turbine, composed by its subassemblies, 10500 failures are distributed throughout the months. A high number of failures is used to grant statistically relevant results, although 10500 failures are chosen due computational limitations. The failures are distributed the same way for every subassembly and for all its maintenance strategies. Thus, all the subassemblies are assumed to fail at the same time in this analysis, even throughout different maintenance strategies. As these failures are not reliability-based, there is no "memory" of failures occurring before, or after, the current failure in analysis. Each failure was analyzed independently. Once a failure is being analyzed it will run the CM module, followed by the PdM module with predictive period 1 and it repeats until the predictive period 5. The PdM module optimizes the maintenance schedule based on the minimization of the total failure costs, as explained previously. With this, failure results are computed for all maintenance strategies.

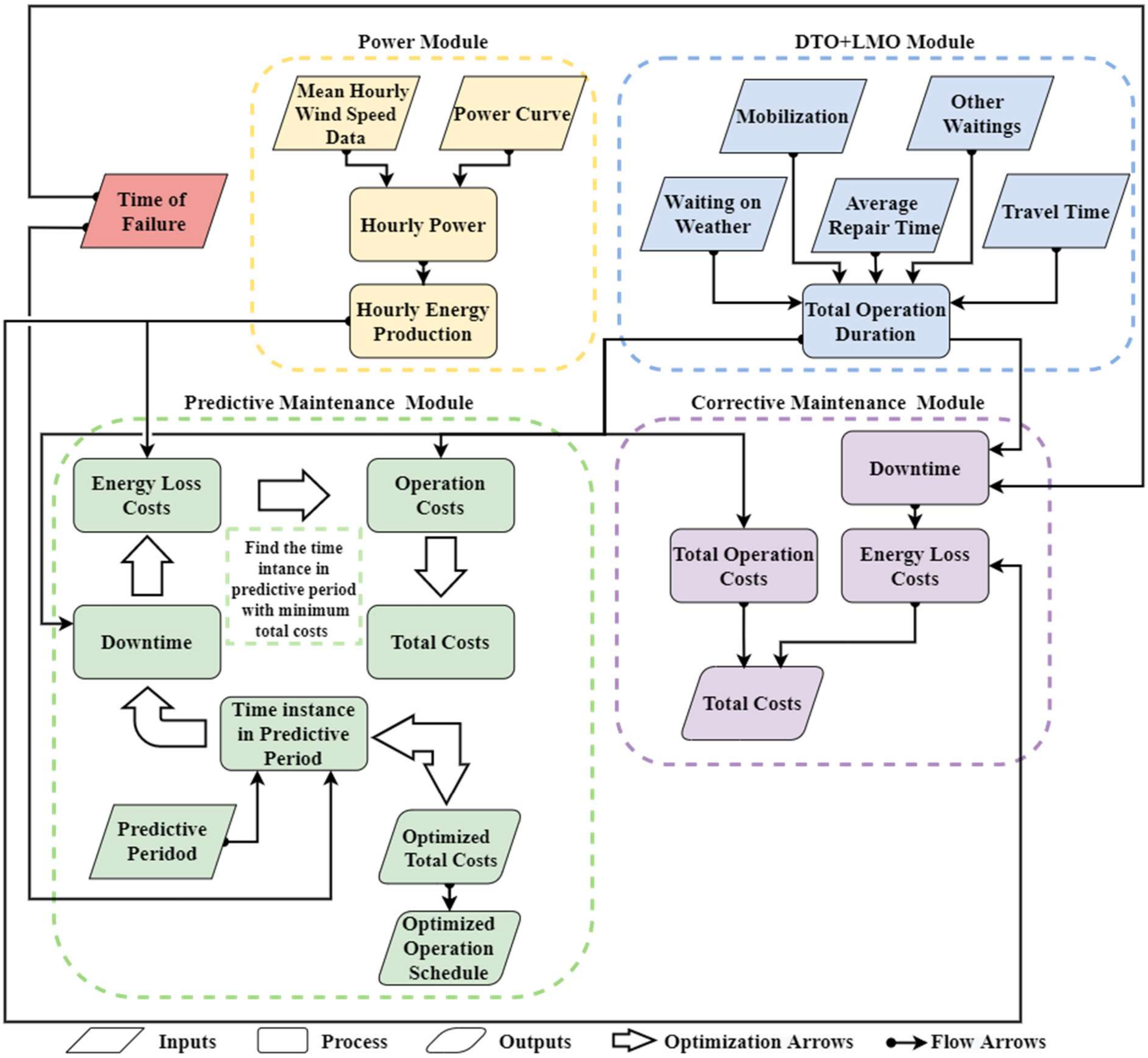


Figure 4.6. Component level analysis diagram.

Chapter 5: Results & Discussion

This section is divided into two main parts where the results of the wind farm and component-level analysis are presented. The wind farm cost results are presented as discounted as the aim is to understand the total costs behavior within a more realistic modeling at wind farm level. In this case, the year where failures are generated is accounted in the total costs. However, the cost results for the component-level analysis are presented without depreciation. This was done because the aim was to find benefits at component level without the extra variability in the results, caused by having failures in different years.

5.1 Wind Farm Analysis

Results were computed in the context of a wind farm. The wind farm analysis is a simulation performed in the time domain where failures are dependent on each other and are reliability-based.

5.1.1 Number of Failures

One of the results of the wind farm analysis is a consequence of the way that the PdM strategy was modeled. The PdM module increased the number of failures that occur during the wind farm's lifetime. This is enhanced for longer predictive periods as it can be seen with a linear tendency correlating the total number of generated failures with the predictive period. Figure 5.1 shows the results of the total number of generated failures for each predictive period.

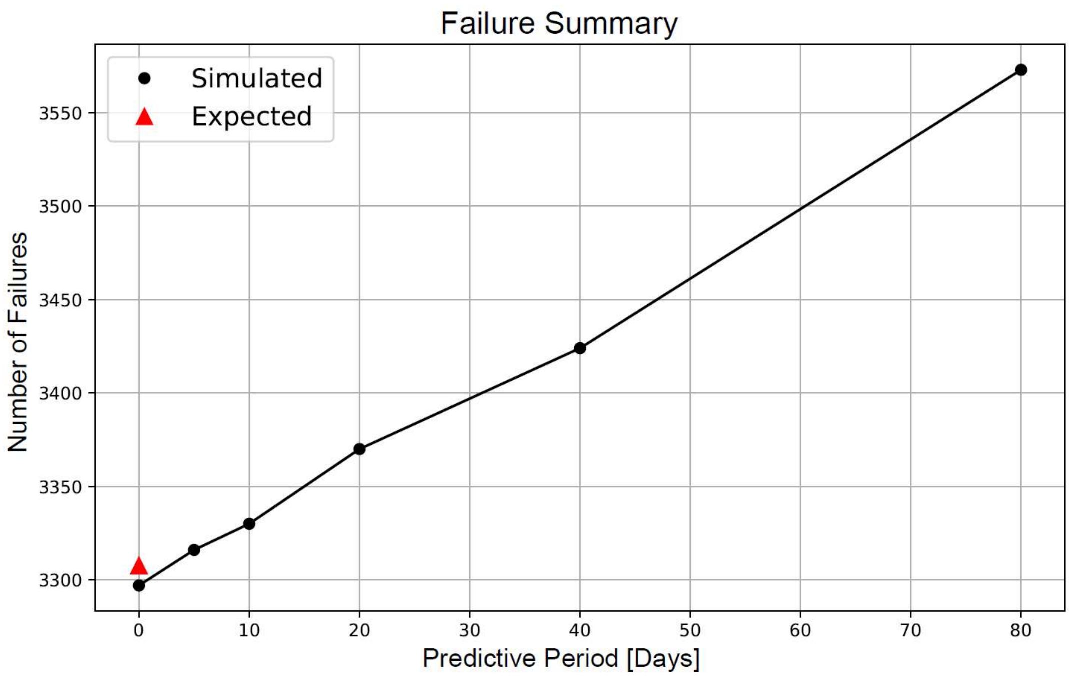


Figure 5.1. Total number of failures generated for each maintenance strategy.

The expected number of failures, marked as red in Figure 5.1, is based on the turbine's total failure rate, the number of turbines, and the number of lifetime years, as shown previously in Equation 3.12. The number of failures for the CM (0 predictive period) is slightly lower than the expected number of failures. This is a result of the stochasticity of the TTFs generated by the reliability module.

When applying a PdM strategy to a wind farm, the aim is to perform maintenance actions before the failure occurrence to reduce costs and downtime. The modeled PdM strategy is analyzes all the hours contained in the predictive period before a certain failure, and computing for each hour, the total costs to find the optimum schedule for the PdM action. With this, there is WUL of the subassemblies. For example, if the minimum total costs are found at the beginning of the predictive period, the WUL of the subassembly will be higher, when compared to the WUL in the case which minimum total costs are found towards the end of the predictive period. On top of that, if a subassembly has many failures throughout its lifetime, the PdM strategy is being applied to all those failures, which leads to more WUL (in a high or small way) with each failure. Thus, the subassembly will have more "room" to fail more times, until the end of the 20-year lifetime. This means that in a modeling scenario, that is time-based, there will be also more failures for simulations with longer predictive periods because they grant more flexibility to schedule maintenance actions further from the predicted failure, which can lead to higher WUL. The modeled CM strategy (the predictive period is zero) does not generate extra failures because in this case the RUL is fully utilized, and the failure always happens spontaneously.

More extra failures were generated for the minor repair maintenance type than for the major repair, and major replacement. Also, the major replacement is the maintenance type with lower extra-generated failures. This is happening because the minor repairs have higher failure rates than the major repairs, and the major repairs, have higher failure rates than the major replacements. Maintenance types with higher failure rates have more extra-generated failures. The higher the failure rate of a subassembly, the higher the number of failures that a subassembly has, and consequently the higher total WUL caused by the PdM module.

5.1.2 Failure Dephasing

The wind farm analysis shows some other unexpected results, besides the extra-generated failures. Similarly, to how there are extra-generated failures, those failures fall out of phase when comparing different maintenance strategies. In the CM case, failures happen spontaneously, and maintenance actions are only undertaken after that. When PdM is applied to a failure, maintenance actions are undertaken before the failure occurs. This means that the subassembly can get back to "full health" earlier when compared to the CM case. When the TTF used to model the next failure is generated, it is added to the point where the subassembly previously got back to "full health". This also means that the TTF will be out of phase when compared with its “twin” TTF in the CM strategy. Ultimately, the next failure will also be out of phase with its “twin” failure in the CM strategy because the TTF that generated that failure is already out of phase. This happens for every failure (except the first failure) of every PdM strategy. The greater the predictive period, the greater the shift can happen. With this, even though, for example in Figure 5.1, the number of generated failures for 5-days predictive period is very close to the number of generated of 10-days predictive period, all the failures, between these two maintenance strategies, happen at different times (except the first failure).

5.1.3 Wind Farm Average Turbine Availabilities

Part of the wind farm analysis results are the three availabilities, previously reviewed. These availabilities were found for each turbine, for their whole lifetime, and all their simulated maintenance strategies, and then the turbine average was computed. Figure 5.2 shows how the availabilities vary with the predictive period of each maintenance strategy.

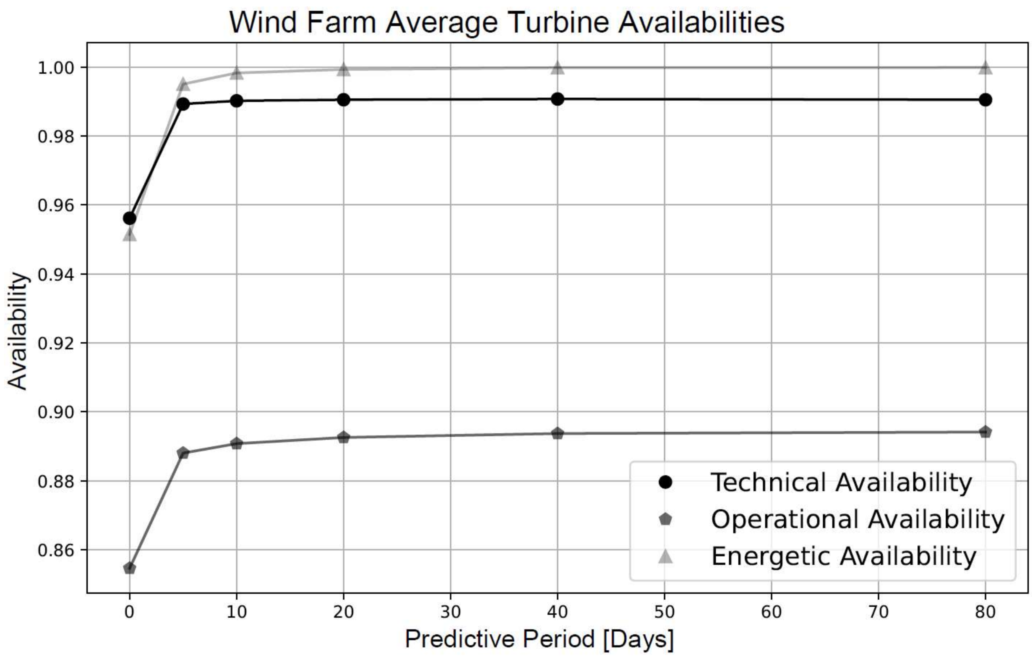


Figure 5.2. Wind farm average turbine availabilities.

All the three availabilities have their lowest value for a CM strategy (where the predictive period is zero). For a PdM strategy with a predictive period of 5 days, there is a significative increase in all three availabilities. This increase represents the highest variation in the availabilities between the 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 from a 10-day predictive period and on. It is only seen decreasing, in an extremely small amount (still at about 0.99), for a predictive period of 80 days due to an increase in generated failures.

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. Although, there is a slightly higher increase of operational availability in the PdM strategies when compared with the technical availability. This may be happening because the PdM strategy is optimizing the scheduling of maintenance to times where energy production is low or zero. The power output when the mean hourly wind speed is out of the power curve is zero, thus the PdM strategies are scheduling the downtime to these times. This translates in a small increase in the operational availability when compared with the technical availability.

The energetic availability is practically maximized for a predictive period of 20 days. The fact that the energetic availability is increasing means that the PdM strategy modeled is optimizing the scheduling of maintenance actions for times with low or zero energy production, for example, times when the mean hourly wind speed is outside of the power curve. The scheduling is so optimized that there is very low energy loss, when compared with the huge amount of energy produced, during the whole turbine's lifetime.

5.1.4 Wind Farm Lifetime Total Costs

Each failure costs were depreciated from the failure time to the commissioning date. The sum of all depreciated failure costs, of all the subassemblies of all turbines, is performed. Ultimately, the total costs of the wind farm are presented in Figure 5.3, for different predictive periods.

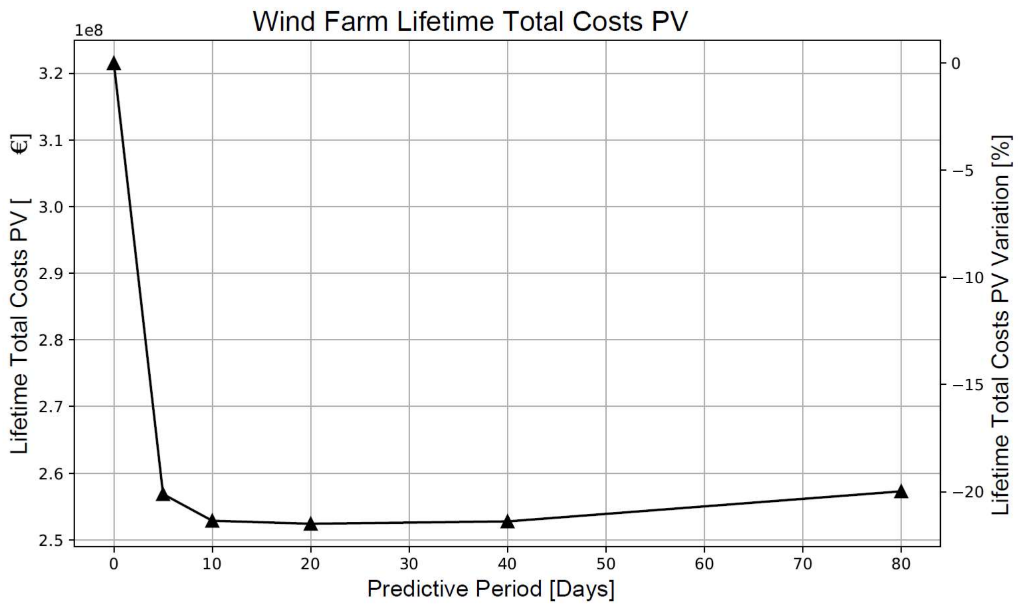


Figure 5.3. Total costs PV variation with predictive period.

In general, total costs variation, along the predictive periods, show a decreasing trend from 0 to 20 days. The largest cost variation occurs when changing from a purely corrective maintenance strategy (equivalent to a predictive period of zero), to a predictive maintenance strategy with a predictive period of 5 days. This variation decreases with the predictive period and arrives at the lowest total costs in the predictive period of 20 days. From 20 to 80 days, the trend shows an increase in total costs.

Even though Figure 5.3 shows a clear advantage when implementing predictive maintenance, results show a slight increase in total lifetime costs for higher predictive periods (40 and 80 days). This increase can be explained by the additional number of failure events generated by the model, as described before. Even though total lifetime costs are increasing for 40 and 80 days, this increase is not very big. A 40-day predictive period generated 54 additional failures than for a predictive period of 20 days. This is translating into an increase of about 350 thousand euros in total lifetime costs. For example, the cost of a single blade replacement is 701222 €, therefore a single additional failure generated for a blade replacement would surpass the 350 thousand euros that are associated with 54 additional failures. The increase in cost represented in Figure 5.3 is very small compared with what 54 more failures could cost. This is because the 54 extra-generated failures come mainly from the minor repair and major repair maintenance types, where the component repair costs are extremely smaller (170€ and 1600€, respectively) than the major replacements. As seen previously, the minor repair maintenance type has higher failure rates, which generate more extra-generated failures than the major replacements (with lower failure rates), for longer predictive periods.

5.1.5 Wind Farm Base Case Convergence

In order to find more accurate results, several base case simulations were performed in the wind farm analysis, each associated with a different computational seed of random numbers for identification. This was done to ensure that the base case was representative of different simulation scenarios.

Figure 5.4 shows the statistical results of different seeds for the total lifetime costs and their variation with the predictive period.

Based on the percentiles, it can be seen that there are some variations along the different base cases. The stochasticity of the TTFs generation is causing different total lifetime costs each time the wind farm simulation is performed. The chosen base case is identified with a seed of 59 and was chosen based on the total cost median (Base Cases p50) to be representative of the 18 different base case simulations scenarios.

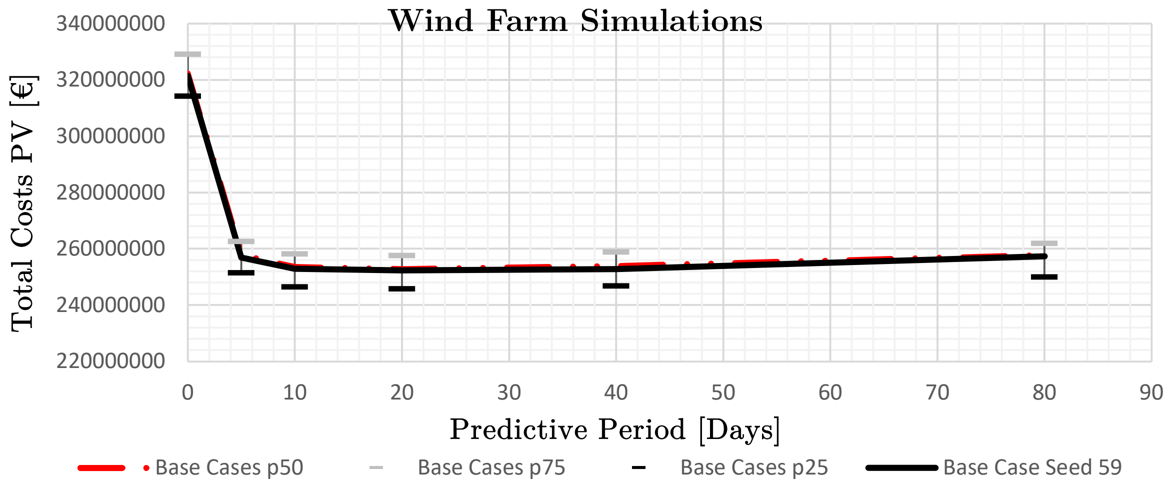


Figure 5.4. Total cost statistics of the 18 base case simulations.

5.1.6 Wind Farm Sensitivity Analysis

To assess the sensitivity of the wind farm analysis, some parameters were varied. The variations of the parameters were made in minus and plus 50% of all those parameters values. Varied parameters include number of turbines, failure rates, WACC, component repair costs, and electricity price. The impact of these variations in the wind farm total costs for different maintenance strategies, when compared with the base case, are presented as a tornado chart, in Figure 5.5.

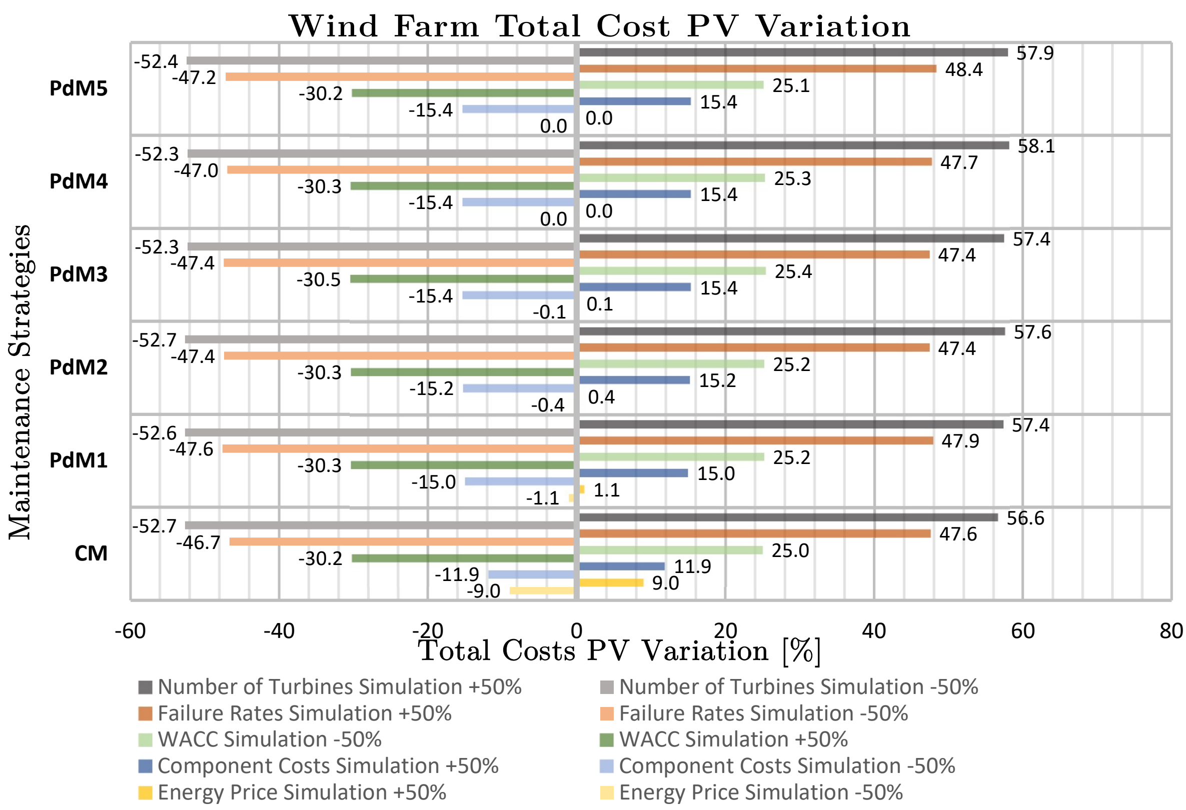


Figure 5.5. Wind farm analysis tornado chart.

The wind farm analysis seems to be slightly more sensitive when the number of turbines is increased (about 57%), than when the number of turbines is decreased (about 52%). These values are almost constant throughout all maintenance strategies.

The increasing in failure rates by 50% is causing an increase of about 48% in total costs. This decrease is practically constant throughout all maintenance strategies. Decreasing the failure rates by 50% is causing about a 47% reduction in total costs for CM.

The increase in the WACC by 50% is causing a decrease of about 30% in the total costs. When the WACC increases it causes total costs to be greatly discounted which will be translated into lower costs. The WACC decrease by 50% is causing an increase of about 25%. These values are practically constant throughout all maintenance strategies.

The impact of the component repair costs, when these vary by 50%, on the total costs are for the CM of about 12%. The impact for PdM strategies is almost constant, about 15%. The PdM strategies are reducing vessel, technician, and energy loss costs, but they cannot reduce component repair costs. This means that for PdM strategies, component repair costs have a greater percentual contribution in the total costs. Thus, the model is more sensitive to a variation in component repair costs for a PdMs than for a CM.

The sensibility of the energy price is low in the CM. Varying the energy price 50% causes a shift of about 6% in the CM's total costs. The sensitivity is decreased greatly for a 5-day predictive period to about 1% and reaches about 0% in the following predictive periods. This phenomenon is happening because the PdM is aiming to reduce energy loss costs. The energy loss costs are based on the energy losses and the energy price. The PdM minimizes the energy losses by scheduling maintenance actions to times when energy production is low or null. Thus, if all the schedule is optimized, increasing the energy price will not have an impact on total lifetime costs because the energy loss is already low.

5.2 Component Level Analysis

The component level analysis aims to statistically quantify the variability of the total costs when failures are distributed at different times of the year, for each subassembly and maintenance type. On top of this, it was also found statistically relevant results in the total cost breakdown accounting all lifetime failures of each subassembly's maintenance types. Statistical benefits are then found in the total costs median results, accounting for all scheduled failures' total costs. In this analysis, due to the high number of results, it is impossible to discuss them all. The results of component level analysis for the blade subassembly are presented and discussed, being one of the most expensive, but also interesting subassemblies. The remaining results of the total cost benefits for other subassemblies are presented in Table 5.1 to Table 5.3, in the Total Costs Benefits section.

5.2.1 Monthly Total Costs

Plots with the statistical monthly total cost results are made that considered all maintenance strategies in order to access the annual variability of the blade subassembly. Total cost results of failure events that were distributed throughout the year are grouped by month. The monthly total costs based on the median, for the other subassemblies, maintenance types and maintenance strategies, are presented in Appendix A.1

Figure 5.6 shows how total costs vary throughout the year, for different maintenance strategies for blade replacement.

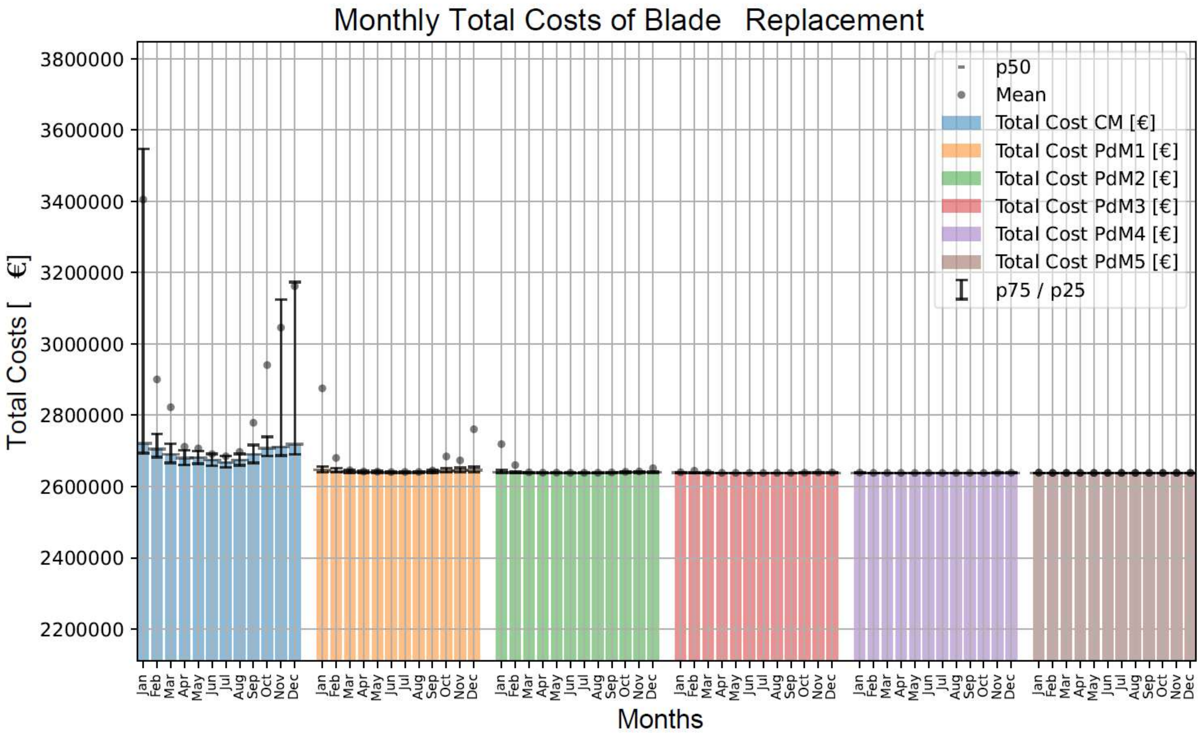


Figure 5.6. Monthly total costs of blade replacement.

It can be seen, in Figure 5.6, that the mean total costs of CM have a tendency throughout the year, where total costs are increasing from the summer to the winter months. The median (p50) also have a small, but similar tendency throughout the year. The annual variability along the maintenance strategies is greatly reduced. From CM to PdM1 strategy, annual variability is reduced. This is due to the optimizations made by the PdM strategy.

Further exploration was made in the blade replacement results. An example is shown in Figure 5.7, with the tendencies of data related to blade replacement. The data includes the monthly mean total costs for the modeled maintenance strategies, the monthly mean potential for energy production, and the monthly mean weather delays (waiting's).

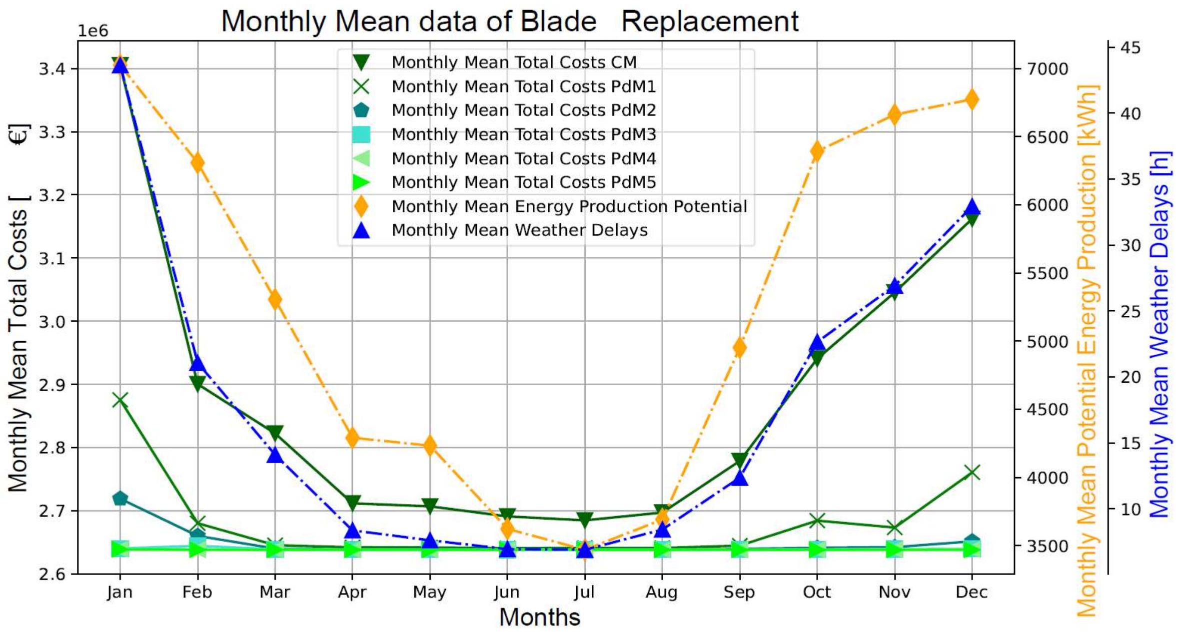


Figure 5.7. Monthly mean total costs, monthly mean potential energy production, and monthly mean weather delays of blade replacement.

The monthly mean total costs are the same as represented in Figure 5.6. These costs in the CM follow a very similar tendency as the monthly mean weather delays. It can be seen that monthly mean weather delays are increasing from summer to winter months. Such a tendency has a correlation with the monthly mean total costs because greater weather delays cause greater vessel and technician costs in the maintenance operation.

In order to calculate the revenue losses when downtime occurs, the potential energy production based on the available wind speed and turbine power curve is being computed. It follows that, downtimes during time periods with higher potential for energy production will result in higher total costs, which include the opportunity cost caused by downtime. The tendency of the monthly mean potential energy production is also increasing near the winter months. However, it seems to be less correlated with the total costs but, for example, in the month of May it can be seen that the weather delays are decreasing, but there is an increase in the mean energy production that may be having a slight impact in the total costs for CM.

The effects of weather delays and downtime during high energy production, in the monthly mean total costs, are being minimized for maintenance strategies with higher predictive periods.

Figure 5.8 shows how the monthly total costs vary throughout the year, for different maintenance strategies, for the blade major repair. For the major repair of the blade, it can be seen that the CM annual variability of the total costs is higher (in percentage) in the summer months, when compared with the blade replacement. Thus, annual variability follows a more defined tendency. The total costs variability is decreasing alongside with the maintenance strategies, only stabilizing in the PdM4.

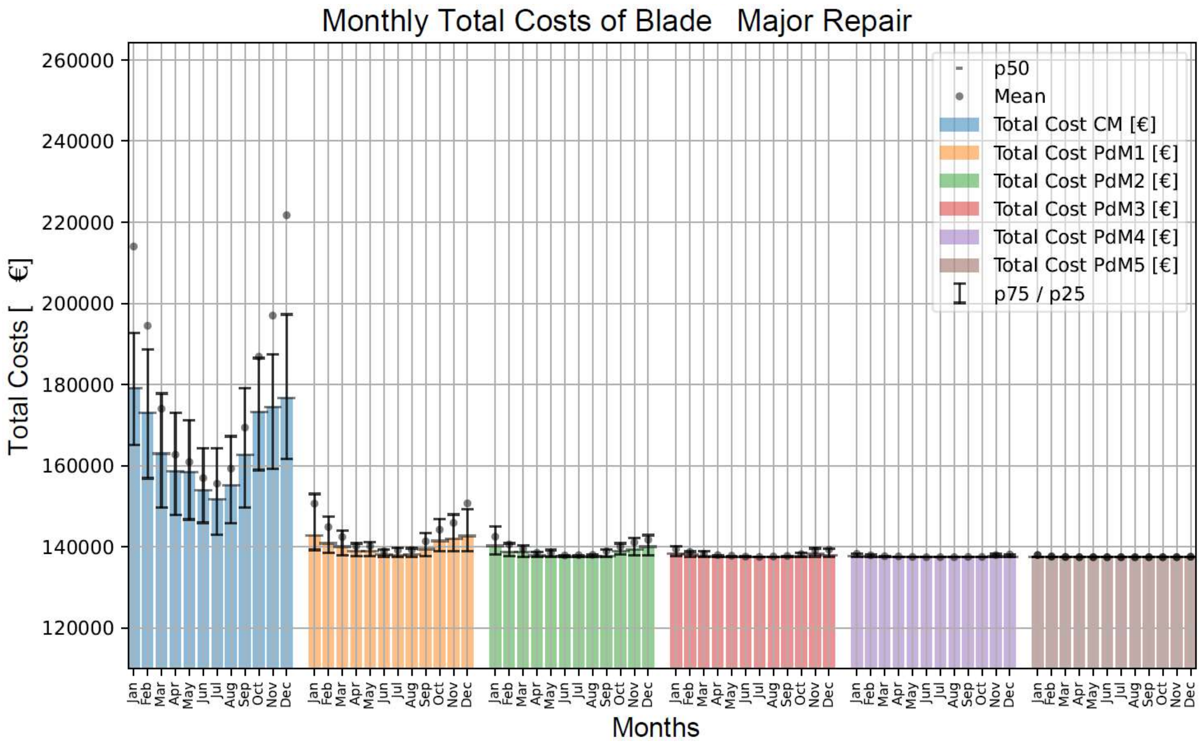


Figure 5.8. Monthly total costs of blade major repair.

Figure 5.9 shows how the monthly total costs vary, with the different maintenance strategies, for blade minor repair.

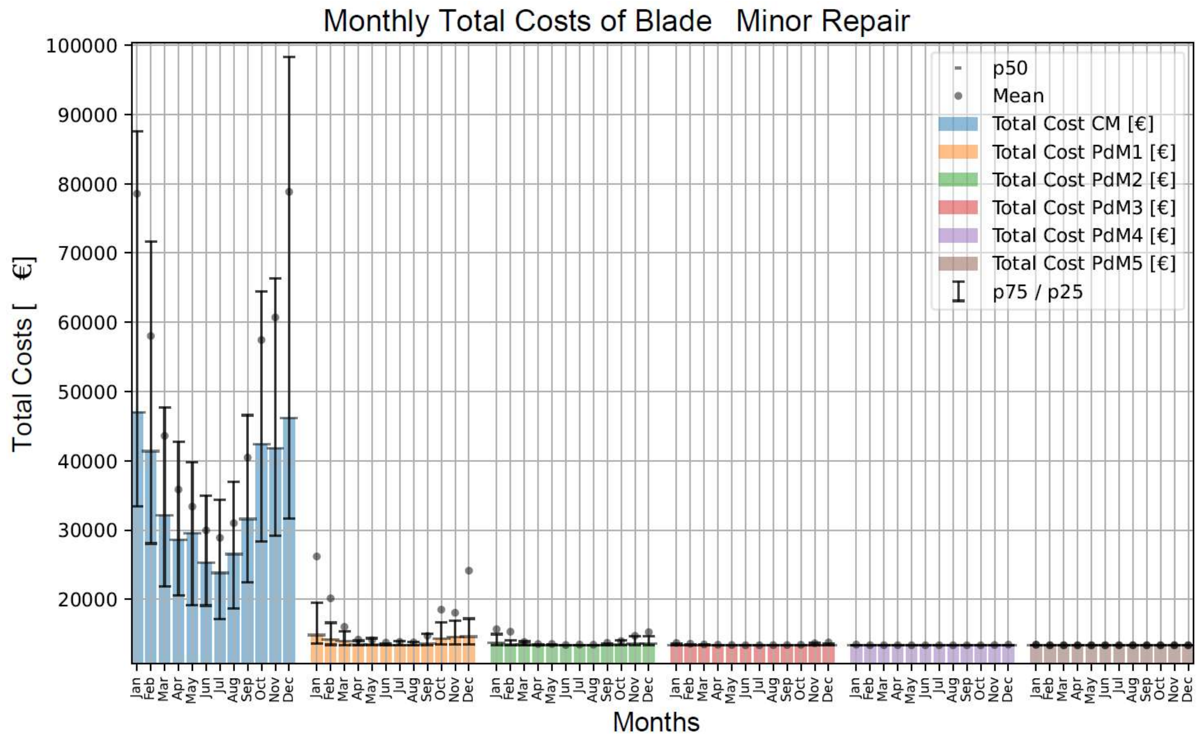


Figure 5.9. Monthly total costs of blade minor repair.

The results for the minor repairs of the blade show the same behavior as the previous maintenance types, however, the monthly total costs variability is higher for the CM. The annual variability is even more noticeable for this maintenance type. The CM of blade minor repair contains the highest decrease (in percentage) in the monthly total costs, when compared with blade replacement and major repair.

5.2.2 Total Costs Breakdown

The model computes the breakdown of the total failure costs (total costs) associated with each subassembly. This means that statistical results were found for all subassemblies and their different maintenance types (minor repair, major repair, and major replacement), of the total costs of the 10500 scheduled failures. The breakdown of those costs is plotted in the following figures for the blade subassembly and its three different maintenance types. The aim is to have a sense of how much each cost element impacts the total costs of a failure.

Figure 5.10 breaks down the total failure costs of blade replacement, showing there is very low variability in the total costs of the blade replacement.

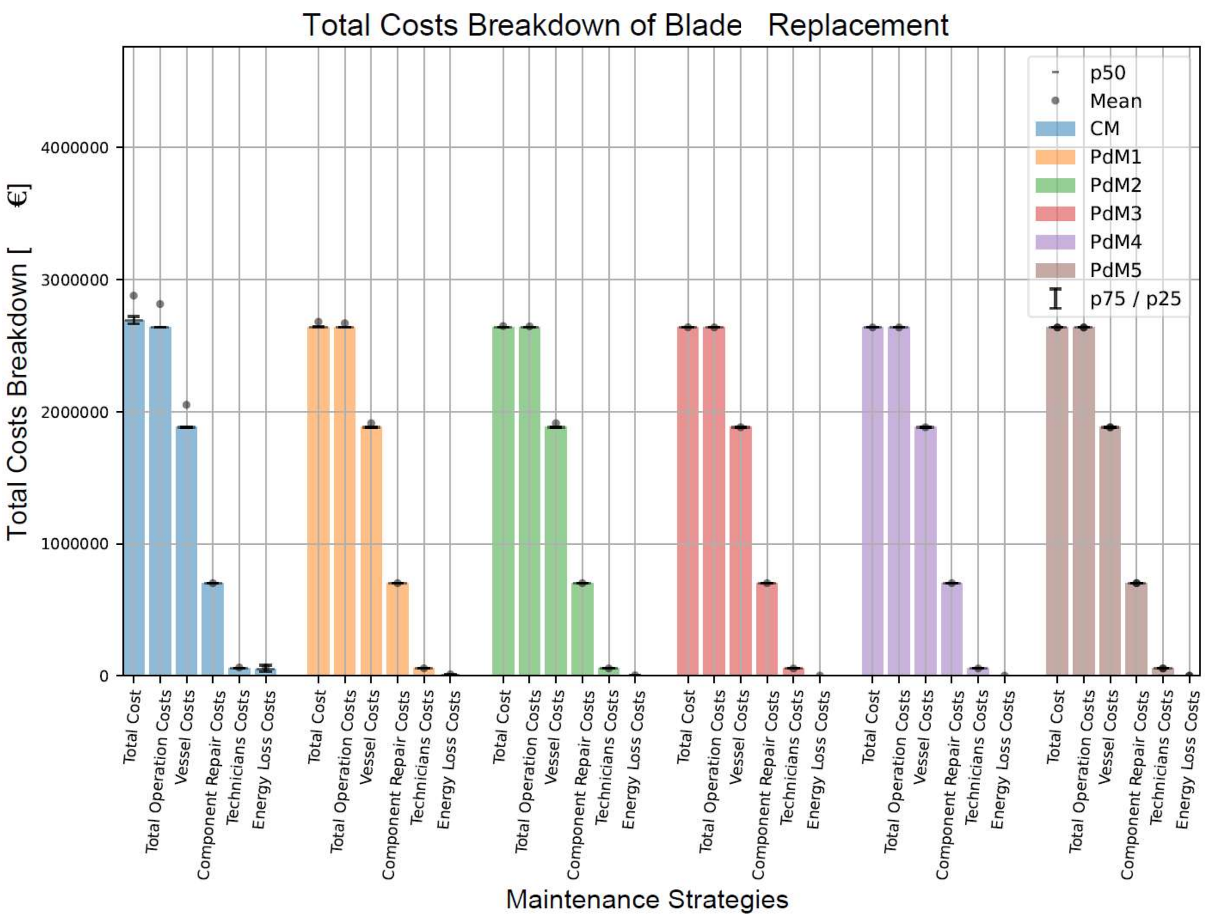


Figure 5.10. Cost breakdown of blade replacement.

Note: The total costs are the sum of the total operations costs with the energy loss costs. The total operation costs are the sum of the vessel costs, component repair costs, and technician costs.

In Figure 5.10, low variability is also seen throughout all the cost elements that compose the total costs, namely the vessel, component repair, technicians, and energy loss costs. For a 5-days predictive period (PdM1) there is a total cost median (p50) decrease of 1.9%, when compared to the CM strategy. For the 10-days predictive period (PdM2), these benefits are kept constant. There is only a slight increase in the benefits obtained by using the median, from 1.9% to 2%, in the 20-days predictive period (PdM3) and these are constant for the following two predictive periods, 40-days (PdM4) and 80-days (PdM5). Results show that, for a blade replacement, the contribution of the total operation costs for the total costs is higher than the contribution of total energy loss costs. Within the total operation costs, the largest fraction can be attributed to vessel costs (including chartering and fuel), which are particularly high because PCV is used in the blade replacement operation. The component repair costs take second place in this contribution. Component repair costs are high because the replacement of a blade itself is expensive. The technician and energy loss costs have a small contribution to the total costs, in this maintenance type.

Figure 5.11 shows the cost breakdown of the total failure costs of blade major repair.

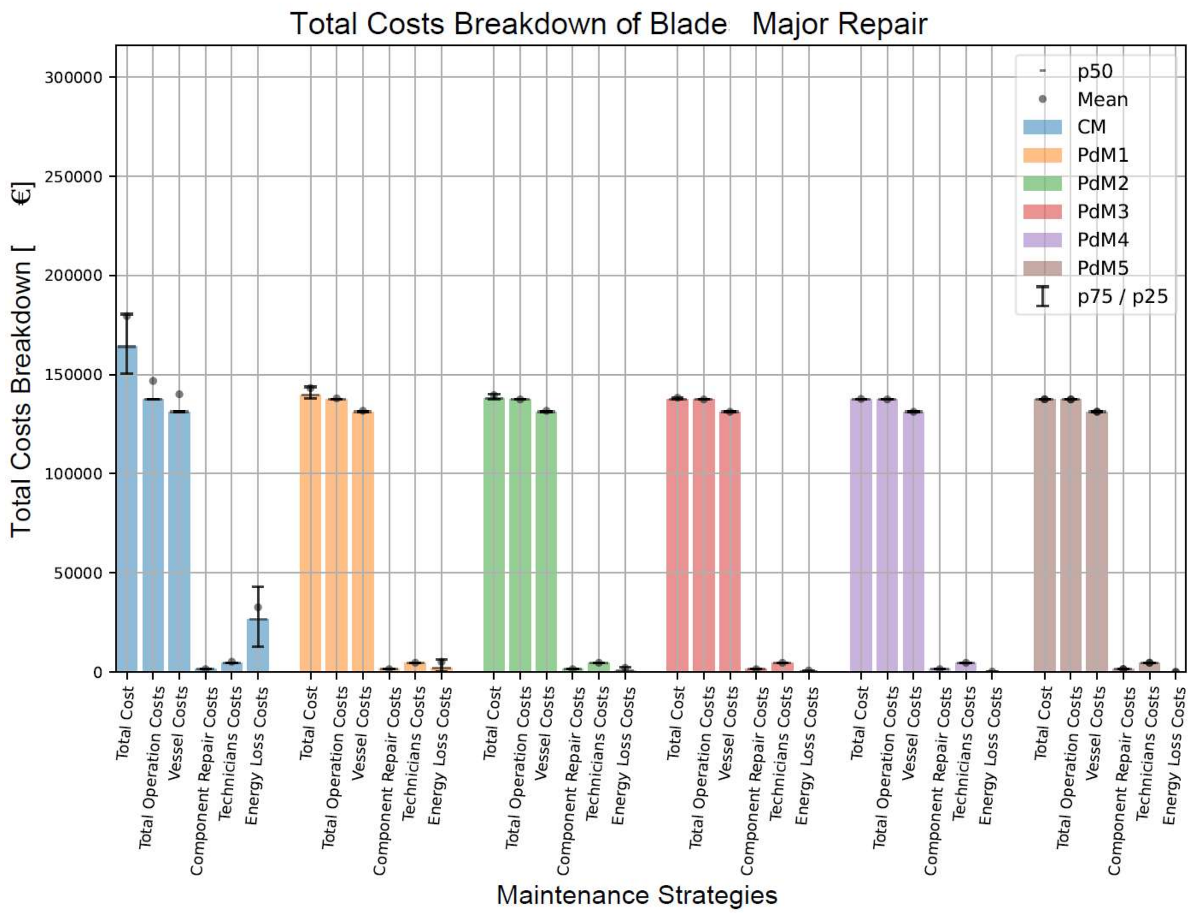


Figure 5.11. Cost breakdown of blade major repair.

Note: The total costs are the sum of the total operations costs with the energy loss costs. The total operation costs are the sum of the vessel costs, component repair costs, and technician costs.

The variability of the total costs for CM is small, as can be seen in Figure 5.11. However, this variation is higher (in percentage) than for the blade replacement. This variability is greatly decreasing with the predictive period. For a predictive period of 5 days (PdM1), the total cost variability decreases by about one fourth of the CM total cost variability, and it is minimal from the 20-days predictive period (PdM3) to the 80-day (PdM5). The major contributor element to this variability is the energy loss costs. The variability of the energy loss costs is higher for the CM and is decreasing with the predictive period because the PdM module is optimizing the scheduling based on minimum costs. These minimum costs include the energy loss costs and its being optimized by scheduling the maintenance downtimes for times where energy production is low or zero, which is resulting in less variability in the energy loss costs of each failure caused by the impact of extreme environmental conditions in the failures downtime. This optimization is greatly enhanced in higher predictive periods; hence, the results will become constant along the predictive period.

For major repair of the blade, results show that there is a slightly higher decrease (in percentage) in the median total costs than for blade replacement. From CM to PdM1 there is a decrease of 14.9% in the median (p50) total costs. This decrease continues until it becomes constant in PdM3 with a decrease of 16.2%, when compared to CM.

For CM, the energy loss cost contribution for the median total costs is higher than for the blade replacement, which is translating into a higher decrease when these costs are minimized by the PdM module. Even just for a 5-day predictive period (PdM1), energy loss costs decrease substantially. These are even further minimized in the following PdM strategies. The contribution of the vessel costs seems to be almost constant for the along all maintenance strategies, even though there might be a bigger decrease from CM to PdM1, but in Figure 5.11 it is not very evident. The contribution of the component repair costs, and technician costs seems to be almost constant across all maintenance strategies, in Figure 5.11.

Figure 5.12 shows the cost breakdown of the total failure costs of blade minor repair. In this maintenance type, there is the highest variability in the total costs, when comparing with the other maintenance types of the blades subassembly. As also seen in the major repair, the energy loss costs are the main source of this variability.

The total costs decrease tendency, along the predictive period, can be better seen for minor repair. The benefits from a CM to a PdM1 in the median total costs are 59.3%, which is a much higher benefit than for the blade replacement, or even the major repair. The benefits are constant from PdM2 and on, with a 60.2% decrease in the median total costs.

The total costs are mainly impacted by the energy loss costs in the CM strategy. The energy loss costs are greatly reduced even just for a 5-day predictive period (PdM1). The other costs of elements, considered in the total costs, seem to be almost constant along the predictive periods, in Figure 5.12.

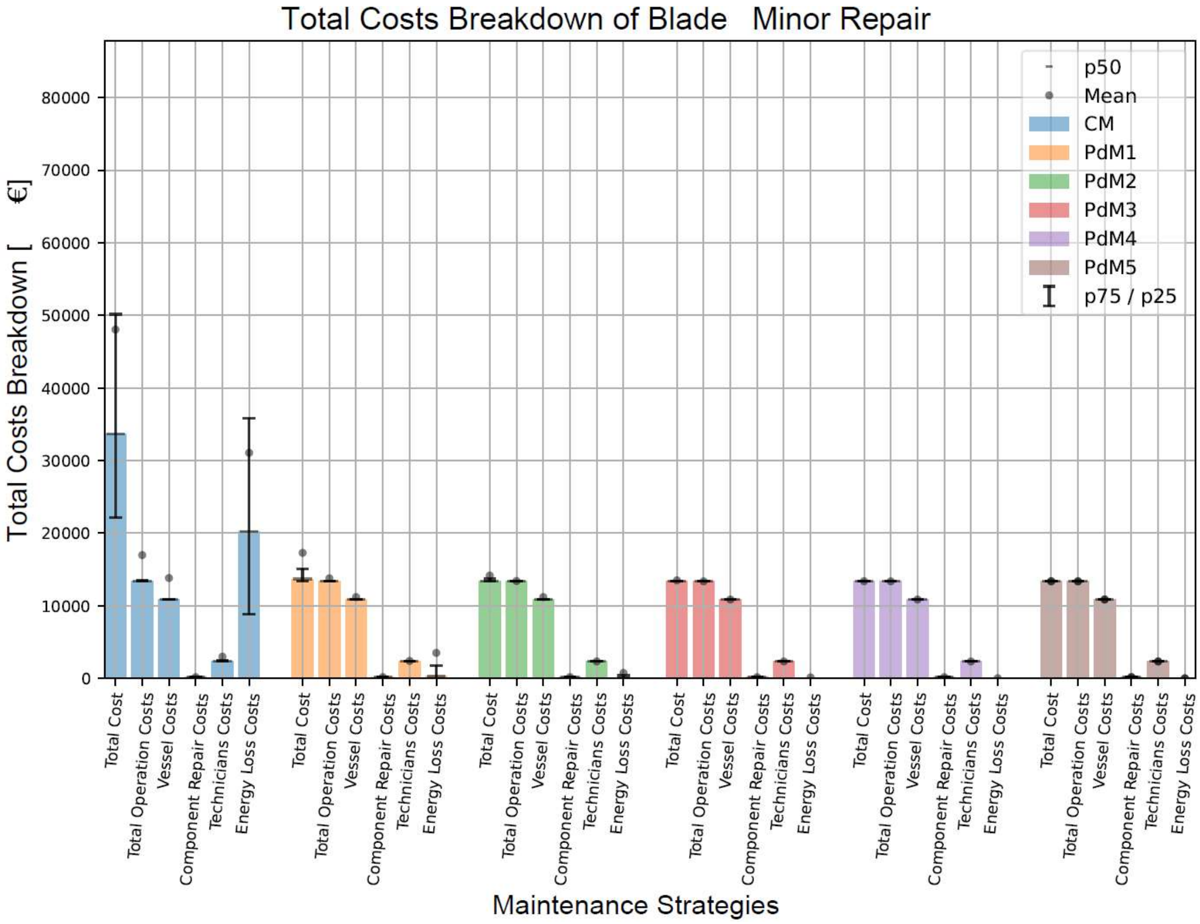


Figure 5.12. Cost breakdown of blade minor repair.

Note: The total costs are the sum of the total operations costs with the energy loss costs. The total operation costs are the sum of the vessel costs, component repair costs, and technician costs.

5.2.3 Total Costs Benefits

To know what the logistical benefits in the component-level analysis for each subassembly's maintenance type are, the median total costs, from all the scheduled failures, were computed. From these, the PdM benefits were computed by benchmarking them against each individual CM result. With this, the median percentual decrease in total costs was found. The results in the total cost breakdown showed that the median benefits of the total costs can vary greatly between different maintenance types, thus maintenance types are presented separately.

Table 5.1 summarizes the computed benefits for the median total costs of the replacement maintenance type. In the major replacement maintenance types, it can be seen a small percentual decrease in the median total costs. The median total costs decrease, for the replacement maintenance type, vary with a PdM strategy from 1.4% to 3.2% Even though the percentual decrease is small, these results represent high-cost savings because the replacement of subassemblies is associated with high total costs.

Table 5.1. Median logistic total costs benefit for each subassembly's replacement of a predictive maintenance strategy comparing to its own corrective maintenance.

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

Table 5.2 summarizes the computed benefits for the median total costs of the major repair maintenance type.

Table 5.2. Median logistic total costs benefit for each subassembly's major repair of a predictive maintenance strategy comparing to its own corrective maintenance.

Subassembly's Major Repair	**Variation in Total Costs [%]**				
	PdM1	**PdM2**	**PdM3**	**PdM4**	**PdM5**
Blade Major Repair	-14.9	-15.8	-16.2	-16.2	-16.2
Contactor/Circuit Breaker/Relay Major Repair	-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 Major Repair	-18.8	-19.5	-19.6	-19.6	-19.6
Gearbox Major Repair	-15.1	-16.0	-16.4	-16.5	-16.5
Generator Major Repair	-15.3	-16.4	-16.8	-17.0	-17.0
Grease/Oil/Cooling Liq. Major Repair	-14.4	-15.1	-15.3	-15.3	-15.3
Heaters/Coolers Major Repair	-18.9	-19.6	-19.7	-19.7	-19.7
Hub Major Repair	-13.3	-15.1	-15.9	-16.5	-16.8
Other Components Major Repair	-14.9	-15.8	-16.1	-16.2	-16.2
Pitch/Hyd Major Repair	-14.6	-15.4	-15.6	-15.7	-15.7
Power Supply/Converter Major Repair	-18.4	-19.1	-19.2	-19.2	-19.2
Pumps/Motors Major Repair	-17.9	-18.3	-18.3	-18.3	-18.3
Safety Major Repair	-16.8	-16.9	-16.9	-16.9	-16.9
Sensors Major Repair	-16.6	-16.6	-16.6	-16.6	-16.6
Tower/Foundation Major Repair	-15.4	-15.4	-15.4	-15.4	-15.4
Yaw System Major Repair	-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 is more advantageous in the 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 5.3 summarizes the computed benefits for the median total costs of the minor repair maintenance type. Minor repairs have the greatest percentual benefits when compared to their total cost for a CM. The costs drop can be between 56.4% and 60.5%. Noting that these cost benefits, in euros, are much lower than for other maintenance types.

Table 5.3. Median logistic total costs benefit for each subassembly's minor repair of a predictive maintenance strategy comparing to its own corrective maintenance.

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

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

Chapter 6: Conclusions and Future Work

As two separate, but complementary, analyses were carried out to quantify the potential logistic benefits of a PdM strategy, the main conclusions are also presented separately.

6.1 Wind Farm Level

- The technical, operational, and energetic lifetime availabilities can be increased with longer predictive periods. However, the largest increase occurs from CM to PdM1, in all three availabilities. The scheduling optimization made by the PdM module reduces downtimes and energy losses. This optimization is already quite noticeable on the availabilities of a 5-day predictive period (PdM1). The computed energetic availability is reaching values of almost 1 from a 20-day predictive period and on.
- An important benefit of the PdM strategy is the total cost reduction. The lowest total costs were found for a 20-day predictive period. However, these results are close to the results of the 10-day predictive period. On the other hand, major benefits in the total costs can already be seen with a change from CM to a 5-day predictive period.
- Higher failure rates in combination with longer predictive periods is causing extra failures to be generated at the end of a subassembly's lifetime. The PdM module optimizes maintenance scheduling of each failure based only on total costs minimization. The maintenance is scheduled to the exact hour with more economical advantages with the aim of finding the maximum benefits. With this, the PdM module can waste a portion of the useful life of the subassembly by scheduling maintenance actions to times before the failure occurs spontaneously. This is enhanced in longer predicted periods because there is more flexibility to schedule maintenance actions ahead of the failure. The total amount of WUL, at the end of each subassembly's lifetime, is correlated with the number of failures, that a subassembly has during its lifetime. High failure rates are the basis for modeling a high number of failures. On top of that, the maintenance of each of those failures, when optimized by the PdM module, is causing the waste of a portion of the subassembly's useful life with each failure. Ultimately, at the end of the subassembly's lifetime there will be "room" to generate extra failures beside the ones expected from the failure rate.
- The impact of the extra-generated failures on total costs is higher in longer predictive periods (40 and 80 days), where total costs increase. The total costs in shorter predictive periods decrease until a 20-day predictive period because the cost

optimization made by the PdM module is compensating the additional costs caused by the extra-generated failures. Taking in consideration that shorter predictive periods have also less extra-generated failures than longer predictive periods.

6.2 Component level

- The time of the year in which a failure event takes place has significant impacts on the costs in a CM strategy. As expected, costs are typically higher during the winter season and lower during the summer season. These costs are reduced with the PdM strategy as the predictive periods increase, for each subassembly. Costs are greatly reduced for longer predictive periods because there is more flexibility to schedule maintenance actions in times where the energy losses and weather delays (waiting times) are lower. This is consequently translated into lower energy losses, as well as vessel and technician costs, which results in lower total failure costs.
- The CM cost breakdown varies mainly between different maintenance types (replacement, major repair, and minor repair). The contribution of the energy loss costs to the total costs is minimal in the blade replacement; however, it becomes higher for major repair and critical for minor repairs. The PdM strategy is able to greatly reduce energy loss costs. The vessel and technician costs can also be reduced, but on a much lower scale. Component repair costs cannot be reduced because these are fixed for each failure.
- Component-level results show that different subassemblies and their maintenance types have different logistic benefits. Major differences were found between different maintenance types, where the median 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%. The total cost benefits are increasing from replacement to minor repair maintenance types. When the median total cost benefits are translated to euro, the replacement of subassemblies has much higher benefits, in terms of costs, than major repair, and these are even higher than minor repairs. Ultimately, the cost savings caused by a PdM strategy are higher in replacements, followed by major repairs, and minor repairs.

6.3 Future Work

- The model can be modified to perform the PdM on a single failure and be used in a practical application to schedule predictive maintenance actions in real-time. A failure can be predicted in real-time, for example, from the output (RUL) of a sensor-based failure prediction algorithm for a subassembly or wind turbine. With this, the modified model would take the predicted failure as input and find the optimum maintenance schedule (to take place in future). It can be done in combination with forecast weather data, for example, a Markov Model trained on historical wind speeds and wave heights, as input to the power, and DTO+LMO modules.

- The model assumes constant failure rates to generate the TTFs, in the reliability module. This feature can be further upgraded to generate TTF based on time-variable failure rates that build the bathtub curve, in reliability engineering, if the failure rate distribution is well known for a certain subassembly or turbine. This also includes the transition points, where the three distributions change, in the bathtub curve.
- The failure rates, average repair times, average technicians and maintenance categories used in this thesis are based on a 2015 study from a non-disclosed site. These were used because of data accessibility and data completion. Nowadays, wind farms have bigger turbines and are more technologically advanced. Finding recent and updated data was a barrier for this study, but that could be further explored to get more accurate results for current wind farms.
- The model considers that each turbine is independent. This means that each maintenance operation is "blind" to what is happening in the rest of the wind farm. Further model development could include PdM combined with group maintenance, which imply, for example, that the same vessel could be deployed to perform several maintenance actions on one or more wind turbines, and not just one, as assumed. This has the potential to greatly reduce O&M costs, and consequently, increase the logistic benefits of a PdM strategy.
- The PdM module's scheduling optimization is based on minimization of the total costs, for each failure's maintenance. It will schedule maintenance actions where those costs are minimal. The current method results in waste of useful life of subassemblies, which ultimately, can lead to an increase in failures by the end of the wind farm's lifetime. This optimization could be further developed to minimize the WUL of the subassembly by setting an acceptable cost margin and schedule maintenance actions the closest it can to the predicted failure without greatly compromising the costs. For example, if the costs of a maintenance, that is performed at the beginning of the predictive period, are very similar to the costs of a maintenance that is performed in the middle of the predictive period. In this case, the model is choosing the maintenance scheduling that has the lowest costs without assessing the WUL. With a cost margin integrated in the optimization, the model could assess which maintenance schedule minimizes the WUL of the subassembly, while minimizing the costs inside the defined margin.
- The model can be further developed by creating a spare-parts module. This module would contain the spare parts stock and could be monthly or annual based. The modeling of stock would also support the modeling of spare parts procurement. When stock is not available for a specific spare part, its procurement must take place, which

will cause greater downtimes and consequently greater energy loss costs. It is expected that a PdM will bring even greater benefits when considering spare part procurement.

- There are some other assumptions that could be further explored. The waiting of vessel, waiting on crew, and waiting on crew rest were neglected. In order to model these remaining operation delays, the model could be expanded to work with some more modules.

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Appendix A

A.1. Monthly Median Total Costs

Blade Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2721024	2647325	2640200	2638521	2638137	2638137
Feb	2705133	2642914	2639070	2638385	2638137	2638137
Mar	2689805	2640998	2638956	2638234	2638137	2638137
Apr	2679768	2639641	2638355	2638137	2638137	2638137
May	2680771	2640124	2638339	2638137	2638137	2638137
Jun	2673646	2639176	2638182	2638137	2638137	2638137
Jul	2666844	2639118	2638137	2638137	2638137	2638137
Aug	2674212	2639414	2638189	2638137	2638137	2638137
Sep	2689496	2640807	2638487	2638137	2638137	2638137
Oct	2707124	2643585	2639275	2638238	2638137	2638137
Nov	2711045	2643817	2639479	2638621	2638170	2638137
Dec	2718598	2645563	2640029	2638432	2638137	2638137

Blade Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	179142	142780	140205	138304	137648	137426
Feb	172944	140858	138649	138053	137509	137426
Mar	162977	140048	138702	137688	137426	137426
Apr	158577	138849	137811	137456	137426	137426
May	158390	138897	137733	137426	137426	137426
Jun	153980	138058	137576	137426	137426	137426
Jul	151726	137916	137426	137426	137426	137426
Aug	155110	138093	137567	137426	137426	137426
Sep	162604	139387	137673	137426	137426	137426
Oct	173181	141419	138970	137597	137426	137426
Nov	174489	142014	139367	138322	137603	137426
Dec	176698	142658	139992	137917	137478	137426

Blade Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	46960	14836	13723	13372	13372	13372
Feb	41387	14213	13437	13372	13372	13372
Mar	32138	13940	13429	13372	13372	13372
Apr	28620	13436	13372	13372	13372	13372
May	29532	13469	13372	13372	13372	13372
Jun	25274	13372	13372	13372	13372	13372
Jul	23830	13372	13372	13372	13372	13372
Aug	26543	13372	13372	13372	13372	13372
Sep	31592	13621	13372	13372	13372	13372
Oct	42372	14297	13461	13372	13372	13372
Nov	41780	14544	13611	13372	13372	13372
Dec	46162	14596	13582	13372	13372	13372

Contactor/ Circuit Breaker/ Relay Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2001960	1933117	1923758	1920507	1919341	1918975
Feb	1989770	1927934	1921502	1919770	1919250	1918956
Mar	1975030	1924524	1921008	1919463	1919104	1918956
Apr	1962638	1922272	1919909	1919057	1918930	1918904
May	1964774	1922764	1919843	1918961	1918904	1918904
Jun	1958360	1921134	1919438	1919081	1918904	1918904
Jul	1950515	1920972	1919128	1918904	1918904	1918904
Aug	1957906	1921545	1919375	1918904	1918904	1918904
Sep	1973818	1923760	1920011	1918930	1918904	1918904
Oct	1991824	1929230	1922081	1919601	1918904	1918904
Nov	1993840	1929598	1922451	1920245	1919406	1918904
Dec	2002167	1931218	1923371	1920103	1919161	1918904

Contactor/ Circuit Breaker/ Relay Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	177950	142235	139915	138269	137736	137639
Feb	171784	140512	138635	138074	137650	137639
Mar	161909	139811	138590	137831	137639	137639
Apr	157698	138717	137887	137639	137639	137639
May	157956	138762	137838	137639	137639	137639
Jun	153313	138141	137736	137639	137639	137639
Jul	151462	137984	137639	137639	137639	137639
Aug	154532	138120	137684	137639	137639	137639
Sep	161415	139123	137845	137639	137639	137639
Oct	171889	141078	138850	137710	137639	137639
Nov	172820	141470	139230	138350	137698	137639
Dec	175398	141813	139726	137967	137639	137639

Contactor/ Circuit Breaker/ Relay Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	42876	13939	13334	13282	13282	13282
Feb	37143	13593	13282	13282	13282	13282
Mar	29113	13403	13282	13282	13282	13282
Apr	26553	13282	13282	13282	13282	13282
May	27415	13282	13282	13282	13282	13282
Jun	23215	13282	13282	13282	13282	13282
Jul	22350	13282	13282	13282	13282	13282
Aug	24403	13282	13282	13282	13282	13282
Sep	29155	13294	13282	13282	13282	13282
Oct	38103	13641	13282	13282	13282	13282
Nov	38188	13774	13282	13282	13282	13282
Dec	41183	13749	13294	13282	13282	13282

Controls Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	1598442	1529585	1524802	1523680	1523551	1523551
Feb	1586638	1526765	1524051	1523582	1523551	1523551
Mar	1571458	1525334	1523929	1523551	1523551	1523551
Apr	1562396	1524432	1523584	1523551	1523551	1523551
May	1562883	1524726	1523570	1523551	1523551	1523551
Jun	1556820	1524074	1523551	1523551	1523551	1523551
Jul	1551434	1524066	1523551	1523551	1523551	1523551
Aug	1557503	1524327	1523551	1523551	1523551	1523551
Sep	1571829	1525306	1523642	1523551	1523551	1523551
Oct	1587271	1527034	1524117	1523551	1523551	1523551
Nov	1589951	1527376	1524369	1523730	1523551	1523551
Dec	1597980	1528137	1524475	1523582	1523551	1523551

Controls Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	129052	96024	94590	93513	93329	93329
Feb	123891	94907	93739	93394	93329	93329
Mar	114673	94465	93698	93341	93329	93329
Apr	110825	93776	93362	93329	93329	93329
May	111624	93818	93329	93329	93329	93329
Jun	106846	93506	93329	93329	93329	93329
Jul	105340	93466	93329	93329	93329	93329
Aug	108391	93510	93329	93329	93329	93329
Sep	113860	94079	93341	93329	93329	93329
Oct	124617	95176	93901	93329	93329	93329
Nov	124262	95482	94088	93628	93329	93329
Dec	127376	95524	94196	93412	93329	93329

Controls Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	46053	14728	13713	13455	13455	13455
Feb	40640	14150	13485	13455	13455	13455
Mar	31741	13916	13504	13455	13455	13455
Apr	28185	13485	13455	13455	13455	13455
May	29126	13506	13455	13455	13455	13455
Jun	24981	13455	13455	13455	13455	13455
Jul	23689	13455	13455	13455	13455	13455
Aug	26343	13455	13455	13455	13455	13455
Sep	31338	13621	13455	13455	13455	13455
Oct	41394	14228	13500	13455	13455	13455
Nov	41145	14441	13621	13455	13455	13455
Dec	45407	14450	13587	13455	13455	13455

Electrical Components Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	1980616	1913262	1905910	1903888	1903317	1903259
Feb	1969274	1908766	1904530	1903663	1903298	1903259
Mar	1955586	1906627	1904301	1903458	1903259	1903259
Apr	1944890	1905159	1903636	1903259	1903259	1903259
May	1946044	1905649	1903608	1903259	1903259	1903259
Jun	1939619	1904570	1903393	1903259	1903259	1903259
Jul	1932361	1904456	1903285	1903259	1903259	1903259
Aug	1940012	1904869	1903347	1903259	1903259	1903259
Sep	1954850	1906461	1903765	1903259	1903259	1903259
Oct	1971625	1909220	1904792	1903503	1903259	1903259
Nov	1972875	1909943	1905092	1904010	1903405	1903259
Dec	1980895	1911820	1905538	1903744	1903259	1903259

Electrical Components Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	128803	95775	94342	93264	93080	93080
Feb	123643	94658	93490	93145	93080	93080
Mar	114424	94217	93450	93092	93080	93080
Apr	110576	93527	93113	93080	93080	93080
May	111376	93569	93080	93080	93080	93080
Jun	106598	93258	93080	93080	93080	93080
Jul	105092	93217	93080	93080	93080	93080
Aug	108142	93262	93080	93080	93080	93080
Sep	113612	93830	93092	93080	93080	93080
Oct	124369	94927	93652	93080	93080	93080
Nov	124013	95234	93839	93379	93080	93080
Dec	127127	95276	93947	93163	93080	93080

Electrical Components Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	43725	13968	13290	13180	13180	13180
Feb	37727	13566	13180	13180	13180	13180
Mar	29747	13362	13180	13180	13180	13180
Apr	26793	13180	13180	13180	13180	13180
May	27662	13180	13180	13180	13180	13180
Jun	23390	13180	13180	13180	13180	13180
Jul	22561	13180	13180	13180	13180	13180
Aug	24821	13180	13180	13180	13180	13180
Sep	29743	13211	13180	13180	13180	13180
Oct	39063	13637	13180	13180	13180	13180
Nov	38810	13795	13206	13180	13180	13180
Dec	41947	13780	13203	13180	13180	13180

Gearbox Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	3785907	3717064	3707706	3704455	3703289	3702923
Feb	3773718	3711882	3705449	3703718	3703198	3702904
Mar	3758978	3708472	3704956	3703411	3703052	3702904
Apr	3746586	3706220	3703857	3703005	3702878	3702852
May	3748722	3706712	3703791	3702909	3702852	3702852
Jun	3742308	3705082	3703386	3703029	3702852	3702852
Jul	3734463	3704920	3703076	3702852	3702852	3702852
Aug	3741854	3705493	3703323	3702852	3702852	3702852
Sep	3757766	3707708	3703959	3702878	3702852	3702852
Oct	3775772	3713178	3706029	3703549	3702852	3702852
Nov	3777935	3713546	3706399	3704193	3703354	3702852
Dec	3786171	3715166	3707318	3704051	3703109	3702852

Gearbox Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	180912	144179	141510	139362	138668	138387
Feb	174538	142013	139733	139071	138519	138368
Mar	164597	141164	139794	138642	138419	138368
Apr	159739	139932	138801	138424	138368	138368
May	159822	140054	138739	138379	138368	138368
Jun	155210	139067	138594	138368	138368	138368
Jul	152790	138908	138394	138368	138368	138368
Aug	156313	139172	138587	138368	138368	138368
Sep	164219	140444	138678	138368	138368	138368
Oct	174967	142724	140217	138591	138368	138368
Nov	176158	143452	140483	139357	138580	138368
Dec	178231	144137	141124	138937	138469	138368

Gearbox Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	45978	14653	13638	13380	13380	13380
Feb	40565	14075	13410	13380	13380	13380
Mar	31666	13841	13429	13380	13380	13380
Apr	28110	13410	13380	13380	13380	13380
May	29051	13431	13380	13380	13380	13380
Jun	24906	13380	13380	13380	13380	13380
Jul	23614	13380	13380	13380	13380	13380
Aug	26268	13380	13380	13380	13380	13380
Sep	31263	13546	13380	13380	13380	13380
Oct	41319	14153	13425	13380	13380	13380
Nov	41070	14366	13546	13380	13380	13380
Dec	45332	14375	13512	13380	13380	13380

Generator Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2659227	2591459	2583564	2581029	2580369	2580120
Feb	2647226	2586708	2581766	2580681	2580177	2580120
Mar	2633535	2584244	2581509	2580399	2580132	2580120
Apr	2622551	2582421	2580705	2580147	2580120	2580120
May	2623659	2582982	2580586	2580120	2580120	2580120
Jun	2617565	2581761	2580390	2580120	2580120	2580120
Jul	2609997	2581603	2580237	2580120	2580120	2580120
Aug	2617614	2582039	2580303	2580120	2580120	2580120
Sep	2632946	2583743	2580844	2580120	2580120	2580120
Oct	2650144	2587300	2582125	2580543	2580120	2580120
Nov	2651536	2588331	2582482	2581098	2580381	2580120
Dec	2659707	2589982	2583203	2580871	2580160	2580120

Generator Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	183283	145807	142305	139992	139212	138854
Feb	176257	142938	140543	139561	139129	138835
Mar	166246	141953	140562	139178	138923	138809
Apr	160959	140618	139435	138915	138783	138783
May	161098	140822	139321	138809	138783	138783
Jun	156188	139697	139144	138813	138783	138783
Jul	153848	139470	138874	138783	138783	138783
Aug	157224	139801	139071	138783	138783	138783
Sep	165373	141315	139321	138794	138783	138783
Oct	176770	143901	140958	139195	138783	138783
Nov	178020	144719	141313	140076	139139	138783
Dec	181182	145385	141799	139599	139040	138783

Generator Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	45508	14461	13573	13357	13357	13357
Feb	39632	13960	13357	13357	13357	13357
Mar	31110	13723	13368	13357	13357	13357
Apr	27805	13357	13357	13357	13357	13357
May	28570	13368	13357	13357	13357	13357
Jun	24439	13357	13357	13357	13357	13357
Jul	23337	13357	13357	13357	13357	13357
Aug	25807	13357	13357	13357	13357	13357
Sep	30843	13465	13357	13357	13357	13357
Oct	40338	14018	13357	13357	13357	13357
Nov	40378	14214	13459	13357	13357	13357
Dec	44080	14229	13425	13357	13357	13357

Grease/ Oil/ Cooling Liq. Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	176996	141734	139578	138067	137581	137529
Feb	171004	140064	138391	137877	137529	137529
Mar	161141	139499	138368	137684	137529	137529
Apr	157179	138461	137751	137529	137529	137529
May	157321	138524	137684	137529	137529	137529
Jun	152708	137953	137600	137529	137529	137529
Jul	150723	137827	137529	137529	137529	137529
Aug	153973	137962	137555	137529	137529	137529
Sep	160848	138792	137698	137529	137529	137529
Oct	171231	140695	138621	137588	137529	137529
Nov	171841	140955	138926	138147	137555	137529
Dec	175020	141276	139362	137775	137529	137529

Grease/ Oil/ Cooling Liq. Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	42580	13643	13038	12986	12986	12986
Feb	36847	13297	12986	12986	12986	12986
Mar	28817	13107	12986	12986	12986	12986
Apr	26257	12986	12986	12986	12986	12986
May	27119	12986	12986	12986	12986	12986
Jun	22919	12986	12986	12986	12986	12986
Jul	22054	12986	12986	12986	12986	12986
Aug	24107	12986	12986	12986	12986	12986
Sep	28859	12998	12986	12986	12986	12986
Oct	37807	13345	12986	12986	12986	12986
Nov	37893	13478	12986	12986	12986	12986
Dec	40871	13453	12998	12986	12986	12986

Heaters/ Coolers Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	128227	95200	93766	92688	92505	92505
Feb	123067	94083	92914	92569	92505	92505
Mar	113849	93641	92874	92516	92505	92505
Apr	110000	92952	92538	92505	92505	92505
May	110800	92993	92505	92505	92505	92505
Jun	106022	92682	92505	92505	92505	92505
Jul	104516	92641	92505	92505	92505	92505
Aug	107567	92686	92505	92505	92505	92505
Sep	113036	93254	92516	92505	92505	92505
Oct	123793	94352	93077	92505	92505	92505
Nov	123437	94658	93264	92804	92505	92505
Dec	126552	94700	93372	92587	92505	92505

Heaters/ Coolers Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	44191	14433	13756	13646	13646	13646
Feb	38197	14032	13646	13646	13646	13646
Mar	30213	13827	13646	13646	13646	13646
Apr	27259	13646	13646	13646	13646	13646
May	28127	13646	13646	13646	13646	13646
Jun	23856	13646	13646	13646	13646	13646
Jul	23027	13646	13646	13646	13646	13646
Aug	25286	13646	13646	13646	13646	13646
Sep	30208	13676	13646	13646	13646	13646
Oct	39529	14103	13646	13646	13646	13646
Nov	39276	14260	13672	13646	13646	13646
Dec	42412	14245	13669	13646	13646	13646

Hub Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2268843	2200000	2190641	2187390	2186225	2185858
Feb	2256653	2194817	2188385	2186653	2186133	2185839
Mar	2241913	2191407	2187891	2186346	2185987	2185839
Apr	2229522	2189156	2186792	2185940	2185813	2185787
May	2231657	2189647	2186726	2185844	2185787	2185787
Jun	2225243	2188017	2186321	2185964	2185787	2185787
Jul	2217398	2187855	2186011	2185787	2185787	2185787
Aug	2224789	2188428	2186259	2185787	2185787	2185787
Sep	2240701	2190643	2186894	2185813	2185787	2185787
Oct	2258707	2196113	2188964	2186484	2185787	2185787
Nov	2260723	2196481	2189334	2187128	2186289	2185787
Dec	2269050	2198101	2190254	2186987	2186044	2185787

Hub Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	243489	202942	196056	188957	186392	185568
Feb	232915	196857	190518	188255	187042	185376
Mar	221116	193944	189605	187362	186166	185042
Apr	214020	189983	186954	186225	185273	184638
May	213818	189826	187442	185376	184743	184560
Jun	208585	188300	186862	185334	184629	184560
Jul	204953	187419	185560	185075	184743	184560
Aug	209125	188383	186469	184861	184658	184560
Sep	220022	191316	187087	185798	184810	184560
Oct	233923	197939	191973	186977	185490	184598
Nov	236269	199216	191973	189034	186884	184950
Dec	242397	201613	192691	188461	186366	185568

Hub Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	48421	15320	14144	13657	13645	13645
Feb	42418	14618	13773	13645	13645	13645
Mar	32998	14321	13759	13645	13645	13645
Apr	29310	13766	13645	13645	13645	13645
May	30303	13801	13645	13645	13645	13645
Jun	25850	13671	13645	13645	13645	13645
Jul	24439	13645	13645	13645	13645	13645
Aug	27049	13657	13645	13645	13645	13645
Sep	32554	13967	13645	13645	13645	13645
Oct	43707	14711	13808	13645	13645	13645
Nov	43115	14972	13978	13683	13645	13645
Dec	47585	15042	13962	13645	13645	13645

Other Components Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	1989081	1920273	1910915	1907664	1906498	1906132
Feb	1976895	1915091	1908658	1906927	1906407	1906113
Mar	1962187	1911681	1908165	1906620	1906261	1906113
Apr	1949795	1909429	1907066	1906214	1906087	1906061
May	1951931	1909921	1907000	1906118	1906061	1906061
Jun	1945517	1908291	1906595	1906238	1906061	1906061
Jul	1937672	1908129	1906285	1906061	1906061	1906061
Aug	1945063	1908702	1906532	1906061	1906061	1906061
Sep	1960975	1910917	1907168	1906087	1906061	1906061
Oct	1978981	1916387	1909238	1906758	1906061	1906061
Nov	1980922	1916755	1909608	1907402	1906563	1906061
Dec	1989177	1918375	1910528	1907260	1906318	1906061

Other Components Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	179899	143537	140962	139061	138405	138183
Feb	173701	141615	139406	138810	138266	138183
Mar	163734	140805	139459	138446	138183	138183
Apr	159334	139606	138568	138214	138183	138183
May	159147	139654	138490	138183	138183	138183
Jun	154737	138815	138333	138183	138183	138183
Jul	152483	138673	138183	138183	138183	138183
Aug	155867	138850	138324	138183	138183	138183
Sep	163361	140144	138431	138183	138183	138183
Oct	173938	142176	139727	138354	138183	138183
Nov	175077	142771	140124	139079	138360	138183
Dec	177343	143415	140749	138675	138235	138183

Other Components Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	43534	13777	13099	12989	12989	12989
Feb	37525	13375	12989	12989	12989	12989
Mar	29556	13171	12989	12989	12989	12989
Apr	26602	12989	12989	12989	12989	12989
May	27471	12989	12989	12989	12989	12989
Jun	23199	12989	12989	12989	12989	12989
Jul	22370	12989	12989	12989	12989	12989
Aug	24630	12989	12989	12989	12989	12989
Sep	29552	13020	12989	12989	12989	12989
Oct	38872	13446	12989	12989	12989	12989
Nov	38619	13604	13015	12989	12989	12989
Dec	41756	13589	13012	12989	12989	12989

Pitch/ Hyd Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2672347	2603592	2594234	2590983	2589817	2589451
Feb	2660154	2598410	2591977	2590246	2589726	2589432
Mar	2645506	2595000	2591484	2589939	2589580	2589432
Apr	2633114	2592748	2590385	2589533	2589406	2589380
May	2635250	2593240	2590319	2589437	2589380	2589380
Jun	2628836	2591610	2589914	2589557	2589380	2589380
Jul	2620991	2591448	2589603	2589380	2589380	2589380
Aug	2628382	2592020	2589851	2589380	2589380	2589380
Sep	2644294	2594236	2590486	2589406	2589380	2589380
Oct	2662300	2599706	2592557	2590077	2589380	2589380
Nov	2664195	2600073	2592927	2590721	2589882	2589380
Dec	2672496	2601694	2593846	2590579	2589637	2589380

Pitch/ Hyd Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	177412	141698	139377	137731	137198	137101
Feb	171247	139974	138097	137537	137112	137101
Mar	161372	139274	138052	137294	137101	137101
Apr	157160	138179	137349	137101	137101	137101
May	157419	138225	137301	137101	137101	137101
Jun	152775	137604	137198	137101	137101	137101
Jul	150925	137447	137101	137101	137101	137101
Aug	153995	137582	137146	137101	137101	137101
Sep	160878	138586	137308	137101	137101	137101
Oct	171352	140540	138312	137173	137101	137101
Nov	172282	140932	138692	137812	137160	137101
Dec	174855	141275	139189	137429	137101	137101

Pitch/ Hyd Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	47222	15098	13985	13634	13634	13634
Feb	41649	14476	13700	13634	13634	13634
Mar	32400	14203	13691	13634	13634	13634
Apr	28882	13699	13634	13634	13634	13634
May	29794	13731	13634	13634	13634	13634
Jun	25536	13634	13634	13634	13634	13634
Jul	24092	13634	13634	13634	13634	13634
Aug	26805	13634	13634	13634	13634	13634
Sep	31854	13884	13634	13634	13634	13634
Oct	42634	14560	13723	13634	13634	13634
Nov	42042	14806	13873	13634	13634	13634
Dec	46425	14858	13844	13634	13634	13634

Power Supply/ Converter Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2650105	2581262	2571903	2568652	2567487	2567120
Feb	2637915	2576079	2569647	2567915	2567395	2567101
Mar	2623175	2572669	2569153	2567608	2567249	2567101
Apr	2610784	2570418	2568054	2567202	2567075	2567049
May	2612919	2570909	2567988	2567106	2567049	2567049
Jun	2606505	2569279	2567583	2567226	2567049	2567049
Jul	2598660	2569117	2567273	2567049	2567049	2567049
Aug	2606051	2569690	2567521	2567049	2567049	2567049
Sep	2621963	2571905	2568156	2567075	2567049	2567049
Oct	2639969	2577375	2570226	2567746	2567049	2567049
Nov	2641910	2577743	2570596	2568390	2567551	2567049
Dec	2650228	2579363	2571516	2568249	2567306	2567049

Power Supply/Converter Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	131357	98329	96895	95818	95634	95634
Feb	126197	97212	96044	95699	95634	95634
Mar	116978	96770	96003	95646	95634	95634
Apr	113130	96081	95667	95634	95634	95634
May	113930	96123	95634	95634	95634	95634
Jun	109151	95812	95634	95634	95634	95634
Jul	107645	95771	95634	95634	95634	95634
Aug	110696	95815	95634	95634	95634	95634
Sep	116165	96384	95646	95634	95634	95634
Oct	126923	97481	96206	95634	95634	95634
Nov	126567	97788	96393	95933	95634	95634
Dec	129681	97829	96501	95717	95634	95634

Power Supply/ Converter Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	45588	14541	13653	13437	13437	13437
Feb	39712	14040	13437	13437	13437	13437
Mar	31190	13803	13448	13437	13437	13437
Apr	27885	13437	13437	13437	13437	13437
May	28650	13448	13437	13437	13437	13437
Jun	24519	13437	13437	13437	13437	13437
Jul	23417	13437	13437	13437	13437	13437
Aug	25887	13437	13437	13437	13437	13437
Sep	30923	13545	13437	13437	13437	13437
Oct	40418	14098	13437	13437	13437	13437
Nov	40458	14294	13539	13437	13437	13437
Dec	44160	14309	13505	13437	13437	13437

Pumps/ Motors Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	125122	93931	92817	92330	92318	92318
Feb	119991	93239	92446	92318	92318	92318
Mar	111498	92956	92432	92318	92318	92318
Apr	107972	92440	92318	92318	92318	92318
May	108934	92474	92318	92318	92318	92318
Jun	104523	92344	92318	92318	92318	92318
Jul	103112	92318	92318	92318	92318	92318
Aug	105722	92330	92318	92318	92318	92318
Sep	111227	92610	92318	92318	92318	92318
Oct	121013	93370	92481	92318	92318	92318
Nov	120684	93568	92651	92356	92318	92318
Dec	123095	93692	92635	92318	92318	92318

Pumps/ Motors Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	42652	13715	13111	13058	13058	13058
Feb	36919	13369	13058	13058	13058	13058
Mar	28890	13180	13058	13058	13058	13058
Apr	26329	13058	13058	13058	13058	13058
May	27191	13058	13058	13058	13058	13058
Jun	22991	13058	13058	13058	13058	13058
Jul	22126	13058	13058	13058	13058	13058
Aug	24179	13058	13058	13058	13058	13058
Sep	28931	13070	13058	13058	13058	13058
Oct	37879	13418	13058	13058	13058	13058
Nov	37965	13550	13058	13058	13058	13058
Dec	40912	13525	13070	13058	13058	13058

Safety Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	123878	94428	93575	93367	93367	93367
Feb	119199	93887	93367	93367	93367	93367
Mar	111120	93643	93378	93367	93367	93367
Apr	107815	93367	93367	93367	93367	93367
May	108556	93378	93367	93367	93367	93367
Jun	104449	93367	93367	93367	93367	93367
Jul	103347	93367	93367	93367	93367	93367
Aug	105817	93367	93367	93367	93367	93367
Sep	110809	93455	93367	93367	93367	93367
Oct	119831	93983	93367	93367	93367	93367
Nov	119540	94059	93468	93367	93367	93367

Dec	121650	94189	93435	93367	93367	93367

Safety Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	40475	13047	12665	12665	12665	12665
Feb	35156	12803	12665	12665	12665	12665
Mar	27687	12716	12665	12665	12665	12665
Apr	25062	12665	12665	12665	12665	12665
May	26002	12665	12665	12665	12665	12665
Jun	21679	12665	12665	12665	12665	12665
Jul	20974	12665	12665	12665	12665	12665
Aug	22882	12665	12665	12665	12665	12665
Sep	27305	12665	12665	12665	12665	12665
Oct	35917	12868	12665	12665	12665	12665
Nov	36306	12938	12665	12665	12665	12665
Dec	38692	12913	12665	12665	12665	12665

Sensors Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	122038	93133	92393	92244	92244	92244
Feb	117457	92682	92244	92244	92244	92244
Mar	109434	92440	92244	92244	92244	92244
Apr	106205	92244	92244	92244	92244	92244
May	107085	92244	92244	92244	92244	92244
Jun	102909	92244	92244	92244	92244	92244
Jul	101904	92244	92244	92244	92244	92244
Aug	104419	92244	92244	92244	92244	92244
Sep	109224	92286	92244	92244	92244	92244
Oct	117788	92759	92244	92244	92244	92244
Nov	117765	92862	92296	92244	92244	92244
Dec	119580	92926	92286	92244	92244	92244

Sensors Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	46111	14787	13772	13513	13513	13513
Feb	40698	14209	13544	13513	13513	13513
Mar	31799	13975	13562	13513	13513	13513
Apr	28243	13544	13513	13513	13513	13513
May	29184	13565	13513	13513	13513	13513
Jun	25039	13513	13513	13513	13513	13513
Jul	23747	13513	13513	13513	13513	13513
Aug	26401	13513	13513	13513	13513	13513
Sep	31396	13679	13513	13513	13513	13513
Oct	41452	14287	13559	13513	13513	13513
Nov	41203	14500	13679	13513	13513	13513
Dec	45469	14508	13645	13513	13513	13513

Service Items Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	45428	14381	13493	13277	13277	13277
Feb	39552	13880	13277	13277	13277	13277
Mar	31030	13643	13288	13277	13277	13277
Apr	27725	13277	13277	13277	13277	13277
May	28490	13288	13277	13277	13277	13277
Jun	24359	13277	13277	13277	13277	13277
Jul	23257	13277	13277	13277	13277	13277
Aug	25727	13277	13277	13277	13277	13277
Sep	30763	13385	13277	13277	13277	13277

Oct	40258	13938	13277	13277	13277	13277
Nov	40298	14134	13379	13277	13277	13277
Dec	44000	14149	13345	13277	13277	13277

Tower/ Foundation Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	116507	90197	89870	89870	89870	89870
Feb	112047	89987	89870	89870	89870	89870
Mar	104892	89882	89870	89870	89870	89870
Apr	102267	89870	89870	89870	89870	89870
May	103202	89870	89870	89870	89870	89870
Jun	98884	89870	89870	89870	89870	89870
Jul	98179	89870	89870	89870	89870	89870
Aug	100087	89870	89870	89870	89870	89870
Sep	104510	89870	89870	89870	89870	89870
Oct	112568	90037	89870	89870	89870	89870
Nov	112406	90087	89870	89870	89870	89870
Dec	114195	90091	89870	89870	89870	89870

Tower/ Foundation Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	44167	14410	13732	13622	13622	13622
Feb	38190	14009	13622	13622	13622	13622
Mar	30189	13804	13622	13622	13622	13622
Apr	27235	13622	13622	13622	13622	13622
May	28104	13622	13622	13622	13622	13622
Jun	23832	13622	13622	13622	13622	13622
Jul	23003	13622	13622	13622	13622	13622
Aug	25263	13622	13622	13622	13622	13622
Sep	30185	13653	13622	13622	13622	13622
Oct	39506	14079	13622	13622	13622	13622
Nov	39252	14237	13649	13622	13622	13622
Dec	42389	14222	13645	13622	13622	13622

Transformer Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2492520	2423994	2414635	2411384	2410219	2409852
Feb	2480555	2418811	2412379	2410647	2410127	2409833
Mar	2465907	2415401	2411885	2410340	2409982	2409833
Apr	2453516	2413150	2410786	2409934	2409807	2409781
May	2455651	2413641	2410720	2409838	2409781	2409781
Jun	2449237	2412011	2410315	2409958	2409781	2409781
Jul	2441392	2411849	2410005	2409781	2409781	2409781
Aug	2448783	2412422	2410253	2409781	2409781	2409781
Sep	2464695	2414637	2410888	2409807	2409781	2409781
Oct	2482701	2420107	2412958	2410478	2409781	2409781
Nov	2484371	2420475	2413328	2411122	2410283	2409781
Dec	2492897	2422095	2414248	2410981	2410039	2409781

Transformer Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	45761	14714	13825	13609	13609	13609
Feb	39884	14212	13609	13609	13609	13609
Mar	31362	13975	13621	13609	13609	13609
Apr	28057	13609	13609	13609	13609	13609
May	28823	13621	13609	13609	13609	13609
Jun	24691	13609	13609	13609	13609	13609
Jul	23590	13609	13609	13609	13609	13609

Aug	26060	13609	13609	13609	13609	13609
Sep	31095	13717	13609	13609	13609	13609
Oct	40591	14271	13609	13609	13609	13609
Nov	40655	14467	13711	13609	13609	13609
Dec	44332	14481	13677	13609	13609	13609

Yaw System Replacement	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	2362601	2293793	2284435	2281184	2280018	2279652
Feb	2350415	2288611	2282178	2280447	2279927	2279633
Mar	2335707	2285201	2281685	2280140	2279781	2279633
Apr	2323315	2282949	2280586	2279734	2279607	2279581
May	2325451	2283441	2280520	2279638	2279581	2279581
Jun	2319037	2281811	2280115	2279758	2279581	2279581
Jul	2311192	2281649	2279805	2279581	2279581	2279581
Aug	2318583	2282222	2280052	2279581	2279581	2279581
Sep	2334495	2284437	2280688	2279607	2279581	2279581
Oct	2352501	2289907	2282758	2280278	2279581	2279581
Nov	2354442	2290275	2283128	2280922	2280083	2279581
Dec	2362697	2291895	2284048	2280780	2279838	2279581

Yaw System Major Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	178705	142867	140285	138608	138011	137857
Feb	172723	141149	138965	138400	137895	137857
Mar	162688	140284	138946	138104	137857	137857
Apr	158484	139110	138151	137868	137857	137857
May	158492	139146	138107	137857	137857	137857
Jun	153986	138416	137992	137857	137857	137857
Jul	152034	138257	137857	137857	137857	137857
Aug	155169	138446	137935	137857	137857	137857
Sep	162432	139522	138102	137857	137857	137857
Oct	172795	141594	139219	137954	137857	137857
Nov	174080	142079	139623	138661	137973	137857
Dec	176229	142515	140219	138275	137883	137857

Yaw System Minor Repair	Total Cost CM [€]	Total Cost PdM1 [€]	Total Cost PdM2 [€]	Total Cost PdM3 [€]	Total Cost PdM4 [€]	Total Cost PdM5 [€]
Jan	43765	14008	13330	13220	13220	13220
Feb	37767	13606	13220	13220	13220	13220
Mar	29787	13402	13220	13220	13220	13220
Apr	26833	13220	13220	13220	13220	13220
May	27702	13220	13220	13220	13220	13220
Jun	23430	13220	13220	13220	13220	13220
Jul	22601	13220	13220	13220	13220	13220
Aug	24861	13220	13220	13220	13220	13220
Sep	29783	13251	13220	13220	13220	13220
Oct	39103	13677	13220	13220	13220	13220
Nov	38850	13835	13246	13220	13220	13220
Dec	41987	13820	13243	13220	13220	13220