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Economic Evaluation of Maintenance Strategies for Offshore Wind Turbines Based on Condition Monitoring Systems

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Abstract

An offshore wind farm's cost of energy is, to a large extent, driven by operation and maintenance costs. Through the optimization of the maintenance strategies for offshore wind farms, the Levelized Cost of Energy (LCOE) will be further reduced, which will *ceteris paribus* lead to a higher competitiveness of offshore wind farms with other energy sources. This study proposes an event-based simulation of an offshore wind farm comprising 400 MW. The aim of the model is to minimize the total cost, and thus to maximize the revenues from the wind farm. Therefore, corrective, condition-based, and scheduled maintenance strategies are compared, and constraints, such as weather conditions and service team shifts, are taken into consideration. When hourly electricity spot prices are applied instead of feed-in tariffs, results show that weekly scheduled maintenance on a Saturday dayshift (starting at 8 am) is the most cost-efficient scenario. Condition monitoring systems have been found to be advantageous and are set as a standard application regarding the turbines. The impact of scheduled maintenance frequency, the distance between the offshore site and the coast, the interest rate, and altering reliability data are further analyzed.

Keywords: Offshore wind; Predictive maintenance strategy; LCOE; Condition monitoring

List of Abbreviations

BMWi	Bundesministerium für Wirtschaft und Energie (German Federal Ministry for Economic Affairs and Energy)
CMS	Condition Monitoring System
CTV	Crew Transfer Vessel
DOWEC	Dutch Offshore Wind Energy Converter
DWD	Deutscher Wetterdienst (German Weather Forecast Service)

ECN	Energy Research Center of the Netherlands
EEG	Erneuerbare Energien Gesetz (German Renewable Energies Act)
EPEX	European Power Exchange
FTA	Fault Tree Analysis
GWEC	Global Wind Energy Council
HVAC	Heating, Ventilation, and Air-Conditioning
LCOE	Levelized Cost of Energy
LEANWIND	Logistic Efficiencies and Naval Architecture for Wind Installations with Novel Developments
MTBF	Mean Time Between Failure
NOWIcob	Norwegian Offshore Wind cost and benefit (acronym from the literature)
O&M	Operations and Maintenance
OMCE	Operation and Cost Estimator (acronym from the literature)
OWECOP	Offshore Wind Energy Cost and Potential
PDF	Probability Density Function
SCADA	Supervisory Control Alarm and Data Acquisition

List of Symbols

c_{dr}, c_w	Cost per man-hour of driving / of work
$C_{fix,i}$	Fixed costs
$CF(t)$	Cash flow in period t
$E(w)$	Energy production at wind speed w
$f(t)$	Probability density function at time t
i	Interest rate (discount rate)
$p_{el}(t)$	Sales price of electricity in period t
PV	Present value
t	Time
t_{dr}	Time of the journey to the offshore site
t_{ins}, t_{repl}, t_{rs}	Time needed for inspection / for component replacement / for regular service
$w(t)$	Wind speed in period t
β	Shape parameter (for the Weibull function)
γ	Location parameter (for the Weibull function)
η	Scale parameter (for the Weibull function)
λ	Failure rate
μ	Mean
σ	Scale parameter (for the Rayleigh function)

1. Introduction

The installed capacity of offshore wind worldwide rose to over 12 GW in 2015 (GWEC, March 20, 2017). Due to the governmental commitments to mitigate greenhouse gas emissions and the advantages of offshore wind sites, such as the faster and steadier wind speeds as well as the vast availability of potential sites for new capacity, further growth of offshore wind capacity can be expected.

When analyzing the costs of offshore wind farms there are two main reasons for examining alternative maintenance strategies. With increasing size and capacities of the wind turbines, it becomes more and more important to improve the operation & maintenance (O&M) strategies, since the availability of a wind farm, and thus the hourly profit, already decreases tremendously in the case of the breakdown of one single turbine.

The reform of the German Renewable Energies Act (EEG), which entered into force on January 1, 2017, stipulates a regime change from feed-in tariffs to an auction-based bidding system for capacity, which will lead to a rise in competition (Appunn, 2016; Voss and Madlener, 2017). A marked price drop in the levelized cost of energy (LCOE) could already be observed after an auction system was introduced in the Netherlands and in Denmark, which led to the lowest bid of €60 per MWh for an offshore wind project in Danish waters (Vorrath, 2016).

As O&M costs can account for up to 30% of the total cost of the electricity produced (van Bussel and Schöntag, 1997), it is of great importance to minimize these costs. Therefore, it is crucial to evaluate alternative maintenance strategies for large offshore wind farms in order to identify the most cost-efficient scenario.

Some recent auctions in Germany comprising three projects with a total capacity of 1380 MW have been won by different operators with zero-subsidy bids (Weston, 2017). With the reform of the EEG, wind farm operators will have to market their energy production directly and will receive a market premium. As the market premium is the difference between the bid price and the average monthly spot market price for electricity, the mentioned German projects will not be subsidized. As a result, the operators will be highly dependent on the spot market and it will be necessary to find the optimal maintenance window considering the varying electricity prices.

The objective of this study is to evaluate alternative maintenance strategies in order to identify the most cost-efficient scenario for offshore wind farm operators. Therefore, a simulation model implemented in MATLAB is used. The model simulates a wind farm's performance over the course of 20 years by using the most critical components of the turbines. Considering turbine-specific data (e.g. failure rates and power curve), weather conditions, restrictions for maintenance, and direct and indirect costs, the life-cycle cost and availability are determined. Probability distributions of these are estimated by conducting a Monte Carlo simulation. Moreover, the lowest opportunity costs stemming from lost revenues are determined. Sensitivity analyses are performed to assess the effect of altering maintenance strategies depending on the electricity price development. In addition, the interest rate, varying distance to the shore, deviating reliability data for the turbine components, and the frequency of scheduled maintenance are analyzed. Taking the different output parameters and their probability distributions into account, different maintenance scenarios can be analyzed and conclusions drawn.

Section 2 provides a literature review, also comprising a general description of the typical setup of an offshore wind turbine and an offshore wind farm. Moreover, maintenance is defined in the general and related literature on maintenance optimization for wind turbines, and an introduction to reliability modeling is given. Section 3 explains the model and the input parameters, which include the components selected, weather conditions and economic parameters. Furthermore, different maintenance scenarios are introduced in detail. Results are discussed in section 4 by analyzing probability distributions of four key indicators: availability, O&M costs, opportunity costs, and total costs. Mean values and deviations are compared in order to evaluate the outcome of the simulation model. Section 5 draws conclusions and proposes potential research topics for future work.

2. Literature Review

In order to get an overview of the technology, the following section focuses on the structure of an offshore wind turbine and an offshore wind farm. Afterwards, information on maintenance is given with a focus on offshore maintenance tasks and a general description of classification. Next, the literature on maintenance optimization for wind turbines is examined, and important findings are presented. In the last section, reliability modeling with its theory is introduced.

2.1. Setup of an Offshore Wind Turbine and an Offshore Wind Farm

An offshore wind power plant consists of a foundation, a transition piece, and the turbine. The turbine itself is divided into tower, nacelle, hub, and blades. The nacelle is the core of the turbine, as nearly all components are located in it (for details, see Tchakoua et al., 2014). When the wind blows, the blades rotate and turn the hub, which is connected to the low-speed shaft. The gearbox converts the rotational speed of the low-speed shaft (30-60 rotations per minute, rpm) to the high-speed shaft (1,000-1,800 rpm). The high-speed shaft drives the generator which converts the mechanical energy into electrical energy. A brake is installed to stop the rotor if necessary. This brake can be mechanical, electrical or hydraulic. Furthermore, a pitch system is used to turn blades in or out of the wind in order to control the rotor speed. The yaw system consists of a yaw drive and a yaw motor and orients the nacelle to follow the direction of the wind in the case that the wind direction changes. The control system and the power electronics system control all tasks of the turbine. A heating, ventilation, and air-conditioning (HVAC) system is installed to control the environment of the components, as the turbine is located offshore, which can lead to harsh weather conditions.

In order to install a turbine offshore, different foundation types are available to meet the requirements of the site. An overview of several foundation types can be found in Bailey et al. (2014). The choice of the foundation type depends on the characteristics of the seabed and the water depth. While monopiles and gravity-based concepts are simple to manufacture, the building of jackets is more complex. Moreover, monopiles and jackets need to be hammered into the seabed, which causes noise and vibrations and can have a huge impact on flora and fauna (Bailey et al., 2014). In comparison, a gravity-based foundation is the more sensible solution even though noise mitigation measures are applied nowadays. Floating structures benefit from the omission of the hammering procedure, and operators are more independent of seabed conditions and water depths. As new wind farm locations face farther distances from the coast and are in deeper waters, these foundation types are currently being further developed and tested.

All turbines together make up the wind farm. To harness the produced electricity, the turbines are connected with an offshore substation via 33 kV inter-array cables. As turbines and the electricity produced increase in magnitude, 66 kV cables are considered in new wind farms. The substation converts the voltage from 33 kV up to 155 kV in order to minimize transition losses when transmitting the energy to the converter station. The layout of an offshore wind farm is optimized through the consideration of several aspects: Micro-siting is used to maximize the energy output of the wind farm by minimizing wake effects. Wake effects occur due to aerodynamic interference between the respective turbines. Moreover, the setup of the inter-array cables is analyzed to minimize losses and to guarantee access to all turbines in the case of the failure of a cable. As an example, loops are used so that the energy flow is still connected to the substation when one cable breaks down.

2.2. Introduction to Maintenance

Maintenance comprises all tasks which are necessary to keep a machine in a good working state. While in former times only corrective maintenance was applied after a breakdown due to missing knowledge about the machines, from the 1950s onwards preventive maintenance was introduced in order to prevent downtimes (Pintelon and Parodi-Herz, 2008). However, it did not take long to realize that the lifetime of some components was not yet exhausted and, as a result, that higher costs were occurring by changing components on a regular basis. Therefore, techniques were developed to observe the state of individual components or of the whole machine. With these results, it was possible to perform maintenance on condition-based rules.

2.2.1. Maintenance Classification

The European Standard defines maintenance as the "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function" (DIN EN 13306). Maintenance activities comprise observation and analyses, such as inspection, condition monitoring, compliance test, function check-out, fault diagnosis, and fault localization, as well as active maintenance, e.g. routine maintenance, overhaul, restoration, repair, temporary repair, improvement, modification, rebuilding, modernization, and exceptional maintenance. Moreover, maintenance task preparation and maintenance scheduling are part of maintenance as well.

Maintenance can be divided into scheduled and unscheduled maintenance, which leads to different maintenance strategies, as shown in Figure 1.

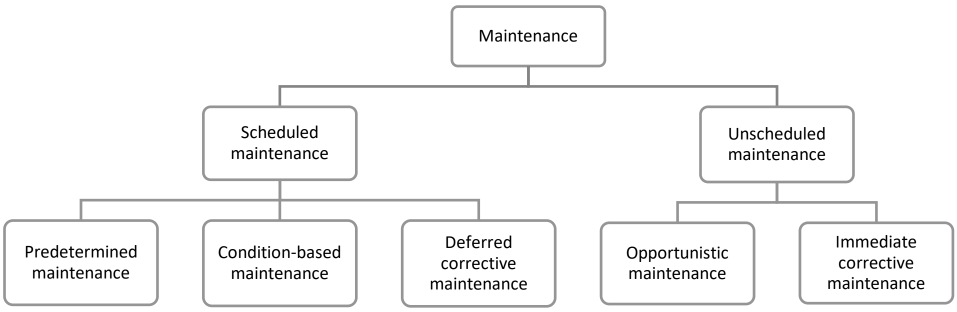

Figure 1: Maintenance Classification

Source: DIN EN 13306

While scheduled maintenance is performed on a regular basis, unscheduled maintenance is performed either after an occurred failure, which leads to corrective maintenance, or as opportunistic maintenance. Scheduled services, inspections, repairs, and replacements are referred to as "preventive maintenance". The objective of preventive maintenance is to have fewer breakdowns. In the case of the ability to observe the state of components, condition-based maintenance can be performed. This may result in significant advantages, because unnecessary downtimes and costs stemming from lost production and costs for exchanged components can be avoided.

2.2.2. Offshore Maintenance

Performing maintenance offshore is notably more difficult than it is for onshore wind farms. This has several reasons: First, logistics are more difficult to schedule, because various constraints, such as suitable vessel types and service teams, as well as longer lead times for major components, need to be considered. Second, offshore operations are dependent on weather conditions. While the vessels are restricted by maximum wave heights, crane operations can only be performed at low wind speeds. As a result, different maintenance tasks have different requirements. Third, depending on the site and its distance from the coast, long travel times occur, since the vessel speed for a jack-up vessel, which is needed for major component changes, is only 12 knots (Bakken Sperstad et al, 2016). Fourth, offshore maintenance faces high costs. Dependent on the required vessel type and the existing contract between operator and ship owner, the day rate for a jack-up vessel can vary between € 77,400 and € 297,000 (Yang, 2016). Fifth, offshore wind turbines are bigger than onshore turbines, and the development leads to bigger and more efficient turbines with every upgrade. As a result, we can expect 10+X MW turbines in the near future.

2.3. Literature on Maintenance Optimization for Wind Turbines

The optimization of O&M strategies was identified as an important task. As a result, there are many papers available which focus on different aspects of O&M, or on O&M as a whole. While methods can be categorized into qualitative and quantitative, many quantitative methods are realized by either mathematical optimization modeling or an event-based stochastic approach.

Hofmann (2011) gives a thorough overview of existing simulation models. He presents 49 different models, which are categorized into application means. He points out that only few models simulate the whole lifecycle of an offshore wind farm and that there is no existing model which takes all necessary aspects into account. Nevertheless, he mentions detailed tools which estimate the total cost by covering important aspects, and he ranks the Dutch Offshore Wind Energy Converter (DOWEC) and the Offshore Wind Energy Cost and Potential (OWECOP) model as the most favorable ones. These models were developed by the Energy Research Center of the Netherlands (ECN), which also proposed the Operation and Cost Estimator (OMCE) model. Furthermore, Hofmann and Bakken Sperstad (2013) present the Norwegian Offshore Wind cost and benefit (NOWIcob) model, which assesses the maintenance costs of offshore wind farms and can be found in several other studies.

Via the application of simulation models, many studies have been conducted to quantify the usage of condition monitoring systems (CMS) (Kerres et al., 2015; Wiggelinkhuizen et al., 2008; McMillan and Ault, 2007; Nilsson and Bertling, 2007; García Márquez et al., 2012; van de Pieterman et al., 2011). Kerres et al. (2015) developed a stochastic model to assess the life-cycle costs and availability of 600 kW onshore turbines. They concluded that CMS are not beneficial for small-scale onshore wind turbines. However, they highlighted that CMS might be favorable for turbines with a higher capacity. It is assumed that CMS for offshore turbines have big advantages, since long-term maintenance planning is difficult in the case of adverse weather conditions and the presence of logistic constraints. Tavner et al. (2009) investigated the correlation between number of failures and turbine size by examining the failure rates of different sized onshore turbines over a period of eleven years. They concluded that bigger turbines have higher failure rates.

Wiggelinkhuizen et al. (2008) performed an assessment of different CMS in a small project with five turbines. They look into whether CMS provide sufficient data to change the maintenance strategy partly from corrective and scheduled maintenance to a condition-based strategy, and find that the CMS provide quite reliable data. However, McMillan and Ault (2007) emphasize in their study on quantifying the benefits of CMS for 5 MW offshore turbines that the assumption of highly reliable CMS was made in many studies. Thus, the effect of the failure rate of CMS on the maintenance strategy needs to be investigated as well, in order to identify the most applicable scenario in a realistic set-up. They find that the CMS must be reliable in circa 60% to 80% of all notifications in order to be cost-efficient.

Nilsson and Bertling (2007) analyze the benefit of CMS for a single turbine onshore and a wind farm offshore. They conclude that CMS are beneficial for offshore wind farms and that the farm's availability needs to be increased by only 0.43% in order to reduce the opportunity cost and to cover the CMS' costs.

García Márquez et al. (2012) analyze the applicability of different maintenance strategies using CMS, and they perform a fault tree analysis (FTA) to identify impacts which lead to turbine failures. While most studies focus on turbine components and their failure rates, van de Pieterman et al. (2011) do not distinguish between special components when using the OMCE.

Other studies focus on the optimization of logistics. Bakken Sperstad et al. (2016) investigate timing and selection of transportation means and proposed pre-determined jack-up vessel campaigns.

Furthermore, as the first floating wind farm (Hywind Scotland) will be commissioned in 2017 after several test sites had been analyzed, studies on floating wind turbines can now be found. Myhr et al. (2014) compared floating with bottom-fixed turbines and considered different maintenance strategies. Laura and Vincente (2014) assessed the life-cycle cost for floating offshore wind farms.

In comparison, mathematical models are less common in the literature, and only few studies are accessible. Besnard et al. (2013) compare different transportation means, such as transfer vessels and a helicopter, using a mathematical model. Byon et al. (2010) give numerical solutions for an O&M decision model under stochastic weather conditions by quantifying risks and uncertainties.

Mazidi et al. (2017) assess strategies by taking a deregulated power system into account and using a mathematical profit-maximization approach. They conclude that profit maximization is given by considering the market with its constantly varying electricity prices.

2.4. Reliability Modeling

Reliability is defined by the European Standard as the "ability of an item to perform a required function under given conditions for a given time interval" (DIN EN 13306). Reliability modeling is used to model failure rates which are based on observations. Different probability functions can be used, and the most important failure distributions will be examined in subsection 2.4.1 by introducing the concept of the Bathtub Curve.

2.4.1. The Bathtub Curve

The lifetime of components can be described using the qualitative graph of the Bathtub Curve (Figure 2). It represents the relative failure rate of a complete population of components and not only of an individual component, which results from combining the curves of early failures, constant failure rate, and wear-out failures.

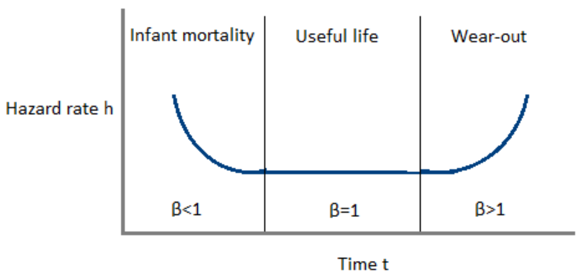

Figure2: The Bathtub Curve

Source: Wilkins (2002)

The Bathtub Curve comprises three sections. Infant Mortality, with a decreasing failure rate, describes failures which occur shortly after installation. These failures are caused by defective design or assembly. This is highly unsatisfactory, as the customer is upset and warranty expense is needed (Wilkins, 2002). Infant Mortality is followed by a period called Useful Life. It has a relatively low and constant failure rate. This period is the most preferable. The third and last period is called Wear-out and is characterized by an increasing failure rate. Failures within this period are caused by fatigue of materials (Wilkins, 2002).

For simulating the failure distributions in all three periods of the Bathtub Curve, a Weibull distribution may be used. It can be described with its general probability density function (PDF):

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

where $f(t) \geq 0, t \geq 0 \; or \; \gamma, \beta > 0, \eta > 0, -\infty < \gamma < \infty$, and β is the shape parameter, η is the scale parameter, and γ is the location parameter.

However, in most cases, the location parameter is not used, as it is responsible for shifting the distribution along the abscissa, which is not favorable when mapping the distribution on the time axis. Therefore, the PDF is reduced from a three-parameter to a two-parameter Weibull distribution:

$$\boldsymbol{f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} \; e^{-\left(\frac{t}{\eta}\right)^{\beta}}}. \tag{2}$$

The scale parameter η determines the time in which a given portion (mostly 63.2%) will fail. The shape parameter β makes it possible to adjust the Weibull distribution to all three periods of the Bathtub Curve. For a decreasing failure rate, such as in the Infant Mortality phase, the shape parameter is less than 1 ($\beta < 1$). For the constant failure rate during the Useful Life period, beta is equal to 1 ($\beta = 1$) and in the Wear-out phase, which is characterized by the increasing failure rate, beta is greater than 1 ($\beta > 1$).

In the special case of $\beta = 1$, the Weibull distribution is equivalent to the exponential density function:

$$\boldsymbol{f(t) = \lambda \; e^{-(\lambda t)^{\beta}}} \; , \tag{3}$$

where $t \geq 0 \; and \; \lambda = \frac{1}{\eta}$ denotes the failure rate.

Moreover, the failure rate is equivalent to the inverse of the mean time between failure (MTBF).

The exponential equation takes only a constant failure rate into account, which suggests that the probability of failure is the same during the entire lifetime of a component. Therefore, the exponential distribution can only be used during the Useful Life phase. As a result, the Weibull distribution should be preferred when modeling component failures in order to cover all phases of a component’s lifetime (Wilkins, 2002).

3. Model Specification and Parametrization

The model simulates the lifetime of an offshore wind farm in order to evaluate different maintenance strategies. Therefore, it estimates the life-cycle cost and availability of offshore wind turbines based on direct and indirect costs. Direct costs are driven by the costs of spare parts, labor, and logistics, while the indirect costs take the opportunity costs from foregone production output into account. Furthermore, a Monte Carlo simulation is conducted to determine the probability distribution of availability and total cost. Sensitivity analyses are performed to assess the influence of important input parameters. The simulation model is based on a model developed by Kerres et al. (2015). The authors compare maintenance strategies for 600 kW onshore wind turbines and analyze the impact of these on economic factors, such as availability and total cost.

3.1. Wind Turbine Model and Reliability Data

The aim of the wind turbine model is to simulate the turbines as realistically as possible. However, the data given in the literature and the principles of the model need to be considered at the same time. Therefore, the LEANWIND 8 MW reference turbine (Desmond, 2015) is used and modeled as a series connection of the most critical components. In the following subsections, the concept and implemented data are presented.

3.1.1. Wind Turbine Component Model

The most important components of a turbine are identified and implemented as a serial connection in order to model the offshore turbine. This implies that as soon as one component fails, the whole turbine will be unavailable. The turbine components can either deteriorate according to binary deterioration or as a consequence of delay time deterioration (Kerres et al., 2015). The former deterioration means that the component can have two different states: either the component is available and functional or a failure has occurred and the component cannot be used any longer. In comparison, delay time deterioration has a further state, which is called ‘defective’ and is between ‘good’ and ‘failed’. In such a state, minor defects can be observed and used as an indicator of an impending failure. However, the component still has the ability to fulfill its function.

3.1.2. Reliability Data

A thorough literature review has been performed to examine several turbine components and to find suitable components and input data for the model. While many statistics of failure causes and turbine downtime due to component failures are available, appropriate input data for the model are hard to find. Therefore, an expert interview with an offshore wind farm operator has been conducted to decide on suitable data.

First, the most critical components need to be identified. Therefore, two different aspects need to be considered. On the one hand, reasons for wind turbine failures are analyzed in order to get an impression of the reliability of components. Thus, a distribution of reasons for wind turbine failures, which is based on data from a study conducted by Tavner et al. (2006) by examining Danish and German wind farms, is used. It can be identified that electrics and electronics are responsible for 33% of failures. Other important components are hydraulics (13%), blades (9%), gearbox (9%), pitch mechanism (8%), and generator (6%).

On the other hand, the downtime of a turbine needs to be evaluated with regard to its causes. Therefore, a wind turbine downtime distribution based on Winstats (2004) is analyzed. Taking a look at the downtime distribution, it can be observed that gearbox (24%), generator (18%), main shaft/ bearing (17%), and rotor (16%) are the most critical components with regard to the downtime of a wind turbine. An expert interview with a German wind farm operator in May 2017 confirms that the replacing of gearbox or generator is associated with high costs due to component costs, long lead times and difficult replacement operations, because big vessel operations are needed for these large and heavy components. Moreover, it can be observed that the hydraulics, for example, do not have much impact on the downtime of a turbine even if they cause quite a few failures. Therefore, hydraulics can be neglected. Electric systems are only responsible for 2% of the downtime. However, it is worthwhile considering electrics/electronics in the model as well, as these are accountable for most of the failures in a turbine.

Second, reliability data for these components need to be found. To consider the different states of a component's lifetime in the model, a Weibull distribution is used (compare subsection 2.4.1.). Therefore, for each component a shape and a scale parameter are needed. Unfortunately, data in the literature are rare and vary considerably (see Appendix, Table A.1). An expert interview with an offshore wind farm operator has been conducted in order to attain sufficient data. Considering available data (Andrawus, 2008; Kerres et al., 2015; Pazouki et al., 2014; Amayri et al., 2011) and expert opinion, Weibull parameters were set and are summarized in Table 1. Moreover, the deterioration model for each component was determined. While generator, gearbox, and main bearing are considered to be delay time components, the electric system and blades are modeled as instant-fail components, which implies the binary concept. These decisions were made due to the feasibility of observing the state of components when using CMS and SCADA.

Table 1: Model Input Data for the Deterioration Model

Component	**Generator**	**Electric System**	**Main Bearing**	**Gearbox**	**Blades**
Deterioration Model	Delay time	Binary	Delay time	Delay time	Binary
Failure α_f [a]	50	12	24	40	15
β_f [-]	1.11	1.3	1.09	1.05	2.4
Defect α_d [a]	0.81	-	0.81	0.81	-
β_d [-]	1.3	-	1.3	1.3	-

Source: Andrawus (2008); Kerres et al. (2015); Pazouki et al. (2014); Amayri et al. (2011)

3.1.3. Turbine Yield Model

The turbine yield model is implemented in two parts: a power curve and a wind model. The wind model is further described in subsection 3.2. The power curve of the LEANWIND 8 MW reference turbine is used, which is based on published data for the Vestas V164 – 8 MW off-shore turbine (Desmond, 2015). It has a rotor diameter of 164 m and a hub height of 110 m. Furthermore, the rotor speed is defined between 6.3 and 10.5 rpm. The power curve can be seen in Figure 3 and is characterized by a cut-in wind speed of 4 m/s, a rated wind speed of 12.5 m/s, and a cut-out wind speed of 25 m/s. Depending on the wind speed, the rated power output can be determined.

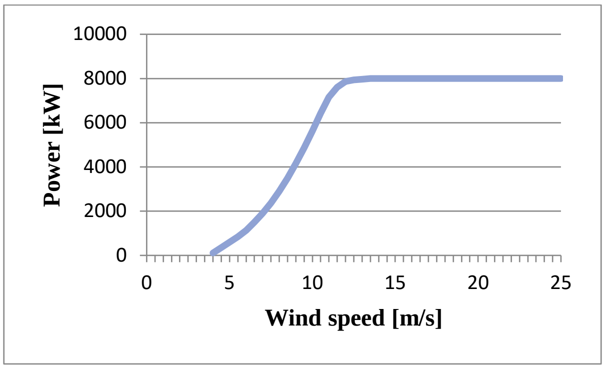

Figure 3: Power Curve of the LEANWIND 8 MW Reference Turbine

With this information and the electricity price, the turbine revenue can be calculated and is shown in subsection 3.4 below.

3.2. Weather Conditions

A wind model is used to simulate the weather conditions at the offshore wind farm. The wind speed model is based on a Rayleigh distribution, which is a special form of the Weibull distribution (cf. subsection 2.4.1.), where the shape parameter is equivalent to two ($\beta = 2$). The Rayleigh distribution is commonly used to model wind speed distributions, and the PDF is defined as

$$\boldsymbol{f(t)} = \frac{\boldsymbol{t}}{\boldsymbol{\sigma^2}} \ \boldsymbol{e}^{-\frac{t^2}{2\sigma^2}}, \tag{4}$$

where $t \geq 0,\ \sigma > 0$ and $\eta^2 = 2\sigma^2$ (to convert from Weibull into Rayleigh form). The mean is given by

$$\boldsymbol{\mu(t)} = \boldsymbol{\sigma}\sqrt{\frac{\boldsymbol{\pi}}{\boldsymbol{2}}}\ , \tag{5}$$

which is needed to calculate the scale parameter σ.

Data on the Fino2 platform, provided by Deutscher Wetterdienst (DWD) are fed into the model. The Fino2 platform is located in Danish Kriegers Flak area of the Baltic Sea, 31 km north of the German island of Rügen. Monthly mean wind speeds in 102.5 m above sea level are available for the period from August 2007 until December 2013 (see Appendix, Fig. A.1) (DWD, 2016).

Rayleigh distributions are common practice for simulating wind data in an easy but efficient way (Seguro and Lambert, 2000). Due to the lack of hourly provided wind speed data for off-shore sites, the monthly mean wind speed was used for the model and a scale parameter σ was calculated. As a result, a Rayleigh distribution was determined for every month (see Appendix, Fig. A.2). Afterwards, for every day of the month a random value chosen from the related Rayleigh distribution was obtained, which was distributed in the range of +/- 30% over the day. This was necessary in order to simulate the wind behavior as realistically as possible, using dependencies on former wind speeds, so that the values do not vary too much from hour to hour. Otherwise, maintenance tasks cannot be performed when the variance between two values is too high. Additionally, it was considered that in German waters, winds are stronger over the day and calmer at night due to the change in solar irradiation. Finally, the determined wind speed data can be used to detect the rated power output by reading out those values in the power curve (see subsection 3.1.3.).

3.3. Service Team, Vessels, and Spare Parts

Well-organized logistics comprising service teams, vessels, and the availability of spare parts are needed in order to perform maintenance. The service team can perform different tasks on-site which are defined as drive, switch on/off, order, regular service, inspect and replace. These tasks can be combined to form one assignment. The total cost of an assignment is driven by several costs for each task, which are summarized in Table 2. The costs involve the time for each task and c_{dr}, the cost per man-hour of driving, c_w, the cost per man-hour of work, and $C_{fix,i}$, the fixed cost of a task in which necessary material is considered. The costs and the time consumption for each task vary for each component. These input parameters for the model are summarized in Table 3 and are based on both a literature review (McMillan and Ault, 2007; Bakken Sperstad et al., 2016) and an expert interview with a German wind farm operator in May 2017.

Table 2: Tasks of the service team

Task	Effect	Time consumption	Turbine available	Cost
Drive	Drive to/from wind farm	t_{dr}	Yes	$2t_{dr}c_{dr}$
Switch on/off	Turbine changes state	0	-	0
Order	Component available after lead time	0	-	0
Regular service	Regular tasks are ful-filled	t_{rs}	No	$2t_{rs}c_w + C_{fix,rs}$
Inspect	Technician knows component state	t_{ins}	No	$2t_{ins}c_w + C_{fix,ins}$
Replace	Component renewed	t_{repl}	No	$2t_{repl}c_w + C_{fix,repl}$

The different service team tasks can be defined as follows: (1) *Drive:* The service team drives to the offshore site using a Crew Transfer Vessel (CTV), which has no impact on the turbine. Costs are incurred by the time which is needed to get to the site. The travel time is calculated by dividing the distance from site to shore by the vessel speed. (2) *Switch on/off:* There are two possible scenarios where the turbine needs to be switched off: Either there is a component failure and the turbine is switched off automatically, or the service team accesses the turbine, which has the consequence that the offline state is mandatory. Although there are no direct costs associated with this task, the downtime will result in opportunity costs of lost production. In either case, the turbine can only be switched on manually. (3) *Order:* Should a spare part not be available, it needs to be ordered. Especially major components have a significant lead time, which can cause quite long downtimes of the turbine. Accruing costs are considered by the cost of the task 'Replace'. (4) *Regular service:* Regular service comprises necessary tasks, such as lubricating moving parts, and retorquing screws, which are performed twice a year. Costs are defined by consumed materials and the man-hours of work. (5) *Inspect:* Inspections are beneficial for components underlying the concept of delay time deterioration. By performing a visual inspection and measuring temperatures and vibrations, minor defects can be found. These can be possibly repaired at lower costs, or the replacement of a component can be scheduled in advance, which leads to shorter downtimes in comparison to an unexpected breakdown (Kerres et al., 2015). (6) *Replace:* The broken component is replaced by a completely new one which has been ordered beforehand. The costs are driven by the procurement of the new component and the replacement time. Moreover, auxiliary logistic items are considered, whose costs are mainly made up of the vessel costs stated in Table 3 as well. While replacement of generator, main bearing, gearbox, or blades requires a jack-up vessel with a day-rate of €140,000, the electric system can be replaced by using a normal CTV with a typical day-rate of €6,200 (Bakken Sperstad et al., 2016). Furthermore, the choice of vessel leads to different installation times. When a jack-up vessel is required, additional time for mobilization and de-mobilization (10 h) and a longer driving time due to the slower jack-up vessel speed are considered.

Table 3: Model Input Data for Component Related Times and Costs

Component	Generator	Electric System	Main Bearing	Gearbox	Blades
t_{ins} [h]	5	2	1	8	12
t_{repl} [h]	24	12	6	24	24
t_{lead} [h]	768	48	768	984	984
$C_{fix,repl}$ [€]	233,803	11,632	107,071	467,606	193,091
$C_{fix,vessel}$ [€]	140,000	6,200	140,000	140,000	140,000

Source: McMillan and Ault (2007); Bakken Sperstad et al. (2016); expert interview

All maintenance tasks are dependent on weather conditions. On the one hand, the vessels have wave height limits and, on the other hand, wind limits, e.g. for crane operations, need to be considered. These restrictions, which are based on a study by McMillan and Ault (2007), are shown in Table 4. If the wind speed is greater than 30 m/s, the service team cannot drive out to the site at all and needs to wait for a better weather window. At wind speeds greater than 20 m/s, it is not allowed to climb turbines (McMillan and Ault, 2007). As a result, regular service, inspections, and replacements cannot be performed. Considering replacements of major components, two different values become important. To replace gearbox, generator, or main bearing, it is necessary to lift the roof of the nacelle due to the component size, which is only possible at wind speeds lower than 10 m/s, whereas replacements of blades are even more wind speed-dependent and can only be performed when the wind speed is lower than 7 m/s. However, to keep the simulation simple and as the storage of postponed events is limited, only two restrictions are implemented: On the one hand, the service team only goes out if the wind speed is lower than 20 m/s, as otherwise they would not be able to perform maintenance anyway. On the other hand, the restrictions for major component changes are simplified to 10 m/s for all components.

Table 4: Maintenance weather constraints (related also to sea state)

Wind speed [m/s]	Restrictions
> 30	No access to site
>20	No climbing turbines
>10	No lifting roof of nacelle
>7	No blade removal

Source: McMillan and Ault (2007)

3.4. Economic Evaluation

The model calculates direct and indirect costs, which are determined by maintenance costs and opportunity costs due to downtimes. The revenue of the turbine, which is also the loss in energy sales during maintenance, is defined as

$$\boldsymbol{CF(t) = E\big(w(t)\big) * \; p_{el}(t),} \tag{6}$$

where $CF(t)$ is the cash flow in period t, $E(w)$ is the energy production at wind speed w, $w(t)$ is the wind speed in period t, and $p_{el}(t)$ is the sales price of electricity in period t.

Moreover, a present value approach is used, as the cash flows occur at different times and need to be made comparable. This can be written as

$$\boldsymbol{PV = \frac{CF(t)}{(1+i)^t},} \tag{7}$$

where PV is the present value, $CF(t)$ is the cash flow in period t, and i is the discount rate per period (Kerres et al., 2015). The Euro's interest rate is set by the European Central Bank. As the interest rate has varied between 1% and 0% since 2012 (TradingEconomics, 2017), for the base case scenario an interest rate of 1% is assumed.

3.5. Electricity Prices

The electricity price is needed to calculate the revenue of the turbine. The electricity price is followed by two different concepts in the model. On the one hand, maintenance scenarios are evaluated using a fixed feed-in compensation, as defined by the German Renewable Energies Act (EEG). On the other hand, uncertain revenues are considered when using the European Power Exchange's (EPEX) electricity spot price.

3.5.1. Fixed Feed-In Compensation

The German Renewable Energies Act (EEG) defines compensation regimes for offshore wind farms. These can be divided into two different types for offshore wind farms which are commissioned before January 1, 2020: Either the basic model, which comprises a compensation of 15.4 €-ct/kWh in 2017 (or 14.9 €-ct/kWh in 2018/2019 and 13.9 €-ct/kWh in 2020) for the first twelve years, or the optional compression model, which guarantees a compensation of 19.4 €-

ct/kWh in 2017 (or 18.4 €-ct/kWh in 2018/2019) for the first eight years of the wind farm's lifetime, can be chosen. After these periods have expired, a basic compensation of 3.9 €-ct/kWh is paid (BMWi, April 22, 2017).

For the base case of this model, an offshore wind farm in Germany, which is commissioned in 2020, is considered. Therefore, a compensation of 13.9 €-ct/kWh for the first twelve years and of 3.9 €-ct/kWh for the last eight years of the wind farm's lifetime is applied.

3.5.2. Electricity Spot Prices

Due to the reform of the German Renewable Energies Act (EEG), which entered into force on January 1, 2017 and stipulates a regime change from feed-in tariffs to an auction-based bidding system for capacity, the EPEX electricity spot price is becoming important. Wind farm operators will market their energy production directly and will receive a market premium for wind farms commissioned in 2020 onwards. The market premium is defined as the difference between bid price of the auction and the average monthly spot market price for electricity.

As subsidy-free bids have been handed in and have been accepted already in the first auctions under the new concept (Weston, 2017), only the EPEX electricity spot price without a market premium is considered in this study. We use the hourly mean EPEX electricity spot price for the years 2011 to 2015. For simplicity reasons, we replicate the data set four times to have sufficient data over the 20-year lifetime of the wind farm. In comparison to the fixed feed-in compensation, the mean EPEX electricity spot price between 2011 and 2015 was €39.2 per MWh.

3.6. Maintenance Scenarios

The maintenance scenario defines what tasks the service team will perform in different situations. It is assumed that the service team will react to non-scheduled call-outs after the elapse of a waiting time. This waiting time is set to 48 hours in the base case scenario.

The base case scenario comprises an offshore wind farm with 50 turbines which are located 30 km away from shore. A pure run-to-failure strategy is performed in which only corrective maintenance after a failure has occurred and regular servicing are carried out. Moreover, the EEG with guaranteed feed-in compensation is applied to the base case.

Three other scenarios are compared to the base case. In the first alternative scenario, corrective maintenance and regular servicing are performed as in the base case, and all parameters are still the same. However, instead of using a fixed feed-in compensation, hourly mean EPEX electricity spot prices are applied to the scenario in order to analyze the impact of uncertain revenues.

In the second alternative scenario, called CMS, a CMS is installed in the turbine. It is assumed that the CMS can detect 90% of the defects of generator, gearbox, and main bearing. The time of defect detection is modeled as a random, exponentially distributed variable. The component which causes an alert will be inspected and found to be broken. Afterwards, a new component will be ordered and installed after the lead time has elapsed. This condition-based maintenance strategy is assumed to be standard afterwards, as CMS are regular features in offshore wind turbines nowadays.

In the third alternative scenario, corrective maintenance is replaced by scheduled maintenance which is performed weekly. As the hourly mean EPEX electricity spot prices vary over a day and over a week, maintenance tasks are scheduled at different times over the day (8 am and 11 pm) and over the week (Wednesdays, Saturdays, and Sundays). Additionally, the scenario is conducted once without a surcharge on the technician's hourly wages and once with a night-based and weekend-based surcharge.

3.7. Implementation

An event-based model is implemented in MATLAB, simulating the lifetime of an offshore wind farm. The whole model is based on a model for an onshore wind farm developed by Kerres et al. (2015). A 20-year simulation period is chosen, which is equal to a typical lifetime of a wind farm. The wind farm and the service team are implemented before different maintenance scenarios are applied. For each scenario, the model calculates the availability of the wind farm and the total costs which were incurred due to maintenance tasks. The results are driven by random failure times which are based on the Weibull distributions for each component. To be able to analyze these random results, a Monte Carlo simulation is used. The probability distribution of the results of each scenario is determined by running the turbine life-cycle 1,000 times. 1000 runs are found to be sufficient, because when several data sets are compared, only minor and thus negligible deviations occur. Finally, the O&M costs, the opportunity costs stemming from foregone production output, and the availability are stored in a file, which allows further evaluation.

4. Results and Discussion

Four key indicators are used to evaluate the outcome of each maintenance scenario: (1) availability, (2) operation and maintenance costs, (3) opportunity costs, and (4) total costs. Unavailability is defined as the ratio of the sum of the turbines' offline hours divided by the wind farm's lifetime. The O&M costs are the present value of all maintenance tasks driven by the service team and spare parts. The opportunity costs are the present value of foregone production, which is defined by the turbines’ downtime. The total costs are the sum of the O&M costs and the opportunity costs.

In subsection 4.1, several probability distributions of the key indicators stemming from different maintenance scenarios are compared and analyzed. In subsection 4.2, the mean values are used to evaluate different strategies. Additionally, standard deviations and confidence intervals are used to quantify the quality of the data sets given by the Monte Carlo simulations. Finally, in subsection 4.3., the results are summarized.

4.1. Probability Distribution

4.1.1. Availability and Opportunity Costs

As the turbines’ downtime and its availability are closely related, the probability distributions of the availability and the opportunity costs are linked. However, the distributions vary from each other, since additional factors, such as wind data, electricity price, and discount rates, are considered by calculating the opportunity costs.

The probability distributions for the availability of the EEG base case (Figure 4(a)), the EEG CMS (Figure 4(b)), and the EPEX weekly scheduled scenario (Figure 4(c)) are shown below. In all plots, it can be noticed that the availability is narrowly spread. While the availability of the EEG base case has a lower bound of 97.9% and an upper bound of 98.7%, the boundaries of the CMS scenario are shifted to 98.6% and 99.1%, respectively. That can be explained by better and faster failure recognition when using a CMS. Moreover, it can be observed that for the CMS scenario, the data are less spread than for the base case, as maintenance can be performed more promptly. The plots of the probability distributions for the availability of the EPEX base case and EPEX CMS scenario are nearly the same as for the EEG scenario and can be seen in the Appendix (Fig. A.3).

In comparison, the probability distribution of the availability in the case of weekly scheduled maintenance (Fig. 4(c)) is shifted to the left again. The lower and upper bound are 95.8% and 98.1%, respectively. This is reasonable, as maintenance tasks are conducted only once a week instead of directly after a failure has occurred. Also, the range of availability is wider spread in comparison to the scenarios with corrective maintenance, due to the possibility that maintenance tasks can be performed within one to seven days.

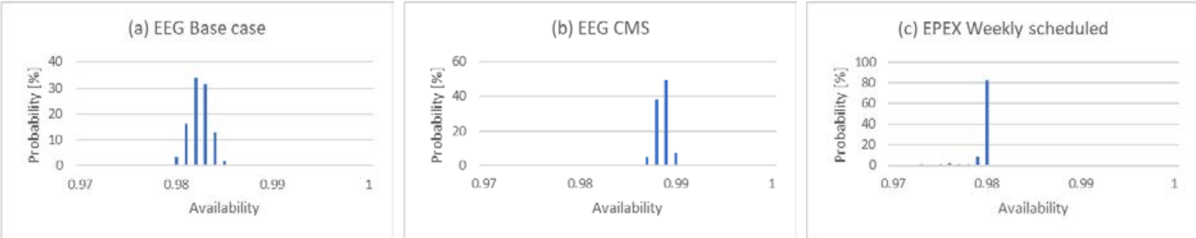

Figure 4: Probability Distribution of the Availability for Different Maintenance Strategies, EEG Base Case (Plot (a)), EEG CMS Scenario (Plot (b)), EPEX Scenario with Weekly Scheduled Maintenance (Plot (c))

The plots of the probability distributions of the opportunity costs are presented in Figs. 5 and 6. As the opportunity costs are linked to the availability, the same trends for the distributions are expected. However, the probability distributions of the different maintenance scenarios differ from each other because further indicators, such as wind data and electricity prices, are considered.

The probability distributions for the EEG scenarios are normally distributed. As the electricity prices are fixed in this scenario, the range of opportunity costs can be explained by the varying wind speeds and the resulting varying production losses. In the base case (Fig. 5(a)), the lower and upper bounds are given at €42 million and €70 million, respectively. In comparison, the normal distribution of the EEG CMS scenario is shifted to the left, with a lower bound of €29 million and an upper bound of €45 million (Fig. 5(b)), respectively. This tendency is expected as the availability increases when using CMS.

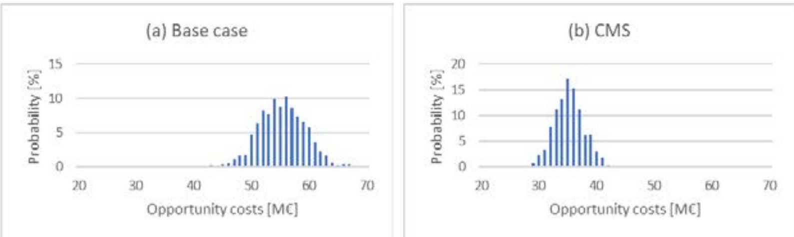

Figure 5: Probability Distribution of the Opportunity Costs for Different EEG Maintenance Strategies, Base Case (Plot (a)), CMS Scenario (Plot (b))

Analyzing the probability distributions of the EPEX scenarios (Fig. 6), the spread of the normal distributions decreases. The center of the distributions shifts towards lower opportunity costs due to lower mean electricity prices in comparison to the EEG feed-in compensation (see subsection 3.5.). While the probability distribution of the opportunity costs of the EPEX base case has lower and upper bounds of 19 and 29 million Euros, the EPEX CMS scenario is characterized by bounds of 13 and 18 million Euros, respectively. The CMS in the EPEX scenario as well as in the EEG scenario leads to less spread opportunity costs, which is associated with the less spread availability of the wind farms.

Discussing the probability distribution of the opportunity costs of the EPEX scenario with weekly scheduled maintenance (Fig. 6(c)), the distribution is barely spread. A peak at €28 million with a probability of 77.7% can be observed. While in the other scenarios maintenance is performed every day in the week, in this case the service team works only once a week at a given day. This leads to quite similar electricity prices at the EPEX spot market and results therefore into similar lost revenues in comparison which explains the different shape of the distribution. Additionally, the higher opportunity costs in this scenario are expected as the availability decreases, when conducting maintenance only once a week.

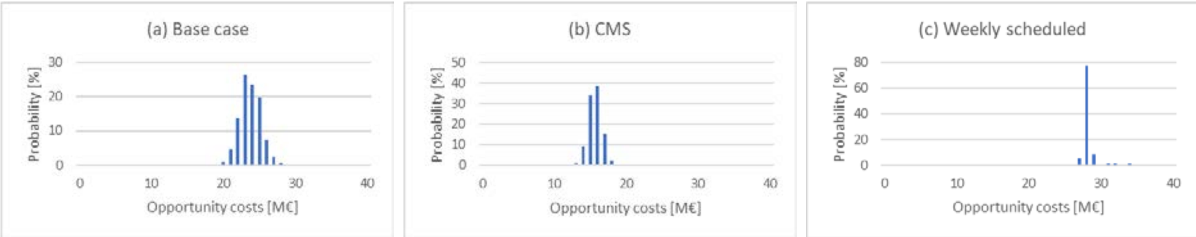

Figure 6: Probability Distribution of the Opportunity Costs for Different EPEX Maintenance Scenarios, Base Case (Plot (a)), CMS Scenario (Plot (b)), Weekly Scheduled Maintenance (Plot (c))

4.1.2. O&M Costs and Total Costs

The probability distributions of the O&M costs and the total costs for the different maintenance scenarios are shown in Fig. 7. The distributions of the EEG and EPEX scenario are nearly the same, since O&M costs are not influenced by the electricity price; the plots of the EEG scenario are attached in the Appendix (Fig. A.4).

The distributions of the O&M costs showing the EPEX base case (Fig. 7(a)) and the CMS scenario (Fig. 7(b)) are very similar with only slightly different bounds. Since the CMS enables better planning of the service team due to alerts, some costs can be saved by repairing components instead of replacing them. However, as O&M costs are defined by costs for the service team and spare parts, it can be concluded that most of the O&M costs stem from service-team-related costs. Otherwise, the CMS would cause significant deviations from the base case. This is quite reasonable when considering the huge effort of maintaining turbines offshore. The costs for the service team include not only the workers' hourly wages but vessel costs as well, which have a huge impact on the O&M costs in total.

This tendency can be observed in the case of weekly scheduled maintenance as well (Fig. 7(c)). The distribution is shifted significantly to lower O&M costs with a peak at €7 million. Instead of going offshore a few times in a week for minor defects, the service team performs maintenance only once a week by concentrating the maintenance actions on this day. Therefore, O&M costs can be saved. Due to fewer opportunities to maintain the turbines, the probability distribution is less spread than the scenarios conducting corrective maintenance.

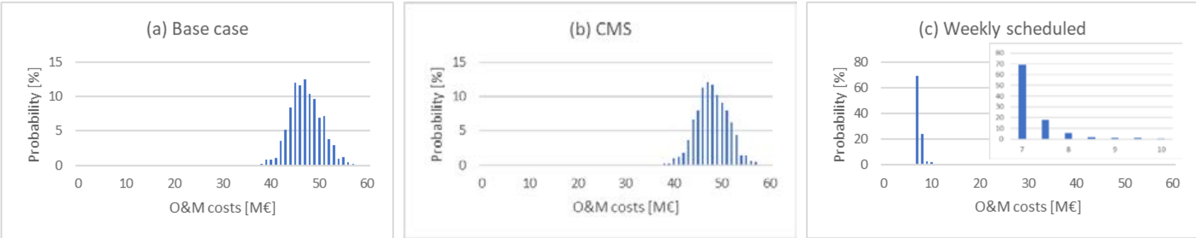

Figure 7: Probability Distribution of the O&M Costs for Different EPEX Maintenance Scenarios, Base Case (Plot (a)), CMS Scenario (Plot (b)), Weekly Scheduled Maintenance (Plot (c))

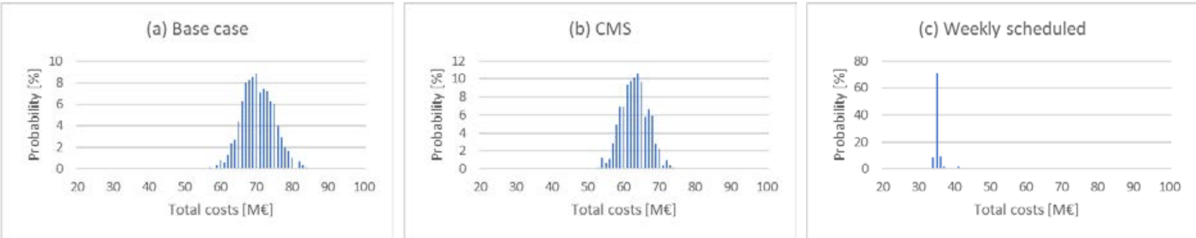

Figure 8: Probability Distribution of the Total Costs for Different EPEX Maintenance Scenarios, Base Case (Plot (a)), CMS Scenario (Plot (b)), Weekly Scheduled Maintenance (Plot (c))

Figure 8 shows the plotted probability distributions of the total costs of the EPEX scenarios. Total costs are composed of the opportunity costs and O&M costs, which were discussed above. For the sake of completeness, the probability distributions of the total costs of the EEG scenarios, which are more widely spread, are reported in the Appendix (see Fig. A.5).

4.2. Mean Value and Deviations

In order to discuss and compare the different maintenance strategies, the probability distributions of availability, opportunity costs, O&M costs, and total costs are assessed by calculating three statistical parameters: the mean value, the standard deviation, and the upper bound of the 95% confidence interval. Since the operator aims for the most efficient maintenance strategy with low risks of unexpected costs, low values of the statistical parameters are preferable.

The base case scenarios considered in subsection 4.1. are analyzed in subsection 4.2.1. In the subsections 4.2.2. to 4.2.6., several sensitivity analyses are discussed. The parameters altered are: the time of scheduled maintenance (4.2.2.), the frequency of scheduled maintenance (4.2.3.), the distance from the site to the shore (4.2.4.), the interest rate for calculating the discount factors (4.2.5.), and the reliability data of the turbine components (4.2.6.).

4.2.1. Base Case Scenarios

The mean value of the availability for the base case scenarios are for corrective maintenance 98.19% and 98.81% when using CMS. Notice that these numbers are the same for the EEG as well as the EPEX scenario as the availability is not dependent on the electricity price. In the case of weekly scheduled maintenance, still using CMS, the availability decreases to 97.94%. These tendencies are reasonable, as a CMS allows better planning of logistics and maintenance tasks, which leads to improved availability.

Nilsson and Bertling (2007) find that an increase in availability of 0.43% is sufficient to cover the CMS' costs by reduced opportunity costs, which they define as the cost of production loss. Since they define opportunity costs in the same way as in our study, comparisons can be made. The improvement of 0.62% from corrective maintenance to the CMS scenario in this case is therefore enough to render the CMS scenario worthwhile.

Switching from corrective to scheduled maintenance results in less availability, as the service team goes offshore only once a week. This implies that failures can be fixed within up to seven days depending on the scheduled maintenance day and when the failure occurs.

For analyzing the costs of the different maintenance scenarios, we need to differentiate between the EEG scenario (Fig. 9(a)) and the EPEX scenario (Fig. 9(b)), because electricity prices have an impact on the opportunity costs. In the case of the EEG scenario, switching from corrective maintenance to CMS leads to lower total costs, as mainly the opportunity costs can be reduced. While in the EEG scenario performing corrective maintenance has higher opportunity costs than O&M costs, the trends change when looking at the EPEX scenario. Due to the lower mean electricity price, the opportunity costs are lower than the O&M costs. This trend increases, as in the EEG scenario as well, when applying the CMS strategy. However, in the case of EPEX electricity prices, the total costs do not decrease as much as in the EEG scenario because the total costs are more driven by the O&M costs.

Comparing the maintenance scenario involving weekly scheduled actions with the CMS scenario, the simulation results differ. On the one hand, O&M costs decrease from €47.4 million to €7.1 million, since the service team (and therefore the vessels) are needed only once a week. On the other hand, opportunity costs nearly double. Since O&M cost savings are immense, the total costs can be decreased overall by 44.67% in comparison to the CMS corrective maintenance scenario. Therefore, it is advantageous to investigate different times and days of the week for performing scheduled maintenance.

Additionally, we found that the total costs of scheduled maintenance increase by €3.7 million if the interest rate is lowered from 1% to 0%. This points out the effect of a decreasing interest rate which can be observed in the last years (TradingEconomics, 2017).

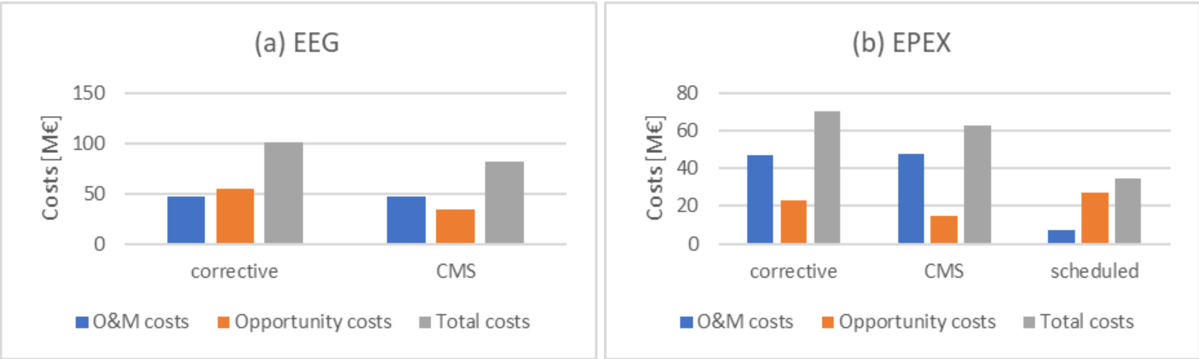

Figure 9: Mean Value of the Costs of Different Maintenance Scenarios, EEG Maintenance Scenarios (Plot (a), EPEX Maintenance Scenarios (Plot (b))

4.2.2. Variation of the Time of Scheduled Maintenance

Figure 10 depicts the cost structure of scheduled maintenance considering different points of time. We distinguish between maintenance on Wednesday, Saturday, and Sunday 8 am and 11 pm, respectively. While the O&M costs are stable in all six cases, opportunity costs differ due to varying average EPEX electricity prices over the day and the week (see Appendix, Figs. A.6 and A.7). For all three days in the week it can be observed that at nights opportunity costs are lower than during daytime. Maintenance scheduled on a Saturday is cheaper compared to maintenance scheduled on a weekday. However, the mean values of the maintenance scenarios on a Sunday are higher than on a Saturday.

To evaluate the quality of the simulation data, the standard deviation and the upper bound of the 95% confidence interval of the opportunity costs are discussed. It is noticeable that the standard deviation (Fig. 11(a)) and the deviation of the upper bound of the 95% confidence interval from the mean value (Fig. 11(b)) are higher during the day and lower during the nights. This is due to more widely varying electricity prices over the day, whereas in the nights the electricity price is more stable. As the maintenance tasks require different time periods depending on the activity, this needs to be considered. Similar results can be found by maintenance scheduled at daytime when comparing a weekday with a weekend day. During the week and the day, the electricity prices vary more than over a day at the weekend. Therefore, the deviations for Wednesday at 8 am are higher than the deviations of Saturday and Sunday. For risk-averse operators and their risk management, smaller deviations are advantageous because the risk is considered during development of the offshore wind farm.

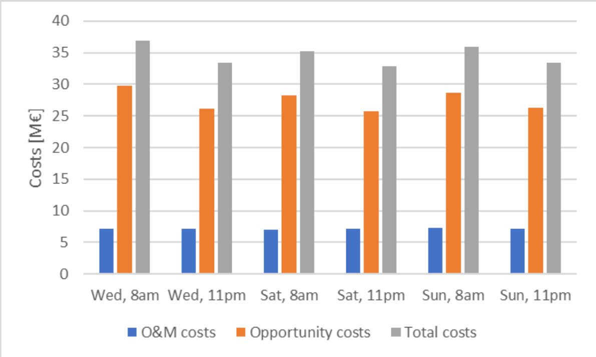

Figure 10: Mean Value of the Costs of Different Weekly Scheduled Maintenance Scenarios

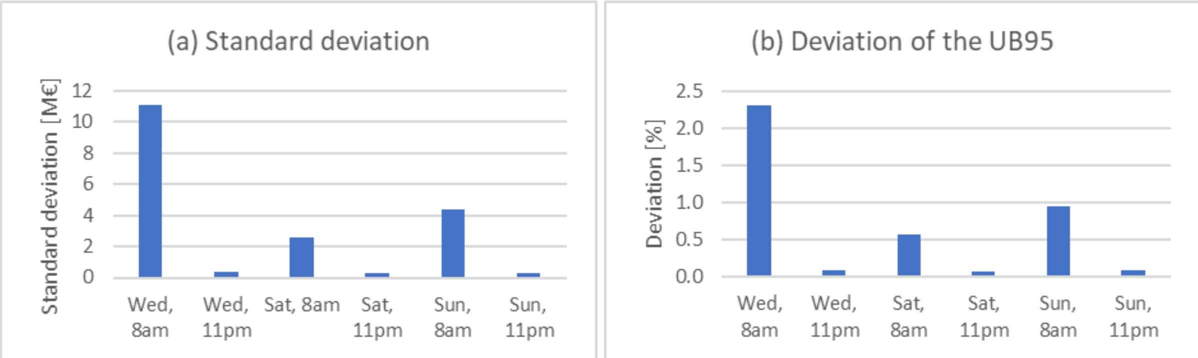

Figure 11: Standard Deviation of the Opportunity Costs of Different Scheduled Maintenance Scenarios (Plot (a)), Deviation of UB95 from Mean Value of the Opportunity Costs of Different Scheduled Maintenance Scenarios (Plot (b))

As it is cost-efficient to perform scheduled maintenance, in a second step, simulations have been conducted which consider night-based surcharge and weekend-based surcharge of the technicians' hourly wages. The German Income Tax Act (§3b EStG) and the Working Hours Act (§2 Arbeitszeitgesetz) define a night-based surcharge of 40% in case the work starts before midnight and a surcharge of 50% for a Sunday. On a Sunday night, these surcharges add up to 90% (Lohn-Info, June 8, 2017). With these numbers, the results shown in Figure 12 were obtained. Thus, scheduled maintenance is most preferable on a Saturday during the daytime followed by Saturday night, which is useful when major component changes take longer than the dayshift. While even with night-based surcharge it is more cost-efficient to perform maintenance during the week at the nightshift, Sundays are not advantageous, as the surcharges result in higher O&M costs which are not outweighed by the low opportunity costs. Therefore, the Saturday dayshift is used as a reference case for the following sensitivity analyses.

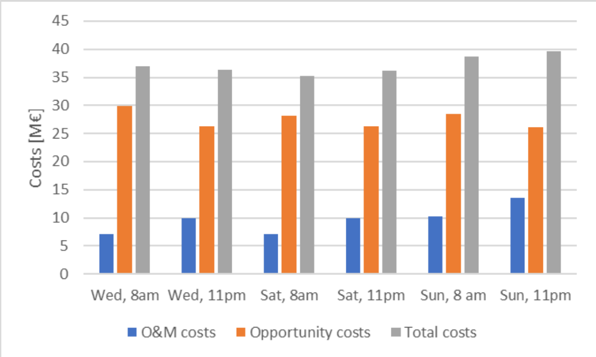

Figure 12: Mean Value of the Costs of Different Weekly Scheduled Maintenance Scenarios Including Surcharge

4.2.3. Variation of the Frequency of Scheduled Maintenance

As the scheduled maintenance scenario becomes profitable in comparison to the CMS scenario due to the decreasing O&M costs, it is reasonable to investigate the frequency of scheduled maintenance. In Figure 13 weekly and biweekly scheduled maintenance is depicted. While the O&M costs drop from €7.1 million to €4.0 million, the opportunity costs rise from 28.2 to 32.1 million Euros. As a result, the total costs are higher when conducting biweekly maintenance. Hence, weekly scheduled maintenance is still preferable even though O&M costs can be saved by sending out the service team fewer times.

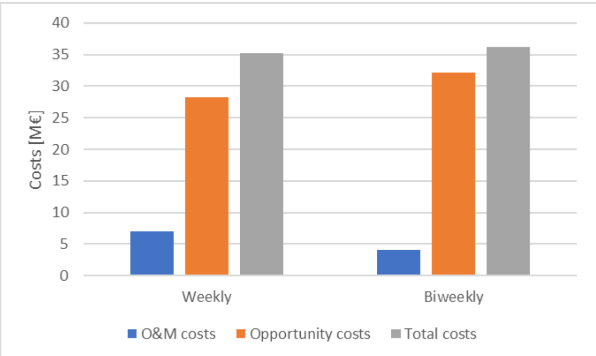

Figure 13: Mean Value of the Costs of Scheduled Maintenance Scenarios with Different Frequencies

4.2.4. Variation of the Distance to the Shore

With a decreasing availability of wind farm sites in shallow waters and improving foundation technology, new wind farms can be located in deeper waters. Consequently, the distance between site and shore increases, and O&M face new challenges. In Figure 14, total costs of scheduled maintenance scenarios are shown for altering distances of 30, 60, and 100 km. In general, the total costs increase the further away the wind farm is located. While the difference from 30 km to 60 km is not too significant, the total costs escalate from €42 million to €103 million when comparing 60 km with 100 km. Longer distances from the coast lead to longer driving times and thus to higher opportunity costs. For example, a standard CTV needs around

45 minutes to reach a windfarm located 30 km away, whereas around 2.5 hours are needed to reach the site 100 km away. Since a jack-up vessel is only half as fast as a standard CTV, time adds up significantly when changing major components (Bakken Sperstad et al., 2016). This can be observed when comparing maintenance campaigns on a Saturday with campaigns on a Wednesday as well. Total costs are nearly the same for 30 km and 60 km. However, a difference of around €3 million can be observed for the site 100 km away. The longer the distance between a wind farm and the coast is, the more weight opportunity costs have, raising total costs.

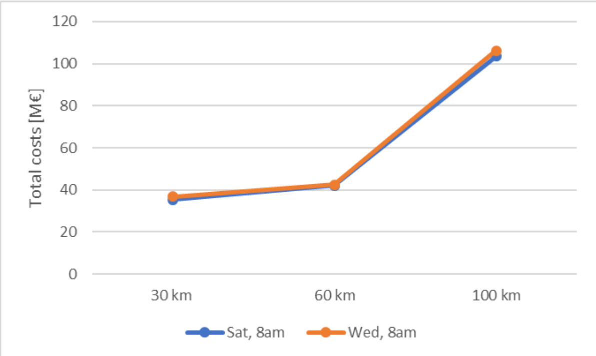

Figure 14: Mean Value of the Total Costs of Maintenance Scenarios with Altering Distances to the Shore

4.2.5. Variation of the Reliability Data of the Turbine Components

The last sensitivity analysis comprises altering reliability data of the turbine components. As reliability data on turbine components in the literature is scarce and an expert interview leads only to indications of numbers because new generation turbines have not been evaluated over the whole lifetime of a wind farm yet (see subsection 3.1.2.), it is necessary to discuss the influence of the components' reliability data on the total costs. Therefore, the scale parameters of the components are varied between -10% and +10%. Results are depicted in Fig. 15. Since the scale parameter α implies that there is a probability of 0.632 that all components for that parameter in the wind farm would have failed within α days (Tavner et al., 2009), a lower α (α – 10%) results in lower availability. Hence, the bigger the scale parameter α is, the higher is the availability of the wind farm. However, it can be observed that the availability and the deviation in comparison to the base case are minimal. The consequences of an altering scale parameter, and thus inaccurate reliability data for the total costs, are depicted. The total costs differ by around €0.5 million, which is equivalent to 1.25% in comparison to the base case.

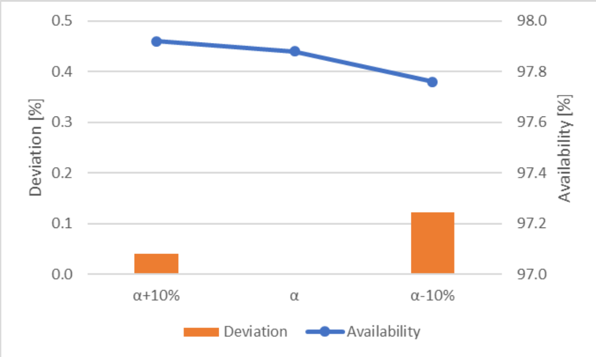

Figure 15: Mean Value and Deviation of the Availability of a Maintenance Scenario with Altering Scale Parameter

4.3. Summary

In this paper, a simulation model is developed to compare different maintenance strategies such as corrective, condition-based, and scheduled maintenance. Corrective maintenance has high total costs due to huge O&M costs stemming from high employment of the service team and the vessel fleet, because maintenance is performed as soon as a component failure occurs. In comparison, condition-based strategies using CMS consist of only slightly higher O&M costs, but opportunity costs can be lowered because of monitored impending failures, which allows repairing or changing components before unnecessary downtimes are caused by long lead times of major components.

As the reform of the German Renewable Energies Act (EEG) has revealed that the fixed feed-in compensation will be replaced by a regime in which wind farm operators will have to market their production directly, consequences for the optimal maintenance strategy were investigated. The O&M costs stayed stable whereas the opportunity costs nearly halved as a result of the lower average electricity price of the EPEX spot market. Hence, the total costs decreased as well.

As the electricity price of the EPEX spot market varies over the week and during the day, it was crucial to analyze maintenance tasks scheduled at different times. Therefore, weekly scheduled maintenance was carried out on three different days of the week (Wednesday, Saturday, and Sunday), evaluating also the difference between dayshift and nightshift. The simulations revealed that opportunity costs nearly double, as the maintenance tasks are deferred up to one week, which leads to longer downtimes and thus higher production losses. However, O&M costs decrease tremendously, mainly due to savings of vessel costs. As a result, scheduled maintenance is the most cost-efficient scenario.

Comparing the possible different times for maintenance, nightshifts especially on a Saturday seemed to be preferable. However, considering night-based and weekend-based surcharge for the hourly wages of the service team, Saturday dayshifts that are followed by Saturday nightshifts are most advantageous. Sundays are least cost-efficient due to high surcharges.

A lower frequency of scheduled maintenance, such as biweekly performed actions, considerably saves O&M costs, but increasing opportunity costs outnumber the savings. Therefore, total costs rise in the case of longer deferred maintenance, and weekly scheduled maintenance remains preferable.

When analyzing the influence of longer distances between offshore site and coast, results show that total costs are the higher the further away the wind farm is located. While the difference between 30 km and 60 km is still bearable, the increase of costs in the case of 100 km distance is immense. Especially O&M costs are accountable for increasing total costs, as offshore employment is dependent on the vessel speed. Additionally, the further away an offshore site is, the more relevant the time of the week becomes, as opportunity costs add up when having longer downtimes.

Furthermore, altering reliability data of the turbines' components were discussed. If the scale parameters of the major components decrease by 10%, which implies that there is a probability of 0.632 that all major components in the wind farm will have failed 10% earlier, total costs increase by around 1.25%.

5. Conclusion and Outlook

By adopting the challenging targets prescribed in the *2030 Climate and Energy Framework* of the EU, as well as the ambitious trend of increasing the share of renewable energy worldwide, offshore wind is a key technology to fulfill these targets. Since the regime switch from feed-in tariffs to an auction-based bidding system for capacity in many European countries, offshore wind is becoming more and more competitive against other energy resources. To enable this process, costs of an offshore wind farm need to be streamlined.

The developed simulation model in this study is a flexible tool for comparing different maintenance strategies in order to give a recommendation for the most cost-efficient scenario. Therefore, O&M costs comprising costs related to the service team, logistics, and spare parts, as well as opportunity costs which stem from foregone production output due to downtimes are calculated. O&M costs and opportunity costs build together the total costs which need to be minimized.

This study focuses on an offshore wind farm with a capacity of 400 MW considering a lifetime of 20 years. Turbines of a capacity of 8 MW are chosen and modeled as a series connection of the most critical components, comprising the generator, the gearbox, the main bearing, the blades, and the electric system. To find the most advantageous strategy, corrective maintenance, condition-based maintenance, and scheduled maintenance scenarios were evaluated.

The results show that with the parameter values assumed, condition-based maintenance is preferable, and that using CMS as standard applications in combination with weekly scheduled maintenance is the most cost-efficient scenario. Further simulations in which hourly mean European Power Exchange (EPEX) electricity spot prices have been applied revealed that Saturday dayshifts are recommended for performing maintenance. Saturday nightshifts and nightshifts on weekdays face higher total costs in comparison but would be still bearable in the case of urgent maintenance tasks. Dayshifts at weekdays and Sundays, regardless of shift, are not preferable. Surcharges for the service team on nightshifts and Sundays have been taken into account. Other important parameters which have an impact on the total costs are the frequency of scheduled maintenance, where weekly actions were found preferable, as increasing opportunity costs outweigh savings in O&M costs, and the distance between offshore site and shore. In the case of wind farms which are located in deeper waters, total costs increase, which needs to be considered in comparison to the higher production output of the wind farm stemming from better winds.

Future work is necessary for challenging some of the assumptions made by this model. Due to the restricted accessibility and availability of reliability data of the turbine's components, estimations have been made only for five major components. In further simulations, more precisely modeled turbines should be applied. Additionally, weather conditions could be modeled more accurately especially focusing on wave heights. It is recognized that the findings of this study may be highly dependent on the assumptions made for the input parameters and thus, should be interpreted with care, although the achieved conclusion seems viable.

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Appendix

Table A.1: Failure Rates Available in the Literature for Selected Components

Component	Failure α_f [a]	β_f [-]	Source
Generator	110	2	Pazouki et al. (2014)
	3300;6600	2	Amayri et al. (2011)
	20699	0.6832	Kerres et al. (2015)
	17541	1.11	Andrawus (2008)
Gearbox	100	3	Pazouki et al. (2014)
	2400;4800	3	Amayri et al. (2011)
	9406	1.3349	Kerres et al. (2015)
	29051	1.05	Andrawus (2008)
Main bearing	125	2	Pazouki et al. (2014)
	3750;7500	2	Amayri et al. (2011)
	3835	1.09	Andrawus (2008)
Electric system	5588	0.6436	Kerres et al. (2015)
Blades	3000;6000	3	Amayri et al. (2011)

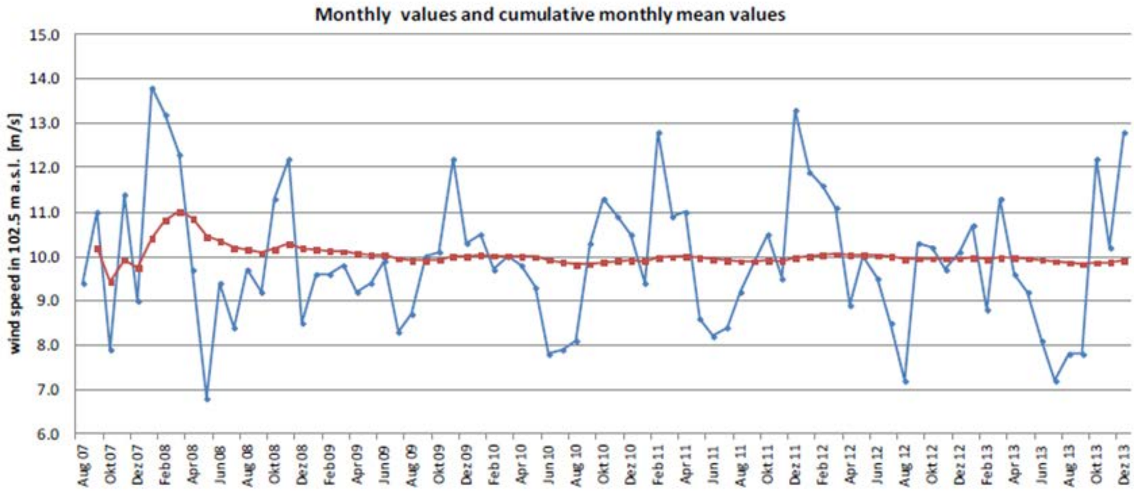

Figure A.1: Monthly Values of the Wind Speed at Fino 2

Source: Own illustration, based on data from DWD (2016)

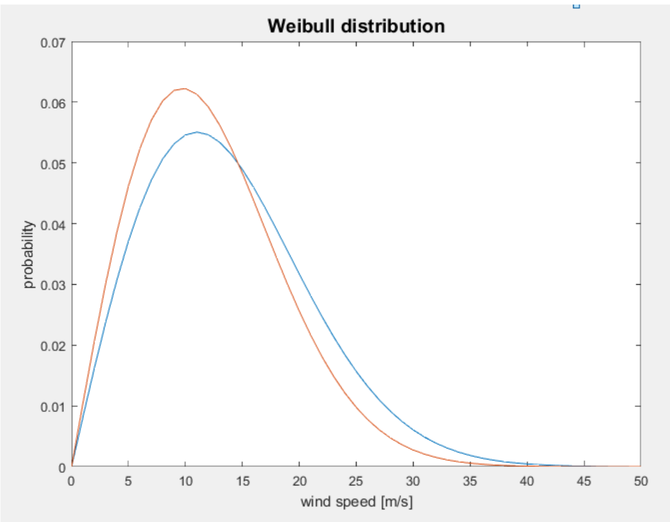

Figure A.2: Rayleigh Distributions of the Wind Speed

Source: Own illustration, based on data from DWD (2016)

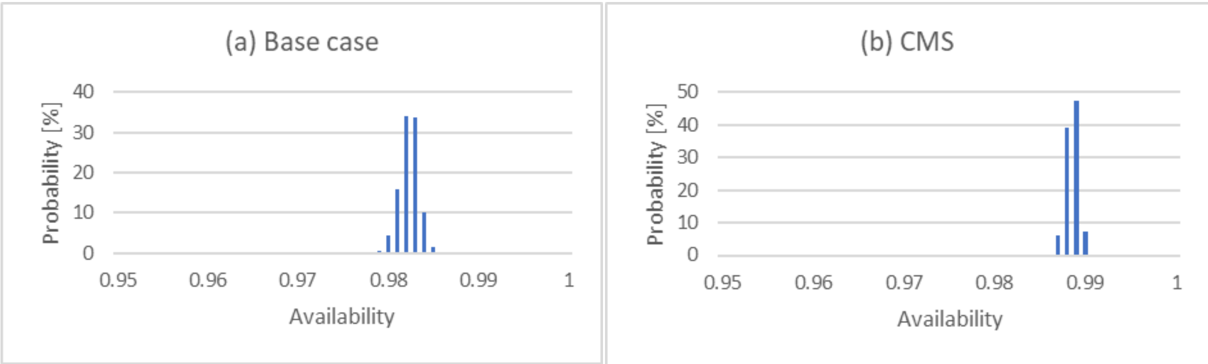

Figure A.3: Probability Distribution of the Availability for Different EPEX Maintenance Scenarios, Base Case (Plot (a)), CMS Scenario (Plot (b))

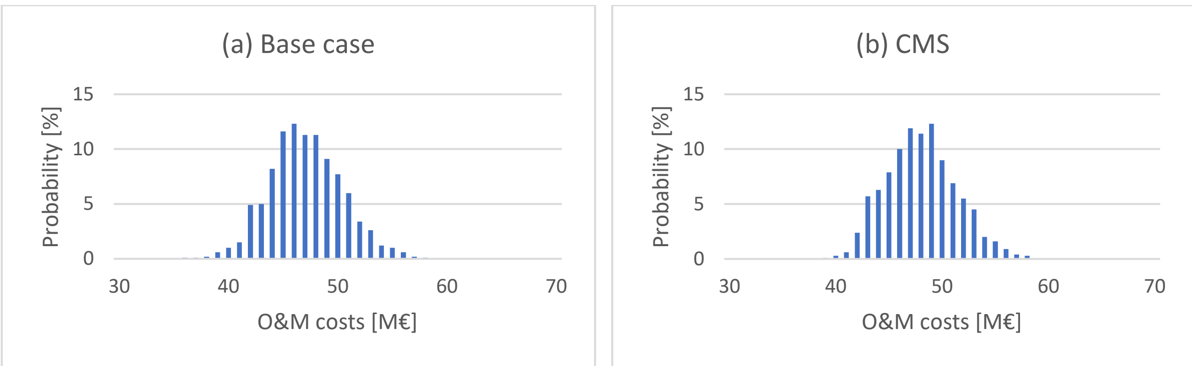

Figure A.4: Probability Distribution of the O&M Costs for Different EEG Maintenance Scenarios, Base Case (Plot (a)), CMS Scenario (Plot (b))

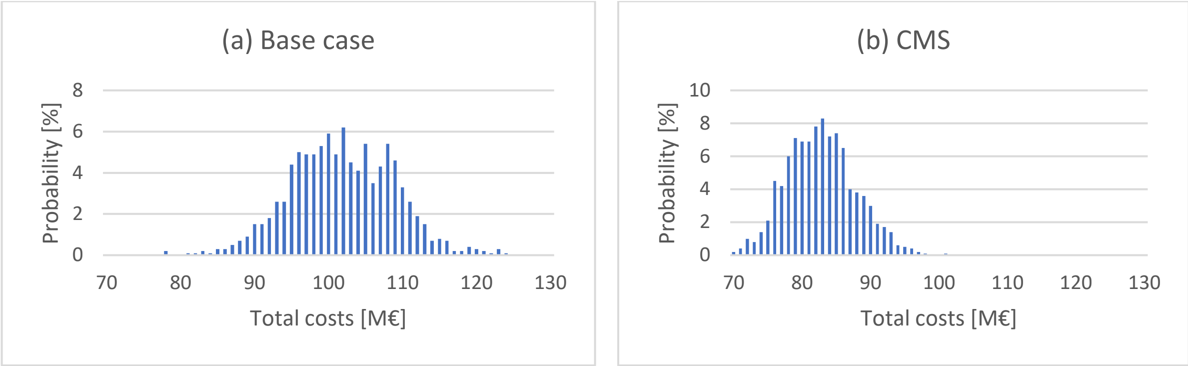

Figure A.5: Probability Distribution of the Total Costs for Different EEG Maintenance Scenarios, Base Case (Plot (a)), CMS Scenario (Plot (b))

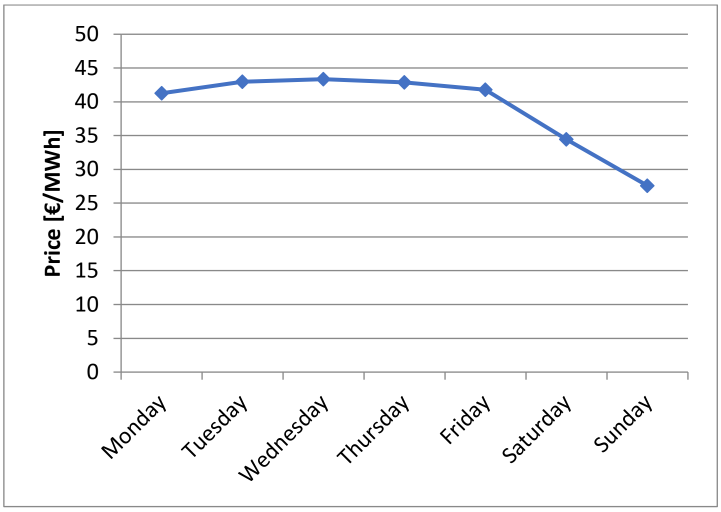

Figure A.6: Average EPEX Electricity Spot Price over a Week

Source: Own illustration, based on data from EPEX Spot SE

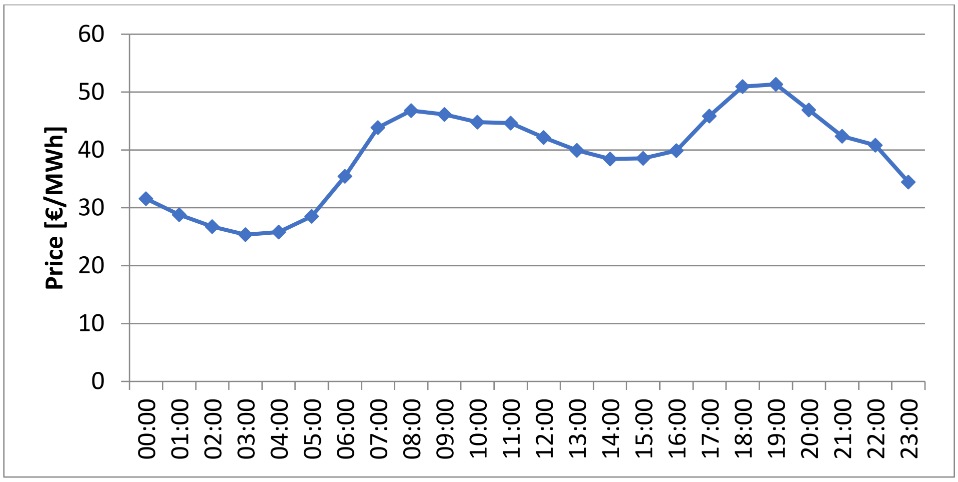

Figure A.7: Average EPEX Electricity Spot Price over a Day

Source: Own illustration, based on data from EPEX Spot SE

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