Major interventions in offshore wind

Predicting the cost of future maintenance

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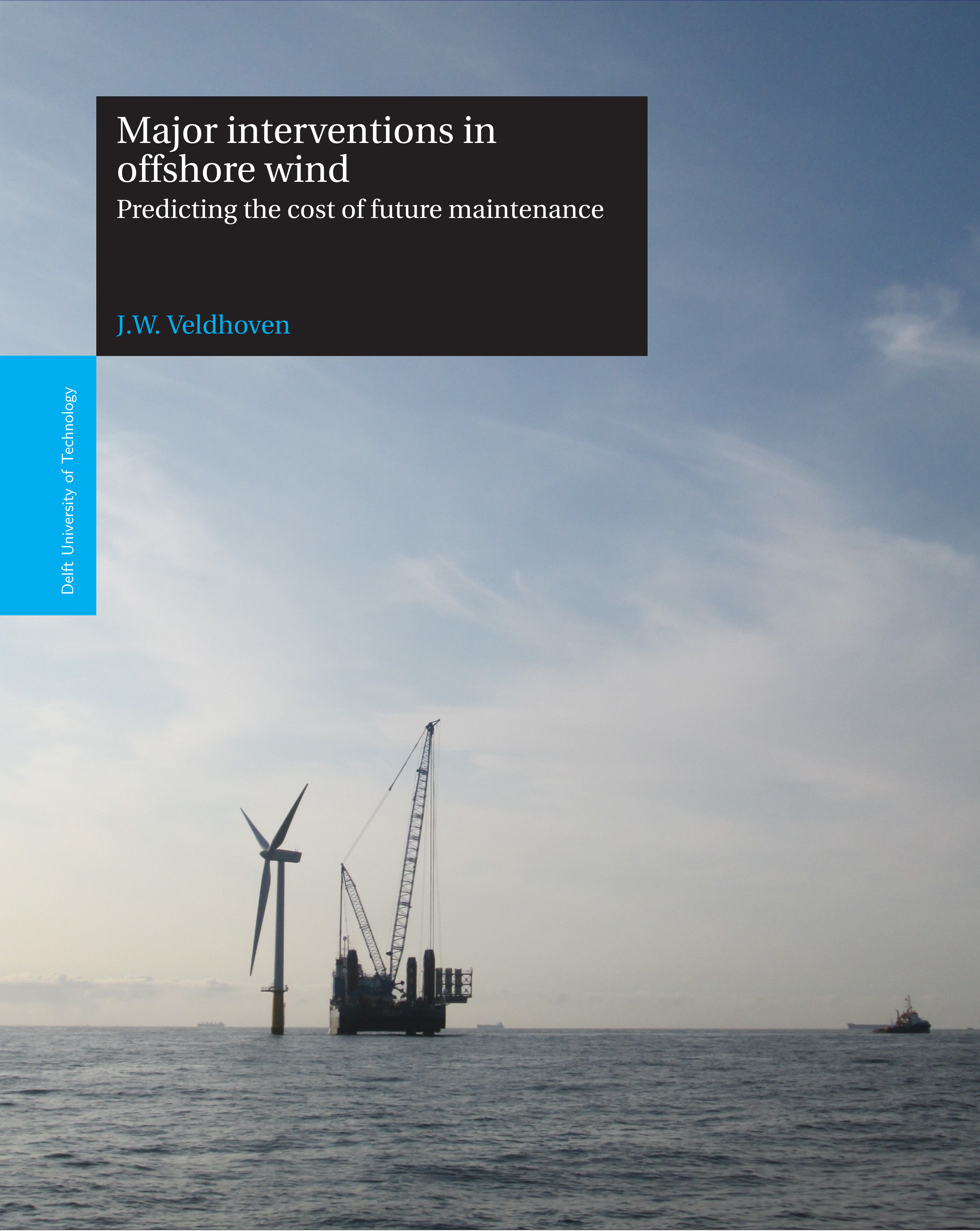

TU Delft Delft University of Technology

Challenge the future

Major interventions in offshore wind

Predicting the cost of future maintenance

by

J.W. Veldhoven

in partial fulfillment of the requirements for the degree of

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J.W. Veldhoven
Delft, May 2015

SUMMARY

Wind energy is one of the fastest growing types of renewable energy. Today, offshore wind represents 14% of the EU wind energy market, and has a huge potential for further growth [1]. Operations and Maintenance (O&M) accounts for 18-23% of the total lifetime cost in offshore wind farms, compared to 12% onshore [2]. The offshore O&M tasks are more costly, being influenced by distance offshore, harsh offshore conditions, wind farm size, wind turbine reliability and maintenance strategy [2]. Exchanges of main components, also known as major interventions, causes significant costs and has been indicated as the largest uncertainty when predicting O&M costs [3]. Major interventions are characterized by the need for a jack-up vessel to perform the exchange. No studies have been found on offshore major interventions. Echavarria has previously performed an analysis on the exchange rates of main components based on the onshore WMEP population, which had an average rated power of 233 kW [4]. Blades and generator were identified as most critical components, but it is not known how this reflects current exchange rates for larger turbines. The goal of this research is therefore to determine future failure rates and predict the cost of offshore major interventions.

Major interventions at the offshore wind farm 'Prinses Amalia Wind Park' (PAWP) have been investigated in this thesis,. PAWP has been commissioned in 2008 and consists of 60 Vestas V80 2MW wind turbines. The gearbox and main bearings have been selected as study object, based on their historical failure rates and the corresponding impact on maintenance costs. 16 gearbox and 5 main bearing exchanges have taken place during the first 7 years of operations. Gearbox failures are bearing related: spalling on planet bearings and axial cracks on IMS and HSS bearings are the main failure modes. Main bearing exchanges are required due to cage and guide ring wear. White-etching areas (WEA) has been indicated by the wind industry as the mechanism which causes early failures, reducing the life of bearings to 1-20% of the bearing design life [5]. The root cause of the formation of WEA is not known, gear and bearing suppliers have different theories. Some expect that it is lubrication related, where others consider tensile stresses or stress waves as a plausible root cause. The local wind regime and the amount of stops at PAWP wind turbines could not be correlated with failure rates. Research on high frequency load data and larger samples sizes is required to find the root causes of these failures. A strong collaboration between bearing-, gearbox- and wind turbine manufacturers and wind farm operators is recommended to share available knowledge and come to a solution.

Weibull analysis has been performed on failure rates at PAWP to make an estimation of future failure rates. A mean-time-to-failure ($MTTF$) of 10.3 years and a β value of 2.68 have been predicted for gearboxes. This indicates that failures are wear-related ($\beta > 1$). Predictions have become more accurate as the number of gearbox exchanges increased from 7 to 16 during the research: the standard error of $MTTF$ reduced from 214.1 to 16.8 months. Comparing the failure rates with an older V80 offshore wind farm ($MTTF = 3.7$ years) proved that significant design upgrades have been introduced. Main bearings have a $MTTF$ of 23.2 years and a β value of 1.89. This indicates that these failures are wear related too. The standard error of $MTTF$ is 14.75 years. This uncertainty is too large to perform maintenance optimization on the expected failure rates. It is concluded that the accuracy of Weibull predictions is relatively low due to the small samples size which are heavily censored. Parameters can change drastically if many failures occur on a short term.

This research has identified the condition monitoring system (CMS) as the most suitable detector for gearbox failures. On average, a CMS alarm is triggered 3 months prior to the gearbox exchange. Not all gearbox failures have been detected through CMS, thus a holistic approach utilizing all data generated by the wind turbines is required. SCADA data has been investigated, but no correlation between oil and HSS bearing temperature and failures has been found. Main bearing failures are more difficult to detect using CMS, due to the low rotational speed of the shaft. Bearing temperatures did not show significant increases with developing failures, but only one bearing failure has been investigated due to data availability. Grease samples could provide more insight in the condition of the bearing: wear is expected to increase iron and copper levels.

Finally, the optimal gearbox exchange strategy for PAWP has been determined. Previous campaigns showed significant cost reductions when moving from a single to batch exchange strategy. Results from the Weibull analysis and failure detectability have been used as inputs. Approx. 83 gearboxes are expected to fail during PAWP's 20 year lifetime, if no reliability increase is assumed for newly installed gearboxes. The 80% confidence bounds are at 77 and 90 exchanges. A 20% reliability increase for 2nd generation gearboxes results in 75 expected exchanges. The optimal strategy during the subsidized period are two- or three yearly campaigns. A single or two annual campaign are preferred after subsidy expiration in 2018. A single campaign strategy results in a larger financial uncertainty, due to the risk of downtime, but becomes preferred if detectability of failures increases. Performing the most optimal strategy at any point in time results in a saving of 21%, or 7.8 M€, compared to a reactive strategy. A sensitivity analysis has been performed on the total costs of gearbox exchanges. It is advised to focus on increasing the detectability of failures by improved monitoring, increase reliability of gearboxes through research on the root causes of bearing failures, and reduce jack-up costs by lowering jack-up mobilization costs. The latter can be achieved by using synergies with nearby wind farms, or using jack-up vessels that are located in the Netherlands. Increasing the up-tower serviceability of gearbox components, such as the front IMS bearing, will also reduce cost. This serviceability should be introduced in new gearbox designs too, although these are becoming more and more complex with the use of several planetary stages.

The strategy optimization has also been performed for a 350MW wind farm consisting of 8 MW turbines, which is equal to the lot size of future Dutch wind farms, such as Borssele. A similar gearbox reliability as in PAWP has been assumed. During the first operational years a reactive strategy is preferred, after year six 3 or 4 annual campaigns per year are optimal. The total costs are again most sensitive to detectability of failures, gearbox reliability and jack-up mobilization costs. Smaller 4 MW turbines results in higher costs than 8MW turbines (+ 19%), whereas 10 MW turbines results in lower total costs (-3.5%). Since main component failures have a significant impact on maintenance cost (30-40% of total O&M cost) , it is advised that monitoring and predicting failure rates becomes a standard part of asset management strategies.

Nomenclature

Abbreviations

CMS	Condition Monitoring System
DFIG	Double Fed Induction Generator
FLH	Full load hours
GoF	Goodness of Fit
HAWT	Horizontal Axis Wind Turbine
HPP	Homogeneous Poisson Process
HSS	High speed shaft
IMS	Intermediate speed shaft
LDD	Load distribution diagram
LSS	Low speed shaft
LSXY	Least squares estimation
MLE	Maximum likelihood estimation
MPTF	Mean power to failure
MTTF	Mean time to failure
MTTR	Mean time to repair
NRS	Non-rotor side
O&M	Operations and Maintenance
OEM	Original Equipment Manufacturer
PAWP	Prinses Amalia Wind Park
PDF	Probability density function
PLP	Power law process
RPM	Rotations per minute
RS	Rotor side
TTF	Time to failure
TTT	Total Time on Test
WEA	White-etching area
WEC	White-etching cracks
WEI	Wind Energy Index
WSF	White structure flaking

WTG	Wind Turbine Generator	

Greek Symbols

β	Shape parameter	[-]
η	Scale parameter	[-]
γ	Guaranteed lifetime parameter	[-]
σ_u	Standard deviation of mean wind speed	[m/s]
σ_m	Standard error	[-]

Latin Symbols

$\overline{u}$	Mean wind speed	[m/s]
C_p	Capacity factor	[-]
$f(t)$	PDF of lifetime distribution	[-]
$h(x)$	Hazard function	[-]
H_s	Significant wave height	[m]
I_{turb}	Turbulence intensity	[-]
L_{10}	Theoretical bearing design life	[-]
N	Number	[-]
P_{gen}	Generator power	[kW]
P_{rated}	Rated power	[MW]
$R(x)$	Reliability function	[-]
T	Torque	[kNm]
T_{amb}	Ambient temperature	[°C]
T_{down}	Downtime	[months]
$T_{exchange}$	Time of exchange	[-]
T_{HSS}	HSS bearing temperature	[°C]
T_{nac}	Nacelle temperature	[°C]
T_{oil}	Gear oil temperature	[°C]
V_w	Wind speed	[m/s]

Other Symbols

$€_{crew}$	Crew day rate	[€]
$€_{down}$	Loss of production	[€]
$€_{GBX}$	Cost of gearbox	[€]
$€_{JU,day}$	Jack-up day-rate	[€]
$€_{JU,mob}$	Jack-up mobilization rate	[€]

Contents

1

Introduction

1.1. Offshore wind energy

Wind energy is one of the fastest growing types of renewable energy: in 2013 it accounted for 13% of the total EU installed power capacity, compared to 2.4% in 2000. More growth is required to reach the targets set by the EU for 2020. Today, offshore wind represents 14% of the EU wind energy market, and has a huge potential for further growth [1]. The offshore capacity in the Netherlands is targeted to have multiplied by nearly a twenty-fold by 2023 [6].

Currently, the offshore wind industry is maturing. The first two offshore wind farms in the Netherlands, Egmond aan Zee and Prinses Amalia, have been operating for 6 and 7 years. The third wind farm, Luchterduinen, is under construction and more wind farms will be developed in the near future. This causes the portfolio of operators to grow. These assets have to be managed in the most optimal way to maintain a healthy, affordable wind farm with good availability. Operations and Maintenance (O&M) is a significant cost contributor. It accounts for 18-23% of the total lifetime cost in offshore wind farms, compared to 12% onshore [2]. The offshore O&M tasks are more costly, being influenced by distance offshore, harsh offshore conditions, wind farm size, wind turbine reliability and maintenance strategy [2]. Therefore, a good understanding of failure rates and wear of wind turbines is crucial to determine future O&M costs and availability of offshore wind farms [7].

The costs and risks corresponding to time-based and condition-based maintenance are becoming more predictable as experience grows [3]. However, unexpected failures of main components, such as gearboxes, still occur regularly. These exchanges, also known as major interventions, require a crane vessel to perform the lifting activities. This causes significant costs and has been indicated as the largest uncertainty when predicting O&M costs [3]. This forms a large financial risk to the operator. Based on historical failure rates predictions of expected life time and the amount of maintenance can be made [4].

1.2. Research goals

Ultimately, the goal of the author's research is to predict the financial impact of major interventions in the offshore wind farm 'Prinses Amalia Wind Park' (PAWP). Past failures in PAWP will be investigated to create the best possible estimate of future failure rates of main components. An optimal exchange strategy will be developed accordingly. This strategy makes a trade off between factors such as downtime and exchange costs. The following goals have been defined for the author's thesis:

1. Select a suitable methods to predict the failure rates of main components
2. Investigate historical failures of major components in PAWP
    a Select main components suitable for further investigation
    b Obtain the main failure modes
    c Quantify the frequency of each failure mode

d Determine correlation between failures and operating regime
  - Wind regime
  - Stops
  - SCADA alarms

3. Predict future failure rates in PAWP

   a Quantify the accuracy of the predictions

   b Determine the detectability of failures using indicators, such as:
     - Condition monitoring systems (CMS)
     - SCADA data
     - etc.

4. Determine and optimize the future financial impact of major components exchanges

   a Determine present financial impact (parts, vessels, crew, lost production, etc.)

   b Define optimal exchange strategy taking into account input uncertainties

   c Quantify the expected future financial impact and the corresponding uncertainty

1.3. OVERVIEW OF THESIS

This thesis has the following structure: firstly, a literature review on wind turbine failures, reliability theory and reliability studies is presented in chapter 2. Secondly, information on major interventions in PAWP is discussed in chapter 3. Thirdly, failure modes and possible root causes are investigated in chapter 4. In chapter 5, long term failure rates are predicted using Weibul analysis. Chapter 6 presents indicators which detect upcoming main component failures. Finally, the Monte-Carlo simulations are performed in chapter 7 to determine the optimal exchange strategy and total cost of exchanges in Prinses Amalia wind farm and a future 350MW wind farm.

2

LITERATURE REVIEW

This chapter provides background information and the state-of-the-art on wind turbine reliability. Background information on wind turbines and wind turbine maintenance is provided in 2.1. Reliability theory is discussed in section 2.2. Section 2.3 describes reliability studies which have been performed in the past years, section 2.4 discusses alternative reliability assessments. Finally, the literature is discussed in section 2.5 and conclusions are drawn.

2.1. BACKGROUND INFORMATION

This section provides a general introduction in wind turbines configurations and types of wind turbines failure and maintenance.

2.1.1. WIND TURBINE CONFIGURATIONS

The two main type of wind turbines that can be defined are the Horizontal Axis Wind turbine (HAWT) and the Vertical Axis Wind Turbine (VAWT). This research focuses on the reliability of operational wind farms, which consists of HAWTs. The predominant design within the HAWTs consists of an upwind, three bladed rotor with an active yaw mechanism, mounted on a nacelle on top of a cylindrical tower [7].

In the HAWTs three main electrical configurations can be defined [8]:

- Direct drive with synchronous generator and fully rated converter
- Variable speed with either induction machine or Doubly Fed Induction Generator (DFIG) and a partially rated converter
- Fixed speed with induction generator (Danish concept)

The direct drive system does not have a gearbox, thereby it differs from the variable and fixed speed turbines. The direct drive system has a low speed generator, while the other configurations have a high- or medium speed generator. The wind turbines in PAWP are DFIG machines.

2.1.2. WIND TURBINE FAILURES

A failure is defined as an event that results in dysfunctioning of a system or sub-system and hence asks for a service crew call-out, thus a physical visit to the turbine. Failures in wind turbines can be categorized according to the following classifications based on a proposal in [9]:

- Major intervention
- Major failure
- Minor failure
- Manual reset

Major interventions require a crane vessel to perform the exchange of a main component, such as a gearbox or blade. These exchanges are preferably scheduled in low wind periods, since the mobilization of a crane vessel or jack up vessel is necessary, which requires a good weather window. The repair will take several days. Major failures requires the use of the internal crane for lifting parts, this could e.g. be the replacement of a pitch engine. Minor failures are typically broken items, such as a fuse or pump. Manual resets are usually required after a software crash, these are preferable performed remotely. Some studies also regard scheduled maintenance or inspections as a failure category. This is questionable, since it is not caused by dysfunctioning of a system but part of the regular maintenance regime. However, it can be taken into account in studies regarding downtime, since there is an optimum between maintenance effort, failure rates and availability.

In general, minor failures (representing 75% of all failures) are responsible for only 5% of the downtime, whereas major failures and exchanges (representing 25% of all failures) contribute to 95% of the downtime according to [10]. This ratio is expected to change for offshore wind turbines: downtime will increase for minor failures due to the increased travel time and reduced accessibility of the site.

Figure 2.1 shows the distribution of failure types for three major assemblies within the ReliaWind project, where category 1 is a manual reset, category 2 and 3 represent minor- and major failures and category 4 represent the replacement of a main component. It has not been mentioned whether this distribution is based on the amount of failures, downtime or cost. However, it shows the significant presence of minor failures and major exchanges.

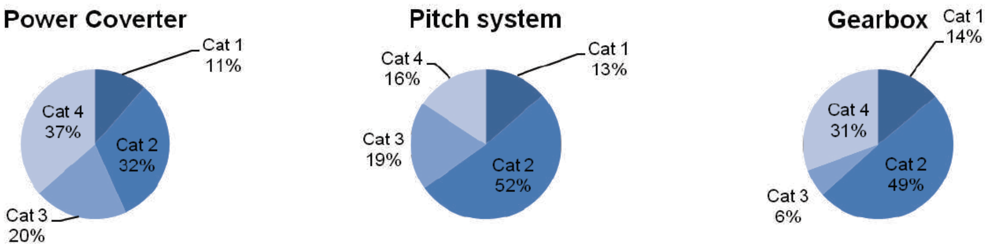


Figure 2.1: Distribution of repair categories for major assemblies in the ReliaWind project [9]

Downtime and failure frequency impact the wind turbines availability and O&M cost. They are therefore frequently investigated in wind turbine reliability studies. High failure frequency cause high logistics costs, crew cost, etc., while high downtime results in high production losses. Some failures occur frequent, but results in low downtime, while other failures are unlikely to occur, but results in high down time. This is visible in Figure 2.2, where the electrical system has the highest failure rate, but the gearbox and drive train cause the highest downtime [10]. The latter indicates why lately much effort has been made to improve the reliability of the gearbox and drive train.

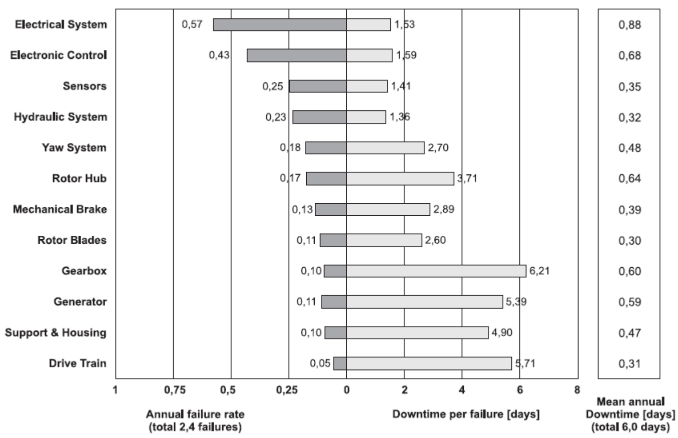


Figure 2.2: Failure rate and downtime in WMEP study [10]

In a research on main component exchanges in offshore wind farms, it makes more sense to study the failure frequency than downtime. The frequency of main component failure is unpredictable and related to reliability, while the downtime is highly biased by external factors. Downtime due to a major exchange can range from a couple of days for a planned preventive exchange in a good weather window, to a number of months for a component which failed unexpectedly. In this case, a vessel needs to be mobilized, which can have a long lead time, and spares have to be purchased in case the operator does not have these on stock. Next to that is, the downtime can be highly affected by the weather conditions in the offshore environment. The turbine can be inaccessible for a longer period during times with high waves or strong winds. Therefore the remainder of this chapter will focus on failure frequencies instead of downtime.

2.1.3. WIND TURBINE MAINTENANCE

Reliability and maintenance have a high impact on each other. A low reliability can cause a higher maintenance need, whereas proper maintenance can results in an increased reliability. Therefore, maintenance is analysed in this section. Three types of maintenance for wind turbines can be defined according to [11]:

Time Based Maintenance (TBM) Maintenance is performed on predetermined regular-intervals. This strategy is usually used for sub-critical components and parts for which the failure pattern is well known. Also, it is implemented to avoid invalidating the Original Equipment Manufacturer (OEM) warranty. The choice of the correct interval is a problem, too frequent increases operational costs, wastes products time and unnecessary replacements, whereas a too low frequency causes failures. Most offshore wind farms are visited twice a year for scheduled maintenance, which lasts about a day.

Failure Based Maintenance (FBM) Maintenance is carried out once the components fails. This strategy is implemented where failure does not results in revenue losses, customer dissatisfaction or health, safety and environmental (HSE) impact. In the offshore environment, FBM can cause problems in times when the site in inaccessible due to environmental circumstances. This can increases downtime.

Condition-Based Maintenance (CBM) In a CBM strategy maintenance is carried out in response to the deterioration in the condition of an asset or component. The condition of the components can be determined by visual inspection by mechanics or by using a Condition Monitoring Systems (CMS), which measures vibrations, or oil analysis. One of the advantages of CBM is that exchange can be planned ahead of time in periods of low wind. This prevents failures in periods when the site is inaccessible or high production losses occur. Also, spare parts can be ordered and the maintenance crew and vessels can be mobilized. Next to that, CBM can prevent catastrophic failures to occur, which mitigates the need to replace whole assemblies.

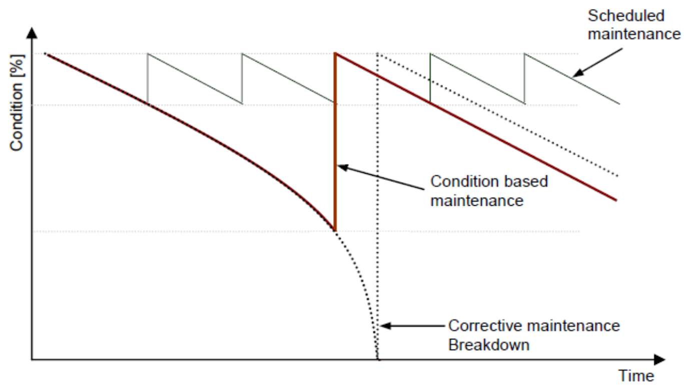


Figure 2.3: Condition-based maintenance compared to time- and failure based maintenance [12]

Most maintenance policies include all the three strategies. A graphical representation of the impact of the different strategies on the Wind Turbine Generator's (WTG) condition is given in Figure 2.3. This shows that CBM reduces the amount of visits compared to TBM, while reducing the impact of a breakdown in case of FBM. Still, if the failure pattern is well known, scheduled maintenance can result in the same amount of visits as CBM.

2.2. RELIABILITY THEORY

The state of a system can either be available or failed. The availability of a system can be computed using the mean time to failure ($MTTF$) and mean time to repair ($MTTR$):

$$Availability = \frac{MTTF}{MTTF + MTTR} \tag{2.1}$$

Reliability is defined as the probability that an item will perform a required function under stated conditions for a stated period of time. It is often defined by $R(x)$. Reliability can be measured in different ways depending on the situation, such as:

- Mean time to failure ($MTTF$)
- Number of failures per unit of time (failure rate)
- Probability that the item does not fail in a time interval [0,t] (survival probability)

Many distributions for reliability modeling exist. The reliability of complex repairable system, such as wind turbines, is commonly modelled using the power law process (PLP), which is Weibull distributed [8]. The Weibull distribution is the most used method to fit reliability data to a formal representation or mathematical model [13]. This is because the Weibull distribution can represent failures of components fitting the normal, exponential, and many other probability distribution functions, and only by changing the value of its parameters: the shape parameter β and the scale parameter η. η represents the characteristic life: it is the point at which 63.2% of failures will have occurred, which can be proven by filling in $x = \eta$ in Eq. 2.3 [14]. A 3-parameter Weibull distribution also exists, which includes the guaranteed lifetime parameter γ. Usually, $\gamma = 0$ is assumed. The 3-parameter Weibull distribution has also been applied for the data studied in chapter 5, results did not converge.

Systems can either be repairable or non-repairable. The repairability of a system is usually based on economic considerations, if the cost of repair is higher than the cost of complete replacement, the item is usually discarded. Reliability theory has been developed to study non-repairable devices [8], but can be applied to both repairable and non-repairable items [15]. In general, a wind turbine is considered a repairable system. However, during the latter of this thesis main components are assumed to be non-repairable. Main component are exchanged for new components, or have been extensively overhauled. During overhaul failed parts are replaced and design upgrades are introduced. Therefore, it can be assumed that the overhauled main components have an equal quality compared to newly manufactured main components.

2.2.1. BATHTUB CURVE

The bathtub curve is widely used in reliability engineering to show the change in failure or hazard rate over the lifetime of a system. The bathtub curve for non-repairable components is given in Figure 2.4b. Here, the population ageing quantity is plotted against the hazard function $h(x)$. The hazard function describes the instantaneous probability of failure of non-repairable systems. $h(x)$ is defined as $f(x)$, the PDF of the lifetime distribution of non-repairables, conditioned to the survival $R(x)$ at x. The hazard function thus represents the risk of failure of the *remaining* or *survivor* population [8].The corresponding equations to compute these function have been given for $\gamma = 0$ in [14]:

$$f(x) = \frac{\beta}{\eta}(\frac{x}{\eta})^{\beta-1} e^{-(\frac{x}{\eta})^{\beta}}, x > 0 \tag{2.2}$$

$R(x)$ can be calculated according to:

$$R(x) = 1 - \int_{o}^{x} f(x)dx = e^{-(\frac{x}{\eta})^{\beta}} \tag{2.3}$$

Next, the hazard function can be computed:

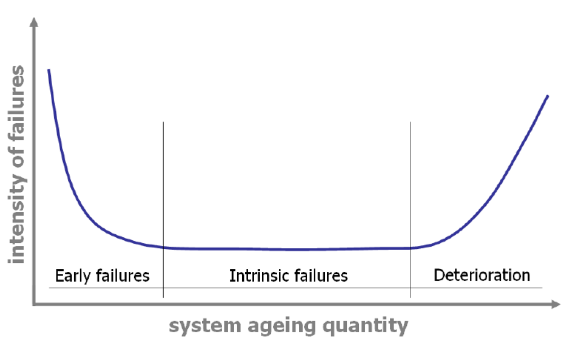
$$h(x) = \frac{f(x)}{R(x)} = \frac{\frac{\beta}{\eta}(\frac{x}{\eta})^{\beta-1} e^{-(\frac{x}{\eta})^{\beta}}}{e^{-(\frac{x}{\eta})^{\beta}}} = \frac{\beta}{\eta}(\frac{x}{\eta})^{\beta-1}, x > 0 \tag{2.4}$$

In the bathtub curve, three common sections can be identified (Fig. 2.4b):

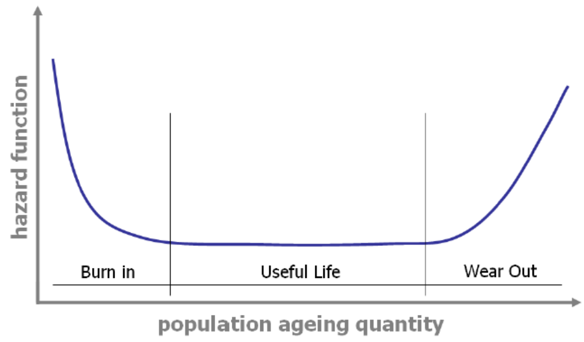
- Early failures ($\beta < 1$)
- Constant probability of failure ($\beta = 1$) : $h(x) = \beta/\eta$
- Deterioration ($\beta > 1$)

The early failures are generally attributed to undiscovered randomly distributed weaknesses in material, components, or production processes. This is also known as infant mortality. Post-production test programs aim to filter out these failures before installation in the field. The section with constant hazard rate is also described as the Homogeneous Poisson process (HPP), which is a particular case of the Poisson process for which the times between failures (TTF) are independent and identically distributed (IID) exponential random variables [8]. Failure rates are increasing with time during the deterioration phase. Failures are attributed to aging, wear out, fatigue, etc. [15].

According to [7], the deterioration phase ($\beta > 1$) has not yet been encountered in wind turbines, probably due to the relatively young age. The author made this statement based on a research conducted in 2004. Therefore, it is likely that this phase has been encountered by today. The author also assumes that wind turbines are likely to be taken out-of-service when deterioration occurs. This assumption holds if the whole system is deteriorating; if only one component of the system deteriorates it is more likely that the component is replaced.



(a) Repairable systems



(b) Non-repairable systems

Figure 2.4: Bathtub curves according to [8]

The failure rate of a system strongly dependents on the operating conditions [15]. This is visualized in the bathtub curves displayed in Figure 2.5, where θ_2 could e.g. be a location with a higher annual number of full load hours.

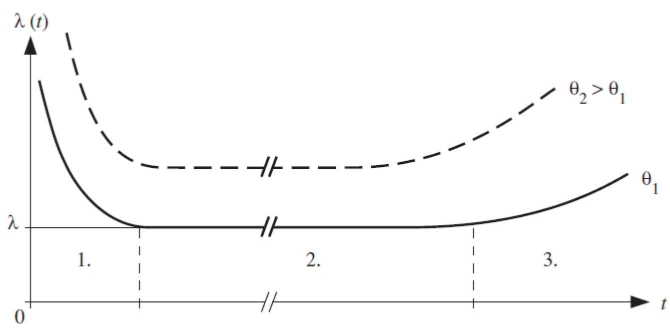


Figure 2.5: Shift in bathtub curve of a system in due to different conditions [15]

A reliability analysis can be performed on failed units only, or operating units can be included too. The latter is known as right censoring and this methodology is described in [13]. This implies that information (age) of operating components is also included in the analysis, since we do not know when these will fail. If these units are not included, the $MTTF$ will purely be based on failed units, causing the $MTTF$ shift to the left.

2.2.2. DIFFERENCE BETWEEN REPAIRABLE AND NON-REPAIRABLE SYSTEMS

In numerous studies, wind turbines components are treated as repairable systems. In [8], an important note is made on the difference between the bathtub curve for repairable and non-repairable system, which is commonly misunderstood. The repairable bathtub curve (Fig. 2.4a) plots the system ageing quantity vs. the failure intensity $\lambda(x)$, which represents the instantaneous probability of failure of repairable systems, whereas in the non-repairable bath curve the hazard function is plotted. The difference between the repairable and non-repairable case is caused by the population size, which is reducing for non-repairable systems. Therefore, the hazard function is a conditional probability, it depends on failures that happened in the past.

There is a clear difference between the first part of the bathtub curves of repairable and non-repairable systems. The decrease in failure intensity in Figure 2.4a is caused by reliability growth due to human effort, the decrease in Figure 2.4b is caused by the disappearance of items prone to early failure, increasing the reliability of the surviving population. The wear out phase for repairable systems is induced by the same phenomena as described for the non-repairable case.
For repairable systems, the repairs can be classified as three models [8]:

- Minimal Repair: the failed unit is brought back to the same condition it was just before the failure.
- Perfect Repair: the failed unit is brought back to the same condition it was as new and time to failure (TTF) are identically distributed.
- Renewal Model: a perfect repair for which the independence of TTF can be assumed (TTF are independent and identically distributed).

For simplification, the renewal model is frequently assumed in wind turbine reliability studies, resulting in Homogeneous Poisson Process (HPP) distributions, which means that $\beta = 1$. The replacement of a main components are often considered a perfect repair or part of the renewal model in literature.

2.2.3. PARAMETER SELECTION

Different independent variables can be used for reliability studies on wind energy:

- Calendar time (CT), or age
- Total time on test (TTT)
- Operational time
- Power production
- Cycles (e.g. no. of cycles of a shaft)

Here, Total Time on Test (TTT) that is the integral of the number of running hours of the entire population for the observed period. Choosing the correct time interval is very important, especially when different populations are compared, such as turbines in a high and low wind speed regions. Their failure rate can be very different in time, but it is possible that their failure rate vs. power production or loads cycles shows similar trends. This is expected for electrical sub-assemblies in particular [8]. In most studies on wind turbine reliability calendar time, total time or operational time is used. This is mainly related to the unavailability of data related to power production or cycles, no literature has been found which studies these parameters.

2.3. RELIABILITY STUDIES

Numerous reliability studies have been conducted on wind turbine field data. The largest and most significant studies are presented in Table 2.1. This gives a general insight in the approach and results of these studies. All studies focus on failure rates or downtime, other consequences of failures such as financial impact or safety and environmental hazard are not taken into account. Development of wind turbines has been very rapid in the past 20 years and technology has changed. This had its impact on turbine reliability, as will be discussed later in this section. Therefore, some studies have been excluded as they were considered outdated.

None of the studies state whether offshore turbines are included, but this is unlikely due to the recent development of offshore wind farms. Neither are root causes studied. This is mainly because the root cause is not known, not available to the researchers or not publicly released.

Table 2.1: Overview of most recent reliability studies based on field data

Study	Population	Results
ReliaWind (2008 – 2011) EU [9], [16]	350 WTG: o Gamesa and Echotechnia o >850 kW, variable speed, pitch regulated o >2 years after commissioning o >15 turbines per site o 1.29 MW avg. rated power	o Normalized failure rate / downtime per (sub-) assembly o Distribution per failure category
VTT (1996 – 2008) Finland [17]	72 WTG o 200 kW - 2.3 MW rated power o 1.01 MW avg. rated power	o Failure rate / downtime per assembly vs. operational lifetime o Assembly failure / downtime distribution
WindStats (1994 – 2008) Germany, Denmark [8] , [7], [18]	Germany: o 1291 – 4285 WTG o 597 – 6349 MW o 100 kW - 2.5 MW rated power Denmark: o 851 – 2346 WTG o 328 – 593 MW o 100 kW - 2.5 MW rated power	o Failure rate per assembly vs. calendar time o Assembly failure distribution o PLP model of failure rates
LWK (1993 – 2006) Schleswig-Holstein, Germany [8], [18]	158 – 643 WTG o 11.5 – 45 MW	o Failure rate per assembly vs. calendar time o Failure rate per wind turbine model o PLP model of failure rate per assembly
WMEP (1989 – 2006) Germany [4], [18], [12]	± 1500 WTG o Capacity: 350 MW o Avg. rated power: 233 kW	o Failure rate vs. operational lifetime per assembly, grouped by: o Rated power (low-medium-high) o Stall / pitch controlled o Induction / synchronous / direct drive generator o Avg. downtime per failure per assembly o Avg. rate and downtime of major and minor failures o Assembly failure distributions

2.3.1. FAILURE RATES

Most studies present their results as average failure rates, making no distinction by the type of failure (major exchange / major failure / minor failure / reset). The use of an average failure rate implies that the HPP is assumed (flat part of bathtub curve), so sub-assemblies are either perfectly repaired or made from non-repairable components that are replaced. Effects of intrinsic failures or deterioration are usually not taken into account.

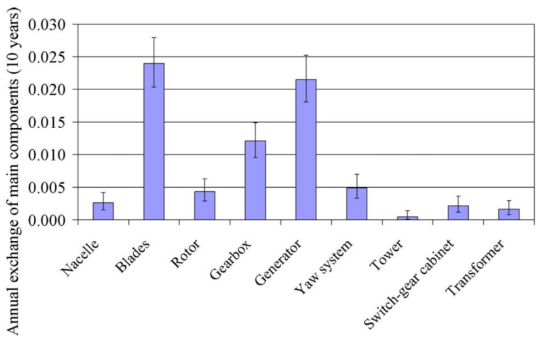


Figure 2.6: Replacement rate of main components in WMEP study [4]

Echavarria has investigated the average annual replacement rate of main components [4]. Results are based on (onshore) WMEP data and shown in Figure 2.6. The blades and generator are exchanged the most frequent, followed by the gearbox. The high replacement rate of blades is explained by the difficulty to repair these on site. Data consists of the first 10 operational years and based on turbines with an average rated power of 233 kW. It uncertain how these results reflect current WTGs exchange rates. Also, it is not determined how rates changes after year 10, when wear and fatigue can cause an increase in exchange rates.

General failure rates differs slightly between the studies. This is caused by the variation in turbine models, location, year of construction, turbine size, etc. In 2002, an average failure rate of 2.3 failures per year was assumed for an onshore turbine without commissioning in [18]. The average failure rates of the WindStats Germany, WindStats Denmark and LWK WTGs are 1.44, 0.73 and 1.85 failures per turbine per year, respectively [16]. The difference between these three studies is explained by the population of the studies, the German population consists of newer, larger and therefore less reliable wind turbines. The Danish population consists of smaller more mature and, more reliable technology. This indicates a relation between reliability and the maturity of technology. The WMEP and VTT studies present an average failure rate of 2.4 and approximately 1.5.

The highest failure is found in the recent ReliaWind study in [16], where an annual failure rate of 24.15 per turbine is suggested. This is significantly higher than all other studies and it would indicate 2 failures on average per month. Normalized failure and downtime distributions per assembly are similar to the other studies. The extremely high failure rate was a preliminary result, not based on the full data-set. In [9], it was linked to the increased failure rate of newer, larger turbines, which is further elaborated upon in section 2.3.2. The inclusion of manual restarts as failures has also contributed to this high failure rate. Moreover, it was suggested that double counting occurred or that other studies include a certain level of under reporting, or failures were reported differently. Availability in WindStats Germany and LWK is over 99%, while a lower availability would be expected according to [16] and [10]. Still, the credibility of the failure rate mentioned in [16] is doubtful, the author of this review also expects lower failure rates based on experience.

The failure rate of different assemblies has also been studied. The ReliaWind study presents normalized failure rates in [9]. Figure 2.7 reveals that the power, rotor module assemblies are most critical for wind turbine reliability. These assemblies also cause the highest downtime. Similar results are found in the other studies. The most critical sub-assemblies are the pitch and yaw system, and the frequency converter. However, this does not imply that these assemblies cause the most expensive failures. This would require repair costs and production losses to be taken into account.

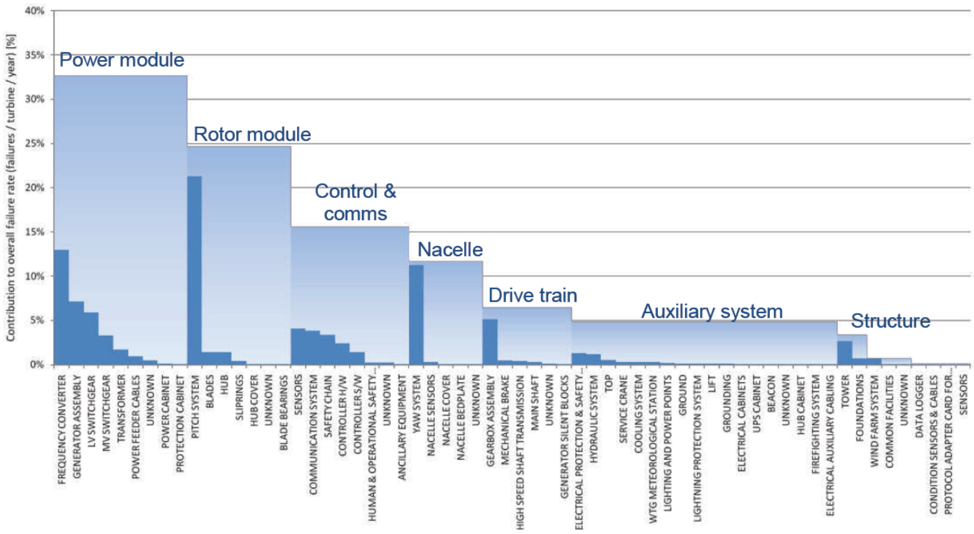


Figure 2.7: Normalised failure rate of assemblies and sub- assemblies for turbines in the ReliaWind project [9]

2.3.2. VARIABLES IMPACTING RELIABILITY

In this section different parameter are discussed that impact reliability according to literature.

TIME

Several authors have applied the PLP model to wind turbine failure data to see how the reliability changed over the lifetime of a turbine. This results in the bathtub curve. Wind turbine are considered repairable systems here. A downward trends thus indicates a reliability increase due to human effort, an upward trends indicates deterioration and fatigue [8].

Tavner has applied to PLP model to WindStats data [7]. A reliability growth was observed in both the German and Danish population, as shown in Figure 2.8. This reliability growth is caused by technological improvements concerning materials, design and manufacturing and cultural aspects about usage, preventive maintenance, corrective maintenance and possibly assisted by improved condition monitoring techniques. The Danish turbines had a lower failure rate due to the use of proven and more simplistic technology, as discussed in the previous section. The German turbines showed a larger reliability growth, since these had more potential for improvements. Faulstich observed that failure rates of the WT and its assemblies in the WMEP population remained constant over the operational lifetime [10]. Spinato tested reliability in different turbines in the LWK database, and observed both growth and a constant reliability over time [19].

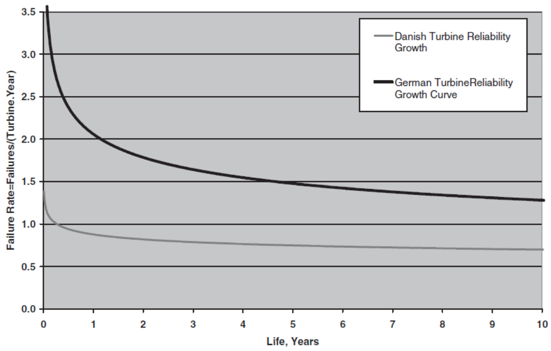


Figure 2.8: Reliability growth in WindStats studies [7]

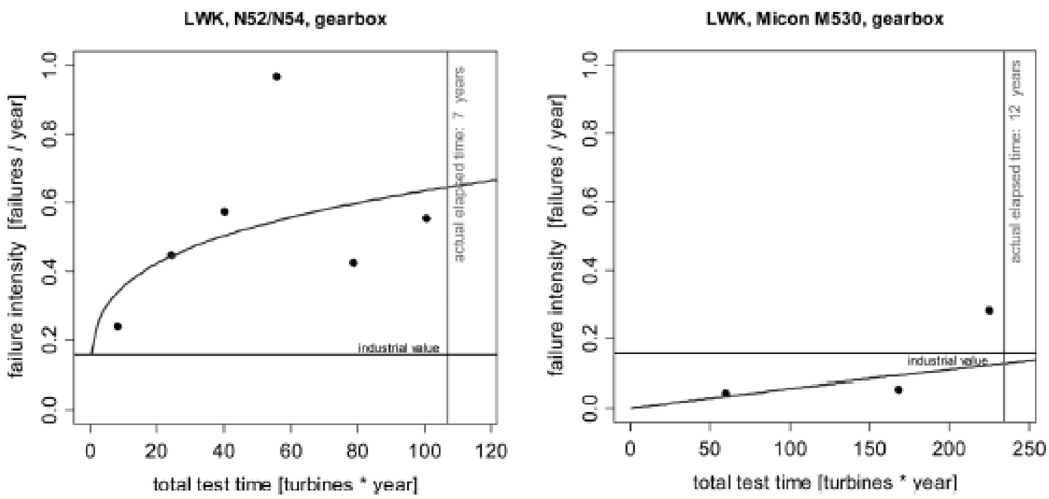


Figure 2.9: PLP model for LWK gearbox data [19]

The PLP model has also been applied to the failure rate of different main components in LWK data by Spinato [19]. The generator, converter and gearbox were selected, since these were considered the most unreliable assemblies. PLP model was tested against a Goodness of Fit (GoF) and null hypothesis of no reliability growth. Results indicate that generator and converter reliability improve with time, the PLP model showed a downward sloped failure rate (β<1). Gearboxes consistently show an increasing failure rate over time, which rises above the industrial value, as presented in Figure 2.9. Spinato suggests that WT gearboxes are of a mature technology and that the machines are operating in the deterioration phase of the bathtub curve. He concludes that substantial improvements in designed reliability for these gearboxes are unlikely, since no real development can be implemented once installed. This has been confirmed by NREL [20], which mentioned that improvements in the design process of gearboxes will lead to the largest reliability growth.

WIND SPEED

The local wind speed has been indicated as one of the main possible factors influencing reliability in [7], [19] and [21]. Turbines are designed to cope with two types of wind loading:

- Large instantaneous loads from gusts, which may cause stresses in excess of the ultimate tensile strength of the sub-assembly component
- Long-term fluctuating loads, which may, in magnitude and time, exceed the fatigue strength of sub-assembly components

If a high correlation is found between failure rates and either maximum loads or fluctuating loads, this could indicate that the design loads underestimate the loads experienced during the operational lifetime.

In 2006, a study was performed based on the observation that WT failure rates in WindStats data from both Denmark and Germany increased during identical months of bad winter weather, when weather conditions over north western Europe were similar [21]. The research studied the relation between failure rates and the monthly Wind Energy Index (WEI) , which is defined as:

$$WEI = \frac{\text{Actual monthly energy production from a collection of wind turbines}}{\text{Long term expected monthly energy production}} \tag{2.5}$$

A clear cross-correlation between WEI and failure rate of about 44% was found (Fig. 2.10). This does not implicitly mean that failure rates are purely wind driven, because a high WEI also causes an increase in production and operating hours. However, it does indicate that failures are not purely age driven. An important result in [21] is that some sub-assemblies are more subject to weather effects than others: the generator, yaw system, mechanical control, mechanical brake and hydraulic system. Sub-assemblies which are close to the input wind forces - gearbox, blades, main shaft, hub and coupling – have the lowest cross correlation. The fact that these components are mainly designed to transfer wind loads is given as an explanation.

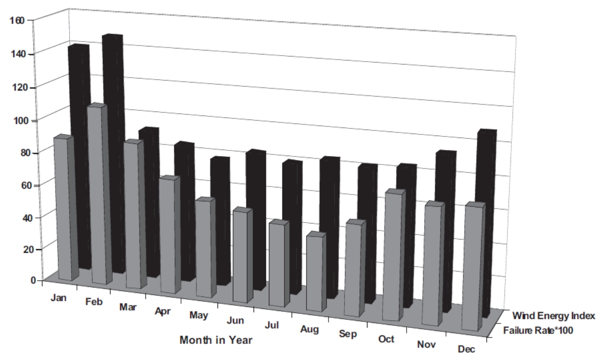


Figure 2.10: Average monthly failure rate and WEI in [21]

A follow up study was performed by the same author on a more limited number of WTGs, of identical design, located at 3 different sites in Germany, with distinctly different weather conditions [22]. A strong cross-correlation (55-75%) was found between failures and weather data when aggregating data into monthly bins. A strong cross-correlation was found for wind speed, temperature and humidity, indicating that failures are related to weather instead just wind speed.

A study on downtime and weather has been performed by Garrad Hassan, which is shown in Figure 2.11 [23]. In this study a database with failure data and SCADA data of over 23,000 wind turbines is combined with environmental data from MERRA. This study indicates that downtime is higher during windier and colder winter months. This is expected to be caused by the increased failure rate in windier months, and logistical issues due to e.g. snow. A relation is shown between temperature extremes and higher failure rates. The turbulence intensity (10-minute standard deviation to mean ratio) is plotted in Figure 2.11(c), which shows a steady increase in failure rate and downtime with higher turbulence. Higher turbulence intensities would normally be expected at lower wind speeds, so this result is contradictory to results in Figure 2.11(a) and Figure 2.11(b). This highlights the important distinction between correlation and causation. No explanation for this detail is given. An important point of discussion of Figure 2.11 is the credibility of results. The highest failure rates are observed at >30 m/s, while most wind turbines have a cut-out speed of 25m/s. The author of this thesis expects that it could be the case that shutdowns have been included as failures.

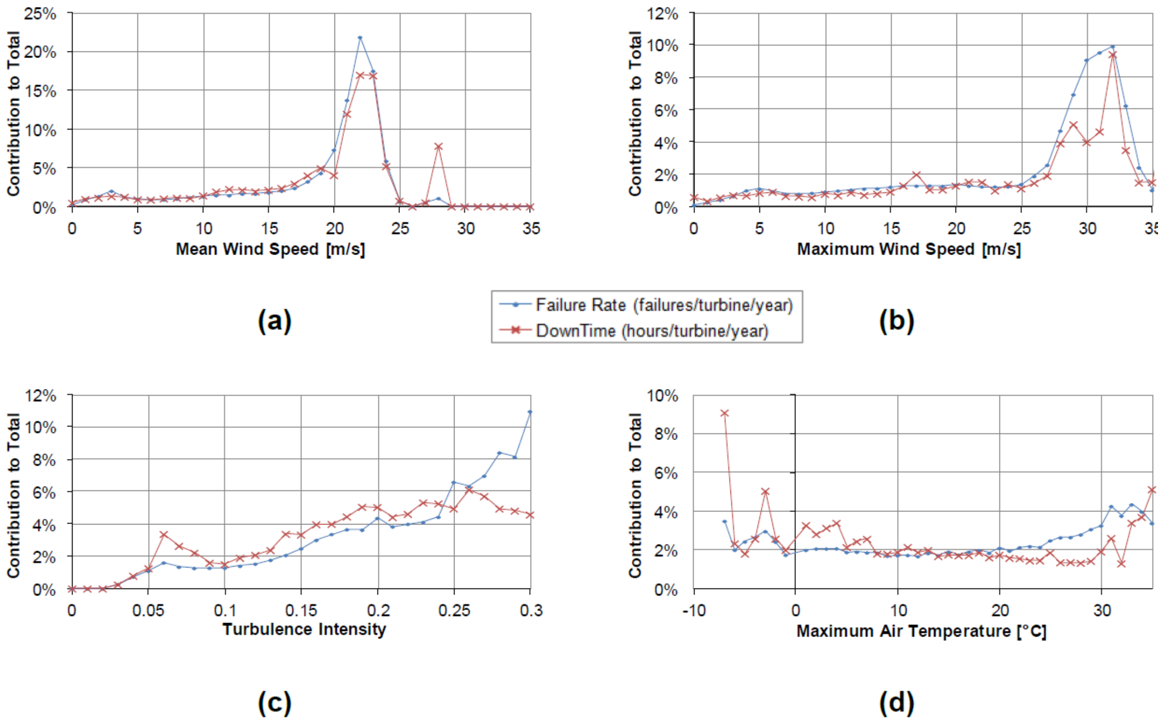


Figure 2.11: Failure rate and downtime as function of various parameters based on 10-minute SCADA data [23]

Garrad Hassan explains that it has normalized the results to remove the impact of the frequency distribution of the wind speeds, i.e. more frequently occurring wind speeds are not the reason for a higher contribution to the total. The normalization process assumes that in case a certain wind speed range occurs 30% of the time, also 30% of the failures should be expected in this range. [21] and [22] do not report that results have been normalized.

TURBINE SIZE

In the past years, there has been a significant development in wind turbines along with the growth in installed power. The rated power of turbines has grown from <1 MW to multi-MW. Currently turbines are being developed with a rated power of up of 8 MW.

In [4], [8] and [16] the difference in failure rates for different turbine sizes is presented based on WMEP, WindStats and LWK data. All draw the conclusion that newer and larger turbines have a lower reliability than the more mature existing and smaller technology. This can be seen in Figure 2.12, where rated power and failure rate are plotted based on LWK and WMEP data. This is supported by the fact that newer turbines often contain technologies such as pitch control and DFIG or direct drive drivetrains, which are more complex than e.g. stall-controlled fixed speed WTGs. However, when studying turbine size also the age has to be taken into account. According to [18], new turbines have three times as much failures as turbines of at least 4 years old. This is contradicted by [4], which shows that failure rate stay rather constant over the lifetime, as shown in Figure 2.13. The authors of [18] state that the complexity of the components increases, but also the quality. Failure rates would thus remain the same when WTGs of the same age are being compared. This cannot be concluded from Figure 2.13. However, it can be the case that failure rates of >1MW turbines in Figure 2.13 are based on a small number of new turbines, of which the design still allows for significant improvements in reliability.

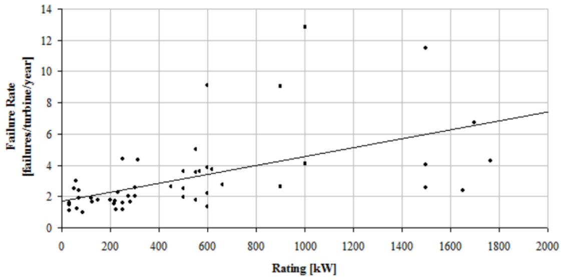


Figure 2.12: Failure rate plotted against rated power of LWK and WMEP data [16]

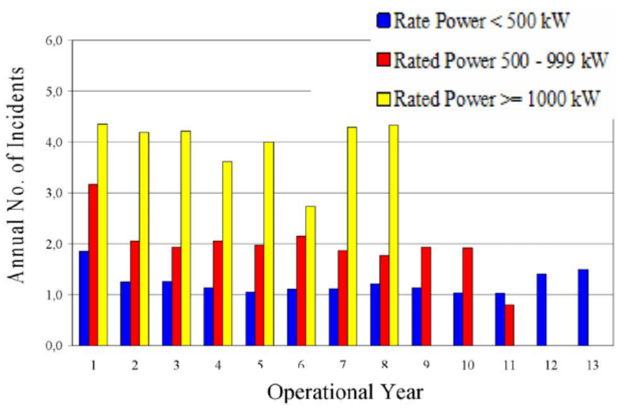


Figure 2.13: Failure rate vs. age plotted for different rated power ranges [4]

TURBINE TOPOLOGY AND MODEL

Echavarria has studied the effect of different WT topologies, or configurations [4]. Results indicate that this has a significant effect on reliability: the failure rate of the rotor system (excl. blades, thus hub and systems) of pitch controlled turbines is 85% higher than of stall controlled turbines. On the other hand, the failure rate of the hydraulic system, brake and gearbox show a decrease in failures when pitch control is applied. The overall higher failure rate of pitch control can be linked to the lower level of maturity and higher complexity of the system compared to stall control. Synchronous, induction and direct drive generators have also been compared. Again differences in failure rates were found, which implies that the use of specific topologies can have both positive and negative effects on components. Therefore, it makes sense to group turbines into standardized topologies in reliability studies.

This was confirmed by Spinato in [19], where differences in reliability of components in different topologies and turbine models were compared. In the same paper, a difference in reliability of components in turbine models with similar topologies was presented. This can be caused by differences in design, manufacturer or component supplier.

2.4. ALTERNATIVE RELIABILITY ASSESSMENTS

Apart from the field data studies presented in the previous section, alternative methods exist to determine the reliability of a system. Reliability studies can also be used to determine the reliability of a system during the design phase prior to commissioning. Not all assessment focus purely on failure rates, they can also investigate reliability in general. This can include financial, environmental or safety hazards or analyzing failure modes of the system. Some methods consists of physical experiments or simulations.

2.4.1. Reliability block diagram analysis

Smolders et al. has determined the reliability of three generic gearbox configurations by developing a reliability analysis model consisting of a reliability block diagram [24]. This is a bottom-up approach compared to the top-down field data studies described in in section 2.3. Each reliability block represents a sub-assembly with an corresponding failure rate. Failure rates of all individual components, such as bearings, wheels, pinions, shafts, etc. were estimated based on the Handbook of Reliability Prediction Procedures for Mechanical Equipment" of the Naval Surface Warfare Center (NSWC07) and failure rates published by Spinato et al. [19]. The failure rates of individual components were summed to establish the failure rate of the corresponding sub-assembly. Multiplication factors were assumed for misalignment, deviations from design speed, deviation from viscosity of lubricant, etc. When the failure rate of each sub-assembly is known, the failure rate of the complete system is calculated through simulations. It was assumed that all components worked in series, thus the failure of a single sub-assembly resulted in the failure of the complete assembly.

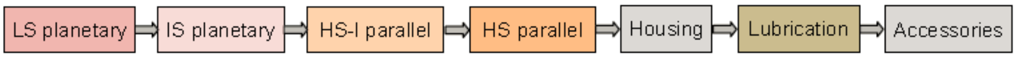


Figure 2.14: Reliability block diagram of 3-stage gearbox [24]

The model could provide a more reliable estimations of gearbox failures if the input data is validated using field data. However, the limited availability of field data has prevented this. Constant failure rates were assumed, hence effects of increasing failure rates due to fatigue and deterioration was not taken into account.

Reliability modelling using reliability blocks has several advantages and disadvantages compared to the methods described in section 2.3, where only field data is used. This approach allows the use of failure data from other industries, but it is uncertain how the differences in loads (highly varying, high gear ratio) effects reliability of components. Validation of the overall failure rate using field data is still required. Results have shown that the systems reliability is highly dependent on interaction between different components in the system, which is hard to model. Therefore, the method is not ideal when determining the reliability of existing system. Still, the method is likely to be powerful when comparing the reliability of new configurations.

2.4.2. Other methods

Two other methods that are described in literature on wind turbine reliability are the FMECA and Accelerated life testing:

Failure Modes and Effects (Criticality) Analysis A Failure Modes and Effects (Criticality) Analysis (FME(C)A) is an inductive bottom-up analysis, which assesses all possible failure modes and their consequences per components. It is mainly used to identify the most critical components or compare wind turbine topologies, as described in [25] and [26]. This method relies on field data or expert judgment to determine failure modes and rates. An exhaustive overview of all failure modes of a wind turbine is presented in [27].

Accelerated life testing This method consists of physical experiments in which the system is subjected to conditions in excess of operating conditions. This should reveal faults and potential failure modes in a short amount of time and is therefore mainly used for systems with a high MTBF [28]. A research conducted by NREL uses accelerated life testing to improve gearbox designs, described in [20].

2.5. Discussion & Conclusion

In this chapter, reliability of wind turbines has been investigated. Weibull modelling has been indicated as the main method to perform reliability analysis on (non-)repairable systems. Many studies have been conducted based on field failure data. In general, the conducted studies shows similar results and use similar techniques. Many studies assume that the wind turbines are in their useful life and that only intrinsic failures occur according to the HPP model. Only the LWK, the VTT study and WMEP study present failure rates per operational year. This includes effects of deterioration. The studies show significant differences in failure rates related to the age and size of wind turbines. In general, larger wind turbines are less mature, consist of more complex technologies and are thus less reliable. Overall turbine reliability tends to increase when the operational age increases, but this differs per component as indicated by Spinato [19]. Only Echavarria has presented results on average exchange rates of main components [4]. How exchange rates evolve over time has not been studied.

Smolders et al. has presented an alternative method to determine the reliability of wind turbine components, in which data from other industries can be used. Unfortunately, this method still relies on field data to validate results and include the wind energy specific variables that influence reliability, such as the gear ratio, load fluctuations, environment, etc. Therefore, this method is not found suitable to predict failure rates in offshore wind turbines. It is more suitable to compare the reliability of different topologies.

No studies have been performed on the reliability of offshore wind turbines. An Offshore-WMEP (OWMEP) study has been announced, but results have not been published yet. Therefore, no conclusions can be drawn on the effect of the offshore environment on reliability. Offshore availability has been studied, which ranged between 67.4% and 90.4% in the first three operational years, compared to an average onshore availability of 98.2% [10]. In later operational years offshore availability increased, but it has not equalled onshore availability.

All studies indicate that many parameters, such as turbine age, rated power, topology, model, weather etc. influence the reliability of wind turbines. Unfortunately, only [4] shows the 95% confidence region of the failure rates. This makes it impossible to determine the spread of failure rates between different locations or wind turbine models. Therefore, in-depth studies are required to predict the failure rates for a specific offshore wind farm, limiting the amount of variables such as turbine model and location. Next to that, the levels of uncertainty need to be quantified.

The author of this thesis also expects the following variables to influence reliability, however no publications on these topics have been found:

- Offshore environment
- Use of Condition Monitoring System (CMS)
- Location of WT within the wind farm
- Supplier of main component
- Maintenance history

3

MAJOR INTERVENTIONS IN PAWP

This chapter provides an introduction on major interventions. In section 3.1, general information on the offshore wind farm 'Princess Amalia Wind Park' (PAWP) is given. A detailed description of a major interventions is presented in section 3.2. The effect of weather on the duration of exchanges is presented in section 3.3. Section 3.4 discusses the impact of major exchanges on the performance of the offshore wind farm. Finally, the gearbox and main bearings are selected in section 3.5 as objects that will be studied during this research, and a detailed description of these components is given.

3.1. CHARACTERISTICS OF PAWP

The Princess Amalia wind farm has been commissioned in 2008 and is located 23km offshore from IJmuiden, the Netherlands. Table 3.1 contains general characteristics of PAWP, the location is given in Figure 3.1.

Table 3.1: Key characteristics of Princess Amalia Wind Farm (PAWP)

Wind farm	Prinses Amalia Wind Park
Commissioned	May 2008
Location	23 km offshore from IJmuiden, NL
Wind turbine model	60x Vestas V80 2MW
Full load hours	3500
Average availability (time-based)	97%
Subsidy regime	10 years

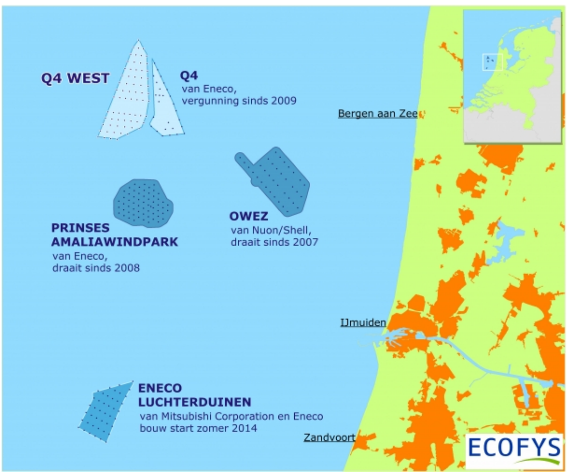


Figure 3.1: Location of Prinses Amalia Wind Park (Ecofys, 2014)

3.2. DETAILED DESCRIPTION OF MAJOR COMPONENT EXCHANGE

Major interventions are exchanges of a main component in wind turbines, which require jack-up vessels to perform the lifting. Main components are the gearbox, main shaft, blades, hub, generator and the transformer. An example of a jack-up vessel is given in Figure 3.2. A jack-up is used instead of a floating crane vessel, since the lifting procedure requires accurate maneuvering of the component inside the nacelle during installation. This requires a stable platform, which is achieved by jacking the vessel out of the water using the legs. This mitigates the propagation of any wave loads into the crane.

The whole process of a major components exchange starts with the detection of a (potential) failure:

1. Detection of defect by either (depending on type of component):
    - Increase in vibration levels (CMS monitoring)
    - Metal chips observed on magnetic dip-stick (in gearbox)
    - High contamination levels in oil (gearbox) / grease (main bearing)
    - SCADA alarm
    - Observation by mechanic
2. On-site visual inspection using a borescope
3. Decision to exchange component; depending on severity of failure the turbine is stopped, de-rated or normal operation is continued
4. Analysis of more turbines, batch exchanges are preferred
5. Planning of main components exchange(s), purchase of parts, mobilization of vessel, etc.

The time between all steps is depending on the severity of the failure. Next, the actual exchange is executed. This process is visualized in Figure 3.3

Figure 3.2: Wind turbine jack-up vessel prior to exchanging a main component (A2Sea, 2014)

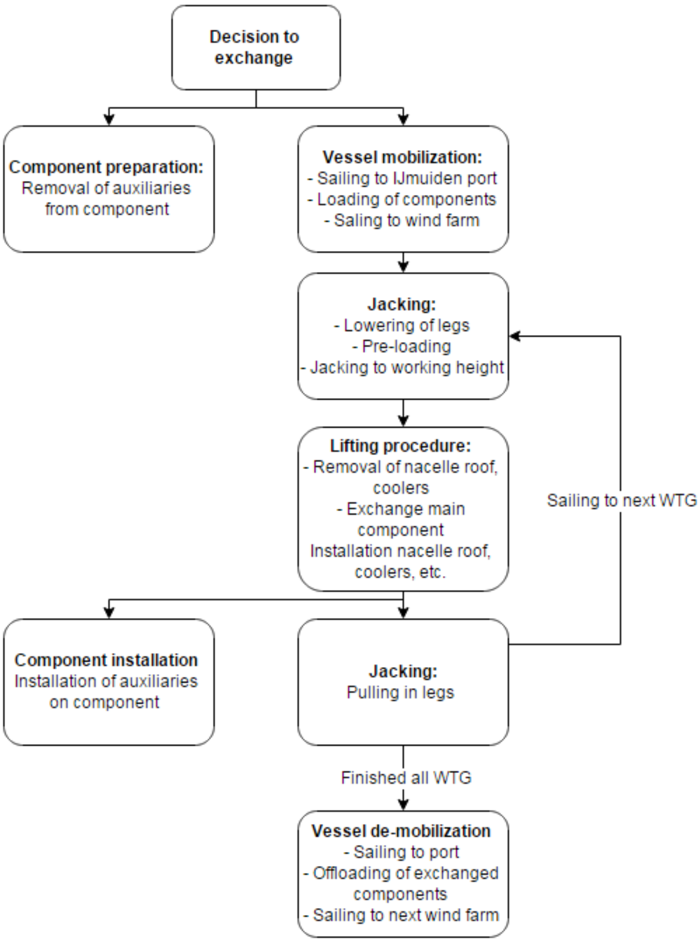


Figure 3.3: Process flow for main component exchange

A gearbox exchange requires a lifting vessel for 12 - 18 hours. This consist of jacking, which takes 3-6 hours depending on the water depth, jacking speed and preloading time. Preloading is when the legs are driven into the seabed, such that no further penetration takes place during operations. The lifting procedure for a gearbox takes approx. 6 hours, including removal and re-installation of the nacelle roof and cooling fans. Main bearing exchanges are more time consuming, as the complete rotor has to be removed. This lifting procedure can take up to 18 hours. The procedure is finished by jacking down again. Preferably, operations only take place during daylight [29]. Working during the night-time only happens when there are no good weather windows during daylight. Therefore, one gearbox can be exchanged each day day, a main bearing takes two days. This also corresponds to the allowable workload for the crew: mechanics can work shifts of 12 to a maximum of 14 hours per day. Vessels usually only have one crew, double crews are too costly for these type of activities.

3.3. WORKABILITY IN PAWP

Weather has a significant impact on the duration of exchanges. The time required to perform the exchange mentioned in the previous section is based on workable weather conditions. Unfortunately, weather can cause significant delays when maximum wind speeds or wave height for safe crew transfer, hoisting or jacking operations are exceeded. The significance of weather on the cost of major exchanges will later be discussed in section 7.1. Therefore, the monthly variation in the amount of workable days is studied. This is based on weather data from IJmuiden Munitiestortplaats, which is located in the proximity of PAWP. The amount of workable days is dependent on the operating limits of the jack-up or crew transfer vessel. Operating limits of typical jack-ups that are suitable for main component exchanges are presented in Table 3.2. The operating limit for safe crew transfer is a significant wave height (H_s) of 1.3 m. On average, the lifting procedure takes 6 hours [29]. Jacking takes approx. 3.5 hours. Therefore, the workable periods are characterized by a minimum of 8 hours (allowing some delays), when the significant wave height H_s are sustained below 1.3 m, wind speeds (V_w) are below 12 m/s, and the current is below 1.5 kts. It is assumed that work can also take place during night. The results of applying these criteria on IJmuiden Munitiestortplaats weather data for the years 2008 - 2014 are plotted in Figure 3.4, showing the variation between the years. An average based on the annual results is presented in Figure 3.5.

Table 3.2: Operating limits of jack-ups suitable for main component exchanges

	DBB Wind	DBB Wind Pioneer	DDB Wind Server	A2Sea SeaJack
H_s [m]	1.25	2.5	3	1.5m
V_w [m/s]	10	14	25.2	
Current [kts]	1	2	3	

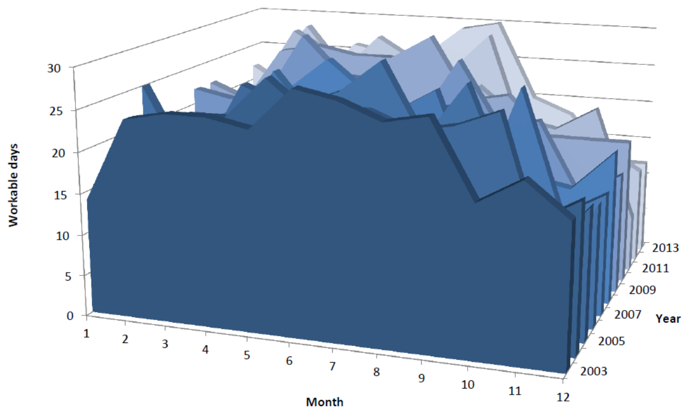


Figure 3.4: Yearly workable days at PAWP based on IJmuiden Munitiestortplaats weather data (2003-2013)and operational limits

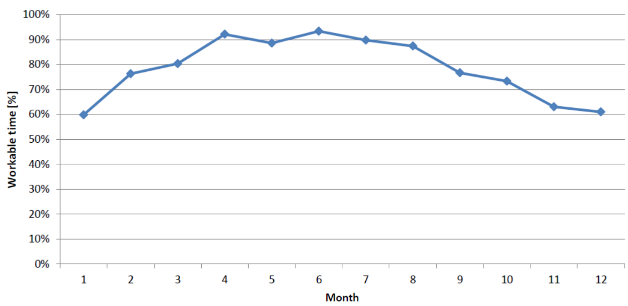


Figure 3.5: Average workability at PAWP (2003-2013) based on operational limits

Summer periods have a higher workability than winter. Based on the results from Figure 3.5, a conservative delay of 25% is assumed for summer periods, 50% for spring and fall and 100% in winter. This will be used as an input in modelling maintenance strategies in chapter 7.

3.4. IMPACT OF MAJOR INTERVENTIONS ON PAWP'S PERFORMANCE

Major component failures have two types of impact on the wind farm's performance: it lowers availability, and thus production, and it causes significant costs to replace the failed component.

3.4.1. IMPACT ON AVAILABILITY

The impact of major component failures on downtime is low, if exchanges are performed prior to breakdown of components, resulting in stopping the turbine. A turbine, which is operating until the actual operation

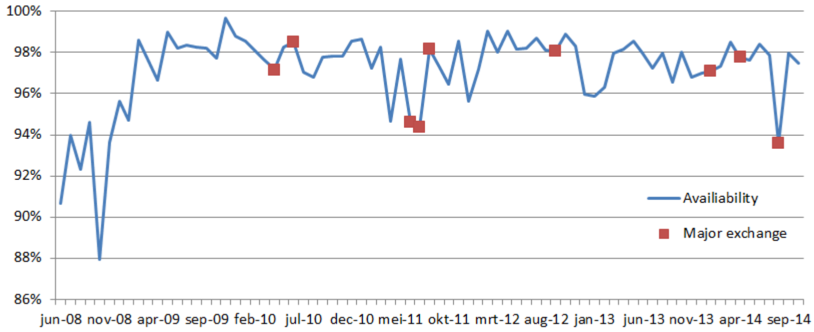


Figure 3.6: Time-based availability of PAWP

takes place, is down for a week at most. A turbine which has failed early and is down for a complete month causes a 1.7% drop in the monthly availability of PAWP, the impact on the annual availability is only 0.14%. The time-based availability of PAWP is given in Figure 3.6, where the execution of major interventions has been indicated. No significant drops in availability are observed, the drop in August 2014 could be linked to other maintenance activities. This is also affected by the current reactive strategy of major component exchanges: a vessel is mobilized if a component expected to fail. Instead, a strategy could be opted in which vessels are mobilized once or twice a year at a fixed date. This increases the cost of downtime, but reduces the mobilization costs when failure rates increase.

3.4.2. IMPACT ON O&M COST

Major interventions have the highest impact on O&M costs, while at the same time it causes the largest uncertainty. This is confirmed by Figure 3.7, which shows a breakdown of the total maintenance cost, incl. the corresponding uncertainty. On average, major interventions account for 30%-40% of the total annual maintenance cost. According to a study performed by Ecofys [3], the main uncertainties in maintenance costs are:

- Exchange rate of main component
- Length of repair campaign
- Jack-up vessel cost

The cost can be highly volatile: when components reach the end of their lifetime exchange costs will be significant, exceeding 50% of the total annual cost, while in PAWP years without exchanges have occurred.

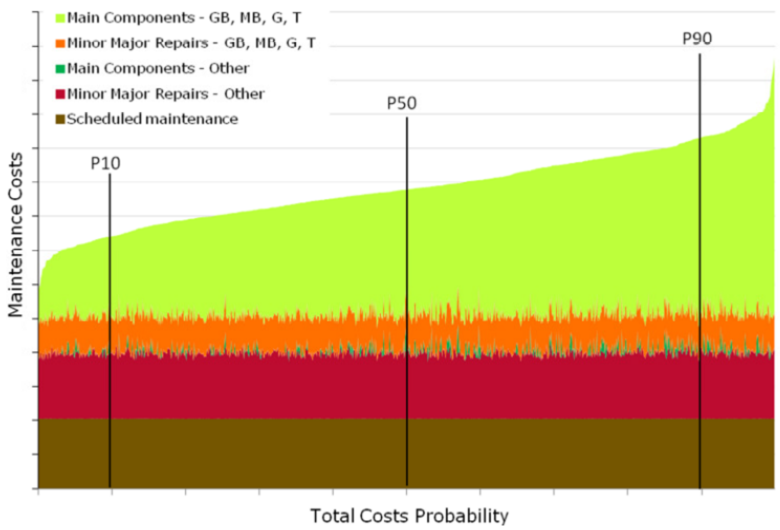


Figure 3.7: Uncertainty in annual maintenance cost (average case)

The costs of parts is rather predictable, but upfront it is not known how many major components will fail during the lifetime of the wind farm. Experience is growing, but significant differences between the failure rates in different wind farm are observed. The length of the repair campaign are uncertain, due to the workability at the site. Vessel costs are highly dependent on the current market demand and availability of vessels. Vessels suitable for main components can be scarce in summer and causing higher day rates. Sometimes even installation vessels are mobilized for major exchanges. Furthermore, mobilization cost cause a high uncertainty, this is dependent on the location of the vessel. Usually the mobilization cost equals sailing time to the wind farm and loading of the components at the normal day rate. The financial impact of historical campaigns at PAWP is investigated in more detail in section 7.1.

3.5. COMPONENT SELECTION AND CONFIGURATION

To scope this research a limited number of main component is selected. This selection is based on historical exchange rates at PAWP.

Table 3.3: Exchanges during 7 years operational lifetime of PAWP

Component	No. of exchanges
Gearbox	16
Main bearings (incl. shaft)	5
Blade	2
Generator	1
Switchgear	1
Transformer	0
Yaw system	0
Hub	0
Tower	0

Table 3.3 shows that gearbox and main shaft failures have mainly occurred in PAWP. This is also indicated as the main concern of the operator. Industry experience and other research has also indicated that gearbox are a main concern, such as NREL [20]. However, the main bearing usually show lower failure rates [30]. Echevaria has studied exchange rates in WMEP data, however she indicated that failure rates were the highest for blades and generators in [4]. It could be the case that manufacturers have significantly improved the design since then. Also, there are other factors which can cause significant differences between exchanges rates of different sites, such as component supplier, year of build, type model and environment. This is discussed in more detail in section 4.3.

Based on the fact that gearbox failure are the highest and an industry concern, and main bearings are higher than expected, it is decided to study these two components during the latter of this research. The exact moment of gearbox and main bearing exchanges are given in Table 3.4.

Table 3.4: Date of gearbox and main bearing exchanges

Date	Gearbox	Main bearing
Apr 2010	1	
Jun 2010		1
Jun 2011	2	
Jul 2011		2
Aug 2011	1	
Sept 2012	1	
Jan 2014	1	
Apr 2014	1	
Aug 2014	3	2
May 2015	6	

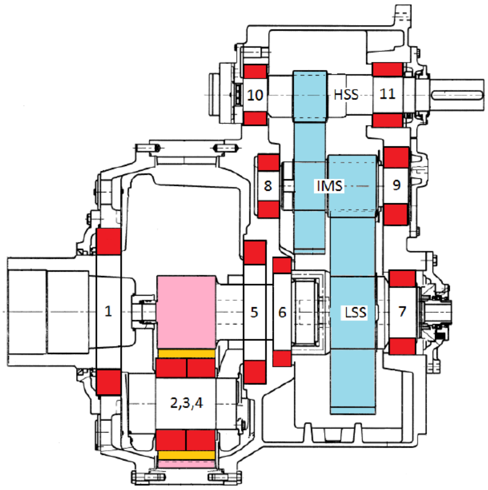


Figure 3.8: Graphical lay-out of V80 gearbox

3.5.1. COMPONENT CONFIGURATION

Configurations of gearboxes and main shafts differ between turbine models. Gearboxes can consist of several planetary or helical stages, whereas main shaft can be supported by a single or double main bearing arrangement.

GEARBOX

The gearbox of the offshore Vestas V80 consists of three stages, which are one planetary and two helical stages. The planetary stage consist of 3 planet gears, which drives the low speed shaft (LSS). The low speed shaft is connected to the Intermediate speed shaft (IMS), which in turn drives the high speed shaft (HSS). General information on the gearbox is presented in Table 3.5 and Figure 3.8. The mapping is explained in Table 3.6. The abbreviations RS (rotor side) and NRS (non-rotor side) indicate on which side the bearing is located. The bearings in the gearbox consist either of single or double bearings. This is visualized in Figure 3.9.

Table 3.6 also indicates whether a component can be exchanged in the nacelle (up-tower) or requires a complete gearbox exchange. The complete HSS and rear bearing of the IMS can be exchanged up-tower. No crane vessel is required if these parts of the gearbox fail. 17 HSS and 2 IMS rear bearing exchanges have taken place until May 2015. In total, 32 gearboxes have been affected by these 35 failures. This means that only 3 gearboxes encountered more than one repair or required an exchange after a repair. This could be an indication that failures occur randomly throughout the gearbox, but that the location determines the required maintenance action. A HSS failure is thus (until today) not an indication for an upcoming planetary stage failure.

Table 3.5: V80 gearbox characteristics

Gearbox stages	1 planetary, 2x parallel (helical)
Gearbox ratio	92.27
Rotor RPM$_{nominal}$	16.7
Generator RPM	1550
V$_{rated}$ **[m/s]**	14

MAIN BEARINGS

The main shaft in the Vestas V80 is supported by two main bearings, as depicted in Figure 3.10a. Other configurations are also existing for other model WTGs, such a single main bearing arrangement. The main shaft and main bearings are exchanged as a whole. The main shaft transfers the loads from the rotor to the gearbox. Each main bearings consists of two rows of spherical rollers. The rollers are held in place by a cage, which can be seen in Figure 3.10b.

Table 3.6: Mapping of V80 gearbox components according to Figure 3.8

No.	Component	Exchangeable up-tower?
1	Planet carrier RS (double)	N
2, 3, 4	Planet bearings (double)	N
5	Planet carrier NRS (single)	N
6	LSS RS (single)	N
7	LSS NRS (double)	N
8	IMS RS (single)	N
9	IMS NRS bearing (double)	Y
10	HSS RS bearing (single)	Y
11	HSS NRS bearing (double)	Y

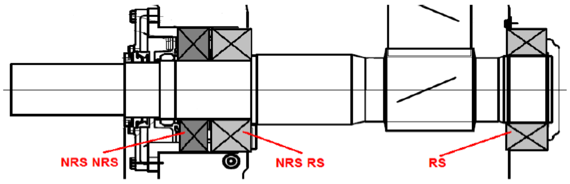
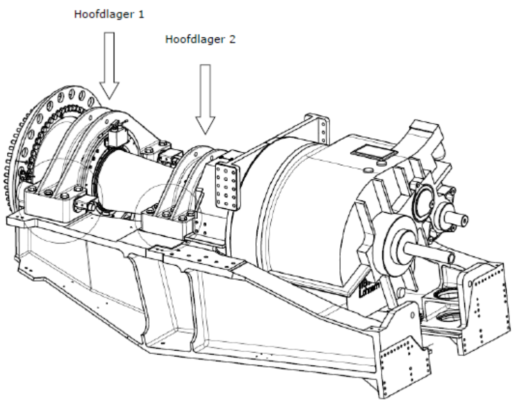


Figure 3.9: Bearing arrangement of HSS, with double (left) and single bearing (right)



(a) V80 main shaft and gearbox arrangement

(b) Configuration with two rows of rollers

Figure 3.10: Main bearing lay-out

CONCLUSION

The following conclusions can be based on the previous sections:

- Major interventions have had little impact on downtime with the current failure rates and reactive exchange strategy.
- Major interventions accounts for 30-40% of the total cost of maintenance.
- The cost of major interventions is volatile due to uncertainty in failure rates, vessel costs and the length of repair campaigns.
- The gearbox and main bearing are selected to study in this research, their failure rates are the highest in PAWP.

4

Failure modes and Root Causes

Failure modes that have occurred on failed gearboxes and main bearings in PAWP are investigated in section 4.1. This provides insight where failure occur and which parts should be monitored in particular. The development of failures and the failure mechanism that is expected to be responsible for early failure of bearings are described in section 4.2 Next, an attempt is made in section 4.3 to find critical operational loads at PAWP that are the root cause for the experienced failures. This serves two purposes: designs can be improved once the critical loads are known; and failure predictions can be based on the loads, allowing the operator to perform additional monitoring or inspections on critical turbines which reach their limit.

4.1. Failure modes

Failure modes are defined as the manner in which a system or component functionally fails, that is, describing to what extent a certain function cannot be fulfilled anymore. The physical process or mechanism yielding degradation of the component and ultimately leading to the physical failure is called the failure mechanism [31]. Failure modes can be split into different categories, from a system level (e.g. failed gearbox for a WTG) to a part level (e.g. cracked inner ring in a bearing).

4.1.1. Gearbox

Failing gearboxes are one of the main concerns in the wind industry. In PAWP in total 35 failure have been encountered until May 2015: 16 gearboxes, 17 HSS and 2 IMS rear bearing exchanges have taken place. The main failures modes of gearboxes have been described in [32] and [20]. The main failures are presented in Table 4.1. All of these failures can be split into more detailed failures modes of the individual components (e.g. fretting, spalling, indentations, cracks etc.), of which an extensive overview is given in [27].

Table 4.1: Gearbox failure modes according to [20] and [32]

Failure mode
Gear failure
Bearing failure
Shaft failure
Lubrication system malfunction

Exchanged gearboxes

The suspected main failures of exchanged gearboxes at PAWP are given in Table 4.2. The suspected main failure is the location where the initial failure is expected to have started. This damage can propagate throughout the rest of the gearbox, by debris damaging other parts. All exchanged gearboxes encountered bearing failures, on either the inner or outer ring. No gear, shaft or lubrication system failures have been encountered. Failures took place at either the the planetary or intermediate stage, which can be explained by the fact that these cannot be exchanged up-tower. Spalling on the inner ring of the planet bearing is observed most frequently (Fig. 4.1). The failed IMS NRS-RS inner ring could have been exchanged up-tower, but it is likely that this failure propagated too far through the gearbox, causing consequential damage. This made a complete exchange inevitable.

The suspected failure mode is found during an inspection before overhaul takes place at the gearbox supplier. Not all gearboxes have been overhauled, since the gearbox was damaged too severely for overhaul. These have not been inspected. Also, some reports could not be retrieved and six gearbox are awaiting overhaul. This causes only 5 out of 16 failures modes to be known. However, the supplier expects that the remaining 9 gearboxes have encountered similar failure modes. It should be noted that the count of failure modes adds up to 17. One gearbox contained two suspected failure modes: it failed on both the Planet 1 RS and IMS NRS-RS inner ring.

Table 4.2: Suspected main failure of exchanged gearboxes

Suspected main failure	Occurrence
Unknown, will be exchanged May 2015	(6)
Unknown (Cracked housing / no report available)	5
Planet 1 RS: progressive spalling on inner ring	3
IMS NRS-RS inner ring - axial crack	2
IMS RS outer ring - spalling	1

Figure 4.1: Progressive spalling on planet bearing inner ring

UP-TOWER EXCHANGES

The suspected failure modes of the components which have been exchanged up-tower are presented in Table 4.3. Again, all failures are bearing related. 5 reports were not available (yet). The NRS-NRS bearing of the HSS has failed most frequently: 12 out of 17 times. This is rear-most bearing of the HSS, and is closest to the coupling with the generator. This can have experienced a misalignment or offset, or high torques which caused the bearing to fail. An example of a cracked IMS bearing is shown in Figure 4.2.

Table 4.3: Suspected main failure of up-tower exchanges

Exchange	Suspected main failure	Occurrence
HSS	NRS-NRS bearing inner ring	*12*
	o axial hairline crack	9
	o (progressive) spalling	2
	o cracked	1
HSS	RS bearing failure - inner ring spalling	1
HSS	Unknown, no report available	4
IMS NRS bearing	NRS NRS : axial hairline crack inner ring NRS RS: cracked inner ring	1
IMS NRS bearing	Unknown, no report available	1

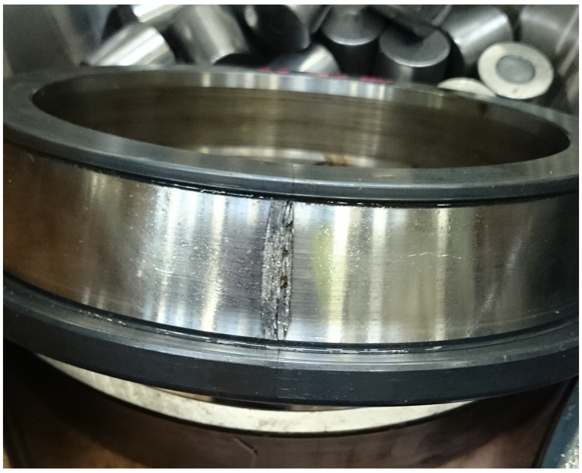


Figure 4.2: Axial crack on inner ring of IMS bearing

4.1.2. MAIN SHAFT

Less research has been performed on failure of main bearings, as this is less of a concern in the wind industry. An overview of main bearing failure modes is given in Table 4.4, which is based on [33]. The five failed main bearings in PAWP have been exchanged based on worn guide rings and cages (copper colored part on Fig. 3.10b). This results in play on the rollers, which, in worst case, can allow them to rotate 90°. This could cause the whole shaft to suddenly jam, resulting in severe damage to the rest of the WTG. Therefore, an exchange is required if wear becomes excessive.

Table 4.4: Main bearing failure modes according to [33]

Failure mode
Material break-out on raceways or rollers
Crack(s) in raceways or rollers
Worn guide ring
Outer bearing ring moves in housing
Seals failing

4.2. FAILURE DEVELOPMENT AND INITIATION

Failures of gearboxes and main bearing usually do not occur instantly. Cracks are initiated or spalling occurs, while the turbine is still operating. The failure can be detected during this time using CMS, grease/oil samples or borescope inspections.

4.2.1. DEVELOPMENT OF THE FAILURE

Figure 4.3 shows how bearing failures usually develop. The time on the x-axis differs for each failure: some develop to a catastrophic failure within hours or days, others can take years. The exchange should be planned during this pre-warning time, preventing a catastrophic breakdown. Typical catastrophic failures are e.g. parts of a bearing breaking loose and getting stuck between the gears. This results in extreme stresses that cause the complete gearbox housing to rupture. A catastrophic main bearing failure is a roller which rotates 90°, causing the bearing to jam. These type of failure should be prevented, since it can cause a lot of consequential damage and environmental spills.

Damages on the HSS and rear bearing of the IMS should be exchanged early. All metal debris from spalling or cracks is ideally captured by the oil filters, however some might find their way to the rest of the gearbox. this can result in damage, such as indentations, on parts which cannot be exchanged up-tower.

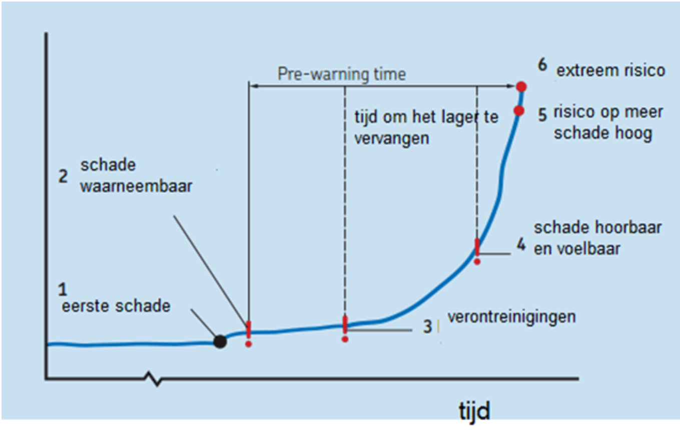


Figure 4.3: Bearing failure progression (SKF, 2015)

4.2.2. FAILURE INITIATION

The gears and bearings in wind turbines are designed such that they should have a nearly infinite life time according to standard bearing fatigue formula's. Unfortunately, the failure modes presented in section 4.1 still occur. At first, it was expected that the axial cracks on the inner ring (Fig. 4.2) were caused by excessive hoop stresses introduced during the process of mounting the inner ring on the shaft [5]. However, this turns out not to be the root cause in the wind industry. Instead, White-Etching Areas (WEA) are frequently mentioned as main contributor to the early bearing failures [5]. Once started, WEA damage can reduce bearing life to just 1 to 20% of the predicted bearing design life (L_{10}) as calculated with conventional rolling-contact-fatigue formulas [5]. This explains how WEA induced axial cracks can cause bearing failures within a few years of operation, while being designed for an operational lifetime of at least 20 years.

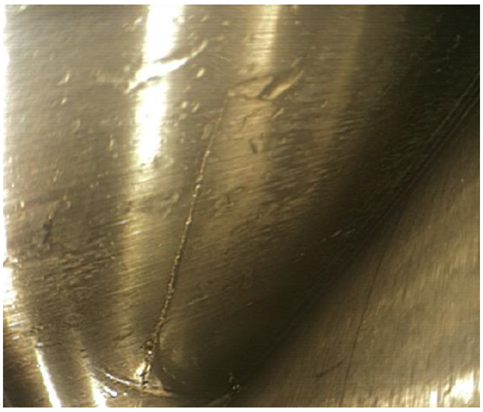
WEAs are characterized as microscopic, white-colored areas at the edge of the cracks, as shown in Figure 4.5b. These cracks are termed White-Etching Cracks (WEC) and are commonly found in through-hardened bearing races. WEA damage can also cause flaking or spalling, which is names White Structure Flaking (WSF). The micro-structural alteration is thought to be a result of severe plastic deformation, possibly linked to unsteady operation of the wind turbine drivetrain, this could e.g. be caused by:

- Extreme events, such as power loss or emergency stop can cause local energy which are needed for WEA formation [5]
- High radial impact loads causing rollers of the bearing to break through the oil film, causing high local stresses [34]
- Idling at low speed, causing the oil film to be broken [35]

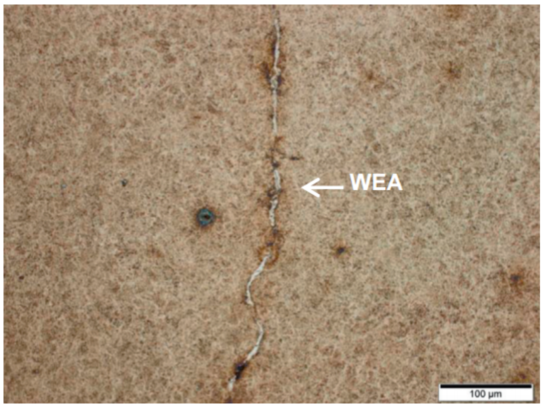
The exact underlying cause is unknown at this time: gear and bearing manufacturers have different theories on the formation of WEA (Fig. 4.4), which are based on different failure mechanisms [36]. These types of failure mechanism are too complex to investigate using data available at PAWP.

Hypothesis	Crack origin	Failure mechanism	Root cause
NSK	Subsurface	Hydrogen enhanced localized plasticity (HELP)	Hydrogen embrittlement, due to lubricant decomposition
SKF	Surface	Brittle fracture followed by crack propagation due to corrosion fatigue cracking	Tensile stress, due to high surface traction
Hansen	Subsurface	Adiabatic shear bands	Elastic stress waves, due to impact on surface asperities
Schaeffler	Subsurface	Severe plastic deformation	Complex interaction between lubricant, surfaces, materials, and loads

Figure 4.4: Theories of different gear and bearing manufacturers on WEC formation [36]



(a) Hairline crack in bearing inner ring at PAWP



(b) WEA around a crack formation [5]

Figure 4.5: Axial crack in bearing inner ring

4.3. ROOT CAUSES

Although the previous section points at complex failure mechanisms and root causes, PAWP SCADA 10-min data is studied to find a possible relation between failures and operational conditions. The wind regime and the amount of stops are investigated. The sample size is relatively small, 60 WTG, but these are all operating under similar circumstances. Variations between wind turbines will mostly be caused by local loads, the manufacturing process and material quality.

It would be of interest to study differences between the onshore and offshore environment, but unfortunately no data of good quality has been obtained on Eneco wind farms. The available data resulted in a very small sample size (10 WTG) and it was unknown which gearbox suppliers were used.

The SCADA alarm history between 2010 and 2014 has also been studied. Few alarms related to the gearbox were observed, these were mainly related to low oil levels or low oil pressure. This were eventually linked to defect sensors. No alarms related to main bearing failure have been found.

4.3.1. WIND REGIME

Drive train exchange rates are a function of failures that are (expected to be) load-driven, it is usually not caused by electrical failures. Wind is the main contributor to loads on the drivetrain, thus this can have a significant impact on when a component fails. The average wind speed, turbulence and local load distributions are therefore investigated. The maximum wind speed has not been studied, since at the maximum wind speed the rotor is yawed out of the wind, reducing the loads. It should be noted that anemometers on the wind turbines are not calibrated.

WIND TURBINE LOCATION

All major interventions on main shafts and gearboxes have been plotted on map of PAWP in Figure 4.6. The wind-rose for this area has been plotted in the top-right corner. The pre-dominant wind direction is south-west, so the bottom left turbines experience most of the high wind speeds. Downwind turbines experience more turbulent flows. It seems as if gearbox exchanges mainly takes place on the south- and west side, where winds are the strongest. All the other exchanges occur randomly trough out the wind farm. More detailed investigation based on wind speeds and turbulence levels are required to find stronger correlations.

AVERAGE WIND SPEED

The average wind speed for WTGs with an exchanged gearbox (red) and main shaft (blue) have been plotted in Figure 4.7 and Figure 4.8, respectively. The average wind speed of the wind farm is plotted in black, non-failed WTGs are plotted in grey. From Figure 4.7 it can be concluded that gearbox exchanges mainly take place on WTGs which experience a wind speed higher than the average, however they do not endure the highest average wind speed. Next to that, two WTGs experience almost the lowest wind speeds of the complete wind farm. These will probably experience higher turbulence levels due to wake effects.

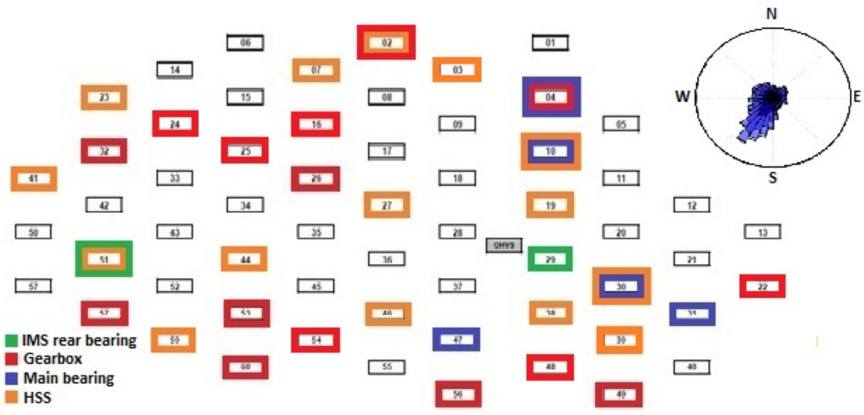


Figure 4.6: Location of main component exchange incl. wind rose

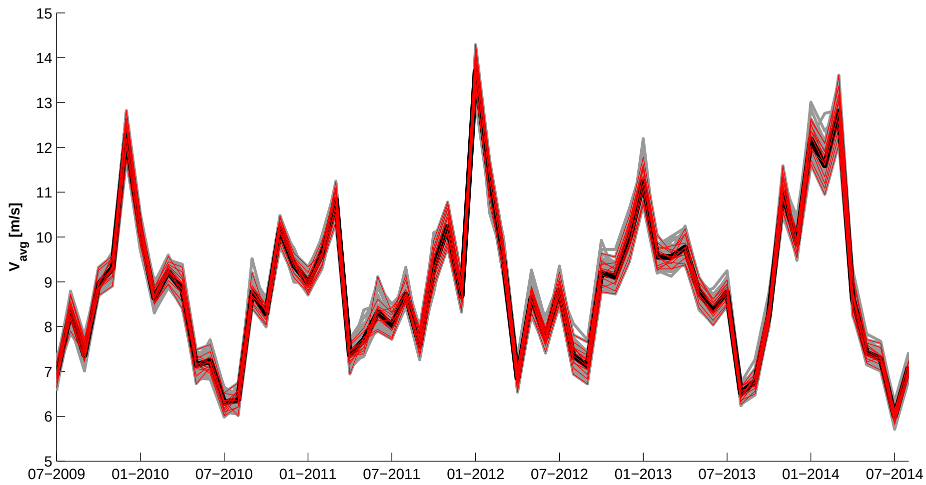


Figure 4.7: Average monthly wind speed for WTGs with exchanged gearbox (2009-2014)

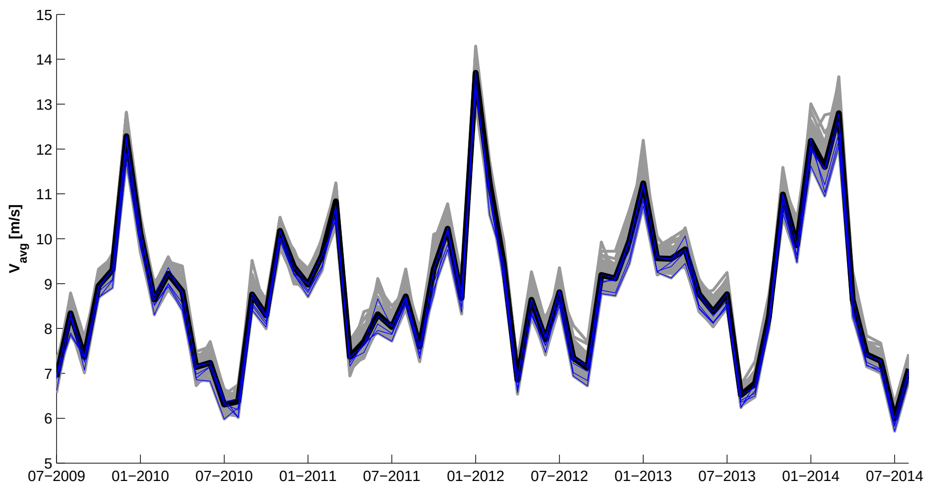


Figure 4.8: Average monthly wind speed for WTGs with exchanged main bearing (2009-2014)

Figure 4.8 clearly shows that the wind speed at WTGs where the main shaft has been exchanged is below the average. This could indicate that turbulence is an driving factor, it can be concluded that high average wind speeds does not have significant effects.

TURBULENCE INTENSITY

The local turbulence intensity at the wind turbine is calculated according to the following equation [37]:

$$I_{turb} = \frac{\sigma_u}{\overline{u}} \tag{4.1}$$

Where σ_u is the standard deviation and $\overline{u}$ is the mean wind speed, both measured at the wind turbine and averaged for a period of 10 minutes. Results for failed gearboxes (red) and failed main bearings (blue) are plotted in Figure 4.9 and Figure 4.10. No direct correlation is observed.

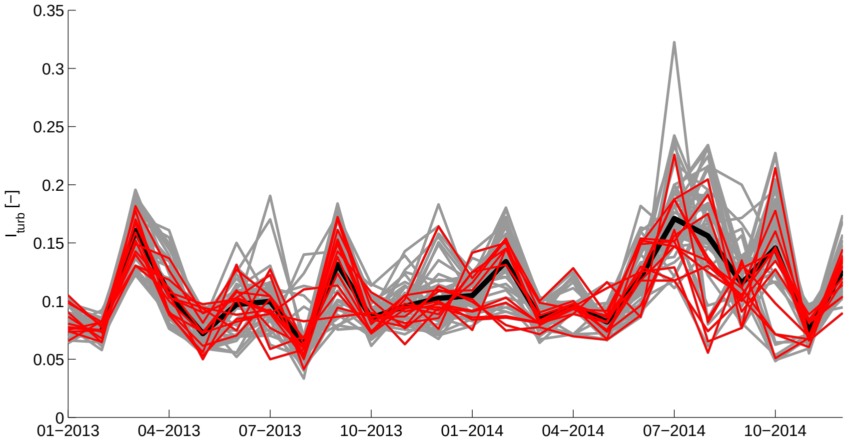


Figure 4.9: Average monthly local turbulence levels for failed gearboxes (2013-2014)

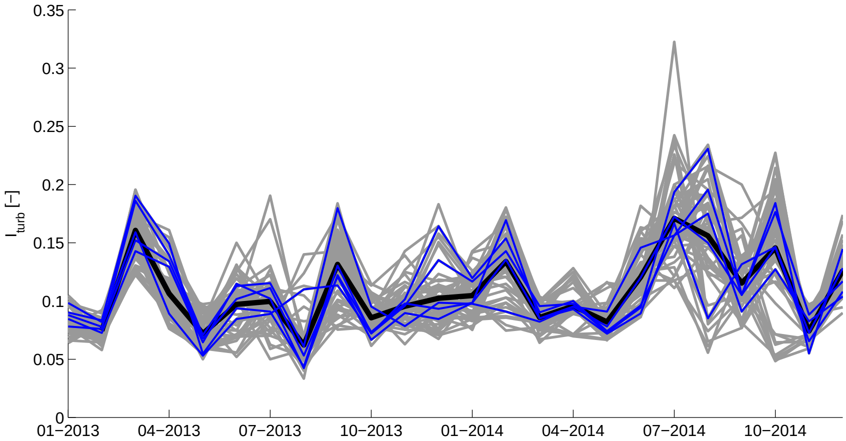


Figure 4.10: Average monthly turbulence levels for failed main bearings (2013-2014)

LOAD DISTRIBUTION DIAGRAM

The loads that the drivetrain experiences can be determined using the calculated equation:

$$T = \frac{P_{gen}}{RPM_{gen}[-]} \cdot 1.1 \tag{4.2}$$

In this equation a factor of 1.1 is added to account for losses of the coupling between the gearbox and the generator, and generator losses. When the torque is calculated using 10-min SCADA data, a histogram of the load that the turbine experienced during its lifetime can be plotted. This is called the load distribution diagram (LDD). Results have been plotted for 5 failed gearboxes and 1 healthy gearboxes in Figure 4.11. A huge spike is observed at the value of 1.32, which is at nominal power.

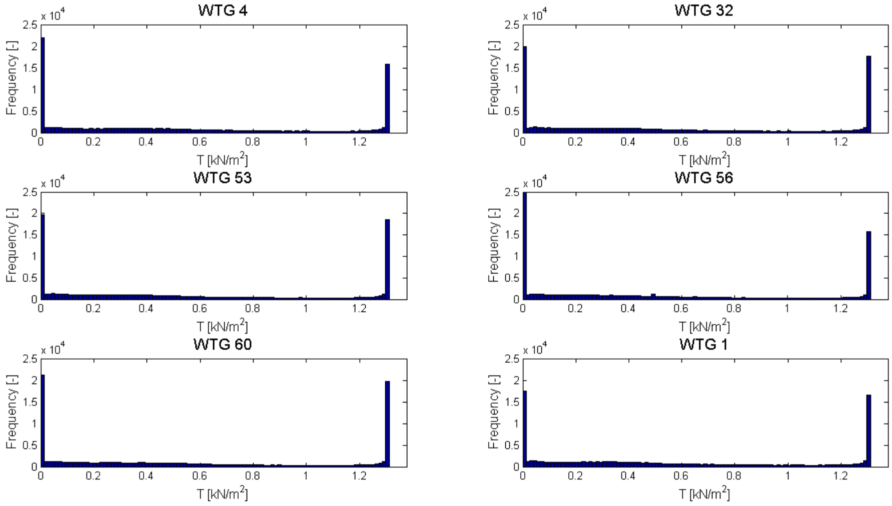


Figure 4.11: LDD for 5 failed gearboxes (4,32,54,56,60) and 1 healthy gearbox (1) [2013-2014 10-min SCADA data]

From Figure 4.11 it is hard to determine if any wind turbines experience more of a specific load, therefore the difference between the WTGs LDD and PAWP average LDD is plotted in Figure 4.12. Here, it can be observed that WTG 53 and 60 operate more frequent at nominal load. This is as expected, since these are located in the south-west of the wind farm (= pre-dominant wind direction). WTG 4, 32 and 56 operate less at rated power. This can be explained by the wake conditions that WTG 4 and 32 experience, while WTG 56 was 3 months down during 2013-2014 period. Concluding, no direct and obvious correlation is observed from these figures. Load diagrams have to be based on higher frequency data, to find the real root causes which cause WEA, as described in section 4.2.

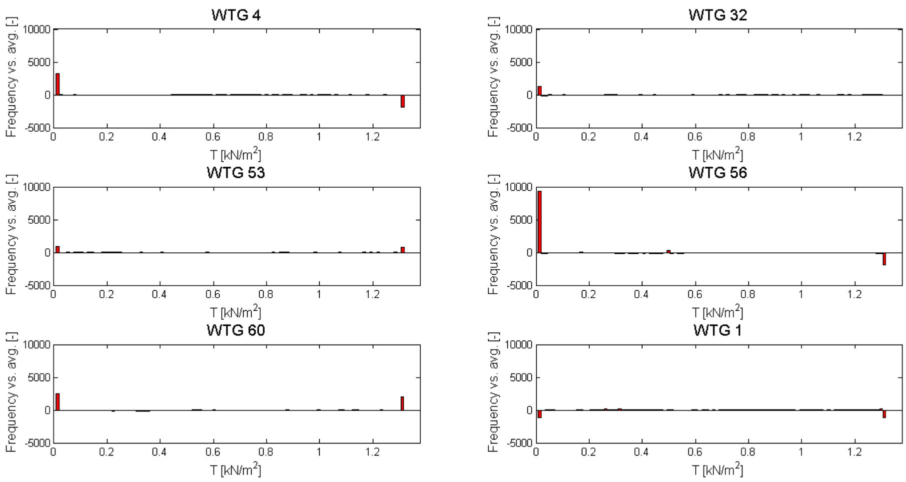


Figure 4.12: Difference with average PAWP LDD for 5 failed gearboxes (4,32,54,56,60) and 1 healthy gearbox (1) [2013-2014 10min data]

4.3.2. NO. OF (EMERGENCY) STOPS

Stops and emergency stops introduce significant loads into the drive train.The loads on bearings during stops were modelled in a study performed by Scott et al. [38]. This revealed that normal stops do not cause more damage than normal operations, but emergency stops show a threefold increase in the damage seen on the planet bearings, compared to a bearing undergoing a normal stop [38]. This is especially the case when an emergency stop follows a loss of grid event.

Studies have also shown that the HSS failures are among the most common failures in the wind turbine drive train, accounting for almost half of bearings failures in the gearbox. This is also the case in PAWP. At the high speed end of the gearbox, the torque is lowest and it is proven that the high speed shafts accumulates the least amount of damage despite undergoing a great deal more revolutions [38].Therefore, it is likely that misalignments, such as indicated by Whittle in [39], are causing excessive damage on that part of drive train during events such as emergency stops. The amount of misalignment in PAWP in not known, but a comparison can be made between the number of (emergency) stops the failed and operating gearboxes have experienced.

Five different types of stops exist for the Vestas V80 wind turbines, which have the characteristics specified in Table 4.5. The reduction in generator RPM for stops and the emergency stops could not be obtained.

Table 4.5: Characteristics of different types of stops

Stop type:	**Blade pitch**	**Brake disk**	**Generator**
Slow pause	$5^\circ/sec$ to 86°	N	125 RPM/s
Fast pause	$5^\circ/sec$ to 86°	N	150 RPM/s
Slow stop	$10^\circ/sec$ to 90°	N	?
Fast stop	$10^\circ/sec$ to 90°	N	?
Emergency stop	$10^\circ/sec$ to 90°	Y, if manual button pushed	?

In Figure 4.13 the amount of stops gearboxes or main bearings in PAWP have experienced until failure (or until today in case they have not failed yet) has been plotted. In this figure no clear correlation is observed between the individual types of stops and failures. Also, the total amount of stops encountered during the life-time does not directly affect the lifetime of gearbox components or main bearings.

This analysis does not take into account under which circumstances the stops occur, numerous stops at low wind speeds are likely less damaging than a single stop at a high wind speed. An assumption is that conditions under which stops take place for wind turbines in a single farm are similarly distributed between high and low wind speeds. However, Figure 4.14 shows the significant variation between the total amount of stops the wind turbines in PAWP have experienced until April 2015. Therefore, it can not be assumed that turbines have performed stops under similar conditions. A more detailed analysis involving the time of the stops and the corresponding conditions will provide more insight. Unfortunately, this data is not available.

Table 4.6: Legend for Figure 4.13

Color:	**Failure**
Red	Gearbox
Yellow	HSS
Cyan	IMS
Green	Main shaft
Magenta	Gearbox & Main shaft
Blue	None

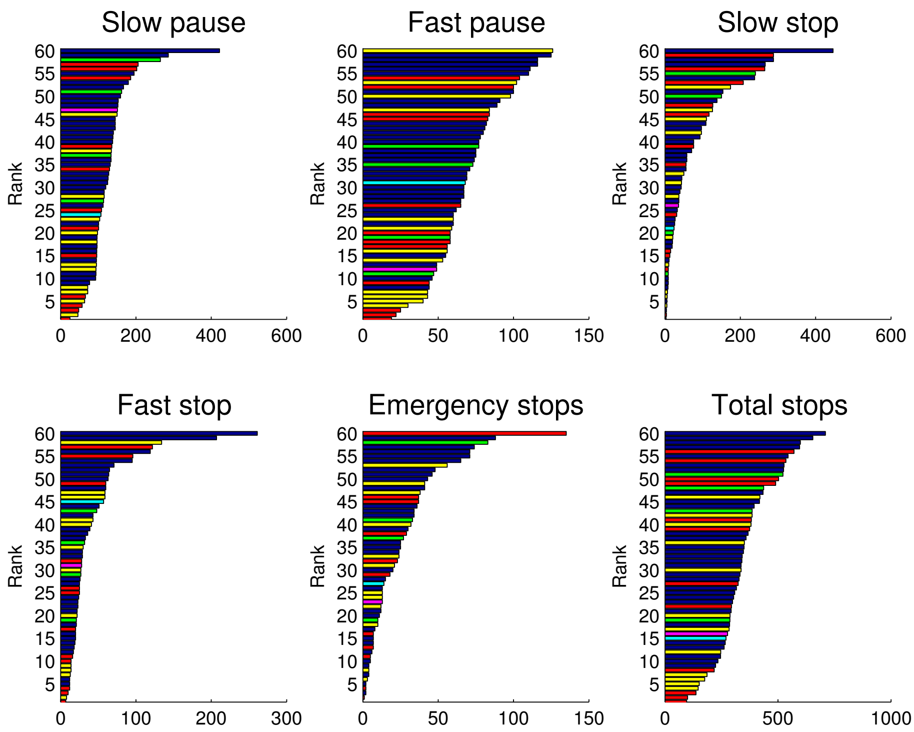


Figure 4.13: No. of stops experienced by existing and exchanged components, sorted from high to low (see Table 4.6 for legend)

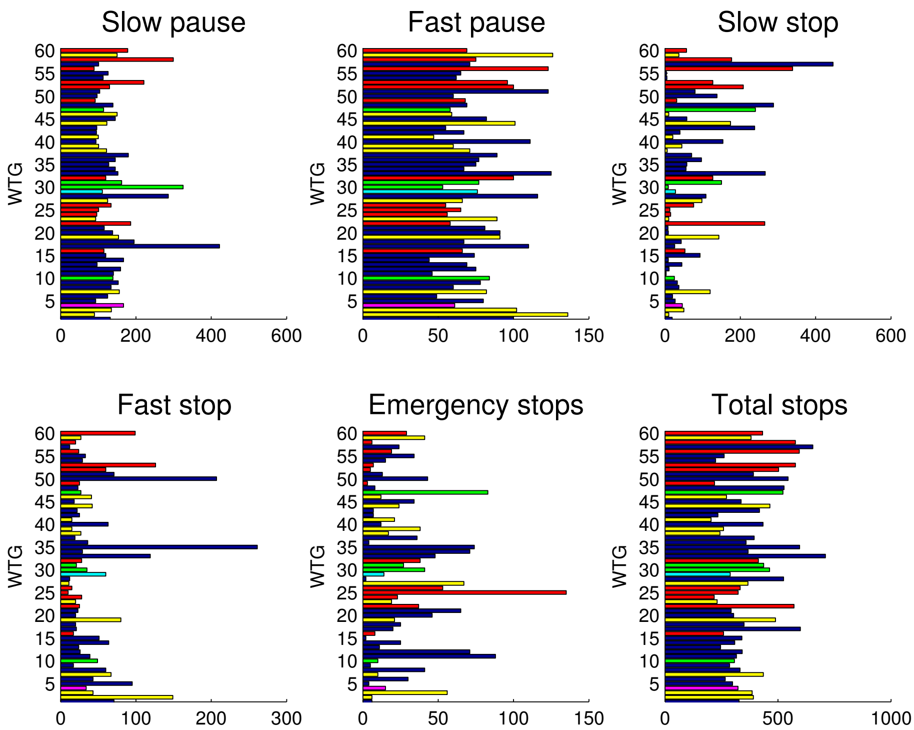


Figure 4.14: Variation in total no. of stops between different turbines during 7 year lifetime

CONCLUSIONS

The following conclusions can be drawn based on this chapter:

- Failures at PAWP are mainly bearing related, extensive monitoring of these components can give early warnings for failures.
- WEAs are indicated as main failure mode for early bearing failures in wind turbines. It is not known which loads initiate the (plastic) formation of WEA, different theories exist.
- No strong correlation is found between loads, such as wind regime and the amount of stops. The sample size is too small, and it is likely that other variations, such as high frequency loads or manufacturing and material quality, have a large effect on which component ultimately fails first within the wind farm.

5

LONG TERM RELIABILITY PREDICTIONS

This chapter covers long term failure rate predictions for PAWP based on statistical methods. Firstly, the Weibull methodology is described in section 5.1 and parameters are selected. Thereafter, the method is applied on the failure rates of gearboxes and main bearings in sections 5.2 and 5.3. The results of these predictions will form an input for the maintenance modelling performed in chapter 7.

5.1. WEIBULL ANALYSIS

A Weibull analysis is performed on the failure data of PAWP according to the methods described in section 2.2. The components are assumed to be non-repairables. The newly installed gearboxes are either completely new, or extensively overhauled, which includes exchange of the damage components and testing. Therefore, the components are assumed to have an as-good-as-new condition. It can even be assumed that newer generation or overhauled gearboxes have an increased reliability, due to design upgrades. The effect of this will be tested in section 7.3.2.

Information of operating gearboxes is included in this method by applying right censoring according to [13]. The age of operating gearboxes is no longer increased when a maintenance actions, such as a IMS or HSS exchange, has taken place. This repair changes the composition of the gearbox and can therefore affect the lifetime. It should be noted that the TTF in the following section is actually the time-to-exchange. The actual failure moment is unknown, most exchanges have taken place before the component breaks down. The actual $MTTF$ of the component will be slightly higher than calculated.

Data is fitted using Maximum Likelihood Estimation (MLE) . This method is selected because Least Squares estimation (LSXY) results in a larger error than MLE for small sample sizes which are heavily censored [40]. Testing confirmed this fact, the standard error for PAWP gearbox exchanges using MLE is smaller than when using the least squares estimation method. The corresponding standard errors are 16.8 and 24.1 months on the $MTTF$ for MLE and LSXY, respectively. In all cases, a 2-parameter Weibull distribution is used, since a 3-parameter Weibull (which includes the guaranteed lifetime parameter, γ) does not converge for the available data.

Ideally, a specific Weibull curve is obtained for each failure mode, as each failure modes develops differently. Some failure modes are likely to occur soon after commissioning (β <1), while other are heavily wear related and will occur in later years (β >3). Performing an analysis per failure mode would require large sample sizes, which are currently not available. Otherwise, it would further decrease the accuracy of the predictions.

5.1.1. PARAMETER SELECTION

The Weibull analysis can be performed on several parameters, as previously discussed in section 2.2.3. The most logical ones for wind turbines for which data is available are:

- Age
- Production [MWh]

- Online hours (Age – downtime)
- Generator hours (Online hours – idling / standstill)

An analysis based on age is easiest to perform, this only requires commissioning date and exchange dates. Moreover, predictions based on age are most meaningful to the operator, since this can be directly used in maintenance modeling: it is independent of production of specific turbines or availability. An analysis based on age is only correct, in case there is a strong correlation between failures and time. If this is not the case, an analysis based on the other parameters will give better results.

The capacity factor (C_p) of all gearboxes has been determined based on the production of the WTGs in PAWP. The C_p represents the correlating factor between time and produced power. Results are presented in Figure 5.1 and Table 5.1. This shows that the mean capacity factor is 39.2%, with a standard deviation of 1.9%. This is a credible value for the offshore environment. The mean capacity factor of WTGs with exchanged gearboxes is 39.5%. However, since this is only a small increase compared to the average. Therefore, it is expected that an analysis based on production will not provide different insight than an analysis based on calendar time. Figure 5.1 does provide a slight indication that gearbox exchanges (red) and HSS exchanges (yellow) correlate with the capacity factor. WTGs with an exchanged main bearing (green) have a slightly lower capacity factor of 37.1%.

Table 5.1: Capacity factor of PAWP WTG

Mean (σ_x)	39.2% (1.9%)
Min / Max	35.0% / 43.3%
Average of failed gearboxes (σ_x)	39.5 % (2.4%)
Average of failed main bearing (σ_x)	37.1% (1.4%)

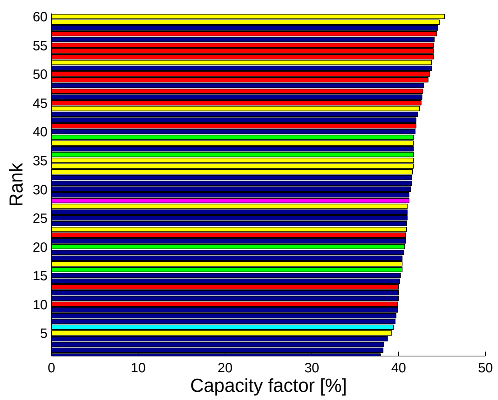


Figure 5.1: Capacity factor of PAWP wind turbines (see Table 4.6 for legend)

Table 5.2 shows the availability of the turbines. Significant differences could have indicated that turbines have been down for a longer period, thus these turbines have experienced less loads. Availability is rather constant. Table 5.3 presents the ratio between generator hours (turbine producing) and online hours (turbine available). This ratio is rather constant over the complete wind farm (94.9%), and not significantly different for failed gearboxes (94.5%). The availability of WTGs with failed main bearing is lower (90.9%), it is unknown what has caused this. It should be noted that some errors were present in the values of running hours and generator hours, which is due a replacement of the logging device or when the turbine produces energy while this device is down. A few WTGs showed a generating % and availability of less <10%, which is not a good representation of reality. These values have already been filtered out.

Eventually, it is determined to base predictions for gearboxes on age and production. Main bearing predictions will be made on age only, since no correlation is found between the capacity factor and failures (Fig. 5.1). Furthermore, it is more complex to determine the amount of online hours and generator hours for operating

WTGs: this information cannot be extracted through the SCADA system currently used at PAWP. Therefore, these parameters will not be used for Weibull modelling.

Table 5.2: Availability at PAWP

Mean (σ_x)	94.9 % (3.2%)
Min / Max	86.8% / 98.5%
Average of failed gearboxes (σ_x)	94.5% (3.2%)
Average of failed main shafts (σ_x)	90.9% (2.6%)

Table 5.3: Ratio between generator (production) hrs and online hours

Mean (σ_x)	85.9% (1.0%)
Min / Max	83.7% / 88.2%
Average of failed gearboxes (σ_x)	85.8% (1.1%)
Average of failed main bearings (σ_x)	85.9% (0.2%)

5.1.2. SAMPLE SIZE

Gearbox from a single gearbox supplier and single type are present in PAWP. It could be opted to include more data of other wind farms when performing Weibull analysis, such as wind farms with gearboxes of a different type or even manufactured by a different supplier.

GEARBOX SUPPLIER

The $MTTF$ for an onshore wind farm consisting of five Vestas V80 wind turbines (commissioned in 2005) has been studied. This wind turbines are equipped with gearboxes from three different suppliers, supplier A-C. The $MTTF$ is presented in Table 5.4. It can be observed that the different supplier have different $MTTF$. One should be aware the the sample size is too limited to make valid conclusions. Unfortunately, this gives an indication that significant differences can exist between the time-to-failure (TTF) of components from different suppliers. Large differences can even be found between the $MTTF$ of two gearbox types manufactured by the same supplier, as will be explained in section 5.2.3. This is caused by design upgrades that have been introduced in between. This reduces the accuracy of failure rates analyses when basing this on a wide range of suppliers and models. Therefore, only PAWP data will be used for analysis.

Table 5.4: MTTF for different gearbox supplier on a reference onshore wind farm

Supplier / model	**Failed / operating**	$MTTF$ **[months]**	**GoF**
A	4 / 1	78.8 (6.6 yr)	10,280
B	0 / 3	N/A, avg. age: 54.4 (4.5 yr)	-
C	2 / 1	47.1 (3.9 yr)	5,197

5.2. GEARBOX ANALYSIS

The Weibull analysis is performed based on historical gearbox exchanges in PAWP. Up-tower exchanges of the IMS rear bearing and HSS have been analyzed too. This gives insight how Weibull parameters differ of the individual parts of the gearbox. The analysis on gearbox exchange rates has been updated numerous times during the research, since failures occurred during the research.

5.2.1. GEARBOX EXCHANGES

The analysis is performed based on 16 exchanges, of which the latter have taken place at the start of May 2015. This is at the time of writing of this thesis. Performing the analysis immediately after these failures had a drastic effect on the $MTTF$, as will be discussed later in this section. Therefore, January 2016 is taken as a reference date: is it assumed that no further exchanges take place until then. This is in line with expectations of the operator and OEM.

The results for gearbox exchanges are presented in Figure 5.2 and Table 5.5. The $MTTF$ is 124 months, or

10.3 years. The mean standard error (σ_m) is equal to 16.8 months. Studying the 80% confidence interval of the $MTTF$ reveals that predictions are have a large uncertainty: this ranges between 8.7 and 12.3 years. This means there is a 20% chance that the actual $MTTF$ smaller than 8.7 years or larger than 12.3 years. A β of 2.68 is obtained, which shows that failures are wear related (β >1), however this effect is not really strong. In that case β >3 according to [8]. The standard error equals 0.6. The adjusted Anderson-Darling Goodness-of-Fit (GoF) test has been performed to check how well the sample data follows the distribution. A value of 205.3 is obtained. Generally, the better the distribution fits the data, the smaller the AD statistic is.

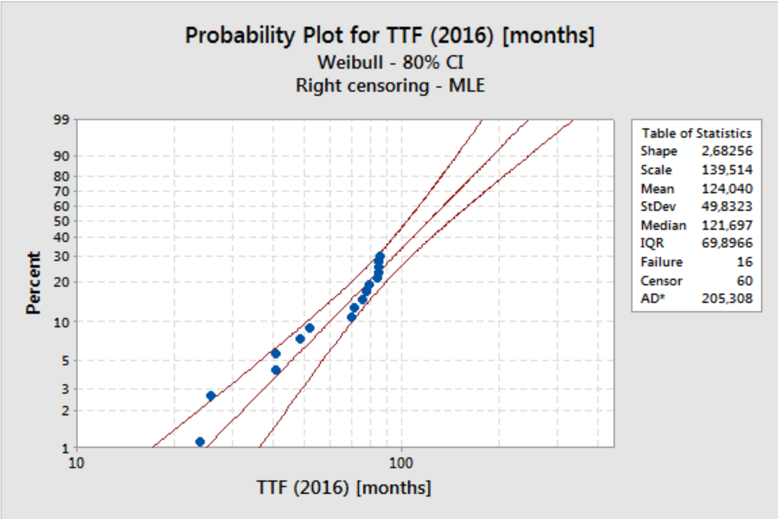


Figure 5.2: Weibull analysis on PAWP gearbox exchanges

Table 5.5: Weibull parameters obtained for PAWP gearbox exchanges based on TTF

Parameter	**Mean**	σ_m	**P10**	**P90**
MTTF [months]	124.0	16.8	104.3	147.6
β (shape parameter)	2.68	0.60	2.01	3.58
η (scale parameter)	139.5	19.7	116.4	167.2
Goodness of Fit (AD (adjusted))	205.3			

The Weibull analysis based on GWh has also been performed, which results in a mean power to failure ($MPTF$). Results are given in Table 5.6. It can be observed that the β value is in the same region as in the analysis on age, 2.68 vs. 2.98. This is logical, since production is rather constant over the years.This confirms the assumption that the analyses do not create large differences, as described in section 5.1.1. The Goodness-of-Fit is significantly smaller at 107.9, thus this model on production is more accurate than on age. However, it is expected that this is affected by the small sample size. Later, it is shown that the analysis on power is not significantly better for IMS and HSS failures.

Table 5.6: Weibull parameters obtained for PAWP gearbox exchanges based on GWh

Parameter	**Mean**	σ_m	**P10**	**P90**
MPTF [GWh]	62.6	7.6	53.7	73.1
β (shape parameter)	2.98	0.69	2.22	4.00
η (scale parameter)	70.2	9.0	59.5	82.7
Goodness of Fit (AD (adjusted))	107.9			

PROGRESS OVER TIME

The amount of gearbox exchanges rapidly increased from 7 in May 2014 to 16 in May 2015. This overlaps with the period during which this research has taken place. The failures have increased the sample size, thereby increasing the accuracy of predictions. Also, it could be an indication for a high β value. The Weibull analysis has been made at different moments. Results are presented in Table 5.7, where significant changes over time can be seen. Unfortunately, the updated Weibull parameters nearly always fall outside the standard error. This means that the first predictions were highly inaccurate. Next to that, the standard error has become smaller when more failures occurred, as expected. It can be concluded that updating the Weibull curves at set moments, or after future failures, increases the accuracy of predictions. This should become a standard part of asset management.

Table 5.7: Progress of Weibull parameters over time

	June 2014	Sept. 2014	May 2015	Jan 2016 (expected)
No. of exchanges	7	10	16	16
$MTTF$ (σ_m) [months]	311.4 (214.1)	156.8 (48.11)	109.0 (12.9)	124.0 (16.8)
β (σ_m)	1.39 (0.50)	2,05 (0.62)	3.04 (0.70)	2.68 (0.60)
η (σ_m)	341.1 (216.1)	177.0 (53.8)	122.0 (15.4)	139.5 (19.7)

5.2.2. RESULTS FOR UP-TOWER EXCHANGES

A Weibull analysis is performed based on the exchanges of the HSS and IMS rear bearing. The failure rates of the two can be analyzed separately, but the failure rate of the IMS is low compared to the HSS (2 vs. 17) and maintenance effort is similar. Therefore, they are combined. Figure 5.3 and Table 5.8 shows that the $MTTF$ is 114.7 months, or 9.6 years. The 80% confidence region is between 8.0 and 11.5 years. β equals 2.30, thus failures are wear related. η equals 129.5. These values are in the same range as the gearbox exchanges, where β and η were 2.68 and 139.5, respectively. Gearbox exchange are performed when the LSS or the front bearing of the IMS fails. Therefore, it seems as if failures occur at the same rate throughout the whole gearbox, but the locations where the failure occurs determines the maintenance actions required. The goodness-of-fit is equal for analyses on age and production: 218 vs. 217, respectively (Table 5.8 and 5.9). Also, the β values are again almost the same.

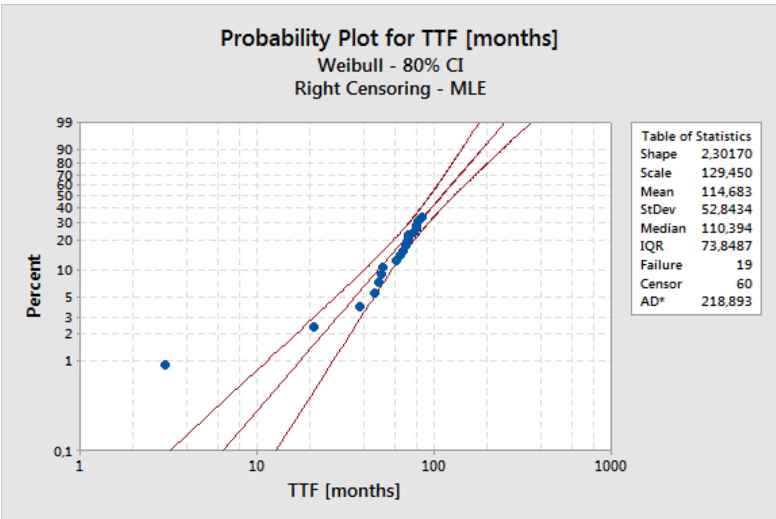


Figure 5.3: Weibull plot on combined IMS and HSS failures in PAWP gearboxes

Table 5.8: Weibull parameters obtained for combined IMS and HSS failures based on TTF

Parameter	Mean	σ_m	P10	P90
MTTF [months]	114.7	16.3	95.6	137.6
β (shape parameter)	2.30	0.49	1.76	3.02
η (scale parameter)	129.5	18.6	107.6	155.7
Goodness of Fit (AD (adjusted))	218.9			

Table 5.9: Weibull parameters obtained for combined IMS and HSS failures based on PTF

Parameter	**Mean**	σ_m
MPTF [GWh]	65.89	9.55
β (shape parameter)	2.26	0.48
η (scale parameter)	74.4	10.9
Goodness of Fit (AD (adjusted))	217.2	

5.2.3. BENCHMARK WITH OTHER POPULATIONS

The results of the Weibull analysis in Figure 5.2 are compared with the failure rate of a reference offshore wind farm, and the whole population of gearboxes of the same model. If differences are small, the populations can be merged to increase the sample size.

SINGLE OFFSHORE WIND FARM

The reference offshore wind farm consists of 30 V80 WTGs and is equipped with gearboxes produced by the same supplier. The gearbox are the previous variant of the one installed in PAWP. These had a $MTTF$ of 46.8 months, or 3.9 years (Fig. 5.4). This is significantly lower than the expected $MTTF$ at PAWP (10.3 years), indicating that significant improvements have been introduced in the PAWP gearbox model. Therefore, this data cannot be utilized for failure rate predictions for PAWP. The β value is 6.9, meaning that failures followed each other quickly. It is plausible that PAWP gearbox will eventually show similar behaviour.

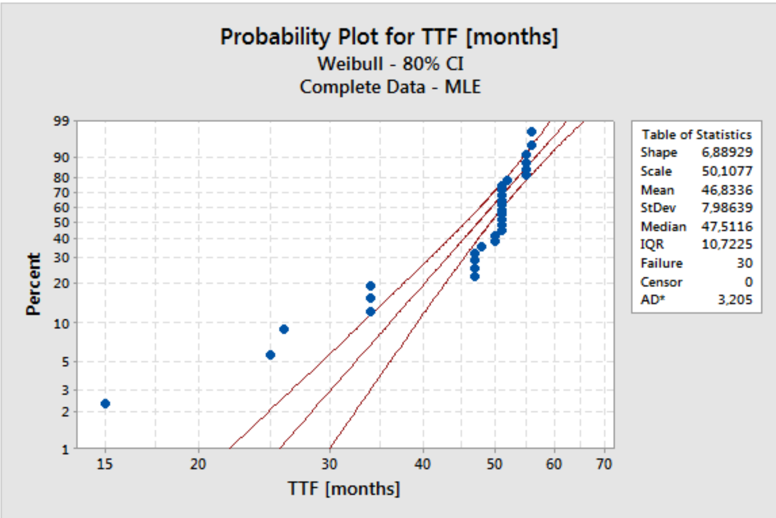


Figure 5.4: Weibull analysis on 1st generation of gearboxes in reference V80 offshore wind farm

WHOLE POPULATION

The complete population of gearboxes of the same type has been studied together with Vestas, Mitsubishi Vestas Offshore Wind (MVOW) and ZF Wind Power to check if the PAWP wind farm was a representative sample for the complete population. In total, over 3000 gearboxes of this type have been installed. Over 95% of these gearboxes have been installed in the onshore environment. The capacity factors is significantly lower onshore, which could have an impact on the average $MTTF$. However, this relation has not been proven yet. A Weibull analysis on the complete population revealed that the $MTTF$ in PAWP was significantly lower. The actual $MTTF$ and Weibull parameters have not been disclosed. Several hypotheses can be made on causes of differences:

- Offshore gearboxes have a shorter lifetime than onshore due to increased loads or harsh environmental conditions.
- Few gearboxes in the onshore population have failed yet (approx 10%), due to a relatively low average age. This high amount of data censoring can cause a significant under-estimation of the $MTTF$, as many failures still have to take place. This is especially the case if $\beta > 3$.

- The PAWP is a specific case due to local conditions (maintenance regime, local conditions, etc.), however this is unlikely.

Unfortunately, no insight is given on the operating conditions of the benchmark population. This makes it impossible to test these hypotheses. Therefore, maintenance optimization is based on PAWP data only in the latter of this report.

5.3. MAIN BEARING ANALYSIS

The Weibull analysis on main bearing exchanges is presented in Figure 5.5. The analysis is only based on time-to-failure, since it has been shown that main bearing failures have no correlation with the capacity factor (section 5.1.1), or wind loads (section 4.3.1). The specific values of the Weibull parameters can be found in Table 5.10. The $MTTF$ is 278 months, or 23.2 years. A β of 1.89 is obtained, which shows that failures can be related to deterioration (β >1), however this effect is again not very strong. Studying the 80% confidence interval for the $MTTF$ reveals that predictions are have a large uncertainty, which ranges between 10.2 and 52.4 years. This spread is rather significant, resulting in a high uncertainty when predicting failure rates.

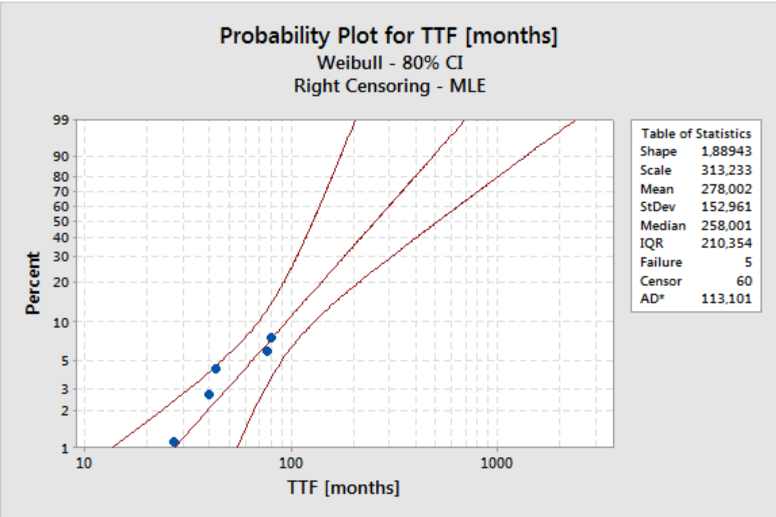


Figure 5.5: Weibull analysis on PAWP main shaft exchanges

Table 5.10: Parameters obtained from Weibull analysis on PAWP main shaft exchanges

Parameter	Mean	σ_m	P10	P90
MTTF [months]	278.0	177.1	122.9	629.0
β (shape parameter)	1.89	0.82	1.08	3.30
η (scale parameter)	313.2	195.3	140.9	696.4
Goodness of Fit (AD (adjusted))	113,101			

CONCLUSION

A short summary of the conclusions that can be made based on this chapter:

- The overall accuracy of Weibull analyses is low, the standard error and 80% confidence intervals are rather large. The Weibull parameters also change significantly as more failures occur, while the standard error decreases. Many gearbox exchanges have taken place recently, indicating that a higher β value could eventually become true. The β value at the reference wind farm was also significantly higher (6.9 vs 2.7)
- The β values based on TTF or PTF do not differ much. This can be explained by the low spread in capacity factors of the different wind turbines and relatively constant production over the years. The Goodness-of-Fit was better on PTF analysis for gearbox exchanges, but this phenomenon was not observed for HSS and IMS failures.

- The Weibull parameters for gearbox exchanges and up-tower exchanges are in the same region. This indicates that a failure is likely to occur after a certain time, but the location of the actual failure determines the maintenance action required.
- Too little main bearings failures have occurred to be able to make high accuracy predictions. The 80% confidence region of the $MTTF$ covers 42 years, the expected $MTTF$ is 23.2 years. Therefore, the use of these results for maintenance modelling is reconsidered.
- When using these Weibull parameters in maintenance modelling, this is based on the 'as-bad-as-old' assumption, thus newly installed components will perform the same as the old versions. This is no good representation of reality, usually design changes have been implemented on newly installed components to mitigate known failure modes. Therefore, an increase of the reliability of 2nd generation will be considered.

6

SHORT-TERM RELIABILITY INDICATORS

An estimate for the future failure rate has been obtained in the previous chapter. In this chapter, indicators of developing failures are studied. These indicators will provide the operator insight in which components require an exchange. Available data from PAWP wind farm is investigated in sections 6.1. Short-term indicators are studied in sections 6.2 and 6.3 for gearbox and main bearings, respectively. The accuracy of these indicator is an input for optimization of exchange strategies in chapter 7.

6.1. AVAILABLE DATA

The PAWP wind farms has the following data available for health monitoring:

- 10-min SCADA data
  - Wind speed (U_{avg}, U_{max}, σ_u, inflow angle)
  - Temperatures (T_{amb}, T_{nac},T_{oil}, T_{HSS})
  - Power
  - Status (available/down)
  - Alarms
- Condition monitoring system
  - Vibrations (Gearbox & main bearing)
  - Temperature (Main bearing)
- Oil samples (Gearbox)
- Grease samples (Main shaft)
- Borescope inspections (only for suspected failures)

SCADA signals from the rough and fine oil filter and the oil flow are also available. Unfortunately, these do not generate representative measurements. It should be noted that borescope inspections are only performed when failures are suspected, since this action is costly. It could be performed regularly when components reach their expected end-of-life.

CMS is located at several location on the main bearing and gearbox (Fig 6.1). It measures vibrations and temperature on the gearbox and main bearing at the locations specified in Table 6.1.

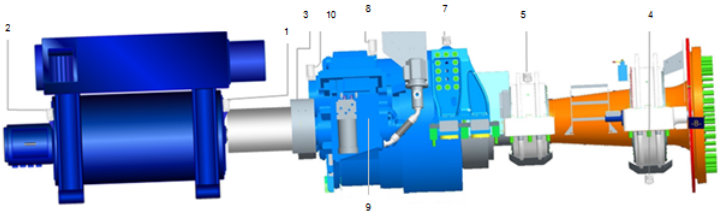


Figure 6.1: Location of CMS sensors

Table 6.1: Location and corresponding measurement of CMS sensors on main bearing and gearbox

No.	Location	Measurement
4	Front main bearing	Vibrations
5	Rear main bearing	Vibrations Temperature
7	Planetary stage	Vibrations
8	IMS rear bearing	Vibrations
9	HSS- front bearing	Vibrations
10	HSS - rear bearing	Vibrations

6.2. GEARBOX

Feng et al. has investigated typical failure modes of gearboxes and identified signals that are most suitable to indicate these failures [32]. Results are given in Figure 6.2.

Failure Modes for Monitoring	Planetary gear failure	Planetary bearing failure	Intermediate shaft bearing failure	High speed shaft bearing failure	Lubrication system malfunction
SCADA data	Oil temperature signals	None	None	HSS bearing temperature signals	Oil pressure level, oil filter status
CMS signals	LSS end vibration signal; Oil debris counts of Non-Ferrous particles	LSS end vibration signal; Oil debris counts of Ferrous particles	LSS or HSS end vibration signals; Oil debris counts of Ferrous particles	HSS end vibration signals (vertical, transverse, axial); Oil debris counts of Ferrous particles	
Additional signals	Rotor speed; Generator speed; Nacelle temperature; Power output				

Figure 6.2: Relevant SCADA & CMS measurements for gearbox health monitoring according to [32]

6.2.1. SCADA SIGNALS

Available SCADA signal are temperature of the gearbox oil and HSS. Feng et al. concluded that oil and gear temperature are a good indicator for upcoming gear failures. This was explained by the energy balance. In case of a failure, the efficiency of the gearbox decreases, thereby causing more heat generation. This phenomenon was observed when Feng et al. compared the temperature 9, 6 and 3 months prior to failure, as shown in Figure 6.3. Here the difference between the oil and nacelle temperature has been plotted, clearly showing an increase in temperature.

The same exercised has been performed on 3 failed PAWP gearboxes (Fig. 6.4). The highest difference is observed 6 months prior to failure. However, this is most likely caused by the ambient temperature, which is the lowest in this period. This causes the nacelle to be cooler, resulting in a larger temperature difference. The effect presented by Feng et al. is thus not observed. It should be noted that Feng et al. indicated oil temperature signals as the best identifiers for planetary *gear* failure (Fig 6.2). In PAWP only planetary *bearing* failures have occurred. This is a good explanation why no similar results are obtained. Also, it is not known how long before the exchange the failures in PAWP were initiated.

The same methodology is performed on the temperature difference between the oil and ambient temperature (Fig. 6.5) and the absolute oil temperature (Fig. 6.6). Again no clear indications for developing failures are observed. Feng et al.'s conclusion that planetary bearing failure cannot be detected using oil temperature is thus confirmed.

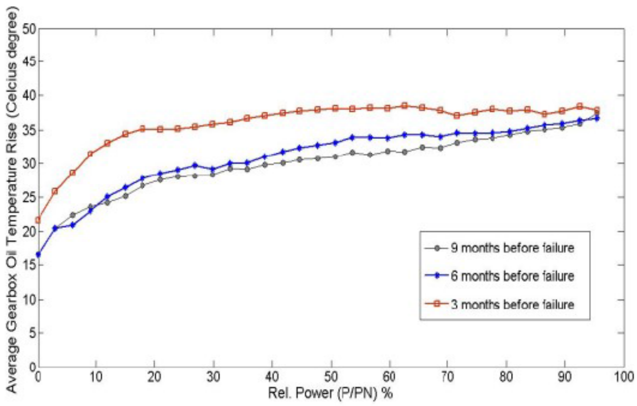


Figure 6.3: Increase in gearbox oil temperature prior to failure according to [32]

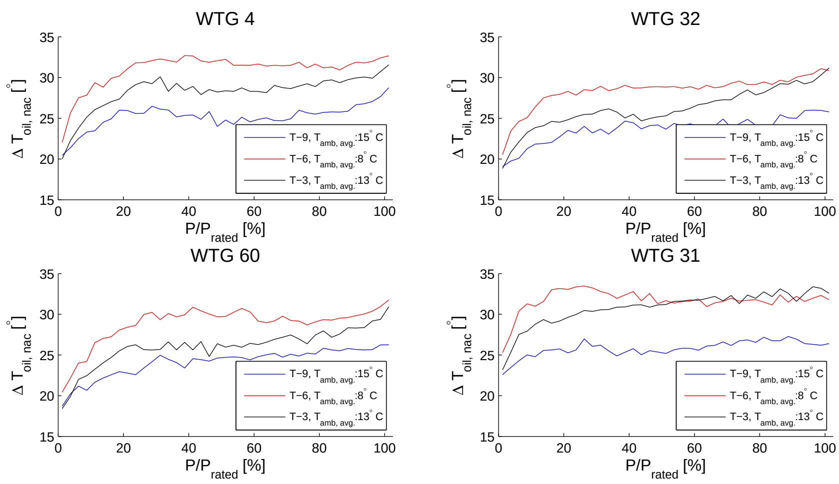


Figure 6.4: Temperature difference between oil and nacelle temperature for three failed (4, 32, 60) and one healthy gearbox (31)

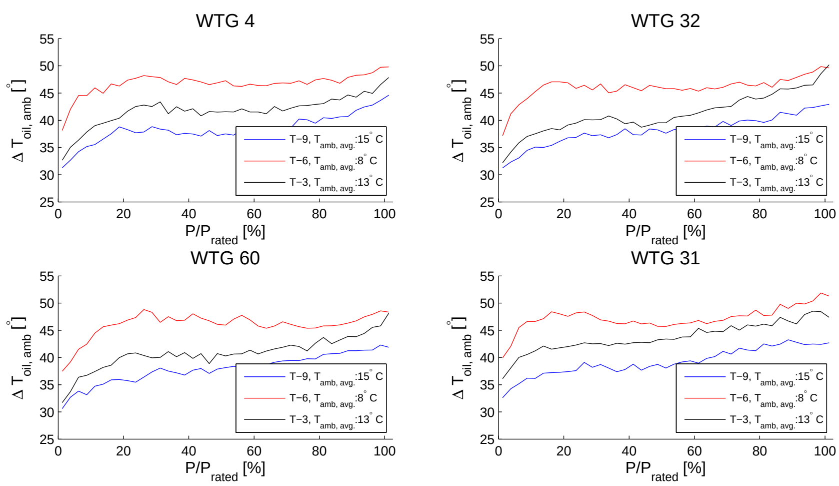


Figure 6.5: Temperature difference between oil and ambient temperature for three failed (4, 32, 60) and one healthy gearbox (31)

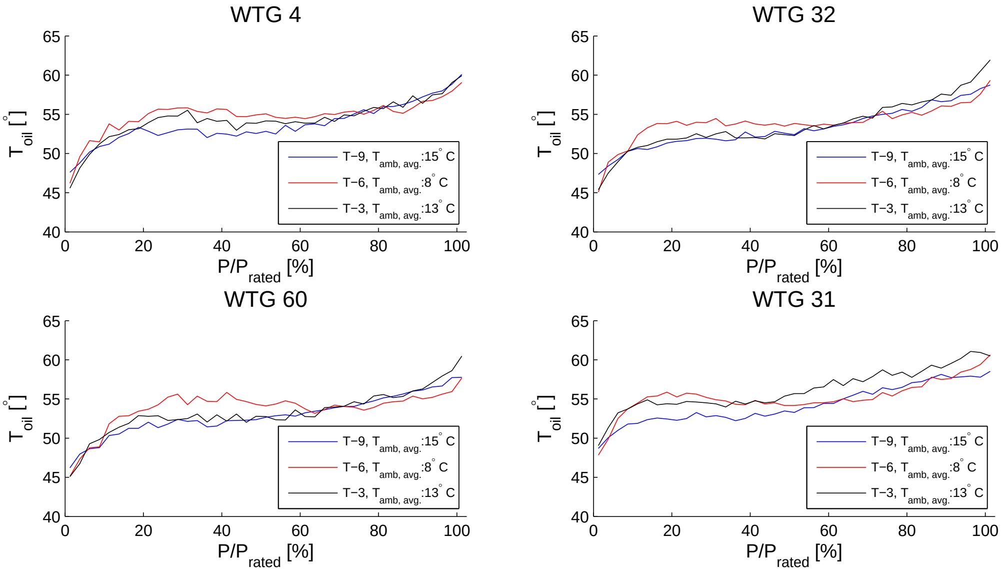


Figure 6.6: Absolute oil temperature for three failed (4, 32, 60) and one healthy gearbox (31)

Feng et al. did indicate the HSS bearing temperature as a relevant signal for bearing failures. Therefore, the same exercise is performed comparing the difference between HSS gear and nacelle temperature and the absolute HSS temperature prior to failure. Results are presented in Figure 6.7 and Figure 6.8. One month has been excluded (WTG 41) because the availability was <10%. Similar results are obtained as previously, in colder months the temperature difference is the largest or the HSS bearing temperature is the lowest. It is therefore concluded that developing HSS bearing failures cannot be observed by studying the bearing temperature using this methodology.

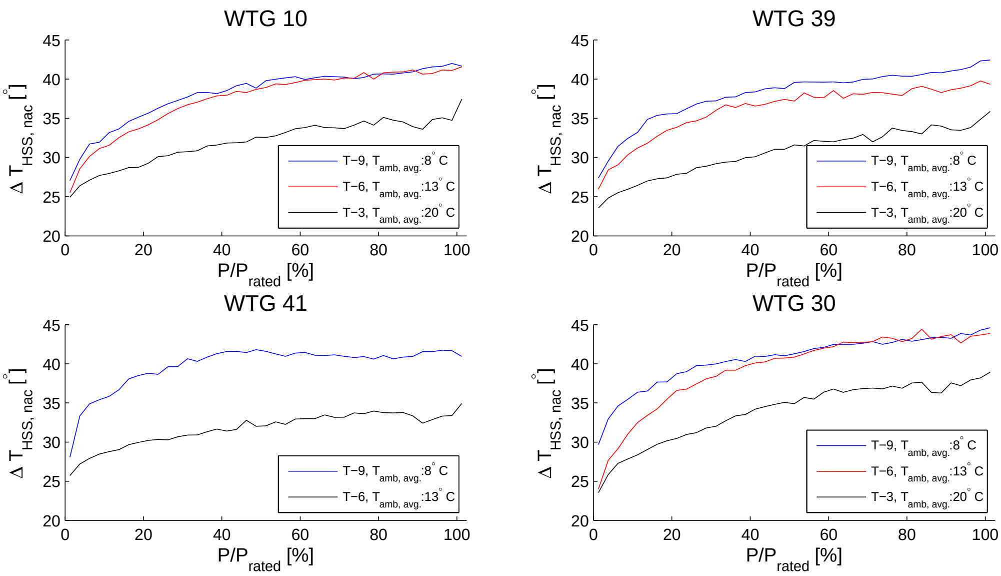


Figure 6.7: Temperature difference between HSS bearing and nacelle temperature for three failed (10, 39, 41) and one healthy HSS (30)

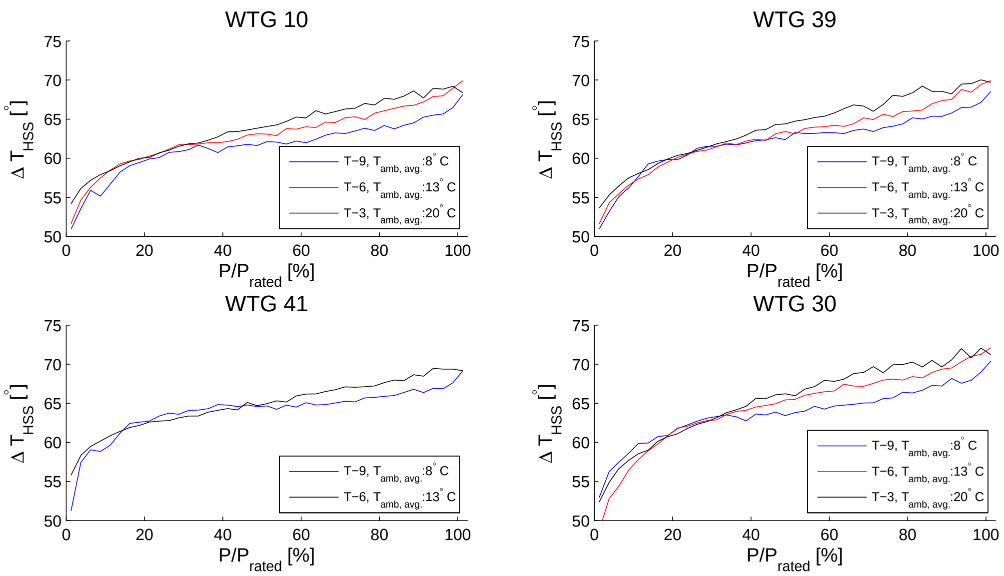


Figure 6.8: Absolute HSS bearing temperature for three failed (10, 39, 41) and one healthy HSS (30) (**Update figure**)

Based on these results, it is doubtful whether oil and bearing temperatures are a good indicators for failures. An attempt has been made to develop a model for oil temperature based on the power level, ambient temperature and nacelle temperature using regression analysis. The model was fed with training data from a period when no failure occurred. Next, the predicted oil temperature was plotted against the measured oil temperature. Large difference between these two can be an indication for a developing failure. Unfortunately, the training data was too clouded, as can be seen in Figure 6.9. No working model could be created. It is very likely that other parameters are required to be able to create such a model, such as the conditions in which the WTG has been running for the past hours.

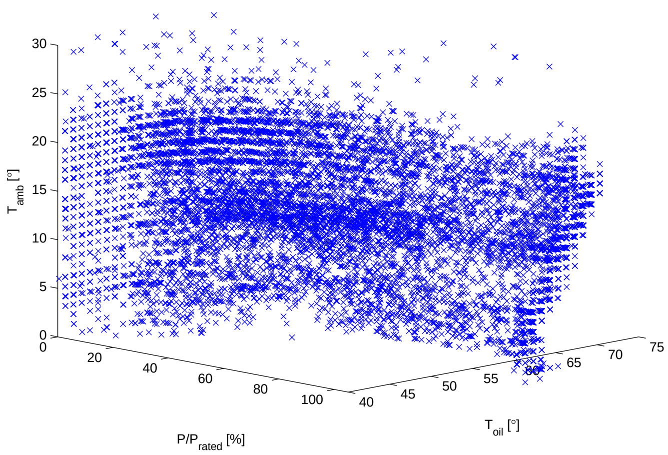


Figure 6.9: Cloudiness of one month of temperature data

6.2.2. CMS SIGNALS

The CMS system is installed to determine the condition of components. Vibration levels are measured, these are expected to increase due to failures. Rollers can e.g. 'bump' through a crack or spalling, which causes increased vibration compared to a smooth rolling surface. The type of failure can be identified by the frequency of the vibration, because the frequencies of the bearings are known, the so called 'ball-passing' frequencies of the inner and outer ring. Gear failures can be identified according to the gear frequencies.

The most important function of CMS system is to provide an early warning before component fails. This allows the operator to exchange the component, lowering the cost of downtime and mitigating catastrophic failures. The time between failure detection and a catastrophic failure is dependent on how fast the failure develops and the sensitivity of the CMS system. Failures on bearing that have a low rotational speed have been found more complex to identify [41]. Vibration levels are lower due to the low rotational speed. Next to that, the planetary stages are located relatively deep inside the gearbox and no sensor is located on the front bearing of the IMS.

Figure 6.10 shows the CMS vibration levels of the planetary stage of WTG 58, which has been exchanged in July 2014. A clear increase in vibrations is measured, it crossed the alert level (yellow) 3 months prior to the exchange. This alert level is based on industry experience.

Figure 6.10: CMS vibration level of PS 6 months prior to GBX exchange **Update**

An assessment has been made on the time between the CMS alarms and exchange of the gearbox. Results are given in Figure 6.11. The average detection time is 3.0 months. It should be noted that this does not equal the time between detection and the actual failure. It is unknown what the remaining lifetime of the gearbox was at the time of exchange. However, on 5 instances the turbine was shut down before the exchange took place, because the gearbox could no longer be operated safely. The standard deviation of the detection time is 2.3 months. Two instances the detection time equals 0 months: one gearbox failed unexpectedly, and another one was exchanged without any CMS alarms triggered. The failure was detected through oil samples and a borescope inspection. HSS exchanges have a longer detection time, the average time between detection and the exchange is 11 months. This is caused by the higher sensitivity of the system on components with a high rotational speed.

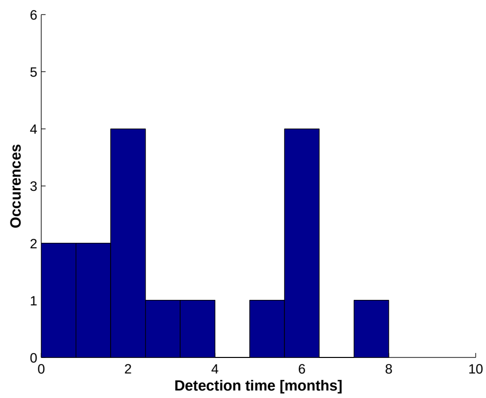


Figure 6.11: Histogram of time between CMS alarm and exchange

6.2.3. OIL FILTER EXCHANGES

A rough and fine oil filter are present inside the oil system of the gearbox: these are exchanged twice a year during planned maintenance activities. All oil that has passed the bearings is directed towards the filters. Any debris from failing bearing should thus be caught by the filters. Damaged bearings can thus results in filters with an high amount of debris, which in turn reduces the oil flow and requires an exchange of the filter. SCADA pressure measurement over the oil filters do not generate representative results. Also it is not known in which conditions filters are when they are exchanged, but data is available on when filters are exchanged for the time period 2012 - 2014. 6 instances were observed during which an oil filter was exchanged outside planned maintenance, vs. 360 planned exchanged (Table 6.2). This table shows during which activity the oil filter exchange took place, and whether or not consequently an exchange was planned. In the same period, 6 gearbox exchanges and 19 up-tower exchanges have taken place. Concluding, 4 out of 25 exchanges were preceded by an oil filter exchange. Oil filter exchange frequencies thus do not provide an indication of degrading gearboxes.

Table 6.2: Overview of non-regular oil filter exchanges in 2012-2014

WTG	Year	Service type	Follow-up
02	2012	Gearbox borescope inspection	HSS exchange
13	2013	Corrective maintenance	nothing
23	2013	Gearbox borescope inspection	HSS exchange
29	2014	Corrective maintenance	IMS bearing exchange
33	2014	Corrective maintenance	nothing
58	2012	Gearbox borescope inspection	GBX exchange

6.3. MAIN BEARING

It more is difficult to determine the conditions of main bearings. CMS is used and analyzed in this section. Next to that, grease samples are being taken at PAWP. Grease samples can provide a good indication of wear of the main bearing. Debris from spalling, flaking or wear can be measured in the grease samples, by excessive iron and copper levels. Grease samples are being taken twice a year, but data from only one instance is available for this research. It is not certain if these are representative samples, and are therefore not included in this research.

6.4. CMS DATA

The main bearings are equipped with CMS system, which measures vibration on the front and rear bearing, and temperature on the rear bearing.

6.4.1. VIBRATIONS

Vibration of the front and rear main bearing is monitored. In Figure 6.12, the vibrational levels of WTG 04, WTG 31 and 10 other randomly selected rear main bearing is plotted. The main shaft of these two WTGs was exchanged in August 2014 due to failure of the rear main bearing. The vibration of these two WTGs started to rise as of October 2013, thus 9 months before failure. Data is plotted here when the turbine was operating at nominal power, therefore data is scarce during summer.

The same analysis has been performed on the vibration levels of WTG 10 and 47, which have been exchanged in July 2011. The vibration levels of these turbines did not show a significant increase (Fig. 6.13). This show that CMS vibration levels are not conclusive to detect main bearing failures.

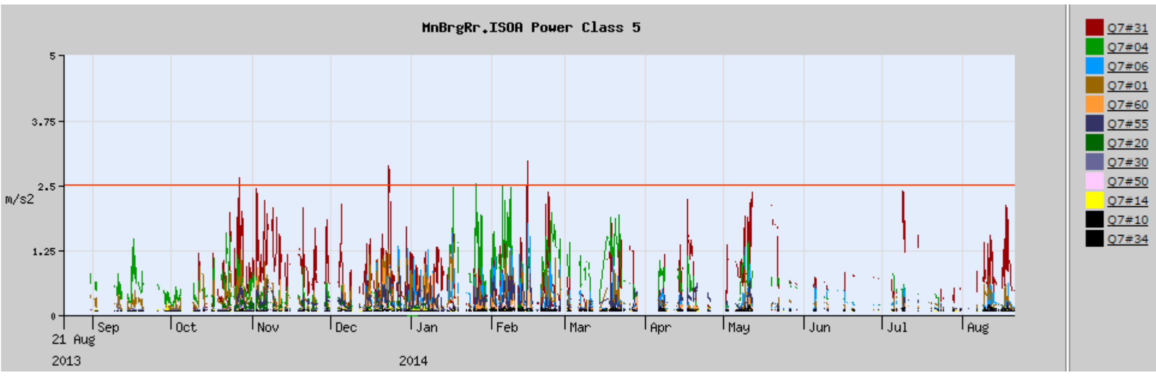


Figure 6.12: Rear main bearing vibration levels of WTG 4, 31 and 10 randomly selected WTGs

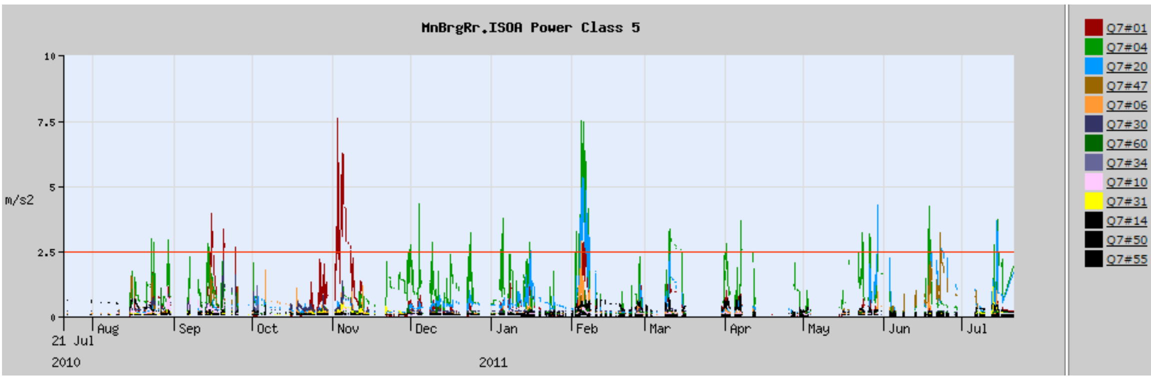


Figure 6.13: Rear main bearing vibration levels of WTG 10, 47 and 10 randomly selected WTGs

6.4.2. TEMPERATURE

The temperature level of main bearings has been measured since July 2012. Since then, 2 main bearings have been exchanged in August 2014. The temperature sensor on one of those bearings was broken, the other has been analyzed. The temperature of the exchanged main bearing (WTG 04) and 10 other randomly selected main bearings manufactured by the same supplier has been plotted for 6 months prior to the exchange in Figure 6.14. No clear increase in the main bearing temperature at WTG 04 is observed compared to the other wind turbines.

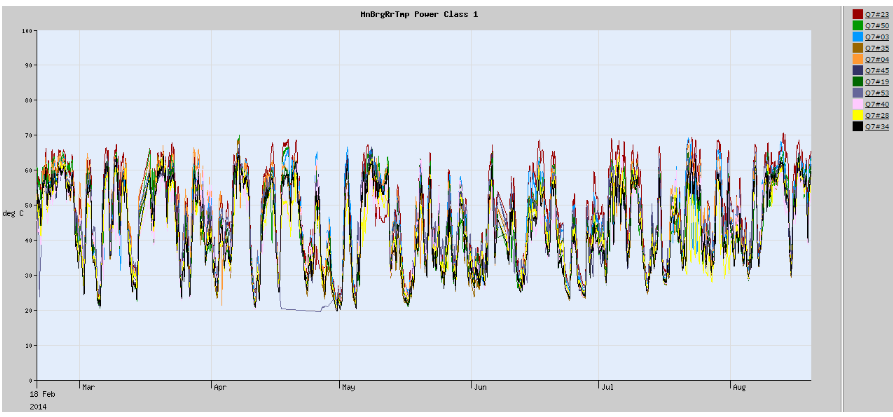


Figure 6.14: Rear main bearing temparature of WTG 4 and 10 randomly selected WTG 6 months prior to exchange

The rear bearing temperature of all WTGs has also been plotted. This resulted in Figure 6.15. When comparing the wind turbine numbers with the corresponding suppliers, it became visible that bearing of the different supplier have different operating temperatures. This is expected to be caused by differences in designs, tolereances or materials. Some outliers are present, but no CMS alarms are active on these bearings. Therefore, it is not known whether these outliers are caused by a developing defect, or a measurement error.

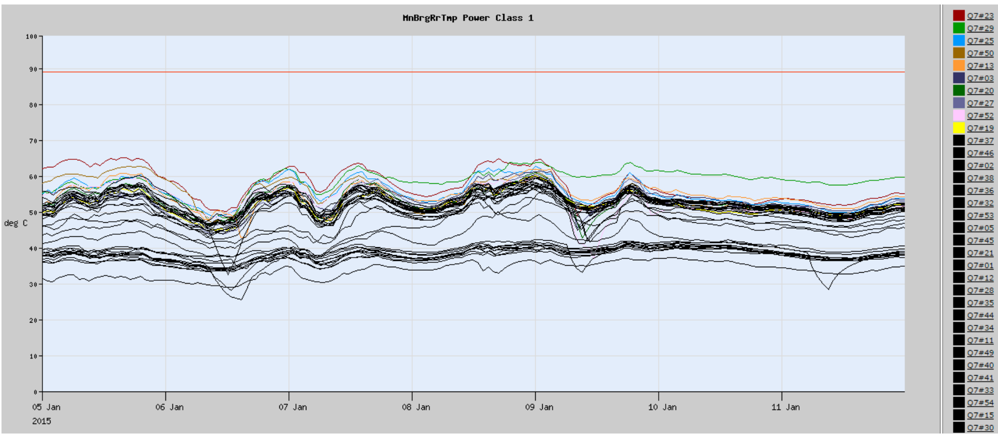


Figure 6.15: Rear main bearing temperature of all WTG, showing temperature difference of different suppliers

Conclusion

The following conclusions can be drawn based on this chapter:

- CMS data is the best indicator for detecting gearbox bearing failures. The average detection time is 3 months, with a standard deviation of 2.3 months. Not all failures are detected using the CMS system. HSS failures are easier to detect, the average detection time is 11 months prior to the exchange.
- The oil and HSS bearing temperature are no good indicator of gearbox bearing failures.
- Main bearing failures are difficult to detect using CMS. Vibrations levels showed an increase in 2 instances, but for 2 other failed main bearings no increase in vibrations was observed. The bearing temperature of one failing main bearing could be investigated, but this showed no temperature increase. Grease samples can provide better insight, because debris from spalling and wear causes increased iron and copper levels. Unfortunately, these samples are not available for this research.

7

DETERMINING THE OPTIMAL EXCHANGE STRATEGY

In this chapter optimized gearbox exchange strategies are designed. This aims at reducing the financial impact of future major interventions. Firstly, a cost breakdown of three separate exchange campaigns is made in section 7.1. A Monte-Carlo based simulation method for exchange strategies is defined in section 7.2. This is applied on PAWP in section 7.3, using the results from the Weibull analysis performed in 5.1 . Finally, the gearbox exchange strategy optimization is also applied on a future 350MW wind farm in section 7.4, which gives insight in the effect of larger wind farms and turbines of increased size.

7.1. COST BREAKDOWN MAJOR INTERVENTIONS

The cost of gearbox exchanged are significant, as discussed earlier. A preliminary cost estimation proposed in [42] resulted in a total gearbox replacement cost of approximately €350k for a 2 MW offshore wind turbine. Other sources estimate a cost of €300k [30]. This includes the cost of vessels, parts, crew, and production losses.

A more detailed breakdown is presented in Table 7.1. Production losses can be quite severe, up to approximately 5800 €/day for a 2MW turbine on a full production day. Unexpected failures in winter can therefore result in significant losses, when winds are strong and the site is inaccessible. The cost of the vessel are predominant, which makes batch exchanges in summer time the preferred strategy [30]. The daily jack-up costs are mainly dependent on the repair time, vessel size, market demand and the cost of tugs (in case of a barge). The mobilization cost usually equals the travel- and loading time multiplied by the day rate, which makes it highly dependent on the location of the jack-up vessel. Mobilizing a vessel travelling at 5 kts from the Irish Sea can take up to 8 days, travel time from Esbjerg (DK) is 4 days [29].

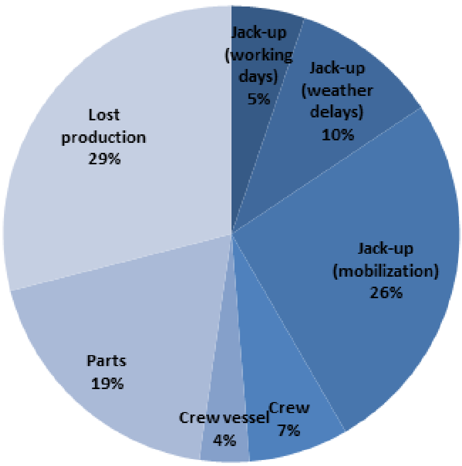
Table 7.1: Different cost categories for major interventions ([30], [3])

Category	Dependent on:	Rate
Production losses	o Down time o Repair time o Weather conditions	130 €/MWh
Personnel	o Crew size, o Repair time o Travel time	200 hr @ 100 €/hr
Crew vessel	o Repair time o Travel time	4k €/day
Jack-up vessel	o Repair time o Vessel size o Market demand o Mobilization cost o Fuel cost o (Tugs cost)	40-80k €/day
Parts cost	o Market price	Variable

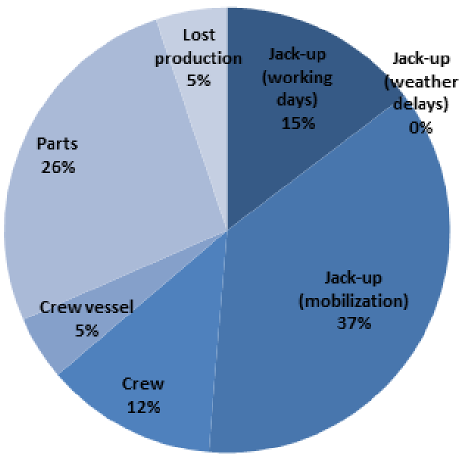
The predominant difference between single and campaign-based exchanges is that the (de-)mobilization cost of the jack-up can be spread out over several wind turbines. This has a significant impact on the cost per exchange. In the following paragraphs 3 exchange campaigns are analyzed, during which 1, 1 and 5 components have been exchanged.

7.1.1. SINGLE EXCHANGE

Two single gearbox exchanges have taken place in January 2014 (exchange A) and April 2014 (exchange B). Exchange A was a corrective exchange, the gearbox had failed unexpectedly 6 weeks before the exchange took place. Exchange B was a preventive exchange, a failure was expected in the near future. The wind turbine was operating until the jack-up vessel arrived. In Figures 7.1a and 7.1b the cost breakdown for the two exchanges is presented.



(a) Exchange A: Corrective



(b) Exchange B: Preventive

Figure 7.1: Cost breakdown of single exchange (total cost of exchange A = 141% of exchange B)

Comparing exchange A to exchange B the followings observations are made:

- The total cost increased by 41% due to corrective exchange
- Increase in lost production due to break down (+689%)
- Increase in jack-up costs due to high weather delays in January (+50%)

- Decrease in crew costs, since no borescope inspection was required (-20%)

Conclusions on single exchanges can be drawn from the two campaigns:

- Mobilization costs are the most significant cost contributor (26% - 37%)
- The impact of weather days can be significant (Exchange A: 10%)
- The total costs of the jack-up are predominant (41% - 52%)

7.1.2. BATCH EXCHANGE

In the summer of 2014 three gearboxes and two main shafts have been exchanged simultaneously. Both the gearbox and main shaft were exchanged on one WTG, resulting in 4 affected WTGs. The campaign took place in August, when good workability was expected. Unfortunately rough weather caused significant weather delays, which accounted for 25% of the total campaign costs. A breakdown of the cost is given in Figure 7.2.

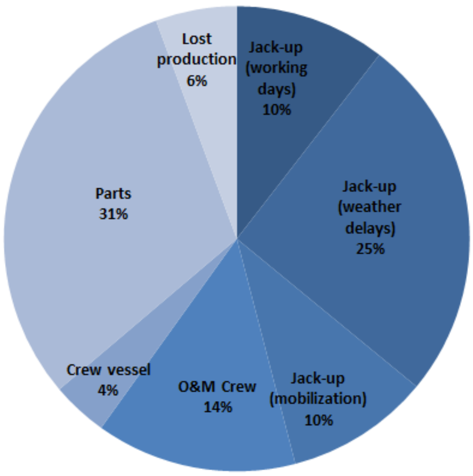


Figure 7.2: Cost breakdown of batch exchange

Figure 7.2 provides the following insights:

- Significant cost due to non-workable days (25% of total campaign cost)
- Part price is more significant (31%), which is a fixed cost

The single and batch exchanges have been compared, without taking into account the real weather delays. The cost of weather delays is significant, and therefore drastically impacts the results. This makes it impossible to make a fair comparison between strategies. The risk of weather delays is dependent on the period during which the exchange takes place, and not on the strategy. Therefore, the strategies are compared assuming a weather delay of 50% (i.e. 50% of the working days is added as weather delay).

Assuming this, the following conclusions can be drawn:

- The cost per component exchange drops by 51% when moving from an average single to a batch campaign. However, this number is affected by the simultaneous gearbox and main shaft exchange.
- The cost per WTG drops by 38% when moving from a single to a batch strategy visiting 4 WTGs.
- The mobilization costs are a significantly smaller share of the total price (31% for a single exchange vs. 12% for batch exchange.)
- Production losses are significantly lower when using a preventive exchange regime (-88%).

7.2. GEARBOX EXCHANGE OPTIMIZATION

It has been decided to focus purely on gearbox failures when optimizing the exchange strategy at PAWP. The accuracy of Weibull prediction of other component, such as the main shaft, is considered too low. The optimal exchange regime is determined by performing Monte-Carlo simulation. n simulations are performed to determine the exchange moments ($T_{exchange}$) of gearboxes for each wind turbine in the wind farm. This is performed for all strategies to account for the different exchange moment the strategies cause. The Monte-Carlo simulation methodology is visualized in Figure 7.3. An n of 5000 resulted in a stable model, the mean number of failed gearboxes shifted by <1% per complete simulation, with a low computation time. The Weibull parameters, that have been used to determine the TTF in each simulation, are generated using normally distributed shape and scale parameters. The mean and standard deviation of this distribution equals the mean and standard error estimated in section 5.2. This accounts for the uncertainty in the Weibull modelling performed previously.

The Monte-Carlo simulations are performed to cope with the following uncertainties:

- Weibull parameters
- Moment of failure
- Detectability
- Moment of jack-up arrival

Each simulation results in the following parameters for each WTG in the wind farm:

1. Moment of gearbox exchange ($T_{exchange}$)
2. Downtime (T_{down}) during each year in months
3. Number of gearbox exchanges during lifetime
4. Number of gearboxes exchanged per year in wind farm ($N_{exchanges,annual}$)

The annual cost due to gearbox failures (€$_{GBX,annual}$) can be computed with the following equations:

$$€_{GBX,annual} = €_{down} + N_{mob,annual} \cdot €_{mob} + N_{exchanges,annual} \cdot (€_{gearbox} + €_{crew} + €_{JU,day} \cdot T_{JU,day}) \quad (7.1)$$

where

$$€_{down} = T_{down,farm} \cdot \frac{FLH_{year}}{12} \cdot P_{rated,farm} \cdot €_{MWh} \quad (7.2)$$

or in case of a reactive strategy:

$$€_{GBX,annual} = €_{down} + +N_{exchanges} \cdot (€_{JU,mob} + €_{gearbox} + €_{crew} + €_{JU,day} \cdot T_{JU,day}) \quad (7.3)$$

The cost of jack-ups (€$_{JU,day}$, €$_{JU,mob}$), crew (€$_{crew}$) and parts (€$_{GBX}$) are based on industry experience, and are given in section 7.1. Different jack-up day rates are assumed based on the demand: demand is average in spring and fall (base price of 40 k€), peaks in summer (40% increase), and slows in winter (20% discount). The electricity price (€$_{MWh}$) is dependent on the subsidy regime. PAWP receives 130 €/MWh until 2018, thereafter electricity is sold at regular APX trade prices. This is assumed to be 35 €/MWh [30]. Production in winter is considerably higher than in summer time, but a constant monthly power production is currently assumed in Eq. 7.2. Including the yearly production distribution is considered a future improvement of the model.

7.3. OPTIMIZING THE EXCHANGE STRATEGY FOR PAWP

Five gearbox exchange strategies have been defined, where a jack-up is mobilized:

- Once a year (each July)
- Twice a year (April & September)
- Three times a year (March, June, October)

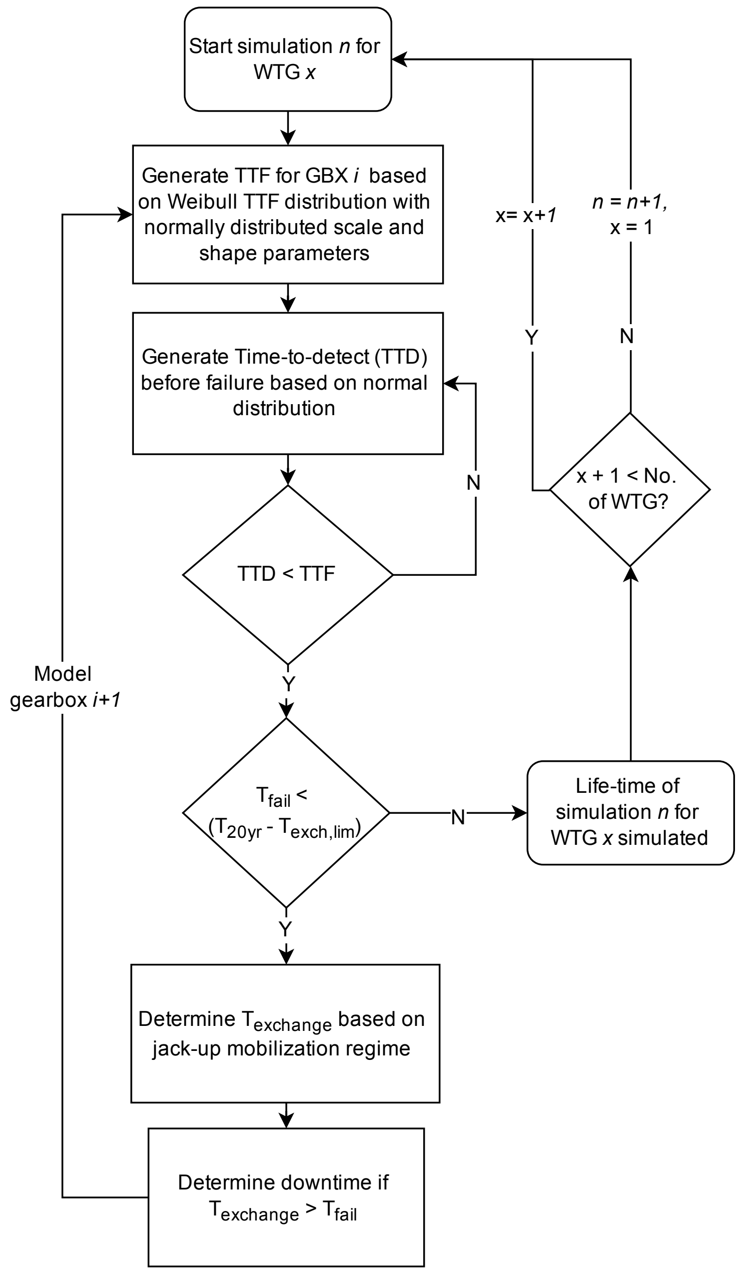


Figure 7.3: Flow diagram of Monte-Carlo simulation methodology

- Four times a year (February, May, August, November)
- Reactive, 6 weeks after detection of the failure

It is assumed that during the last 1.75 years no more gearboxes are exchanged: the revenues from electricity production are lower than the cost of a gearbox exchange. The four campaigns a year strategy has only been applied to the 350MW wind farm in section 7.4, as 3 annual campaigns gave promising results. A gearbox is exchanged when a failure has been detected and will not last until the next jack-up arrival window. No strategy is considered which waits for the gearbox to fail completely: a catastrophic failure can e.g. cause the gearbox to crack, which in return causes an unallowable environmental spill.

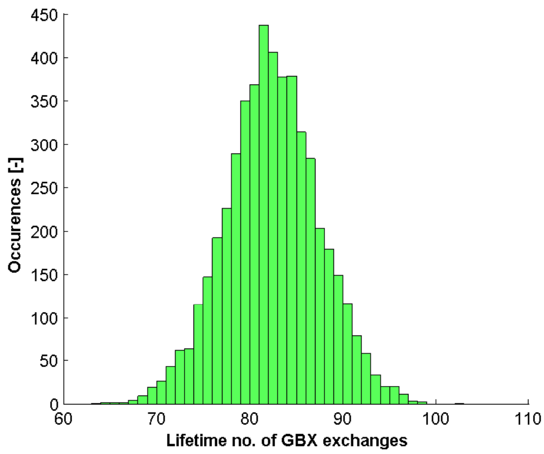


Figure 7.4: Distribution of total number of exchanges for single campaign strategy

7.3.1. RESULTS

The simulation are performed based the Weibull parameters of gearbox exchange rates, as determined in section 5.2. This results in a distribution of the total amount of gearbox that is expected to be exchanged during the lifetime of PAWP. Results for the single campaign strategy are displayed in Figure 7.4.

A mean exchange number of 83.3 is predicted during the lifetime of PAWP when applying a two campaigns per year strategy, with 80% confidence interval ranging between 77 and 90 exchanges. The total number slightly differs between the different strategies, which is caused by the amount of downtime. When a turbine is down for a longer time, the new gearbox is installed at a later moment resulting in less gearboxes being consumed. This is effect is however minor, as presented in Table 7.2.

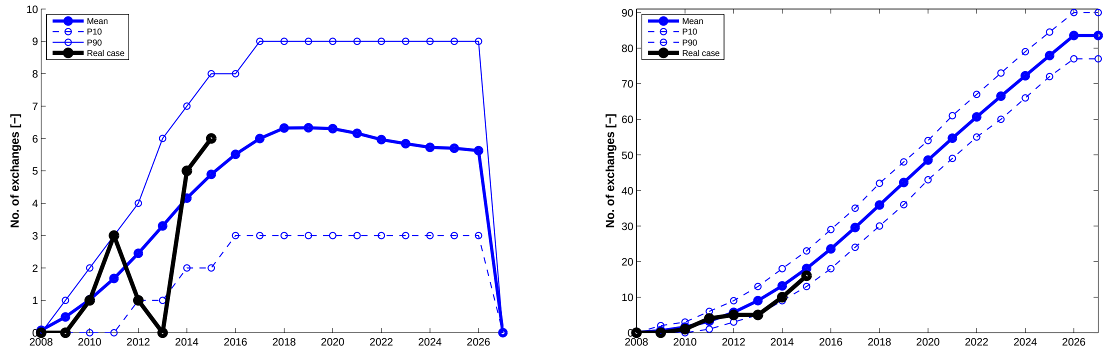
Table 7.2: Total number of exchanges for 4 different strategies

Strategy	Mean of total exchanges
1 annual campaign	81.2
2 annual campaigns	83.3
3 annual campaigns	82.5
Reactive strategy	84.3

The fact that exchange rates for 3 annual campaigns is lower than for 2 annual campaigns is not expected, since this strategy results in less downtime. However, this is caused by the fact that the last exchange for the 3 annual campaigns strategy takes place in June 2027, where the exchange limit is September 2027. The last visit for the two annual campaigns strategy is scheduled in September 2027, allowing more gearboxes to be exchanged.
The annual failure rate and uncertainty in these predictions has also been determined (Figure 7.5a). A peak failure rate is observed in 2017-2018 at 6 failures per year, when the wind farm age reaches the $MTTF$. Thereafter, a slight decrease is observed and the failure rate stabilizes at approx. 6. The P10 and P90 values are between 3 and 9. This is quite a large range, but it can be seen that actual failure rates have even exceeded this range in 2013. It should be noted that it is very unlikely that P10 occurs every year, a bad year will likely be followed by a better year.

The expected and actual cumulative failure rate is given in Figure 7.5b. The actual cumulative failure rate for 2015 does not match the expected failure rate, but this is because the model takes into account the complete history. Accordingly, the annual number of failures in 2015 is already higher than expected.

Next, the cost of downtime corresponding to each of the strategies has been determined (Figure 7.6). Logically, a single campaign per year results in the majority of the downtime. At the same time, the uncertainty is the largest for this strategy. Due to the subsidy regime which ends in 2018, a significant drop can be observed in the cost of downtime. A reactive or more frequent exchange strategy causes little to no downtime.



(a) PAWP annual exchange rate

(b) Cumulative exchange rate

Figure 7.5: PAWP exchanges rates for single campaign strategy and actual failure rate

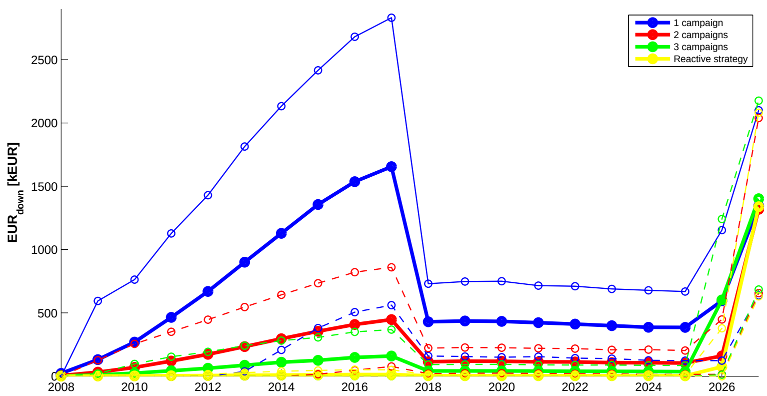


Figure 7.6: Annual downtime cost due to gearbox failures.

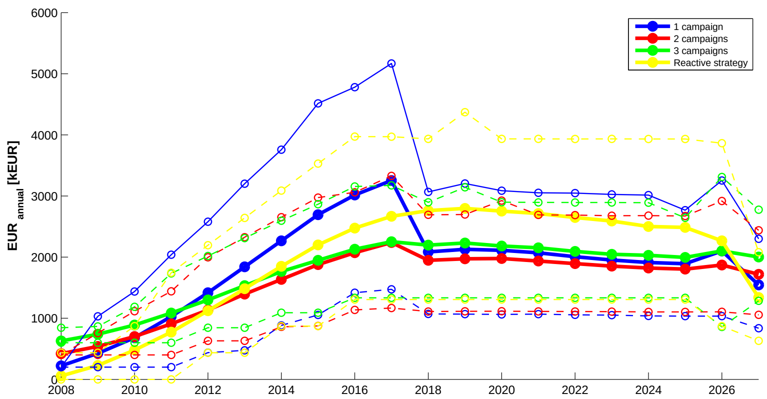


Figure 7.7: Total annual gearbox exchange cost.

The total cost of gearbox exchanges using each strategy is visualized in Figure 7.7. The optimal strategy differs during the lifetime. A reactive strategy causes the lowest costs when failure rates are low and subsidy is received. As of 2012, two annual campaigns is cheapest, closely followed by three annual campaigns. A breakdown of the costs in year 10 is given in Figure 7.8. The breakdown of costs for all years can be found in Appendix A. A single campaign becomes close to optimal when the subsidy regime ends, but this strategy results in a higher financial uncertainty than the two campaigns strategy. Choosing for two annual campaigns results in a savings of 17% compared to a reactive strategy (Table 7.3). When the most optimal strategy is selected at each time of the complete life cycle, as indicated with the dotted line in Figure 7.9, a total savings of 20.7% is established, which equals 7.9 M€.

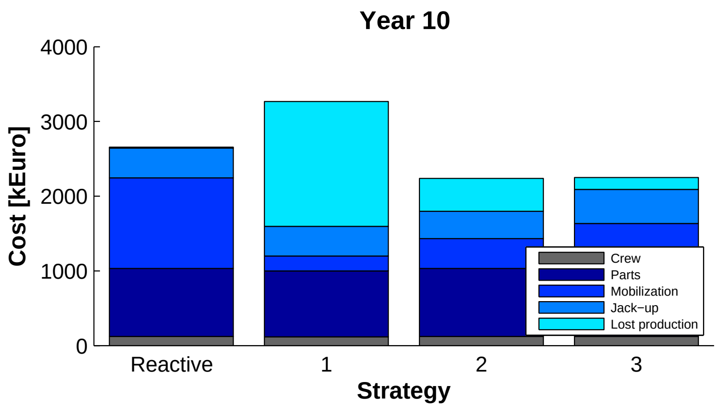


Figure 7.8: Breakdown of costs for each strategy in year 10

It should be noted that currently no flexibility is allowed on the arrival of the jack-up for the campaign based strategies. Allowing flexibility, i.e. pulling the jack-up window forward when unexpected failures occur or postponing it when no failures are detected could further reduce the cost of exchanges.

Table 7.3: Total cost of gearbox exchanges during lifetime compared to reactive strategy (mean)

Strategy	Total cost
Reactive strategy	100%
1 annual campaign	96.0%
2 annual campaigns	83.0%
3 annual campaigns	92.4%
Optimal	**79.3%**

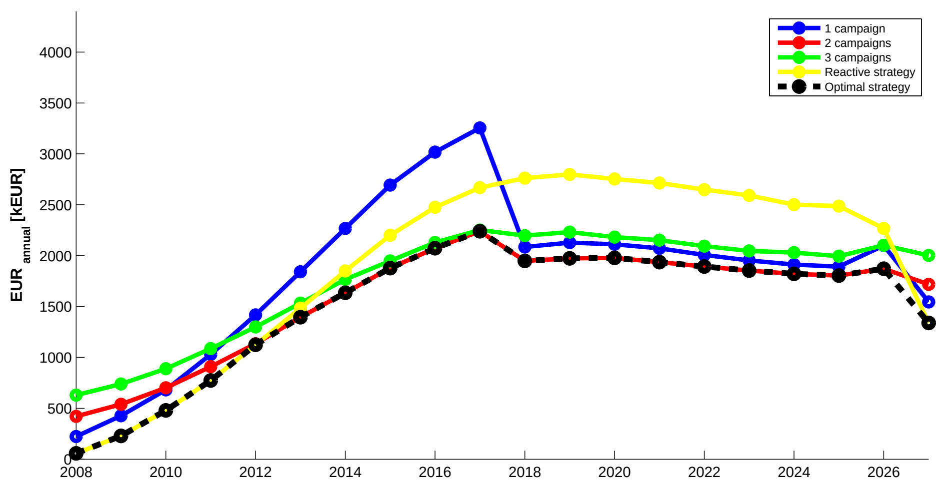


Figure 7.9: Optimal strategy selection for PAWP

7.3.2. PARAMETER SENSITIVITY ANALYSIS

A sensitivity analysis is performed on the inputs of the Monte-Carlo simulations. The inputs are defined in Table 7.4: each time only one input has been changed. The table specifies how the total costs of gearbox exchanges changes in relation to the base case. Mobilization and jack-up day rates can change due to a shift in demand or supply. A change in reliability is caused by a statistical error in the Weibull predictions made in chapter 5. The parameters have been updated by adding or subtracting the standard error.

It can also be assumed that the reliability of gearboxes installed during an exchange have an increased reliability. The supplier implements design updates during production of new gearboxes or during overhaul of failed gearboxes. These updates are introduced to mitigate failure modes that have been experienced so far. Conservatively, no reliability improvement is taken into account in the base case. A reliability increase is expected for 2nd generation gearboxes in the other cases, which is done by increasing the scale parameter. The shape parameter (β) only determines how failures progress (early failures / random / deterioration), as explained in section 2.2. It is assumed that this is related to the component characteristics and therefore does not change. The scale parameter η is thus altered to update the $MTTF$. Increasing the scale parameter by e.g. 20% also results in an increase of the $MTTF$ of 20%. This is shown in Eq. 7.4, which gives the expected mean value for the Weibull distribution [14]:

$$E(X) = \eta \cdot \Gamma(1 + \frac{1}{\beta}) \tag{7.4}$$

It is decided to use the optimal strategy as a base case: this allows the simulation to choose the optimal strategy according to the inputs. If a reactive strategy would be chosen as a base case instead, and the mobilization costs would double, the cost would only increase by $N_{exchanges} \cdot €_{mob}$, while a more optimal strategy could reduce this effect, as would happen in real life.

Table 7.4: Sensitivity analysis on input parameters for PAWP

Parameter	Base case	Best case	Effect	Worst	Effect
Mobilization cost	200 kEUR	100 kEUR	-11.3 %	300 kEUR	+10.2 %
Jack-up day rate	40 kEUR	30 kEUR	-3.0 %	50 kEUR	+2.8 %
Scale parameter - η	139.5	159.2	-13.7 %	119.8	+17.9 %
Shape parameter - β	2.68	3.28	-4 %	2.08	+5.3 %
Reliability increase 2nd gen.	0%	+20%	-7.6 %	-20%	+9.6 %
Detectability	3 months	6 months	-18.9 %	1.5 months	+6.5 %

It can be concluded that the lifetime cost of gearbox exchange in PAWP is most sensitive to:

1. Detectability of failures (-18.9% — +6.5%)
2. Scale parameter - η (-13.7% — +17.9%)
3. Mobilization cost (-11.3% — +10.2%)

If failures can be spotted at an earlier stage by increased detectability, downtime is reduced significantly. This results in a 19% cost reduction. It can be achieved by improved/increased monitoring of the gearbox using e.g. CMS, SCADA data and borescope inspections. Mobilization cost can be reduced by using jack-ups which are located in the proximity, such as the port of Rotterdam or Antwerp, or have performed work in nearby wind farms. Also, framework agreements with jack-up companies can be considered. This would results in a savings of 11.3%. An 20% reliability increase for 2nd generation gearboxes results in a savings of 7.6%. 75 gearboxes are expected to fail, compared to the present 83, with 80% confidence between 70 and 81 exchanges. An underestimation of the mobilization costs and scale parameter η holds the largest risk for the total costs.

7.4. OPTIMIZATION THE EXCHANGE STRATEGY FOR 350MW WIND FARM

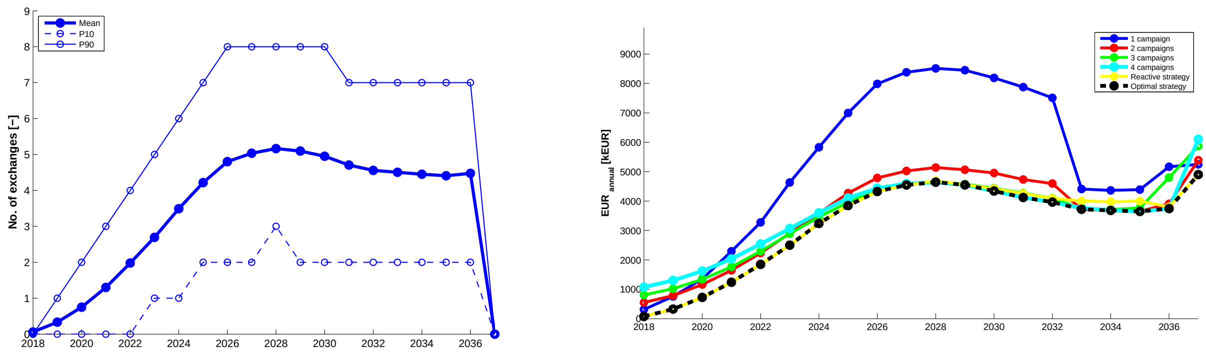
The Monte-Carlo simulation method has also been applied to determine the optimal exchange strategy for a future 350MW wind farm. This equals the lot size at the Borssele wind farm (NL) that will be tendered in 2015, and the 'Noord-Hollandse kust' and 'Zuid-Hollandse kust' lots which will be tendered in subsequent years. The characteristics for a 350MW base case are defined in Table 7.5: an 8 MW reference turbine has been selected. It is conservatively assumed that Weibull parameters and detectability of failures in the new gearboxes are equal to present numbers. Part costs are multiplied by the multiple in rated power.

Table 7.5: 350MW wind farm characteristics

Parameter	**Base case**
P_{rated}	8 MW
Mobilization cost	250kEUR
Subsidy scheme	110 €/MWh (15 yrs)
Detectability	3 months
Weibull parameters	$\beta = 2.68$, $\eta = 139.5$

7.4.1. RESULTS

The optimal strategy for the 350MW lot based on the failure rates (Fig. 7.10a) is given in Figure 7.10b. The total expected costs for gearbox exchanges of the lifetime are 58.7 M€, when using a reactive strategy at the start and shifting to a four campaigns per year strategy after 11 years. Costs would increase by 1.8% and 9.4% when using a reactive or 3 annual campaigns strategy only. The effect of wind farm and wind turbine size becomes clearly visible when this is compared with Figure 7.9. Firstly, the impact of downtime is more significant since the turbines have a four times higher rated power, causing an one- or two-campaign strategy to become costly. The subsidy regime lasts for 15 instead of 10 years, causing the impact of downtime to decrease only after 15 years. It can be concluded that higher production per turbine (either due to high E-prices, rated power) has an favorable impact for reactive or multiple campaigns per year strategy. In this case the cost of downtime is more dominant than mobilization costs.



(a) Annual exchange rate

(b) Optimal strategy selection

Figure 7.10: 350 MW wind farm with 8MW WTGs

7.4.2. PARAMETER SENSITIVITY ANALYSIS

A sensitivity analysis is also made on the input parameter of the Monte-Carlo simulation of the 350MW wind farm. The inputs are defined in Table 7.6, each time only 1 inputs has been changed. The table specifies how the total costs of gearbox exchanges changes in relation to the base case. When the rated power is decreased in the simulations, the mobilization costs and jack-up day rate are changed accordingly, to account for the use of a smaller vessel. The cost reductions in the 2nd and 3rd row are caused by cost reduction of jack-up vessels on itself, due to e.g. more competitive market or a vessel located in the proximity.
It can be concluded that the lifetime cost of gearbox exchange on a 350MW lot is most sensitive to:

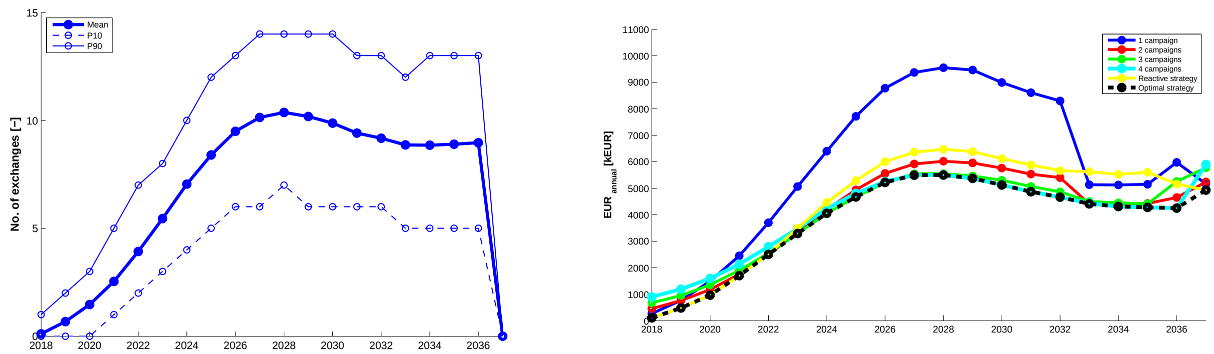
1. Detectability of failures (-20.9% - +7.5%)
2. Weibull scale parameter (-17.5% - +33.4%)
3. Mobilization cost (-14.3% - +7.3%)
4. Wind turbine size (-3.5% - + 19.0%)

Table 7.6: Sensitivity analysis on input parameters for 350MW wind farm

Parameter	Base case	Best case	Effect	Worst	Effect
P_{rated}	8 MW	10 MW	-3.5 %	4 MW	+19.0 %
Mobilization cost	250 kEUR	100 kEUR	-14.3 %	350 kEUR	+7.3 %
Jack-up day rate	50 kEUR	35 kEUR	-3.2 %	65 kEUR	+2.4 %
Scale parameter	139.5	160	-17.5%	120	+33.4 %
Detectability	3 months	6 months	-20.9 %	1.5 months	+7.5 %

The most sensitive parameters are equal to the ones observed at PAWP. The wind turbine size also impacts the total cost, especially when smaller turbines are selected (+19.0%). The corresponding failure rates and optimal strategies for a 4MW and 10MW are presented in Figures 7.11 and 7.12, respectively. A smaller turbines results in more frequent exchanges (approx 9-11 annually), requiring more frequent visits. The impact of downtime becomes smaller, due to the lower rated power. Therefore, a four campaigns per year strategy is optimal.

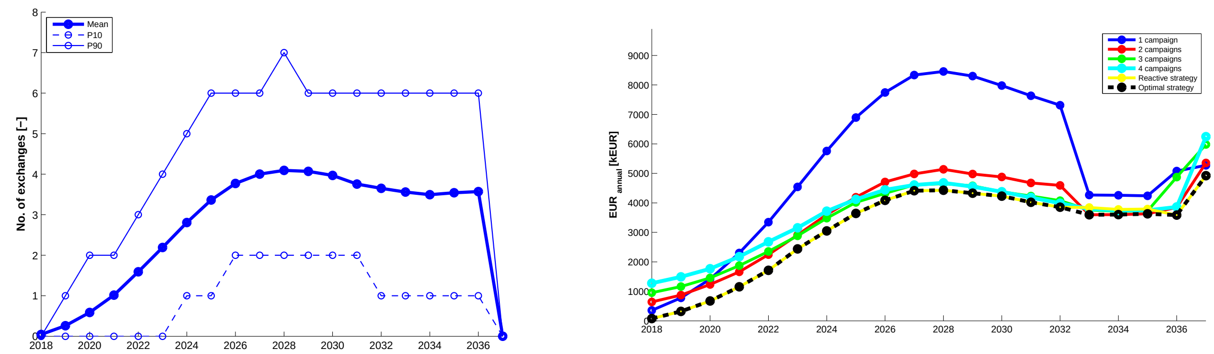
A reactive strategy is optimal for a wind farm with 10MW WTGs. This flexibility causes the least downtime, while the cost of downtime is significantly higher than the mobilization costs. On average 3 to 4 gearboxes are exchanged annually. It should be noted that these conclusions are based on current gearbox reliability and detectability of failures. Changes in these parameters can cause other strategies to become preferred.



(a) Annual exchange rate

(b) Optimal strategy selection

Figure 7.11: 350 MW wind farm with 4MW WTGs



(a) Annual exchange rate

(b) Optimal strategy selection

Figure 7.12: 350 MW wind farm with 10MW WTGs

CONCLUSION

The following conclusions can be drawn from this section:

- Approximately 83 gearboxes are expected to fail during the lifetime of PAWP, with a 80% confidence interval ranging between 77 and 90 exchanges. 75 gearboxes are expected to fail when a reliability increase of 20% is assumed for 2nd generation gearboxes.
- Optimizing the jack-up mobilization strategy resulted in a saving of 21%, which equals 8 M€, compared to a reactive strategy. During the first years of operations an reactive strategy was optimal. The optimal strategy during the latter of the subsidy period is a two- or three campaigns per year strategy. A single or two campaigns per year strategy is preferred after subsidy expiration. A single strategy has a larger uncertainty, due to the risk of downtime.
- The total costs are most sensitive to changes in detectability of failures, gearbox reliability and jack-up mobilization costs.
- Strategy optimization has also been performed for a 350MW lot consisting of 8 MW turbines. During the first operational years a reactive strategy is selected, after year ten 3 annual campaigns per year are cheapest. The total costs are again most sensitive to detectability of failures, gearbox reliability and jack-up mobilization costs. Smaller 4 MW turbines results in higher costs than 8MW turbines (+ 19%), wheras 10 MW turbines results in lower total costs (-3.5%)

Conclusions & Recommendations

At this point the research is finished. Predictions of future failure rates have been made and an optimal strategy to minimize gearbox exchange costs at PAWP has been defined. Finally, this chapter discusses the conclusions and subsequently recommendations for future research given.

Conclusions

The thesis started by selecting the gearbox and main bearing as components that were further investigated based on the experienced failure rates. Failure modes and root causes were looked into:

- All observed failures are bearing related. Spalling on the planet bearing and axial cracks in the IMS front bearing require the complete gearbox to be exchanged. Axial cracks in the rear IMS and HSS bearings are also seen; these are solved by exchanging the components up-tower. This maintenance intervention results in lower costs: no jack-up vessel is required. Main bearing in PAWP are exchanged due to guide ring and cage wear.
- White-etching cracks have been indicated as main failure mechanism by the wind industry. This phenomenon reduces the bearing life to 1% to 20% of the predicted bearing design life. The underlying cause on the plastic formation of WEA is not known yet, gear and bearing supplier have different theories. Some expect that it is lubrication related, where others consider tensile stresses or stress waves as a plausible root cause.
- The local wind regime at PAWP, 10-min averaged loads and the number of stops do not have a significant correlation with failure rates of main components at PAWP. It is likely that cracks and spalling (and formation of WEA) is caused by high frequency load fluctuations. These type of loads cannot be identified from 10-min SCADA data.

Statistical Weibull analysis has been used to predict future failure rates at PAWP. Also, indicator were failures have been studied and their accuracy has been quantified.

- Gearboxes have a $MTTF$ of 10.3 years and a β value of 2.68. This indicates that failures are wear-related. Predictions have become more accurate as more failures occurred during the research, the standard error of the $MTTF$ is 16.8 months. Similar results were obtained when performing the analysis based on production. Comparing the failure rates with an older V80 offshore wind farm equipped with the previous type gearbox ($MTTF$ = 3.7 years) proved that significant design improvements have been introduced.
- Main bearings have a $MTTF$ of 23.2 and a β value of 1.89. This indicates that failures are wear related too. The standard error of $MTTF$ is 14.75 years. This uncertainty is too large to perform maintenance optimization on the the expected failure rates.
- The accuracy of Weibull predictions is relatively low due to the small samples sizes which are heavily censored. Parameters can change drastically if many failures occur on a short term. The failures during the past year and the shape parameter β value of a reference V80 wind farm (6.9) shows that PAWP's β value can be underestimated. This mean that many failures are likely to happen soon, which would also lower the scale parameter η.
- All data that can provide insight in the condition of a component is required to determine which component is about to fail. On average, vibration CMS alarms are triggered 3 months prior to gearbox exchanges. HSS and IMS failures are easier to detect, on average their detectability is 11 months prior to the exchange. Oil and bearing temperatures did not show significant changes for failing units. Increasing the detectability of gearbox failures to 6 months in advance reduces exchange costs by 19% over the complete lifetime.

The optimal strategy for gearbox exchanges has been defined for PAWP:

- Approximately 83 gearboxes are expected to fail during the lifetime of PAWP, the 80% confidence interval ranges between 77 and 90 exchanges. A 20% reliability increase for 2nd generation of gearboxes results in 75 expected gearbox exchanges, which is based on design improvements introduced by the gearbox supplier.
- Performing the most optimal strategy at any point in time results in a saving of 21%, or 7.8 M€, compared to a reactive strategy. During the first years of operations a reactive strategy was cheapest. The optimal strategy during the latter of the subsidized period is a two- or three campaigns per year strategy. A single or two annual campaigns are preferred after subsidy expiration in 2018. A single strategy results in a larger financial uncertainty, due to the risk of downtime.
- The total costs are most sensitive to changes in detectability of failures, gearbox reliability and jack-up mobilization costs.
- Strategy optimization has also been performed for a 350MW lot consisting of 8 MW turbines. During the first operational years a reactive strategy is selected, after year ten 4 annual campaigns are optimal. The total costs are again most sensitive to detectability of failures, gearbox reliability and jack-up mobilization costs. Smaller 4 MW turbines results in higher costs than 8MW turbines (+ 19%), whereas 10 MW turbines results in lower total costs (-3.5%)

RECOMMENDATIONS

Increasing the reliability and robustness of gearbox and main bearings would eventually complete solve this issue. Far fewer exchanges would be required if the components fulfill the wind farm's lifetime of 20 or 25 years. This increase in reliability should be strived for, unless this increases the component cost more than the cost of exchanges. Increasing the reliability can be achieved by:

- Prevent bearing related failures by performing extensive research on root causes which initiate WEA. This requires a better understanding of the operational loads of wind turbines. This can be achieved by performing accelerated life testing using inputs obtained from high frequency load measurement campaigns at operational wind farms.
- Research should consist of collaborative studies between bearing- , gearbox- and wind turbine manufacturers, research institutes and wind farm operators. This strategy has been executed during this research, which proved its value. It has been experienced that much knowledge and data is present among the different parties, but bringing this together gives far better results.
- Increasing serviceability of main components, such as the gearbox. One can e.g. think of increased up-tower exchangeability of bearings and shafts. This reduces the need for jack-up vessels. However, this is unlikely with the increasing complexity of new gearbox designs, consisting of several planetary stages.
- Few V80 wind farms exist, and different gearbox models exist. This results in a too small sample size for proper root cause analysis. Research should be focused on larger wind farms, such as Gemini (150 WTG) or wind turbine models which have a larger installed base.

These actions do not immediately lower the cost at operational wind farms. Still, there are opportunities to reduce cost for the operational team of PAWP:

- Switch to a one or two annual campaigns when subsidy expires. A single exchange strategy becomes most suitable when predictability of failures increases. In case of an unexpected failure long before a jack-up visit, a trade-off should be made between mobilization costs and production losses.
- Increase predictability of exchanges by performing additional monitoring on bearings and increasing the performance of CMS system on the main bearings and planetary stage. This reduces downtime and allows exchanges to be clustered.
- Focus on lowering the cost of jack-ups: mobilization costs can be lowered by utilizing jack-ups that are based in Dutch or Belgian ports. Clustering major interventions with nearby wind farms, such as Luchterduinen and OWEZ, should be considered.

- Monitoring and predicting failure rates of main components should become a standard part of asset management. It has the 30%-40% impact on the total cost of maintenance, thus good knowledge on expected failure rates is required when deciding on future maintenance strategies.

The Monte-Carlo optimization model developed for this research can also be improved by e.g.:

- Including failures of other components, such as main bearings, blades, generators, etc. in the optimization of exchange strategies.
- Making the model 'smarter', each time a failure occurs the trade-off between mobilizing a jack-up and downtime should be made.
- Including annual variability in power production, and try to obtain a correlation between time of the year and failures.

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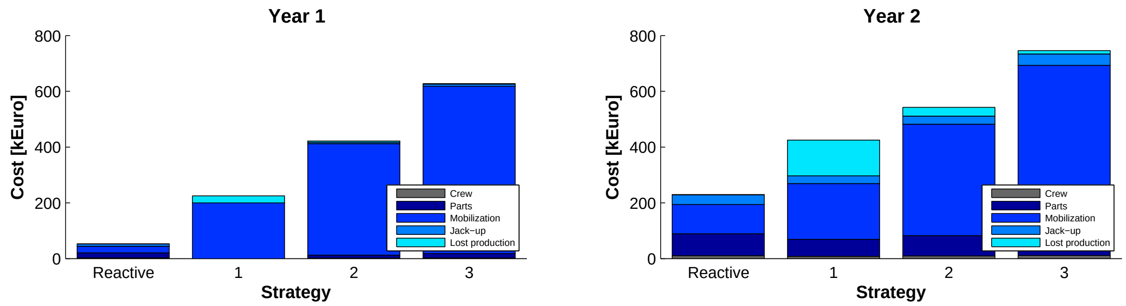
A

BREAKDOWN OF ANNUAL COSTS FOR PAWP



(a) (b)

Figure A.1: Breakdown of costs for each strategy in year 1 & 2

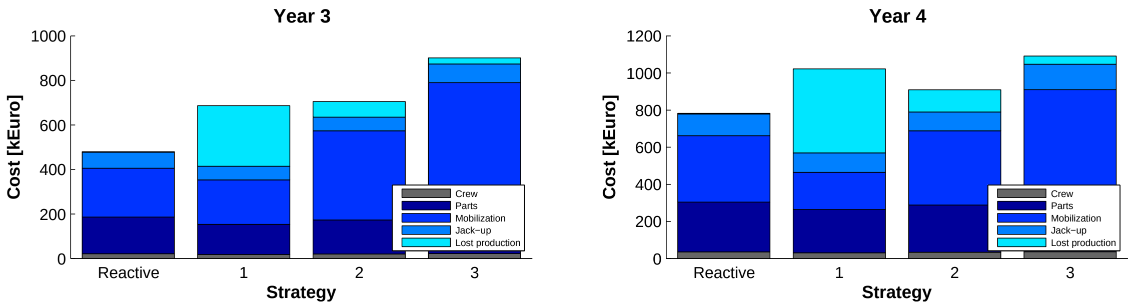


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Figure A.2: Breakdown of costs for each strategy in year 3 & 4

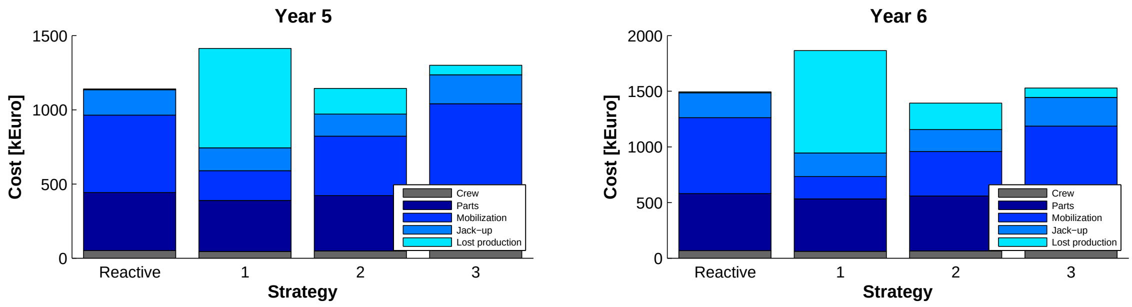

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Figure A.3: Breakdown of costs for each strategy in year 5 & 6

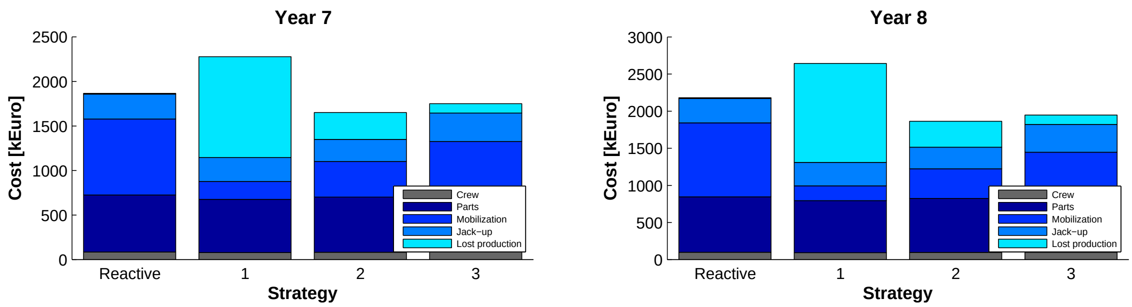

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Figure A.4: Breakdown of costs for each strategy in year 7 & 8

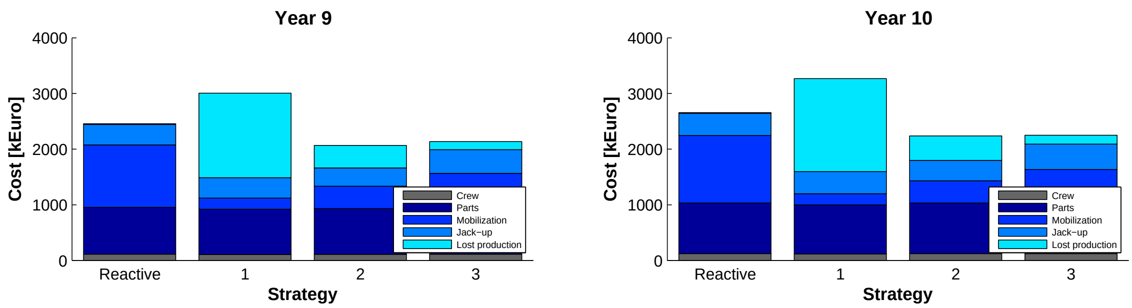

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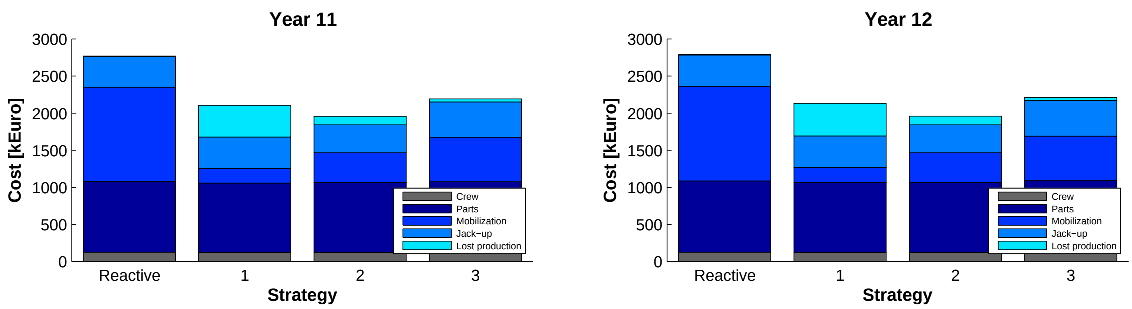
Figure A.5: Breakdown of costs for each strategy in year 9 & 10



(a) (b)

Figure A.6: Breakdown of costs for each strategy in year 11 & 12

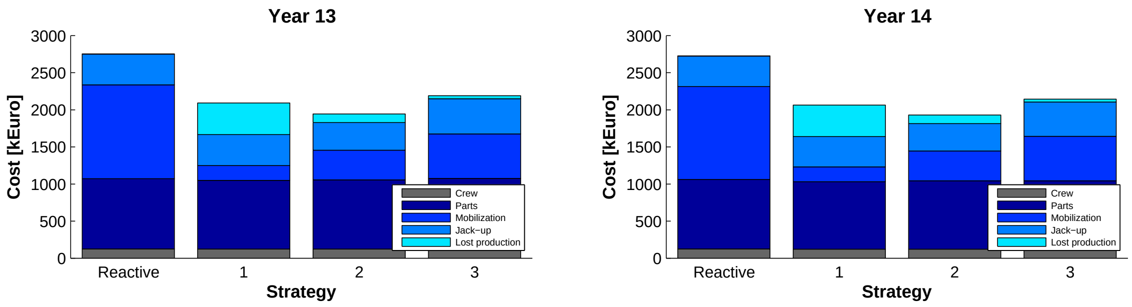


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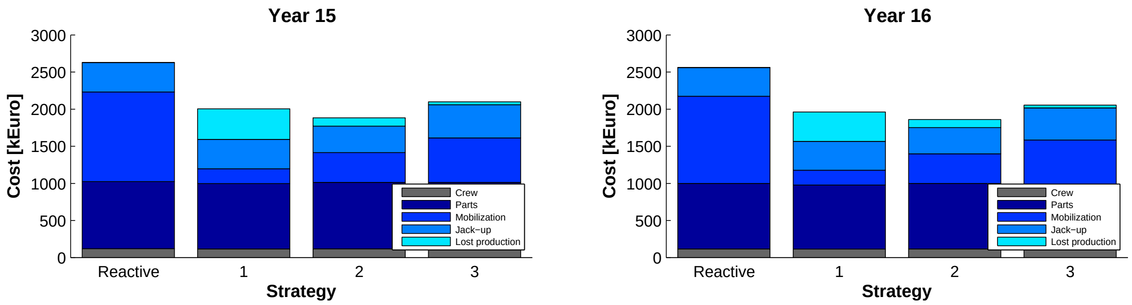
Figure A.7: Breakdown of costs for each strategy in year 13 & 14



(a) (b)

Figure A.8: Breakdown of costs for each strategy in year 15 & 16

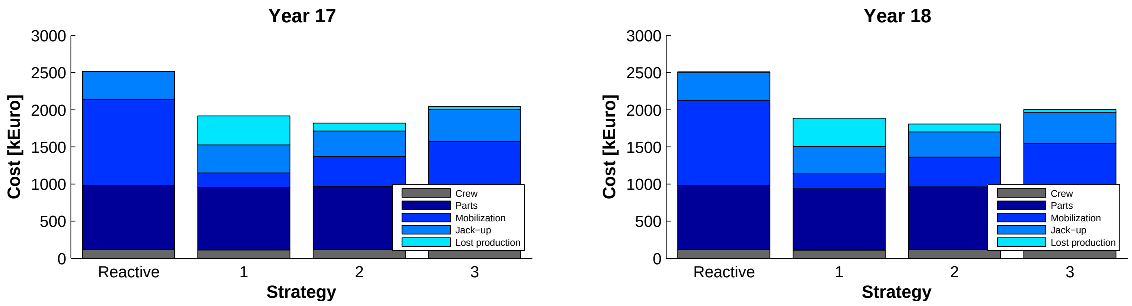


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Figure A.9: Breakdown of costs for each strategy in year 17 & 18

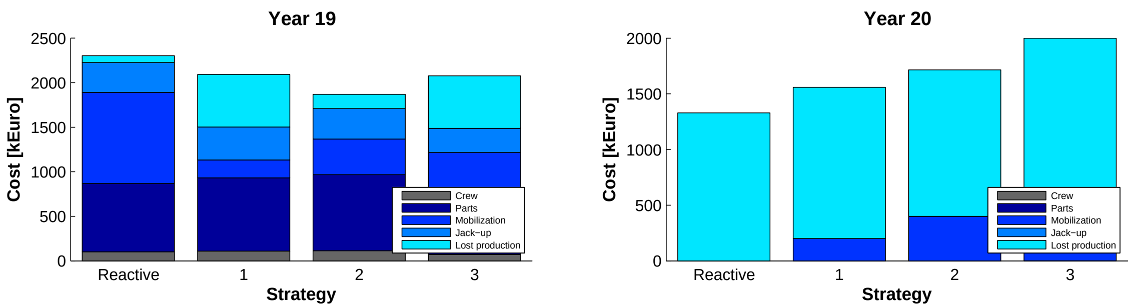

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Figure A.10: Breakdown of costs for each strategy in year 19 & 20