OFFSHORE INVENTORY MANAGEMENT

Inventory management of Main Components from offshore wind turbines by statistically predicting expected failures using historical failure data to determine optimal stock levels

UNIVERSITY OF TWENTE.

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By

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Executive Summary

This thesis was written within Vattenfall's Analytics team in Amsterdam. Vattenfall is looking to minimize the costs of failures and thus downtime in offshore wind turbines. The main downtimes are mainly caused by critical parts, which we will refer to as Main Components (MCs). To ensure minimum lost revenue due to the downtime of these MCs, Vattenfall constructed a central warehouse to store spare MCs. To find this optimal balance of inventory, we first have to obtain the lifetime distribution to determine the expected failure rate characteristics of the MCs, which leads us to the following research question:

"Develop and validate an expected lifetime distribution, to predict expected failure rates of MCs given their current state and integrate it into a spare part optimization model to determine the optimal spare part policy and level, thereby achieving maximum cost efficiency."

Complying with the literature, we have used Weibull distribution as the lifetime distribution to model the MC failure characteristics, which we use to determine the expected failure rate of components. Furthermore, we calculated various inventory models, which we tested using a Monte Carlo simulation. For this simulation we used test data, which represent the MCs. We compared various experiments for multiple replications to average all Total Relevant Costs (TRC) for a proper comparison between results.

From the results of the experiments we conclude that it is always better to not keep any inventory when the Jack-Up vessel lead time exceeds or is equal to the component lead time, the Jack-Up lead time can be utilized to order the component itself. We see this back in the sensitivity analysis, where the Jack-Up and component lead time have the biggest impact on the TRC. The least amount of TRC is always when the two lead times are equal. Therefore, it is beneficial to invest in either shorter Jack-Up or component lead times to equalize one with the other.

Furthermore, the only changes which seemed to benefit the inventory management over not keeping inventory is the batching of components in groups of two including a batching discount of 10%. The other change is a higher lost revenue per month. However, this benefit will only pay out over a prolonged period, of which the benefit is based on the number of failures of the component and the holding costs. When a lot of failures are expected, the benefit is earned back faster, which also goes in hand with an increase in population size or older components, which are more likely to fail.

All with all, we recommend to build upon this research by utilizing real scenarios to determine when it becomes beneficial to keep inventory for their own components and to continuously update the parameters for more exact predictions of the failures. Additionally, once the predictions become adequate, to invest into proactively ordering the Jack-Up vessel, which will save a lot of money for industry wide.

Preface

Before you lies the master thesis ‘Offshore Inventory Management.’ The research was performed for the fulfilment of the requirements for the master’s degree of Industrial Engineering and Management at the University of Twente during the period from February until July 2022.

The research project was performed at Vattenfall, where I worked within the offshore analytics team under supervision of Peter van Heck. I would like to thank Peter and all the people at Vattenfall for sharing their insights and ideas for the project and providing feedback on my work.

I would also like to thank my supervisor from the University of Twente, Engin Topan for his excellent guidance and support throughout the research. This has helped me greatly in performing the research and writing my thesis.

Lastly, I would like to thank my friends and loved ones for supporting me during this period and for providing me with the encouragement and strength to finish my master thesis. This has helped me immensely to stay focussed during my research.

I hope you enjoy the reading.

Remy Jetze Dijkstra

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Glossary

- **ADI (Advanced Demand Information)** –Monitoring of components, which can indicate future demand.
- **Backorder** – Amount of components ordered but not yet received.
- **EBO (Expected Backorders)** – Expected demand that cannot be fulfilled right away.
- **Echelon** – A level or station within the supply chain.
- **ESC (Estimated Shortage per Cycle)** – Expected shortage of spare components per cycle period.
- **Failure rate** – Frequency in which a component fails, expressed in number of failures per unit of time.
- **Fill rate -** which indicates the probability of fulfilling demand without delay.
- **Indenture** – sub-part of a higher-level component (represented by SRUs and LRUs).
- **LR (Lost Revenue)** – Revenue lost by Vattenfall due to the wind turbine downtime caused by a failed MC.
- **LRU (Line Replaceable Unit)** - Complete functional components (e.g. Gearbox).
- **OEM (Original Equipment Manufacturer)** – Original manufacturer of the components in question.
- **OM (Operations and Maintenance department)** – Department for the day-to-day operations within a company.
- **PDF (Probability Density Function)** – A function, which value represents the probability of a random sample being close to that value.
- **Pipeline** - All components part of the owner's inventory, which are either in inventory or still in transit .
- **Polynomial time** – The relation between the execution time of a computation, and the complexity of the function of the polynomial *n*.
- **SA (Supply Availability)** - SA is equal to one minus the EBO and represents the fraction of demand fulfilled from inventory.
- **SRU (Shop Replaceable Unit)** - sub-part of an LRU, representing component functions (e.g. gear in the Gearbox).
- **SS (Safety Stock)** – Extra inventory to reduce the risk of not having an item on stock when needed.

1. Introduction

This master thesis is written for the completion of the Master Industrial Engineering and Management as part of the Production and Logistics Management track within the faculty of behavioural, management and social sciences from the University of Twente. Research has been conducted at Vattenfall in Amsterdam within the offshore wind turbines analytics team.

In this chapter, the research performed at Vattenfall will be introduced. Section 1.1 provides background information about Vattenfall and offshore wind energy. Section 1.2 provides the scope and the operation and maintenance (OM) related to the research subject and is used to formulate the problem statement and the scope in Section 1.3. Subsequently the research objective and questions are formulated in Section 1.4. Section 1.5 will describe the research approach and methodology used and an overview of the research layout.

1.1 Vattenfall & offshore wind energy

1.1.1 Vattenfall

Vattenfall is a leading European energy supplier company, which was founded in 1909 as a state-owned enterprise in Sweden as it currently still is. In the Netherlands, Vattenfall was formerly known as NUON but changed its name to Vattenfall in 2018, after Vattenfall bought NUON, back in 2009. Vattenfall's headquarter is located in Solna, which is within the municipality of Stockholm. The head office within the Netherlands is located in Amsterdam. Vattenfall operates in 8 European countries, where they currently employ around 20,000 people (Vattenfall, 2021). Vattenfall is on the forefront in the fight against climate change as an energy supply company, and therefore focus their aim to enable fossil-free living within one generation. They are working to achieve this, by constantly acquiring more alternatives to fossil fuels (e.g., wind, solar, nuclear, hydro, biomass, biogas). This has made Vattenfall one of the leading players in the European renewable energy market. The focus of this research paper will be on the offshore wind sector.

Figure 1. Offshore Windfarm Vattenfall

1.1.2 Offshore wind power

Large scale wind power has recently grown towards offshore locations, due to lack of space, noise, aesthetics, and in addition to the extra electricity generated per amount of capacity installed, due to more favourable wind resources (Krogsgaard & Madsen, 2010). This has caused the offshore wind generation to gain increasing interest on the renewable energy market and induced a tremendous growth the last decade. In 2020 the offshore wind sector had a capacity of around 35.3 gigawatts (GW) (Global Wind Energy Council, 2021). These wind farms are typically located a few kilometres away from the coast, and the grid transports high voltage energy onshore through cables buried deep in the seabed. Due to the European climate and energy measures, many countries like the Netherlands are interested in further developing the offshore sector, since it can be crucial to meet these measures. One of the Dutch measures in the field was producing 14% of their total energy production through utilizing renewable energy sources by the year 2020, which increases to 32% in 2030 (Government of the Netherlands, 2019). This has initiated a new project, where Vattenfall is currently constructing a new wind farm in the North Sea near the Dutch coastline, called “Hollandse Kust Zuid.”

However, the offshore wind energy industry is still facing a multitude of challenges, such as the harsh marine environment, and the difficult soil properties. Blades that endure this harsh saline environment show an accelerated increase in surface roughness. This increase in surface roughness increases friction drag, which negatively reduced performance (Slot, Gelinck, Rentrop, & van der Heide, 2015). This increased level of leading-edge erosion has drastically reduced the initial expected life expectancy of offshore wind turbine blades (Keegan, Nash, & Stack, 2013). Additionally offshore wind turbines must endure extra loads created by the waves and currents and overcome water depths by building deep foundations embedded into the seabed. These technological and economic issues are part of the aspects in which onshore and offshore wind turbines differ. However, as mentioned before, the favourable wind resource with increased production and locations, still makes offshore wind turbines an interesting alternative compared to their onshore counterparts.

1.2 Offshore Operations and Components

1.2.1 Contributing Components

Although all components and parts are required to efficiently operate the wind turbine, there are a few components which are of great complexity and of significant importance when contributing to the effective uptime of a wind turbine, we will refer to these components as "the main components" (MC) as some can be seen in Figure 2. Each of these components has their own tasks ensuring the operationalization of the wind turbine. However, these MCs sometimes fail to perform their tasks due to their loss of ability, which we call a failure. “A failure is the termination of the ability of an item to perform a required function” (International Electrotechnical Commission, sd). Faulstich, Hahn, & Tavner (2011) showed in their study regarding wind turbine component failure rates that minor failures, which represent 75% of the failures, cause only 5% of the downtime. In contrast to the main failures caused by MCs which corresponds to only 25% of the failures, but 95% of the overall downtime. For the problem context we will only focus on the main failures, which require the component to be replaced, which causes the long down time. These MCs, their functionality within the wind turbine, and failure causes will be described in more detail in Section 2.1.2. To tackle the long down times, it is important for Vattenfall to understand the failure rate characteristics of the MCs and to anticipate such a failure. In Section 3.2 we will go more in depth surrounding the failure distributions.

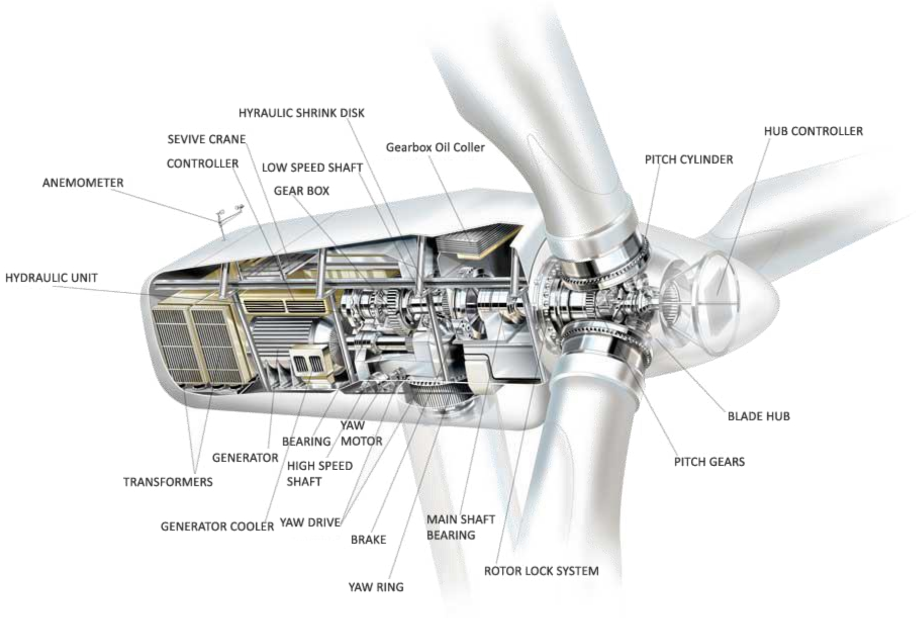

Figure 2. Cross-section Wind Turbine

1.2.2 Operations and Maintenance

OM management aims to improve the availability of the wind turbines and reduce overall maintenance expenses. This is a complex task to accomplish, due to the different sizes of the components and due to the components having to be lifted high up in the air at sea, which are hard to reach due to varying weather conditions. This causes the operations and maintenance tasks surrounding offshore wind turbines to be much more difficult, time-consuming, dangerous, and expensive. Furthermore, this causes minor failures to have bigger effects on the availability of offshore wind turbine and additionally their operational expenses, in comparison to onshore wind turbines. These expenses consist of part purchases, labour, transportation, Jack-up vessel rental, and lost revenue.

Most expenses are quite self-explanatory, apart from the Jack-up vessel. A Jack-up installation vessel is a self-lifting service rig, which allows for safe installation of heavy foundations and components of offshore wind farms, see Figure 3. It performs these tasks by lifting itself above sea level, using its "legs," which results in a stable platform for lifting heavy components up in the air. For all MC operations surrounding placement and replacements on a wind turbine, a Jack-Up installation vessel is required. These Jack-Up vessels are subcontracted from an external company, and since all offshore wind parks use these vessels, these vessels are in high demand. Since these vessels are in such high demand, the corresponding lead time of availability can go up to three months and beyond.

Figure 3. Jack-Up Vessel

1.3 Problem Statement & Scope

1.3.1 Problem Statement & Problem Cluster

From Sections 1.1 and 1.2, we can conclude the importance of minimizing the downtime of the offshore wind turbines to maximize availability. To identify the core problem causing this downtime, all problems are stated and connected to form a problem cluster. The root problem can be classified as the core problem. The last problem is the action problem (Heerkens & van Winden, 2017), indicating the required action to be taken to solve the core problem. Figure 4 shows the problem cluster including the core problem and action problem.

In the problem cluster we can see that the action problem indicated in grey is caused by a multitude of factors, like the Jack-Up lead time, component lead time, weather conditions, and complexity of replacement or repair. Certain factors, like the weather are uncontrollable, and others like the complexity of replacement or repairs are currently seen as a given and are thus outside of the scope of this research. The Jack-Up lead times are a bit more flexible. These are currently set in contracts with the vessel contractor, where a vessel should be available within a given period. However, it is possible to set up new contracts with lower lead times for a higher price. Finally, the component lead time: When a failure occurs of a component, this component is either directly ordered from the OEM, or bought from a refurbished component market. Some components are no longer produced by the OEM and thus must be bought elsewhere However, since these are relatively large and complex parts, buying the parts from the OEM, if possible, will have a higher reliability but also a higher component lead time. This higher component lead time is of course undesired by Vattenfall, since this is causing a lot of lost revenue where the wind turbine is down waiting for a part, which are indirect costs for Vattenfall. To counteract this downtime from waiting for a part, Vattenfall has decided to construct a central warehouse for a more centralized storage of MCs. There are already local warehouses in place, which are used as cross-docking warehouses for the MCs, which are required for an offshore replacement. Additionally, the local warehouses are used to store smaller components. These local warehouses are located in the harbours near an offshore wind park and are therefore expensive storing locations. Additionally, since MCs have such a low failure occurrence, these spare parts often catch dust and require maintenance and when located in a warehouse, which is not economically viable against 25% component price as holding costs (Durlinger, 2014). Therefore, the local warehouses act as a cross-docking warehouse for MCs. The central warehouse is supposed to offer a more centralized approach by providing an intermediate holding location, which can provide to all the local warehouses, minimizing the total number of spare components required and thus minimizing the holding costs. Since this central warehouse is still being built, the assumption of 25% of the components price for storing still holds for the central warehouse until new information is released. However, since the storing costs are so high and MCs fail with such low frequency it is uncertain whether it is or can be economically beneficial for Vattenfall to store these spare MCs in the central warehouse at all. If it is beneficial, Vattenfall is still uncertain what policy is optimal to minimize holding costs and downtime. All these problems start with finding an answer to the following core problem:

What is the optimal inventory management system for cost efficiency given the current state of the MCs, considering the uncertainty of MC failure occurrence.

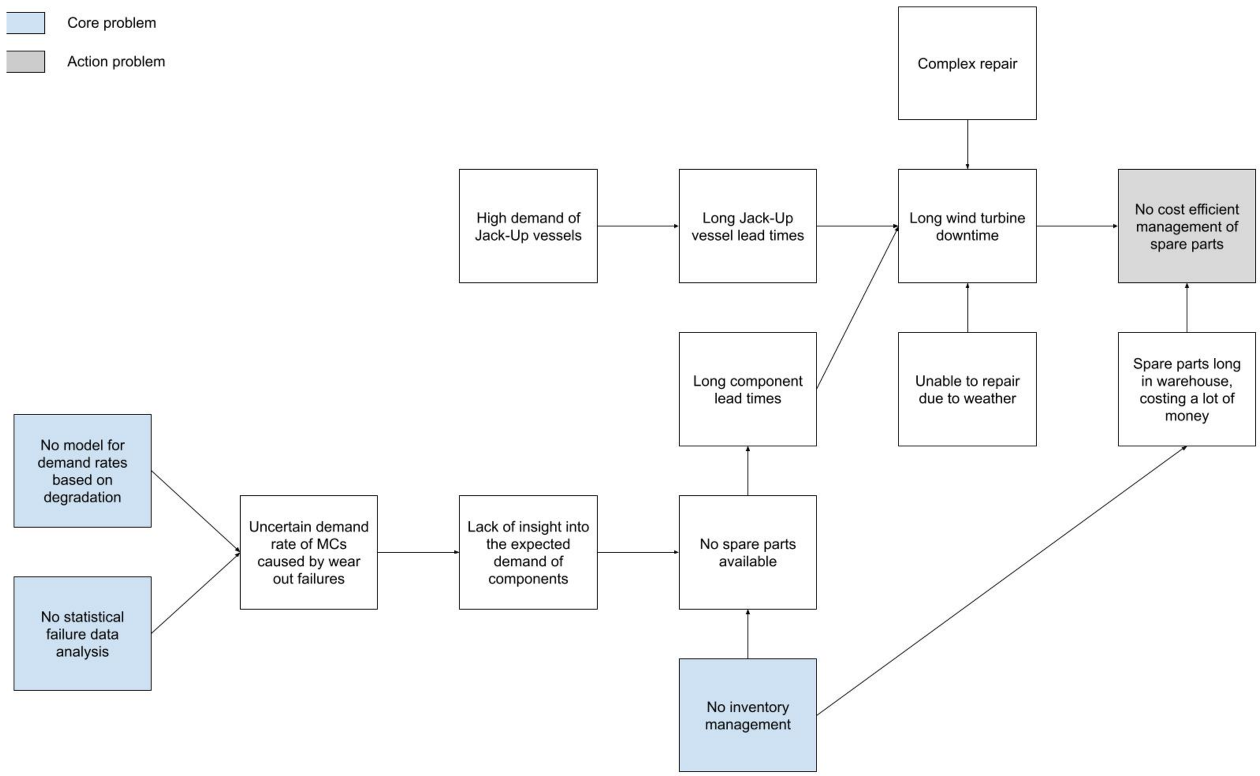

Figure 4. Problem Cluster

1.3.2 Scope

The scope of the project is on two out of the three of the action problems in blue as stated in the problem cluster, Figure 4. We do not consider the modelling of demand based on the degradation process, since Vattenfall have their own condition-based monitoring team. This team offers an expected forecast based on experience using the limited data available, which is information that can be used in expected failures. The other two action problems are divided into two stages. The first stage estimates failure rates of expected failures of the MCs based on historical data. The second stage will use this demand rate to implement in an appropriate inventory model. Additionally, we will only focus on the MCs as a Line Replaceable Unit (LRU), and not on their corresponding Shop Replaceable Units (SRUs), which makes it a single-indenture system since we only look at the components as a single part. The estimated failure rates of the MCs are based on the statistical analysis of historical failures. Additionally, condition-based monitoring is performed by Vattenfall, which provides installed base information. This installed base information provides an indication when a component is not working according to what is expected, which can indicate an upcoming failure. This information is only available for certain MCs, since not all MCs at an age at which they have provided enough data points. However, this will not be considered in the scope of the project since no data is ready to be incorporated. For the inventory management, we only focus on the central warehouse since no real stock is kept at the local warehouses. The Central warehouse is located in Denmark, which is supplied by the OEM and will supply all local warehouses. This makes it a single-echelon, multi-item, single-indenture system. It is a single-echelon problem, since the inventory will only be optimized for one echelon level, the Central warehouse. A multi-item problem because multiple components will be incorporated. Lastly, a single-indenture problem, since no sub-components of the MCs will be considered, only the MCs themselves.

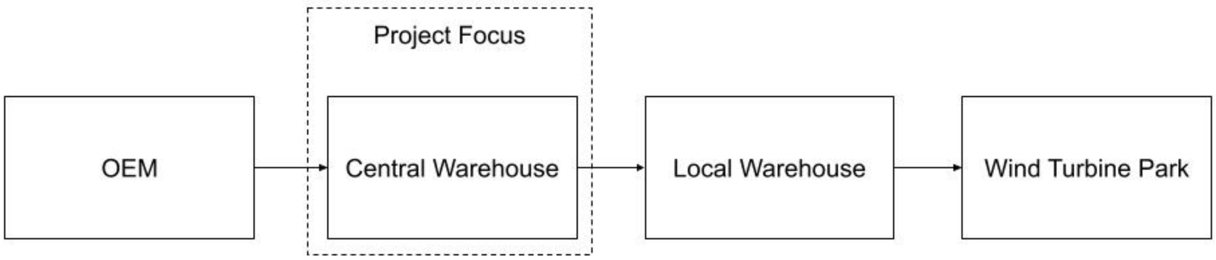

Figure 5. Project Scope

1.3.3 Requirements

In this section we will elaborate on certain criteria set by Vattenfall for the project. We will use these criteria for the model selection and creation to ensure the model suffices the correct requirements. The requirements are summed and are as follows:

1. Optimum inventory levels must be provided and updated at least every month for every component.
2. Demand rates of components should be computed based on historic data, including non-failed components. If this is not available, standard failure rate provided by the OEM should be used instead.
3. Manufacturing prices and lead times should be considered for the inventory model.
4. Storage cost should be weighed against the lost revenue costs. The lost revenue costs should be based on the current electricity prices.
5. For the offshore wind parks, the spare components must be stored at the central warehouse, if there are any.
6. The inventory model should be able to be integrated into Python, using the standardized structure of the analytics team of Vattenfall.
7. The results should be generated for a timeframe of three years.

1.4 Research Objectives

1.4.1 Research Aim

The aim of this research is to determine the expected demand rate of MCs, based on the expected failure distribution statistics. These analyses are used as input for the inventory management analysis, to determine optimal spare part policy and parameters. The result from the inventory management analysis is then validated and evaluated, which we will go more in depth into in Section 5.

Combining these two stages, gives us the following research objective:

"Develop and validate an expected lifetime distribution, to predict expected failure rates of MCs given their current state and integrate it into a spare part optimization model to determine the optimal spare part policy, thereby achieving maximum cost efficiency."

1.4.2 Research Questions

Given the research objective, the following research questions are defined to help achieve the research objective of obtaining the most efficient cost solution. The research question is divided into multiple sub questions, thereby sub-structuring the research questions.

Firstly, we would like to familiarise ourselves with the current state of the processes surrounding the MCs degradation process and the practises surrounding the repair and operations of the MCs.

1. What causes failures, and what are the corresponding current practises and available data related to the problem context?
    a. Which factors influence the current failures of MCs?
    b. What is the current practice regarding MC spare parts stocking?
    c. What are the current supply processes regarding repair/maintenance operations?
    d. What are the costs surrounding MC storing and replacement?

Secondly, we would like to utilize the literature available surrounding the forecasting of the expected statistical failure analysis. In addition, the relationship between the forecasting of the degradation process regarding the spare parts optimization modelling approach.

2. What information can be found in literature related to the research objective and question?
    a. What type of failure behaviours are differentiated?
    b. What distributions for lifetime expectancy are used for varying failure rates and how are they fitted?
    c. Which spare part optimization models and inventory policies related to the lifetime distributions are available in literature?
    d. How to validate and evaluate the performance and accuracy of the expected spare part demand and spare part optimization tool according to literature?

Thirdly, after conducting the literature research, we utilized the findings for setting up the modelling approach of the expected lifetime model and the inventory management.

3. How to set up the modelling approach for the expected failure rate, and inventory management?
    a. How to fit the lifetime distribution and validate it?
    b. How to model the expected failures statistics of MCs?
    c. How to use the statistical analysis to use as demand rate input for inventory model?
    d. How to model optimal spare parts control, while incorporating logistical difficulties?
    e. How is the performance of both models (statistically) evaluated and validated?

Lastly, the focus will be on testing and validating the performance and accuracy of the models regarding the degradation process, forecast and inventory policy.

4. Will failure rate predictions and replenishment policies for spare parts be economically beneficial for the offshore wind industry to implement?
    a. What is the performance of the models?
    b. Does the model offer a valid solution to the problem?
    c. What are the possible costs saving areas of the models?
        i. If no savings, what should Vattenfall change for it to be cost effective?
    d. What is required to implement the models in the standardized working method?
    e. What are limitations for implementing the model?

f. What are the steps looking forward?

Answering all the above-mentioned research, and research-sub questions would collectively lead to the answer on the research objective.

1.5 Approach and Methodology

To ensure the fulfilment of the research objective, multiple research questions are developed. To answer these research question, the research approach can be summarized in six methods as shown in Figure 6.

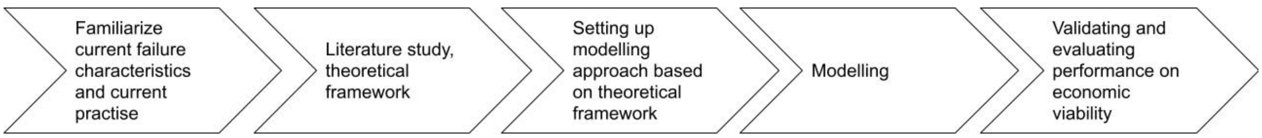

Figure 6. Research Approach

1.5.1 Field Study

To understand and familiarize ourselves with the current situation, the problem and desired solution, field study has been conducted by gathering information from the internal database and utilize the knowledge of employees involved in the project and or involved in maintenance and operations, data gathering. Since little data is available regarding MCs failures, as mentioned before, majority of the data acquisition will be based on internal knowledge and data related to potential failure rate detection. Additionally, information provided by OEM regarding MC failure rates will also be utilized. More in-depth information of the related processes will be provided in Chapter 2.

1.5.2 Literature Study

As described in the research questions, the literature study focusses on two scientific areas, the statistical analysis of expected failures, and inventory management of spare parts. These scientific areas are studied for the better understanding and application of the different models in the wind energy sector. In addition, the lifetime distribution of components, data censoring, and model evaluation and validation are all described in Chapter 3.

1.5.3 Modelling Approach

After the field study and the literature study, the most relevant models and data are used for conceiving the theoretical design of the expected failure rate model and the spare part optimization model. This includes the assumptions, scope, and limitation of both models. For the modelling of the models Python, which is the standard computer software used by the Analytics team within Vattenfall, is used. Python is a high-level general-purpose programming language meant to be easily accessible and readable for all users. Therefore, it is an industry wide accepted programming tool used for modelling complex systems, thus time is spend learning more about Python programming and the structure used by the Analytics team. Chapter 4 will introduce the modelling approach and describe the models themselves.

1.5.4 Validation and Evaluation

To ensure the validity, accuracy and performance of any newly developed model, verification and validation is important. Various methods are widely available and will be introduced in chapter 3. These methods ensure that the proposed model offers a valid solution for the problem context and ensure the usability for the problem owner. The proposed methods will be applied in Chapter 5, the experimental design.

2. Main Components Management

In this chapter we will explore the operational side of a wind turbine, corresponding operations, failure distribution, and supply chain. Firstly, we will take an in-depth look at the operating of a wind turbine and its corresponding MCs and failure modes in Section 2.1. In Section 2.2 the current situation regarding MC operations for offshore wind turbines is described. Followed by Section 2.3, where the current supply chain activities and policies are discussed. Lastly, section 2.4 gives an economic overview of the current operational situation and components.

2.1 Wind Turbine & Main Components

In this section we will explore the operating of an offshore wind turbine. Firstly, in Section 2.1.1 we will elaborate in more detail on the operating of an offshore wind turbine and the offshore wind parks of Vattenfall. This is followed by a more concise description of the MCs and their degradation and failure process in Section 2.1.2. Lastly, in Section 2.1.3 we will look at the different seasonal effects on the failure rate of MCs.

2.1.1 Operational Wind Turbine

The basic concept of a wind turbine dates back centuries, of which the main aspects have not changed. In today's wind turbines the blades are set in motion by the passing of the wind, and this causes rotation. This rotation of the blades is transformed into electric energy that can be used to power houses, lights, etc. Here we will go more in depth about what causes wind, how does wind rotate the blades, and how is this rotation of the blades transformed into usable energy.

Wind is a combined effect from the sun on atmospheric temperature gradients, which results in convection, and of Coriolis forces due to the rotation of Earth. This results in a convectional air flow, which we call wind. Wind is a three-dimensional unsteady phenomenon, where it is a function of time and location, and it is best described and used by its velocity. In general, the average wind velocity at the hight of the wind turbine is used to determine expected energy generation. Therefore, it is of high importance to be able to predict wind velocity and thus economic viability of various locations. This determines the optimal locations to build a wind park. Wind power available for extraction in these locations is denoted by Function (2.1).

$$P = \frac{1}{2}\rho A U^3 \tag{2.1}$$

In Function (2.1) ρ denotes the air density at the given location, A the surface area swept by the blades of the wind turbine, and U the average wind velocity (Njoku, Ekechukwu, & Onyegegbu, 2013). This equation may include η the efficiency of the wind turbine, and C_p the rotor power coefficient. To optimally determine the average wind velocities in an area, a dense measuring network of multiple measuring stations must collect data for 5-10 years. Since this is often not possible in practise, multiple methods can be applied to determine average wind velocity for a specific area. (Landberg, et al., 2003) gives an overview of multiple methods of how a wind resource as a function of wind velocity at a certain site can be estimated. This wind velocity estimation gives the ability to compute the expected energy generation. Modern wind turbines are placed in these optimal wind source locations, with sufficient distance between them due to the turbulence caused by other turbines to minimize the loss.

Once a location is chosen and wind turbines are placed, the electricity generation can begin. A wind turbine typically consists of four parts, which are required for the generation of electricity, namely the *rotor assembly*, the *nacelle*, the *tower, and the foundation*. *The rotor assembly* is the beak of the wind turbine holding the blades. The *nacelle* is the box containing all the electrical components, which is connected to the *rotor assembly* via the main axis. The *tower* supports the *nacelle* up in the air. Lastly, the foundation is required for the stabilization of the wind turbine, which can all be seen in Figure 2.

The *blades* of the wind turbine are constructed with an aerodynamic shape, causing lifting power when the wind passes, which generates rotational energy. A pitching system is used to rotate the blades into the optimal position. This rotational energy generated by the blades is then transferred into a *gearbox* to increase rotational speeds. This rotational energy is then transferred into a *generator*, where it gets transformed into electricity. To ensure the wind turbine catches the optimal amount of wind, a *yaw system* is used to rotate the *nacelle*, *rotor hub and the blades* into the wind for optimal efficiency.

Currently, Vattenfall is operating 20 offshore wind parks located in 5 different countries. Additionally, 2 are still being built as part of “Hollandse Kust Zuid”. Appendix A. shows where the parks are located, number of wind turbines, the commission year, and manufacturer. The difference in wind turbine manufacturers per park is caused by two reasons. Firstly, the rapid developments in the wind energy sector creates new advancements rapidly, and thus creating more efficient wind turbines. Secondly, the difference is location cause different wind turbines to be more efficient in different environment.

2.1.2 Main Components & degradation

As described in Section 1.2.1, there are a few important components, the so called "Main Components." In this section we describe the functions within an operational wind turbine and their most common failure causes, based on the failure definition mentioned earlier. This can be seen in Table 1. In Appendix B. Main Components, a more detailed description of the components, their function and their most common failure types can be found.

Table 1. Main Components

Component	Use	Failure Causes
The Blades	Transform wind into rotational energy	Extensive wear due to harsh environment (Leon Mishnaevsky, 2022)
Main Bearing	Transmit rotational energy to gearbox	Degrading lubricant, environmental conditions (Kopeliovich, 2014)
Main Shaft	Transmit rotational energy to gearbox	Debris, high Axial, and radial loads (Nyberg, 2011)
Gearbox	Increase rotational speeds for the generator	Axial cracking, debris, small cracks (Foti, 2018)
Generator	Transform rotational energy into electricity	Varying loads caused by varying wind speeds (Gowdar & Gowda, 2016)
Transformer	Increasing the low voltage from generator to a higher distribution voltage	Varying loads caused by varying wind speeds (Sims, 2019)
Switchgear	Control, protect, and isolate electrical equipment	Faulty modifications, lack of operating knowledge, or inappropriate resets (Paoletti, 2017)

Since different wind parks use diverse types of wind turbines, with each their own technologies. These diverse types of technologies indicate that the wind turbines from different parks with different technologies do not use the same type of MCs, and thus the MCs inventory management is based per type of wind turbine. Appendix A. gives the names of the different wind turbine types used and the corresponding number of turbines of this type in the current situation.

2.1.3 Seasonality

In this section we will look at the impact of seasonal changes regarding failure of the MCs. Seasonal changes have a big impact on the renewable energy sector, where the power generation is reliant on the weather conditions. Wind is no different, and experiences different generation performances throughout the year. A study performed by Tavner, et al. (2013) showed the effects of varying conditions on wind turbine reliability. They monitored various conditions and failures over a prolonged period and concluded that weather has a positive cross-correlation between 9-31% with failures depending on the location. This result was achieved with a small but precise data set, which helped them achieve >99.9% level of significance. This indicates that indeed weather has a small correlation with the failures of MCs. Additionally, they showed that the correlation increases during the winter month by an average of 5%, which indicates that colder weather effects and thus higher winds have a higher effect on failures. Therefore, a seasonality exists, where reliability is slightly lower in the winter months. How much the seasonality impacts the failures of MCs exactly is however uncertain since no data is available and no precise information can be found in literature. Therefore, we decided to not take seasonality into account while determining the failure rate of MCs. However, once such seasonal data becomes available, an extension of the model can include these seasonal effects. Additionally, we will consider the seasonality surrounding production rates of wind turbines based on indications of Vattenfall regarding the average monthly production rates throughout the year. This information will be used in the calculation of lost revenue per month per turbine. However, we do not take in to account the weather effects on the repair lead time since this would increase the complexity of the problem significantly.

2.2 Main Component Operations

In this section a more detailed overview of all the operations surrounding MCs will be given. Firstly, we will discuss the monitoring of the MCs in Section 0. Secondly, in Section 2.2.1 MC decision making regarding the operations will be brought to light. Lastly, Section 2.2.2 will describe the operations organization in more detail. Additionally, Appendix C. Condition Based

Monitoring, describes the process of monitoring the condition of the component, which might be interesting to add later but for now is outside of the scope.

2.2.1 Operational Decision Making

To determine when a MC should be replaced is dependent on a multitude of variables. Ideally you require three sources of information regarding the specific component, namely, current state of component by means of condition monitoring, expected failure rates based on historic data, and the expected life expectancy given by OEM. Vattenfall is looking for an internal calculation of the expected failure mode on top of the failure mode given by the OEM to increase accuracy. Since MCs fail with such low frequency, a more accurate failure becomes more important for the decision of inventory management. Additionally, monitoring of MCs is a strong technique for detecting failure or damages on rotating components used in the wind turbine. When a potential damaged component is detected, which can eventually cause a failure, or a failure is expected, a decision must be made regarding how to act to minimize downtime of the wind turbine.

From an analytics perspective, the damaged component must be replaced as soon as possible, since you want the optimal performance out of your wind turbine, even though it might be functioning near perfect and still operating at full or near full capacity. Therefore, the team responsible for operating the wind turbines, prefers waiting until it is of high priority to replace the part. This is the trade-off between preventive and reactive replacement. The cross-over point of the trade-off is based on the cost of replacing a MC and the missed revenue due to downtime. This is an important break-even point, which determines when a repair is required and thus when a spare component is required. However, this decision will not be taken inside of the scope, as this would require the on-site information of the current state of components.

2.2.2 Operational Organization

When a MC is in their early life phase they are still under warranty at the OEM. Therefore, the OEM maintains full control over the component, and they monitor the components and replace the faulty ones. Therefore, when a component wears out while under the supervision of Vattenfall, it is assumed to be in the wear out phase or from a random failure. Once a replacement is required a planning must be made as to when the component can be replaced. Once the specific date has been chosen based on the availability of the Jack-Up vessel and the lead time of the component, preparations for the replacement are brought into place. The required component is transported either from the central warehouse, or from the OEM to the local warehouse in the port near the offshore wind park waiting for the component. Once the Jack-Up vessel has arrived, the component is lifted onto the vessel and the vessel goes towards the corresponding wind turbine waiting for the part. The faulty component is brought back ashore and taken for analysis and repair, either at the OEM or in house. If the component was repaired, it can either be stored in the warehouse or sold on the refurbished spare component wind turbine market.

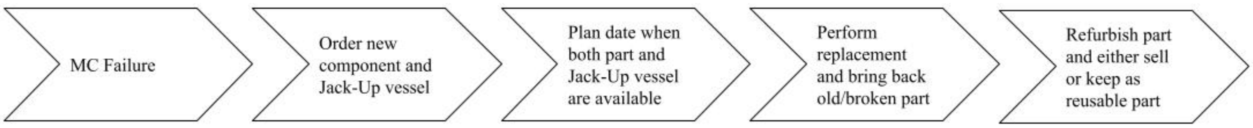

Figure 7. Operations

2.3 Supply Chain

In this section we will discuss the current supply chain in place at Vattenfall regarding the MCs. Here the current inventory model being used at Local Warehouses and future inventory model for the new Central Warehouse in Denmark will be discussed. Additionally, we will discuss the supply chain coordination and corresponding lead times to the MC operations.

2.3.1 Supply Chain Logistics

A lot of actions must be planned before a component can be shipped out on sea to replace a failed component of a wind turbine. The component must be ordered by the OEM and shipped towards the desired location. The Jack-Up vessel must be ordered for a specific day when the new component is ready in the harbour. All these activities have their own lead time, which must correspond with one another.

The average component lead time differs per component and can be seen in Table 2 (Rajendra & Rajendran, 2020), where we increased the lead time for some components to monitor the effects. We have taken this as a given as this is the only indication available, since no data is available for the variability of this lead time and thus no variable lead time can be assumed. Additionally, the transportation lead time is three days. Furthermore, the average Jack-Up vessel lead time is assumed to be 88 days (The Crown Estate, 2014), which we round off for simplicity to three months. Since the Jack-Up lead time is longer than the component and transportation lead time together for some components it would not be beneficial to keep stock at all. However, we will experiment with different Jack-Up lead times demonstrating whether Vattenfall can benefit from shorter lead time contracts with Jack-Up vessel suppliers or other scenarios.

Table 2. Component Lead Time

MC	Lead time (months)
Blades (3x)	1 months
Main Shaft	1 months
Main Bearing	2 months
Gearbox	4 months
Generator	4 months
Transformer	3 months
Switchgear	3 months

Additionally, the storage space of spare components in the new Central Warehouse is a limiting factor for the number of components that can be stored. Therefore, we have taken the size of the warehouse and the components into account as a restricting parameter while developing the model.

2.3.2 Inventory Model

Currently Vattenfall has no inventory management in place since the new Central Warehouse is not fully constructed yet and thus no MC storage space is available. Therefore, MCs are only ordered from the OEM when a component has failed and a new one is required for the replacement of the failed one. This means that the corresponding wind turbine has a down time equal to the lead time of the production and transportation of the component, where we neglect the installation time for sake of simplicity. This is very inefficient, since this is a lot of lost revenue for Vattenfall. To ensure minimum downtime, Vattenfall started building the new Central Warehouse for the storing of spare components and is thus looking for an inventory model to orchestrate the spare components.

2.4 Cost Breakdown

In this section, all the costs included in the project are given in a cost breakdown analysis. This will include component purchase costs, holding costs, and lost revenue. Transportation and Jack-Up vessel costs will be taken out of scope, since for comparing the use of a spare component or not, it is irrelevant, since both situations require transportation and a Jack-Up vessel.

According to (Stehly, Beiter, & Duffy, 2019), the average installed offshore wind turbine in 2019 has a capacity-weighted average of 6.1 MW. These turbines have a rotor span of 151 meters and have a 102-meter-high hub. They estimate the average price of an offshore wind turbine to be 4,077 dollars/kW. This results in an average cost of 25 million dollars per wind turbine placement. Only 31.9% consists of turbine components, resulting in an average price of 8 million dollars per wind turbine.

Cost per Main Component

The total costs of all offshore wind turbine components are split up, and only the MCs are used. These MC costs percentages are based on IRENA cost analysis report (2019) (International Renewable Energy Agency, 2012), and can be seen in Table 3. These costs represent the purchase price of the components, which we included into the model, and final decision-making process under the assumption that this includes the transportation costs from OEM to customer.

Table 3. MC Cost Division

MC	Percentage of total costs	Costs (dollar)
Blades (3x)	22,20%	1761200
Main Shaft	1,91%	151500
Main Bearing	1,22%	96800
Gearbox	12,91%	1024200
Generator	3,44%	272900
Transformer	3,59%	284800
Switchgear	1,32%	104700

Holding costs

For the holding costs of MC in the new central warehouse, a percentage of the component price is used as an indication. For the holding costs, an industry standard of 25% of the component purchase costs is used per year, this includes deprecation, capital investment, damage, lifetime, and cost of storage space in warehouse (Durlinger, 2014).

Lost Revenue

When a wind turbine is not operating, it does not produce electricity. This lack of electricity production can be described as lost revenue, which as a company you want to minimize as much as possible. For the offshore wind electricity production, we can look at the monthly production of an offshore wind park to ensures we take seasonality of production into account when calculating the lost revenue. We compute the lost revenue per time unit in two steps. Firstly, the average forecasted production per kWh per month for the next three years is taken, which thereby incorporates seasonality. Secondly, for the electricity price, we take the global weighted-average production costs of offshore wind energy over a 25-year lifetime period. This is roughly 4.7 cents per kWh (Lensink & Pisca, 2019). To overcome these costs, municipalities can provide a subside to encourage the transition to a decarbonised society. This is stated in the Contract for Difference (CFD). The CFD states that once the electricity price goes below a certain threshold, the government will provide the subside for companies for the remaining costs. However, once it goes above the threshold the generator (in this case Vattenfall) has to pay back the difference. One of the CFD contract in the United Kingdom for the years 2025-2027 states that this threshold for offshore wind is equal to 5.5 cents per kWh. We will use as an indication of the electricity prices (Department for Business, Energy & Industrial Strategy, 2021). Combining this with Vattenfall's forecasted electricity's price each month dependent based on trends in the electricity market for seasonality gives us the price per month. Combining the two parts gives us the following equation:

$$lost\ revenue = Capacity\ factor(t) * Rated\ power * time\ unit * Price(t) \qquad (2.2)$$

where,

Capacity factor(t): percentage of full power in month t (Percentage)

Rated power: power rating of their maximum output (MW)

Price: electricity price per megawatt hour in month t (Euros)

3. Literature Review

In this chapter the performed literature review will be elaborated upon. Various methods and techniques will be discussed, which are relevant for the problem context. In chapter 4, the chosen models, methodologies, and approaches will be discussed, which will use this literature review as a basis. The literature review is divided into five parts. First, the types of failure behaviours and censoring of data are discussed in Section 3.1. Secondly, the different continuous failure distributions and models are brought to light in Section 3.2. Thirdly, the inventory policies and performance measures are discussed in Section 3.3. Fourthly, in Section 3.4 the different inventory models applicable to the problem context are elaborated upon. Lastly, the different validation and verification techniques are discussed in Section 3.5.

3.1 Failure Rate & Censoring

To perform a statistical analysis of the expected failure rate of a MC, a distribution for the estimation of the life expectancy is required. Extensive research has been performed about failure rates since predicting expected failures is important for critical operational decision making, such as main component repair analysis. At Vattenfall statistical modelling is used, which is very limited due to the lack of MC failures data. This is caused by the long-life expectancy of the wind turbine and its components, which were constructed in recent years. There are various types of failure behaviours, which are described in the "bathtub curve," as seen in Figure 8. The bathtub curve differentiates between three types of failures, infant mortality with Decreasing Failure Rate (DFR), random failures with Constant Failure Rate (CFR), and wear out failures with Increasing Failure Rate (IFR). The focus of the research is on the wear out failures of the MCs, meaning there is an IFR over time.

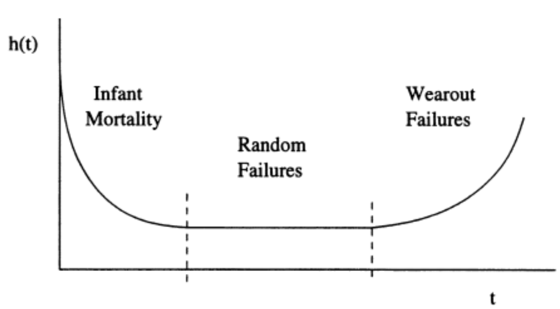

Figure 8. Bathtub Curve

Since the focus is on long-life components, uncomplete data sets are a common case. This indicates that observations of failures are terminated even before a component failed, this is called right censoring. Additionally, when it is unknown when a component was put into operation, we talk about left censoring. Using these censoring notations, we distinguish four types of censoring (Rausand & Hoyland, 2004).

Type I Censoring

All components are activated at time t=0 and the monitoring or life test is terminated at time t0. Therefore, only the lifetime of components that failed before t0 are known, and the number of components that have not failed yet is also known. Both information types should be utilized, this is characterized as right sided censoring.

Type II Censoring

When limited time is available to perform a lifetime test, the test can be terminated after a fixed number of r lifetimes is observed. Like Type I Censoring, we assume all components are activated at time t=0 and terminated when r lifetimes are reached. The survived components should again be utilized, and this is also characterized as a right sided censoring

Type III Censoring

Type III censoring is a combination of both type I censoring and type II censoring, where you either stop at a given time t0, or after a fixed number of r lifetimes of components are observed. This is also characterized as a right sided censoring

Type IV Censoring

Type IV censoring is when identical components are put in place at different time points but can be adjusted to set all activating point at the same time (time t=0). This results in the time for censoring of an individual observation to become stochastic. An example of this would be a medical experiment, where patients come in at random times.

3.2 Lifetime Distributions & Models

In this section we will look at different distributions and models, which can be used for their application in modelling varying failure rate systems for the given problem context. These give a more realistic representation than non-varying distributions of failure properties, since a new component is less likely to fail due to wear out than an older component. Additionally, assuming a constant failure rate, like a compound Poisson process, will often result in excess or lack of stock, due to not incorporating the changing conditions of the components. In Appendix D. Poisson & Exponential Distribution, the Poisson and Exponential distribution are shortly described

3.2.1 Gamma/Erlang Distribution

Gamma Distribution

The gamma distribution can offer a good fit for flexible life distributions sets. It is a time-to-first-event distribution and can be seen as a group of exponentially distributed random variables. This makes the Gamma distribution commonly used in queuing theory (NIST/SEMATECH, 2013).

The Gamma distribution is commonly a two-parameter continuous probability distribution. It has shape parameter k and scale parameter λ. Additionally, a three-parameter Gamma distribution is available, which introduces the threshold parameter γ (R. & Nathan, 2016). The threshold describes the shift of the distribution (to the left or right). This is not relevant for the context of the research. Therefore, it is taken outside of the scope.

To estimate the parameters of the two-parameter Gamma distribution, the method of moments can be used. The method of moments first estimates the mean and the variance. The mean and variance can then be used to calculate the estimators of k and λ. When the shape parameter k is equal to one, we have a constant failure rate, and are in the random failures part of the bathtub curve. When k is bigger than one, it has an increasing failure rate, which represents the wear out failures. The estimation of the mean and variance is given by Function (3.1) and Function (3.2). Where *n* represent the total number of observed failures at time t_i (Gomes, Combes, & Dussauchoy, 2022).

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} t_i \tag{3.1}$$

$$\hat{\sigma}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(t_i - \hat{\mu})^2 \tag{3.2}$$

Using this estimation of the mean and the variance, we can calculate the estimator of the parameters of the Gamma function as seen in Function (3.3).

$$k: \frac{\hat{\mu}^2}{\hat{\sigma}^2}, \qquad \lambda: \frac{\hat{\mu}}{\hat{\sigma}^2} \tag{3.3}$$

The estimators of the parameters can be used to determine the probability density function f(t), as seen in Function (3.4). Γ represent the gamma function. The density function can then be used in determining the reliability of component at time t, since the reliability function R(t) = 1-F(t), where F(t) is the integral of the probability density function (Rausand & Hoyland, 2004).

$$f(t) = \frac{\lambda^k t^{k-1} e^{-\lambda t}}{\Gamma(k)} \tag{3.4}$$

The disadvantage of the method described above is, that it does not consider survival data, which is a very important factor for accuracy when limited failure data is available.

Erlang distribution

The Gamma distribution is almost identical to an Erlang distribution, where the parameter k can be a positive real number for a Gamma distribution compared to a positive integer number for the Erlang distribution. Additionally, the scale parameter used in the Gamma distribution is often referred to as the rate parameter in the Erlang distribution (Kim, 2019).

3.2.2 Weibull Distribution

The Weibull distribution is a continuous probability distribution that can take the shape of an extensive range of distributions based on its parameters. This ensures Weibull provides a good fit with the data obtained for many applications. Therefore, Weibull can just like the Gamma distribution formulate all 3 phases of the bathtub curve. Because of this versatility, the Weibull distribution is widely used in reliability engineering within life cycle analysis. (Burtin & Pittel,

1972) Said “For an arbitrary monotone system with independent and non-renewable components, the system lifetime can be approximated by a Weibull distribution”.

To compute the Weibull distribution, we first need the parameters. Weibull consists of either two or three parameters, namely η, β, and γ. η is the scale parameter, which represents the point at which 63.2% of all Weibull failures have occurred. β is the shape parameter, which correlates to the different failure rates of the bathtub curve, and γ is the location/threshold parameter. However, γ is the difference between the two- and three-parameter Weibull distribution and is often not used or set to zero, which results in the same outcome. Function (3.7) gives the PDF of the Weibull distribution. The parameters are determined based on the observations of the time to a failure $X_{(i)}$, where *i* represents the i^{th} failure. Additionally, the total number of parts observed, either failed or not, is described as *n*. The components that have not yet failed are described as censored data. For the problem context we use a two parameter Weibull distribution, for which the parameters are estimated using the following steps. Firstly, Function (3.5) gives the expected empirical distribution function, which are used with Function (3.6) for performing a regression analysis (Rausand & Hoyland, 2004). An alternative approach for multi-censored data is proposed by (Zaiontz, 2022), which can be seen in Appendix E. Multi-Censored Weibull Parameter Estimation.

$$\hat{F}\left(X_{(i)}\right) = \frac{i - 0.5}{n} \tag{3.5}$$

$$\begin{cases} y(t) = \ln\left(ln\dfrac{1}{1 - \hat{F}(X_i)}\right) \\ x(t) = ln\ (t) \end{cases} \tag{3.6}$$

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3.7}$$

Secondly, the Weibull parameters are taken from the regression, where β is equal to the coefficient of x(t) of the regression, C is the coefficient of intercept, and $\eta = exp(-C/\ \beta)$ (Abernethy, 2001). The obtained parameters are used in the calculation of reliability and the failure rate function. The reliability function of Weibull is given in Function (3.8). This determines the reliability of a component at time t, thus the probability of it not breaking down at time t.

$$R(t) = \bar{F}(\mathrm{t}) = \begin{cases} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}}, & t > \gamma \\ 1, & 0 < t \leq \gamma \end{cases} \tag{3.8}$$

The scale parameter is determined based on the types of failures, $\beta < 1$: infant mortality, $\beta = 1$: random failures, and $\beta > 1$: wear out failure. For the problem context, we are only interested in the failure rate function of the wear out failures, which is given by Function (3.9), where the increasing failure rate is a function of the time t (Klutke, Kiessler, & Wortman, 2003) (Xie & Lai, 1996).

$$\lambda(\mathrm{t}) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \quad or \quad \lambda(\mathrm{t}) = \frac{f(t)}{R(t)} \tag{3.9}$$

For a system of *n* identical and independent components, which have indistinguishable failure rate functions, the cumulative failure rate can be described as the sum over the individual failure rates. Furthermore, the reliability function of the entire system can be denoted by Function (3.10). These calculations of the reproductive property only hold true when the shape parameters are identical, otherwise the failure rate distributions will not be Weibull distributions anymore (KMUTT, 2019) (Kemmner, 2012).

$$R(t) = \bar{F}(\mathrm{t}) = \prod_{i=1}^{n} e^{-(\frac{t-\gamma_i}{\eta})^{\beta}} \tag{3.10}$$

Lastly, the mean and variance of the Weibull distribution can be determined based on the parameters as calculated above. The mean and variance are calculated as seen in Function (3.11), (3.12), and (3.13).

$$\Gamma(r) = \int_0^{\infty} x^{r-1}e^{-x}dx \tag{3.11}$$

$$E(T) = t_o + \eta\Gamma(1 + \frac{1}{\beta}) \tag{3.12}$$

$$Var(T) = \eta^2(\Gamma\left(1 + \frac{2}{\beta}\right) - \Gamma^2\left(1 + \frac{1}{\beta}\right)) \tag{3.13}$$

3.2.3 Proportional Hazards Model

The proportional hazard model is classified as a methodology for statistically analysing censored survival data, relating to passing of time before a specific event occurs. It was introduced to estimate the different effects of various factors impacting the time to failure of a part by D.R. Cox in 1972 to analyse collected reliability data, which have not been under the same conditions. These various conditions made the expected reliability of a component less reliable, and therefore it is desirable to isolate the various factors and estimate their influence. These various factors should be identified and quantified using numerical variables. These various factors, generally, called covariates can either be constant or varying over time (Dhananjay & Bengt, 1994).

The proportional hazard model has potential in processing reliability data without the need for making any specific assumptions for the hazard rate (failure rate). The total hazard rate $\lambda(t)$ is a function of the base hazard rate $\lambda_0(t)$, which is dependent on time only, and the positive function term $\psi(z;\beta)$, where z is the row vector of the covariates, and β is the column vector of the regression parameter, giving Function (3.14).

$$\lambda(t) = \lambda_0(t)\ \psi(z;\beta) \tag{3.14}$$

It is assumed that the functional form of $\psi(z;\beta)$ is known and can also be used in different function forms. The most common function form is the exponential form for $\psi(z;\beta)$, which is seen in Function (3.15).

$$\lambda(t) = \lambda_0(t)\ \exp\left(\sum_{j=1}^{q} \beta_j z_j\right) \tag{3.15}$$

Where $z_j, j = 1,2,..,q$ represents the covariates of the system, and $\beta_j, j = 1,2,..,q$ corresponds to the unknown parameters defining the effects of the covariates on the hazard rate. The corresponding reliability function is given by Function (3.16).

$$R(t;z) = (\exp[-H_0(t)])\ \exp\left(\sum_{j=1}^{q} \beta_j z_j\right) \tag{3.16}$$

Where $H_0(t)$ represents the cumulative baseline hazard rate. Additionally, the maximum likelihood method can be used to estimate the unknown parameter β, and can be obtained by considering the individual time to failure contribution to the hazard rate. However, it is not an optimal approach when a lot of parameters are present. The maximum likelihood function without failures tied together is given by Function (3.17).

$$L(\beta) = \prod_{i=1}^{k} \frac{\exp(s_i \beta)}{\sum_{m \in F(t_i)} \exp(z_m \beta)} \tag{3.17}$$

Where $F(t_i)$ represents the risk set of items that were functioning before the observed failure at time t_i. Additionally, m represents a small group of components as part of $F(t_i)$, and s_i is equal to the sum of covariates z_q of observed items. The estimated value's significance can be tested to verify the effect on the failure behaviour of the component (Cox, 1972).

After the estimation of parameter β is known, it can be used to estimate the base hazard rate $\lambda_0(\mathrm{t})$. For the base hazard rate, no specific distribution is assumed but it is assumed to be a step function, which is constant between the time to failure. The maximum likelihood gives the estimation of the base hazard rate at every point by Function (3.18).

$$\lambda_0(\mathrm{t}) = \frac{d_i}{(t_i - t_{i-1}) \sum_{m \epsilon F(t_i)} \exp(z_m \beta)} \tag{3.18}$$

3.2.4 Conclusion Expected Demand Rate

Each method has their own application in different scenarios, giving them their own strengths and weaknesses. Gamma and Weibull are both extremely versatile and can mimic other distributions based on their parameters and can both be seen as a generalized version of the exponential distribution. Gamma is however not commonly used as a life distribution or failure distribution for failures. The Proportional hazard model adds another layer of complexity by taking the various covariates into account if that information is available. In the following sections more in-depth information will be given how these methods can be used as input for spare part inventory systems.

3.3 Inventory Management

In this section we will discuss various inventory policies and spare part performance measures, which could be applied to the problem. First, we will express the notation of inventory policies and present the inventory policies expressed in literature, which could be applicable to the problem context. Secondly, we will discuss various inventory performance measurements, which are used to measure the performance of an inventory model.

3.3.1 Inventory Policies

Spare part inventories policies are used to help determining the optimal inventory management of spare components. The literature distinguishes between different policies based on various parameters. Silver, Pyke, Thomas (2016) distinguishes between three basis variations, how often inventory should be checked, when a replenishment order should be placed, and how large the replenishment order should be. These three basic variations can be described in a policy using different variables consisting of: (Review period, Replenishment order threshold, Replenishment order Quantity)

The replenishment order quantity represents the number of units ordered for replenishment, either a fixed amount *Q*, or a variable order-up-to quantity *S*. The review period indicates how often the inventory level should be checked indicated by *R*, otherwise a continuous review, indicating that a system keeps track of how many spare components are present at all times. The replenishment order level indicates the threshold for the inventory, indicating that when the pipeline quantity goes below it a replenishment order should be placed, which is indicated by *s* if applicable. Lastly, the demand multiplicity indicates in what quantities the demand arrives, whether it is one by one or minimum of two items. Combining these various parameters into policies gives us diverse options split up into four main groups, as seen in Table 4 (Rego & Mesquita, 2011).

Table 4. Inventory Policies

	Continuous review	**Periodic review**
Fixed lot size	(s,Q), (s,nQ), (S-1, S)	(R,s,Q), (R,s,nQ)
Variable lot size	(s,S)	(R,S), (R,s,S)

These policies all offer a solid stationary inventory management solution for a constant demand rate, since they assume that the demand is known. However, for the problem context, the demand of components is a continuous function of time. This indicates that the stationary policies require adjustments based on the degradation rate of the components. Therefore, parameters should be flexible to relate to the current state of MCs. (Van Houtum & Kranenburg, 2015) propose several interventions to adjust the corresponding spare component policies. These interventions that are of interest for the scope of the research are as follows:

1. Increase stock level: Increase the current replenishment order quantity for more stock to represent a higher upcoming demand rate. The order is delivered under the component lead time.
2. Decrease stock level: Decrease the current replenishment order quantity to reduce the upcoming inventory level to represent a lower expected demand rate of components.
3. Decrease repair and/or component lead time: To reduce the repair and component lead time a contract can be put in place with the OEM and Jack-Up vessel facilitators to reduce the lead time of availability. This intervention ensures the repair of a failed component to be more responsive and eventually require less inventory.

Combining the first two interventions gives us a variable inventory stock level for components, which we can adjust on a periodic or continuous bases. Intervention 3 is stuck behind contractual agreements between the parties and can only be adjusted once a new contract is set in place and the new service agreements are discussed. Therefore, intervention 3 will be considered during the evaluation and accuracy of the performance measures in the sensitivity analysis.

3.3.2 Spare Part Classification

To assess whether an inventory model meets expectations, various performance measures are suitable. Spare part inventory management differs from other inventories management, whereas for spare part inventories the goal is to minimize downtime while minimizing inventory costs. The parts are often classified according to criticality in the categories: Desirable, Essential, and Vital (Gajpal, Ganesh, & Rajendran, 2003). Whereas consumer goods inventories are to ensure maximizing demand rate for optimal profit, which are usually classified according to a three-tier ABC-classification described in a Pareto graph, where A products are most important to a business and C the least important (Silver, Pyke, & Petterson, Inventory Management and Production Planning and Scheduling 3rd edition, 1998) (Teunter, Babai, & Syntetos, 2010).

3.3.3 Spare Part Performance Measures

Spare part management and maintenance are intertwined management activities since no replacement can be performed without a spare part. Most focus is projected onto the optimum number of parts required and the selection of the optimum inventory policy. However, the joint management of maintenance and spare part are rarely addressed (Barkany & Biyaali, 2020). For the problem context, we are interested in the optimal management of spare components and inventory. Commonly used metrics for evaluating spare part storing are: holding costs, average waiting time (W), Fill Rate (FR), Expected Backorders (EBO), Supply Availability (SA), and Lost Revenue (LR). The metrics can be calculated using the following equations:

$$EBO(s) = \sum_{n=s+1}^{\infty} (n-s) * \frac{(mT)^n * e^{-mT}}{n!} \tag{3.19}$$

$$SA(s) = 1 - EBO(s) \tag{3.20}$$

$$W(s) = EBO(s)/m \tag{3.21}$$

$$FR(s) = \sum_{n=0}^{s-1} \frac{(mT)^n * e^{-mT}}{n!} \quad or\ FR = 1 - \frac{ESC}{Q} \tag{3.22}$$

Where ESC represents the Estimated Shortage per Cycle and Q represents the order quantity, also denoted by Economic Order Quantity (EOQ). EOQ is calculated according to Function (3.23).

$$Q = EOQ = \sqrt{\frac{2 * Demand * ordering\ costs}{Holding\ costs}} \tag{3.23}$$

3.3.4 Preventive vs Reactive Replacements

Preventive maintenance is the replacement of a component before it fails. The main objective is to replace the component as late as possible but before it wears out completely and production losses occur. Condition based monitoring like described in Section 2.1.1 can help determine when a component is likely to fail, and thus when a replacement is beneficial. Additionally, reactive replacements are performed when a component has already failed and needs a replacement. Various methods are available in literature discussing the trade-off between preventive and reactive replacement, two of these are age-based replacement and block replacement.

Age based replacement

Age based replacement is preventive replacements of components after a set amount of operational time. It is one of the most used preventive replacement methods in maintenance operations. In most cases no effects of surrounding conditions are considered. (Jin & Yamamoto, 2017) proposes an extension to the basic age-based replacement model by adding a cumulative exposure model for considering variable operating conditions. This is achieved by proposing a new time scale to determine the optimal replacement interval based on the monitored conditions as well. Here the optimal replacement time is the minimizer of the cost rate function. Additionally, (Kurt & Maillart, 2009) formulated the deterioration of the components using a Markov process, where the replacement is carried out based on the deterioration of the components, which can be monitored using the condition-based monitoring. Both monitoring of environment and condition of components are utilized in the wind energy sector, which can be combined for determining the optimal replacement age of a component. Thus offers a great framework for the application of age-based replacement policies.

Block replacement

Block replacement policies are an alternative to age-based replacements, where time is split up periodically, with each time slot called a block. At the end of each block the replacement of components is performed, or a component is replaced if it failed before the end of the block (Hua & Kai, 2016). This can be beneficial by combining various periodic maintenance or replacement activities all together. The block is described as “the time between two consecutive preventive maintenance instances,” with a fixed cycle length (Heijden M. v., sd). To determine the expected number of failures within a block, the renewal function from renewal theory is used, where it is equal to the infinite sum of the n-fold convolution of the time to failure. The n-fold convolutions are distribution dependent. Additionally, several variations on the basic block replacement policies have been discussed in literature. (Nakagawa, 1982) (Sheu, 1992) both suggest a failed component can be replaced by a used component or undergo small repairs, while the replacement block has not been reached. Where (Sheu, 1992) adds that it can remain inactive as well if that is the most cost-efficient solution.

Block replacement can offer a great solution for the offshore wind industry, as you can replace various components at the same time while only having to use a single Jack-Up vessel. However, for the scope of this project we will not look further into the block replacement of multiple components.

3.4 Inventory Models

Most spare components inventories are managed according to a monotonic failure rate, with the memoryless property of the exponential distribution of the time between demand occurring. This indicates that once a part is replaced it is likely to fail shortly again. However, this often leads to excessive stock. In this section we will discuss various spare component inventory management systems proposed in literature for maximizing the service level and minimizing excessive inventory for a non-homogeneous failure rate.

3.4.1 Application of Inventory Management in Offshore Wind Sector

There have been some studies regarding the inventory management of Offshore wind parks. However, they have been limiting as the offshore wind industry is regarded as still being in its initial state (Tusar & Sarker, 2022). One of the methods takes a part from the playbook of aviation and applies it to the offshore wind sector (Soraghan & Lewin, 2017). However, they only take improvement measures from aviation and do not incorporate any inventory management. A different study utilizes agent-based modelling for the development of analysing the benefits of a central shared storage location. Here the behaviour of the supply chain is modelled and evaluated based on generated profit margin, and the Mean Time to Repair (MTTR) (Jäger-Roschko, Weigell, & Jahn, 2019). Here they compare the risk factors for each of the inventory management policies in place and calculate the corresponding costs. They conclude that the right spare part strategy lies in maximizing the revenues by increasing the MTTR rather than reducing the costs included.

3.4.2 Inventory Optimization Model Using Weibull Failure Function

Since inventory management models are very limiting in the offshore wind sector, we expanded our scope to general non-homogenous failure rate inventory models. Failure rates are of profound effect as input parameters for determining the optimal spare component levels. Where most models assume a monotonic failure rate derived from exponential interarrival times between failures, this fails to mimic increasing failure rates of the wear out stage of a components lifetime. Therefore, widely used inventory models, like VARI-METRIC (Sherbrooke, 1986), which are focussed on monotonic failure rates are therefore not applicable in their standard form for the problem context. (Slay, 1996) considers a non-stationary failure rate dependent on the number of hours the component has been in use and is based on the non-stationary (non-homogeneous) Poisson process. This provides a general form for non-stationary failure rate inventory models. (Moon & Lee, 2017) propose an extension to this model by incorporating the Weibull failure function for minimizing the total costs (purchase costs and shortage costs). They used the Weibull distribution as a basis for the non-homogeneous Poisson process of the non-stationary failure rate. The Weibull distribution was hypothesised for the fitting of the data, and the parameters η, and β are estimated according to one of the methods proposed by (Lei, 2008) and (Abernethy, 2001). The various estimations methods are the Maximum Likelihood Estimation, Methods of Moments, and Least Squares Method. After estimating the parameters, the time-varying failure rate for each of the components is determined. According to (Axsäter S. , 2006), "a common assumption in stochastic inventory models is that the cumulative demand can be modelled by a nondecreasing stochastic process with stationary and mutually independent increment". Therefore, we can assume the demand rate at time to be constant, despite the non-homogeneous Poisson process. According to as can be seen in Figure 9 (Slay, 1996).

Using the demand rate as mentioned above, an optimization model is created for determining the optimal stock level for each type of component at each echelon level. The optimization model is formulated as a linear integer program, where the echelon index and repair probability are not considered for the scope of this research objective. The optimization model minimized the purchase costs and shortage costs. It achieves this by limiting the purchase costs with a maximum budget M, and by saying that the total purchase costs should always be larger than the total shortage costs (Moon & Lee, 2017).

3.4.3 Inventory Model

Using the Weibull or Gamma failure function as input for a demand distribution has multiple applications other than discussed in Section 3.4.2. When the shape parameter is equal to 1, the distributions are equal to a (shifted) exponential distribution between interarrival times, where the count of arrivals over the given time interval has a homogeneous Poisson distribution (Rausand & Hoyland, 2004). Using this information, the continuous failure rate of a components wear of the bathtub curve can be approximated by assuming Poisson demand rates with time varying demand rates. These changing demand rates are determined based on the either the Weibull or Gamma demand rates, where the continuous time domain is split up into discretised intervals and thereby approximating the continuous changes, see Figure 9, where the y-axis represents the failure rate, and the x-axis represents time. In the figure you see the horizontal lines, which represent the homogeneous failure rates approximated by a Poisson distribution. Splitting the continuous failure rates into discretised intervals of homogeneous Poisson failure rates can offer the basis for most inventory models, like (VARI-) METRIC because of their requirement of a constant demand rate (Sherbrooke, 1986) (Topan, Transform Weibull Failure Rate into homogeneous Poisson failure rates, 2022).

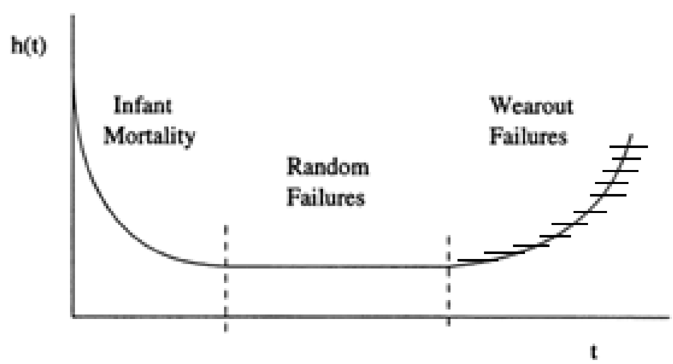

Figure 9. Assuming Constant Demand Rate

(VARI-) METRIC

As mentioned, (VARI-) METRIC is one of the more commonly used inventory models in reliability engineering. METRIC assumes Poisson demand rates allows backordering, uses a *(S-1,S)* inventory policy, and assumes failed components are either repaired or discarded. The inventory level of a multi-item problem can be determined based on the desired performance measures. The efficient frontier is an example of this, which shows the optimal service level given a certain investment in spare components. An easy way of solving this is by using a "Greedy Heuristic," according to the following steps (Heijden M. v., Multi-item, single site spare part optimization, 2020) (Axsäter S. , Inventory control, 2nd edition, 2006):

1. Initialize all stock levels to 0.
2. Calculate the marginal EBO reduction for all components, which indicates how much the EBO decreases per euro invested in one spare component.
3. Select component, which offers the "biggest bang for the buck" if budget is sufficient.

Supply Chain Inventory Control System

The policies, like mentioned in Section 3.3.1 have a different application, where the inventory level or order-up-to level is determined by the forecasted demand during lead time, and if applicable review period. Combining these periods gives the demand during which a replenishment order arrives. Additionally, it is also determined by the preferred performance measure. A policy which is often used for slow moving items, is the *(R,S)-policy*. Since slow moving items often only must be updated on a periodic basis instead of the continuously. Combining this with the varying failure rate on a monthly basis, a variable order-up-to level is required for the optimal cost-efficient solution. The order-up-to level of a (R,S)-policy can be adjusted on a periodic level (R) based on the forecasted demand during review period plus lead time, which is one of the main advantages of this policy. In Section 3.3.2 we see the calculation for the order quantity (Q), which can be modified to Demand times Review period for the (R,S)-policy (Axsäter S. , Inventory control, 2nd edition, 2006) (Silver, Pyke, & Thomas, 2017).

Supply chain inventory control systems can determine stock based on two different approaches. The first approach indicates demand during lead time (and review period) and safety stock based on customer service, such as demand satisfied from inventory (fill rate). The second approach determines stock based on demand during lead time (and review period) and the safety stock based on minimizing costs. For the problem context, we are interested in minimizing the costs between storing and lost revenue. Minimizing costs for safety stock can be described in four different ways, namely: specified fixed cost per stockout occasion (B1), specified fractional charge per unit short (B2), specified fractional charge per unit short per unit time (B3), and lastly the specified charge per customer line item short (B4) (Silver, Pyke, & Thomas, 2017). A unit short results in wind turbine downtime, which results in lost revenue. The most appropriate case for the problem context is B3, which specifies the fractional lost revenue per unit short per unit time and is described by the lost revenue calculations.

3.4.4 Inventory Model Using Erlang Failure Function

To ensure no overstocking is of place, a spare part demand by renewal process is more appropriately modelled by a varying failure rate demand interval distribution. As mentioned in Section 3.2.1, an Erlang distribution covers a continuous treatment of time for a various selection of spare part demand. (Saidane, M., M., & Ouajdi, 2011) propose a model for spare part demand following an Erlang distribution for the failure rate, with demand size following a Gamma distribution with a base-stock *(S-1,S)-policy*, which is often used in inventory management. They assume this increasing failure rate to follow an Erlang-k distribution, which is advantageous according to (Gupta, 2010), since Erlang-k distributions can follow a wide range of distributions dependant on a varying k parameter. The demand inter arrival times are independent and identically distributed according to Erlang-k distribution, meaning that rate λ gives mean inter arrival times of T=1/λ, implying that duration between failures is exponentially distributed. Where λ is determined based on calculations as shown in Section 3.2.1. Unfortunately, this can only be achieved once the demand rates of components stabilizes.

The steady-state probabilities, giving the probabilities of m number of components failed (demanded) during lead time are given based on the renewal theory (Kleinrock, 1975) (Larsen & Thorstenson, 2008) . This is slightly simplified to Formula (3.24).

$$P_m = \sum_{i=0}^{k-1} \frac{(k\lambda \mathrm{L})^{(km+i)}}{(km+i)!} e^{-k\lambda \mathrm{L}} \tag{3.24}$$

Using these steady-state probabilities, the minimum expected total costs can be calculated for S*, which represent the optimal stock policy, which gives the minimum expected total costs. S* can be determined by studying the convexity of the expected total costs expression with respect to S. However, since an infinite number of solutions are possible, a truncation is required to determine the lower bound *Sl* and upper bound *Su* of *S**, which is proposed by (Babai, 2011) such that Sl ≤ S* ≤ Su.

3.5 Validation and Accuracy

To validate whether a fitted distribution fits the data properly, or whether an inventory model suffices the necessary needs, various validation and evaluation/accuracy techniques are available. In this section we will go over various techniques to ensure the suggested model functions appropriately.

3.5.1 Goodness-of-fit Test

The goodness-of-fit test is a test that statistically hypothesises whether variability of observations is likely from a specific distribution under the null hypothesis. It provides this information by evaluating if the sample data set is a good representation and fit of the distribution for the entire population. The most common goodness-of-fit test, the Chi-Square, is commonly only applicable for discreet distribution (Glen, 2014). Luckily, the Kolmogorov-Smirnov Goodness-of-fit test provides an alternative only for continuous distributions. However, it has a serious limitation in that the distribution must be fully specified, where the parameters have to be known instead of estimated. Otherwise, it causes the critical values to be invalidated (Stephanie, 2016). To overcome this problem, a Monte Carlo simulation for determining the parameters is required. Alternatively, some tables of various distributions have been published for various distributions, like the Normal and Exponential distribution. However, due to the limitations of this research where the real parameters are unknown, and a Monte Carlo simulation is not available, such an approach becomes not applicable to the situation.

To still give an indication of the fit of the distribution, one can still perform a Chi-Square test on a continuous distribution using the method described in (Winston, 2004). It works by taking n observations, then creating k time intervals, where $k = \sqrt{n}$ and each interval having equal probability, being equal to $F(S_{i+1}) - F(S_i)$. Then, determining the number of observations per interval, and calculating the expected number of observations per interval my multiplying the number of observations with the probability per interval. After which, the test statistic can be calculated using Function (3.25).

$$Q_{k-1} = \sum_{i=1}^{k} \frac{(O_i - P_i)^2}{P_i} \tag{3.25}$$

The test statistic can then be compared with the value of the Chi-Square distribution with k-1 degrees of freedom. If the test statistic is lower, you can accept the H0-hypothesis stating that with 95% certainty that the observed data can be classified as the predetermined distribution (Winston, 2004).

3.5.2 Sensitivity Analysis

Sensitivity analysis describes the effect of changes in parameter on the optimal solution and shows how stable the given solution is. This is important since parameters in real life may often change due to various conditions or change in contracts. The sensitivity analysis offers a fast solution to these changes in parameters without having to rerun the entire model. The objective coefficient ranges provides the ranges for which the current solution remains optimal and is denoted by the allowable increase and allowable decrease of parameters (Winston, 2004). A common way to carry out a sensitivity analysis is to change the parameters one by one in increments and study the effects on the optimal outcome.

3.5.3 Scenario Analysis

To ensure the validity, accuracy and performance of any newly developed model, verification and validation is important. This can be ensured by the use of multiple scenarios as a sensitivity analysis. These scenarios are generated according to the formal scenario analysis method by (Hsia, et al., 1994) consisting of three steps. Initially, these scenarios will be created using a dummy dataset following the failure distributions as found in the study. Afterwards, the scenarios will be formalized and verified based on boundaries to ensure realistic situations and validated based on inconsistencies. To achieve this, a simulation of the problem can be created, to confirm in different scenarios the accuracy of the model. In addition, each scenario should be run for a determined number of replications, which should ensure the accuracy of the model outcome.

4. Modelling approach

In this chapter, the modelling approach is discussed, which is based on the requirements as discussed in Section 1.3.3 and the literature found in Chapter 3. The model we constructed can determine expected failure rates and reliability of the MCs. Additionally, we use this information to determine the optimal inventory policy parameters for the optimal inventory management of MCs. Firstly, the lifetime distribution, and the corresponding parameters will be determined in Section 4.1. Followed by Section 4.2, where we will determine the demand rates of MCs. Lastly, in Section 4.3 we will compute the inventory management model and corresponding inventory levels.

4.1 Lifetime Distribution & Parameters

In this Section, we will discuss the most appropriate lifetime distribution based on the requirements given by Vattenfall in Section 4.1.1. Afterwards, we will fit this distribution with the given historical failure data to determine the corresponding parameters in Section 4.1.2.

4.1.1 Requirement Lifetime Distribution

To determine the most appropriate lifetime distribution, we look back at the requirements of Vattenfall mentioned in Section 1.3.3. Requirement 2 stated the following: "Demand rates of components should be computed based on historic failure data, including non-failed components. If this is not available, standard failure rate provided by the OEM should be used instead." Both the Weibull distribution, as the Gamma/Erlang distribution can determine the demand rates based on historical data. However, we only found that Weibull can consider the non-failed components (long-life components), which should be incorporated to properly determine the corresponding parameters. Therefore, the Weibull distribution is the more appropriate lifetime distribution for the problem context.

4.1.2 Weibull Distribution

The lifetimes of the MCs are considered to be type I and IV censored as described in Section 3.1, which means that we still have non-failed components, and the components were put into place at different points in time. We adjusted the time points in such a way that all components start at time t=0. This means that the location parameter is set to 0, which means the location parameter becomes unnecessary. This concludes that a two-parameter Weibull distribution can be used. First, dummy data for 100 wind turbines will be generated consisting of failed components, and non-failed components. The dummy dataset will therefore show the failure times and the corresponding lifetime durations of all the components. This dummy data will fulfil two requirements (Jacobebbinghaus, Müller, & Orban, 2010):

1. Disclosure risk: The dummy data must be anonymous. Meaning there is no risk of disclosure, and no information shall be inferable to a person or firm.
2. Utility: The model runs similarly on the dummy data as it would on real data.

After the dummy data is created, to determine the Weibull distribution parameters, the second method mentioned in Appendix E. Multi-Censored Weibull Parameter Estimation by (Zaiontz, 2022) will be used. We will use this approach because of the multi-censored data that is available. The method works as follows:

We assume m+n components enter the system, which can be at various times, and they can be removed at various times from the system. Here we have n components failing at time $X_1, \dots, X_n$ and m components have not failed yet after $Y_1, \dots, Y_m$ units of time. For the estimation of the parameters, the approach uses Newton's method with the extension on an iterative approach, with the following two steps:

- Make an initial guess for β_o
- Iterative step: assume estimate of β_k and define new more accurate estimate β_{k+1}, do this until β_k converges. The steps look at follows:

$$\beta_{k+1} = \beta_k - \frac{h(\beta_k)}{h'(\beta_k)} \tag{4.1}$$

where

$$h(\beta_k) = \frac{1}{\beta} + \frac{u}{n} - \frac{p+w}{r}, \qquad h'^{(\beta_k)} = -\frac{1}{\beta^2} - \frac{p'+w'}{r} + (\frac{p+w}{r})^2 \tag{4.2}$$

and

$$u = \sum_{i=1}^{n} \ln (X_i) \qquad v = \sum_{i=1}^{n} X_i{}^{\beta} \qquad z = \sum_{i=1}^{m} Y_i{}^{\beta} \qquad r = z + v \tag{4.3}$$

$$w = \sum_{i=1}^{n} X_i{}^{\beta} \ln(X_i) \qquad w' = \sum_{i=1}^{n} X_i{}^{\beta} \ln(X_i)^2$$
$$p = \sum_{i=1}^{m} Y_i{}^{\beta} \ln (Y_i) \qquad p' = \sum_{i=1}^{m} Y_i{}^{\beta} \ln(Y_i)^2 \tag{4.4}$$

When β_k converges, we calculate the Eta value as follows:

$$\eta = (\frac{r}{n})^{1/\beta} \tag{4.5}$$

We carried out the above-mentioned steps for the MCs for which dummy data could be created in accordance with the requirements. Next, we used these calculated parameters for the calculation of demand/failure rates and eventually the inventory model, which we will elaborate on in the remainder of this chapter.

4.2 Demand Rates

In this section, we will elaborate on the demand rates of MCs, which is based on the calculated Weibull distribution parameters in Section 4.1. The demand rates are represented by the Weibull distribution failure rates but assumed to be Poisson distributed over a discretized timeline, as shown in Figure 9. To calculate the failure rate, we first look at the reliability of a specific component. Since we already know the component has survived a set amount of time T until now, the failure rate will be calculated using the conditional reliability function of the Weibull distribution given by Function (4.6), where the reliability is calculated after the component has survived for T months already. After the conditional reliability, we also computed the PDF of the Weibull distribution using Function (3.7). Using these two calculations, we can then calculate the conditional failure rate according to Function (3.9).

$$R(t|\mathrm{T}, \eta, \beta) = e^{-((\frac{t+T}{\eta})^{\beta} - ((\frac{T}{\eta})^{\beta}))} \tag{4.6}$$

To ensure enough stock is kept, we will also compute the failure rate of a component for the next months, since the components have between 1-4 months lead time from the OEM, which we will denote by *L*. However, when a failure occurs, we also require a Jack-Up vessel. The Jack-Up vessel is only ordered on a reactive basis (when the failure actually occurs) because the costs of ordering a Jack-Up vessel are in the in the hundreds of thousands. Because the Jack-Up vessel is only ordered on a reactive basis, this ensures that causes the component to always have a downtime at least equal to the lead time of the Jack-Up vessel. Therefore, it is not beneficial to order any spare components equal to the Jack-Up vessel lead time in advance. Thus the first available time of the Jack-Up vessel becomes the time of demand realization. To incorporate this, we therefore subtract the Jack-Up lead time, which is denoted by J, from the component lead time when deciding how far to look ahead for demand. This leaves us with the demand during component lead time minus Jack-up lead time, denoted by D_{L-J}. We do this for all individual components of the same type, and then add all of them up to get the aggregated demand rate as mentioned in Section 3.2.2.

Once the D_{L-J} is determined for a specific moment *t*, the demand is assumed to be Homogeneous Poisson distributed like in Figure 9, for the sake of simplicity in calculations. In addition, Poisson has the characteristic that the mean-to-var ratio is equal to 1. This means that the expected demand rate calculated is equal to the expected variance of the demand rate, which we will use in Section 4.3.

4.3 Inventory Model

In this section, we will elaborate on the most appropriate inventory model and policy regarding the problem context. Selecting the right inventory policy is crucial for minimizing inventory costs, while maintaining optimal production/operating levels. In addition, we will describe the computations of the parameters of the selected inventory policies.

4.3.1 Optimal Inventory Policies

According to the requirements stated in Section 1.3.3, the inventory model should be updated at least every month. Additionally, most MCs are slow moving items, based on past experiences. This indicates that often no multiple spare components are required in the same month. These requirements show that a *(R,S)-policy*, *(s,Q)-policy*, or *(S-1,S)-policy* offer an appropriate inventory management, which we discuss in Section 3.4.3. However, *(R,S)-policy* is usually used for items of lesser importance due to the less frequent ordering of components because of the review period. Additionally, when the review period is set to 0, it is equal to the *(s,Q)-policy*, which means that a (R,S)-policy can be taken out of the equation. Additionally, when the order quantity Q from the (s,Q)-policy is equal to 1, it becomes a (S-1,S)-policy. Therefore, it might be interesting to investigate whether having an order quantity bigger than one can be beneficial. This is dependent on the ordering and transportation costs of a component. Ordering multiple components at the same time will safe transportation costs since they can be transported simultaneously. However, firstly we will discuss how the different parameters of the two policies can be calculated.

4.3.2 Policy Parameter Calculation

(s,Q)-policy

For the (s,Q)-policy, the order quantity Q can be predetermined, which is required for calculating the order-level *s*. To calculate the order-level *s*, we use Function (4.7), where additional to the demand, we also require the Safety Stock (SS), which is denoted by *SS*.

$$s = D_{L-J} + SS \tag{4.7}$$

The SS is additional inventory used for minimizing the risk of downtime weighted against the holding costs. To calculate the SS the following equation will be used (Silver, Pyke, & Thomas, 2017):

$$SS = k * \sigma_{L-J} \tag{4.8}$$

where,

$L = Component\ lead\ time; in\ months$
$J = Jack - up\ vessel\ lead\ time; in\ months$
$k = Safety\ factor$
$r = Holding\ costs\ per\ component\ per\ month; in\ euros$
$B_3 = Shortage\ costs\ per\ component\ per\ month; in\ euros$
$E(D) = Expected\ demand; in\ units\ per\ month$
$\sigma_x = Standard\ deviation\ of\ expected\ demand$
$\sigma_{L-J} = Standard\ deviation\ of\ expected\ demand\ during\ lead\ time\ minus\ jack - up$
$G_u(k) = Special\ function\ of\ the\ unit\ Normal\ variable$

$$\sigma_{L-J} = \sqrt{L-J} * \sigma_x \tag{4.9}$$

$$\sigma_x = \sqrt{E(D)} \tag{4.10}$$

$$G_u(k) = \frac{Q}{\sigma_{L-J}} * (\frac{r}{B_3 + r}) \tag{4.11}$$

$$k = \frac{a_0 + a_1 z + a_2 z^2 + a_3 z^3}{b_0 + b_1 z + b_2 z^2 + b_3 z^3 + b_4 z^4} \tag{4.12}$$

where,

$$z = \sqrt{\ln (\frac{25}{G_u(k)^2})} \tag{4.13}$$

$a_0 = -5.3925569$	$b_0 = 1$
$a_1 = 5.6211054$	$b_1 = -0.72496485$
$a_2 = -3.8836830$	$b_2 = 0.507326622$
$a_2 = 1.0897299$	$b_3 = 0.0669136868$
	$b_4 = -0.00329129114$

Following the equation steps as mentioned above from Function (4.7) to Function (4.13), we end up with the order-level *s* in a specified month. The expressions do not assume a specific distribution and can therefore be used in conjunction with any other distribution, which fits the Poisson distribution that we assumed (Silver, Pyke, & Thomas, 2017).

Increasing the order quantity Q to two or more, can have financial benefits for Vattenfall. It can reduce the transportation costs, when multiple components can be transported at the same time, using the same transportation vehicle. Additionally, older components, which are taken out of production, are a lot more expensive due to requiring a new mould to be produced. Therefore, it can be more financially beneficial to order multiple components at the same time, reducing the costs per component drastically. Unfortunately, how much one can benefit from ordering multiple components at the same time is uncertain. Therefore, during the experiments we will experiment with various savings per order quantity.

(S-1,S)-policy

For the base stock policy, we will use the exact (look ahead) method. For the method we use the same notations as the method described above. The method uses an enumerative approach to find the optimal stock level according to a predefined cost function. The enumerative approach works by first Initializing the base-stock at 0 and then following the steps as mentioned below:

1. Determine the demand D_{L-J}.
2. Calculate the probability of the inventory level being equal to x according to the following Function (4.14), which can be written as Function (4.15). The expected inventory level is then calculated using Function (4.16).

$$P(I = x) = \begin{cases} P(D = S - x), & x = 1, .., S \\ P(D \geq S), & x = 0 \end{cases} \tag{4.14}$$

$$P(I = x) = \begin{cases} \dfrac{e^{-\lambda L}(\lambda L)^{S-x}}{(S - x)!}, \ x > 0 \\ 1 - \displaystyle\sum_{u=0}^{S-1} \dfrac{e^{-\lambda L}(\lambda L)^{u}}{u!}, \ x = 0 \end{cases} \tag{4.15}$$

$$E[I] = \sum_{x=0}^{S} (x)\, P(I = x) \tag{4.16}$$

3. Calculate the Expected Backorders (EBO) according to function:

$$EBO = E[D] - S + E[I] \tag{4.17}$$

4. Calculate the cost function of the given stock level based on the expected inventory and expected backorders:

$$C(S) = r * E[I] + B_3 * EBO \tag{4.18}$$

5. Increase S by one and go back to step 2, until cost function increases compared to the previous enumeration. Enumeration with lowest costs gives the optimal stock level (S) (Axsäter S. , 2006) (Shang & J-S., 2003).

4.4 Experimental Design

In this section, we will introduce the experimental design, which we will use for the validation and the performance of the model. We will accomplish this by comparing various parameter settings and policies with the use of Monte Carlo simulation.

4.4.1 Experimental Settings

To determine the optimal inventory policy for the problem context given certain parameters. The (s,Q)-, and the (S-1,S)-policy will be compared using a Monte Carlo simulation. Here we will set the order quantity Q, of the (s,Q)-policy equal to 2, since if its equal to one, it is the same as a (S-1,S)-policy. Furthermore, “A Monte Carlo simulation is a model used to predict the probability of different outcomes when the intervention of random variables is present” (Kenton, 2021). In this Monte Carlo simulation, we will increment over time simulating component failures and recreate the orders of components based on the given parameters of the policy following the calculations from Section 4.1, Section 4.2, and Section 4.3. The component failures will occur based on their reliability against a random number from a given random number seed, ensuring an even comparison for the different policies.

The simulations will be run for a timeframe of three years, to demonstrate the component orders and order-up-to levels, which goes in accordance to the requirements in Section 1.3.3, which was formulated by the Supply Chain department of Vattenfall. Since three years in not enough to include different phases of the bathtub curve, we initialize the simulation of a park when the park has been operating for a set amount of years. To ensure, we also include a different time period of the bathtub curve, we change the commission date during the experiments to monitor the impact. The structure of the Monte Carlo simulation can be found in Appendix G. Oversight Model and Monte Carlo Simulation.

Number of replications

To ensure we can draw the right conclusions form the results, we must reduce the variability, increasing the significance, and increasing the confidence level of the results. We accomplish this by running multiple replications of the same experiment with different random numbers, which will ensure the validity of the decision of the best policy. To determine the number of replications, we will use the method described by (Law, 2015), which is called “the sequential procedure”. The procedure works by increasing the numbers of replications incrementally until the confidence interval half width of the sample mean and sample variance using the Key Performance Indicator (KPI) is smaller than the relative error corrected target value. To determine the number of replications we continue running replications until this target is met. The steps and calculations of the procedure to determine the number of replications are as follows:

1. Determine the accepted value of the relative error γ and desired confidence interval α.
2. Determine the corrected value of the relative error $\gamma' = \gamma/(1+\gamma)$.
3. Run the model on predetermined settings for a large number of replications.
4. Calculate the sample mean and sample variance for each number of replications, according to the following Functions.

$$\bar{X}_n = \frac{1}{n}\sum_{j=1}^{n} X_j \tag{4.19}$$

$$S_n^2 = \frac{1}{(n-1)}\sum_{j=1}^{n} |X_j - \bar{X}_n|^2 \tag{4.20}$$

5. Calculate the confidence interval half width for each number of replications, according to the following function.

$$\delta(n,\alpha) = t_{n-1,1-\alpha/2}\sqrt{S_n^2/n} \tag{4.21}$$

6. If the confidence interval half width is smaller than the corrected value of the relative error, than that is the minimum number of replications.

KPI

The KPI of interest is the Total Relevant Costs (TRC) given by Function (4.22) by summing over all months of the simulation.

$$TRC = \sum_{t=1}^{T} I_t * r + S_t * B_3 + CC_t * (1 - QD) \tag{4.22}$$

where,

$t = Time\ in\ months; t = \{1,..,T\}$
$r = Holding\ costs\ per\ component\ per\ month; in\ euros$
$B_3 = Shortage\ costs\ per\ component\ per\ month; in\ euros$
$I_t = Inventory\ level\ at\ time\ t$

$S_t = Shortage\ at\ time\ t$
$CC_t = Costs\ of\ ordering\ all\ required\ components\ at\ time\ t$
$QD = Quantity\ discount\ for\ ordering\ larger\ quantities\ at\ once$

4.4.2 Sensitivity Analysis

We use a sensitivity analysis to determine the variables, which have a significant impact on the performance of the model. An important aspect to consider when performing a sensitivity analysis is to use the same random numbers to have control over the randomness of the experiment. This ensures that the change in the KPI is not confounded by a change in the randomness (Law, 2015). In addition, when determining the sensitivity of multiple parameters, one can perform a cross-statistical experiment showing the interactions between the parameters. However, in our case, we are not interested in the interaction between different parameters, which would costs a lot of time, but only the sensitivity of the solution when changing a single variable. Therefore, we will not perform a cross-statistical analysis. All parameters which we will vary, and their ranges are described in Table 5.

Table 5. Experiment Settings

Variable	Range
Jack-up lead time	{2,3,4} months
Component lead time	* months
Holding costs	{20%, 25%, 30%}
Order quantity**	2,3
Order quantity discount**	{0%, 5%, 10%)

*One month longer and one month shorter than lead time stated in Table 2

**Only applicable for the (s,Q)-policy

Combining all these parameters in different experiments would result in 2+2+2= 6 different experiment for the (S-1,S)-policy, and 2+2+2+2+2=10 different experiments for the (s,Q)-policy. Additionally, we run each individual experiment until the confidence interval half width is smaller than the relative error or until 50 replications have been reached. To ensure a valid comparison can be made between the experiments, we will reset the random number seed for each experiment setting, ensuring the same failures occurring over time for the different replications of each experiment.

5. Experimental Results

In this chapter we will elaborate on the validation and performance of the model, which consists of the generated results from the experimental design as discussed in Section 4.4. Firstly, the model and approach will be validated in Section 5.1. Secondly, the results of the experiments will be discussed in Section 5.2. Lastly, all the results and result findings will be concluded in Section 5.3.

5.1 Model Implementation and Validation

In this section, we will validate the model, which we proposed in Chapter 4. We will do this by performing a goodness-of-fit test, setting up the Monte Carlo simulation and determining the number of replications necessary. First, we performed the goodness-of-fit test as described in Section 3.5.1, to determine whether a Weibull distribution is indeed the prober distribution to use. Secondly, we implemented the model to prepare the calculations for the inventory management. Thirdly, we set up the Monte Carlo simulation to be able to run the model using various settings. Lastly, we ran the simulations and determined the optimal number of replications based on the KPI.

5.1.1 Goodness-of-fit test

To ensure that we are using the right distribution type, we will first perform a Goodness-of-fit test for one MC, since only for this one component enough data is available to perform this test. For this component we have 45 observations. Following the steps as mentioned in Section 3.5.1, this gives us 7 intervals ("bins"), where each interval has an equal probability with the size of $F(S_{i+1}) - F(S_i)$. Counting the observations per interval and calculating the expected number of observations per interval can be seen in Figure 10. We then calculate the Chi-Square value using an alpha of 0.05 to give us a 95% confidence interval. This results in a value of 12.59, while the test statistic, which is calculated according to Function (3.25), is 4. This means that we can say with 95% certainty that we can accept the H0-hypothesis stating that the observed values are according to a Weibull distribution. We assume that this will be true for all MC, since we cannot test this due to lack of data.

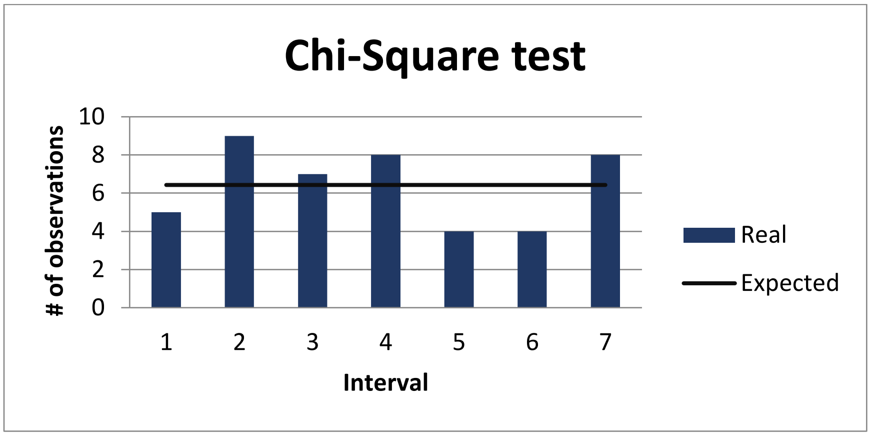

Figure 10. Chi-Square test

5.1.2 Standard Model Settings

We constructed the model described in the previous chapter in Python using the parameters found in literature, which can be seen in Table 6. These parameters are used as base setting for the model and will be changed during the sensitivity analysis using the Monte Carlo simulation, which we constructed in Excel VBA. Additionally, we implemented the static parameters like the component costs from Table 3, and the lost revenue as described in Section 2.4, based on Function (2.2) and the settings from Table 6. These settings are based on the dummy park created for the experiments. The power rating is based on the average turbines as mentioned in Section 2.4. The practical ranges of the capacity factor is between 20% and 70% (TUDelft), for which we take the low average, and experiment with this in Section 5.2.4. For the number of turbines, we took from Appendix A. Offshore Wind Parks the biggest offshore wind park Vattenfall is operating.

Table 6. Base Settings

Parameter	Setting
Jack-up lead time	3 months
Component lead time	Dependent per component
Holding costs	25%
Order Quantity	2
Order Quantity Discount	0%
Number of turbines	100
Power Rating	6.1 MW
Capacity Factor*	0.2

*varies per month, as it is a seasonal effect

Furthermore, for the Monte Carlo simulation, we determine the Weibull parameters, and the average failure rate of the three-year period based on the dummy data we created for 7 made-up components, as can be seen in Table 7. These dummy components use indications of real components such as the component price and lead times as we found in literature. Some of the dummy data ended up with very little failures, which is caused by the very high Eta value. Such high Eta values are likely not always representative. However, we will still use them to model their impact on the model results.

Table 7. Weibull Parameters and Failure Rate

MC	Beta	Eta (months)	Average Expected Failure Rate Per Month*	Price in Euros (*1000)	Lead time (months)
Component 1	3.271	467	0.037	1,761.2	1
Component 2	5.297	186	0.389	151.5	1
Component 3	3.023	191	0.403	96.8	2
Component 4	2.202	70	1.084	1,024.0	4
Component 5	1.067	1,119	0.071	272.9	4
Component 6	1.826	962	0.036	284.8	3
Component 7	4.126	143	0.425	104.7	3

*Calculated for a park consisting of 100 wind turbines

Because the later stages of the bathtub curve, with higher failure rates, are more interesting because more failures occur and thus inventory has a higher probability of being beneficial, we initialized the commission year at 2010 for all components. We did this except for component 4, since component 4 has a relative low Eta value. Therefore, we initialized the commission year for Component 4 at 2016.

5.1.3 Monte Carlo Simulation

We set up a Monte Carlo Simulation, where we iterate over the three-year period and simulate component failures using multiple replications. It consists of multiple steps. First, we take the dummy data set. From the dummy data set we determine the Weibull parameters as described in Section 4.1. Secondly, we calculate the expected demand over the future period as described in Section 4.2, and calculate the parameters of the given policy as described in Section 4.3. Once we know the policy parameters, we simulate a failure based on calculating the conditional reliability given the age of the component and drawing a random number. If the random number is higher than the conditional reliability, we assume the component to have failed in that month. Additionally based on the inventory policy parameter we determine how many components should be ordered in each month on top of the failed components of that month. The components that have broken down, and thus the wind turbines stay out of order until a spare component has arrived or is ready from inventory and the jack up vessel has been ordered jack-up lead time beforehand. If a component is required for a broken wind turbine, but the jack up vessel is not ready yet, the component will be dropped in the inventory. Table 8 gives an example of the results of the first seven months of a single experiment running on the base parameters of the *Component 4* and using the (S-1,S)-policy.

We first determined whether an individual wind turbine breaks down by looking at the conditional reliability against a randomly generated number. All of these are summed and denoted in the first row as number of breakdowns in each month. Once a breakdown has occurred, a replacement component is required. Additionally, we also order the components to increase the pipeline level to match the Order-up-to level S. This results in the order quantity being equal to 5 in the first month (2 breakdowns, and an order-up-to level of 3). The pipeline represents how many components are in inventory or on their way from the OEM. The order-up-to level is determined based on the policy calculations. The order arrival represent when an earlier placed order has arrived (order from x component lead time before). Lastly, the #WT down, represents the total number of wind turbines down in month t, which are waiting for a part.

Table 8. Monte Carlo Simulation

Year	**2022**	**2022**	**2022**	**2022**	**2022**	**2022**	**2022**
Month	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Breakdowns	2	3	4	0	4	0	0
Inventory	0	0	0	0	0	0	2
Order	5	3	3	0	4	0	0
Pipeline	3	3	2	2	2	2	2
S	3	3	2	2	2	2	2
Order arrival	0	0	0	0	5	3	3
#WT down	2	5	9	9	8	5	4

Since Vattenfall is a commercial company and they are the user of the wind turbines, they are only interested in minimizing the costs. Therefore, we will only consider the corresponding costs per experiment as KPI, which is given by Function (4.22).

5.1.4 Method Performance

As mentioned, we will test the performance of the different policies and overall method by using the Monte Carlo simulation with the basic parameters as described in Section 5.1.2. The results can be seen in Table 9.

Table 9. Method Performance

MC	No Inventory	(s,Q)		(S-1,S)	
	TRC	TRC	s	TRC	S
Component 1	**2.87**	4.24	-	**2.87**	-
Component 2	**4.98**	5.10	-	**4.98**	-
Component 3	**4.31**	4.38	-	**4.31**	-
Component 4	**110.47**	113.59	2.22	111.68	2.25
Component 5	**1.07**	1.72	1	1.11	0.11
Component 6	**0.53**	0.70	-	**0.53**	-
Component 7	**8.76**	8.82	-	**8.76**	-

*All values are in millions

Al the best performing results can be seen in bold, and we see that *No Inventory* performs the best for each one of the MCs. For some of the MCs, the *(S-1,S)-policy* performs equally as good as the *No Inventory*. However, this is only true for the components, where the Component lead time is equal or shorter than the Jack-Up lead time. This is because when the Jack-Up lead time is equal or longer than the component lead time, the expected demand D_{L-J} is equal to 0, which means that the *(S-1,S)-policy* becomes equal to the *no inventory* (only order when you have demand). For the other components like the *Component 4,* and *Component 5*, we see that using the inventory policies the costs increase. We can explain this due to the costs of purchasing a component being so high that in the three-year period these costs still have not paid off. Increasing the period to 10 years decreases this gap but remains in the benefit of not keeping inventory. For *Component 4* and *Component 5,* we see the average policy parameter over the time period and replications, which we will use later on in the sensitivity analysis as a reference. Additionally, when we look at Table 9 we see that the *(s,Q)-policy* is outperformed, when not considering any order quantity discounts. This is expected, since for a lot of the components for the most months you only require one component, but you must order in quantities of 2. This results in having too many components.

Overall, when using these standard settings, we see that not using any inventory management is more economically beneficial than using any inventory. This concludes that with these settings, the Central warehouse offers no benefit for Vattenfall.

5.2 Experimental Results

In this section, we will explore the sensitivity analysis described in Section 4.4.2, where we will vary the parameters as described in Table 5. Doing so will give us an indication on how much impact these parameters have on the final outcome, and whether it is beneficial for Vattenfall to invest or safe money for different contracts.

5.2.1 Sensitivity Analysis

We performed the sensitivity analysis for all components and all policies, where we looked at the percentual change of the TRC when increasing or decreasing the variables as stated in Table 5. This shows us the impact each of these variables have on the TRC over the time period for different components. This percentual change is based on the TRC as provided in Table 9, and is shown per policy in the Figures below. From Figure 11 we see that most negative effects are from increasing the component or Jack-Up lead time, which indicates that the solution is quite sensitive to variations in the lead time. The most benefit is gained from either reducing the component lead time or reducing the Jack-Up lead time. However, reducing the Jack-Up lead time is only beneficial for the components who’s component lead time was not already bigger than the Jack-Up lead time. This makes sense as increasing this gap would result in ordering more components for stock, and thus paying more holding costs.

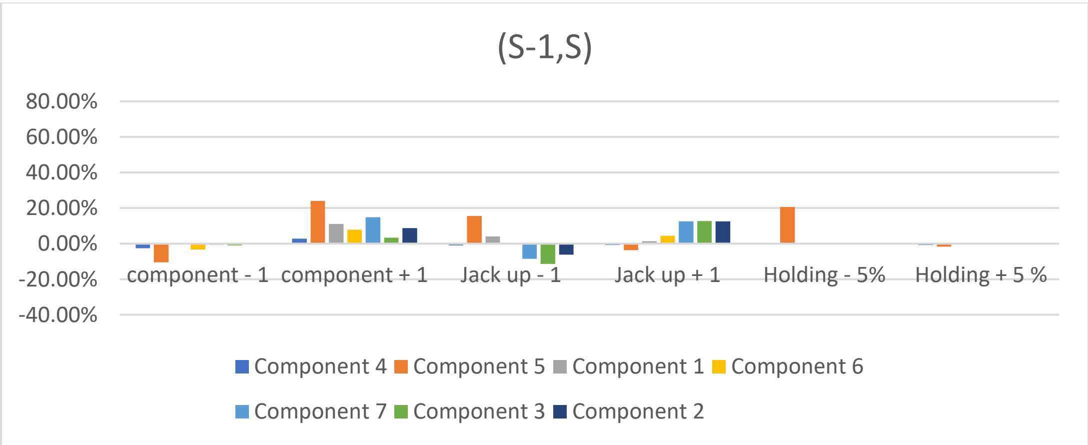

Figure 11. (S-1,S) Sensitivity Analysis

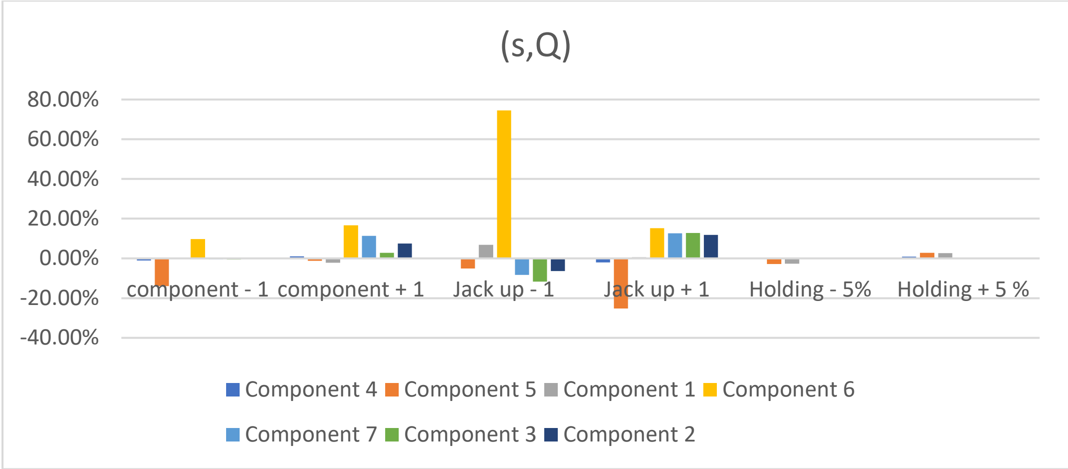

Figure 12. (s,Q) Sensitivity Analysis

From Figure 12 we can see a lot various effects on the different components. The main points that jump out are decreasing the Jack-Up lead time for *component 6* has a dramatically bad effect on the TRC. This can be explained by the fact that the component lead time was equal to Jack-Up lead time, which would be offset by decreasing the Jack-Up lead time. This would lead to ordering extra components and keeping them on stock. However, because the Eta is so high and thus so little failures are expected, the extra costs of keeping inventory has major effects on the TRC.

In addition, by increasing the Jack-Up lead time *component 5* actually benefits a lot. This is cause because again this takes away the difference between component lead time and Jack-Up lead time, which takes away the need for inventory or unnecessary downtime, which explains the benefit in TRC.

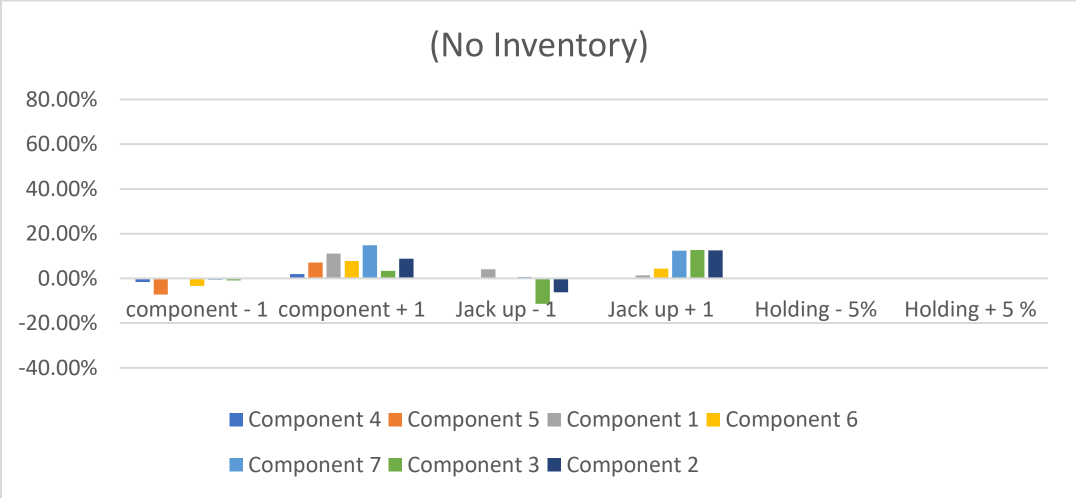

Figure 13. No Inventory Sensitivity Analysis

Lastly, Figure 13 shows results, which are expected, since you are not incorporating any inventory. Therefore, decreasing the component lead time or Jack-Up lead time generally decreases the TRC and increasing the component or Jack-Up lead time increases the TRC. As expected varying the holding costs is not effecting the TRC since no inventory is being held.

All the intermediate results per component per policy can be found in Appendix *F. Sensitivity Analysis*. When comparing all the results and impacts, we see that only for *component 7* the *(S-1,S)-policy* to outperform *no inventory* by 600.000 when decreasing the Jack-Úp lead time from 3 months to 2 months. This would result in an order-up-to level of 2 for most months. This benefit can be used to incorporate the *(S-1,S)-policy* and invest the benefit for a 1 month shorter Jack-Up lead time for all *component 7* orders. For all other instances, the *No Inventory* stayed the optimal policy. Additionally, we see that varying the holding costs hardly has any effect on the TRC.

5.2.2 Batching

In this section we will look at the impact of batching on the performance of the *(s,Q)-policy*, and the impact of potential discounts when ordering larger batches. As discussed in 4.3.2, batching of MCs can be beneficial once certain components are no longer being produced or when a mould is no longer available and is required to be build. To see the impact of this, we set up a similar sensitivity analysis, which includes increasing the batch size to 3 or 4, and a component discount of 0%, 5%, or 10%. Figure 14 shows the average results in this specific order.

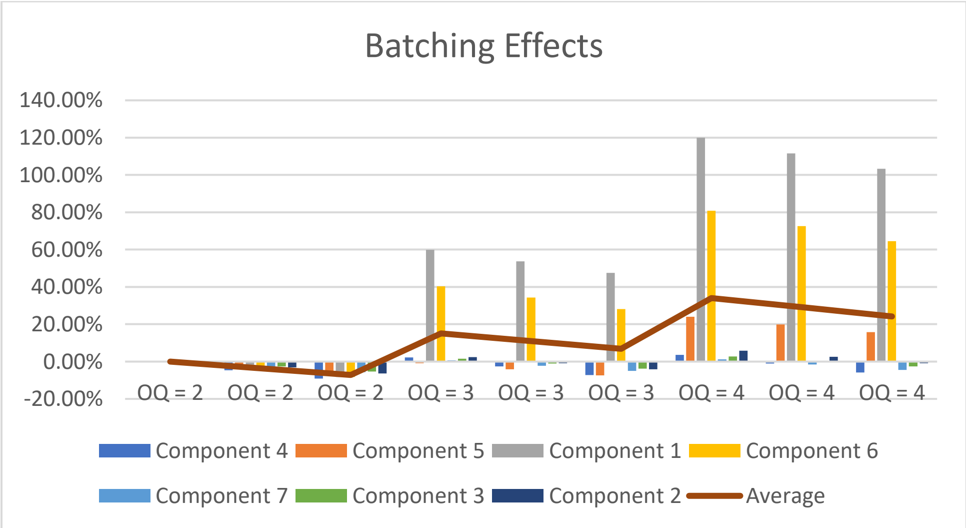

Figure 14. Batching Effects

In Figure 14 we can see that including a quantity discount has a positive effect for all components, when the order quantity stays equal to 2. When the maximum order discount of 10% is applied to the order quantity of 2, we see that *Component 4, Component 7, Component 3,* and *Component 2* suddenly outperform the other policies resulting in lower TRC.

Additionally, we see that increasing the order quantity has very strong negative effects on a few components, *Component 1, Component 6,* and a little bit the *Component 5.* We suspect this is caused by the high Eta value of these components, which makes failures quite uncommon, and thus having a high order quantity will result in having a lot of spare components in stock. All with all, we see that increasing the order quantity has worse effects on all components but by incorporating an order quantity discount, might lead to the *(s,Q)-policy* with an order quantity of two being the best solution for the problem.

5.2.3 Impact of Aging and New Wind Parks on Inventory Policies

An interesting aspect, which came forward in the Monte Carlo Simulation, is that aging of components can have quite an impact on the parameters such as the order-up-to-level of the inventory policies. Since only *Component 4* and *Component 5* have a component lead time longer than the jack-Up lead time and thus are the only components, which are interesting to look at. In a three-year period, the order-up-to-level of these components can change multiple times as a result of the components aging or failures occurring. When in a period of a few months no failures occur, the probability of a failure occurring in the next month's increases, resulting in the order-up-to level to increase. When a lot of failures occur in a short timeframe, we see that the total number of expected failures decreases and so does the order-up-to level. Another interesting aspect to consider is the number of wind turbines, which use a specific component. In general, when more turbines are using the same component, we can say that the expected number of failures for that specific component is higher and thus keeping one in storage can be more beneficial. To see this effect, we tested it with the Gearbox by constructing a new wind park of 60 wind turbines, which are the same type. This creates a total population of 160 wind turbines, which is the near the same size of the biggest wind park in operation currently. Figure 15 shows the average order-up-to-level and expected failure rate over time of the normal park vs the park including a new park.

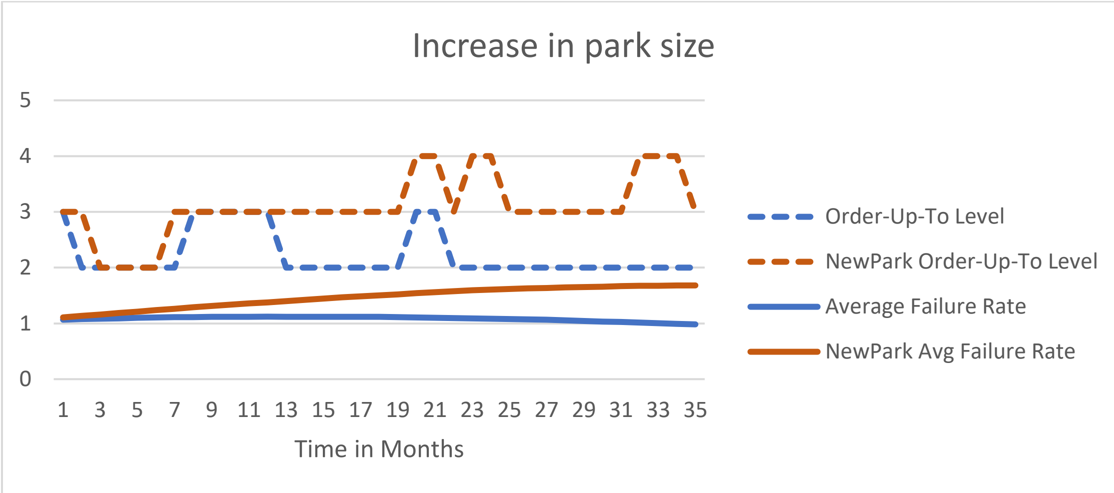

Figure 15. Effects of Aging and New Parks on Component 4

Using this knowledge, we can say that when a new wind park is built, the likelihood of expecting a failure is relatively low in the beginning, with the opposite being true for older parks. All of these above-mentioned effects show the importance of updating the policy parameters on a monthly basis to ensure you always order the optimum number of components in a given month. However, *no inventory* still outperforms the *(S-1,S)-policy* within the three-year period.

Additionally, to demonstrate the varying failure rate over time, we looked at the failure rate of each component over a 25 year period, which is the standard lifetime of a wind park, while using the Eta's as stated in Table 7. You can see this in Figure 16. Here we see that apart from the *Component 4*, *Component 7*, *Component 3,* and the *Component 2* the failure rate hardly increases over a 25-year period. This is caused due to their Eta's begin relatively small compared to the other components. The Eta's are within the 25-year period, meaning that a larger portion of these components will have failed. This is representative in the industry as some components are not resistant to all the environmental factor, and thus most of them will not last the 25-year period (Froese, 2018). For these components, the expected number of failures increases over time more drastically. However, for an older park with higher expected failure rates for these components, will still not overcome the high costs of ordering extra components by itself. It does however, make using the *(S-1,S)-policy* more beneficial than before, which in combination with a higher capacity factor and thus higher lost revenue, which we experiment with in the next Section, can result in the *(S-1,S)-policy* to outperform *no inventory*.

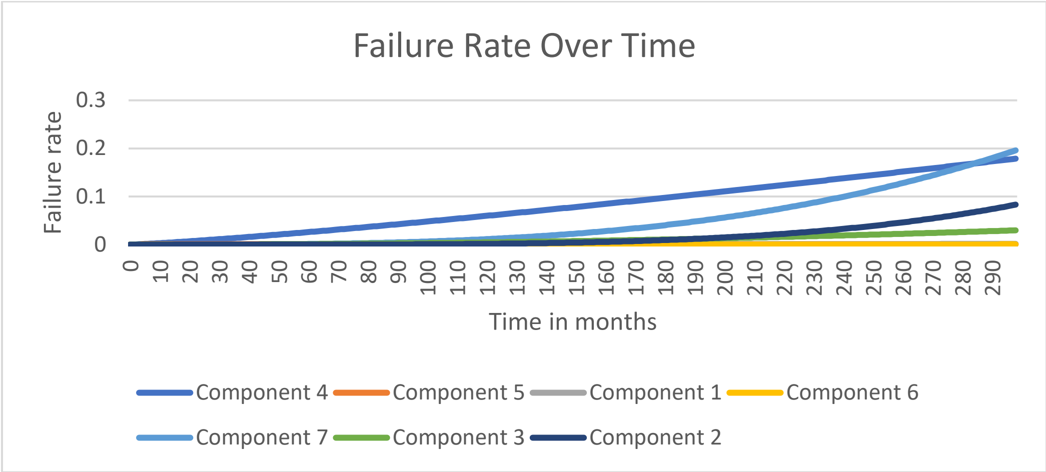

Figure 16. Failure Rate Over Time

5.2.4 Downtime Costs

From the results we saw that the high purchase costs of a component causes the benefit of keeping stock to become negligible .To ensure that these high component costs are overcome, a bigger benefit of using inventory (and thus reducing overall downtime) is required. One can achieve this by having higher downtime costs, which translates to higher power rated or capacity factor wind turbines. To see how much the downtime costs would have to be, we ran some experiments by changing he capacity factor from 0.2 to 0.165, 0.25, 0.33, and 0.4 but keeping the power rating the same at 6.1 MW. We ran these experiments only for *Component 4* and *Component 5*, since these are the only components with a component lead time longer than the Jack-Up lead time. Table 10 shows the results for *Component 4*, once the downtime costs are at least 80,000 euro's per month, which translates to a capacity factor of 0.33, that over a 10 year period the base stock policy becomes more beneficial for *Component 4* by a slight margin and thus it will be beneficial to keep stock according to the policy. Table 11 shows the for *Component 5* the base stock policy only becomes beneficial after the ten-year period once the lost revenue costs reaches 160,000 on average per month. This corresponds to capacity factor of 0.66, which is twice as high as for *Component 4.* This difference can be explained by the *Eta* value of both components. The *Eta* value of *Component 4* is way lower than the *Eta* value of *Component 5*, which means that *Component 4* has a lot more failures per month, which can be seen by the higher failure rate in Table 7. More failure means that they will have more inventory and thus benefit more from higher lost revenue in regards to less failures.

The average capacity factor for offshore wind turbines in the period from 2020/2021 is 0.381 (SPARTA, 2021). This means that on average for most offshore wind turbines it will be beneficial to store spare parts for components similar to *Component 4* over a 10-year period according to the *(S-1,S)-policy* but not for components similar to *Component 5*.

Table 10. TRC with Varying Downtime Costs Experiment Component 4

Capacity Factor		0.165	0.25	0.33	0.4
Lost Revenue per Month		**40,000**	**60,000**	**80,000**	**100,000**
No Inventory	**3 years**	99.35	106.01	112.67	119.33
	10 years	650.61	693.75	736.89	780.03
(S-1S)	**3 years**	102.44	108.62	114.80	120.98
	10 years	651.64	694.24	736.84	779.44
Difference	**3 years**	**3.09**	**2.61**	**2.13**	**1.65**
	10 years	**1.03**	**0.49**	**-0.04**	**-0.58**

**TRC are in millions*

Table 11. TRC with Varying Downtime Costs Experiment Component 5

Capacity rating		0.165	0.25	0.33	0.4	0.5	0.58	0.66
Lost Revenue per month		**40,000**	**60,000**	**80,000**	**100,000**	**120,000**	**140,000**	**160,000**
NO POLICY	**3 years**	0.87	1.03	1.19	1.35	1.51	1.67	1.83
	10 years	3.78	4.44	5.10	5.76	6.42	7.08	7.74
(S-1S)	**3 years**	1.24	1.38	1.52	1.66	1.80	1.94	2.08
	10 years	3.98	4.60	5.22	5.84	6.46	7.08	7.70
Difference	**3 years**	**0.38**	**0.36**	**0.34**	**0.32**	**0.30**	**0.28**	**0.26**
	10 years	**0.20**	**0.16**	**0.12**	**0.08**	**0.04**	**0.00**	**-0.04**

**TRC are in millions*

Table 10 shows us that the higher the capacity factor, the higher the lost revenue per month, the more beneficial it will be to keep inventory against the lost revenue. In the future when the technology improves further and further, and bigger parts of higher power rated wind turbines are produced, the benefit of keeping a component in inventory according to the *(S-1,S)-policy* becomes more and more beneficial.

5.2.5 Decoupling of the Jack-Up Vessel

Until now we have used the assumption that the Jack-Up vessel is only ordered reactively. This means that when a failure occurs, the component will at least have a downtime equal to the lead time of the Jack-Up vessel regardless of inventory levels. However, for future instances the failure predictions will become more and more accurate resulting in a high certainty of expecting a failure. This means that it might be possible to order the Jack-Up vessel proactively just like the spare components, which would decouple the two lead times. To simulate this, we assume that we always have the Jack-Up vessel exactly when we need it, and thus in the simulation model set the Jack-Up lead time equal to zero. From Table 12 we can see the impact this has on the TRC compared to the basic situation. The full results can be seen in Appendix F. Sensitivity Analysis Table 17. We see that perfectly predicting the demand and ordering the Jack-Up vessel prematurely has major economically benefits for Vattenfall. For *Component 3, Component 4,* and *Component 7* it even becomes more beneficial to utilize the *(S-1,S)-policy* in comparison to *no inventory*.

Table 12. Reactive Jack-Up vessel

	No Policy No Jack-Up	(S-1S) No Jack-Up
Component 1	47.30%	47.30%
Component 2	-61.34%	-58.48%
Component 3	-29.26%	-45.35%
Component 4	-0.56%	-1.69%
Component 5	-2.14%	0.00%
Component 6	-18.53%	-18.53%
Component 7	-24.61%	-46.54%

From Table 12 we see that only for *Component 1* it doesn't have beneficial results. When further investigating this, we see that this is caused due to the very high *Eta* and thus only around 1-2 failures occurring in the three-year time frame. In some replications one of these failures happens in the very last month of the simulation, where in the basic situation we would wait with ordering. However, when there is no Jack-Up lead time to take into account we immediately order, resulting in extra component costs, which make up this difference. Otherwise, it would have been beneficial due to the lower lost revenue. This shows how much Vattenfall is able to gain by accurately predicting the demand and prematurely ordering the Jack-Up vessel. However, more research has to be done regarding the situation where the demand is not accurately predicted and the Jack-Up vessel is ordered without a job.

5.3 Conclusion

In this chapter, we have discussed the results resulting from the modelling approach and model as discussed in Chapter 4. We have achieved this in four parts, first we validated the distribution by using a Chi-Square test in Section 5.1.1. Secondly, we created the Monte Carlo simulation to run the model with standard settings to compare the different policies compared to using no policies. Lastly, we ran a sensitivity analysis to see the impact of the different variables on the result, which shows the magnitude of the variables impact on the TRC.

From Section 5.1.1, we can conclude that the proposed Weibull distribution is a good approximation for the failures of MCs. Knowing this, we estimated the parameters, calculated the failure rates, and determined the policy parameters. To achieve this, we assumed the expected failure rates to be Poisson distributed, which provided us with an easy way of determining the mean and variance of the expected failures. Using all the above-mentioned information and using the base settings as found in literature, described in Table 6, we set up the Monte Carlo simulation as can be seen in Section 5.1.4. Here we can conclude that for all the MCs, using *No Inventory* is more economically beneficial when looking at the TRC compared to using an inventory policy.

From Section 5.2 sensitivity analysis, we see that different changes have different effects on the various MCs. One would expect that decreasing the component lead time or Jack-Up lead, would have positive effects on all MCs. However, MCs mainly only benefit from it when it makes the component lead time equal to the Jack-Up lead time. This is because it results in the least amount of downtime and no inventory required. Additionally, reducing the holding costs will not result in an inventory policy outperforming *No Inventory*, due to having to order more components that even in a three-year period the component costs are higher than the money saved by downtime.

Lastly, we discussed the impact of batching, aging, increased lost revenue, and constructing new wind parks using wind turbines types that are already in use. Here we saw that batching only brings benefits when it goes combined with batching discount of at least 10%. This is likely way too much for such big and expensive parts that it becomes unrealistic for the *(s,Q)-policy* to be beneficial. From the aging we see that updating inventory policy parameters is very important, since they are likely to change over time. However, we see no increased benefit of an inventory policy once the components reach an older age and the probability of failure increases. Additionally, increasing the capacity factor, which directly increases the lost revenue, has major effects on the benefit of utilizing a inventory policy. The average capacity factor of 0.381 is above the threshold of 0.33 for when the *(S-1,S)-policy* becomes more beneficial than the *no inventory* over a 10-year time period. This means that on average over a prolonged period of time the keeping of inventory can actually be beneficial for components, which have a component lead time longer than the Jack-Up lead time. Finally, constructing new wind parks can benefit from using the same turbine types, but the exact benefit should be further investigated.

6. Conclusion and Discussion

Throughout this report, we answered the research questions as mentioned in Section 1.4.2 to help achieve the research objective. The research objective: *"Develop and validate an expected lifetime distribution, to predict expected failure rates of MCs given their current state and integrate it into a spare part optimization model to determine the optimal spare part policy, thereby achieving maximum cost efficiency."* The research questions are answered in the chapters following the research question. In Chapter 2, we provide an overview of the current situation in the offshore wind sector, the logistic complexity of MC replacements, and the current practises at Vattenfall. In Chapter 3, we discuss the found literature regarding lifetime distributions, failure rates, inventory models, and validation of the model. Using this knowledge, we set up our lifetime distribution calculations and inventory model in Chapter 4. The validation of this model by means of a Monte Carlo simulation is performed in Chapter 5, which also describes the results. Lastly, in Chapter 6 we will conclude the findings, discuss the implications, and give recommendation.

6.1 Conclusion

6.1.1 Practical Contribution

During this study, we developed a model for Vattenfall's central warehouse related to the MCs storing of offshore wind turbines. The model makes use of inventory policies based on the logistical complexities. The inventory policy is dependent on the expected failures of MCs during lead time, minus Jack-Up lead time. Where we assume the Jack-Up lead time to be equal to three months and the component lead time dependent on the component, as can be seen in Table 2. We subtract the Jack-Up lead time, because it does not make sense to keep inventory when the Jack-Up lead time is equal or bigger than the component lead time, since you only order the Jack-Up vessel once a component has failed. Therefore, even if you have a component in inventory, you would still have to wait the lead time of the Jack-Up vessel to perform the replacement, which is time in which you could order the component.

To determine the expected failures, we first determined the most appropriate lifetime distribution to be a Weibull distribution and evaluated the distribution using a goodness-of-fit test, with a test statistic of 4 being well below the Chi-Square value of 12.59, resulting in a good fit. Using this distribution we estimated the Weibull distribution parameters, which we used to calculate the conditional reliability and PDF to determine the expected failure rate. Using this expected failure rate as input for the inventory management model.

To evaluate which inventory policy performs best for the proposed settings and component, a Monte Carlo simulation is constructed, which will show the results for the coming three years given the knowledge of today. This Monte Carlo simulation is therefore used for the validation of the inventory model and used to evaluate the impact of changing the parameters of the model. From the results we see that while using the standard settings, using *no inventory* model is actually the best. When performing the sensitivity analysis, we see that only for the *Component 7* when we decrease the Jack-Up lead time from 3 to 2 the *(S-1,S)-policy* outperforms *No Inventory* by 600,000 TRC over the three-year period. This means that for this instance one can invest this 600,000 into shortening the Jack-Up lead time by one month only when requiring a *Component 7* and applying the *(S-1,S)-policy*, which would result in a better outcome.

Lastly, we looked at different aspect such as batching and batching discount, the impact of aging, impact of increased lost revenue, and the impact of constructing a new wind park using the same wind turbines as already in use. Firstly, when looking at batching, we see that using an order quantity of 2 performs overall better than 3 or 4, where when using an order quantity discount of at least 10% results in the *(s,Q)-policy* outperforming for *Component 4, Component 7, Component 2,* and *Component 3* suddenly outperform the *No Inventory* and the *(S-1,S)-policy* resulting in lower TRC. Secondly, the impact of aging and using the same wind turbines when constructing a new wind park both have impact on the parameters of the inventory policies, but it will not cause the policies to outperform not having any stock. Thirdly, the increase in lost revenue have big impacts on the benefit of keeping inventory. When the capacity factor reaches 0.33 and the lost revenue equals 80,000 per month it becomes more beneficial to incorporate the *(S-1,S)-policy* over a 10-year period. Lastly, we see no benefit in the constructing of a new wind park using the same component types as already in use by Vattenfall.

All with all, we can say from our results that it is economically beneficial for Vattenfall to not hold any stock in the central warehouse with the current setting unless the lost revenue of the wind turbines in question reaches a certain threshold. This will result in not requiring the central warehouse for MCs storing. It is unfortunate that we discover this result after the central warehouse is already being built.

6.1.2. Scientific Contribution

With this research, we contribute to the field of inventory management by connecting non-homogenous lifetime distributions to inventory policies, which includes logistical complications. To our knowledge some previous research has been performed regarding non-homogenous lifetime distributions for inventory management but lacked the logistical complexity as presented during our research. Incorporating this logistical complexity is the main contribution from our research, which includes the incorporation of the Jack-Up vessel, which makes keeping inventory a lot harder to be beneficial. Additionally, the Monte Carlo simulation helps provide insights into for what settings a specific inventory policy with the corresponding parameters might be beneficial compared to not utilizing any policy and not keeping any stock.

Our scientific contribution will provide Vattenfall with a lot of insights and gives them the opportunity to further play with different settings to see how they can further optimize the benefits regarding the central warehouse in relation to the TRC.

6.1.3. Research Limitations

During our research we came across various limitations, limiting certain aspects of the research. Certain aspect which we will discuss are the limitations regarding the research, method and approach, and results.

Firstly, the data regarding the failures, costs and lead times regarding the MCs are all very limited. In addition to the data being limited, the data that was available is not public. Therefore, we had to use data found in literature or data based on indications of the real data and use it in such a way that it is not retraceable to any of the OEMs. This made the assumptions of the research limiting in regard of the modelling results.

Additionally, because of this limitation in data, we were somewhat limited in our methodology since we were not able to utilize cross-validation due to not having enough data to cross-validate

with. Furthermore, we were not able to use Machine learning for the calculations of expected failures as this also requires a larger data amount to train the model.
Lastly, all the calculations are based on the biased that the lead times are fixed, which in practise can be unrealistic due to the fluctuations in production for the component lead time and changing weather conditions for the Jack-Up lead time. In the sensitivity analysis we saw the effects of changing these lead times by one month on the TRC.

6.1.4. Future Research and Recommendations

This research, just like many other research did not provide a complete overview of all the possible answers to all the scenarios. Thus, this research can be used as an initial starting point for answering more complex problems in the future. Therefore, we recommend Vattenfall to build upon this research by looking into a standardized way of utilizing the installed based information, which we talk about in Appendix C. Condition Based Monitoring, for the inventory model. This will increase the precision of the expected failures and create a more accurate model.

Secondly, since most of the experiments show that it is more economically beneficial for Vattenfall to not keep any inventory. It might be interesting to investigate whether this can be outsourced to the OEM instead. This would mean that they set up a Service Level Agreement (SLA) with the OEM, which states that the OEM should keep spare components for them, which would drastically decrease the lead time.

Additionally, more research can be done regarding the precise effects of constructing new wind parks, which use the same wind turbine types to increase the population, which can benefit from the same spare component. We recommend Vattenfall to further investigate these effects with their System Design Hub team, which looks into new wind parks with the use of simulations.

Lastly, we advise Vattenfall to keep updating the failure dates of the MCs to get a more accurate estimation of the Weibull distribution parameters. These parameters are of great importance as these offer the basis of all calculations for the model but also for the Monte Carlo simulation. Therefore, it might be interesting for future research to request and validate these parameters from the OEMs and compare the results.

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Appendix

Appendix A. Offshore Wind Parks

Country	Location	Turbines	Commission year	Manufacturer
DK	Offshore	24	2021	-
DK	Offshore	48	2021	-
DK	Offshore	21	2019	-
DK	Offshore	20	2019	-
DK	Offshore	79	2002	Vestas
DK	Offshore	49	2018	MHI
GE	Offshore	0	2009	Multibrid & REPower
GE	Offshore	80	2014	Siemens
GE	Offshore	72	2017	Siemens
NL	Offshore	0	2022	-
NL	Offshore	0	2022	-
NL	Offshore	0	2006	-
SE	Offshore	0	-	-
SE	Offshore	0	-	-
SE	Offshore	48	2007	Siemens
UK	Offshore	11	2018	MHI
UK	Offshore	15	2015	Vestas
UK	Offshore	30	2005	Vestas
UK	Offshore	30	2011	REPower
UK	Offshore	100	2010	Vestas

Appendix B. Main Components

1. *The blades*

The blades are designed to convert wind into rotational energy at optimal output. The blades are made of fibre glass reinforced epoxy and carbon fibre for achieving high strength but maintaining flexibility. Most offshore wind turbines use blades with a length of 80-100 meters, which is almost the size of a football field. Because of their aerodynamic shape, they catch wind, which decreases pressure on one side of the blade, and the difference in air pressure creates lift. The lift causes the rotor to spin (Wind Energy Technologies Office, sd).

Because of the harsh marine environment, the blade's ability to generate lift is negatively impacted due to the extensive wear. Luckily, the necessity to repair only shows when the efficiency becomes drastically low, and it becomes more cost efficient to replace the blades. When this point is reached, we see the blades as having failed. This process of decreasing efficiency can be monitored and thus be used in failure predictions. However, the monitoring of components will not be part the research scope.

2. *Main bearing*

The main bearing supports the main axis in the transmit of rotational energy in the form of torque from the rotor to the gearbox by ensuring the main axis can rotate with the least amount of friction. Since the rotor generates high loads, the main bearing is subject to a broad range of dynamic loads, especially high axial loads. Therefore, the main bearing requires high resilience against these high loads to ensure high reliability. Unfortunately, the main bearings are susceptible to failure due to multiple aspects like environmental conditions, operating, and maintenance practices. These aspects can cause the lubrication of the bearing to degrade, or to cause vibrations within the bearing, which both cause the bearing to wear out before it should. The rest of the failures are just caused by the standard wear and tear of the bearing.

The literature is divided around the failure rate of main bearings and whether it should be included in analysis or not, (Edward, et al., 2020) states "historically the main bearing has not been reported as resulting in high rates of failure. For example, prominent and oftencited reliability studies either neglect the main bearing entirely or appear to lump it in with other components." While (Michele, 2020) shows that supplier Schaeffler obtained data of approximately 10,000 wind turbines, where a significant percentage of wind turbine failures occurred in bearings. Most damage was found internally on the axially loaded row primarily on the surface, also known as surface distress. This indicates that the bearings are of higher threat to the reliability of the wind turbine than other components. Additionally, they require a complex operation to replace them, which takes a longer period of time than other components.

3. *Main shaft*

The *main shaft* is a tube, which is responsible together with the main bearing for conveying the rotational energy from the rotor to the gearbox. The main shaft should be able to withstand high axial and radial loads and be operational in extreme conditions, which can continuously change and be the main factor in failures. Just like some other components, the *main shaft* is monitored using condition-based monitoring to continuously check the condition of the component based on all the axial and radial loads. Additionally, the main shaft is susceptible to debris of other component failures. To protect the main shaft from these environmental influences, and debris caused by other component failures, the main shaft can be covered with a seal. The seal is vital for ensuring the longevity of the main shaft by keeping everything out, and lubricant in, no matter the environmental conditions.

4. *Gearbox*

The *gearbox* is used to increase the rotational speed of the rotor hub, from 10-18 revolutions per minute (RPM), to at least the minimum RPM of 1500 RPM, which is required for a generator to produce the service rated power. This minimum RPM is based on the frequency of the connected network, which in Europe is 50 Hertz (Hz). A common *gearbox* used in wind turbines consists of two stages. Firstly, the multi- stage planetary (or epicyclic) system, see Figure 17, as this is capable of handling high incoming torque of the main shaft. It consists of three main components, the sun gear (in the middle), the planet gears (three gears around the sun gear), and the ring gear (surrounding all gears). A carrier is used to connect the planet gears around the sun gear, to ensure they roll without slip. The rotor hub transfers the rotational energy onto the main shaft, which transfers it to the ring gear, and thereby the planet gears, which transfer their rotation into the sun gear. This transfer of rotations increases the rotational speed and reduced the high torque loads. The second stage consist of helical gears, where the big gears get transferred onto a smaller gear, which is part of the high-speed shaft, to increase rotational speed and reduce torque (Musial, Butterfield, & McNiff, 2007).

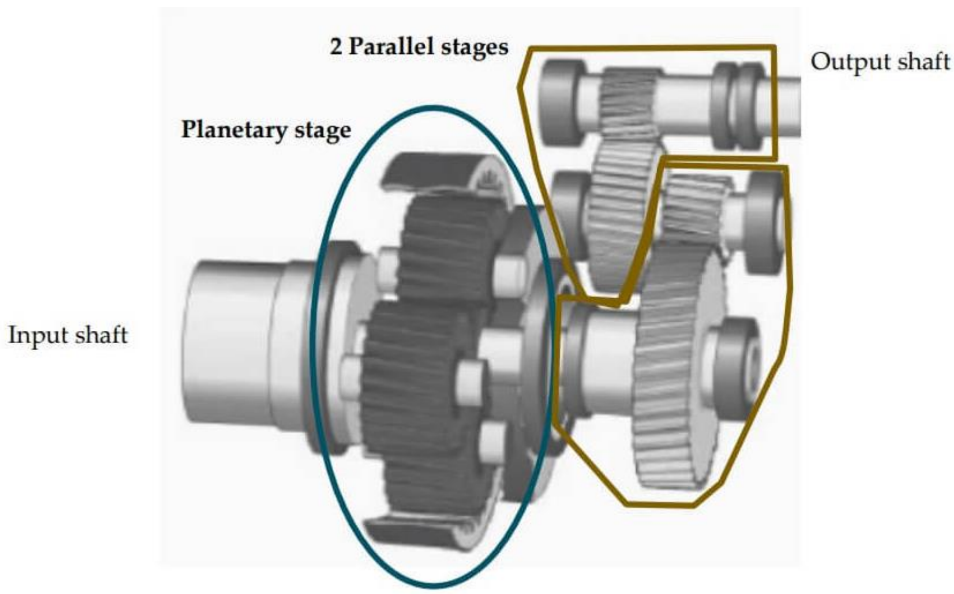


Figure 17. Gearbox (Dvorak, 2017)

The gearbox is prone to failure caused by numerous reasons, this includes the size, poor understanding of turbine loads, debris, or axial cracking. Especially axial cracking has become one of the leading causes of gearbox failure, it occurs on the inner ring during installation due to the excessive hoop stresses. These hoop stresses are created by heating up the ring during assembly and place it onto the shaft. After the ring cools of, it shrinks creating a lot of stress. This causes the *gearbox* to break down prematurely. Additionally, the *gearbox* is prone to failure caused by debris or small cracks from excessive loads. These can be picked up using the condition-based technologies described in Section 0.

5. *Generator*

The captured kinetic energy caught by the blades and enhanced by the gearbox is converted to electrical energy by the *generator*. We distinguish two types of *generators*, the *induction generator*, and the *synchronous generator*. The *induction generator*, also called the *three-phase asynchronous generator* is most used by wind turbines and is a type of alternating current electrical generator to produce electric power. It generates power when the high-speed shaft spins faster than the synchronous speed, at 1500 RPM. Induction generators are ideal for wind turbines due to their ability to generate power at varying rotor speeds (Wildi, 2000).

The *Synchronous generators* are used for variable speed gearless wind turbines, where the rotor is directly connected to the generator without the use of a gearbox. It is called a *synchronous generator* because the generated waveform voltage is synchronized with the rotation of the rotor and thus the generator, this is also called *Direct-Drive*. This is possible by including multiple poles to control the speed of the generator. This results in a wider and larger diameter generator, which is more complex to manufacture, but less air pollutant. Additionally, the failure possibility of the gearbox is eliminated. This makes the synchronous generator a competitive solution to the more standardized induction generator despite having higher start-up costs (Goudarzi & Zhu, 2013).

Generator reliability in wind turbines typically behave negatively when compared to other industries, and it is believed this is caused by the bothersome nature of the loading and unloading of the generator due to varying wind speeds, and the environment in which the generator operates (Whittle, 2013). This causes the generator in wind turbines to fail more often, and this will be represented in the historical data analysis.

6. *Transformer*

The transformer is the link between the wind turbines generator and the distribution grid. The transformer receives the low output voltage from the generator and increases it to a higher distribution voltage, thereby reducing the required current, which decreases the possible power loss that happens when transmitting the current over great distances. (Jose & Chacko, 2014) State that the transformer is considered the sensitive and weak component of a wind turbine due to the widespread failures caused by the variable wind speeds and their varying loads. Since conventional transformers are not designed as wind turbine transformers, special transformers have to be produced for wind turbines.

7. *Switchgear*

A switchgear is used in large electrical power systems used to control, protect, and isolate electrical equipment when necessary. The switchgear in wind turbines consists of two main components. The first switching device is associated with the wind turbines transformer, and the second switching device is part of the control system containing control panels, etc. Switchgear's main purpose is protecting against interruption of overload and short-circuit failures, and thereby enhancing the availability of a wind turbine. Even though it protects against failures within the wind turbine, it is prone to failure itself due to lack of operating knowledge, faulty modifications, or inappropriate resets (RenewableUK, 2015). These failure types are hard to discover and can therefore only be expected based on historical failure data.

Appendix C. Condition Based Monitoring

To monitor the condition of a MC is difficult tasks. This is caused by the fact that most of the MCs are inside the *nacelle*, where you are unable to perform field observation on the MCs. As commonly known, the monitoring of components is important for the understanding of the operational behaviour and additionally the structural safety of the offshore wind turbines. To overcome this problem, Vattenfall is using vibration monitoring as one of their monitoring systems, since this is a particularly helpful solution for pin-pointing problems in deterministic machines. A wind turbine can be seen as a deterministic machine, since if the rotational speed of the rotor or generator is known, then the rotational speed of all other shafts, bearings, and rollers can be determined based on the geometric data of these components. The rotational speed of components causes vibrations, and since the rotational speed of all components is known, the expected vibration frequency is known. The basic vibration off the offshore wind turbine is characterized under five different conditions: standstill, normal, start-up, shutdown, and extreme weather conditions. These different operational conditions are analysed to establish a relationship with the environmental factors. Vattenfall uses different vibration failure detection analysis techniques, one of which is an envelope analysis, which is used for bearing failure detection. An envelope analysis is a vibration analysis technique for studying the amplitude modulation of vibrations signals. It works by filtering out the unwanted vibration signals until a clear failure signal can be detected, enabling easier diagnosis of failures (Gaudel, 2001). Figure 18 shows an example of a vibration monitoring graph showing a developing failure over time, as can be seen by the increased vibration intensity. The x-axis represents time in a given time block, the y-axis represents vibration intensity, and the z-axis represents the time blocks over time. The advantage of vibration monitoring is that only a few sensors are required to monitor multiple components.

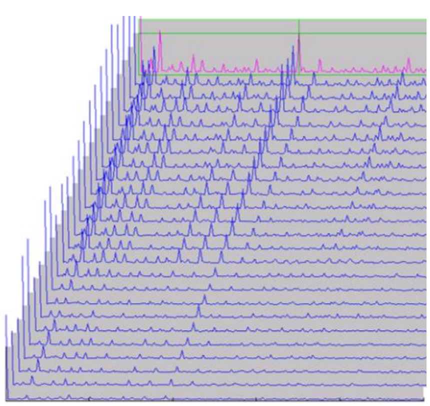


Figure 18 Condition Based Monitoring

Vibration monitoring works best for repetitive signals since it is a strong tool for identifying significant change in vibrations, which indicates a developing failure. However, this means that certain failures are hard to detect like surface friction and material fatigue. This information of increasing vibrations is used at Vattenfall to estimate the remaining lifetime of a component. The estimation is forecasted for the remaining lifetime of a component and is used as input for the expected demand rates of MCs.

Imperfect Advance Demand Information Inventory

The failure of a component is a highly unpredictable and therefore by definition stochastic process, this often leads to a higher inventory than actually required. Condition monitoring as mentioned in Section 2.1.1 offers a framework for continuously monitor numerous condition indicators, which can navigate extracting useful information from the data to predict future failures. These indications of failures are considered Advanced Demand Information (ADI). However, these ADI's can be imperfect in a way that they fail to produce a warning, uncertain when the failure will occur, or provide a false positive (Topan, Tan, Houtum, & Dekker, 2018). Auweraer, Zhu, & Boute (2021) propose an inventory model based on ADI, which is a dynamic program for generating replenishment orders assuming lost sales. Additionally, Topan, Tan, Houtum, & Dekker (2018) propose an alternative model by introducing imperfect information as mentioned before. Benjaafar, Cooper, & Mardan (2008) propose a production-inventory systems with imperfect demand information access. They formulated the production control problem as a continuous-time Markov decision process, showing an optimal state-dependent inventory policy. The theorem states that for each vector of announced orders based on the imperfect ADI a specific threshold exists, which indicates whether it is optimal to order a new spare component when the current spare inventory level is below a specified order point. Using this ADI in addition to expected failure rates increases the accuracy of expected demand rates and thus provide a more accurate inventory model.

Appendix D. Poisson & Exponential Distribution

Poisson distribution

Poisson is a commonly used discreet distribution is reliability analysis, such as failure predictions with a constant failure rate. It shows that if earlier failures have no influence, so no correlation, over the probability of a new failure occurring, where the interarrival time between failures is distributed according to an exponential distribution. This is described as a Homogeneous Poisson process, where the probability of new failure occurring increases exponentially over time. The failure may occur at any time in the interval. The Poisson probability density function is given by function below, were λ represents the rate at which a specific event is reached, and k represent the number of events. Poisson is only characterized by λ, and k is a support parameter (Axsäter S. , Inventory Control, 2000). The Poisson distribution shows the number of failures in each period, the failure rate.

$$f(\mathrm{k};\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

To also know the reliability of a component, the reliability function is given in function below.

$$R(t) = \sum_{x=0}^{r} \frac{(\lambda \mathrm{t})^x e^{-\lambda \mathrm{t}}}{x!}$$

Exponential Distribution

As where the Poisson distribution focusses on the number of failures in each time period. The Exponential distribution looks at the time between failures as time flows continuously. The Exponential distribution only has one parameter η which is the mean time between failures with a constant failure rate of: z(t) = 1/ η. It is like a Weibull distribution without a location/threshold parameter and a shape parameter equal to one. To determine the estimator of parameter η, the Method of Moments can be used, as seen in function below (Rameshwar & Debasis., 2007).

$$\hat{\eta} = \frac{1}{n}\sum_{i=1}^{n} t_i$$

Appendix E. Multi-Censored Weibull Parameter Estimation

There are various types of censored data, four main types are already described. However, combinations of these four are also possible, which makes the estimation of the parameters even harder. Here we will describe the approach, proposed by (Zaiontz, 2022) for a multi-censored Weibull distribution.

We assume m+n components enter the system, which can be at various times, and they can be removed at various times from the system. Here we have n components failing at time $X_1, \dots, X_n$ and m components have not failed yet after $Y_1, \dots, Y_m$ units of time. For the estimation of the parameters, two approaches are discussed. Firstly, the log-likelihood function for the Weibull distribution will be given, for which the parameters will be chosen that maximized the log-likelihood function, as can be seen below:

$$LL(\alpha, \beta) = -\sum_{i=1}^{m} (\frac{y_i}{\eta})^{\beta} + n[\ln(\beta) - \beta \ln(\eta)] + (\beta - 1)\sum_{i=1}^{n} \ln(x_i) - \sum_{i=1}^{n} (\frac{x_i}{\eta})^{\beta}$$

The second approach uses Newton's method with the extension on an iterative approach, with the following two steps:

- Make an initial guess for β_o
- Iterative step: assume estimate of β_k and define new more accurate estimate β_{k+1}, do this until β_k converges. The steps look at follows:

$$\beta_{k+1} = \beta_k - \frac{h(\beta_k)}{h'(\beta_k)}$$

Where

$$h(\beta_k) = \frac{1}{\beta} + \frac{u}{n} - \frac{p + w}{r} \qquad h'^{(\beta_k)} = -\frac{1}{\beta^2} - \frac{p' + w'}{r} + (\frac{p + w}{r})^2$$

and

$$u = \sum_{i=1}^{n} \ln(x_i) \qquad v = \sum_{i=1}^{n} {x_i}^{\beta} \qquad z = \sum_{i=1}^{m} {y_i}^{\beta} \qquad r = z + v$$

$$w = \sum_{i=1}^{n} {x_i}^{\beta} \ln(x_i) \qquad w' = \sum_{i=1}^{n} {x_i}^{\beta} \ln(x_i)^2 \qquad p = \sum_{i=1}^{m} {y_i}^{\beta} \ln(y_i) \qquad p' = \sum_{i=1}^{m} {y_i}^{\beta} \ln(y_i)^2$$

When β_k converges, we calculate the Eta value as follows:

$$\eta = (\frac{r}{n})^{1/\beta}$$

Appendix F. Sensitivity Analysis

Table 13. Sensitivity Analysis for No-Inventory

(No Policy)	component - 1	component + 1	Jack up - 1	Jack up + 1	Holding - 5%	Holding + 5 %
Gearbox	-1,62%	1,98%	-0,20%	0,22%	0,00%	0,00%
Generator	-7,21%	7,07%	0,06%	-0,06%	0,00%	0,00%
Blade		11,14%	4,03%	1,34%	0,00%	0,00%
Transformer	-3,40%	7,78%	-0,04%	4,38%	0,00%	0,00%
Switchgear	-0,66%	14,82%	0,60%	12,43%	0,00%	0,00%
MainBearing	-0,99%	3,29%	-11,34%	12,67%	0,00%	0,00%
MainShaft		8,76%	-6,27%	12,50%	0,00%	0,00%

Table 14. Sensitivity Analysis for (s,Q)-policy

(sQ)	component - 1	component + 1	Jack up - 1	Jack up + 1	Holding - 5%	Holding + 5 %
Gearbox	-1,04%	1,11%	0,03%	-1,95%	-0,17%	0,86%
Generator	-13,88%	-1,15%	-5,02%	-25,27%	-2,76%	2,76%
Blade		-2,12%	6,89%	0,52%	-2,69%	2,69%
Transformer	9,72%	16,75%	74,44%	15,24%	0,00%	0,00%
Switchgear	-0,48%	11,32%	-8,35%	12,59%	0,00%	0,00%
MainBearing	-0,59%	2,86%	-11,73%	12,79%	-0,15%	0,15%
MainShaft		7,45%	-6,33%	11,84%	-0,17%	0,17%

Table 15. Sensitivity Analysis for (S-1,S)-policy

(S-1S)	component - 1	component + 1	Jack up - 1	Jack up + 1	Holding - 5%	Holding + 5 %
Gearbox	-2,68%	2,81%	-1,01%	-0,86%	-0,11%	-0,83%
Generator	-10,59%	24,02%	15,65%	-3,70%	20,58%	-1,67%
Blade		11,14%	4,03%	1,34%	0,00%	0,00%
Transformer	-3,40%	7,78%	-0,04%	4,38%	0,00%	0,00%
Switchgear	-0,66%	14,82%	-8,46%	12,43%	0,00%	0,00%
MainBearing	-0,99%	3,29%	-11,34%	12,67%	0,00%	0,00%
MainShaft		8,76%	-6,27%	12,50%	0,00%	0,00%

Table 16. Impacts of Batching for (s,Q)-policy

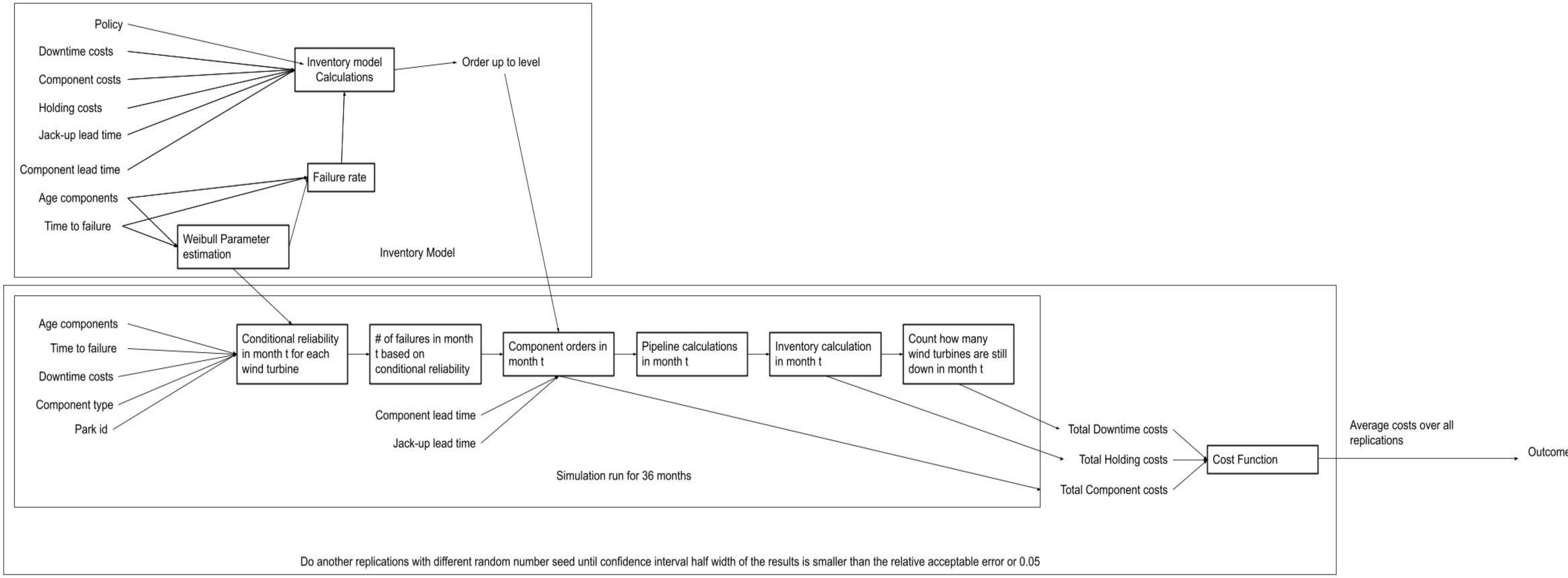
(s,Q)-policy	OQ = 2	OQ = 2	OQ = 2	OQ = 3	OQ = 3	OQ = 3	OQ = 4	OQ = 4	OQ = 4
	OQD = 0	OQD = 0.05	OQD = 0.10	OQD = 0	OQD = 0.05	OQD = 0.10	OQD = 0	OQD = 0.05	OQD = 0.10
Gearbox	0,00%	-4,59%	-9,18%	2,15%	-2,53%	-7,20%	3,65%	-1,07%	-5,80%
Generator	0,00%	-3,65%	-7,30%	-0,84%	-4,13%	-7,41%	24,00%	19,90%	15,80%
Blade	0,00%	-4,15%	-8,30%	59,95%	53,72%	47,50%	119,89%	111,60%	103,30%
Transformer	0,00%	-4,10%	-8,21%	40,39%	34,26%	28,14%	80,77%	72,63%	64,49%
Switchgear	0,00%	-2,81%	-5,63%	0,70%	-2,15%	-5,00%	1,26%	-1,62%	-4,50%
MainBearing	0,00%	-2,63%	-5,26%	1,56%	-1,12%	-3,80%	2,74%	0,05%	-2,64%
MainShaft	0,00%	-3,16%	-6,33%	2,34%	-0,88%	-4,10%	5,88%	2,52%	-0,84%
Average	0,00%	-3,59%	-7,17%	15,18%	11,03%	6,88%	34,03%	29,14%	24,26%

Table 17. No Jack-Up Lead Time

	Component 1		Component 2		Component 3		Component 4	
	No Inventory	(S-1S)	No Inventory	(S-1S)	No Inventory	(S-1S)	No Inventory	(S-1S)
No Jack up	4230000	4230000	1930000	2070000	3050000	2360000	109860000	109800000
3 months jack up	2870000	2870000	4980000	4980000	4310000	4310000	110480000	111680000
% change	47,30%	47,30%	-61,34%	-58,48%	-29,26%	-45,35%	-0,56%	-1,69%

	Component 5		Component 6		Component 7	
	No Inventory	(S-1S)	No Inventory	(S-1S)	No Inventory	(S-1S)
No Jack up	1050000	1120000	440000	440000	6610000	4690000
3 months jack up	1080000	1120000	540000	540000	8770000	8770000
% change	-2,14%	0,08%	-18,53%	-18,53%	-24,61%	-46,54%

Appendix G. Oversight Model and Monte Carlo Simulation



The Model

The picture above shows the structure of the model and the Monte Carlo simulation. First, the inventory model calculates the expected Weibull distribution Parameters, based on the current age of the components and the time to failure of the failed components. These expected Weibull distribution parameters are then used in combination with the current age to determine the conditional reliability and the PDF, which are used to determine the expected failure rate of each component. Because we assume the same expected Weibull distribution parameters, we can summarize these expected failure rates without a problem. The total expected failure rate, in combination with the policy, component lead time, Jack-Up lead time, and all involving costs are used to calculate the parameters of the chosen policy.

The Monte Carlo simulation uses these parameters in combination with the age, expected Weibull distribution parameters, current month, component type, park id, and downtime costs as input. Here the age and expected Weibull distribution parameters are first used to determine the conditional reliability for the upcomment month. Then a random number between 0 and 1 is taken and if it's higher than the conditiona reliability of the specific component, we fail the component. Then based on how many components have failed in that specific month, policy paramteres, component lead time, and the Jack-Up lead time, we determine how many components to order that month. This is determined based on the pipeline of the previous month, the policy paramter (Order-up-to level), and the demand of the current month based on the lead times. If the Jack-Up lead time is longer than the component lead time, we wait the difference in months before ordering for that specific failure. If the Jack-Up lead time is shorter then we immediately order for that failure. Knowing all this information, we can determine when a component arrives, we know how many are used and how many are going to be stored in inventory and how many wind turbines are down waiting for a new component to arrive. Using all this information we can calcualte the TRC for each month and store this value in an array. We then run this entire experiment again (New replication) but with a different randomnumber stream to ensure different outcomes. After each replication we determine the confidence interval half width of the results and run a new replication untill the confidence interval half width is smaller than the relative acceptable error. We do this for each experiment type.

Psuedo code

Def Monte Carlo simulation

Define parameters

Initialize parameters

***While** enough replications*

Call CalculateParameters (calculate expected parameters)

Call ReadParameters (read remaining parameters from sheet)

Initialize parameters for each replications

***For each** month*

Calculate expected Demand

Determine Policy parameters

Determine order quantity

Determine pipeline quantity

Determine inventory quantity

Determine how many wind turbines are still down

Add costs to TRC for this replication

Determine confidence interval half width of new replication

Return Average TRC of all replicati