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Variability in the Lifetime of Maritime Thruster Components

An Exploratory Analysis of Component Breakdown

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Abstract

In this thesis we conduct and exploratory analysis of the variability in the lifetime of maritime thruster components. The main objectives for the thesis have been to determine what causes the variability in the lifetime and to determine if weather variables can be one of the factors that affect the variability in lifetime.

We have used a Random Forest classifier which is a method within machine learning. The Random Forest classifier was used to establish which characteristics that are important when determining if a component has sustained or failed. We also conducted a descriptive analysis to visualise and present the characteristics of the breakdown data. For the descriptive analysis have included data on seasonal weather patterns and locations for the breakdown of the components. This is to determine the relationship between them.

We have concluded that the Random Forest classifier has a high probability of capturing whether a component sustain or fail based on the variables we have used to build it. The model reveal that a vessel's physical characteristics are the best indicators of whether a component will fail or sustain its expected lifetime. From the descriptive analysis we have concluded that we do not have enough data or information to definitely establish the relationship between weather and the breakdowns of components. At the same time we don't reject the possibility of a correlation between adverse weather and component failure.

Keywords – Thruster Components, Machine Learning Model, Random Forest Classifier, Failure, Adverse Weather, Lifetime Variability, Spare Part Management, Condition Monitoring, Maritime Industry, Propulsion, Weather Seasonality

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1 Introduction

The maritime shipping industry is one of the largest industries globally and carries more than 80% of the world's trade volume. Consequently, the industry is highly volatile during global crises, which also directly affect supply chains in the global trading market (UNCTAD, 2022). In the 2023 Review of Maritime Transport, UNCTAD's Secretary-General Rebeca Grynspan emphasised the importance of balancing environmental sustainability, regulatory compliance, and economic demands to create an equitable and resilient future for maritime transport (UNCTAD, 2023).

Given its vast scale, the maritime industry offers a substantial customer base. The need for reliable propulsion is a universal requirement for all vessels. Thruster components, which are vital for the propulsion, have an expected lifetime and require regular replacement. When manufacturing series of identical components, similar lifetimes are expected for these components. However, due to various factors, there can be significant variations in their actual lifetimes. Understanding why these variations occur presents an opportunity for optimising spare part management. This optimisation can lead to better predictions of spare part demand and further reduce vessel downtime because of unexpected repairs.

In the shipping literature, there is a vast amount of research that tries to quantify weather-related impacts on maritime operations. Ship weather routing is an approach to finding the optimal path and speed for a voyage while considering adverse weather conditions such as wind and waves. The objectives of ship weather routing research have varied, but typically relate to economic optimisation, like fuel consumption (Zis et al., 2020).

Despite extensive studies of how weather affect vessel operations, there remains an unexplored area on weathers impact on component lifetime in the maritime shipping industry. The existing literature has outlined that there is a relationship between rough weather conditions and the load the vessel experience. This gives us reason to believe that adverse weather can have an effect on the wear of components on the vessel, and thereby also the variability in lifetime. This thesis aim to investigate the gap in the literature where we will analyse weathers potential effect on thruster component breakdowns. We will focus on thruster components, which are highly affected by resistance and load caused by weather conditions.

Based on existing theory, we hypothesise that there is a correlation between weather conditions and the breakdown of vessel components. This hypothesis is founded on the understanding that adverse weather conditions place a higher load on propulsion systems, which leads to increased wear of components. This thesis will conduct exploratory research, applying existing theories to address the research questions. Due to the broad nature of our research design, we will divide the research questions into two parts for a more in-depth analysis. The first part will try to answer the following research question:

What thruster and vessel characteristics can distinguish the components that sustain its expected lifetime?

The objectives for this research question are threefold. First, we aim to identify relevant characteristics for predicting the lifetime of a thruster component by making an educated choice based on the literature review. This involves selecting influential vessel characteristics. Second, we will develop a Machine Learning (ML) model using Random Forest classification that incorporates our chosen variables. Finally, we will analyse and present the model's results, focusing on determining which variables most effectively distinguish the sustained from the failed components. In the second part of the analysis we will try to answer the second research question:

How does the weather affect the variability in the lifetime of thruster components?

The objectives for this research question are, firstly, to select weather variables that may influence component failure, based on our literature review findings. Secondly, we aim to conduct a comprehensive descriptive analysis of the collected data, related to weather and component breakdowns. This includes examining the variability in component lifetimes, comparing the locations from breakdown and the weather. Our main objective is to identify patterns linking weather to component breakdowns.

By addressing these research questions, we discovered that the physical characteristics of the vessels are important features to determine whether a component will sustain its lifetime or fail prematurely. Additionally, we identified patterns linking breakdowns to adverse weather in the form of wave height and wind speed, suggesting a relationship between them.

Our thesis is organised in the following manner: First, we present the theory and literature review as a background for the research topic of our thesis. Here, we explain the theory regarding vessel propulsion, ship weather routing, and spare parts management. Second, we introduce the data we have used and analysed, which includes records related to the breakdowns of components, vessel characteristics, weather data and location data. In this section, we will also explain how we split and merge the data specifically for each of the two research questions. Third, we present the methods used to analyse the data, transforming the data into useful insights. Finally, we present the results from our ML model and perform the descriptive analysis, before moving on to the discussion and conclusion of our thesis.

2 Theory & Literature Review

The following section provides a foundational understanding of various elements crucial to maritime operations and thruster component analysis. It delves into the mechanics of vessel propulsion, examining how principles of physics and engineering intersect to enable vessel movement. This section also looks into ship weather routing, highlighting the impact of weather conditions on maritime navigation and the methodologies used to optimise routes. Furthermore, it delves into spare parts management, focusing on the balance between inventory control and operational efficiency. The insights gained from this literature review form the bedrock for understanding the complex interplay between vessel operation, component durability, and external environmental factors.

2.1 Propulsion

In maritime vessel operations, understanding propulsion is key to how vessels move through water. Propulsion is the mechanism that drives a vessel forward, and this subsection delves into the basal principles of this process, going into the mechanical engineering of the propulsion, Newton's laws of motion, and fluid dynamics.

2.1.1 Propulsion Mechanism

A vessel's propulsion is primarily achieved through its propeller (Carlton, 2018). The principles of Newton's laws of motion are applied in this context. Newtons first law explains the law of inertia. In the context of a vessel it would imply that the vessel remains stationary or maintains a constant speed unless acted upon by a force. The second law, expressed as $F = ma$, highlights that the propeller's force dictates the vessel's acceleration, linking the propeller's exerted force directly to changes in the vessel's speed. Moreover, external factors like wind, waves, and currents also play a significant role in influencing the vessel's velocity (Lewis, 1988; Lloyd, 1998). The third law, each action has an equal and opposite reaction, becomes evident in the propulsion process. The propeller transforms the engine's power into rotational energy, conveyed via the propeller shaft. The propeller's rotation creates a force that thrusts water in the opposite direction causing the reaction that propels the vessel forward.

In addition to Newton's laws, fluid dynamics and hydrodynamics play a significant role in propulsion. Bernoulli's principle state that a rise in a fluid's velocity leads to a drop in its static pressure or potential energy and is essential for grasping the operation of propellers. This principle is applied in the design of marine propeller blades to generate thrust. As these blades spin through water, they are crafted to lower pressure at the front, while elevating it at the rear. This design effectively drives water backwards, creating the propulsion force necessary to move the vessel forward.

In propeller design, the blade pitch and the type of propeller are of utmost significance. The blade pitch is defined as the theoretical distance a propeller would move through the water in one revolution. This distance is determined by the angle of the propeller blades relative to the propeller shaft. However, in actual operation, there is a difference between the theoretical pitch and the actual forward movement in water, known as slip (AB Marine, 2023; Wärtsilä, 2023). Propellers are designed as either Fixed Pitch Propellers (FPP), which have a set blade angle, or Controllable Pitch Propellers (CPP), which feature adjustable blade angles. This adjustability in CPPs allows for changes in vessel speed without adjusting the engine rotations per minute (RPM), offering benefits in fuel efficiency and maneuverability. However, they require a higher initial investment and more complex maintenance (Marine Insight, 2023).

In summary, propulsion in maritime vessels is an intricate interplay of mechanical design, application of fundamental physics laws, and fluid movement dynamics. A comprehensive understanding of these aspects is essential to grasp how various external factors, including weather and sea conditions, can influence a vessel's performance and the reliability of its components.

2.1.2 Propulsion Research

We have now established the forces that are set to motion during a vessel's sea operation. An extensive amount of research have been analysing these forces in practice and how they affect the economical operation of the vessel. The literature have focused on diverse methodological strategies to minimise operating expenses and fuel consumption given both the oceans natural resistance due to its chemical matter and the added resistance caused by weather. Added resistance, that lead to increased fuel consumption, is referred to as the weather margin or the sea margin in the literature.

Magnussen (2017) have done a review of a variety methods of calculating the weather margin to make a new rational calculation of weather margin. The thesis support the theory of added resistance due to weather in the context of calculating the weather margin. Magnussen (2017) emphasises the importance of accurately calculating the sea margin because it is crucial for estimating the required power for a vessel's operation, which affects fuel consumption and, consequently, operating costs. When calculating the added resistance Magnussen's thesis uses a method from the International Organisation for Standardisation (ISO) 15016:2015. The selection of International Organization for Standardization (2015) for Magnussen's thesis is based on its status as a widely recognized standard and its simplicity. The resistance is calculated as in Equation 2.1.

$$\Delta R = R_{AA} + R_{AW} + R_{AS} \tag{2.1}$$

In this equation, ΔR represents the total increase in resistance. R_{AA} is equal to the added resistance due to wind, R_{AW} is added resistance due to waves, and R_{AS} is added resistance due to deviations in water temperature and density. Magnussen (2017) further decompose each variable mathematically and explains in detail how they effect the total added resistance. For the sake of our thesis we will explain it in simpler terms. Firstly, the R_{AA} is a function of the angle and density of air, the vessels speed over ground and the transverse projected area of the vessel above the waterline. Secondly, the R_{AW} is a function of wave frequency, density and height relative to the size of the vessel. This variable omits waves that are not head on the vessel. Lastly, the R_{AS} is a function of water density, temperature, and friction, which again is a function of the wetted surface area of the vessel and its speed. The effects from calculating the R_{AS} was found to make a small difference in the overall result and was therefore omitted from the method. In addition to using ISO 15016 to calculate the resistance, Magnussen (2017) also investigates the added resistance due to deterioration in the form of hull roughness and fouling.

Nilsson and Nilsson (2021) wrote a thesis where they tried to capture the seasonality of weather margin using ML models. They highlight the fact that vessel speed is the number one predictor for fuel consumption, which is also agreed upon in the literature (Adland et al., 2020; Gkerekos et al., 2019; Wang et al., 2018). Nilsson and Nilsson (2021) use a function by Meng et al. (2016) to explain how increased resistance also increase the effective power needed to move the vessel thorough the water. The effective power, P_E, is denoted as

$$P_E = R_T \times V \tag{2.2}$$

where V is the vessel speed and R_T is the total resistance. The total resistance is further decomposed into

$$R_T = R_F + R_R + R_A \tag{2.3}$$

where R_F is the frictional force of the hull and the propeller, R_R is the residual resistance mainly caused by waves, and R_A is the resistance caused by wind. This theory is an explanation for the forces that drive fuel consumption, and increase weather margin.

To calculate the seasonal variability in weather margins, Nilsson and Nilsson (2021) did a case study where they selected two vessels for two specific voyages in assistance with Western Bulk. One was a Handysize vessel in the North Pacific Ocean, where Western Bulk had noted highly variable fuel consumption, and the other was a Supramax vessel in the North Atlantic Ocean. In their case study, they found a seasonal variance of 12.3% and 6.4% for the Handysize and Supramax, respectively. There is a degree of uncertainty in these results. Nonetheless, the study demonstrated that, despite the uncertainties, their vast amounts of historical weather data could be utilised to estimate averages and variances in seasonal weather margin (Nilsson & Nilsson, 2021).

The research of Magnussen (2017) and Nilsson and Nilsson (2021) summarises the impacts of natural and weather-induced resistances on maritime operations. It emphasises the importance of precise weather margin calculations and highlights how the vessel's speed and resistance influences the power required for movement.

2.2 Ship Weather Routing

In relation to increased resistance from weather, there has been developed methods to finding the optimal travel path for a vessel, also known as ship weather routing. This method is a specific approach that aims to determine the most economical route between ports and avoid unfavorable weather conditions. Ship weather routing is built on the assumption that weather has an impact on the economical performance of a vessel. Various methods, including path finding algorithms, ML, and artificial intelligence, have been explored to optimise vessel operation variables such as fuel consumption, travel time, and overall costs (Zis et al., 2020). We aim to summarise literature that can say anything about how adverse weather, due to increased resistance, affect the lifetime of thruster components. Specifically, how weather can affect the cost of maintenance due to breakdowns.

Staveland and Strømsnes (2022) investigated the extent to which climate risk is assessed when calculating the Time Charter Equivalent (TCE) for a given route. The TCE is a performance measure for a vessel, calculating the average daily revenue for a given voyage (Hayes, 2021).

$$TCE = \frac{\text{Voyage Revenues} - \text{Voyage Costs}}{\text{Roundtrip Voyage Duration in Days}} \tag{2.4}$$

Staveland and Strømsnes (2022) substantiate the argument that severe weather increases the forces driving the vessel forward, which can lead to wear on thruster components. They discovered that the most fuel-efficient routes are those encountering the lowest wave heights and wind speeds. These factors significantly impact vessel resistance, thus influencing the power required to propel the vessel. They also concluded that weather variations should be considered in decision-making related to fuel consumption. Hence, their thesis supports the theory that weather conditions significantly influence the resistance faced by a vessel during operation.

Gershanik (2011) briefly address the topic of how weather conditions relate to the breakdown of vessel components. The paper states that there are benefits of avoiding rough weather to reduce vessel damages while it allows for better predictions of estimated time of arrival (ETA) to ports. Better estimation of ETA increase the possibility to plan port operations, maintenance and repairs at dock and reduce the demurrage[1].

[1] Demurrage is a fee that the charterer pays daily to the vessel owner for not completing the loading or unloading process within the allotted time specified in the charter party. This charge becomes applicable when a vessel exceeds the agreed timeframe. The demurrage charges continue uninterrupted once they begin, regardless of any standard non-working days that may occur during the period (Panayides, 2018).

In a paper, presenting a new approach for ship weather routing, Chen (2002) notes the scarcity of literature on vessel damage caused by the weather conditions. Chen suggests a new approach to weather routing while questioning the effectiveness of current weather routing strategies in preventing accidents and losses. The paper contributes to the literature by introducing the Vessel Optimisation and Safety System (VOSS). It is a software designed to predict a ship's seakeeping and speedkeeping capabilities in any sea state. Specifically, it has an advisory module that answer 'what if'-modules e.g., like how changing speed and heading will affect the vessel's roll[2] and pitch[3].

The VOSS software system is built using advanced technologies for accurate weather forecasting using supercomputers, major organisations, and satellites. It predicts the ship's response to waves using naval architecture and hydrodynamics, in addition to sensor technology to notify the ship's crew of the motion and stress the hull is experiencing, even in situations with poor visibility[4].

The literature review conducted by Zis et al. (2020) implicitly makes it clear that there is a gap in the literature, where there is limited focus on material damage caused by weather. Among the papers mentioned in the review, we found only one instance that focuses on material damage due to weather. This particular instance of material damage was related to containers lost at sea, as recorded by the World Shipping Council, an organisation working to enhance safety and reduce the number of containers lost at sea (World Shipping Council, 2023).

In this section, we've explored how weather conditions affect maritime operations, particularly focusing on vessel component breakdown and ship weather routing. The literature review conducted by Zis et al. (2020) reveals a notable gap in understanding the material damage caused by weather. Staveland and Strømsnes (2022) found that routes with lower wave heights and wind speeds are more fuel-efficient, highlighting the influence of weather on vessel resistance and fuel consumption. Gershanik (2011) discussed the operational benefits of avoiding rough weather like reduced damages and improved ETA.

[2]Roll refers to the side-to-side or port-starboard tilting motion of a vessel, occurring around the ship's longitudinal axis.

[3]Pitch is the up-and-down movement of a vessel's bow and stern, happening around the ship's transverse axis.

[4]A client's internal study showed an 80% decrease in heavy weather-related delays, 73% reduction in structural damage claims with a 29% decline in claim costs, and an 87% decrease in cargo damage claims.

2.3 Spare Parts Management

This section will focus on the challenges related to planning for spare part departments, laying the groundwork for analysing the consequences of unforeseen failures in vessel components. The consequences can be seen in the light of the vessel-owners or the spare part suppliers. We will try to have a holistic approach to the theory as spare parts management can be a advantageous in both the supply and demand side of the equation. For example, integrating a conditional monitoring system on vessels can aid in planning component renewals for vessel-owners, while suppliers can offer integrated monitoring solutions for their specific components.

The maritime industry is a capital intensive industry, characterised by high-value assets with long expected lifetime. Inventory management is a crucial aspect of spare parts management and involves avoiding both excess stock and stock-outs. For capital intensive companies, the cost of ownership plays a significant role in the decision-making process. Consequently, spare parts management departments must conduct a trade-off analysis between stock levels and asset availability. In other words, they need to find the optimal balance between inventory holding and inventory turnover (Durán et al., 2023). Excessively high inventory levels are associated with costs such as storage, insurance, obsolescence, and capital being tied up, which could be more effectively used elsewhere. Conversely, excessively high inventory turnover may lead to a sudden inability to meet market demand, resulting in lost sales and the potential damage of customer relationships (Muller, 2003; Stevenson, 2018).

A well-informed choice about inventory size can be made by attempting to forecast demand. Generally, the demand for spare parts exhibits a lumpy, erratic, or intermittent pattern with large variations in the interval between two occurrences of demand, i.e. long series of zero demand. This is due to spare parts characteristics, like having a longer lifetime and the nature of the demand pattern (Mouschoutzi & Ponis, 2022; Pinçe et al., 2021). In the maritime industry, the demand for spare parts is largely driven by maintenance policies. These policies can be divided into corrective maintenance (CM) that take place after the failure of a component, and preventive maintenance (PM) that is proactive, aiming to maintain items in a specific condition and predict the remaining useful lifetime (RUL). PM uses strategies and methods like periodic inspections and continuous condition monitoring to time their maintenance and plays a role in the deterministic (partially) planned demand for spare parts. On the other hand you have the unplanned demand for CM operations where you don't know the timing nor quantity in advance. The demand for spare parts in CM is therefore stochastic and hard to predict (Mouschoutzi & Ponis, 2022).

Based on the characteristics of spare part demand, various techniques have been employed to predict and forecast spare part demand. One widely used approach is the analysis of historical time series data (Pinçe et al., 2021; Van der Auweraer et al., 2019). The advantage of this method lies in its simplicity, as it relies solely on historical consumption data to forecast future demand (Mouschoutzi & Ponis, 2022). However, a significant drawback of this approach is the maritime sector's lack of sufficient failure-related data (Xu et al., 2014).

2.3.1 Conditional monitoring

To address the substantial costs incurred from CM following component failure, we will explore theories on the potential advantages of implementing condition monitoring as a proactive maintenance approach. Condition monitoring is the process of continuously collecting data on various parameters related to the health of a component (Ahmad & Kamaruddin, 2012).

Knutsen et al. (2014) have published a position paper on behalf of DNV to explore condition monitoring in the maritime industry. The motivation behind this paper stems from the observation that a significant portion of component failures follows a random distribution. Research conducted by United Airlines identified six failure patterns, as illustrated in Figure 2.1, revealing that 89% of failures were not age-related (Nowlan & Heap, 1978). In the shipping industry, the proportion of random (or non-age-related) failures is found to be just over 70%. The most effective way to address these random failures is to detect them before they occur, which can be achieved through condition monitoring.

Knutsen et al. (2014) outlines specific methods for performing condition monitoring. Relevant to this thesis is the data-driven approach, which utilises historical failure data to identify failure patterns using techniques such as clustering and neural networks.

However, this method has a drawback: it requires a substantial amount of detailed data on past failures. Additionally, it assumes a consistent underlying stability in the system or component being monitored.

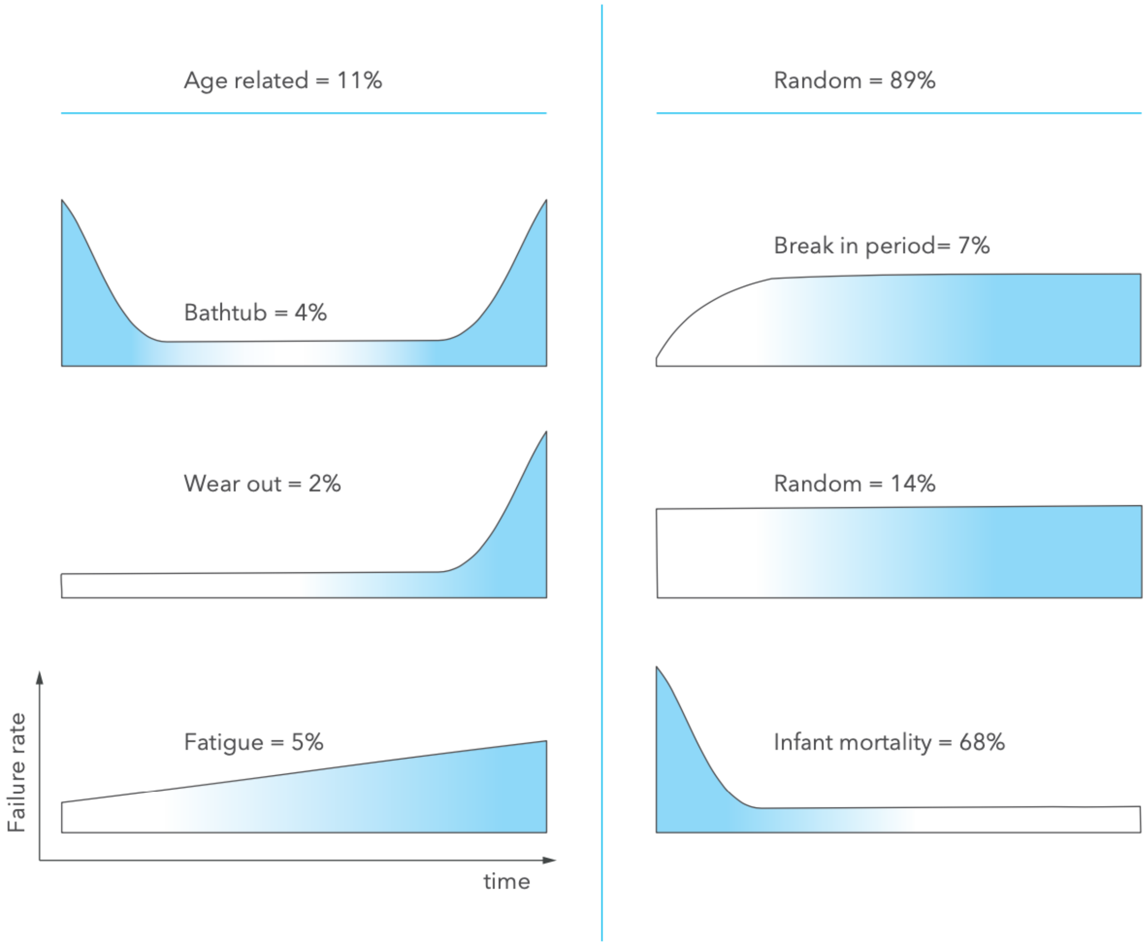

Figure 2.1: Possible failure rate patterns by United Airlines (Knutsen et al., 2014).

Leppänen (2021) has written a master thesis with the focus on creating a digital twin for predicting fatigue in bearings and shafts of thruster drivelines[5]. The thesis is written in collaboration with Kongsberg Maritime (KM) and their digital twin project. A digital twin is a representation of a physical asset in a digital environment, allowing for detailed analysis. The thesis emphasises the potential of using digital twins in predictive maintenance, allowing for more efficient planning and unexpected failures. Leppänen (2021) also elucidates the bearing model and its expected lifetime where he outlines the theoretical basis for bearing life calculations, referencing ISO standards. International

[5]A thruster driveline in vessels refers to the mechanical system that transmits power from the engine to the thruster. This system typically includes components such as shafts, bearings, gears, and couplings, and is crucial for efficient and controlled navigation, especially in challenging environments.

Organization for Standardization (2004) divides the bearing failure into six modes: fatigue, wear, corrosion, electrical erosion, plastic deformation, and fracture and cracking. This specific component is relevant to our thesis, as roller bearings are included in the breakdown data from KM that we will present and analyse.

Leppänen (2021) discusses the interconnected nature of failure modes in bearings, illustrating how e.g. corrosion can lead to particle contamination in lubricants. This contamination may subsequently cause wear not only in the bearing itself but also in other components along the lubrication line, highlighting the complexity of bearing failure mechanisms.

In summary, this section has outlined the challenges and strategies in spare parts management for the maritime industry. It emphasises the importance of balancing inventory levels with asset availability, especially in the context of high-value, long-lifetime assets. We have discussed the impact of the maintenance policies on spare parts demand, distinguishing between CM and PM, and addressed the challenges in predicting spare part demand due to its intermittent nature. We have explored the potential of condition monitoring as a proactive approach to maintenance. This section also highlights the complexities of maintenance and the benefits of digital technologies, like digital twins, for predictive maintenance.

3 Data

The main dataset for our master's thesis is data on thruster component breakdowns, which was provided to us by KM. Additionally, we have collected weather data from the Climate Data Store provided by Copernicus Climate Change Service (C3S). To compare the weather with the component breakdowns, we needed to determine the vessel's location. This was achieved using data collected from the Automatic Identification System (AIS) via the UN Global Platform.

3.1 Breakdown data

To analyse the potential relationship between the failure of thruster components due to adverse weather, we will rely on component breakdown data received from KM. KM has retrieved and merged this data from internal databases within their Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), and Product Lifecycle Management (PLM) systems. The dataset is a time series and includes information about the installation of propulsion components. The raw data comprises 214,394 rows with 1,992 unique International Maritime Organisation (IMO) numbers. Each row in the data represents the installation of a thruster component for a specific vessel. When a component is replaced, its replacement date is recorded, indicating that the component is no longer in use. Additionally, the new component appears as a new row in the data. For more details on the structure of the data, see Appendix A.

The column *var_ match* in the data shows if the component has *sustained* its expected lifetime or *failed* prematurely. All the components gets an initial classification of being *sustained* when they are first installed. If the component is replaced before its expected lifetime it will get marked as *failed.* Since the installed base are all categorised as *sustained* even though they have not yet lived their expected lifetime, the ratio between number of *sustained* and *failed* components are skewed. Figure 3.1 shows this distribution.

A weakness with the data is that there is no guarantee that the date of installation perfectly correlate with the real date of component breakdown. The replacement date is recorded by an Installed Product Data Base (IPDB) that monitors whether the unique combination of components in the thrusters sytem has been altered. If it monitors any

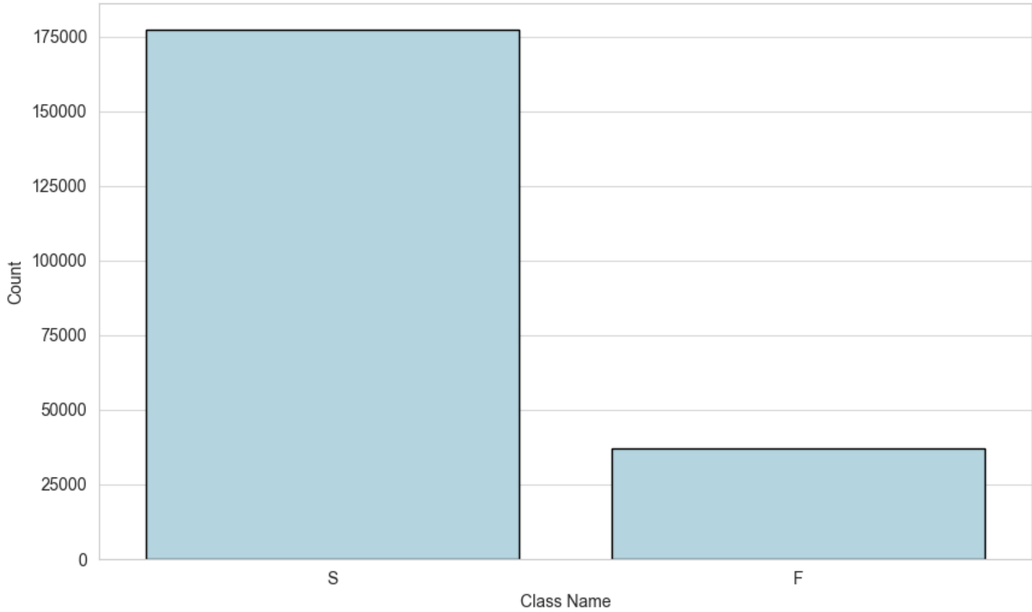

Figure 3.1: Distribution of *sustained* (S) and *failed* (F) components.

changes in the combination it records the "time of replacement" in the system. This means that there can be variations in the failure of the component and the time of replacement if the vessel do not have a spare part available at the time of failure. As we noted in the literature by Stevenson (2018), there is a high cost of having excessive spare parts in storage. Therefore we can assume that some spare parts has to be ordered by the vessel-owners, and that it may take time from failure until replacement. Delivery and replacement time may vary, but we can still assume a correlation between the replacement date in the data and the moment of failure.

3.2 Vessel data

For information about the vessel we have gotten access to Lloyd's List Intelligence (LLI). This is used to establish the physical characteristics of the vessels we will analyse from the break down data. The LLI enables access to the most recent vessel information by utilising algorithms and AI tools. These tools interrogate and validate millions of data points, thereby collecting rich and reliable maritime data (Lloyd's List Intelligence, 2023). From the vessels physical characteristics we have chosen to look closer at the variables as shown in figure 3.1.

Variable	Description
IMO	International Maritime Organisation number, a unique reference for ships and vessels.
BUILT	Year when the vessel was built.
DWT	Deadweight tonnage, a measure of how much weight a vessel can safely carry.
VESSEL_GEN_TYPE_CODE	General type code for categorising the vessel, which explain for which purpose the vessel has been built.
LOA	Length Overall, the maximum length of the vessel.

Table 3.1: Description of variables in Lloyd's List Intelligence.

The characteristics we have chosen are based on findings in the literature regarding increased resistance. In accordance with Newton's law and the effective power needed to move a vessel through the water, we decided to use deadweight tonnage (DWT) as a measure of the vessel's mass. Furthermore, we wanted to use length overall (LOA) to consider the increased resistance from waves and wind on the vessel's surface area. We also wanted to see if the type and age of the vessel had an effect on the durability of the thruster.

3.3 Weather data

In order to assess the effect weather may have on thruster component breakdown, we rely on third-party weather data from C3S. The dataset used in this thesis is the *ERA5 hourly data on single levels from 1940 to present* (Hersbach et al., 2023). This dataset has an hourly temporal resolution and contains a large range of weather variables.

For the purpose of our thesis we have made a selection of weather variables to investigate. This selection was guided by insights from previous research. As highlighted in our literature review, studies such as those by Lewis (1988) and Lloyd (1998) emphasise the impact of external factors like wind and waves on a ship's velocity. Additionally, the master's thesis by Staveland and Strømsnes (2022) provides further reasoning, stating that routes with the lowest fuel consumption per day are those encountering the lowest wave heights and wind speeds. In addition they claim that these weather variables are known to contribute to vessel resistance and, consequently, increase fuel consumption.

For our analysis of wind variables, we are primarily interested in the speed of the wind. While the direction of the wind can also be relevant, its impact is more meaningful when considered in conjunction with the vessel's direction. Magnussen (2017) calculations of added resistance due to wind, take into account the relative wind direction, resulting in varying resistance depending on the wind's orientation to the vessel. The ERA5 dataset includes the 10-meter u and v wind components, denoted as u10 and v10. These represent the wind speeds 10 meters above the surface, with u10 indicating the west-to-east and v10 the south-to-north wind components. Both are measured in meters per second. Analysing these wind components separately in individual heatmaps might not yield significant insights. However, by using the $u10$ and $v10$, we can calculate the average wind speed for the different seasons, offering a more comprehensive understanding of wind conditions and their potential impact on maritime operations. The wind speed is calculated by Equation 3.1 and is the wind speed in knots from any given direction (European Centre for Medium-Range Weather Forecasts, 2023).

$$Wind\ Speed = \sqrt{u^2 + v^2} \tag{3.1}$$

When considering the different wave variables, we aimed to capture the effect of adverse weather, and therefore chose to focus on the maximum height of the waves, averaged over the seasons. This variable is an estimate of the height of the expected highest individual wave within a 20-minute time window. By averaging the maximum wave height across each season, we can gain insights into the seasonal variations in wave conditions.

For the creation of heatmaps, we used the Climate Data Store API to download weather data. We downloaded data for each of the selected weather variables at three-hour intervals, covering every season of each year globally, from 2019 to 2023. We computed the mean values across all the time points for each season. The means were then visualised as heatmaps, providing us with an averaged representation of each season over the specified years. The decision to download data at three-hour intervals, as opposed to hourly, was necessitated by the sheer volume of data involved.

In addition to the API, we have used time series data on wave height in the North Sea collected from the Climate Data Store Toolbox Editor (Copernicus Climate Change

Service, 2023). The Toolbox processes the specified variables, in our instance the maximum wave height, and computes the maximum value for each month, averaged over the chosen location. Considering the significant seasonal variations worldwide, we have focused our analysis on a smaller area. For the purpose of this insight, we have narrowed the area down to the North Sea, with longitude from -4.8 to 11.04 and latitude from 50.99 to 61.06 (Appendix A). This results in a graph from January 2019 and onward, depicting the monthly maximum wave height for the North Sea.

3.4 Location data

To be able to analyse the weather that has impacted the vessels, it was necessary to retrieve data about their travel paths. The location dataset was sourced from the AIS data provided by the United Nations Global Platform, UN-CEBD. By using the IMO numbers from the breakdown datset, the vessels were filtered from a 12 TB AIS database including 4 billion positions. Data processing was carried out in a Spark environment within a big data cluster hosted on Amazon Web Services (AWS).

The extracted data is in EPSG:4326 format and includes approximately 9 million positions distributed on 1804 vessels. The data spans from January 1st 2019 to October 30th 2023, and is collected with three hour intervals. There are some missing values in the data where locations are not collected at the 3 hour intervals for each vessel.

3.5 Data mining and pre-processing

This section include the choices we have made regarding merging and cleaning of the data. Since the analysis is two folded and each part requires different data we will end up with two different datasets; one for the ML model and another for the descriptive analysis. In Table 3.2 the processing and reduction that is common for both the datasets are presented.

3.5.1 Filtering and Selection

We start with the breakdown data, with 214,394 rows. Within this dataset, certain IMO numbers appeared unusual, such as 1111111. Closer examination revealed that these

Processing Step	**Data Length**	**Reduction**
Initial data length	214,394	-
Removing unusual IMOs	207,839	6,555
Keeping only FAMILY 'TT'	206,597	1,242
Filling expected lifetime	206,597	0
'Installation_Year' $\geq$ 2003	195,255	11,342
Dropping NaN 'Installation_Year'	195,255	0
Dropping NaN 'Replaced_Year'	49,223	146,032
'Days_Difference' $\leq$ 7	47,534	1,690
Final data length	47,534	-

Table 3.2: Data processing steps and reduction count.

IMO numbers contained multiple vessels, deviating from the standard of representing a single vessel. Given the critical role of the IMO number in merging and gathering of data, we opted to exclude those entries. This exclusion resulted in the removal of three IMO numbers, affecting 6,555 rows, which suggests that not all records in the dataset have been registered with the correct IMO number.

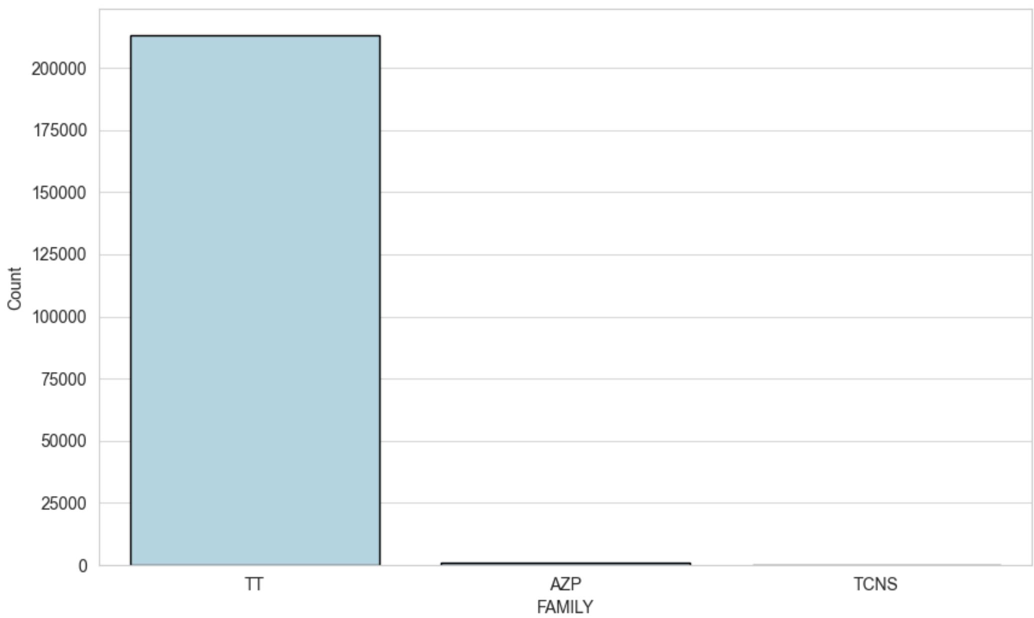

Figure 3.2: Distribution of the FAMILY categories.

In the breakdown data, we find information related to three types of thrusters: the classical tunnel thruster (TT), the azipull thruster (AZP), and the swing-up azimuthing thruster (TCNS). Figure 3.2 shows the distribution of components for each type of thruster. There is an abundance of components related to the TT, which is also the standard thruster used by KM. Our focus on the TT led to the exclusion of 1,242 rows from the data, with the distribution of TCNSs and AZPs removed detailed in Appendix A. This filtering where we only focus on TTs is based on several reasons. Firstly, the TT represents the largest product class. Secondly, excluding the other thruster types reduces the dataset by only a small margin, making the TT data more representative. Finally, the results of our analysis are likely to be more consistent, as the data will be more homogeneous, exhibiting similar characteristics. Moreover, this also enhances comparability.

To measure if the component has *sustained* the expected lifetime, we need to know what the expected lifetime for all components. There are some missing values in the expected lifetime column, as shown in the appendix, Table A.2. Components that share the same product ID has identical expected lifetime. We can therefore reliably fill in the missing values for these components by matching them with the expected lifetimes from the same product ID.

	count	**min**	**25%**	**50%**	**75%**	**max**
Installation	203,615	1937-01-01	2008-04-17	2011-04-05	2016-04-18	2023-09-19
Replaced	50,753	2007-05-31	2014-07-14	2018-01-12	2020-06-15	2023-09-19

Table 3.3: Summary statistics for installation and replaced years Before Filtering.

Table 3.3 shows that the registration of installations start in 1937, but 75% of the data is registered from 2008 and onward. Figure 3.3 shows the distribution of installation and replaced year. The figure shows that there is a low number of registration of installation prior to around 2003. Post-2003, there is an increase in the number of registered installations. Based on the lack of data prior to 2003, we will only consider installations from 2003 and onward in our analysis. A consequence of this reduction is that components with an expected lifetime of 30 years, that has *sustained* its expected lifetime, are not represented in our dataset. By dropping installations prior to 2003, we also removed the missing values in installation year.

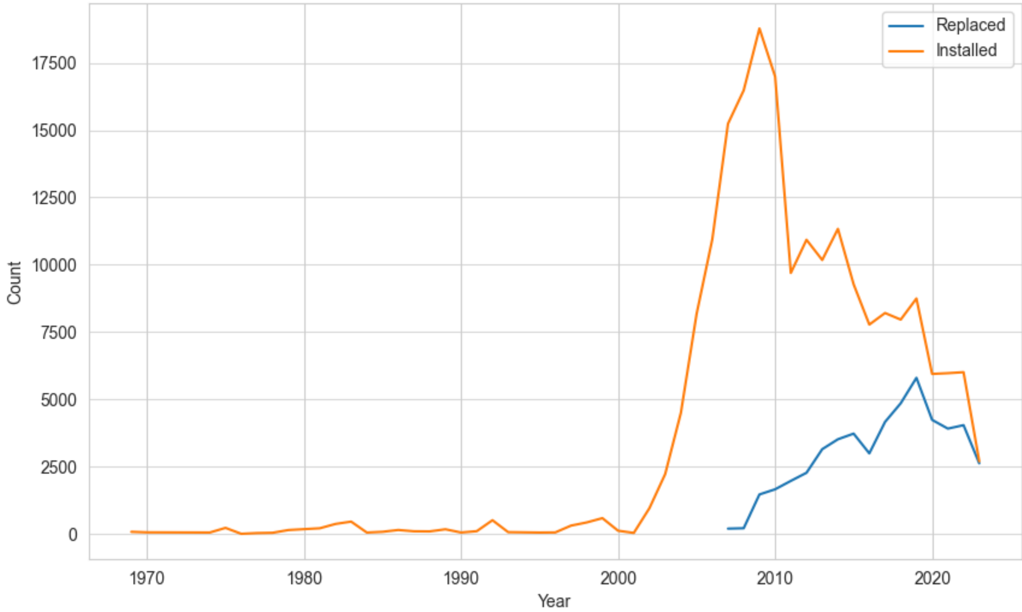

Figure 3.3: Distribution of installation and replaced dates after 1969.

Furthermore, we have excluded components that are currently onboard vessels, i.e. missing values in replaced year. This exclusion is grounded in our research interest, which centers on determining the durability of these components: whether they have endured their expected lifetime or *failed* prematurely. By focusing on components with a complete life cycle (from installation to failure or replacement), we aim to gain insights into the factors contributing to their longevity or early failure, thereby excluding components still in use that have yet to reach the end of their service life.

In the dataset, there are instances where the installation and replacement dates are identical, resulting in a calculated lifetime of zero. Upon further examination, it became evident that these entries are not representative but duplicate, as the correct values for installation and replacement dates exist in other rows. After consulting with the data owners, we concluded that components replaced within 7 days of installation are likely wrongly recorded. Consequently, we decided to remove these rows from the dataset.

These steps reduce our dataset to 47,534 components, distributed on 1,566 vessels. We will now look at the different merges and further cleaning we have done on the dataset for the ML model and the descriptive analysis.

3.5.2 Descriptive analysis dataset

Analysing weather data requires knowledge of what type of weather the vessel, and subsequently the component, has been exposed to. We therefore pair the breakdown data with the location of the vessels. We were only able to extract location data for a set of vessels from January 2019, until October 2023. Consequently, we are only able to look at the effect of weather in this time frame. Components that has been replaced before 2019 has therefore been excluded from the data due to lack of location data. In addition there some vessels we were not able to get location data for, these will also be excluded. These changes leaves us with 45,451 components distributed on 1,476 vessels.

3.5.3 Machine learning dataset

To adapt the data for the ML model, we merged the breakdown data with the LLI data, which resulted in some missing values, as presented in Table 3.4. Considering the dataset's large size and the relatively small number of missing values, we opted to remove rows with missing values. Imputing these values would have increased the uncertainty in our predictions and necessitated extra caution in interpreting the results. By eliminating all the missing values, we removed 237 components, leaving us with 47,306 components to build our model.

Column	Missing Count
BUILT	5
DWT	195
LOA	53

Table 3.4: Count of missing values for the ML model.

4 Methodology

In this chapter we will move on to the method that we used to analyse the data. We want to take a closer look into what may cause the variability in the actual lifetimes of components. An indicator of this variability is whether a component has *failed* or *sustained* its expected lifetime. We have selected two primary methods for our analysis. First, we will develop a ML model, specifically a Random Forest model. Second, we will present an descriptive analysis with an exploratory approach.

4.1 Machine Learning Models

The purpose of our ML model is to predict if a component will *sustain* or *fail* based on vessel characteristics and thruster characteristics. This will tell us if some of the variance in lifetime may be explained by the different types of vessels and the thruster the components are installed on.

Within ML there are a lot of different models and areas of use. The common denominator among all ML models is that you have data, then perform some algorithm on that data, and finally you get an output. What type of output you get depends on how you build your model. ML models can be distinguished based on their training approach, either supervised or unsupervised learning. This distinction is based on whether the model learns from a dataset with labeled outcomes or not. Since we have labeled breakdown data that tells whether a component has *failed* or *sustained* we are using a supervised ML model.

4.1.1 Supervised Machine Learning

Supervised ML involves training algorithms using labeled datasets, where the model is provided with input data and corresponding output labels during its training phase. The main objective for the model is to to discern patterns or rules that link the input to the output variables. This enables the model to make predictions on new, unseen data. The effectiveness of the model heavily relies on the comprehensiveness and quality of the training dataset as the data directly influences the models predicting capabilities. Supervised learning is broadly categorised into two main types: classification and regression. Since the response variable is *failed* or *sustained* we will be using a classification model.

Classification models in supervised learning are designed to predict discrete outcomes by categorising the input data into distinct classes. These models are useful when the output is categorical, such as *Yes* or *No*, or *fail* or *sustain* in our particular case. This output is also known as the response variable in a ML model. We have a variety of classification models to choose from. When choosing the type of model one should consider the purpose of the research, what kind of data you have and the importance of accuracy vs interpretability.

4.1.2 Random Forest

To accurately predict whether a component will endure its expected lifetime or *fail* prematurely, we have chosen to employ a supervised ML approach, specifically utilising a Random Forest classifier. The Random Forest classifier is able to manage large datasets and are less prone to overfitting. Additionally the model has good interpretability, and has good accuracy even in unbalanced datasets.

4.1.2.1 Data Preparation for Random Forest Classification

Before applying a Random Forest classifier to our dataset, it is necessary to process the data to ensure compatibility with the model. The dataset includes both categorical and continuous variables. For the model to be able to handle the categorical variables, we encode these variables using label encoding. Though label encoding is typically not recommended for the predictors in regression models because of its potential to introduce an arbitrary order, it has no effect in the classification model, and so it is a fitting approach for our categorical variables.

As seen in Figure 4.1, the cleaned data is imbalanced, with the occurrences of *failed* being almost three times as frequent as those of *sustained*. This imbalance can be effectively managed in the Random Forest classifier by weighting the response value. By doing so, the model will pay more attention to the class with higher weight during the construction of the decision trees. Nonetheless, for our purposes, the skewed data helps decrease the number of false negatives, which is beneficial since we aim to minimise this category. False negatives occur when the model incorrectly predicts that a component will *sustain* its lifetime, when in fact, it *fails*. This type of classification error is the most costly,

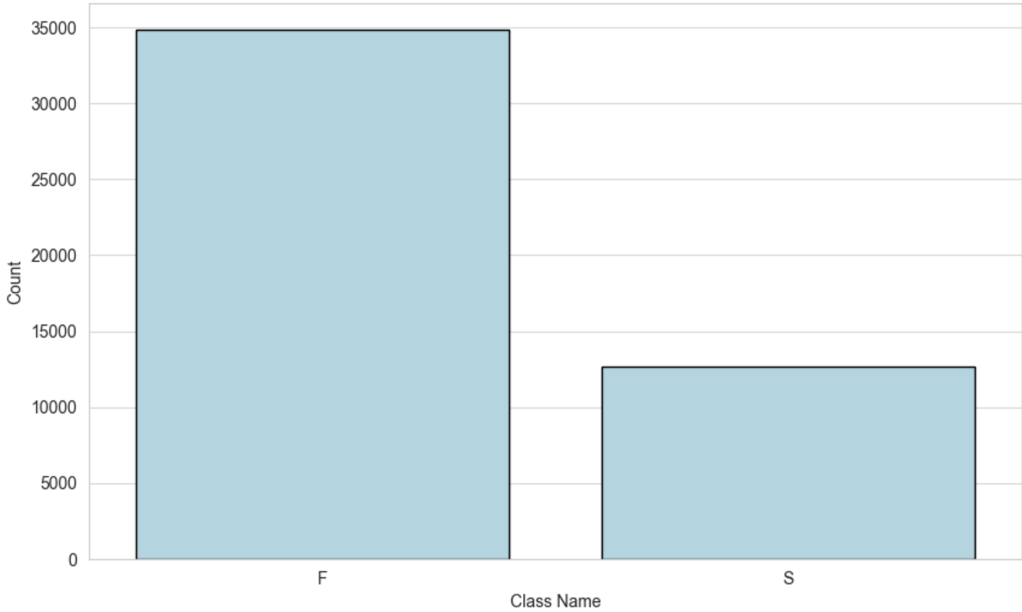

Figure 4.1: Distribution of *failed* and *sustained* components for the ML model.

as it can lead shipowners to require unscheduled maintenance or docking, resulting in lost operating time and income. Furthermore, it affects the management of spare parts, leading to income loss due to stockouts caused by inaccurate prediction of spare parts demand. Although the imbalanced dataset increase the number of false positives, this is preferable to having a larger number of false negatives.

In the construction of the Random Forest model, the data was divided in two: a training set, comprising 80% of the total data, was used to train the model; a test set, consisting of the remaining 20%, was employed to evaluate the model's predictive accuracy.

4.1.2.2 Selection of variables

Based on the data we received from KM and the LLI, we have selected variables that reflects the characteristics of the vessels or thrusters. Table 4.1 lists the variables selected for our ML model.

The *Class* variable is the response value. It takes one of two values: *S*, indicating that the component has *sustained* its expected lifetime, or *F*, indicating that the component has *failed* before reaching its expected lifetime. In the model these values are converted to 0 for *failed* and 1 for *sustained*.

Name	Original Name	Explanation	Type
Class	var_match	Response value	Categorical
SUB	Sub System	Subsystem information	Categorical
DESC	ItemDesc	Specific item name	Categorical
CFG	CONFIGURATION	Thruster configuration	Categorical
DSG	DESIGNATION	Thruster designation	Categorical
GEN	VESSEL_GEN_TYPE_CODE	General vessel type	Categorical
EXP	Expected_LifeTime	Expected lifetime	Integer
BUILT	BUILT	Construction year	Integer
DWT	DWT	Deadweight tonnage	Float
LOA	LOA	Length overall	Float

Table 4.1: List of variables for the ML model.

The variable *DESC* is the name of a component and *SUB* is the sub category the component belongs to. *CFG* give insights into the operational conditions to which the thruster is subjected. *DSG* determine whether the thruster is of a fixed pitch or a controlled pitch type. The variables *GEN*, *EXP*, *BUILT*, *DWT*, and *LOA* are characteristics of the vessel on which the component is installed, indicating, for example, whether it's a supply vessel, a cruise ship, or another type of vessel. We are particularly interested in these vessel characteristics to determine if they can provide insights into the lifetime variability of the different types of components.

4.1.2.3 Tuning

The Random Forest model consists of multiple decision trees. Each tree consists of nodes and branches. The nodes splits the components based on a condition in one of the features decided by the model. Based on the condition, the components are split onto one of two branches, and taken to the next node. Each node measures the impurity of the split, also called gini (Saini, 2021). A pure split means that the feature splits all the components into the correct class. We therefore want to have a gini, or impurity, that is as small as possible. To get a smaller gini and thereby enhance the model's predictive accuracy, it is possible to tune the model through Scikit-Learn functions. The functions finds the best hyper parameters, such as number of trees, depth of the tree and more, for predicting the correct class. The tuning of the model is presented in Appendix B. Since the tuned model required higher compute and only had a small increase in the accuracy, we have used the default parameters in the original model for predicting the class of the components. The default settings bootstraps 100 trees considering all features in every tree. It also has no boundary for the depth of the tree (Pedregosa et al., 2011).

4.1.3 Performance Metrics

To evaluate the performance of our Random Forest, we will use performance metrics designed for classification models. The performance metrics is based on calculations from the numbers in a confusion matrix. Table 4.2 shows the confusion matrix specific for our context, with the distribution between predicted values vs the actual values of a classification model. For our model we will try to predict if a component on a thruster will *fail* or *sustain*.

	Actual Values	
Predicted Values	**Sustain**	**Fail**
Sustain	Correctly Predicted Sustain (TP)	Missed Fail (FN)
Fail	Incorrectly Predicted Fail (FP)	Correctly Predicted Fail (TN)

Table 4.2: Confusion matrix for thruster component prediction.

The true positives (TP) counts how many times the model predicted a positive value when the value actually was a positive value. The true negative (TN) counts how many times a the model predicted a negative value and the value actually was a negative value. The false positive (FP) is when the model predicts a positive value, but the actual value was negative. Lastly you have the false negatives (FN), which is when the model predicts a negative value, but the actual value was positive (Bhandari, 2023).

From the confusion matrix we can first calculate the accuracy (Equation 4.1). The accuracy represents the proportion of correctly identified outcomes in relation to the total number of predictions. A negative side with accuracy is in the case where you have a dataset with an imbalanced number of *sustained* and *failed*. Here, the model could potentially predict the whole data to the class with highest number, and it would result in a high accuracy. This means that we can not measure how good the predictions are solely based on accuracy (Vidiyala, 2020). We will therefore also present other performance metrics.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{4.1}$$

Positive Predictive Value (PPV)(Equation 4.2), more commonly known as precision, is a performance metric that tells us how many of all the positive identifications that where correctly classified (Bhandari, 2023; Pennsylvania State University, 2023). In our case it would be how many of the components we predict as *sustained*, is actually *sustained*.

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{TP + FP} \tag{4.2}$$

We are also interested in determining the accuracy of our predictions for components labeled as *failed*. Specifically, we want to know how many components predicted as *failed* actually are *failed*. This measure is known as the Negative Predictive Value (NPV). NPV, along with the PPV, is influenced by the count of each response variable in the data, with a higher likelihood of correctly predicting the variable that is most frequent in the dataset (Pennsylvania State University, 2023). Equation 4.3 shows the calculation for NPV.

$$\text{Negative Predictive Value (NPV)} = \frac{TP}{TP + FN} \tag{4.3}$$

Recall (Equation 4.4) is another performance metric, also known as the sensitivity or the true positive rate (TPR) of the model. This number measures the proportion of actual positives that were correctly identified by the model. In other words, it indicates how many of the real *sustained* cases were captured by the model's predictions.

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP + FN} \tag{4.4}$$

In our case it is costly to have a model that fails to predict the *failure* of components. Therefore we will also look into the true negative rate (TNR), also known as specificity (Equation 4.5)(Monaghan et al., 2021). For a high value of TNR it would mean that if the model doesn't predict *failure* it should be a very low likelihood that you get a *failure*.

$$\text{True Negative Rate (TNR)} = \frac{TN}{TN + FP} \tag{4.5}$$

4.2 Descriptive Analysis

The second part of our analysis will consist of a descriptive approach where we visually present the data. Here we will visualise figures such as box plots, bar charts, graphs, and maps that include location and weather data. These visualisations aim to facilitate interpretation from the cleaned data. The purpose is to highlight specific findings discovered during our analysis. The figures will help in understanding the distribution of values within the data, and in identifying geographical and temporal trends. From these figures, we will attempt to dissect and understand any relationships that exist between the data and the causes of component failure.

5 Analysis

In this section we will present an analysis of the data. We will stay consistent in using the term *failure* about components that has not *sustained* their lifetime. A *breakdown* and the *occurrences* of break down refer to both the *failed* and *sustained* components.

5.1 Result From the Random Forest Classifier

The Random Forest classifier returns a confusion matrix as presented in Figure 5.1. Our model correctly predicts the component *sustain* 1,578 times and *fail* 6,354 times on the test set. The matrix reveals that the number of false negatives is considerably lower than that of false positives. In total, the model predicted that 2,190 components would *sustain* and 7,272 would *sail*, compared to the actual values of the test set where 2,496 components *sustained* and 6,966 *failed*. From the confusion matrix, we will also calculate the performance metrics, which are shown in Table 5.1.

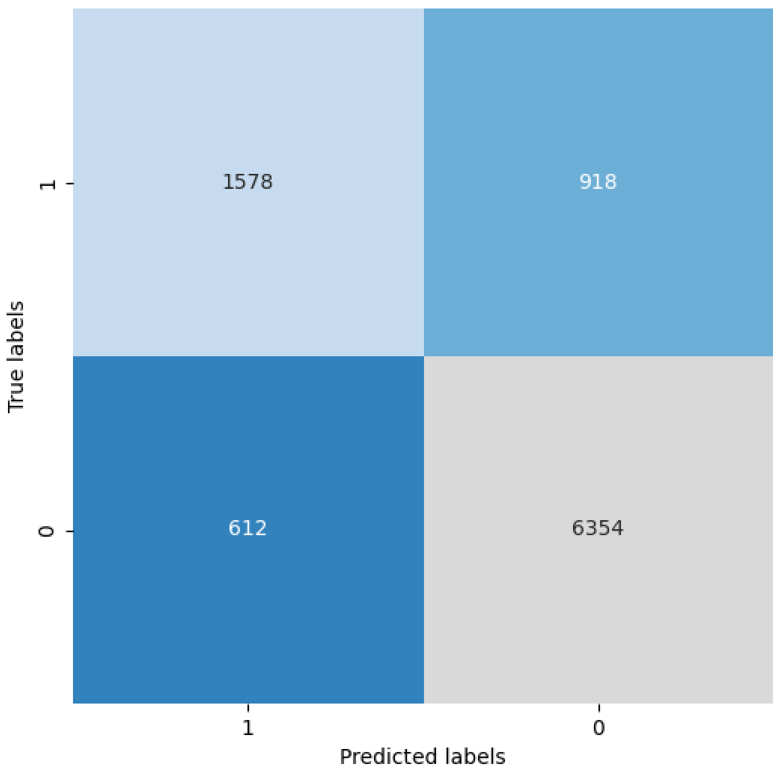

Figure 5.1: Confusion matrix for *sustained* (1) and *failed* (0) predictions.

Metric	Calculation with Numbers	Value
Accuracy	$\frac{1578+6354}{1578+6354+612+918}$	83.83%
PPV	$\frac{1578}{1578+612}$	72.05%
NPV	$\frac{6354}{6354+918}$	87.38%
TPR (Recall)	$\frac{1578}{1578+918}$	63.22%
TNR (Specificity)	$\frac{6354}{6354+612}$	91.21%

Table 5.1: Performance metrics for the Random Forest classifier.

The model has an overall accuracy of 83.83% which means that the model predicts the label for the response variable correctly 83.83% of the time.

The PPV is 72.05%, while the NPV is 87.38%. This indicates that the model has a high probability of correctly predicting instances labeled as *sustained* or *failed*. A higher NPV compared to PPV is expected because our dataset contains a greater number of *failed* components. Having a high NPV is advantageous, as it means we can predict with greater confidence whether a component has *failed*.

Furthermore, we have calculated the TPR and TNR to be 63.22% and 91.21%, respectively. This indicates that the model correctly identifies 63.22% of the actual *sustained* cases and 91.21% of the actual *failed* cases. The model is considered well-performing, and the high TNR suggests that there is a low likelihood of a *failure* occurring if the model does not predict one.

In our ML model we have not focused on environmental operational factors, like air temperature, humidity, vibration, and others, that could potentially influence the lifetime of a component. Including them would mean a further reduction of the size of our initial data, since data on operational factors was not available for the vessels in this extensive dataset. Although the inclusion of these indicators might enhance the predictions, the model still performs well given the variables that we chose.

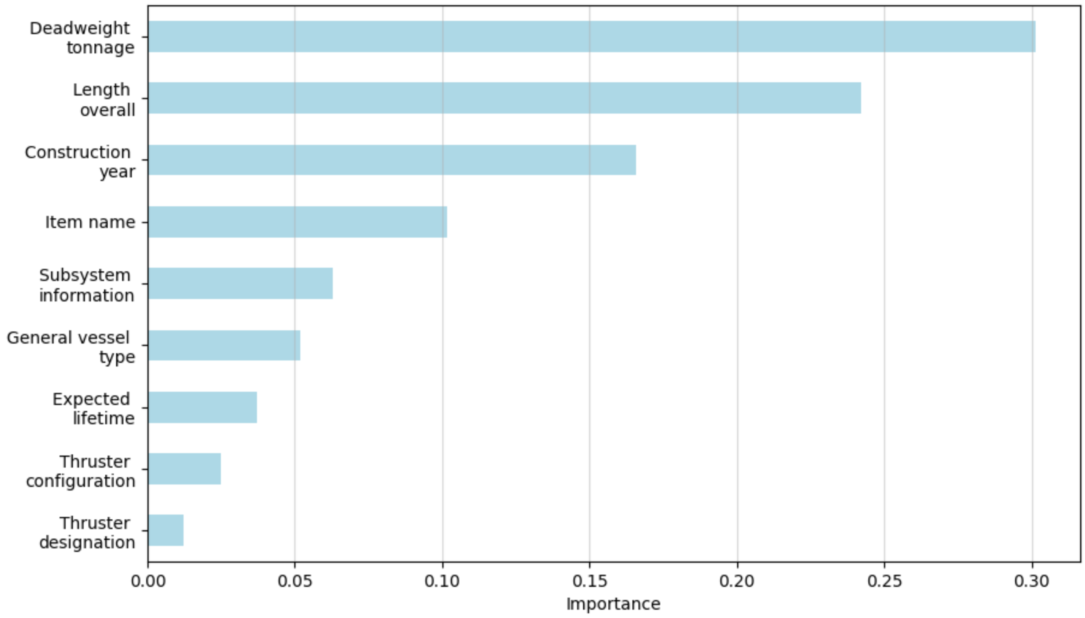

Figure 5.2: The importance of features in the Random Forest model.

The most influential features for the model are illustrated in Figure 5.2, where the size of the vessel seems to be important. Additionally, we observe that the age of the vessel serves as a good indicator of the model's predictions. What type of component we are dealing with is also holds some importance in predicting whether a component *fail* or *sustain*. This can be due to the variance in lifetime between component, that we will look closer at in the descriptive analysis. The propeller designation, FPP or CPP, appears to hold the least importance for the model's performance.

Even though deadweight tonnage (DWT) appears as a highly important feature in the Random Forest classifier, it's important to note that this doesn't necessarily imply a direct positive or negative correlation between a vessel's weight and the lifetime of its components. Rather, the importance of DWT in the model indicates that it is effective in differentiating between components that have *sustained* and those that have *failed*. Essentially, DWT may serve as a key variable that contributes to the best splitting of data in the model.

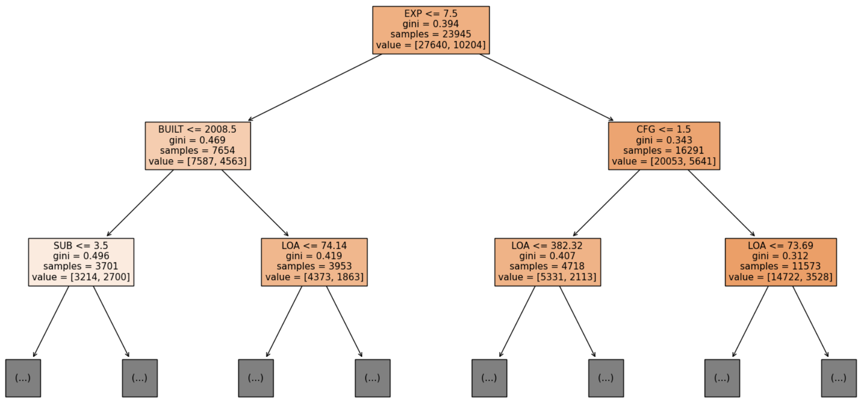

Figure 5.3: The top of the first decision tree in the Random Forest model.

Figure 5.3 shows the top of one of the 100 decision trees from our model and how it splits the data. Our model employs the default setting for the tree depth, which means that the model is allowed to expand the tree to whatever depth is necessary to accurately predict the classifications. In our case, this approach has resulted in trees with a depth of 41. Based on the different splits in the tree each component ends up in a end-node that predicts the label. The prediction that occurs most frequently for a component across all the decision trees, decides which label to return as the prediction.

5.2 Descriptive Analysis

A thorough understanding of various factors that lead to vessel component breakdown is important for improving the efficiency of maritime operations. This descriptive analysis is dedicated to explore the link that may be found between weather condition and their influence on component *failure*.

5.2.1 Component Lifetime Variance

Upon analysing the dataset of breakdowns we found a large degree of variations in the lifetime of the components, even though they have similar expected lifetimes of 5, 10, 20 and 30 years. We will now look closer into these variations.

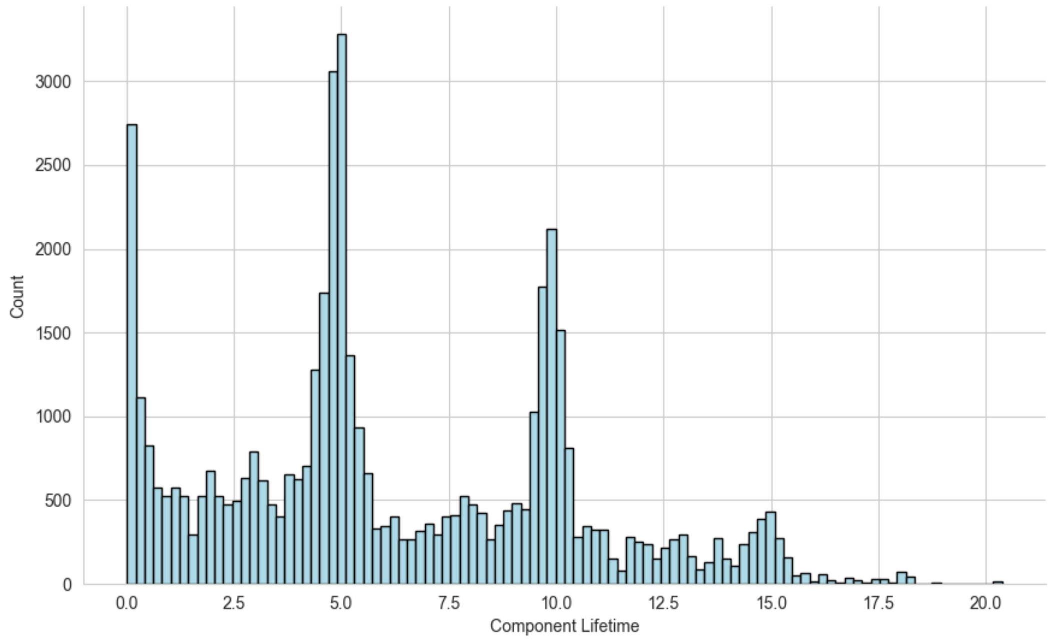

Figure 5.4: Distribution of component lifetime.

Figure 5.4 shows the distribution of the actual lifetime of the components we are analysing. From the figure we can see similarities to infant mortality and the bathtub distribution presented in Figure 2.1 from the literature, by Knutsen et al. (2014). The model by Knutsen et al. (2014) proclaims that the *bathtub* distribution of breakdown is age related while *infant mortality* is random (or non-age related).

The infant mortality is characterised with having a high number of breakdowns early in their lifetime. We can claim that the infant mortality pattern is present in the figure because there is an high number of breakdowns that happen in the first years of the lifetime. The distribution of lifetime for our components also show trends that support the bathtub pattern. The bathtub has a breakdown distribution with a high number of breakdowns in the beginning and end of the time period, in addition to a period with few breakdowns in between the peaks. Specifically, we have a higher number of replacements after 5 and 10 years lifetime, in addition to the early breakdowns.

The peaks in component lifetime of around 5 and 10 years could be explained by routine docking schedules that also occur every 5 and 10 years. During the docking different components are checked and replaced based on their last inspection or maintenance dates.

When analysing the distribution of lifetime for the components, We also noticed a large variance of the mean time before failure (MTBF) for the different component items. We have chosen to present this finding using components with 10 years expected lifetime, but the remaining components with similar patterns can be seen in Appendix C.

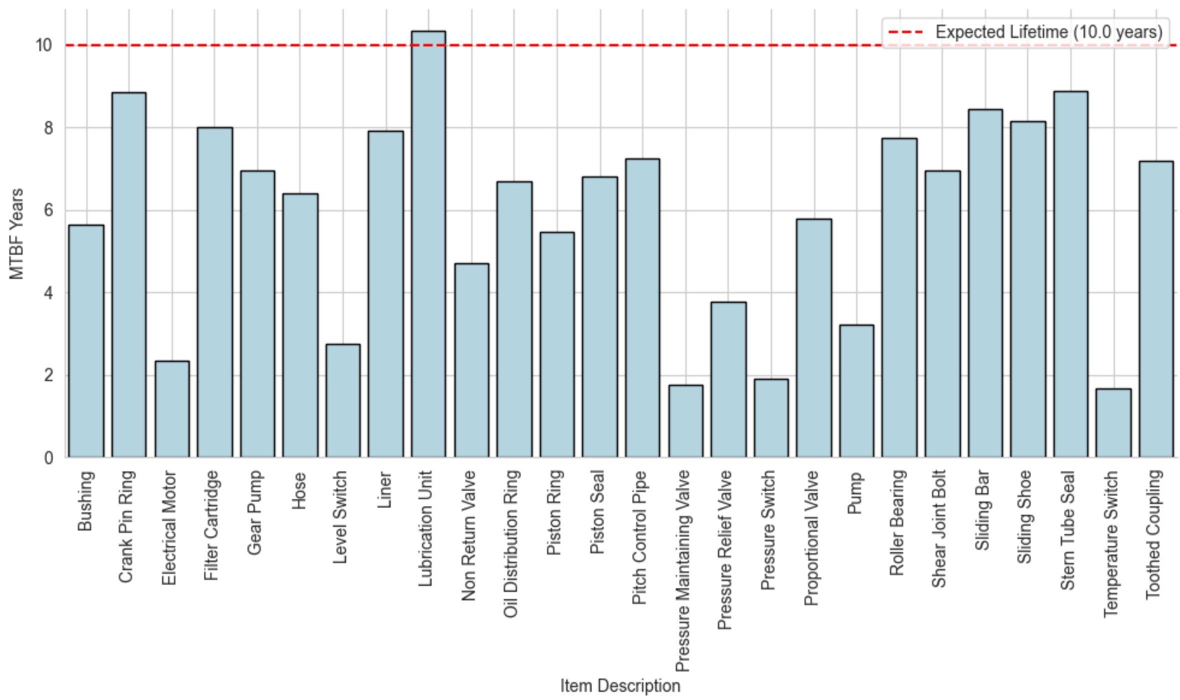

Figure 5.5: MTBF for components with 10 years expected lifetime.

The MTBF serves as a metric for measuring product reliability. Upon calculating the MTBF for our cleaned data, we uncovered further evidence indicating that the components are not meeting their expected lifetimes. In Figure 5.5 we generally see a considerable negative deviation from expected lifetime, like for the different types of valves and switches, suggesting that the components have a reliability below their expected lifetime. This lead us to further analyse the variation of lifetime for each of the components, using box plots.

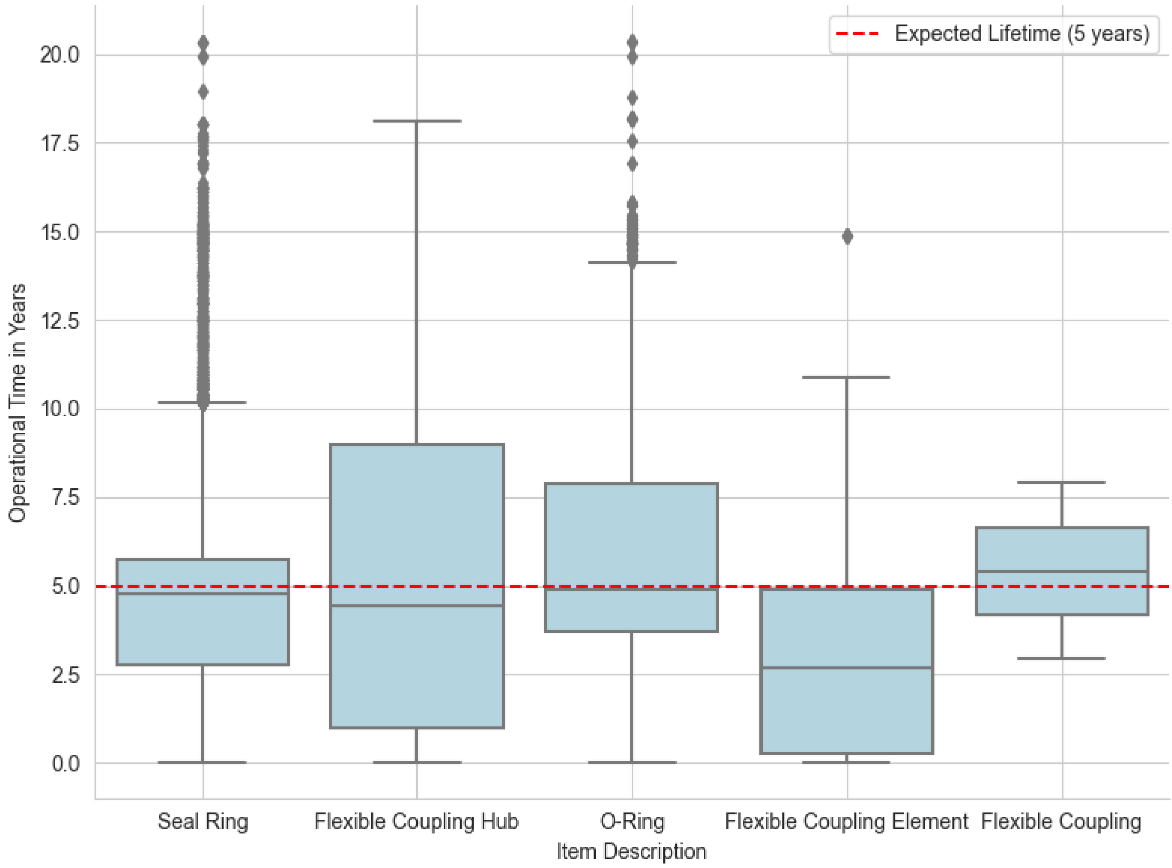

Figure 5.6: Variance in lifetime for components with 5 years expected lifetime.

In Figure 5.6 we see that even though some of the components have a mean close to expected lifetime, there is still a notable degree of variation for the real lifetime. Take for instance the flexible coupling hub shown in Figure 5.6. Here, we note that the actual lifetime spans from zero to nearly 18 years, despite an expected lifetime of five years. This wide range in lifetime suggests that although components are nearly identical post-production, there may be external variables impacting each component differently, resulting in the observed variation in lifetimes.

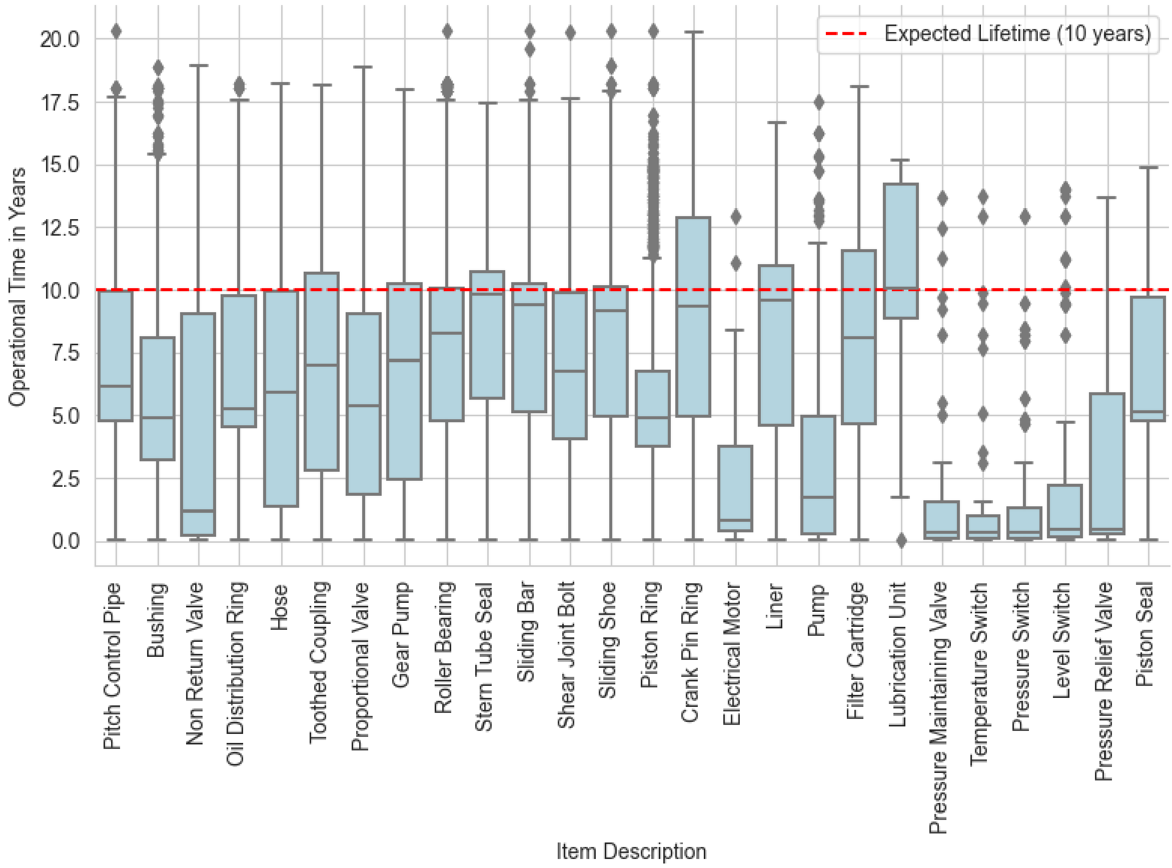

Figure 5.7: Variance in lifetime for components with 10 years expected lifetime.

This variance is found for all components regardless of what their expected lifetime is set to be. In Figure 5.7 we see a box-plot that shows high variance between the components as well. In the box-plot we see that most of the components have not met their expected lifetime. A large portion of the items experience that approximately 75% of the components *fail* before reaching their expected lifetime. It is also noteworthy that no more than one of the items have a median that is above expected lifetime. As with the 5-year components we can see that the expected lifetime is not a reliable measurement of a components lifetime. This finding is significant, as it corroborates the suspicions raised earlier regarding the potential underestimation of expected lifetimes.

The box plots shown in Figure 5.6 and Figure 5.7 also support that the distribution of lifetime has an infant mortality distribution since there are a high number of components that are replaced prematurely in regards to their expected lifetime.

5.2.2 Travel Paths and Breakdowns

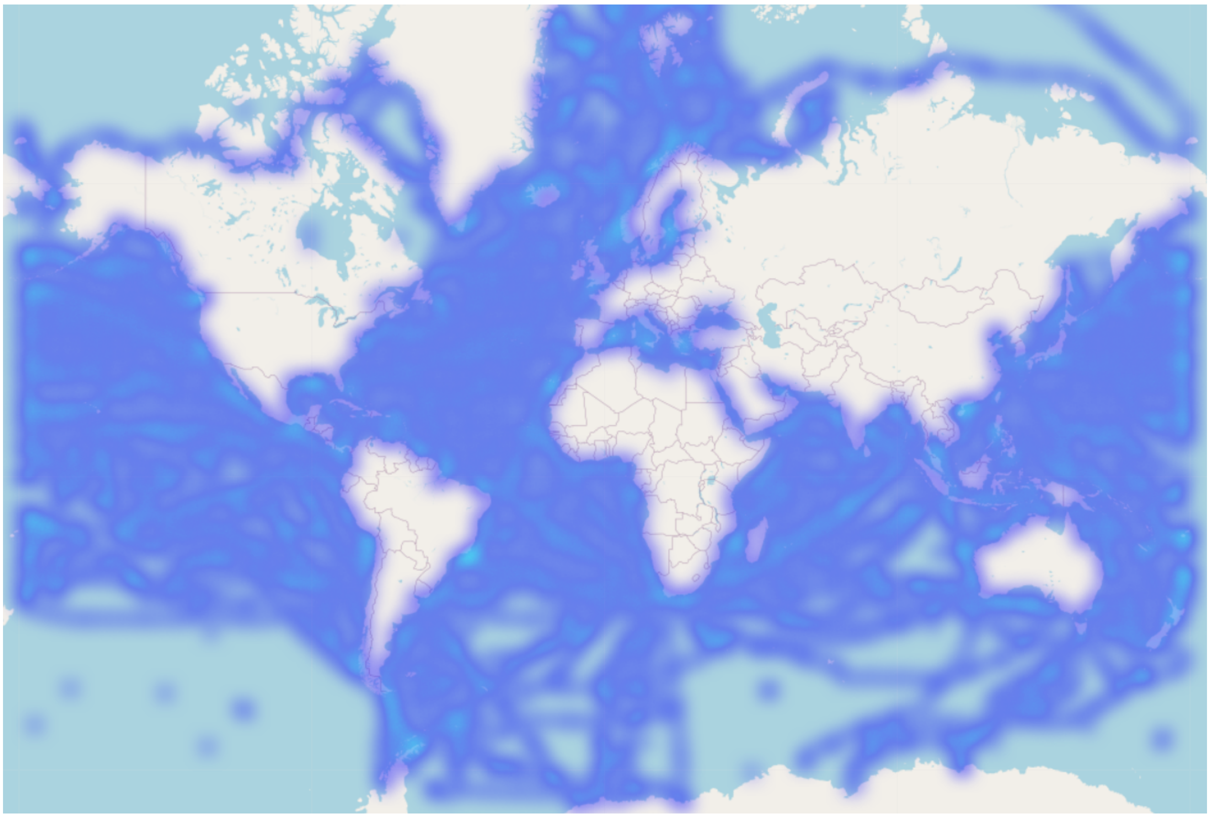

Figure 5.8: Travel paths from January 2019 to October 2023.

Using the location data retrieved from AIS-data we have plotted all the available data points for our selected vessels. Figure 5.8 shows the accumulated travel paths for 1,476 vessels that has components from KM on board from January 2019 to October 2023. It indicates that maritime traffic is relatively evenly distributed across the world's oceans, with the exception of the regions near the polar areas. There are some visible outliers in the AIS data from Figure 5.8. This tells us that there is a chance of inconsistencies in the quality of data. These inconsistencies can be explained the by missing values in the location data, or faulty registrations by the AIS.

The highlighted colors on the map reveal that certain travel routes are more frequented than others. These appear to correspond to the shortest paths between two waypoints, as shown in Figure 5.9, which aligns with the theory presented in the section on ship weather routing. In that section, it is explained that most algorithms used to calculate the cost of a journey favor the shortest path between two waypoints. At the same time, the real travel path presented in Figure 5.8 show that our selection of vessels also travel outside the shortest path in a fairly large degree. This can be explained by the variety of vessel types and their various purposes, represented in our data.

Figure 5.9: Main maritime shipping routes (Port Economics, Management and Policy, 2023).

Further, we aim to examine where breakdowns occurred, distinguishing between components that *failed* and those that were *sustained*. To localise the instances of breakdowns, we took each instance of component replacement and found the corresponding vessel's location on the day of replacement. We have assumed a correlation between the replacement day and the actual occurrence of a breakdown. Given that we might have up to eight locations for a vessel per day, we paired each vessel with its first available location on the replacement date. Due to missing location data for some vessels, we identified breakdown locations for only 7,787 instances across 585 vessels. To compensate for the absence of position data on the replacement date, we adjusted our code to include locations from the previous day. This adjustment expanded our dataset to 9,861 breakdown points across 726 vessels.

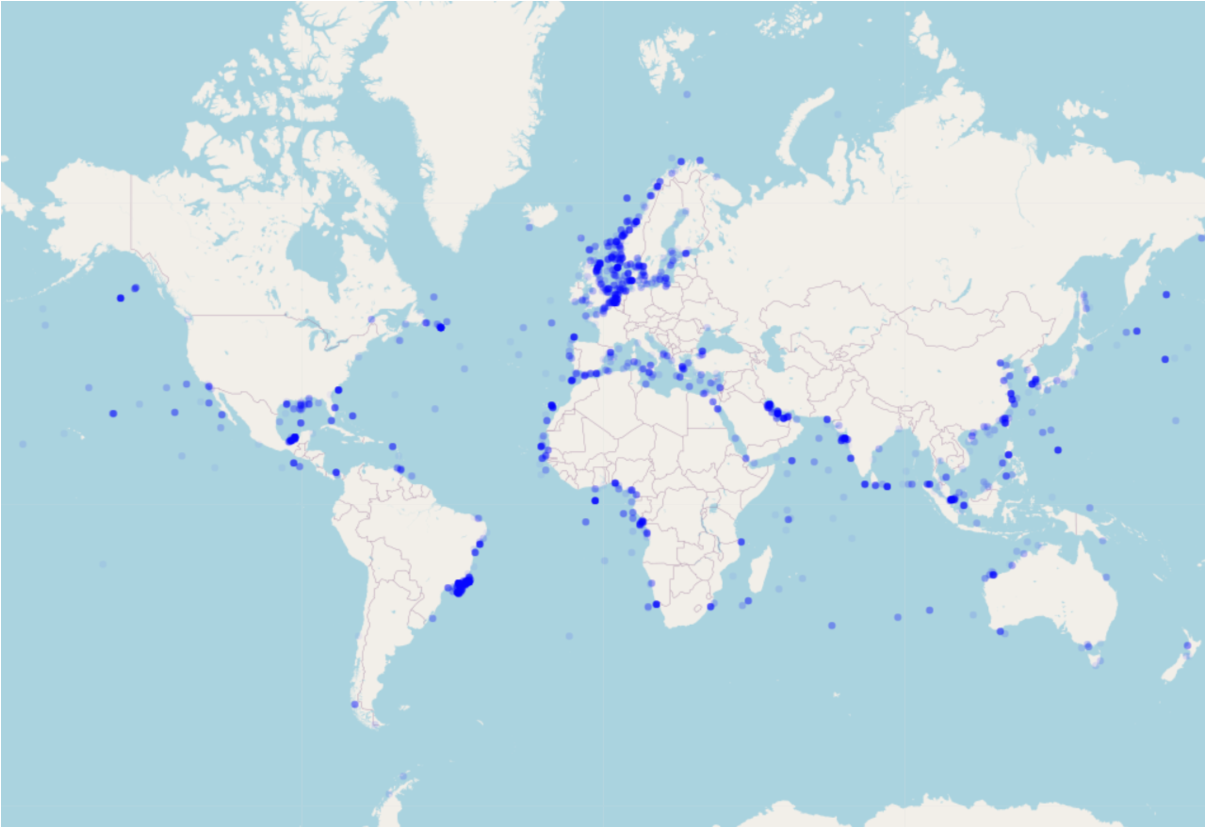

Figure 5.10: Locations for *failed* components.

The next step involved mapping where component *failure* occurred. In Figure 5.10 we see the location for all the *failed* components. From the figure we see that some clustering of *failures* are evident. A majority of them happen close to shore. An example of this is the high density of recorded *failures* in the North Sea, extending towards the Norwegian Sea and along the coast of Norway. This could be explained from the travel paths of our vessels (Figure 5.8), because logically a breakdown will occur where the vessel operate and spend most of its time.

There is also a notably high density of *failures* throughout the English Channel (between England and France) and further down the coast of Africa. A number of hot-spots, with higher number of *failures*, is also worth mentioning. There is one in the south-east coast of Brazil, another one at the east coast of Mexico, and in the middle of the Persian Gulf and the Gulf of Oman. There are also some notable gathering of *failures* near Singapore and close to the coast of Taiwan, China, and Japan. These areas are therefore interesting for further analysis to understand what goes on in these areas.

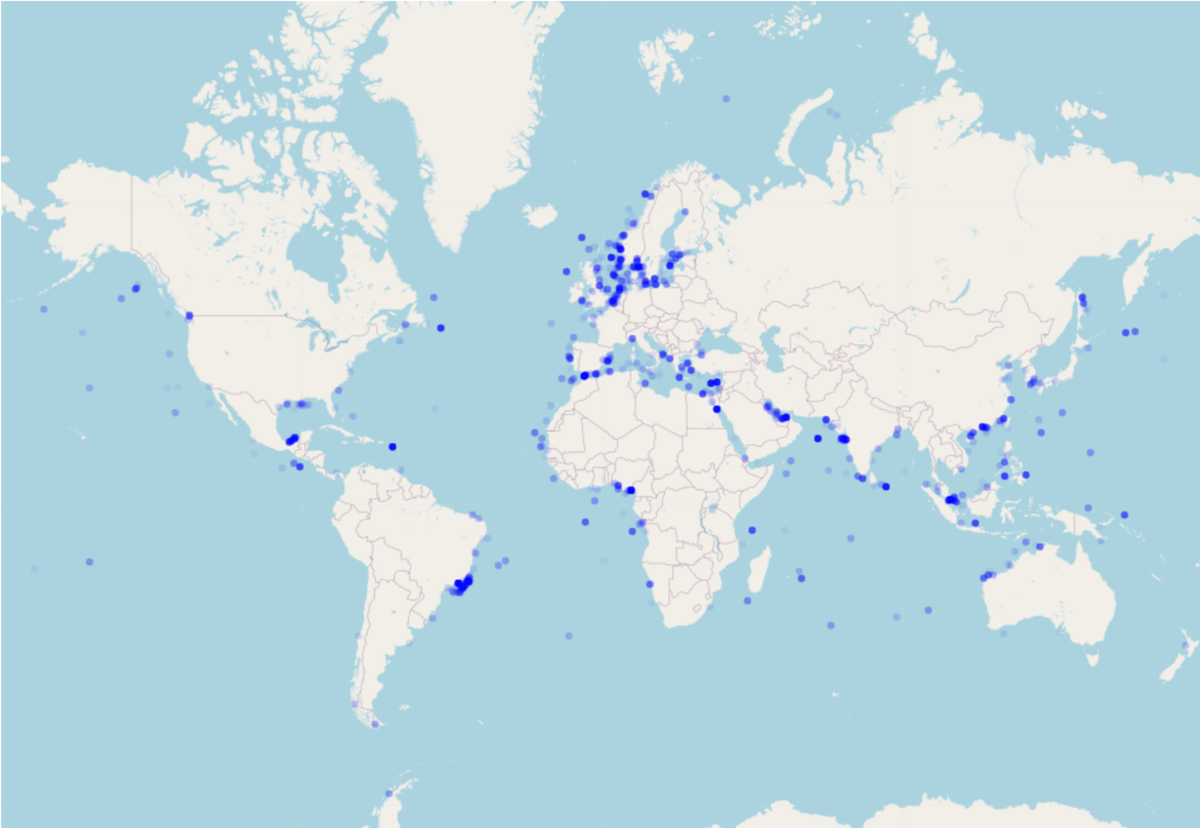

Figure 5.11: Locations for *Sustained* components.

We can see the geographical distribution of the *sustained* components of the replacement date in Figure 5.11. In this figure there is a lower number of total points because of the skewed distribution of components that *sustained* and *failed*. It is harder to interpret anything from a map of break downs on *sustained* components, since the components have already lived past their expected lifetime. Intuitively, the *sustained* components are due to be replaced and also have a higher chance of breaking down at any given moment, compared to a component that has not yet lived their expected lifetime. Nonetheless, a sudden occurrence of adverse weather can still be the decisive moment or a tipping point for a break down regardless of RUL. Since we aim to analyse when a component break down, either if it *sustained* or *failed*, we can still look for correlations with adverse weather situations and breakdowns on *sustained* components.

In summary, there are similar geographical trends in where the *sustained* and *failed* occurrences have gathered. As an additional note, if we compare Figure 5.11 and Figure 5.10 we see that there are a higher number of *failed* components compared to the *sustained* components in the North Pacific Ocean. The same trend can be said to be found north in the Indian Ocean. Further than that, it is hard to identify any immediate difference from the figures, partly due to the skewed occurrences of *failed* and *sustained*.

Upon examining Figure 5.8 for the travel paths, with Figure 5.10 and Figure 5.11, discerning any clear interpretable pattern is also challenging. If the breakdown happened randomly we could expect the breakdowns to be more distributed on the map. On the contrary, the breakdowns do not appear to follow an equally distributed pattern.

Even though it is hard to confirm any pattern in the data, there are notable similarities between the maritime shipping routes in Figure 5.9, and the locations of breakdowns on both *failed* and *sustained* components. This similarity might be explained by the reported date of replacement, which we use to determine the vessels's location.

Figure 5.12: Kongsberg Maritime office locations in the world.

It's possible that the replacement date actually represents the day the vessel reaches a dock and undergoes component replacement. Therefore, it might be more insightful to examine the vessel's location prior to the actual breakdown. The absence of AIS data on the replacement day, as previously stated, could be because the AIS could have been deactivated when the vessel was not in operation, e.g. during docking for component replacement (Marine Traffic, 2023). The breakdown data comes from components sold by KM, increasing the likelihood of vessels being near KM's location due to physical component sales and maintenance. Simultaneously, KM's strategic geographical positioning of their business in high-traffic areas is logical. To more accurately interpret this relationship, a clearer understanding of what the replaced date truly represents in the data is needed.

5.2.3 Seasonal Variations

The gap in the literature on weathers impact on component breakdown is noteworthy and makes weather an interesting factor to explore. The aim of our analysis is to investigate whether weather should be considered as an explanatory variable for the variance in component lifetime, suggesting the need for further analysis.

The weather could potentially affect components in two ways: an immediate effect, where adverse weather conditions lead to abrupt breakdown, and a cumulative impact, where exposure to adverse weather contributes to gradual wear over the component's lifespan. Additionally, these factors may interplay; a component with significant wear may be more prone to sudden breakdown when subjected to harsh weather conditions.

Figure 5.13: Monthly distribution ratio of *sustained* and *failed* components.

To address the immediate effects of weather, we examine the correlations between weather variations and the locations of component breakdowns. Analysing the ratio of *failures* from breakdowns for each month since January 2019, reveals a pattern suggestive of seasonality in the failure rates, as illustrated in Figure 5.13. The seasons that exhibit a higher ratio of component *failures* predominantly occur during the autumn and winter months. However, while the ratio may indicate one trend, the actual count of breakdowns, as depicted in Figure 5.14, is also critical to consider. In this figure, there is a noticeable spike in sustained components in October 2019. Consequently, even though the number of *failures* peaks during this month, the large number of sustained components skews the *failure* ratio, making it appear relatively low when looking at the distribution in percentage (Figure 5.13). Additionally, the variations observed in count (Figure 5.14), may stem from weather-related factors or the scheduling of maintenance services.

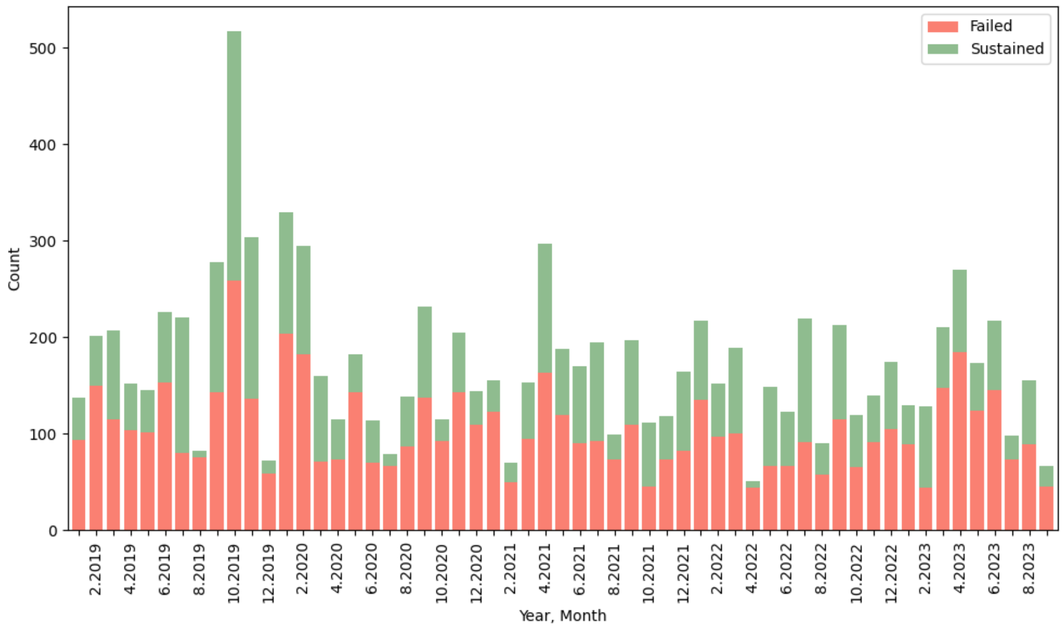

Figure 5.14: Monthly distribution of *sustained* and *failed* components, count.

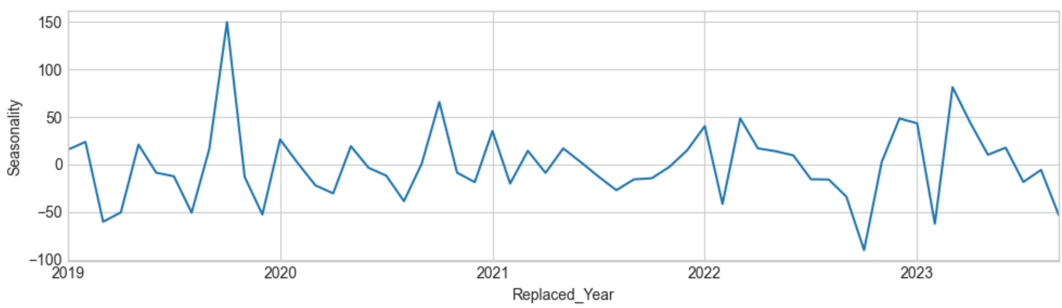

Figure 5.15: Monthly trends in component *failure*, from January 2019 to October 2023.

To further investigate the presence of a trend, we performed a trend decomposition on the *failed* components, as shown in Figure 5.15. From the decomposition, we observe a gentle seasonal pattern with higher occurrences around the turn of the year. The figure reveals seasonal trends in breakdowns, particularly when comparing data from 2019 to 2020. While discerning clear trends for 2023 is challenging, given that our data only extends up to October, the observations suggest that the failure rates for this year may follow a similar pattern to those observed in 2022. However, there are considerable fluctuations in the observed trend.

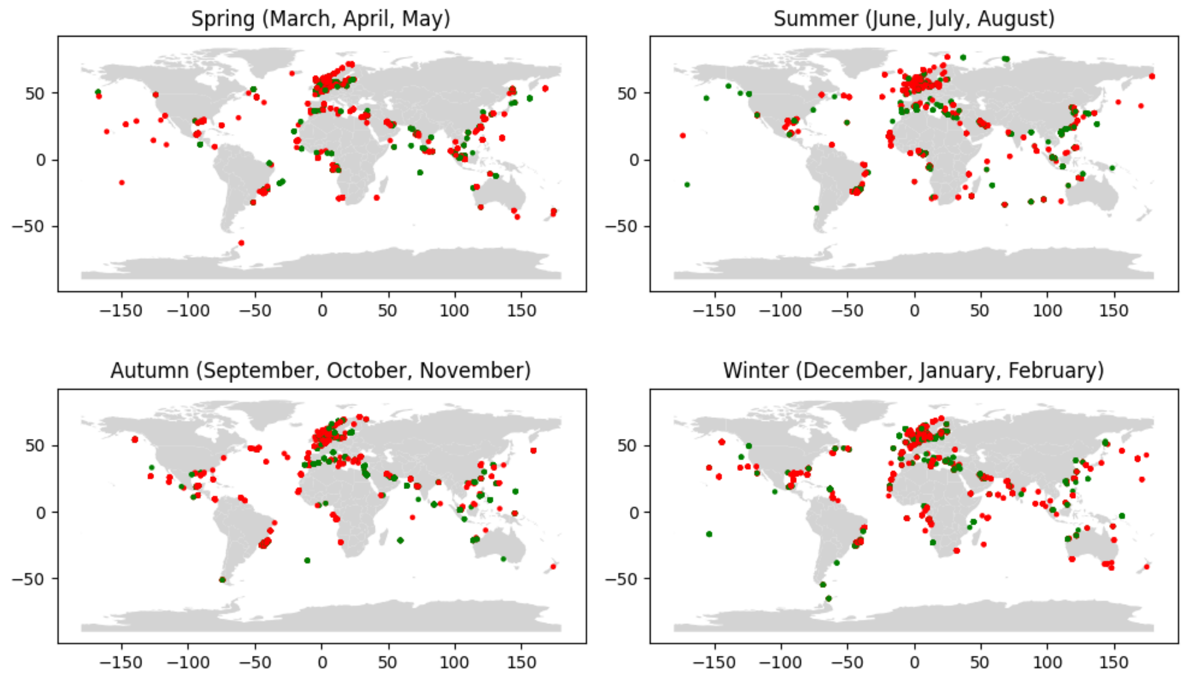

Figure 5.16: Location of breakdowns by season, *sustained* in green and *failed* in red.

To delve deeper into the seasonality, we have made a two-by-two plot displaying the locations of the breakdowns for each season in Figure 5.16. To investigate if the weather have affected the breakdowns we will present figures with heatmaps representing the seasonal weather. Figure 5.17 show the average maximum wave heights, while Figure 5.18 show the wind speeds for each season. The seasonal plots on breakdowns and weather parameters are aggregated from 2019 to 2023. By dividing the breakdowns by season we can see the same trends as in the locations where the components have *failed* or *sustained*, but some areas has more seasonal variations than other.

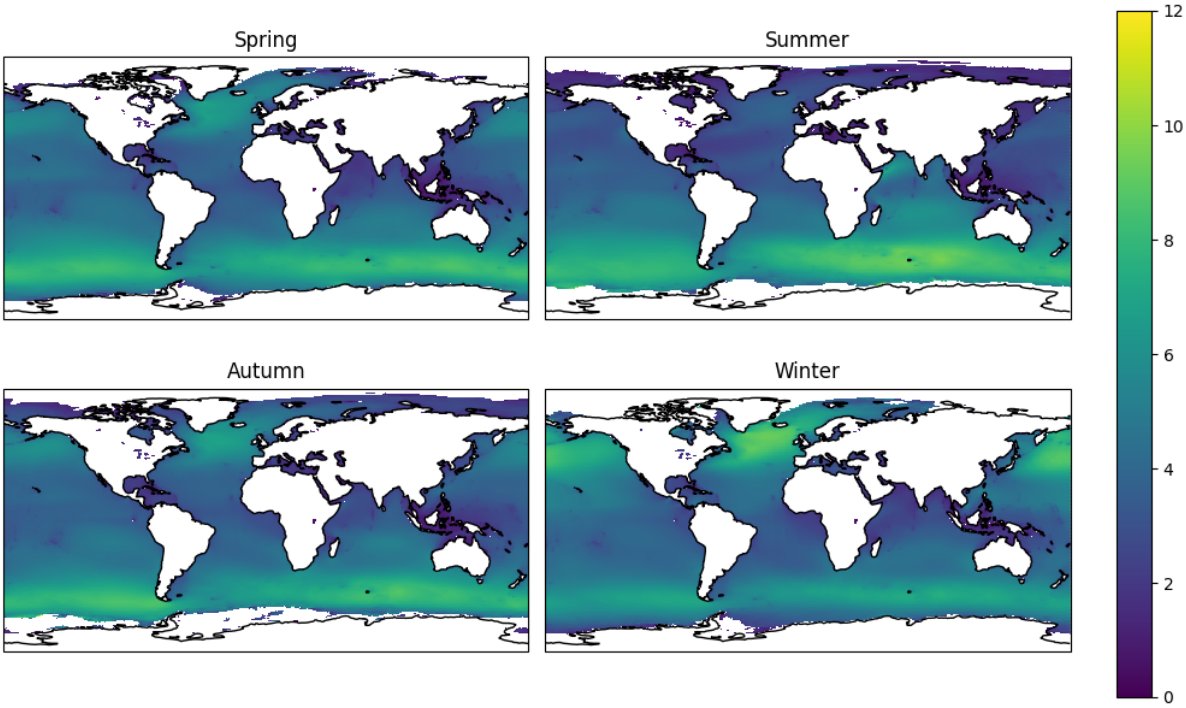

Figure 5.17: Mean of the max wave height (m) by season.

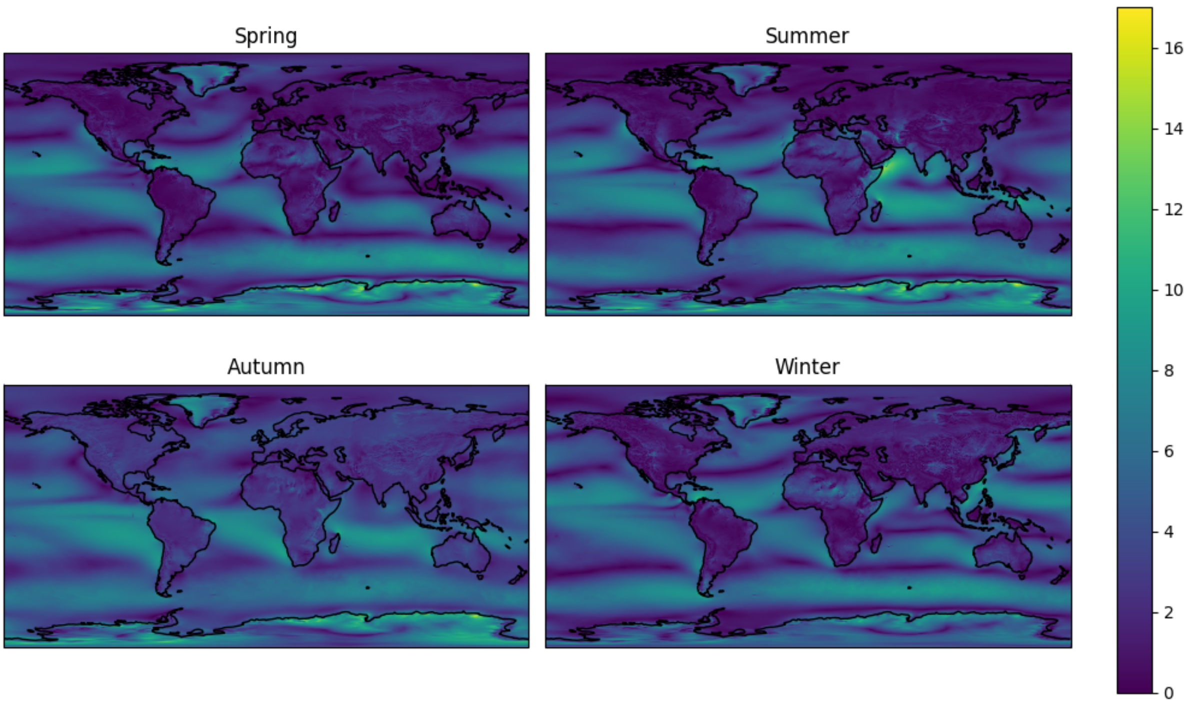

Figure 5.18: Average wind speed (kn) by season.

5.2.3.1 North Pacific Ocean

As mention before there are a higher number of *failed* components in the North Pacific Ocean. When we look closer at the seasonal distribution of breakdowns (Figure 5.16) for this area, we observe an increased frequency of *failures* during the winter and spring. This observation aligns with the fact that the average maximum wave height in this region is at its peak during the winter season, as seen in Figure 5.17. During the spring we do not observe the same level of adverse weather as winter, but there may be correlations between winter weather and proceeding spring breakdowns. Specifically, if the weather was particularly harsh towards the end of winter and a breakdown occurs at the start of spring, this could indicate a connection between the two. Even though the heatmaps indicate less adverse weather in the spring for the Pacific Ocean, this does not rule out the possibility that there have been days with adverse weather during the period that can have affected the breakdowns.

5.2.3.2 North Indian Ocean

Observing the northern Indian Ocean during the summer, in Figure 5.18, there is a noticeable increase in average wind speed compared to the rest of the seasons for this region. A similar pattern is seen with wave height in Figure 5.17. However, when analysing the distribution of breakdown locations, the highest proportion of *failures* for this area occurs in the winter. It does not necessarily imply the absence of any weather-related effects but rather that fewer vessels may have been influenced by these immediate conditions. The heightened occurrence of *failures* during winter could be due to other reasons than weather, but can also be attributed to adverse weather effects, as weather can vary significantly within a season. Our mean representation of weather data may not fully capture these fluctuations, therefore, further investigation is required to make more concrete conclusions.

5.2.3.3 North sea

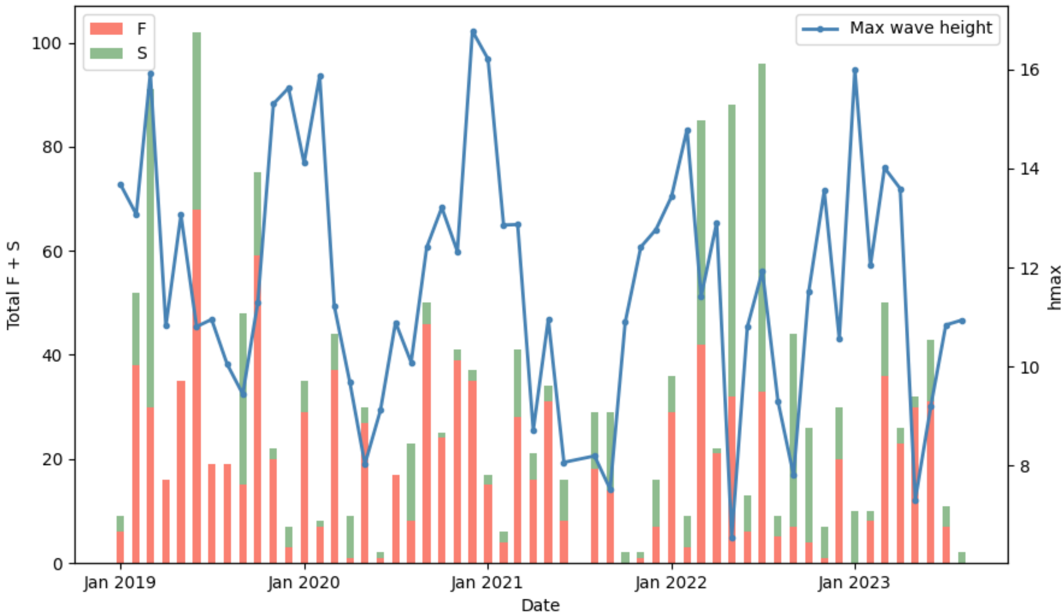

Figure 5.19: Max wave height (m) and *sustained* and *failed* components by month in the North Sea.

It is important to recognise that aggregating weather data over years and seasons can obscure variations. For instance, particularly harsh winters in certain years might elevate the mean value. To determine if the seasonality observed in weather from 2019 to 2023 is representative, we delved into the monthly variations in maximum wave height for the North Sea. Figure 5.19 illustrates both the distribution of breakdowns in the North Sea and the maximum wave height for each month starting from January 2019. From Figure 5.17, showing wave heights in a heatmap, it is evident that winter months typically have the highest wave heights in the North Sea. This trend is consistent in Figure 5.19, where the highest waves are noted during December, January, and February, suggesting that this is a seasonal pattern rather than an anomaly skewing the results.

Figure 5.19 also serves as a practical example to illustrate how challenging it can be to interpret the immediate effect of weather on breakdowns. Even though we have narrowed down the area to the North Sea, it is still a large area that can experience different weather conditions in various locations simultaneously. Therefore, we cannot know with certainty the specific weather conditions to which the vessel has been exposed. Nevertheless, we cannot deny the existence of a relationship, as we do not know for sure what weather conditions the vessel might have experienced prior to the breakdown.

5.2.3.4 Additional Observations

By the east-coast of Mexico there are a fair amount of *failures* in every season, but especially in the autumn and winter. From the heatmaps we do not see large seasonal variations in mean wave height as we can see in other areas. The wind patterns, in Figure 5.18, are quite similar for each season but has some fluctuations, with the winter appearing to be the season with the strongest winds.

By the west coast south in Africa (west to Gabon, Congo and Angola) has an increase in *failures* during the winter time. The heatmaps of wave height do not reflect any seasonal variations for this area. For the heatmaps of the wind speed, we can see a small increase in the mean wind speed during the autumn.

6 Discussion

In the upcoming section, we will aim to broaden our perspective from the analysis and examine our findings within a larger context.

6.1 The Machine Learning Model

From our analysis of the ML model, we determined that DWT, LOA and the year of build are the most effective variables for distinguishing between *sustained* and *failed* components. These attributes, being fixed characteristics of the vessel, are not easily altered. From the perspective of vessel owners, there is limited scope for enhancing a component's lifetime by altering the vessel's size. Although directly influencing a component's longevity is not feasible, implementing price differentiation based on the vessel's size is a viable option. This approach would entail charging vessel owners in accordance with the expected lifetime of the component, which is influenced by the vessel's size, thereby ensuring they pay for the actual value received.

6.2 Descriptive Analysis

In our descriptive analysis, we aimed to identify the immediate effects of weather on component *failure*. The heatmaps reveal a seasonal connection between adverse weather and component breakdowns, but the breakdowns don't exclusively happen for the seasons and areas with the most adverse weather. Because of large fluctuations in weather for each season it is not certain that the vessel has been exposed to the weather we see in the heatmaps, there can be two reasons for this.

The first reason can be the distance the vessel have travelled. The downside of aggregating data on three-month seasons, is that it doesn't capture the vessels mobility and that they can traverse vast distances during this period. Consequently, the weather conditions we analyse may not accurately reflect the specific conditions to which the vessels were exposed to for the time leading up to a breakdown.

The other reason can be due to the voyage and navigation choices done by the vessel operators. As Staveland and Strømsnes (2022) suggests the vessels should chose routes that avoid adverse weather. It is reasonable to assume that vessel operators do not intentionally choose the travel routes with the most adverse weather because of the operational hazards and increase in fuel consumption. This assumption is supported trough the literature review of Zis et al. (2020) and the thesis of Staveland and Strømsnes (2022).

Despite the vessel operator's efforts to avoid unfavorable weather conditions, it's not always feasible to do so. Weather patterns are inherently unpredictable, and even during seasons typically known for milder conditions, unexpected adverse weather can still occur, affecting the vessels.

The weathers inherent unpredictability is a challenge because standard weather forecasts and seasonal predictions may not always capture the nuances and sudden fluctuations within a season (Hasselmann, 1976). For instance, a season generally expected to be calm in a specific ocean region could still experience sudden periods of adverse weather, potentially causing immediate breakdowns.

Given the observable relationship between adverse weather conditions and breakdowns, it is reasonable to hypothesise a link between the long-term effects of adverse weather and the wear of thruster components. Frequent exposure to severe weather can lead to cumulative stress and load on thruster components, potentially accelerating their degradation. The gradual impact of adverse weather on the reliability of the components can therefore be a reason for variety in component lifetime.

A natural extension of the ML model in our thesis would be to incorporate weather variables. We believe that this addition could enhance the model's predictive power, based on insights from our descriptive analysis and the literature. For instance, in the theses of Nilsson and Nilsson (2021) and Staveland and Strømsnes (2022), attempts are made to capture the impact of weather using ML models. They propose that the operational variability caused by weather seasonality should be integrated into decision-making processes.

Another reason to incorporate weather variables into the ML model, which could enhance its predictive power, relates to the interconnected nature of component *failures*, as indicated by Leppänen (2021). Component *failure* is rarely due to a single cause. By increasing the model's complexity to include weather factors, we may better capture the influence of weather on component *failure*.

6.3 Condition Monitoring

Predicting the immediate impact of weather on vessel component breakdowns is challenging. Instead, focusing on the accumulated weather effects over time is more practical. This approach is feasible for components with known weather exposure histories. One of the challenges this arises is the need for having high quality data. This data can be collected through implementing condition monitoring on the vessel. In Knutsen et al. (2014) we have already noted that there is a high percentage of *failures* that follow a random distribution of *failure*. If condition monitoring was implemented, by developing digital twins for the components, we could get an increased understanding of the underlying *failure* patterns. If we can use the data to determine why there is *failure* in the components, we can possibly recalculate the expected lifetime to take into account factors that cause breakdowns.

The implementation of condition monitoring could also be used to determine the weather conditions a vessel has encountered. Continuously monitoring the environmental conditions faced by vessels, in conjunction with the state of their components, allows for a deeper understanding of how various weather conditions contribute to wear on the components. When using condition monitoring you have more information regarding RUL, leading to more efficient planning of maintenance and replacements. The monitoring system can also be used by spare part management department to keep an overview of the conditions of the components. This can further be used in the planning of inventory levels.

6.4 Variability in Component Lifetime

Variations in component lifetime can be linked to differences in maintenance practices, as poorly maintained components may not last as long as those receiving adequate care. Mouschoutzi and Ponis (2022) highlight the significant costs associated with both PM and CM. While CM can be more costly due to interconnected *failures* and potential revenue losses from delays, operators might prefer PM for its long-term cost-effectiveness. This strategy, despite higher initial cost, could prevent expensive breakdowns and downtime. Understanding this variance and quantifying the cost savings of PM over CM could motivate operators to enhance their maintenance routines.

The lifetime of thruster components varies greatly. Understanding the factors behind this variability is crucial, as it enables the development of more durable spare parts and a nuanced pricing strategy. Our analysis indicates that weather exposure and physical vessel characteristics influence the component's lifetime.

7 Conclusion

In this section we will revisit our research question and draw a conclusion based on the findings in this thesis. The research question we have explored are as follows:

What thruster and vessel characteristics can distinguish the components that sustain its expected lifetime?

How does the weather affect the variability in the lifetime of thruster components?

7.1 Conclusion

To address the first research question we built a ML model on thruster and vessel characteristics. Based on our ML model the best characteristics to differentiate components that *sustain* their expected lifetime are based on physical vessel characteristics. These vessel characteristics are DWT, LOA and the year of build. The explanatory power of DWT and LOA is supported in the theory related to added resistance. We found a low importance in the features related to the thruster components in the ML model. The overall accuracy of the model was 83.83% with performance metrics that support that the model performs well.

To determine how weather affects the variability of component lifetimes, we analysed component breakdowns on maps and compared them to seasonal weather patterns. It was challenging to identify a direct connection between breakdowns and weather conditions. However, we observed some patterns suggesting that weather may impact the variability in component lifetimes. We believe that a number of factors contribute to this variability. To conclusively attribute breakdowns to weather, we need greater certainty that other potential causes of breakdowns are not present in our data and analysis.

7.2 Robustness

We want to comment on the thesis reliability, validity and potential weaknesses to establish the quality of our research. The breakdown data have been shared with us from KM, a large company within the maritime industry. Nevertheless, the analysis done on the data is performed without any restrictions from the company. The validity of the data may be influenced by the fact that it has gone through merging processes. Other threats to validity stems from the temporal distribution of data that can threaten internal validity due to instrumentation. That is if the way to measure data and collect has changed over time (Saunders et al., 2019). Still, we have performed cleaning and filtering of the data that aim to make the data representative and measurable for the purpose of our thesis.

7.3 Further Research

This research opens avenues for extended analysis. Future studies could focus on quantifying the cumulative effect of weather on component durability, offering a more definitive stance on its impact on component *failure*. Additionally, predicting component lifetime in years by analysing the vessels and thrusters characteristics, alongside cumulative weather effects could yield interesting insights. There's also potential in enhancing lifetime predictions of thruster components, balancing economic considerations for both suppliers and buyers.

This thesis has already established that there is a variance in the lifetime of components. To increase insight to what factors cause this variance could help companies to develop precise estimations of expected lifetime. This also aids in accurately valuing components for pricing strategies. We recommend starting this investigation with operational data for the given components, such as temperature, load, and RPM.

Investigating vessel travel routes and breakdown hot-spots could aid in optimising logistics for spare parts. For instance, analysing areas with high vessel traffic but limited service presence could be beneficial for companies like KM in planning strategic service locations. One example of a high traffic area is the hot-spot we found in Brazil during the analysis, where KM is not yet located. This approach could significantly improve maintenance efficiency and component sales in high-demand zones.

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Appendices

A Data and Cleaning

In this appendix you find supplementary figures and tables related to the cleaning of the data.

Column	**Non-Null Count**	**Dtype**
Configuration	214394 non-null	object
VesselDesc	214394 non-null	object
IMONo	214394 non-null	int64
Sub System	214394 non-null	object
SubSystemItem	214394 non-null	object
SubSystemItemDesc	214394 non-null	object
Item	214394 non-null	object
ItemDesc	214394 non-null	object
Expected_LifeTime	214191 non-null	float64
PRODUCT_ID	214394 non-null	object
FAMILY	214394 non-null	object
SIZE	214394 non-null	int64
CONFIGURATION	213381 non-null	object
DESIGNATION	214357 non-null	object
Installation_Year	203615 non-null	datetime64[ns]
Replaced_Year	50753 non-null	datetime64[ns]
var_match	214394 non-null	object
ServiceOrder	50906 non-null	object
LineNumber	50906 non-null	float64
Qty	214394 non-null	int64

Table A.1: Dataframe structure.

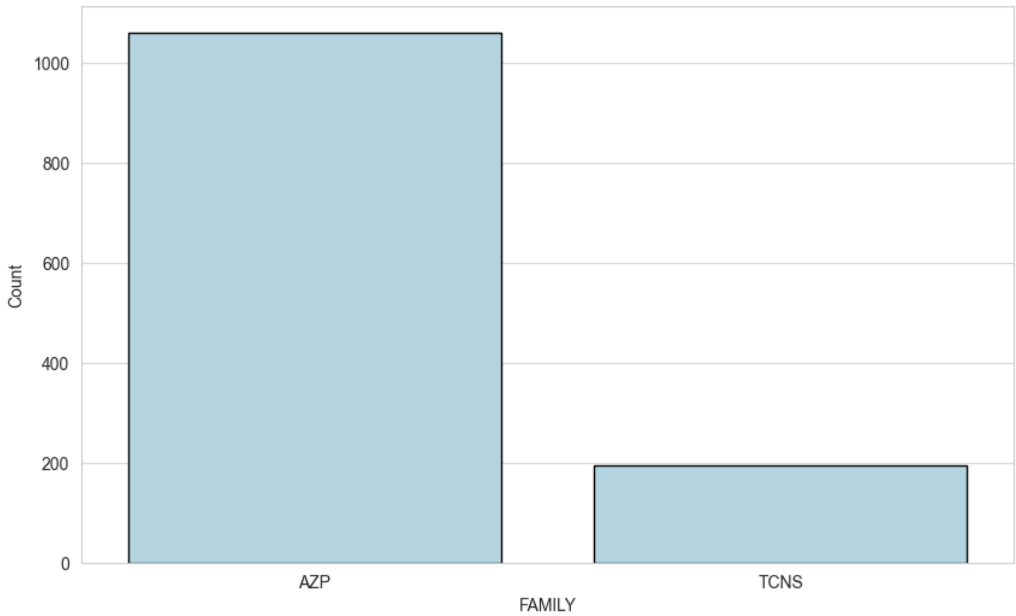

Figure A.1: Distribution of AZP & TCNS in the raw data.

Column	**Missing Count**
Expected_LifeTime	203
CONFIGURATION	1013
DESIGNATION	37
Installation_Year	10779
Replaced_Year	163641
ServiceOrder	163488
LineNumber	163488
Days_Difference	163641
Year_Difference_float	163641

Table A.2: Columns with missing values for all TT.

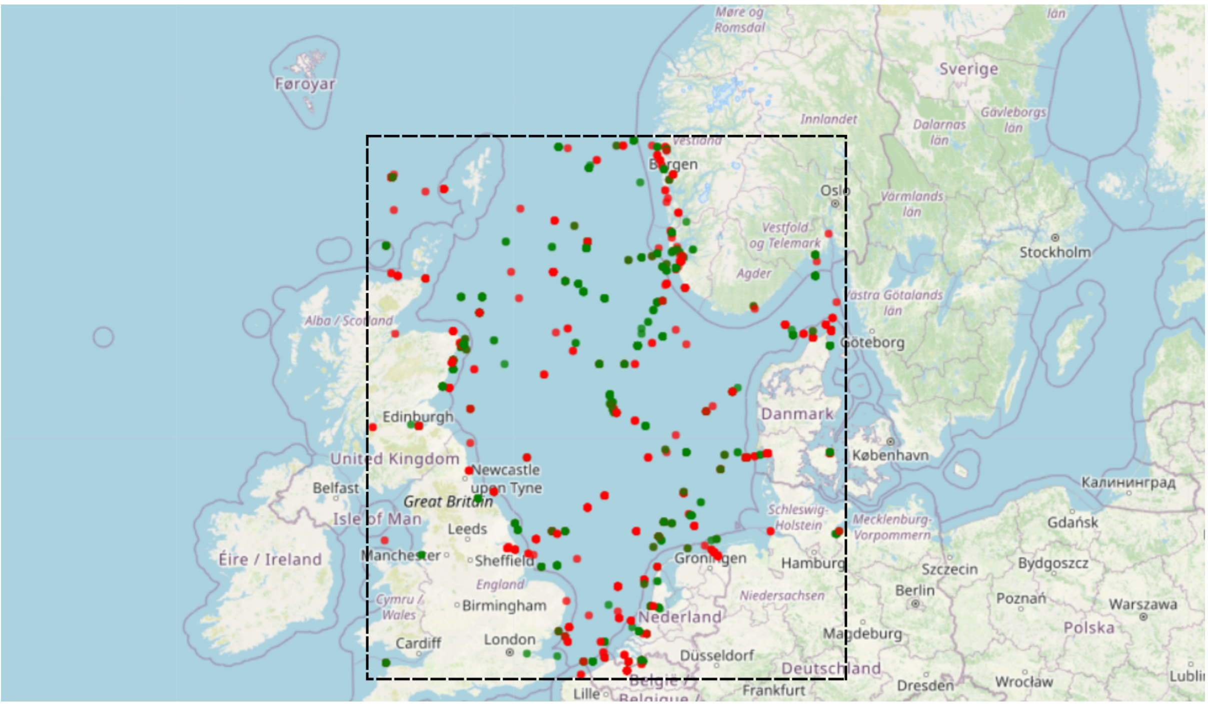

Figure A.2: Selected area in the North Sea and corresponding breakdowns.

B Tuning of the Random Forest model

We applied Random Hyperparameter Tuning using the RandomizedSearchCV method in Python. First we ran the random forest classifier from Scikit-Learn with the default settings. The default settings bootstraps 100 trees considering all features in every tree. It also has no boundary for the depth of the tree. To try to make the model better, we tuned the parameters. First by using RandomizedSearchCV that takes a range of new values for the parameters and chooses some at random to go through. This returns a narrower range for each hyperparameter. In our case we fitted 3 folds for each of 100 candidates, totalling 300 fits. That gave us these parameters: n estimators: 1800, min samples split: 10, min samples leaf: 1, max feature': 'log2', max depth: 30 and bootstrap: False. Based on these values we made a new search, but now with GridSearchCV, this runs through all the specified combinations (not selecting just selection at random). with the GridSearchCV we fitted 3 folds for each of 270 candidates, totalling 810 fits. In return we got these parameters: bootstrap: False, max depth: 20, max features: 'log2', min samples leaf: 1, min samples split: 10, n estimators: 1800. The results from using these parameters is shown in the table below.

Table B.1: Classification report.

	Precision	Recall	F1-score	Support
0	0.87	0.92	0.89	6966
1	0.73	0.63	0.67	2496
Accuracy			0.84	9462
Macro avg	0.80	0.77	0.78	9462
Weighted avg	0.83	0.84	0.84	9462

Before tuning the model the accuracy of the model was 0.8383. After the tuning the accuracy of the model was: 0.8394. The tuned model used a lot more compute than the original model, and had only slight improvements. Therefore we used the original model for our predictions.

C Descriptive Statistics and Analysis

C.1 Mean Time Before Failure

The MTBF is a common metric for measuring the reliability of components. In this appendix we present the calculated MTBF for each of the thruster components in the filtered breakdown data used in the analysis.

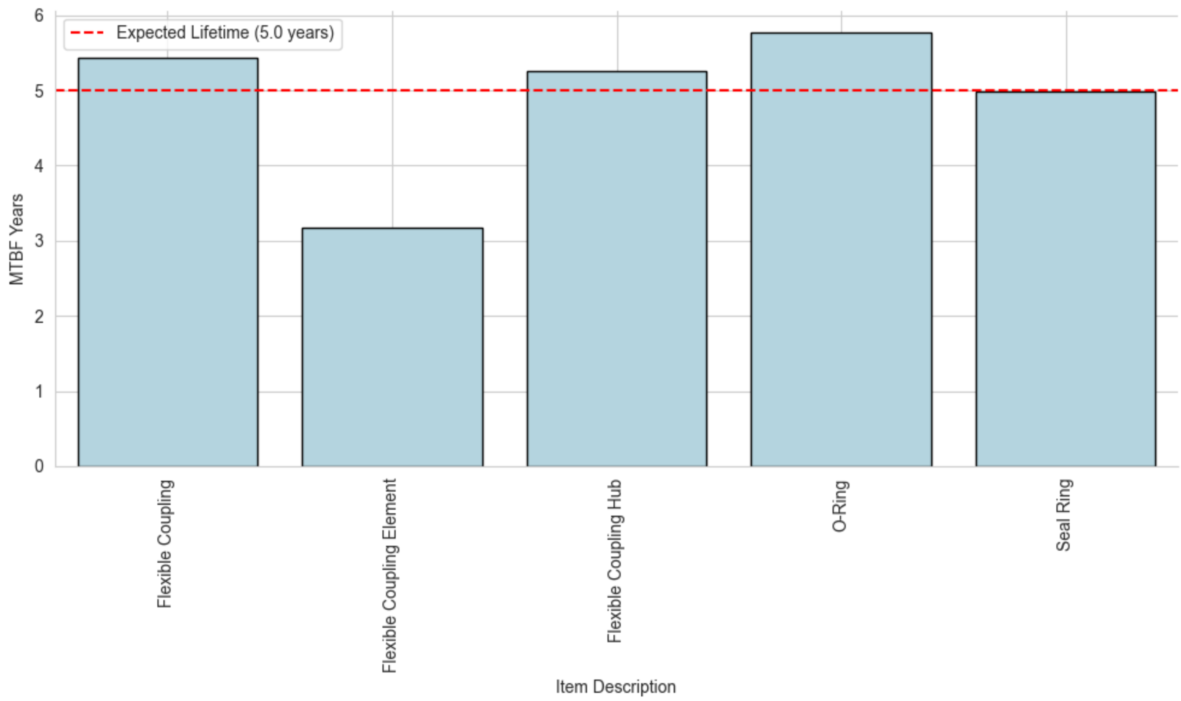

Figure C.1: MTBF for components with 5 years expected lifetime.

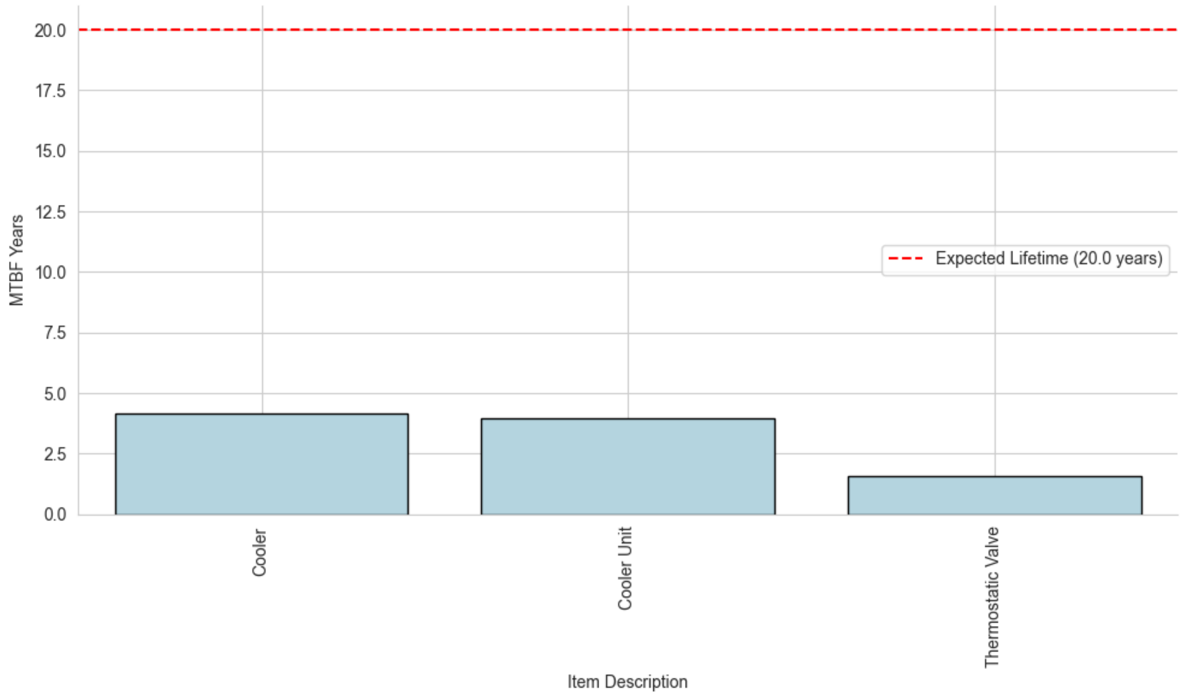

Figure C.2: MTBF for components with 20 years expected lifetime.

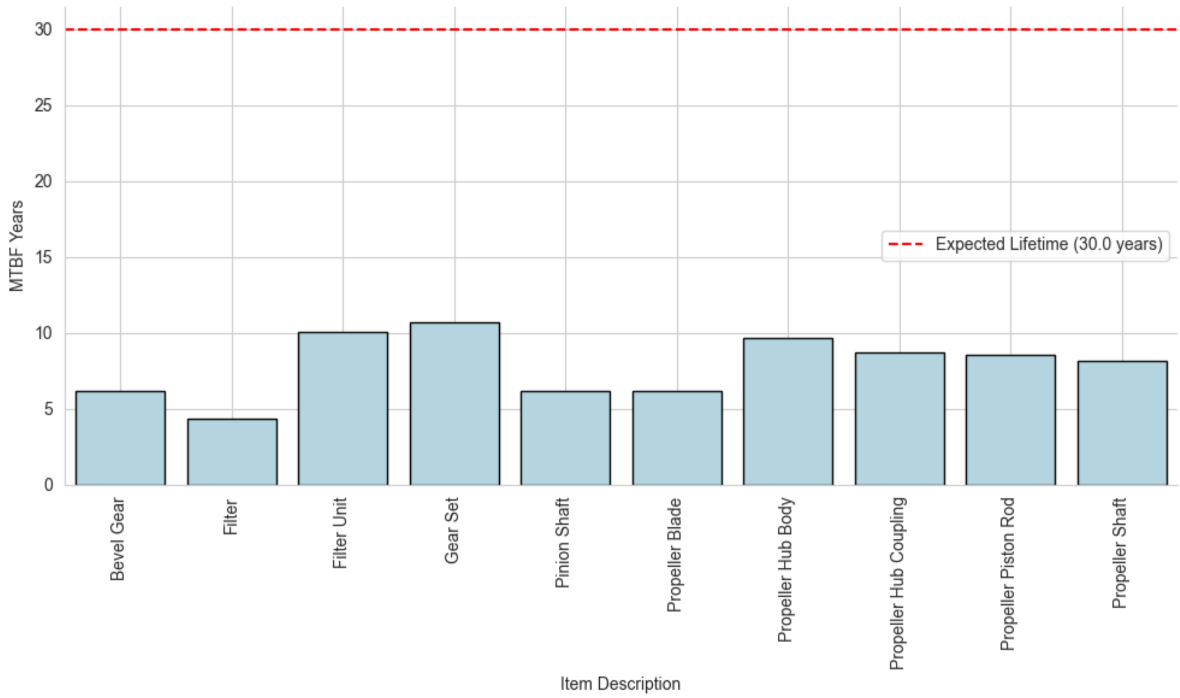

Figure C.3: MTBF for components with 30 years expected lifetime.

C.2 Variance expected lifetime

Below are the variance of the operational times for the expected lifetime of 20 and 30 years.

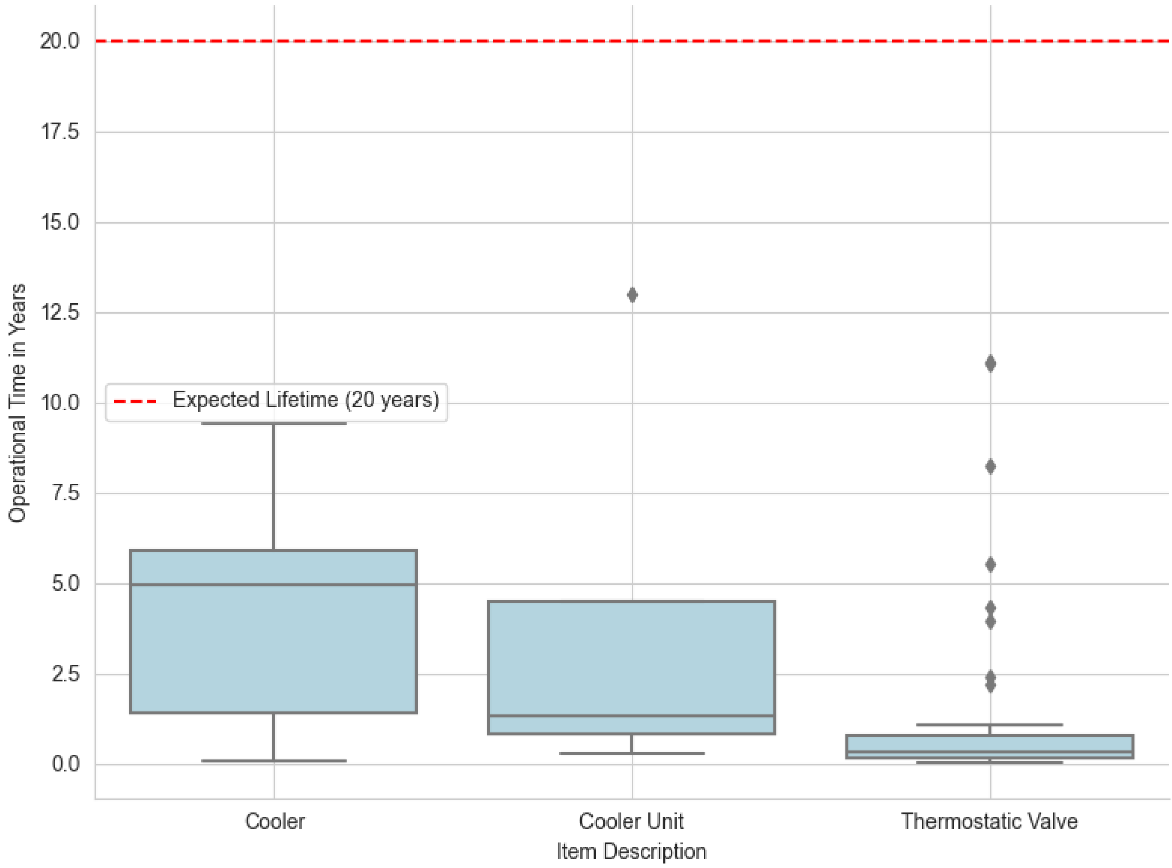

Figure C.4: Variance in lifetime for components with 20 years expected lifetime.

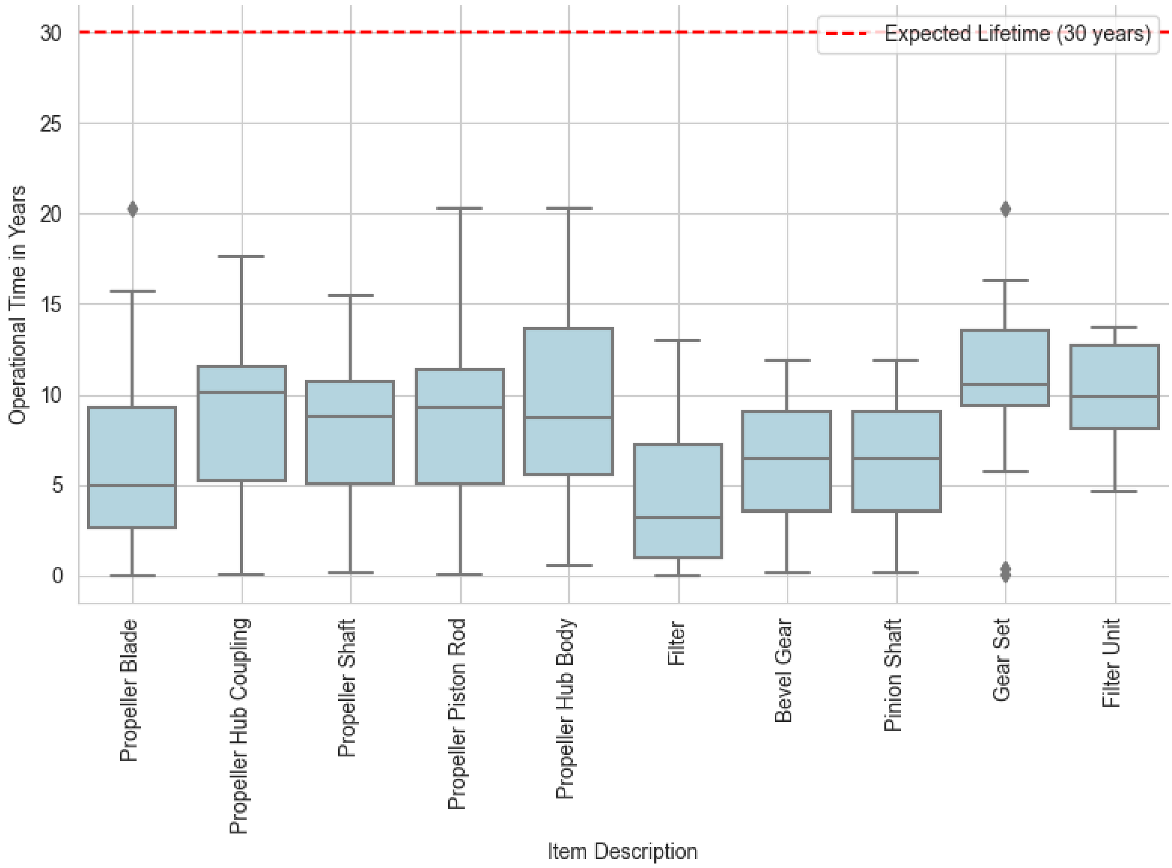

Figure C.5: Variance in lifetime for components with 30 years expected lifetime.