A Compound Novel Data-Driven and Reliability-Based Predictive Maintenance Framework for Ship Machinery Systems

Authored by

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Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: Michail Fragkiskos Cheliotis

Date: 12/10/2020

"Don't try"

Charles Bukowski (1920 - 1994)

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To friends and family, made, kept and lost

Research Output

Journal Papers

Michail Cheliotis, Iraklis Lazakis, and Gerasimos Theotokatos (Nov. 2020). "Machine learning and data-driven fault detection for ship systems operations". In: *Ocean Engineering* 216, p. 107968. ISSN: 00298018. DOI: `10.1016/j.oceaneng.2020.107968`. URL: `https://linkinghub.elsevier.com/retrieve/pii/S0029801820309203`

Michail Cheliotis, Iraklis Lazaks and Angelos Cheliotis. (Dec. 2019). "Developing a Combined Bayesian and Machine Learning-Based Diagnostic Framework for Ship Systems Applications". In: *Ships and Offshore Structures*. **Under review**

Michail Cheliotis et al. (Sept. 2019). "A novel data condition and performance hybrid imputation method for energy efficient operations of marine systems". In: *Ocean Engineering* 188. ISSN: 00298018. DOI: `10.1016/j.oceaneng.2019.106220`

Conference Papers

Michail Cheliotis and Iraklis Lazakis (2018). "Ship machinery fuzzy condition based maintenance". In: *Smart Ship Technology 2018* Ed. by RINA. London:

Royal Institute of Naval Architects. ISBN: 9781909024632

Michail Cheliotis and Iraklis Lazakis (2015). "Assessing key reliability and criticality aspects of ship systems for improved energy efficiency". In: *SSC 2015: Shipping in Changing Climates Conference 2015.* Glasgow: University of Strathclyde

Michail Cheliotis, Eirini Tryvyza, et al. (2016). "Project AUTONOMAD : The design of an unmanned coast guard vessel integrating the use of drones for emission regulation enforcement and territorial water protection in the Mediterranean". In: *MSO 2016: Maritime Safety and Operations.* Glasgow: University of Strathclyde

Invited Presentations

Michail Cheliotis (2017). "Maintenance and reliability assessment for enhanced safety and energy efficiency". In: *University of Strathclyde Annual SNAME Symposium.* Glasgow: University of Strathclyde

Michail Cheliotis (2018). "Ship Machinery Fuzzy Condition Based Maintenance". In: *University of Strathclyde Annual SNAME Symposium.* Glasgow: University of Strathclyde

Michail Cheliotis (2019). "Making Sense of Data for Maintenance in the Maritime Industry". In: *University of Strathclyde Annual SNAME Symposium.* Glasgow: University of Strathclyde

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Acronyms

AI	Artificial Intelligence.
ANN	Artificial Neural Networks.
APE	Absolute Percentage Error.
BCM	Business Centered Maintenance.
BN	Bayesian Network.
BWTS	Ballast Water Treatment System.
CBM	Condition Based Maintenance.
CL	Center Line.
CM	Corrective Maintenance.
CUMSUM	Cumulative Sum.
DA	Data Analytics.
DAQ	Data Acquisition.
DBSCAN	Density-BasedSpatial Clustering of Applications with Noise.
DS	Data Science.
EB	Expected Behaviour.
EU	European Union.
EWMA	Exponentially Weighted Moving Average.
FD	Fault Detection.
FMEA	Failure Modes Event Analysis.

FMECA	Failure Modes Event and Criticality Analysis.
FO	Fuel Oil.
FR	Failure Rate.
FT	Fault Tree.
FTA	Fault Tree Analysis.
GDP	Gross Domestic Product.
GHG	Green House Gas.
HE	Hard Evidence.
IGG	Inert Gas Generator.
IM	Importance Measures.
IMO	International Maritime Organisation.
IoT	Internet of Things.
LCL	Lower Control Limit.
LNG	Liquefied Natural Gas.
LO	Lubricating Oil.
MAPE	Mean Absolute Percentage Error.
MCS	Minimal Cut Sets.
ME	Main Engine.
MGE	Main Generating Engine.
MICE	Multiple Imputation by Chained Equations.
ML	Machine Learning.
MRV	Monitoring Reporting and Verification.
MTBF	Mean Time Between Failures.
NN	Nearest Neighbours.
OEE	Overall Equipment Effectiveness.
OLS	Ordinary Least Squares.
OREDA	Offshore and Onshore Reliability Data.
PdM	Predictive Maintenance.

PM	Preventive Maintenance.
RA	Reliability Assessment.
RBD	Reliability Block Diagrams.
RCM	Reliability Centered Maintenance.
SVM	Support Vector Machine.
TC	Turbocharger.
TPM	Total Productive Maintenance.
UCL	Upper Control Limit.
VE	Virtual Evidence.

Abstract

Shipping is a major driving force of the global economy, as seen by the 90% of the volume of the yearly trade transported by ships. As a result, shipping has a significant financial, environmental impact. Maritime maintenance can be used to safeguard shipping's impact by improving safety and avoiding accidents. This is especially true, when considering that nearly 22% of all the accidents between 2011 and 2017 were attributed to improper maintenance. Consequently, maritime maintenance can be used as a hazard mitigation tool, improve ship safety by reducing accidents. Modern maritime maintenance is best applied through predictive maintenance schemes, which take advantage of the developments of Shipping 4.0. Under this scope, the goal of this thesis is the development of a compound novel data-driven and reliability-based predictive maintenance framework for ship machinery system. The novel framework tackles the areas of maritime predictive maintenance holistically by addressing the topics of critical equipment selection, data preparation, fault detection and diagnostics. Each of the framework's topics are developed in individual methodologies and assessed in unique case studies demonstrating their effectiveness in the respective tasks. Initially, the methodology for the critical equipment selection includes the novel combination of Fault Tree Analysis with data clustering for the identification of critical equipment, as applied in the case of an LNG Carrier. As a result, the most critical components are identified by taking into account reliability indices and repair costs for the considered components. Identifying critical components im-

proves safety, as it focuses the maintenance efforts in items whose failures can have economic consequences and safety implications. Next, the methodology for the data preparation is developed, which includes the novel integration of the kNN and MICE algorithms for the imputation of missing data. Combining these two algorithms allows for the novel integration a data-driven approach with domain knowledge in a single imputation model. The imputation methodology is applied in the case of a Chemical Tanker, showcasing the effectiveness of the novel method against a pure MICE and pure kNN approach. The treatment of missing values can improve ship safety, as it safeguards information contained within datasets and leads to more accurate condition assessing models. Following that, a novel Fault Detection methodology is established based on Expected Behaviour models, using Machine Learning, and Exponentially Weighted Moving Average control charts. This methodology aims at detecting developing faults in their early stages while avoiding the shortcomings of black-box approaches and having reasonable data requirements for training. Lastly, the diagnostics methodology is formed, which includes the novel integration of pre-processing and Machine Learning-based Fault detection with a diagnostic network using Bayesian Networks. The resulting methodology can identify the root cause of a detected fault, without using black-box Neural Network approaches, nor complicated and time-consuming physics-based models. Even though the Fault Detection and diagnostics methodologies are developed individually, they are both evaluated in the same case of a Bulk Carrier. The use of the same case study was dictated by restrictions in collecting additional data and by the use of the output of the Fault Detection methodology in the diagnostics. The detection of developing faults and the identification of their root-cause has a profound effect on ship safety, while also allowing for targeted maintenance actions.

Chapter 1

Introduction

1.1 Chapter Overview

This chapter presents the essential background information required for the establishment of the present thesis. Also, this chapter presents the direction of this work in terms of the research question, the aim and objectives. A brief outline of the different chapters alongside with an indication of their content is also given.

1.2 Maritime Industry Basics

Shipping has been crucial to the development and evolution of the global trade and economy. It helps to transport people and commodities across the globe and allows for the facilitation of commerce between nations. Shipping can form the backbone of a nation's economy, as it can create numerous streams of revenue and employment. The performance of seaborne trade is a proxy of the performance of the global economy, as it tends to mimic the cycles of the world's Gross Domestic Product (GDP) (Stopford 2018; IUMI 2018).

Seaborne transport is one of the most cost-effective ways of carrying commodities, due to the economies of scale. Notably, for the last half-century, shipping has been carrying approximately 90% of the volume and 70% of the value of the global trade (UNCTAD 2018b). These values are even higher in developing countries, where air and land transport options are as common.(UNCTAD 2018b). During the relatively same period, the amount of cargo carried from shipping has increased by approximately 8'000 million tons (UNCTAD 2017). Keeping in line with the positive overview of shipping, its future remains bright as seen by the 2.6% and 4% volume increases in 2016 and 2017 respectively (UNCTAD 2017).

The structure of the world fleet can influence its overall performance and trends. Notably, at the beginning of 2018, the world fleet consisted of 94'171 ships, as a result of the 3.7% dead-weight increase in 2017. In terms of ship types, the world fleet consists predominantly of dry bulk carriers and oil tankers. In detail, in 2018 the world fleet comprised of 42.5% of dry bulk carriers, 29.2% of oil tankers, 13% container ships, 4% cargo ships and 11% of other types, as seen in Figure 1.1 (UNCTAD 2018b). Moreover, from the 11% of other ship types, 37% of them were offshore vessels, 29% gas carries (e.g. Liquid Natural Gas carriers) and 20% chemical tankers, as seen in Figure 1.2 (UNCTAD 2018b).

In terms of the vessels' age, in 2018 the average age of the world's fleet was 20 years, with that number being higher for developing countries. In general, the average age of the world fleet has been increasing since 2016 as a result of a decrease in the number of new ship deliveries (UNCTAD 2017). The prevailing age group for bulk carriers includes vessels aged between 5 and 9 years old, representing 41% of the bulk carrier fleet, according to Figure 1.3. Similarly, the prevailing age group for oil tanker includes vessels aged over 20 years old, representing 38% of the oil tanker fleet, according to Figure 1.4 (UNCTAD 2018b).

Considering the increased age of the predominant ship types, maintenance is becoming an ever more important issue for tankers and bulk carriers, in order to avoid failures and accidents. This principle also applies to the remaining fleet,

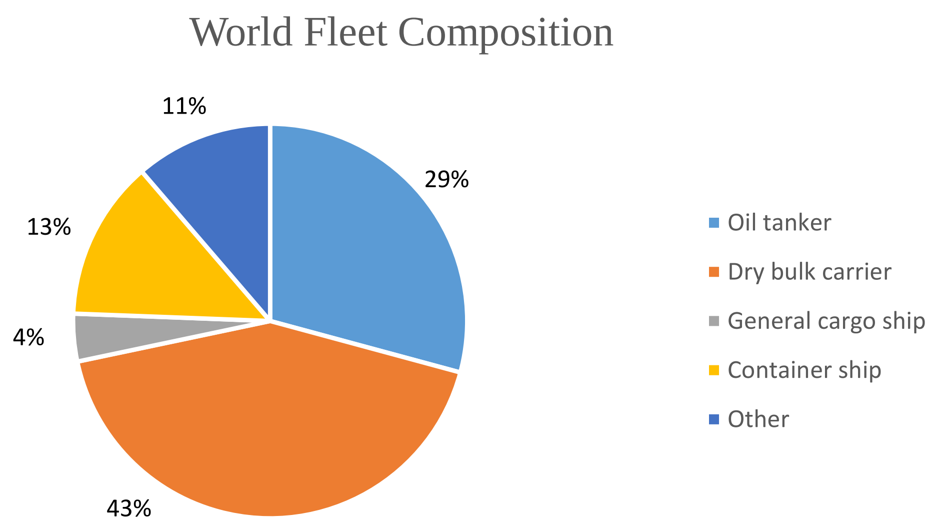

Figure 1.1: Overview of the world fleet by ship type, adopted from (UNCTAD 2018b)

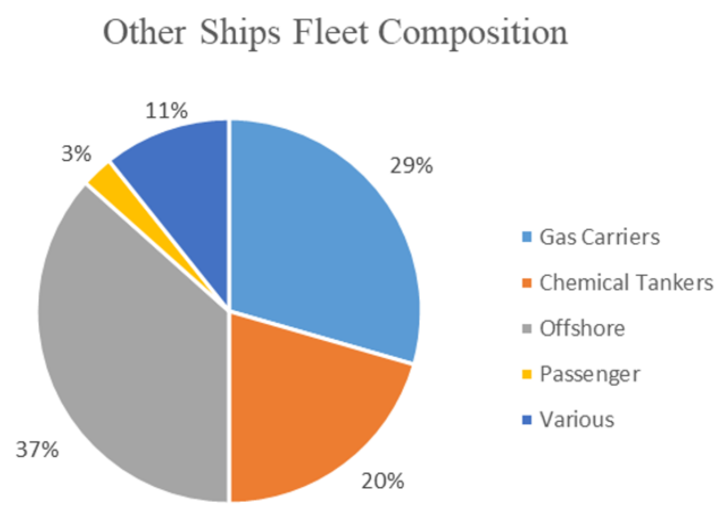

Figure 1.2: Overview of the remaining ship types of the world fleet, adopted from (UNCTAD 2018b)

considering its rising age and the already high average age of its vessels. In other words, maintenance can be used to prevent failures and reduce the likelihood of maintenance related accidents, especially for order vessels, as further discussed in the following sections. Under that scope, maintenance is required to ensure that

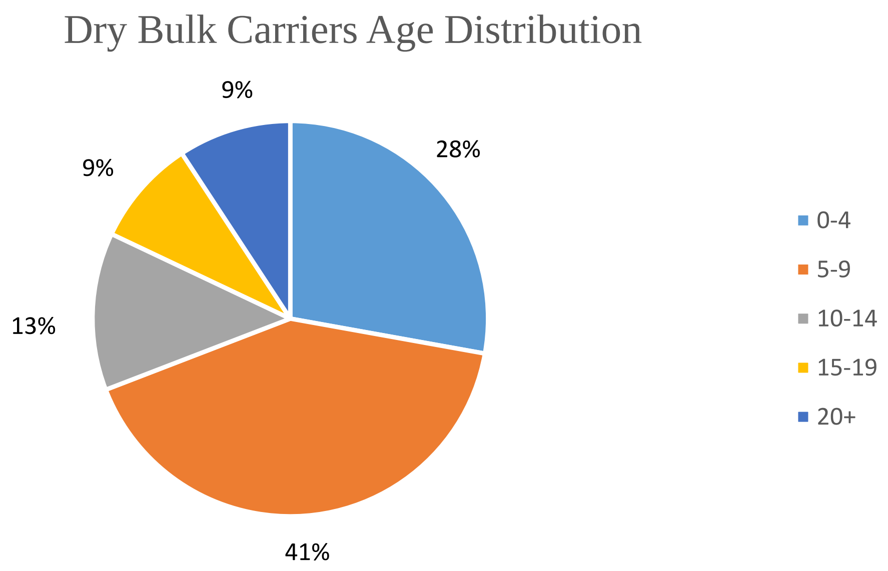

Figure 1.3: Bulk carriers age distribution, adopted from (UNCTAD 2018b)

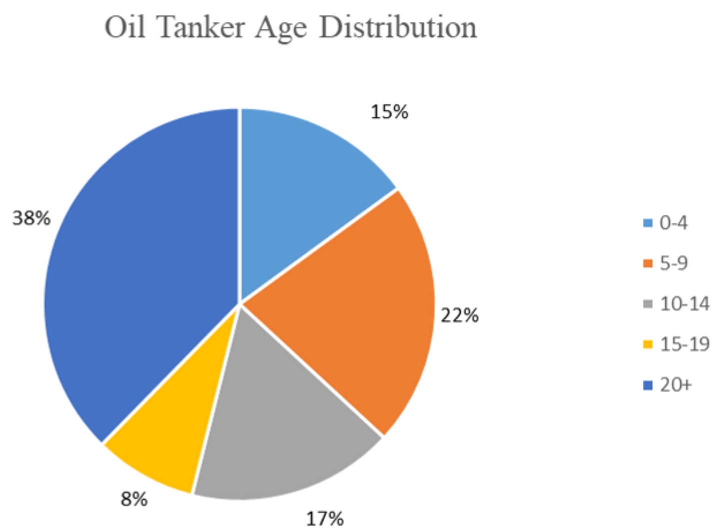

Figure 1.4: Oil tankers age distribution, adopted from (UNCTAD 2018b)

the world fleet continuous its prosperous trends by maintaining its functionality and reliability (Zhang and Wang 2014).

The development of shipping has transformed developing countries, especially in Asia, to crucial parts of the global supply chain. Even though this has had a positive impact on the economy of these countries, it has also increased the global demand for reliable shipping operations. The same requirements for increased reliability in shipping have also been introduced by the evolution of the just-in-time economies of the developed world (UNCTAD 2018a). Therefore, maintenance can safeguard reliable shipping operations by reducing the likelihoods of accidents, which can disturb supply chains and sensitive just-in-time economies.

1.3 Impact of Shipping

1.3.1 Financial Impact

As demonstrated in the previous sections, the impact of shipping in the global economy is unquestionable. Notably, in 2015, the European Union (EU) shipping industry employed 640'000 people, with salaries above the European average. This translates to €57 billion direct contributions to the EU's GDP. When considering the indirect benefits, the EU shipping industry in 2015 contributed €140 billion to the EU's GDP (Oxford Economics Ltd 2017).

Proper ship maintenance safeguards the profit-making capabilities of vessels and improves their profitability. This is achieved by reducing the downtime caused by accidents related to improper maintenance. Between 2017 and 2018, the freight rates of the majority of the ship types increased, resulting in an average daily earning of $10'986 in all segments of the fleet (UNCTAD 2018b). This positive behavior continued has continued into 2019, with bulk carriers' earnings reaching $31'000 per day and oil tankers $55'000 per day (one year time-charter) (Fearnleys Research 2019b; Fearnleys Research 2019a). This positive behaviour has even led some tankers to achieve a reported record-breaking $300'000 per day during October of 2019 (Fearnleys Research 2019c). Therefore, the potentially avoidable downtime of vessels due to maintenance-related accidents during highly profitable periods could have negative implications on the financial performance of the respective shipping companies.

1.3.2 Environmental Impact

Apart from its economic importance, shipping can have a significant positive environmental impact. Ships in degraded physical conditions have an increased risk of causing environmental damages. When ships and their machinery are not appropriately maintained, their state degrades faster than the expected wear-and-tear. Premature equipment degradation can have adverse effects, including sub-optimal operations which can lead to increased fuel consumption and emissions. Regarding emissions, the global shipping industry produces only 2.2% of the global Greenhouse Gas (GHG) emissions, even though it carries 90% of the world's trade. The emissions produced by maritime transport are much lower compared to other modes of transportation, include rail, air and road transport. Despite the low emissions levels, the shipping industry has set goals to further reduce its emissions by the implementation of various schemes. From a regulatory point of view, most of these efforts are embedded in the Maritime Pollution (MARPOL) Convention, established by the International Maritime Organisation (IMO). Under the same scope, the EU's Monitoring, Reporting and Verification (MRV) scheme aims to control the emissions of GHGs (UNFCCC 2014). To meet the required emissions levels and reduce shipping's impact on the environment, the adoption of adequate maintenance schemes that ensure the proper upkeep of the assets is encouraged (Duran, Uriondo, and Moreno-Gutiérrez 2012; Lindstad et al. 2015).

1.3.3 Safety Impact

Poor maintenance practices can undermine the safety of ships, which in turn increases the risk of accidents. Ship accidents can cause environmental and economic damage, as well as lead to the loss of life. The lack of proper maintenance can be a significant accident contributor, especially if it is combined with design flaws and human errors. The absence of apt maintenance can manifest itself in the form of engine trouble, propulsion trouble, mechanical issues, generators malfunctions, electrical problems, and plumbing failures. In detail, during the 2011-2017 period, a total of 20'616 casualties and incidents were recorded, which resulted in 683 fatalities in total (EMSA 2017). During this period, the second most common contributing factor to the recorded accidents is equipment failure relating to maintenance actions. In detail, cargo ships recorded around 297 fatalities corresponding to approximately 32 lost vessels. Since 20% of these accidents were caused by equipment failures relating to maintenance actions (Figure 1.5), approximately 59 people and 6 ships were lost due to improper maintenance. Likewise, fishing vessels recorded around 209 fatalities corresponding to approximately 111 lost vessels. As 45% of these accidents were caused by equipment failures relating to maintenance actions (Figure 1.5), approximately 94 people and 50 ships were lost due to improper maintenance. Also, passenger ships recorded around 97 fatalities corresponding to approximately 13 lost vessels. Since 30% of these accidents were caused by equipment failures relating to maintenance actions (Figure 1.5), approximately 29 people and 4 ships were lost due to improper maintenance. Lastly, service ships recorded around 50 fatalities corresponding to approximately 16 lost vessels. Since 25% of these accidents were caused by equipment failures relating to maintenance actions (Figure 1.5), approximately 13 people and 4 ships were lost due to improper maintenance (EMSA 2018).

For example, a high profile case of a maintenance-caused machinery failure resulting in an incident is the case of M/V Carnival Triumph. The vessel owned by Carnival Cruise Line, suffered from an engine room fire while sailing in the Gulf of Mexico, carrying 3140 passengers and 1100 crew. The fire caused a total loss of power, which lasted for several days, created numerous health hazards to the crew and passengers, and damaged the company's image. The initial fire was caused by an under-maintained flexible fuel oil pipe, while the failure to

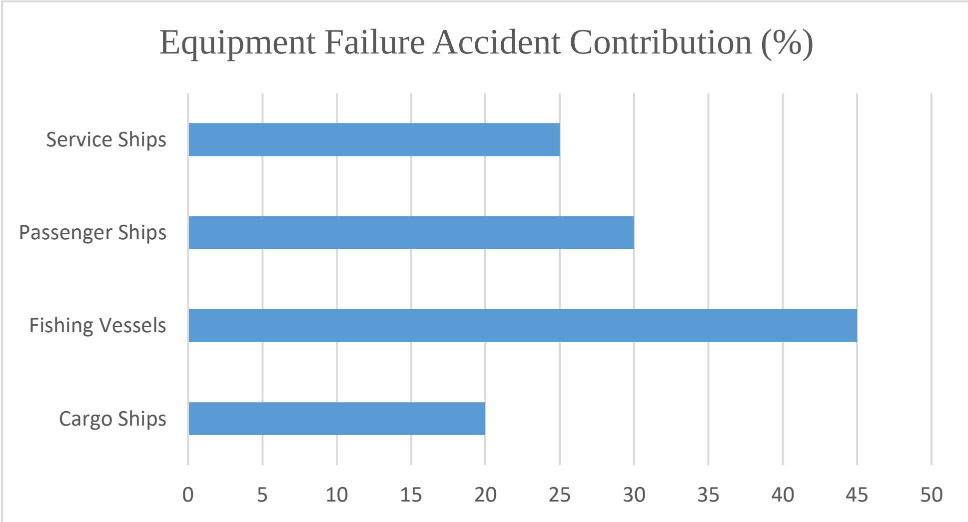

Figure 1.5: Equipment failure, per ship type, leading into accidents percentage. Adopted from (EMSA 2018)

contain it was attributed to a combination of failures in the main fire hydrant and emergency generator (The Bahamas Maritime Authority 2013). Similarly, in 2015 the container ship M/V Maersk Gunde, owned by Maersk lines, suffered a fire in its engine room. The fire caused damages to the vessel and substantial delays. The fire was caused by a leak in an under-maintained seal of the fuel supply of one the generating engines (NTSB 2015).

Taking the above into account, it is apparent that maintenance can be used as a hazard mitigation tool, as proper maintenance can reduce the likelihood of maintenance related accidents. Well-maintained vessels can exhibit fewer failures in their systems, thus promoting safety and reducing risk. Lastly, proper maintenance can safeguard the profit-making capabilities of the vessels by reducing downtime and increasing availability.

1.4 Research Direction

Having established the impact of maintenance and shipping, this section sets the main direction of this research. It presents the main research question, which translates to the main aim. Lastly, this section sets the objectives required to meet the main aim.

1.4.1 Research Question

The research question of this thesis serves as the starting point for this work. It represents the main research drive and it influences all the facets of this research. This question can be expressed as following:

How can ship operators make real-time maintenance decisions based on the actual condition of specially selected equipment, by taking advantage of the developments in the fields of data analytics and machine learning and with the aim of improving safety?

1.4.2 Aim and Objectives

The main aim of this research is to answer the question detailed above, thought the development of a compound novel and data-driven reliability-based predictive maintenance framework for machinery systems. As a result, the main aim is to provide a complete solution ranging from the criticality evaluation of ship systems to diagnostic tasks. In order to achieve the stated aim, the following distinct objectives are set:

The creation will allow the answering of the research question, by providing

1. The investigation of the relevant literature regarding maintenance strategies, reliability assessment and data-drive predictive modeling in a factual

and critical manner, in order to identify gaps and direct the novelty of the present research.

2. The proposal of a novel, data-driven and reliability-based predictive maintenance framework, tailor-made for the needs of the maritime industry.

3. The development of a novel methodology for the identification of the critical equipment of ship systems, aimed at prioritising maintenance efforts.

4. The establishment of a novel data preparation methodology, specifically concerned with handling missing values from data sets used on condition monitoring tasks.

5. The development of a novel fault detection methodology, lessening the amount of data-associated assumptions, and tailored to the needs of the maritime industry.

6. The establishment of a diagnostic methodology combining in a novel way, machine learning applications with domain knowledge for practical applications of ship systems.

7. The demonstration and validation of the effectiveness of the proposed predictive maintenance framework through different case studies, such as the main engine of a bulk carrier.

8. The discussion of the main outcomes of the developed framework together with suggestions for future work.

1.5 Shipping 4.0

The shipping industry is transforming under the effects of state-of-the-art technology. The applications of modern Data Analytics (DA), Artificial Intelligence

(AI), Machine Learning (ML), cloud computing, big data analysis, cybersecurity, and the Internet of Things (IoT) are pushing the shipping industry into modernity, namely into the era of Shipping 4.0 (Lambrou 2017).

The application of these tools is transforming and affecting many of the industry's practices, as it increases the use of automation in practices traditionally relying on empirical knowledge and expert know-how. One of the most prominent examples is the push of the maritime industry for unmanned and autonomous vessels. Data-driven Fault Detection (FD), smart diagnostics, reliability and criticality evaluation, and real-time route optimisation are some of the prerequisites for unmanned and autonomous shipping (Kvamstad-lervold 2017).

Apart from autonomous shipping, another area that is pushing the maritime industry to the 4.0 era is the advancement towards digital twins. Digital twins can be used to create digital replicas of ships, fully modelling the physical and functional characteristics. Digital twins are used in every stage of a ship's lifecycle and can help to achieve optimal ship operations and ship maintenance. Digital twins rely on the real-time collection of performance and condition data and their subsequent analysis in various models (Bradley and Hehenberger 2016).

Despite the changes brought upon by the digital revolution, the shipping industry is adopting the new challenges with a rate higher than its average. There is a rapidly expanding literature providing data-driven and ML-based solutions on many different issues ranging from fault detection and diagnostic to marine data pre-processing, both from individual research groups and larger research consortia.

1.6 Maritime Maintenance Regulatory and Industrial Framework

Because of its importance, ship maintenance is a heavily regulated area. There exists a plethora of regulations, guidelines and regulatory bodies both at national and international levels. Ship maintenance is concerned with the performance and condition of shipboard machinery, as well as with the ship hull and its appendages. All the relevant regulations aim to set the minimum requirements and create a basic structure for the implementation of maintenance.

1.6.1 The International Maritime Organisation (IMO)

The main regulatory body of the maritime industry is the International Maritime Organisation (IMO). IMO was established in 1948 by the United Nations (UN) with the task of improving safety at sea by developing guidelines, regulations and treaties (IMO 2013). For that reason, IMO has developed regulations and codes that recognise maintenance as a hazard mitigation tool and provide information on how it should be addressed.

1.6.1.1 The International Safety Management (ISM) Code

To tackle the issue of safety in a complete way, IMO adopted the International Safety Management (ISM) Code in 1993. The ISM Code became mandatory in 1998 and provides guidelines to increase the safety profile of the maritime industry. The ISM Code is conceptualised to provide international standards for the safety of ships with respect to the environment and human life. It provides standards for the management and operation of vessels. The ISM code is developed by taking into account that no two shipping companies operate and manage their assets in the same way. Therefore, the code is expressed in broad terms, and it provides a scope for shipping companies to adopt their own Safety Management

System (SMS). The SMS is an extensive document that each shipping company develops based on the ISM Code. As a result, each company has its SMS.

The ISM Code is divided into 13 sections, each of which covers a different aspect of ship management and operation. A particular section of interest is section 10, which is concerned with the maintenance of the ship and its equipment. In detail, it is specified that it is the responsibility of the shipping company to make sure that their assets are maintained according to relevant rules and regulations. The maintenance should be carried out in a structured and planned way by appropriate personnel while having safety as a priority (IMO 2015).

1.6.1.2 The Safety Management System (SMS)

As previously mentioned, each company must create its SMS in compliance with the ISM Code. The SMS is a document developed by a shipping company that deals with the safety of operations in a holistic view. Each chapter of the SMS corresponds to a chapter in the ISM Code. Consequently, chapter 10 of an SMS deals with the maintenance of the ship and its equipment. The company's objectives are embedded on its SMS, and it has to institute measures to ensure that its ships are maintained in conformity with classification and statutory requirements. It is the company's responsibility to implement the most cost-effective maintenance scheme while keeping high maintenance standards.

Chapter 10 contains the appropriate information that links the safety of operations with maintenance. More specifically, the SMS addresses the maintenance strategy, maintenance management, planned maintenance schedule and maintenance actions of ship systems including the lifesaving appliances, electrical and electronic devices and engine room equipment (IMO 2015).

1.6.2 Classification Societies

Apart from IMO's ISM code, there are industry bodies that regulate the issue maritime of maintenance. Classification societies, like the American Bureau of Shipping (ABS), Lloyd's Register (LR) and Bureau Veritas (BV) together with the International Association of Classification Societies (IACS) are bodies which produce regulations, guidelines and recommendations for maritime maintenance. The purpose of the classification societies, and consequently IACS, is to confirm the reliability of ship systems and to verify that systems and components are maintained appropriately. Therefore, such organisations develop their own rules and standards. However, classification societies and IACS are not guarantors of safety, as they do not have control over how a ship is crewed and operated. IMO recognises the role of the class societies and their contribution to maritime safety through the International Convention for the Safety of Life at Sea (SOLAS) in 1988 (IACS 2015).

Over the years, IACS members have agreed on a set of Unified Requirements (URs) that each class society has to adapt on its own rules. URs set minimum standards for important topics that the rules of each class must cover. More specifically, an area of interest is the UR-Z which deals with issues ranging from survey requirements to PMS requirements (IACS 2017). Class surveys are essential, as their findings can help to schedule maintenance tasks. Additionally, surveys can be used as a tool to assess the effectiveness of the companies PMS. As a result, UR Z sets minimum survey periods that shipping companies must comply with (IACS 2017).

Apart from the URs, the different classification societies provide guidelines and recommendations for specialised topics, including ConMon, ProMon, PeMon and PdM. Indicatively, LR has published recommended procedures for the integration of ConMon and PdM in the design and construction of vessels (Lloyd's Register 2007). Similarly, ABS has available guidelines and recommendations for the selection of the appropriate ConMon and PdM techniques for ship systems (ABS 2016).

1.6.3 The Tanker Management Self Assessment (TMSA)

A major contributor to maritime safety is the use of various self-assessment schemes for ship operators. The Tanker Management Self Assessment (TMSA) is an example of such programs. The TMSA is tailor-made for tanker operators, and it was introduced by the Oil Companies International Marine Forum (OCIMF) in 2004. It aims to improve safety through the promotion of self-regulation and constant improvement among tanker operators. One of the TMSA's aims is to improve the reliability of ships and increase their safety. The TMSA provides a basic framework for the assessment of a ship operator's safety management systems. It is structured in 13 distinct elements, each of which deals with a specific topic. Of particular interest is the TMSA Element 4, which deals with issues surrounding reliability and maintenance standards. In detail, Element 4 describes the best practices that ship operators should adopt to increase the reliability of their assets, adhere to high maintenance standards and identify critical equipment (OCIMF 2004).

1.7 Thesis Layout

The presented thesis consists of seven individual main chapters. Each chapter is included in the following synopsis, along with a brief description of its content. In the following synopsis, along with the brief description of each chapter, the generated novelty of each chapter is also shown.

***Chapter 1*.**

This chapter includes the essential background information required to establish this thesis and provides a necessary introduction to the maritime industry. It establishes how shipping can affect the economy and the environment and explores the use of maintenance as a hazard mitigation tool. Moreover, the regulatory framework surrounding maritime maintenance is presented before concluding with some of the future challenges the industry will face.

Chapter 2.

Chapter 2 sets the main direction for the research presented in this thesis. It includes the main research question that prompted the developed work and sets out the main aim mapped-out through a series of clear objectives.

Chapter 3.

Chapter 3 includes a review of the relevant literature. This chapter aims to uncover gaps in the current literature so that the novelty of this work can be directed. For that reason, the review is not only factual, but also critical. Initially, the current practices and state-of-the-art regarding the identification and selection of critical equipment are examined. This leads to the conclusion that the status quo is lacking in the incorporation of cost elements of components, together with the traditional reliability indices. Afterwards, the literature regarding the preparation of data (pre-processing) for fault detection and other maritime applications is examined, resulting in the identification of a gap for tailor-made tools for maritime applications. Lastly, the bibliography of fault detection and diagnostic tools for engineering applications is examined, resulting in a profound gap for maritime applications.

Chapter 4.

This chapter details the proposed framework that was developed during this work. The proposed framework generates novelty by addressing the gaps that are uncovered during the critical review of the examined literature. In this chapter each methodological component of the framework is examined in detail in order to establish its theoretical background and intended functionality.

Chapter 5.
Chapter 5 describes the case studies that are used to apply the developed framework. This chapter provides the introductory information regarding the different case studies and presents and generalised outline.

Chapter 6.
Chapter 6 includes the results of the developed framework, as applied in several cases studies. The case studies demonstrate the effectiveness of the framework and its methodological components, to assure that the desired functionality is achieved.

Chapter 7.
This final chapter provides an in-depth summary of the key learning outcomes and conclusions of the submitted work. In this chapter, the manner in which the proposed novelty covers the identified gaps in the pertinent literature is examined. Furthermore, the shortcomings of this work are presented together with possible future research efforts required to address them.

1.8 Chapter Summary

In this chapter, the importance of shipping in terms of the global economy was established. Also, the use of maintenance as a hazard mitigation tool was examined. In addition, the research question, the aim and objectives were presented. Lastly, some of the challenges facing the maritime industry were presented before presenting an overall layout for the rest of the thesis.

Chapter 2

Literature Review

2.1 Chapter Overview

This chapter includes the examination of the relevant literature in terms of maintenance concepts, frameworks, predictive maintenance tools and predictive maintenance processes. The main aim is to perform a factual and critical review to uncover several gaps and orient the novelty of this work. To this end, this chapter gives a detailed explanation of all the aspects required to tackle the main research question, presented in Section 2.2. Initially, the different maintenance concepts and different maintenance frameworks are presented and subsequently, compared. Then, the tools that are required for predictive maintenance are presented into two categories, including Reliability Assessment (RA) tools and Data Science (DS) tools. Following that, the predictive maintenance processes that can be attained by using DS and RA tools are described. These processes include the identification of critical equipment, preparation of data, fault detection, and diagnostics and are further examined under the scope of the maritime industry. Lastly, by comparing the advancements of the maritime predictive maintenance processes with those from other industries, the existing gaps are identified. These gaps are then used to orient the novelty of this work.

2.2 Maintenance Introduction

Modern society is a complex functioning system comprising of many different components, each of which carries out a specific task. The condition of these components is directly related to the state of the broader system they belong to. This description applies to almost any physical system, including economic, communication and transportation systems. Another common link that all these systems share is the unavoidable failures, which may take different forms depending on the system. All systems are inherently unreliable to some extent, as all components suffer from age-based degradation, usage-based fatigue and other design flaws. Eventually, when a component is no longer able to perform its intended task, it fails.

The failure of a component can affect its wider system in many different ways. On the context of this work and according to the British Standards (BS) failure is defined as *"the termination of the ability of an item to perform a required function"* (BSI Standards Publication 2010). A failure can have little or no effect on the system's operation and safety, or it can trigger disastrous chain reactions that can even include loss of life (Kobbacy 2008).

Following the failure of a component, its wider system can be restored to its original state of operation by replacing or repairing the failed part. This process is known as corrective maintenance and forms the starting point for the development of more complex and elaborate maintenance frameworks. Components and systems failures can never be eliminated, due to their inherent unreliability and the plethora of operational and performance variables. Nonetheless, their occurrences can be controlled through the implementation of maintenance frameworks. These frameworks can include actions ranging from visual inspections to the use of advanced performance and condition monitoring tools. It should be noted that the maintenance needs of different systems may vary. Different systems have different maintenance requirements depending on their operational environment and the relevant regulatory framework. Choosing an appropriate maintenance scheme can reduce the likelihood and consequences of failures and breakdowns (Kobbacy 2008). According to the British Standards(BS) maintenance is defined as *"the combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required action"* (BSI Standards Publication 2010). In more detail, when maintenance is performed effectively, it can extend the lifespan of systems, sub-systems and components.

Currently, the maintenance practices in many sectors, including the maritime, are rapidly advancing. Maintenance is currently adopting practices from the fields of modern data analytics and AI. Recognising the above, the submitted work examines maintenance as an ensemble of different activities. Therefore, in this work maintenance is not only limited to upkeeping tasks, but is also combined with the identification of critical components, the processing of relevant data and the early identification of developing faults.

During the review of the relevant literature, the maintenance concepts and frameworks are presented first, followed by the predictive maintenance tools and processes. Then, the focus is directed in the area of maritime predictive maintenance which yields the identified gaps regarding maritime predictive maintenance.

2.3 Maintenance Concepts

Maintenance concepts represent the most basic approaches used in the maritime and other sectors and define how maintenance tasks are perceived and addressed. The discussed maintenance concepts were developed in chronological order and were driven by technological advancements and increased requirements for safety (Kobbacy 2008; Mohanty 2015). The basic maintenance concepts are shown in

Figure 2.1, and they are Corrective Maintenance (CM), Preventive Maintenance (PM) and Predictive Maintenance (PdM).

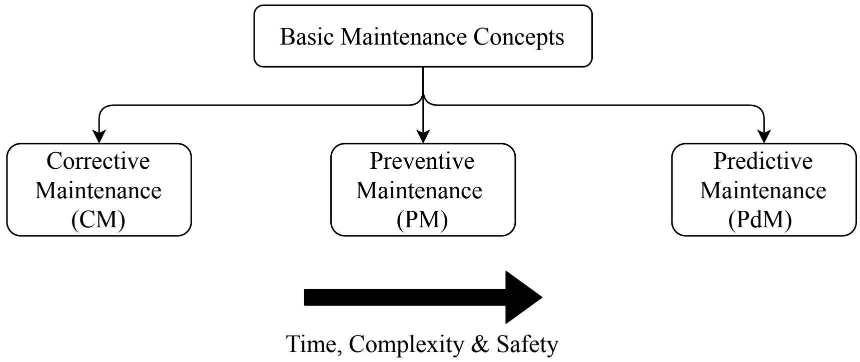

Figure 2.1: Basic maintenance concepts

2.3.1 Corrective Maintenance

Corrective maintenance, also known as reactive or unplanned maintenance, is the oldest and simplest maintenance concept. The predominant CM approach is known as run-to-failure, were machinery operate until they fail, exploiting the entirety of their useful life (Shreve 2003). According to BS corrective maintenance can be defined as *"maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function"* (BSI Standards Publication 2010). In the run-to-failure approach, any repairing or replacing actions take place by the available personnel following a machinery's failure (Wang 2002). Due to its simplicity, CM poses a logical starting point when dealing with maintenance in many industries (Arunraj and Maiti 2007).

The fact that some failures are unavoidable, due to the aforementioned inherent unreliability, makes CM a popular choice. Nonetheless, current proactive approaches, such as predictive maintenance, are usually more effective (Wang et al. 2014). In that sense, proactive approaches can avoid failures by maintaining systems based on their actual condition, prior to a failure. Modern maintenance approaches can significantly reduce the possibility of critical failures with disastrous effects (loss of life, pollution etc.), which is the biggest shortcoming of reactive maintenance (Prajapati, Bechtel, and Ganesan 2012). For that reason, CM can be used on non-critical auxiliary systems, where the risk of failure is low. Viable candidates for CM can include ship entertainment systems, lighting systems, secondary air conditioning systems, pipe filters, sealing gaskets and various other minor components (Mobley, Higgins, and Wikoff 2008).

One of the biggest challenges CM approaches face is the identification of the components to replace, given a system's failure (Fedele 2011). Complex systems have many different failure modes that can lead to a breakdown (Zhou, Xi, and Lee 2007). The challenge of corrective maintenance lies with its ability to identify the causes of each failure and consequently, relies heavily on acquired empirical knowledge. Moreover, CM relies heavily on the availability of spare parts, as any rectifying actions depend on the available spare parts inventory (Kobbacy 2008; Dikis 2017).

Another major disadvantage of CM, compared with other approaches is its associated cost. CM can result in increased operational expenses, primarily if it is used in all the systems of an asset (e.g. ship) (Fang and Zhaodong 2015). The increased cost can include downtime cost, cost of the repair and cost of cascaded damages. When using CM, there is an increased probability that a failure can cascade and cause damages to subsequent systems (Stenström et al. 2016). The probability of this can be reduced by identifying components that link different systems and failures can propagate through them. This process can be part of the critical equipment selection and under the scope of this work, it is considered as part of more advanced maintenance concepts(Polotski, Kenne, and Gharbi 2019).

Despite the above, CM is still applied in the maritime industry due to its simplicity and minimal maintenance planning cost. When CM is used, it is subjected to regulations and standards. Any use of CM must ensure that the shipping company complies with requirements set by the International Management Code for the Safe Operation of Ships and for Pollution Prevention (ISM Code) (IACS 2017). Lastly, the advantages and disadvantages of CM are summarised in Table 2.1.

Table 2.1: Corrective maintenance advantages and disadvantages

Corrective Maintenance	
Advantages	**Disadvantages**
Simple for operators	Failures can cascade in other systems
Simple maintenance plan	No information for fault-finding
Ideal for non-critical items	More failures than proactive concepts
Exploits the entire life of the equipment	Heavily relies on available spare parts
Minimal maintenance planning cost	Can be very costly for the operator

2.3.2 Preventive Maintenance

Preventive Maintenance (PM) represents a more advanced maintenance concept compared to CM. PM was developed shortly after WWII, at the beginning of the 1950s, and is a concept that aims in minimising failures, moving beyond the reactive character of CM (Garg and Deshmukh 2006). According to BS preventive maintenance can be defined as *"maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item"* (BSI Standards Publication 2010). In its core, PM is a task-oriented approach with tasks that are embedded in the everyday duties of the relevant personnel. PM is a structured maintenance concept and allows preemptive actions and planning of the maintenance. These tasks aim to prevent the equipment's degradation and can include visual inspections, testing, servicing and replacements (Smith and Mobley 2008).

Stepping away from CM can have a positive financial impact on companies and organisation. Notably, replacing CM with non-reactive approaches that schedule maintenance actions based on the actual needs of the asset (i.e. dynamic approaches) can have up to a 50% reduction in the overall maintenance cost (Stenström et al. 2016). This reduction arises from the increased reliability of the assets, which reduces the number of unexpected failures. This, in turn, reduces emergency expenses and allows companies to plan maintenance and take preemptive measures (Prajapati, Bechtel, and Ganesan 2012). The minimisation of unexpected failures also requires fewer spare parts to be stocked by companies. Having a reduced spare parts inventory allows for more efficient operations and reduces unnecessary parts procurement costs (Mobley, Higgins, and Wikoff 2008).

In PM, maintenance efforts occur when the system under examination is still operational. Several PM approaches are divided on usage-based and management-based (Wang 2002). In general, the usage-based approaches specify criteria which determine when the repair or replacement of a system's component will take place. A popular usage-based approach is an age-dependent PM. In this approach, a system's component is replaced at a predefined age, T, assuming that a failure has not occurred (Kuboki and Takata 2019). Another popular usage-based approach is calendar-dependent PM. In the calendar-dependent PM, components are maintained at fixed time intervals (i.e. every Z hours of operation) or after a set usage (i.e. every X kWh) (Goossens and Basten 2015).

Despite the above, the successful implementation of PM can be heavily dependent on experience, practical and empirical knowledge. PM may be more dynamic than CM, as it is non-reactive and aims to schedule maintenance actions based on the actual needs of the asset. However, PM is not the most accurate approach for predicting the actual maintenance needs of the asset (Gandhare and Akarte 2012). In other words, the operational wear and various environmental factors are not taken into account. Therefore, systems can be unnecessarily maintained too often (over-maintained) or maintained too seldom (under-maintained); both of these situations can lead to unnecessary expenses or unexpected failures. Over-maintaining can increase operational expenses, as the full operational life of the

Table 2.2: Preventive maintenance advantages and disadvantages

Preventive Maintenance	
Advantages	**Disadvantages**
Structured and organised approach	Can over-maintain or under-maintain
Aims at the minimisation of failures	Failures can still occur
Allows for preemptive actions	Relies heavily on empirical knowledge
More advanced than CM	Not as dynamic as possible
More efficient use of spare parts	Can increase operational costs

equipment is not exploited (Lin et al. 2019). Similarly, under-maintaining can result in failures and downtime. This can directly affect the profit-making capability of the asset in question, as the operational costs can increase (Yang et al. 2019). More dynamic maintenance concepts (based on the condition of the asset) can be used to maintain systems based on evidence of developing faults, prior to a failure taking place, as seen by the developments of this work. Lastly, the advantages and disadvantages of PM can be summarised in Table 2.2.

2.3.3 Predictive Maintenance

Predictive Maintenance (PdM) represents one of the most recent maintenance concepts. PdM was established around 1970 and represents a more dynamic and complex approach compared with CM and PM. PdM tries to minimise failures by scheduling the maintenance actions when the machinery and components are still operational (Sullivan et al. 2010a). As defined by the U.S Office of Energy Efficiency and Renewable Energy *"Predictive maintenance attempts to detect the onset of a degradation mechanism with the goal of correcting that degradation prior to significant deterioration in the component or equipment"* (Sullivan et al. 2010b).

PdM approaches aim at determining an equipment's state and condition based on data collection and non-destructive testing. The underlying philosophy of PdM is that equipment failures are the result of a gradual deterioration. Therefore, the use of appropriate, and real-time, condition-describing data could detect signs of degradation and identify developing faults before breakdowns occur (De Faria, Costa, and Olivas 2015). The successful implementation of PdM is based on the integration of condition-describing data with data-processing modules to achieve Fault Detection (FD) and possibly even proceed with diagnostic and prognostic tasks. It is becoming apparent that PdM can be used as a starting for additional innovation and further advancements (Niu 2016).

What sets PdM apart from PM, is the use of the equipment's actual condition for maintenance and inspection, instead of predefined and arbitrary age-based and use-based thresholds. Moreover, PdM can overcome the PM issues of over-maintaining and under-maintaining equipment while also moving beyond the reactive character of CM (Tian et al. 2011). In addition, PdM allows for better planning of maintenance, as the condition of the equipment can be assessed in real-time (Sharma, Yadava, and Deshmukh 2011). Regarding the maintenance cost, PdM can be up to 35% more cost-efficient than CM and up to 10% than PM. This is attributed to the improved efficiency of the spare parts use, viewed as part of the optimisation of the operational costs of the asset (Dikis 2017; Dikis and Lazakis 2019).

Despite the above merits, the implementation of PdM requires a shift in the culture of the company. Maintenance needs to be viewed as a hazard mitigation tool and not as a simple technical task. PdM requires an extra capital expense for its initiation, as it depends upon further training of personnel and the procurement of the appropriate equipment (sensors, communication relays, etc.). Moreover, PdM depends on additional expertise and know-how to accurately assess the various collected parameter (Lughofer and Sayed-Mouchaweh 2019). In summary, the advantages and disadvantages of PdM can be found in Table 2.3.

Table 2.3: Predictive maintenance advantages and disadvantages

Predictive Maintenance	
Advantages	**Disadvantages**
Real-time condition assessment	Requires cultural change
Dynamic nature	Associated capital costs
Reduced long-term maintenance cost	Additional expertise
Optimisation of maintenance	Additional crew training
Starting point for innovation	Added complexity

2.4 Maintenance Frameworks

The different maintenance concepts have given rise to several different maintenance frameworks. Maintenance frameworks address the concept of maintenance under a broader scope and often in conjunction with the management and profitability of a company. Maintenance frameworks do not only specify criteria for a component's maintenance but layout broader strategies that involve the entire organisation (Smith and Mobley 2008; Cheliotis and Lazakis 2015; Azadeh and Abdolhossein Zadeh 2016). Such frameworks usually involve more than one department of a company and can include both technical and managerial levels (Lazakis and Ölçer 2015). There are many different maintenance frameworks applicable to the maritime and other industries, for which there are a plethora of available literature (Eruguz, Tan, and Houtum 2017; Borjalilu and Ghambari 2018). However, this work focuses on Total Productive Maintenance (TPM), Business Centered Maintenance (BCM), Reliability Centered Maintenance (RCM) and Condition Based Maintenance (CBM) as these frameworks are found to be the most popular in terms of application.

2.4.1 Total Productive Maintenance

TPM is a maintenance framework that originated in Japan's automotive sector in the 1970s and has since then expanded in other sectors, including the manufacturing and nuclear. Nonetheless, TPM has very limited applicability in the maritime sector. TPM aims at maximising the equipment's effectiveness by maintaining components in their optimal state (Chan et al. 2005; Venkatesh 2003). This is achieved by minimising unnecessary breakdowns, downtime, defects and accidents and in general, by increasing the Overall Equipment Effectiveness (OEE) (Singh et al. 2013).

TPM is considered by many as a more advanced version of PM (Shafiee et al. 2019). In TPM, the maintenance actions are based on productivity-based criteria, as opposed to age-based and use-based thresholds (Deepak Prabhakar and Jagathy Raj 2014). TPM's advanced character stems from the belief that equipment degradation is accelerated when upkeeping efforts are not efficient (Sherwin 2000).

An essential characteristic of TPM is that it tries to involve all the departments of a company for its implementation. TPM is a highly structured framework and requires detailed preparation and planning for its fruition. It is essential for the successful use of TPM that an effective communication and collaboration system between different departments of a company is present (Ahuja and Khamba 2008). The requirements of TPM are summarised by the presence of five main pillars, as discussed in Braglia, Castellano, and Gallo (2019). The first pillar is the increase of the OEE. This is achieved by the minimisation of breakdowns, set-up and adjustment times, small stops, reduced speed, quality defects and start-up losses. The second pillar is the establishment of a comprehensive PM system, implemented for the entirety of the assets life cycle. The third pillar includes the involvement of different departments within a company for the implementation of TPM. The fourth pillar is centred around the participation of both white-collar and blue-collar employs. Finally, the fifth pillar is the promotion of PM through autonomous and self-motivated small groups.

Eruguz, Tan, and Houtum (2017) distilled from the above that TPM's primary advantage is the promotion of synergy within a company, which can have a positive effect on the quality of the maintenance. Along the same lines, Azadeh and Abdolhossein Zadeh (2016) discussed that TPM promotes the efficient use of the machinery, which can help to optimise the production process and improve profitability. Despite the above merits, TPM has several shortcomings. First of all, it is a resource-expensive framework that can be cumbersome to perform and implement, as discussed by Arca and Prado (2008). Moreover, any benefits from TPM can take a long time to manifest, creating an illusion of ineffectiveness. Lastly, according to Alsyouf (2009), TPM lacks on the technical aspect, as it does not specify detailed maintenance measures, and it does not set engineering-related goals.

2.4.2 Business Centered Maintenance

BCM is a framework that incorporates the optimal maintenance of assets in the overall strategy of the company, and hence it can be considered as a maintenance optimisation framework. BCM is considered to be an evolved form of TPM with an added emphasis on the company's productivity (Fedele 2011). Currently, BCM has applications in production-oriented organisation, including the manufacturing and automotive sectors, in various industrial processes and healthcare systems (Kelly 2006; Salim, Mazlan, and Salim 2019). Regarding the maritime industry, there are limited instances of BCM especially compared to the other discussed frameworks. Taher, Lazakis, and Turan (2014) established a BCM influenced framework for marine control systems based on probabilistic networks. Even thought this framework represents one of the few examples of maritime BCM, it does not address several issues. For instance, the effects of the data requirements of the maritime industry are not discussed and the topic of data preparation is also omitted. Similarly, the areas such as fault detection and diagnostics are not thoroughly elaborated.

The main aim of BCM is the continuous improvement of the maintenance quality and the various maintenance-related tasks (Kelly 2006). In BCM, the objectives of a company are considered as a function of the company's profitability. Moreover, BCM examines the specific inputs of the objectives of the business in its wider framework (Braglia, Castellano, and Gallo 2019).

Salim, Mazlan, and Salim (2019) stated that when BCM is applied correctly, it can have a positive influence on the profitability of the company. In the same publication, the authors stated that BCM is best suited for complex organisations with various complicated internal structures. As presented by Waeyenbergh and Pintelon (2002), a point of criticism for BCM is that it can quickly become very complicated and cumbersome, if it is not appropriately managed. Similarly, Gandhare and Akarte (2012) described that BCM is resource expensive both in terms of resources and human capital and that the positive results require a long time to manifest.

2.4.3 Reliability Centered Maintenance

RCM is a maintenance framework that originated from the aviation industry and more specifically, during the development of the Boeing 747 aircraft (Ten-Wolde and Ghobbar 2013). RCM has also spread in many other industries, including the offshore renewable and the maritime. More specifically, there are numerous RCM implementations for the maritime industry. For instance, Mokashi, Wang, and Vermar (2002) developed and RCM framework applied in the fuel purification system of a ship. However, the developed approach was based on qualitative methods and lacked quantitative aspects. Also, Vorkapic, Kralj, and Martinovic (2017) proposed an RCM framework for petroleum gas carriers, however, the work was qualitative and did not discuss technical aspects in-depth. RCM was conceptualised to improve the safety of systems by examining maintenance from a reliability improving viewpoint (Ten-Wolde and Ghobbar 2013). According to Moubray (1991) RCM can be defined as *"A process used to determine what must be done to ensure that any physical asset continues to fulfil its intended functions in its present operating context"*. Unlike TPM and BCM, RCM is a more technical oriented framework. Instead of involving all the facets of a company, RCM is contained in the technical and maintenance departments. As a result, RCM requires more technical expertise and a deeper understanding of the functions of a system (Manzini et al. 2010).

A unique characteristic of RCM is its focus on the reliability of the components, as a function of their condition. Simply put, failures that do not reduce the reliability of a system are given a lower priority, under an RCM framework. For that reason, RCM can also be viewed as a maintenance prioritisation framework (Selvik and Aven 2011). As a result, the main aim of RCM is two-fold. This framework tries to increase safety and reliability while minimising maintenance costs (Kobbacy 2008).

For RCM to fulfil its aim, a sequence of processes must be followed. Initially, the examined system must be functionally decomposed and studied. Then, the mapping of the reliability of the components must take place, which allows for the selection of critical and non-critical components (Selvik and Aven 2011). The selection of critical components can take place either through the use of Failure Modes, Effects and Criticality Analysis (FMECA) or by using alternative data-driven methods (Takata et al. 2004). Finally, appropriate maintenance tasks are assigned to the different components, and a comprehensive maintenance plan is created (Cheliotis and Lazakis 2018).

As it can be inferred, RCM combines different maintenance concepts. Several non-critical components can be maintained under run-to-failure approaches, following the CM concept. Also, PM approaches can be used in components with low, to intermediate, effects on the system's reliability and safety. Lastly, critical components can be maintained using PdM concepts to optimise their reliability and minimise the probabilities of failures. However, this requires additional steps in terms of fault mapping and subsequent analysis. The use of multiple maintenance concepts in a single maintenance framework requires the combination of different areas of expertise. This can be a challenging task during the maintenance planning and requires a degree of coordination within the company (Fedele 2011; Ben-Daya et al. 2009).

An important advantage of RCM is its technical orientation. As discussed by Eruguz, Tan, and Houtum (2017) and Borjalilu and Ghambari (2018), the performed maintenance actions are a function of the technical requirements of the equipment. Moreover, RCM can be used to prioritise upkeeping tasks, which can help to streamline operations and minimise costs, as discussed by Smith and Mobley (2008). RCM is a framework that proactively addresses maintenance, and as such, it can be used as a stepping stone for more advanced approaches. Despite the above merits, RCM is a maintenance framework that is sometimes viewed with scepticism in the industry. Afzali, Keynia, and Rashidinejad (2019) explained that this is due to the resource-demanding nature of RCM, both in terms of its planning and implementation. In addition to that, RCM requires significant involvement from managerial levels, which can lead to complex systems (Lazakis 2011). Moreover, RCM requires the use of additional expertise and knowledge, which can also increase costs, as discussed by Mokashi, Wang, and Vermar (2002) and Cheliotis and Lazakis (2015).

2.4.4 Condition Based Maintenance

CBM is a maintenance framework that was developed at the same time as PdM and traces its origins in the railway sector. The concept behind CBM is the minimisation of failures through the assessment of the condition of the examined equipment (Prajapati, Bechtel, and Ganesan 2012). According to the BS, CBM can be defined as *"the maintenance policy carried out in response to a significant* *deterioration in a machine as indicated by a change in a monitored parameter of the machine condition"* (BSI Standards Publication 2010).

As it can be seen, CBM follows a proactive approach in maintenance, utilising relevant real-time condition-describing parameters (Prajapati, Bechtel, and Ganesan 2012). In CBM, maintenance actions are a function of the equipment's actual condition and are not based on arbitrary age and usage thresholds. A successful CBM framework should not only be able to identify the failure of equipment, but also to capture its degradation and even make predictions on its development and underlying cause (Bengtsson 2004). Therefore, CBM requires the integration of data collection techniques with fault detection, diagnostic and prognostic modules (Sullivan and Andridge 2015).

There are numerous publications discussing in detail all the different approaches of CBM. For instance, Jardine, Lin, and Banjevic (2006) performed a comprehensive review of the advancements in machinery CBM with emphasis on the diagnostic and prognostic tasks. Similarly, Liu et al. (2018) examined the use of AI for CBM applications in rotating machinery (e.g. pumps and turbines). Moreover, Hong et al. (2007) discussed and reviewed the developments in CBM, with an emphasis in fault detection, under the scope of offshore wind turbines. Lastly, Bernal, Spiryagin, and Cole (2019) elaborated on the advancements of real-time CBM in the freight railway sector. In this publication, the advancements in the enabling sensor technology and the developments in the available fault detection algorithms are discussed. It can be inferred from the above, that the area of CBM is under intensive development from a plethora of different sectors. CBM is taking advantage of modern technological advancements (e.g. ML, AI and advanced data analytics) with a high rate. It is also seen that CBM frameworks can easily integrate different models and algorithms for the completion of a single task. For example, different ML algorithms can be deployed in series in a single FD model, as seen in Liu et al. (2018).

Based on the selection of the monitored parameters, CBM, and be classified into Condition Monitoring (ConMon), Performance Monitoring (PeMon) and Process Monitoring (ProMon) (García Márquez et al. 2012). ConMon includes the use of condition-describing parameters. Such parameters can include vibration levels, Lubricating Oil (LO) characteristics, temperature distributions (thermography), acoustic emissions and electrical signature analysis (Wiggelinkhuizen et al. 2008; Mohanty 2015). For instance, ConMon can be used in various pumps, motors and engines (Liu and Zhang 2019). On the other hand, PeMon uses parameters that are directly related to the performance and output of the equipment. An example of such parameters can include the power output, torque output and rotational speed (Papagiannakis and Hountalas 2004; Rakopoulos et al. 2006). For example, PeMon can be used for the generating and Main Engine (ME) of a ship (Tsitsilonis and Theotokatos 2018; Baldi, Theotokatos, and Andersson 2015). Lastly, ProMon uses parameters that are related to the internal processes of the equipment. For example, the Exhaust Gas (EG) temperature, injection pressure, cooling temperature and oil viscosity can be used in ProMon (Zaher and McArthur 2007). ME, Turbochargers (TCs) and various other systems are typical candidates for ProMon (García Márquez et al. 2012). Apart from the different types of parameters used, ConMon, PeMon and ProMon have the same aim of describing, in real-time, the condition of the equipment (Kobbacy 2008).

An important decision in any CBM framework is the selection of the equipment that will be subjected to this approach. In addition to that, the examination of the failure modes of the equipment and a fault mapping must be conducted. Both of these tasks are based on domain knowledge and require additional expertise (Mobley, Higgins, and Wikoff 2008).

The successful implementation of CBM can have many benefits within a company. As discussed by Logan (2015), the proactive character of CBM can reduce maintenance costs for up to 30% and reduce unexpected failures by up to 70%. Also, CBM can allow for better planning of the maintenance and allocation of the available resources.

The advantages of CBM are numerous, as seen through the examination of the relevant literature. As deducted by examining Lazakis, Raptodimos, and Varelas (2018b), an advantage of CBM is that takes into account the real-time condition of the equipment in the maintenance decision making process. Consequently, operational efficiency and cost can be optimised dynamically, as confirmed by Dikis and Lazakis (2019). Even though CBM can offer significant benefits, there are still some limitations and issues that need to be addressed. Firstly, there is an associated capital cost regarding the procurement and installation of the data gathering equipment (Azadeh and Abdolhossein Zadeh 2016). Moreover, if the data gathering is continuous, there needs to be infrastructure for the storage of the data. In addition, the analysis of the data for the detection, diagnostic and prognostic tasks requires additional expertise, as presented by Bae et al. (2019). Lastly, the transition to CBM frameworks may require a cultural change within companies which can prove challenging (Jardine, Lin, and Banjevic 2006).

CBM has many applications in the maritime industry, and as seen through the evaluation of the literature, it is amongst the frameworks with the most maritime applications. For instance, Wang, Hussin, and Jefferis (2012) developed a CBM framework for marine main engines based on metal contamination analysis of the lubricating oil. A shortcoming of this framework is that it is based on periodic sampling and as such, it may not be the best option for continuous real-time monitoring. Also, Anantharaman (2013) applied a CBM framework for the propulsion plants of ships. This framework is focused on the use of a specific tool without emphasis on data preparation, fault detection or diagnostics. Similarly, Giorgio, Guida, and Pulcini (2015) deployed a CBM framework applicable to cylinder liners of marine main engines. However, the way in which this framework can be expanded to include other components or systems is not clear. Moreover, Lorencin et al. (2019) also used an ML based CBM framework with applications to marine propulsion plants. This developed framework displayed promising results, even thought data preparation was not addressed and the developed model was compared with the status quo.

2.4.5 Comparison of Frameworks

The previous sections presented the basic maintenance framework, detailing qualitatively their respective benefits and shortcomings. This section aims to perform a side-by-side qualitative comparison of the identified frameworks, as seen in Figure 2.2. Through the examination of the relevant literature, six criteria are distilled for the comparison of the different frameworks. These are simplicity, ease of application, fast results, required expertise, required training and sustainability. As seen, the criteria are selected based on their ability to assess the performance of the different frameworks broadly and inclusively, covering both technical and managerial criteria. Lastly, the selection of the discussed criteria is validated as in Deepak Prabhakar and Jagathy Raj (2014) and Lazakis and Ölçer (2015) report similar findings.

In detail, the simplicity criterion examines the overall complexity of the different frameworks. As seen in Figure 2.2, CBM outperforms the remaining frameworks. More specifically, RCM requires the additional mapping of the components' reliability, which increases its complexity, as also observed by Deepak Prabhakar and Jagathy Raj (2014). Similarly, both TPM and BCM include the incorporation of business-based and productivity-based considerations which results in more complex frameworks.

The ease of application criterion examines the required time to set-up and implement the various frameworks. Since CBM does not include additional reliability analysis, or business-oriented objectives it outperforms the other frameworks.

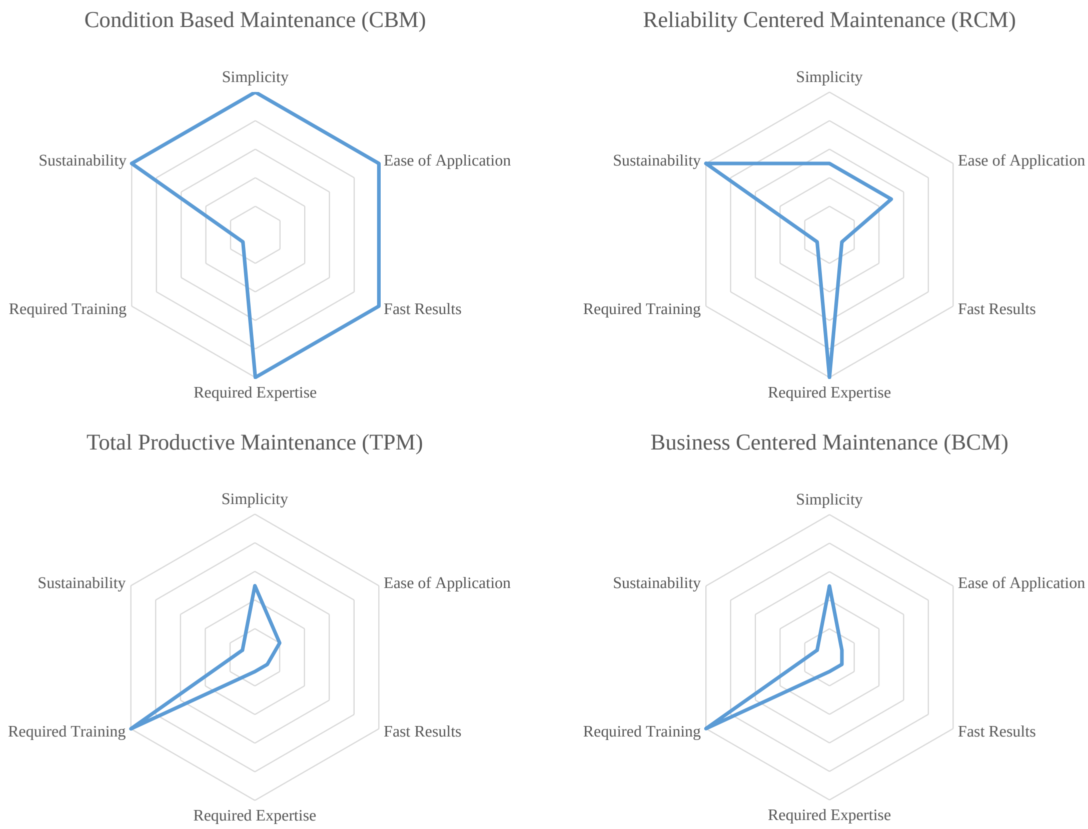

Figure 2.2: Maintenance frameworks qualitative comparison

Similarly, RCM is found to be easier to apply compared to TPM and BCM due to their additional business-oriented objectives.

The fast results criterion considers the required time to improve the effectiveness of maintenance by improving safety. As seen in Figure 2.2, CBM has the highest score since it can assess in real-time the condition of assets, mitigating the risks of failures.

The required expertise criterion gauges the requirements for additional know-how, or expert knowledge, necessary to implement the frameworks. As demonstrated in Figure 2.2, RCM and CBM are the best performing frameworks, since these frameworks are isolated to the technical and maintenance departments. As a result, there is no need for managerial expertise that is required to coordinate and manage the complex functions of TPM and BCM frameworks, as also discussed by Shafiee et al. (2019) and Borjalilu and Ghambari (2018).

The required training criterion considers the need for supplementary training of the maintenance staff. As presented in in Figure 2.2, CBM and RCM are the lowest performing frameworks. This is caused by the additional skills that are required for the reliability analysis of RCM and for the handling and interpretation of the condition describing parameters of CBM. On the other hand, TPM and BCM are more focused on the communication and synergy of the different departments, rather than the development of new technical skills.

Finally, the sustainability criterion examines the potential for effective long-term application of the different frameworks. As discussed by Shafiee et al. (2019) and Azadeh and Abdolhossein Zadeh (2016), the sustainability of CBM is preferable, followed by RCM, TPM and BCM.

2.5 Predictive Maintenance Tools

When adopting a PdM concept, implemented through any PdM-based framework, numerous tools can be used. These tools are broadly divided into Reliability Assessment (RA) tools and Data Science (DS) tools. Each of these categories can be used for different tasks, and their selection depends on the specific application at hand. Moreover, the RA and DS tools represent the building blocks based on which different tasks and processes performed.

2.5.1 Reliability Assessment (RA) Tools

RA tools are extensively used in PdM concepts and especially in RCM. These tools are used to analyse the risk, safety, reliability and criticality of systems. Commonly, RA tools can be classified as qualitative or quantitative and as top-down or bottom-up approaches. Qualitative RA tools address the issues of risk, safety, reliability and criticality descriptively, whereas quantitative RA tools try to quantify these issues numerically. Similarly, top-down tools, focus on the broader context of risk, safety, reliability and criticality by analysing the causes of specific events. On the other hand, bottom-up approaches examine the behaviour of a system subjected to disturbances (Raptodimos 2018; Lazakis 2011).

2.5.1.1 Fault Tree Analysis (FTA)

Fault Tree Analysis (FTA) is one of the most common and widely recognised RA tools. FTA was conceptualised in 1962 by the US Air Force and was quickly adopted by the wider aviation industry (Haasl et al. 1981). Nowadays, FTA is applied in many industries, including the manufacturing, nuclear, automotive, maritime and offshore sectors (Kabir 2017).

FTA utilises logic-gates and events to represent an engineering system (e.g. fuel supply system) and to create a visual model with interconnected pathways that can lead to an undesirable failure within the system (Kang, Sun, and Guedes Soares 2019). The logic-gates simulate the functional dependencies within the examined system, and they are usually employed to represents sub-systems and sub-assemblies. On the other hand, events are used to model components, and they are located at the lower level of the system's model architecture. The events are also used to quantify the Fault Tree, as they require the input of failure statistics (e.g. failure rate, probability of failure) for each component (e.g. fuel injector) (Henriques de Gusmão et al. 2018a). Once a Fault Tree is quantified, the failure statistics of each event are used for reliability calculations in the modelled gates. As a result, the failure statistics propagate through the Fault Tree's structure, leading to the investigation of the examined top-event. FTA is a top-down approach and initiates by stating an undesirable event, which is referred to as a top-event. Common undesirable top-events can include software failure, machinery failures and structural failures. The examination of the top event is a function of the fault tree's structure and a set of logical rules represented through Boolean Logic and more recently, Fuzzy Logic, as seen in Yazdi, Nikfar, and Nasrabadi (2017) and Kabir et al. (2016). From an analytical perspective, FTA can be considered both as a qualitative and a quantitative method (Ruijters and Stoelinga 2015). Qualitatively, FTA can be used to represent functional dependencies within a system. For quantitative tasks, FTA can be used to compute the reliability of systems and other metrics, including failure rates and reliability Importance Measures (IM).

As previously mentioned, FTA can be used to identify paths to failures. To achieve this goal, the scope of the analysis must be set, through the system definition step. Following this, the top-level faults are selected to define the failure of interest, leading to the investigation of their possible causes. Then, the next level of events is investigated, as the causes of the top-events also have precipitating events. Following this top-down approach, the root-causes are identified, and they represent the lowest level of the Fault Tree. The root-causes are the initiating points of the different sequences that lead to the different failures (Haasl et al. 1981; Vesely 2002). Figure 2.3 demonstrates a rudimentary Fault Tree structure that is derived using the above approach, comprising of two root-causes and a single top-level fault. In this case, the presented Fault Tree examines how two basic events (Input A, Input B) influence the occurrence of a top-event (Output A), through a Boolean AND-gate. With the AND-gate, the Output A occurs when Input A and Input B occur at the same time (Relex Software Corporation 2003). For example, the presented figure could be used to examine the loss of function in a redundant power generation systems with two generating engines operating in parallel (Kabir 2017). Alternatively, OR-gates can be used, where the examined output occurs if any of the inputs occur. For instance, an OR-gate can be used to model the loss of function of a propulsion system with only one ME (Vesely 2002). There are more gates available, apart from OR-gates and

AND-gates, which are used for different applications. For a detailed accounting of the available gates, the reader is referred to Relex Software Corporation (2003) and Rausan and Hoyland (2004).

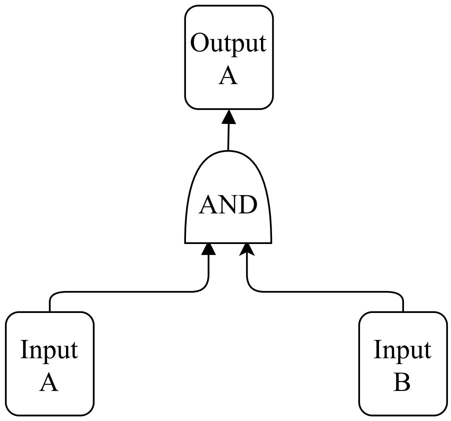

Figure 2.3: Representation of a basic fault tree structure

As previously mentioned, FTA has widespread applicability. Whiteley, Dunnett, and Jackson (2016) employed FTA for the qualitative and quantitative reliability assessment of a Polymer Electrolyte Membrane Fuel Cell. Yazdi, Nikfar, and Nasrabadi (2017) developed a methodology for the assessment of failure probabilities in components of chemical plants, aiming at reducing the number of accidents. Also, Henriques de Gusmão et al. (2018b) used FTA in conjunction with fuzzy theory under the context of cybersecurity. More specifically, the developed methodology was used to manage cybersecurity risks and investigate the vulnerability of systems. Lastly, Khare, Nema, and Baredar (2019) used FTA for the reliability assessment of renewable energy systems. The developed methodology used weather data and power-consumption information to control the occurrence of critical faults.

FTA is a well-established and widely recognised RA tool. Also, as concluded from this research, FTA is easy to learn and offers quick and interoperable results. Moreover, FTA can be used both as a qualitative and a quantitative tool, significantly improving its flexibility. Despite the above merits, FTA cannot model effectively multiple functional dependencies and can become cumbersome when modelling large systems (Fussell 1975; Vesely 2002). Moreover, obtaining the required failure statistics for quantitative analysis can sometimes be difficult (Jiang et al. 2018).

2.5.1.2 Bayesian Networks (BN)

Bayesian Networks (BN) is a popular RA tool that traces their origin in computer science, where they were developed in 1985 by Judea Pearl (Pearl 1985; Pearl 1988). Like FTA, BNs have a widespread recognition with applications in many industries including the nuclear, manufacturing and recently maritime sector (Cai et al. 2019).

BNs are probabilistic Directed Acyclic Graphical (DAG) models that depict functional and causal dependencies between random variables. In other words, BN represent a joint probability distribution of a set of random variables. Like FTA, BN consist of a qualitative part and a quantitative part. The qualitative part is defined by a DAG model where each variable is depicted as a node. Depending on how the nodes are connected, they can be subdivided into parent, child, leaf and root nodes (Ruggeri, Faltin, and Kenett 2007). The qualitative part also includes directed links between the nodes to define causal relationships and functional dependencies. Similarly, the quantitative part is defined by the conditional probability distribution in the Conditional Probability Table (CPT) of each node (variable).

Figure 2.4 represents an indicative BN. In the presented network, the four random variables $X1$, $X2$, $X3$ and $X4$ are represented as nodes and complete the qualitative part of the network. The directed links demonstrate the causal relationships between the nodes. In more detail, the $X1$ node is the parent node for nodes $X2$ and $X3$. Also, the $X1$ node is a root node, as it only has child nodes. Similarly, the $X4$ node is the child node of nodes $X1$ and $X2$, and it is also a leaf node as it only has parent nodes. BNs are based on Baye's theorem, with the goal of calculating the posterior conditional probability distribution of a fault, state, or condition given some observable evidence.

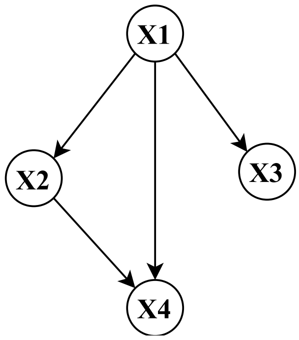

Figure 2.4: Representation of a basic Bayesian Network

Due to the causal dependencies, BNs are widely used for a variety of diagnostic tasks ranging from medical to engine diagnostics (Langseth and Portinale 2007; Borunda et al. 2016). Yuan et al. (2015) developed a methodology for the risk analysis of dust explosions based on BNs. The methodology also examined the relationship between causing factors and consequences. Shin et al. (2015) employed BNs to evaluate cybersecurity risks in the nuclear industry by incorporating procedural and technical aspects. Also, Hosseini and Barker (2016) used BNs to examine resilience-building strategies in infrastructure systems. Moreover, Cai, Liu, and Xie (2016a) developed a methodology for probabilistic reasoning and real-time root-cause analysis in industrial processes based on BNs. Lastly, Cai, Huang, and Xie (2017a) provided an extensive literature review of the application of BNs for FD and diagnostics in engineering systems.

In general, BN can accurately model very complex systems, which makes them ideal candidates for diagnostic tasks. However, as noted from this research, diagnostic BN require a plethora of failure statistics which are not always readily available. Similarly, with FTA, BNs can be used both as qualitative and quantitative tools. The structure of the network can give a qualitative description of a system and the functional dependencies within. Also, BNs can perform powerful reliability calculations by integration information from different sources (i.e. sensor fusion) (Zhang and Thai 2016; Mittal and Kassim 2007). Despite the above merits, BNs can become too complicated. As also noted from this research, when modelling complex networks, attention needs to be paid to avoid unnecessary connections between nodes. Since the number of connections between each node increases to complexity of the CPTs, the network must not have unneeded connections, so that the CPTs are manageable Similar results regarding the complexity of the BNs as a function of their size are noted by Horný (2014) and Cai, Huang, and Xie (2017b).

2.5.1.3 Failure Modes Event Analysis (FMEA) and Failure Modes Event and Criticality Analysis (FMECA)

FMEA and FMECA are two very similar RA tools that are widely used in many different sectors (Ben-Daya et al. 2009). FMEA and FMECA can be used to foresee possible failures during the design of a system, by identifying all of the potential failure modes, through the examination of engineering hazards (Mobley, Higgins, and Wikoff 2008). The main philosophy of these two RA tools is the anticipation and prevention of failures in a system by examining the different ways a system can fail (CDNSWC 2010).

FMEA and FMECA were developed around 1950 and represent some of the earliest structured reliability improvement methods (Mohanty 2015). Both tools require extensive engineering knowledge of the studied system, and their results are presented in a tabulated format (Lughofer and Sayed-Mouchaweh 2019). FMEA can be considered as a qualitative tool, which is developed by using chained *"what-if?"* questions (Kobbacy 2008; Isermann 2006). On the other hand, FMECA is quantitative as it tries to quantify the criticality of each failure, caused by the different hazards. In other words, FMEA can be performed first, and after, a criticality analysis through FMECA can follow (Bertsche 2007).

As previously mentioned, FMEA and FMECA have applications in many industries. Lazakis, Turan, and Aksu (2010a) used FMECA in a ship reliability improvement methodology, aimed at minimising downtime and improving operability. Dinmohammadi and Shafiee (2013) developed an integrated methodology combining FMEA with fuzzy logic for the reliability assessment of wind turbines. More recently, Peeters, Basten, and Tinga (2018) combined FTA with FMEA for failures analysis for the manufacturing sector. Lastly, Balaraju, Govinda Raj, and Murthy (2019) used FMECA for reliability modelling in the mining sector to improve productivity by examining failure behaviours.

Both FMEA and FMECA are widely applicable tools, as they provide a structured approach to reliability improvement (Mobley, Higgins, and Wikoff 2008). These tools address in detail the technical issues of the examined system, provide a starting point for mitigating risk (Spreafico, Russo, and Rizzi 2017). FMEA and FMECA can also be used for the prioritisation of maintenance, which enhances their functionality (Peeters, Basten, and Tinga 2018). Despite the above merits, these approaches face several shortcomings. Initially, they require a substantial amount of resource for their completion (Alsyouf 2009). Moreover, they can be very complex and cumbersome, primarily when used in extended systems (Tixier et al. 2002; Verma, Ajit, and Karanki 2010). Lastly, FMEA and FMECA may need to be re-initiated after extensive repairs or alterations of the specific system (Joshi and Joshi 2014). This may be required, since significant alterations to a system can either introduce new hazards (i.e. through the addition of new components) or alter the significance of existing ones (i.e. through the change of the system's architecture). In either case, the criticality and importance of components and hazards need to be reconsidered, and FMEA and FMECA re-initiated.

2.5.1.4 Event Tree Analysis (ETA)

Event Tree Analysis (ETA) is a popular RA tool that examines the possible outcomes in a system resulting from an initiating event, usually a failure (Ben-Daya et al. 2009). ETA is often used to identify the potential chains of events and resulting outcomes by examining the response of a system to a disturbance (Tixier et al. 2002). Moreover, it can be used to identify procedural and technical weaknesses and to manage risks by calculating the probabilities of different scenarios, (Dikis, Lazakis, and Theotokatos 2015). ETA was conceptualised around 1970 in the nuclear sector and currently is used in many industries and for different applications (Jankovsky, Denman, and Aldemir 2018; Mobley, Higgins, and Wikoff 2008).

ETA is a quantitative approach and requires the input of failure statistics, to assess, through binary logic, the probabilities of different possible outcomes (Mohanty 2015). In more detail, each of the different events are represented in individual branches that also include the probability of the different events. ETA is performed sequentially and initiates by stating an examined event (e.g. failure). The consequences of the initiating event are examined through a series of different outcomes, with each different outcome represented in its branch (Smith and Mobley 2008; Rausan and Hoyland 2004). As the ETA progresses, the scenarios represented by the structure of the Event Tree are considered and the different chains of events are investigated. Completing an ETA results in quantified chains of events with computed probabilities for the different branches.

ETA is used in many different application from different sectors. Ramzali, Lavasani, and Ghodousi (2015) assessed the effectiveness of safety barriers in oil and gas drilling systems by using ETA, to minimise the impact and occurrence of accidents. Fu and Zhang (2016), combine ETA with fuzzy logic for the investigation of accident scenarios and related consequences of ships stuck in ice in Arctic waters. Also, Raiyan, Das, and Islam (2017) examined the root-cause of maritime accidents by using ETA. Aziz et al. (2019) developed a methodology for the quantification of risks related to ship systems, under different failure scenarios. Lastly, Mares, Nagy, and Radu (2020) focused on the investigation of work accidents in the construction sector by applying ETA to identify procedural and technical weaknesses.

ETA is a widely recognised RA tool that is accepted in many industries and for a variety of purposes. It is instrumental in modelling successive events and analysing the propagation of hazards. Moreover, ETA can identify both procedural and technical problems (Ben-Daya et al. 2009; Mokashi, Wang, and Vermar 2002). However, ETA is limited in the analysis of only one initiating event at a time. As a result, it can be pervasive when trying to study multiple initiating events (Mobley, Higgins, and Wikoff 2008). Lastly, ETA operates under the premise that the modelled events are independent, which can lead to inaccurate results when this assumption is violated (Fu and Zhang 2016; Raiyan, Das, and Islam 2017).

2.5.1.5 Comparison of RA tools

The previous sections presented some of the necessary RA tools, describing their characteristics and discussing their respective shortcoming and benefits qualitatively. The main goal of this section is to complete a qualitative assessment of the discussed RA tools.

The RA tools are assessed against five criteria, which were identified in the previous sections. These criteria summarise the performance of the RA tools transparently and range from user-based to more technical ones. More specifically, the used criteria include how well established and flexible each tool is, the different applications of each tool and the ability to model functional dependencies and sophisticated systems. In detail, the flexibility criterion examines the ability of each tool to be used in both qualitative and quantitative manners. Also, the applications criterion assess the variety of applications each tool can be used. The functional dependencies criterion explores the ability of each tool to model systems with intricately interconnected components. Lastly, the complex systems criterion considers the ability of each tool to model complex systems by also incorporating information from different sources (i.e. sensor fusion).

Figure 2.5 shows the performance of the examined RA tools against the distilled criteria from the previous sections. FTA is a well-established tool with high

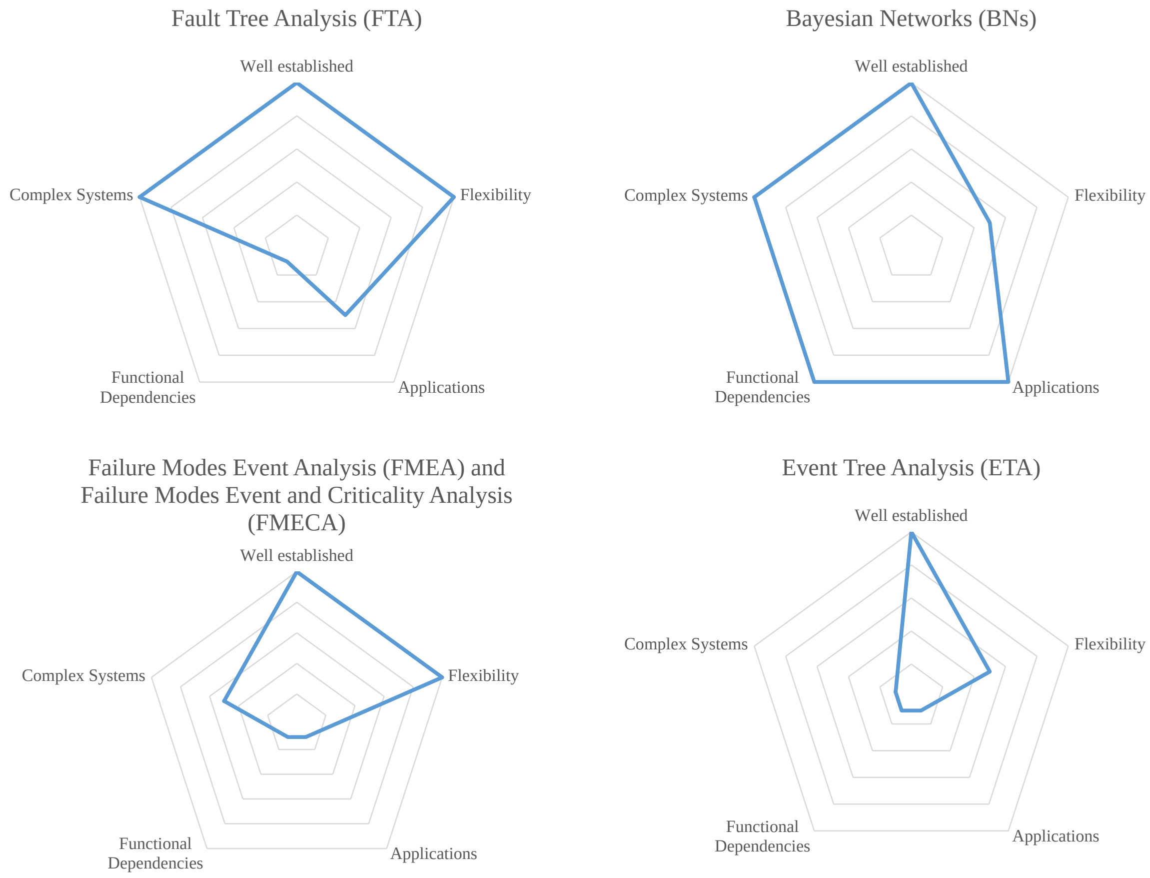

Figure 2.5: RA tools qualitative comparison

flexibility, as it can be used for both qualitative and quantitative tasks. It can be used in several sectors; however, it is usually restricted with reliability-related tasks (e.g. reliability analysis, criticality analysis). FTA is also limited in its ability to model functional dependencies in examined systems. Lastly, FTA can model complex systems and could use information from different sensors. Similarly, BNs are well established; however, they are not suitable for quantitative analysis. BNs can be used in many applications, ranging from diagnostics and FD to decision support, and they can also model functional dependencies effectively. Lastly, BNs are suitable for modelling complex systems and are very good at integrating information from different sources. FMEA and FMECA are also well-established tools which can be used both for qualitative (FMEA) and quantitative (FMECA) purposes. These tools are limited to reliability analysis and cannot model functional dependencies. Lastly, FMEA and FMECA can model complex systems; however, the process of doing that can be time consuming, due to its exhaustive tabulated format. ETA is also a very well established RA tool. Its flexibility is limited to only quantitative analysis; however, the structure of the Event Tree may give a rudimentary understanding of the chain of causality. ETA is limited in its applications, with most examples from the areas of accidents investigations and reliability analysis. Lastly, ETA cannot model complex systems and situations, as the resulting Event Tree can become too complex and cumbersome.

It is seen that BNs demonstrate well-rounded behaviour. They are useful in modelling functional dependencies and have a vast range of applications, with many examples from the area of FD and diagnostics. As a result, they are good in modelling complex systems, provided that the required data are available. Similarly, FTA is very flexible and can be used both for qualitative and quantitative tasks, which makes it an ideal tool for the initial steps of an analysis. FTA is a good candidate for reliability analysis and can provide more precise results than FMEA or FMECA.

2.5.2 Data Science (DS) Tools

DS tools represent another set of tools and methods that are frequently used in PdM-based schemes. As described by Han, Kamber, and Pei (2012), the aim DS tools are to provide the means with which to analyse data and extract useful information about a studied system. DS tools are used when the PdM-based framework is heavily based on the use of data. That could include cases where the reliability of equipment is calculated based on collected data (e.g. RCM), or when the condition of the equipment is inferred by process, performance or condition describing parameters (e.g. CBM).

DS tools represent a different approach to tackling problems in PdM schemes. Apart from that, there are several practical differences between DS and RA tools. Firstly, DS tools have a larger degree of utilisation of data than RA tools. In more detail, DS tools may require a substantial amount of data to train different algorithms, as further discussed in the following section (Bishop 2006). Also, RA tools are usually employed for reliability and risk assessment tasks. In contrast, DS tools tend to have wider applicability, with applications ranging from condition assessment to fault detection and diagnostics. In other words, DS tools offer a higher degree of modularity between the different approaches. Lastly, DS tools do not have qualitative aspects, as they are purely quantitative, which places a greater emphasis on the requirements for data.

PdM-based frameworks can be developed by using traditional analytic tools and methodologies from DS. For example, statistical models have been employed in the nuclear sector as seen in Hoseyni, Di Maio, and Zio (2019), in the offshore sector as seen in Taylor and Jeon (2018), in the coastal engineering sector as seen in Chen and Mehrabani (2019) and in the maritime sector as seen inDikis and Lazakis (2019). Additional maintenance frameworks based on other DS tools, and more specifically on control charts, have also been proposed. For instance, Salmasnia, Kaveie, and Namdar (2018) examined the use of the Hotelling control chart in an application for production plants. Also, Boullosa-Falces et al. (2019) used the Cumulative Sum (CUMSUM) control chart for the optimal maintenance of heat exchangers. Moreover, Holmes and Mergen (2000) examined the application of the Exponentially Weighted Moving Average (EWMA) control chart for fault detection, while Badodkar and Dwarakanath (2017) focused its use for detecting developing cracks in mechanical gears.

There are also numerous PdM-based frameworks that are developed using ML. ML is a sub-field of DS with increasing applicability not only in PdM frameworks but in most of the aspects of modern society. The primary purpose of ML is to extract knowledge from data in the same way as humans do. ML is unique in its ability to learn from data and even improve certain processes, without being explicitly programmed to do so (Kirk 2017). In the core of ML are the various algorithms which can be broadly divided into three categories: a) supervised learning and b) unsupervised learning Müller and Guido (2015).

2.5.2.1 Supervised Learning

Supervised learning is one of the most common categories of ML algorithms. The main objective of supervised learning is to fit a function to the available data, to automate a specific process by generalising from provided samples (Kirk 2017). In supervised learning, the algorithms are given sets of inputs and known outputs, (Bishop 2006). Based on that information, the algorithm tries to uncover patterns and relationships between the input/output pairs (mapping) so that it can later produce outputs based on previously unseen inputs. This process is called training, as the algorithm is trained (i.e. learns) based on the given data. Nonetheless, the training of an algorithm can be a laborious and challenging task. As observed from this work, training algorithms has many intricacies that can lead to inaccurate models if overlooked. Similarly, assessing the accuracy of the training is a crucial task that can be prone to misinterpretation with negative consequences. Similar findings are also reported by Müller and Guido (2015).

Supervised learning algorithms can be further subdivided in regression and classification algorithms, both of which aim at predicting the value of a variable. Regression algorithms aim at predicting the value of a continuous variable, whereas classification algorithms are concerned with the value of discrete variables (Ayodele 2010).

There are a plethora of supervised learning algorithms both for classification and regression tasks. Notably, the most common classification algorithms include Support Vector Machines (SVM) and Logistic Regression (Mohammed and Wagner 2014). Similarly, the most widely recognised regression algorithms include Ordinary Least Squares (OLS) Regression, Ridge Regression and Lasso Regression. Apart from these, Artificial Neural Networks (ANN), Decision Trees and k-Nearest Neighbours (kNN) can be adapted and used for both regressive and classifying purposes (Bishop 2006).

There are vast applications of supervised learning algorithms ranging from facial recognition and credit card fraud detection to fault detection and diagnostics (Bishop 2006). King, Feng, and Sutherland (1995) provided one of the earliest benchmark comparisons between the performance of different classification algorithms. Caruana and Niculescu-Mizil (2006) performed a large scale comparison of various supervised learning algorithms, including SVMs and kNN. The comparison was facilitated by analysing the classification performance of the different algorithms in a normalised dataset obtained from the University of California Irvine Machine Learning Repository (Irvine 2020). Similarly, Ahmed et al. (2010) performed a large scale comparison of regression models under the context of time series forecasting. In the study, the most prominent ML algorithms, including ANNs and kNN, were compared on a dataset obtain from the International Institute of Forecasters (International Institute of Forecasters 2020). Also, Raczko and Zagajewski (2017) compared classification algorithms, including SVMs and ANNs, with emphasis on time-series forecasting and image recognition. Lastly, Louzada, Ara, and Fernandes (2016) presented a systematic review and evaluation of the most prominent classification algorithms under the scope of the credit score sector.

2.5.2.2 Unsupervised learning

Unsupervised learning is another broad category of popular ML algorithms. The main objective of unsupervised algorithms is to examine and scrutinise the data without any feedback. Unlike supervised algorithms, unsupervised algorithms do not have a training phase. In other words, there is no mapping between inputs and know outputs (Bishop 2006). Instead, the various algorithms attempt to make inference of the data without being given explicit examples. Despite the absence of a training phase, unsupervised algorithms are useful in many applications (e.g. market segmentation), albeit they are sometimes harder to interpret (Müller and Guido 2015; Kirk 2017).

The primary purpose of unsupervised learning is to understand, group, and quantify how similar, or dissimilar, the given data are. The most common unsupervised learning methods is known as clustering, or segmentation analysis (Han, Kamber, and Pei 2012; Kirk 2017). Clustering methods aim at creating groups (i.e. clusters) of data that are used to find hidden patterns within the dataset or to categorise the data. Data in the same cluster are considered similar, and dissimilar with those in another cluster. In addition, distance metrics can be used to quantify the degree of similarity (Mohammed and Wagner 2014).

There are many ways in which clustering algorithms can be categorised. Selim and Ismail (1984) suggested that clustering algorithms can be divided between soft and hard clusters, depending on if single data points can have partial membership between two clusters. Alternatively, as suggested by Han, Kamber, and Pei (2012) clustering algorithms can be divided between hierarchical and partitional, depending on the underlying method for the specification of the clusters. The most common and widely applied clustering algorithms are the k-means, c-means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and agglomerative hierarchical clustering (Schubert et al. 2017; Müller and Guido 2015; Rahmah and Sitanggang 2016).

The applicability of clustering ranges from market segmentation to anomaly detection (Bishop 2006). Saxena et al. (2017) and Renjith, Sreekumar, and Jathavedan (2020) presented an overall review of the different clustering algorithms in terms of their characteristics, performance and applicability. Also, Hegde and Rokseth (2020) provided an extensive review of ML tools, including unsupervised models, applied for the quantification and control of risk in engineering systems. Similarly, Fan et al. (2018) and Miller, Nagy, and Schlueter (2018) reviewed the applications of unsupervised models for the enhancement of the energy efficiency of large buildings. Lastly, Mukherjee et al. (2020) presented a clustering approach streamlined for the large volume information requirements of IoT applications.

2.6 Predictive Maintenance Processes

Based on the PdM tools discussed in Section 3.5, the main processes and applications of PdM-based frameworks are identified. These processes include the identification of critical equipment within the examined system, the preparation of the required data, the creation of FD and diagnostic modules.

2.6.1 Critical Equipment

The manner in which a failed component affects its system depends on the component's criticality. The criticality of a component denotes its overall importance to the mission of the system it belongs. It can be a quantitative risk index that examines different failure modes of components and how these affect the different systems (ABS 2016). Therefore, identifying the critical components of the system under consideration becomes an essential task. It is a crucial first step towards more effective management of the systems and assets under examination and also a prevalent starting point for RCM and CBM frameworks.

In general, the critical components identification process is divided into four broad categories, depending on the underlying identification method. These categories, as reviewed by Erozan (2019) and Sarih et al. (2018), include methods based on Network Analysis, Expert Judgement, DA and Reliability Related Techniques.

Network Analysis is a very popular critical components identification method that is widely used in the field of electrical power distribution systems (Chen et al. 2018). Network Analysis is often used to identify critical branches, buses and generators of large power grids. This method is effective when examining large interconnected, and grid-like systems. As seen in Chen et al. (2018), these methods can be used for examining the flow of power transmission in complex network models. Moreover, as examined by Xu et al. (2012) and expanded by Pordanjani, Wang, and Xu (2013), electric circuit analysis based on Thevenin circuits can be incorporated with channel components transform to detect critical components on power grids.

Apart from Network Analysis, methods based on Expert Judgement are often used for identifying low-reliability and high-risk items. These methods are developed as they are easier to impart domain and first-principle knowledge. In contrast with Network Analysis, Expert Judgement methods have a wider applicability with examples in industrial machinery and offshore wind turbines. Dehghanian et al. (2012) developed a method for the identification of critical components for power grids by combining Fuzzy Logic with Analytical Hierarchy Process (AHP). Similarly, Musman and Ahmad (2018) also created an AHP methodology combined with Fuzzy Logic with an emphasis on autonomous maintenance actions. This methodology was showcased in an application for lathe Computer Numerical Control (CNC) machines. Also, Gupta and Mishra (2018) developed a methodology based on Analytical Network Process (ANP) for the identification of critical parts in CNC lathes. Lastly, Özcan, Ünlüsoy, and Eren (2017) developed an integrated framework combining the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the AHP for the identification of critical components in large-scale hydroelectric power plants.

As mentioned earlier, critical component identification can also be based on DA. This group of methods has received the least attention and is currently under development. For instance, Sarih et al. (2018) created a methodology for critical components for the media and broadcasts sector. The developed methodology was based on recorded data from various components and used logistic regression and Pareto analysis. Also, Erozan (2019) developed a critical component identification methodology for the manufacturing sector. The proposed method was based on the exponential distribution and in the safety shock and redundancy effects.

Another popular group of methods for the identification and selection of critical components are based on reliability related techniques. This group of methods employ various RA tools and Reliability Indices (RI) with applications in many industries, including the offshore and maritime sector. For instance, Hilber et al. (2007) created a methodology for critical components in power grids combining the component reliability importance index calculated through Monte Carlo simulations. In the same sector, Dehghanian and Fotuhi-Firuzabad (2012) developed a methodology based on the common load RI, which was used as part of an RCM framework. Also, Afzali, Keynia, and Rashidinejad (2019) developed a new weighted importance RI for the identification of critical components, used for the maintenance prioritisation of mechanical components in distribution centres. Two of the most common tools for critical component identification are FMEA and FMECA (Erozan 2019). In that respect, Narayanagounder and Gurusami (2009) developed an improved FMEA framework, incorporating ANOVA analysis for applications in industrial motors. Also, Choudhary and Sidharthan (2016) used FMECA for critical components identification of electronic components. Similarly, Cevasco, Collu, and Lin (2018) developed an FMECA framework for offshore Wind Turbines (WT). The framework was developed as part of an RCM framework aiming at minimising maintenance costs.

2.6.2 Data Preparation

Apart from the identification of critical components, another vital process of PdM frameworks includes the preparation of data, also known as pre-processing. Data pre-processing improves the effectiveness of PdM frameworks by improving the quality of the used data, as extensively reviewed by Han, Kamber, and Pei (2012), Tan, Steinbach, and Vipin Kumar (2006), Mohammed and Wagner (2014), and Kotsiantis, Kanellopoulos, and Pintelas (2006). Under the scope of this work, the data preparation efforts are divided into two categories, including Outlier Detection and Imputation, presented next.

2.6.2.1 Outlier Detection

Outliers are considered as sparse data points with significantly different values from the rest of the instances of the same variables. Outliers are usually caused by sensor errors and other instrumental faults and are not part of a fault indicative pattern. For example, negative EG temperatures and power outputs above an engine's rated power are considered as outliers. Consequently, outliers can be perceived as data "anomalies" and unreliable readings, and if they are not removed, they can skew the results and decrease the accuracy of the developed models (Javed and Wolf 2012). The methods based on which outliers are detected can by divided into algorithmic and domain knowledge processes (Karkouch et al.

2016; Hodge and Jim 2004).

Domain knowledge processes are simplistic and involve the manual check of the data to identify points that do not conform to an expected behaviour. These processes can rely on information from the equipment's manufacturer, by filtering the data against alarm levels, operational limits and benchmark tests. Moreover, visualisation tools, including scatter plots, can be used to visually check the data. For example, Cheliotis et al. (2019) detected outliers by comparing recordings with limits obtain from engineering principles. Similarly, Dikis and Lazakis (2019) detected outliers from ship-system signals by comparing the available data with the alarm limits set by the manufacturers.

Algorithmic outlier detection is suitable for faster and automated processes and does not require domain knowledge. A common detection method is based on the assumption that the data follow a specific distribution (e.g. Gaussian distribution) (Maimon and Rokach n.d.). For example, Lazakis, Gkerekos, and Theotokatos (2018) detected outliers based on the distance of each data point from the data mean, under the normality assumption. Even though the normality assumption is a popular choice, it is frequently unrealistic for given datasets. To counter this shortcoming, clustering algorithms can be used to detect outliers in an unsupervised manner. Çelik, Dadaşer-Çelik, and Dokuz (2011) used the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to detect outliers in a dataset containing daily average ambient temperatures. Similarly, Chen and Li (2011) used the DBSCAN algorithm to detect outliers under the scope of cyber-security and more specifically in detecting unauthorised accesses in private systems. Thang and Kim (2011) also examined the use of DBASCAN for the detection of outliers related with cyber-security issues. Lastly, Ijaz et al. (2018) used DBSCAN for the identification of outliers for medical applications, including data for hypertension and diabetes.

2.6.2.2 Imputation

Missing values befall in most data-driven research efforts and applications and involve the loss of relevant information (e.g. outliers). If they are not dealt with in a case-appropriate manner, they can reduce the power of models and skew results. As discussed by Domingos (2012) and Cheliotis et al. (2019), reducing the number of missing values has a positive effect on the accuracy of any subsequent models, as it preserves the predictive power of the used datasets. Imputation is a very popular approach in managing missing values and includes techniques for replacing missing values with substitutes.

Understanding the underlying causes of missing data is an important step in data imputation, as it dictates the way the missing data can be handled. In general, three mechanisms affect how data are missing as established by Rubin (1976), Taylor and Rubin (1996), and Little and Rubin (2002). The Missing Completely at Random (MCAR) mechanism refers to cases where the missingness is independent of the data. In that case, there is no correlation between the missing data and the variables in the dataset, as the missingness is entirely unsystematic. For example, in the maritime domain, a random failure of the fuel flow meter will lead to data that are MCAR. Missing at Random (MAR) is when missing data are related to other observations. In other words, the missingness is conditional on another variable. Even though MCAR and MAR seem similar, they should not be used interchangeably as the key difference lies in the condition of the missingness. For instance, if a ME is not operational, data from dependant systems may not be recorded, for example, the TC speed or the EG temperature. Missing Not at Random (MNAR) refers to cases where the missingness of an observation depends only on the variable with the missing data; that is, the missingness is conditional to itself. This is inherently a complicated mechanism to identify. For example, MNAR could result when missing data originate from a data collecting sensor has an established failure during the time of the recording.

A very common imputation technique is called vertical imputation, which uses information from the same column as the one with the missing value. In this case, it is very common to carry forward the last value, or use mean, or mode of the observed values (Pigott 2003). As reviewed by Donders et al. (2006) and McKnight et al. (2007), vertical imputation is easy to implement; however, it is not suitable for successive missing points as it artificially increases the observations' frequency.

An alternative to vertical imputation is to impute the missing values with ones from similar parameters, or by using other logical rules. This is commonly known as horizontal imputation as information from the same record is used. Indicatively, this approach could be used to treat missing values between two identical pieces of machinery (e.g. pumps). The main drawback of this approach is that there may not be two similar parameters in the available dataset; therefore this approach is not always viable (Longford 2005; Gibert 2014)

Hot-deck imputation is an approach that is based on the similarity of a missing instance with a complete one, as initially suggested by Ford (1983), Rizvi (1983), and Roth (1994). This approach matches donors (i.e., instances with observed values) with recipients (i.e., instances with missing values). A pool of possible donors is formed based on the similarity between the recipient and the complete instances. The similarity is quantified using a variety of different metrics, including the Euclidean distance, Manhattan distance, Mahalanobis distance and maximum deviation. The main benefit of hot-deck imputation is that it does not rely on parameter specific models, hence the imputation is not influenced by any parameter selection. Also, as the imputation is based on actual values, the dataset is not completed by artificial ones. However, there is no explicit mathematical model behind the hot-deck methodology. Taking into account the merits of hot-deck imputation, it is worth examining in greater detail its most useful and widespread implementation, kNN. kNN can be an effective imputation tool on its own, and can easily be used in hybrid models. Moreover, kNN is a "lazy" algorithm, and as such, it does not require an explicit training phase; this dramatically reduces the required computational cost and increases the efficiency (Batista and Monard 2003; Armina et al. 2017). Also, the effectiveness of kNN imputation has been demonstrated in various examples, including Zhang (2012), Huang et al. (2017), Cheliotis et al. (2019), and Zhang et al. (2018).

Fitting a regression model to appropriate instances with recorded values is another widely used imputation method. Regression-based imputation is more complicated compared with vertical and horizontal imputation (Lang and Little 2016). A regression model is fitted between the target variable (i.e. variable with missing data) and the selected independent variables. The regression model can be linear, polynomial, or of another type, depending on the dataset. The resulting regression equation is then used to impute instances with missing points in the target variable (Enders 2001). As shown by Longford (2005), the general form of regression-based imputation, between the associated variables Y (with missing instances) and W (complete data set), is provided by:

$$Y = f(W) + \epsilon \tag{2.1}$$

In Equation 2.1, $f(W)$ is some appropriate function (e.g. linear, polynomial, etc.) and ϵ is the error term which is used to account for the uncertainty.

Multiple Imputation (MI) represents a modern and more sophisticated approach to imputation. MI can increase the accuracy of the imputation while reducing bias. As discussed by Azur et al. (2011), MI allows for better accountability of the statistical uncertainty, as opposed to single imputations. MI is based on the improved use of predominant imputation techniques. Assuming an incomplete dataset Y, MI follows the subsequent steps:

1. Impute the missing values of Y m times.

2. Analyse separately the m different datasets.

3. Merge the m different results into one dataset.

MI depends on certain user-specified selection steps. Initially, the imputation method has to be specified; selection can include deterministic or stochastic methods. Next, the number of imputation cycles must be identified. Increasing the number of cycles can improve the model's accuracy; however, this comes at a computational cost. The final selection involves the determination of the concluding missing values from m different datasets. The selection can be facilitated in either a deterministic (mean, median) or a stochastic (random or probabilistic selection) way. All of the above choices are case- and application-dependant. Through the recent literature, it is seen that the Multiple Imputation by Chained Equations (MICE) approach is one of the most promising and accurate implementations of MI (Royston 2004). MICE is an effective imputation tool that can be used both as a stand-alone solution and in hybrid models. MICE aims to cyclically fit regression models to the different variables with missing data. This process is repeated for a predefined number of iterations, as the predictions for the missing data are gradually improved (Royston and White 2015). The effectiveness of MICE has been demonstrated in different research efforts including Cheliotis et al. (2019), Buuren and Oudshoorn (1999), and White, Royston, and Wood (2011).

2.6.3 Fault Detection (FD)

Following the identification of critical components and the data preparation stages, FD is often the subsequent process of a PdM framework. The area of FD has been rapidly expanding in the past decades and currently is commonly facilitated using various condition describing signals, as shown by Martinez-Guerra and Luis Mata-Machuca (2013), Sari (2013), and Sayed-Mouchaweh (2018). As reviewed by Jardine, Lin, and Banjevic (2006), FD includes a variety of different methods ranging from statistical to ML, all aimed at identifying the presence of a fault in the examined system.

As discussed in Isermann (2006), the most basic statistical approach for FD is through limits checking (e.g. maximum and minimum values). In contrast, more advanced approaches are built around the identification of specific trends (e.g. cyclic patterns, rates of change, etc.). The use of the EWMA for FD is an approach gaining popularity due to its versatility and accuracy and based on the identification trends in the examined signal (Garoudja et al. 2017). FD models based on the EWMA use selected signals and plot the signals' EWMA in a control chart, which contains upper and lower control limits for the detection of faults (Nounou et al. 2018). This type of FD creates easy to visualise models that can be used to detect various faults. For instance, Harrou et al. (2015) combined partial least squares with EWMA for the detection of faults in industrial processes. The effectiveness of this model was showcased through its ability to detect developing faults in distillation columns. Similarly, Badodkar and Dwarakanath (2017) developed a methodology based on EMWA for the detection of broken teeth in mechanical gearboxes. The EWMA analysed time-series acceleration signals, which showed excellent performance in detecting faults in their early stages. Awad, AlHamaydeh, and Faris (2018) developed a method for the detection of structural damage in buildings, based on ANNs and control charts. Nounou et al. (2018) proposed a condition monitoring scheme for grid-connected photovoltaic panels. The scheme was based on the monitoring of environmental and performance parameters (voltage, current, and frequency) in an EWMA control chart. Finally, Adegoke et al. (2019) proposed the use of an EWMA-based FD methodology for the manufacturing sector. The effectiveness of the methodology was showcased in an example of a continuous stirred tank reactor.

As discussed by Ma and Jiang (2011), FD based on data-driven ML approaches are gaining popularity in a variety of applications, including the manufacturing, nuclear and offshore sectors. ML-based approaches for FD are traditionally based on classification algorithms, like SVM and Logistic Regression, as reviewed by Liu et al. (2018). However, these algorithms are restricted and not easily used in FD models trained on fault-free data only. Also, classification-based FD models are not easy to integrate with prognostic and diagnostic task (Hong et al. 2007).

FD based on Expected Behaviour (EB) models is an alternative approach to classification models (Hong et al. 2007). EB models are often used for FD tasks as part of a PdM framework in a variety of applications, including the offshore, automotive, nuclear and manufacturing sectors. The use of such models offers several advantages, as they replicate the normal behaviour of various signals, leveraging ML, and assesses any deviations from the normality to detect faults. Zaher et al. (2009) examined the use of an ANN for the development of an EB model for FD in wind turbines, based on operational data. The ANN was trained with more than three months of operational data and was used to monitor the condition of the turbine's gearbox. Similarly, Schlechtingen and Ferreira Santos (2011) examined the application of ANNs and polynomial regression models for the development of EB-based FD for wind turbines. The examined models showed good performance in detecting faults in the stator and gearbox of a wind turbine, by modelling the power, speed, and various temperatures. The same authors developed an ANN-based EB model for the detection of a variety of faults in wind turbines based on operational data. The networks were trained by using more than 30 months of operational data (Schlechtingen, Santos, and Achiche 2013; Schlechtingen and Santos 2014). Lastly, Bangalore and Patriksson (2018) studied the topic of optimal maintenance planning for wind turbines by using an ANN-based EB model for the detection of faults in critical components. As with the previous cases, the developed models were trained on readily available operational data.

2.6.3.1 FD Discussion

ML classification models are the standard choice for FD and offer accurate results when they are trained in the presence of faulty data. However, since in some cases labelled faulty data are not available for training, EB models are developed. EB models have a wide application for FD in many different sectors, as previously discussed. They detect faults by assessing a signal's deviation from an expected normal behaviour. The majority of these models employ ANN to create models which require large amounts of training data. Even though ANN exhibit good predictive behaviour, models that are less reliant on large training datasets, and are equally effective, ought to be explored. In addition, EWMA control charts have an increasing application for FD. They create visual models that can detect developing faults in the early stages. Moreover, EWMA-based FD can also define an envelope of normal operation, for a selected signal, using different control limits. Finally, EWMA control charts can be easily combined with other approaches to offer enhanced detection capabilities.

2.6.4 Diagnostics

The performance of diagnostic tasks is often one of the final processes in a PdM framework and is the following step after FD. Diagnostics aims to identify the root cause of a detected fault, anomaly or error (i.e. localisation). In general, diagnostic models can be divided based on either the type of data, or the types of models used, as seen in Figure 2.6.

Diagnostic efforts, when examined in terms of the data they use for the fault localisation, can be subdivided into a) ConMon, b) PeMon and c) ProMon, as also mentioned in Section 3.4.4. In brief, ConMon uses condition-describing parameters, including vibrations and acoustic emissions. PeMon is based on the use of

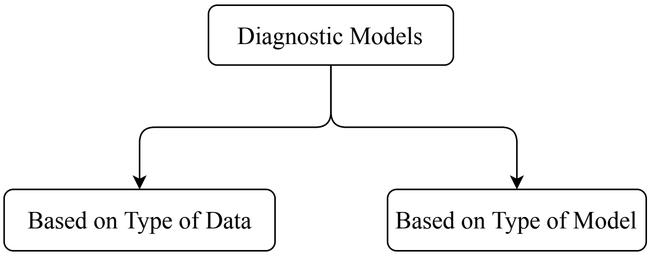

Figure 2.6: Initial division of diagnostic models

information relating to the output of the examined system, including power output. Lastly, ProMon uses information which reflect the internal processes of the examined system such as injection pressure and cooling temperature. Apart from providing insight into the type of data used, this division of diagnostic models is not very useful in explaining how faults are localised.

Diagnostic efforts when examined in terms of the types of models used can be further subdivided into a) physics-based models, b) data-driven models and c) knowledge-based models (Jardine, Lin, and Banjevic 2006; McKee et al. 2014), as seen in Figure 2.7. This type of division can be more useful in providing an

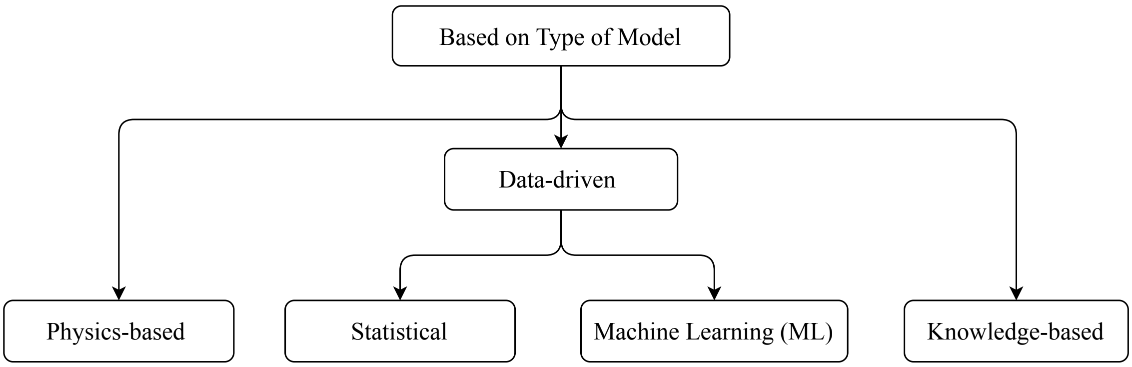

Figure 2.7: Further division of diagnostic models based on the specific approach

understanding of the working process of fault localisation.

Physics-based models use physical principles to create mathematical equations that describe the examined system and the respective failures (Nordmann and Aenis 2004). For instance, physics-based models can include thermodynamic, inertial and fluid models; however, the majority of machinery-based diagnostic models are based on thermodynamic principles (Jardine, Lin, and Banjevic 2006). Cocquempot and Izadi-zamanabadi (2006) created an inertial physics-based model for the identification and isolation of faults in centrifugal pumps driven by induction motors. Similarly, Murphy et al. (2015) developed a thermodynamic-based model for the isolation of faults of marine diesel engines under the scope of reducing the engine's environmental impact. Lastly, Theotokatos et al. (2018) developed a thermodynamic model based on extended mean values for the PdM of marine two-stroke engines.

Data-driven models use data-oriented methods to uncover patterns and behaviours that relate to specific faults in the examined systems. Data-driven models can be further split into ML or statistical-based. Statistical approaches can be based on hypothesis testing and other statistical tests and processes. For instance, Trachi et al. (2017) developed a diagnostic methodology for induction machines based on hypothesis testing and by using the likelihood ratio test. Also, Davarifar et al. (2013) developed a fault localisation methodology for photovoltaic systems based on statistical signal processing. Likewise, Weimer et al. (2013) employed an invariant hypothesis testing approach for the FD and diagnostics in Heating Ventilation and Air Conditioning (HVAC) systems. On the other hand, ML-based approaches use a plethora of both supervised and unsupervised methods (Galar Pascual 2015; Liu et al. 2018). Lu et al. (2001) examined the application of back-propagating auto-associative neural networks for diagnostics in combustion engines. Kim, Ball, and Nwadiogbu (2009) patented a methodology based on self-organising maps clustering for diagnostics in steam and gas turbines. Radionov et al. (2015) used subtractive clustering techniques for the diagnosis of faults in power transformers. Also, Giorgi, Campilongo, and Ficarella (2018) developed a PdM and diagnostic model gas turbines by using ANNs and SVMs based on the use of synthetic machinery data.

Lastly, knowledge-based models are examined which aim at mimicking specialists' reasoning, while effectively handling uncertainties and having increased modularity (Lin, Chen, and Zhou 2013; Diakaki et al. 2015; Atoui, Verron, and Kobi 2015; Cai, Liu, and Xie 2016b). In general, knowledge-based models have many implementations, but the more prominent approaches are based on Fuzzy Logic or BN (Nourian, Mousavi, and Raissi 2019; Chojnacki, Plumecocq, and Audouin 2019). Diagnostic models based on Fuzzy Logic have many applications, but they can be less modular and fast to set-up, compared with BNs (Nourian and Mousavi 2019; Wang et al. 2019; McKee et al. 2014). Riascos, Simoes, and Miyagi (2007) developed a diagnostic network, based on BN, for the diagnosis of different faults in a proton exchange membrane fuel cell. Also, Diakaki et al. (2015) developed a decision support system for merchant ships. This system addressed the issues of route optimisation and fault localisation leveraging BN. Atoui, Verron, and Kobi (2015) examined the use of a BN-based classifier for the detection and diagnosis of three different faults present in chemical process plants. Moreover, Zhao, Wen, and Wang (2015) and Zhao et al. (2017) created a multi-mode BN for the diagnosis of more than 27 faults in industrial air handling units. The developed networks demonstrate the versatility of BN, as they make use of data fusion. Similarly, the versatility and accuracy of BNs are demonstrated in the work of Wang et al. (2017), through the development of a diagnostic network for chiller units which can also handle classification problems. Amin, Khan, and Imtiaz (2018) looked at the development of dynamic BN for FD and root-cause analysis for chemical process plants, generating evidence for collected data under the assumption of a Gaussian distribution.

2.6.4.1 Diagnostics Discussion

Diagnostic methods can be divided either based on the type of data they use or based on the models they employ, with the latter categorisation providing more insight into the working process of the fault localisation tasks. Regarding the different types of diagnostic models, the majority of physics-based models for machinery diagnostics are based on thermodynamic modelling. Even though these models are accurate, they are time expensive, both in terms of the set-up time and the required maintenance of the models. Data-driven models, both statistical and ML, have good performance; however, they can employ black-box tools (e.g. ANNs). Moreover, statistical diagnostic models have reduced modularity and interoperability. Lastly, knowledge-based models are developed to counter the difficulties of building mathematical models while providing accurate results. Knowledge-based BN is a versatile diagnostic tool that can effectively handle uncertainty. They are extremely popular in diagnostic tasks due to their compact nature, consistency, and modularity.

2.7 Maritime Predictive Maintenance

Maritime maintenance is a continually evolving dynamic area. Technological advancements, complex managerial schemes and strict safety and reliability criteria, are all factors that contribute to the development of marine maintenance (Borjalilu and Ghambari 2018). In addition, advancements in maintenance in other industries (e.g. manufacturing, nuclear, automotive and renewables) are having a positive influence on the development of maritime maintenance (Lazakis and Ölçer 2015; Cheliotis et al. 2019). The following sections will present the maritime predictive maintenance processes, summarising the state-of-the-art and presenting in detail the relevant developments.

This section will discuss the status quo in the maritime industry in terms of critical equipment selection, data preparation, FD and diagnostics. Regarding the identification or selection of critical equipment, the available literature is limited, especially when comparing to other industries. In general, the identification of critical equipment is most often performed using FTA and FMECA, and in some cases based on BN. However, there are some cases that are based on accident's report analysis. In more detail, Ersdal and Kvitrud (2000) identified critical equipment with respect to green-water ingress in product carriers. The critical equipment was identified as a result of a post-hoc analysis of green water ingress reported in the studied ships. Next, Lazakis, Turan, and Aksu (2010a) combined the use of FMECA with FTA in a methodology for critical components identification, applied in the electric generation system of a cruise ship. Moreover, Anantharaman et al. (2014) developed a methodology for the identification of critical components in the main propulsion system of a merchant ship. The methodology was applied in the lubrication sub-system and was based on the use of FTA. Also, Dikis, Lazakis, and Turan (2014a) developed a methodology for the identification of critical equipment in ship systems as a part of a broader risk assessment framework for ships. The developed methodology was based on reliability analysis using FTA and BN. Lastly, and most recently, Lazakis, Raptodimos, and Varelas (2018a) identified critical components in ship systems by also using FMECA and FTA.

Regarding the imputation of missing data, applications in the maritime domain also have limited literature. In general, imputation in the maritime industry is predominantly examined under the scope of maritime operations, including traffic management, logistics and situational awareness. As a result, most applications really on operational, non-dense datasets. In detail, Iphar, Napoli, and Ray (2015) used an imputation method for maritime data originating from Automated Identification Systems (AIS). The treatment of the missing data is part of a broad data-driven methodology aimed at increasing situational awareness in sea-passages. Similarly, Claramunt et al. (2017) used the imputation of missing data as part of a traffic management methodology aiming to increase ship safety and security. Also, Fruth and Teuteberg (2017) used data imputation under the scope of optimising maritime logistics to improve safety. Lastly, Dobrkovic, Iacob, and Hillegersberg (2018) also used imputation on AIS data in a methodology to improve barge logistics.

In contrast with critical components identification and data imputation, the literature on maritime FD is much richer. The state-of-the-art of maritime FD can be divided into EB models based on ML, ML models based on classification, methods leveraging RA tools (e.g. BN, FTA) and physics-based models. For example, the benefits of predictive maintenance have been addressed under a decision support framework using fuzzy–sets enhanced with AHP (Lazakis and Ölçer 2015). Also, Ahn et al. (2017), examined the use of a fuzzy-based FMEA approach to study the risk profile of the gas turbine system of specialised tankers. Similarly, Cem Kuzu, Akyuz, and Arslan (2019) proposed the use of a fuzzy-based FTA to analyse the inherent risks of ship mooring operations. Dikis, Lazakis, and Turan (2014b) examined the use of data-driven dynamic BN for the maintenance prioritisation of multiple ship systems. Expanding on this, the coupling of BN with data mining and Markov Chains (MC) has been studied for the development of a predictive maintenance scheme of marine ME and their supporting systems (Dikis and Lazakis 2019). The application of a regularised feed-forward ANN classifier for the monitoring of the EG valve of a marine two-stroke engine, using acoustic emissions signals, has also been examined (Fog et al. 1999). Also, Li et al. (2011) examined the use of a back-propagating ANN classifier for the condition monitoring a marine gearbox, based on the spectrum analysis of a vibration signal. Similarly, the use of a three-layer feed-forward ANN for the condition monitoring of the air intake and fuel injection system of a medium speed marine engine has been examined (Basurko and Uriondo 2015). Raptodimos and Lazakis (2018) and Lazakis, Raptodimos, and Varelas (2018b) examined the application of ANNs and their combination with Self Organising Maps (SOM) and inter-clustering for the monitoring, prediction and healthiness assessment of a marine

ME. Lazakis, Gkerekos, and Theotokatos (2018) demonstrated the use of SVMs for the classification of faults and the development of a data-driven normality index for a marine generating engine. Similarly, Zhan et al. (2007) and Zhan, Shi, and Liu (2007) examined the use of a multi-class SVM for the fault diagnosis of marine ME cylinder covers, based on vibration analysis and Principal Components Analysis (PCA). Lastly, the combination of data simulation, through physical modelling, with both supervised and unsupervised ML algorithms has been examined with application to system decay in naval vessels (Cipollini et al. 2018; Coraddu et al. 2016).

Moving away from FD, the area of maritime diagnostics for shipboard systems is minimal and underdeveloped. The state-of-the-art of maritime diagnostics can be divided into approaches based on thermodynamic modelling and simulations and on ML-based approaches. For instance, Silva et al. (2018) developed a methodology for the diagnosis of faults in the electric drive system of electric-powered ships by employing two-dimensional wavelet transforms from sensor data. Moreover, Campora, Cravero, and Zaccone (2018) combined an ANN with thermodynamic modelling, for data simulation, in order to diagnose faults of a naval gas turbine. Korczewski (2016) investigated the use of the ME EG Temperature (EGT) in thermal engine models for the diagnosis of internal engine faults. Also, Homik (2010) developed a methodology for FD and diagnostics of torsional vibration dampers and marine ME crankshafts. The methodology is based on the combination of vibration analysis with statistical testing. Lastly, Ranachowski and Bejger (2005) used a wavelet analysis in acoustic signals to diagnose the most common faults of the fuel injection sub-system of a marine diesel engine.

2.8 Identified Gaps

From the previously cited literature, and mainly by comparing the maritime predictive maintenance status quo with other industries, the following conclusions regarding maritime critical equipment selection, data preparation, FD and diagnostics can be made. Based on these gaps, the contribution of this work is developed and the novelty is directed. The contribution of this work, concerning maritime predictive maintenance processes, is summarised in Table 2.4. To highlight the discussed contribution, Table 2.4 also summarises the state-of-the-art (status quo) of the maritime predictive maintenance processes, also detailed in the previous section.

Firstly, predictive maintenance, in the maritime sector, is at its infancy and is severely lagging compared to other industries. There is a gap in a complete predictive maintenance framework taking into account the particular needs of the maritime industry and providing data-driven and knowledge-based solutions. However, data-driven solutions are heavily influenced by the characteristics of the available data (i.e. size, density and quality). In more detail, the age of the examined vessel plays a vital role in the data characteristics. Older vessels tend to have sparser data, due to the absence of modern DAQ systems, in contrast to newer ships which are fitted with DAQ systems during their newbuilding stage. Also, the operating environment of ships can reduce the quality of the gathered data, due to loss of sensor calibration, the loss of sensor connectivity, and the inherent difficulty to replace failed sensors. Lastly, the lack of proper data storage facilities, coupled with the possible confidentiality of the data, create issues unique to the maritime sector.

Critical equipment selection methods in the maritime industry are very simplistic, as seen from the presented literature. They typically rely on some combination of RA tools, including FTA, FMEA, or FMECA. Consequently, there is a gap in the incorporation of data-driven tools for the identification of critical components. Similarly, there is also a gap in combining cost aspects with reliability characteristics for identifying critical components. As a result, the contribution of this work includes the combination of ML approaches with FTA and the incorporation of costs with reliability IMs for the identification of critical equipment (Table 2.4). This ensures that critical equipment are selected based on a subjective and multi-criteria approach.

Regarding data preparation, there is a substantial lack of a formalised approach in the maritime industry. Despite the growing popularity of modern data analytics, attempts for outliers detection and imputation based on modern ML are scarce. The lack of a formalised and modern imputation approach for the maritime industry is very concerning, as datasets used for maritime predictive maintenance contain from 4.4% to 26% missing values, depending on the application (Lazakis, Gkerekos, and Theotokatos 2018; Tsitsilonis and Theotokatos 2018). The same need is demonstrated when considering the increased use of ML algorithms which are sensitive or restrictive to missing values, as discussed in Cheliotis et al. (2019). Lastly, the urgency for the above can be seen from similar attempts in other sectors, including the offshore wind industry, as discussed by Martinez-Luengo, Shafiee, and Kolios (2019). A major gap in the maritime industry is the lack of a formalised and accurate approach for the imputation of missing data that includes all necessary imputation preparatory steps, and any further post-imputation processes have not yet been suggested. Consequently, this work contributes with the development of an imputation approach for maritime ProMon data, combining data-driven and knowledge-based approaches (Table 2.4). This safeguards ProMon datasets, as otherwise missing information is preserved.

In terms of FD, there is a gap in the application and use of FD models addressing the particular needs and requirements of maritime predictive maintenance. Moreover, it is seen that the majority of the EB models for FD are based on ANNs. Even though ANNs offer good prediction results, they require large datasets for training, which usually are not always available within the maritime industry, and have a more complex model development phase. In addition to that, ANNs are black-box approaches, which makes it difficult to impart domain knowledge as there is no insight into how outputs are produced. Also, despite the numerous applications of ANNs, there is an upcoming trend among data science practitioners to increase the applications of white-box approaches, as discussed by Loyola-Gonzalez (2019). Consequently, the selection of the underlying approach for the EB models should serve the application, the data available and take into account the above issues. In cases of limited data and when accurate and fast results are required, regression-based EB models should be examined. Regression-based models, such as the ones presented in this work, offer a white-box approach to EB modelling. This allows for the creation of models that are easy to explain, interpret and impart domain and previous knowledge. This is achieved as the form of models allows the examination of the influence each predictor has on the output. The selection of the EB model approach for the detection of faults is also beneficial when compared to the alternative classification approaches. Firstly, with EB models, there is more flexibility in the selection of the underlying algorithms used. With classification approaches, in the absence of observed faulty data, one-class SVM is the standard choice, with limited alternatives. In contrast with classification, EB models have greater flexibility in the selection of the algorithm (e.g. ANNs, polynomial regression). Moreover, the output of the EB models (i.e. a time-series) is more interpretable and useful for future tasks (e.g. diagnostics), when compared to the output of classification approaches (i.e. decision space). Therefore, the contribution of this work includes the investigation for the optimal regression model, used for EB modelling combined with EWMA control charts for FD (Table 2.4). This creates FD models that can be developed without labelled faulty data, improving their flexibility and bypassing the discussed issues of black-box ANN modelling.

Concerning diagnostics, it is observed that most such attempts are physics-based. Even though these models are well-performing, they are time-consuming to develop and apply. Likewise, data-driven diagnostic models also exhibit good behaviour, but they depend on extensive training datasets, which are scarce in the maritime industry. On the contrary, knowledge-based diagnostics, including BN, offer accurate performance, as seen in this work, without requiring lengthy set-up times. Also, knowledge-based diagnostics do not require dedicated training phase, which simplifies their development. Moreover, knowledge-based diagnostics are modular, which improves their compatibility with FD modules and makes it easier to expand in other engineering systems. As a result, the contribution of this work is the integration of ML-based FD model with a BN for diagnostics (Table 2.4). This allows for the investigation of the root-case of a detected fault.

Table 2.4: Status quo and added contribution

Critical Equipment Selection	
Status quo	Based on RA tools (FTA, BN, FMECA) No combination of costs with reliability metrics
Added Contribution	Combination of ML clustering with FTA Examination of costs with reliability IMs
Data Preparation	
Status quo	Developed for ship operations application Majority of purely data-driven models
Added Contribution	Imputation of ProMon data Combination of data-driven and knowledge-based approaches
Fault Detection	
Status quo	Based on ML classification and ML EB models Thermodynamic models and RA tools are also used
Added Contribution	Combination of ML-based EB models with EWMA control charts Investigation of optimal regression model
Diagnostics	
Status quo	Based on ML approaches Thermodynamic models and simulations are also used
Added Contribution	Integration of ML-based FD with BN for diagnostics Combination of data-driven with knowledge-based approches

2.9 Chapter Summary

This chapter presented the factual and critical review of the relevant literature. Initially, the fundamental maintenance concepts and maintenance frameworks were presented. Afterwards, the reliability assessment and data science tools used in predictive maintenance together with the resulting processes were examined. Then, the predictive maintenance processes of critical equipment selection, data preparation, FD and diagnostics in the maritime field were compared with those in other domains. Consequently, this comparison allowed to uncover several gaps for maritime applications which then oriented the novelty of the present thesis.

Chapter 3

Methodology

3.1 Chapter Overview

After the gaps of the literature are identified, through the critical examination of the relevant literature, this chapter aims to present in detail the overall framework, while highlighting the generated novelty. The framework aims to address maritime predictive maintenance holistically, by including topics ranging from critical equipment selection to system diagnostics. Section 4.2 gives a detailed outline of the generated novelty, and Section 4.3 provides a high-level description of the overall framework. The methodology addressing the critical equipment selection is presented first. Then, the data preparation methodology is shown. Finally, the methodologies for the FD and diagnostics are presented in turn.

3.2 Novelty

By considering the gaps in Section 3.9, this thesis aims to propose a novel framework, holistically addressing the requirements of maritime predictive maintenance. Thus, the proposed framework combines in a novel manner the identification of critical equipment, data preparation, FD and diagnostics. In more detail, the novelty of this work is listed below:

- This work is based on the novel combination of the developed methodologies to address the issues of maritime PdM. This work combines FTA and data mining for the identification of critical components, with the development of a kNN and MICE-based imputation approach, coupled with the use of regression and EWMA based FD which leads into a BN-based diagnostic tool. The developed novel methodologies, addressing the different needs of maritime PdM, can be used in series and in a single vessel, conditional on the availability of the required data.

- To address the limitations regarding the selection of critical equipment, a novel methodology is developed. The methodology combines proven RA tools with data-driven efforts. In more detail, FTA analysis is performed to obtain specific reliability Importance Measures (IM). Then, the IMs are clustered together with repair and replacement costs, using the k-means algorithm, to obtain the resulting critical components.

- To tackle the gaps regarding data preparation, the novelty of this study lies within the proposal of a new hybrid imputation method that combines data-driven solutions with valuable First Principles (FP) domain knowledge. This approach is shown to yield more accurate results compared to traditional, application-agnostic, imputation methods, as it will be shown in the following sections. Moreover, alongside the hybrid imputation method, all the needed pre-imputation and post-imputation steps are presented.

- In terms of FD, the novelty of this thesis lies in the combination of the pre-processing steps, with the regression-based EB modelling and EWMA control charts for FD. Moreover, the novelty includes a systematic and structured examination for the selection of the optimum regression model. This encompasses the selection of the ideal predictor variable and types of training datasets (recorded data vs shop test data). The developed FD methodology also includes the combination of data-driven models with engineering analysis, resulting in interpretable and effective models using real data.

- Lastly, with respect to diagnostics, the novelty of this work lies in the development of a novel framework that combines an ML-based FD module with a BN-based diagnostic module. The FD module is combined in a novel way with the diagnostic module which includes the mapping of faults and the construction of a BN. Evidence of detected faults is propagated in a BN network. The output of the BN diagnostic is the quantified probabilities of the mapped faults, together with the fault profiles of different failure modes.

3.3 Overview of the Novel Framework

This section gives a detailed account of the proposed novel framework. As mentioned above, the main aim of this framework is to address the topic of maritime predictive maintenance in a comprehensive and robust manner, by individually addressing the topics of critical equipment selection, data preparation, fault detection and system diagnostics. Each of these methodologies is developed and assessed individually, as described in detail in Chapter 5.0. Despite this sequential development, all of these methodologies are integral parts of the proposed PdM framework.

Figure 3.1, illustrates the overall novel framework by specifying the sequence of the developed methodologies together with the required inputs and expected output in each case. The first step of the framework is the identification of the critical equipment of ship systems. This is a crucial first step, and forms the starting point of the proposed novel framework, as it allows to focus the maintenance efforts on components which have the maximum impact on safety, reliability and availability. As seen in Figure 3.1, this methodology requires the use of the maintenance schedule and repair costs to identify the critical equipment by using the novel combination of FTA with k-means clustering. Once the critical equipment selection methodology is developed, the topic of data preparation is addressed. The data preparation methodology is developed to ensure that the knowledge extracting potential of the used data is maximised. As depicted in Figure 3.1, this methodology is based on the use of ship performance data to detect outliers and impute missing values by employing the novel combination of the MICE and kNN ML algorithms. Then, the FD part of the framework is developed, which aims at the early detection of developing faults. The FD is facilitated by using shop tests and ProMon data in a novel combination of regression-based EB models with residuals-based EWMA control charts. The last part of the framework includes the development of a diagnostics methodology. This methodology is developed to identify the root-cause of detect faults, as shown Section 5.5. As seen in Figure 3.1, the diagnostics are based on aggregated results from the FD part, operating manuals and data banks. This novel methodology also requires a fault mapping process to create a diagnostic BN, which is used to calculate the probabilities of mapped faults, based on evidence of faults from the FD part.

3.4 Critical Equipment Selection

The critical equipment selection is the first part of the proposed framework. This first part of the proposed novel framework includes a novel methodology for the identification and selection of critical ship equipment. This is a process that takes into account both criticality indices and cost-related information. The aim is to create a methodology that allows for the systematic identification of critical

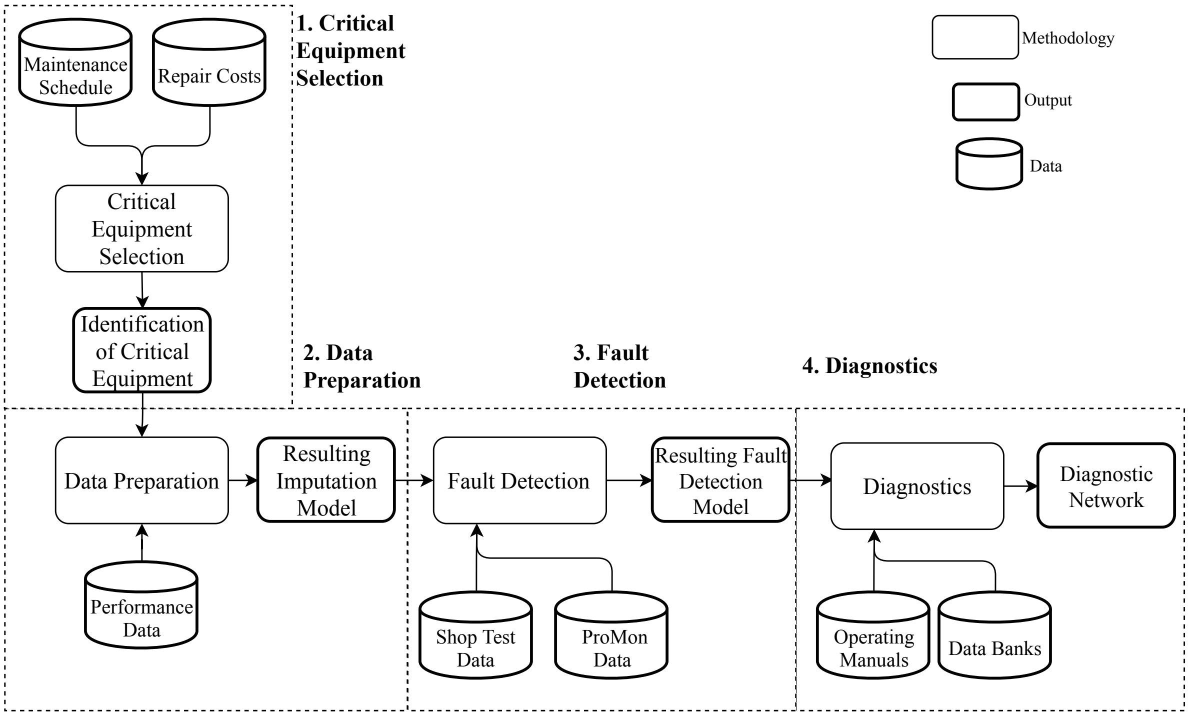

Figure 3.1: Layout of the novel work, depicting the different methodologies, the required inputs and the derived outputs of each part.

components of ship systems. The developed methodology, not only examines components with respect to their importance on the mission of the system they belong to (criticality), but also with respect to the financial implications of their failure on the ship operation.

3.4.1 Overview

The critical equipment methodology initiates with a data collection effort, which aims at fulfilling the methodology's data requirements, as seen in Figure 3.2. The collected data include information regarding the maintenance schedule (i.e. maintenance interval) of the examined vessel and the repair costs of the machinery. These data were selected for collection after examining the data requirements of similar research efforts, such as in Lazakis, Turan, and Aksu (2010a) and Lazakis, Raptodimos, and Varelas (2018b).

After the required data are collected, the ship system analysis step initiates. This step allows the examination of the ship in terms of its systems, sub-systems and components, a process which is based on first-principle knowledge. This is also the stepping-stone for the FTA, as the structure of the Fault Tree (FT) is based on the analysis of the ship systems.

The FT is quantified by using the Mean Time Between Failures (MTBF) of each of the components. The MTBFs are extracted from the maintenance schedule of the vessel, and they represent one of the most common ways for quantifying FTs. Once the FT is quantified the analysis initiates by selecting a calculation method, as further explained in Section 4.4.4.3. As a result, the Birnbaum IM (I^B), Criticality IM (I^{CR}) and Fussel-Vesely IM(I^{FV}) for each component are obtained. The IMs for the depicted components are analysed, and the most appropriate are selected for the next step of the methodology.

Then, the cut-sets of the FT are obtained and the events in the lower order cut-sets (i.e. the smallest sets of events that can lead into failures) are identified for the next step of the analysis. The selected IMs for these components, together with the associated repair costs are clustered using the k-means algorithm. The use of the k-means clustering algorithm allows for the creation of a visually descriptive model that categorises the data based on their criticality and cost. Therefore, to avoid added complexity and to maintain the model's practical application, the clustering algorithm is limited to three dimensions. This allows the identification of the critical components, which belong to the cluster of components that have the highest values for the selected IMs and the highest repair costs. The critical components selection methodology of the proposed framework is demonstrated in Figure 3.2 and are presented in detail in the following sections.

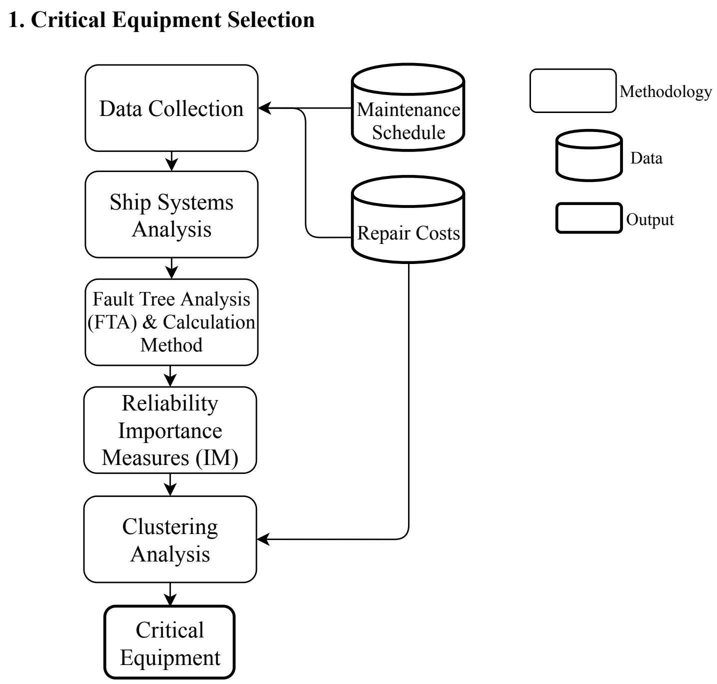

Figure 3.2: Layout of the critical components selection methodology of the proposed framework

3.4.2 Data Collection

Data collection is the initiating step of the critical equipment methodology. This step ensures that the required data to quantify the FT (i.e. MTBF) are available. To this end, the entire maintenance schedule and maintenance plan of the studied vessel is obtained. Moreover, the repair costs for the various ship components are collected, as required for the identification of the cluster of critical components. Such data are usually available from ship owners and ship operators.

3.4.3 Ship Systems Analysis

Following the data collection, the ship systems analysis step takes place. This step allows the examination of the ship in terms of its systems, sub-systems and components. Also, the identified systems, sub-systems and components are organised in a table format, which helps with the determination of the structure of the Fault Tree (FT). This is a very common starting step when performing FTA in engineering systems, as discussed in Bertsche (2007). As also mentioned above, the ship systems analysis is the stepping-stone for the creation of the structure of the FT.

3.4.4 Fault Tree Analysis (FTA)

FTA is a well-established and flexible RA tool that can effectively model complex systems, as described in Section 3.5.1.5. The use of FTA in the developed methodology serves two functionalities. First, the qualitative part of the FTA (i.e. the FT structure) gives a clear depiction of the reliability dependencies between different systems and sub-systems of the ship. Then, the calculation of the different IMs (i.e. the quantitative part) allows for the numerical assessment of the criticality of the various components. In summary, the FTA aims to perform a pictorial and quantified representation of how sub-systems (intermediate-gates) and components (basic-events) can lead into the loss of the reliability of the broader systems they influence (top-gate) (Verma, Ajit, and Karanki 2010).

3.4.4.1 Examined Gates and Events

As mentioned above, the structure of the FT was derived as a result of the ship system analysis, as demonstrated in Figure 3.3. The identified systems and sub-systems are represented in the FTA using gates, and the components are described as basic events. The gates used to connect the systems with their respective sub-systems and components were selected based on the different functional dependencies (Verma, Ajit, and Karanki 2010).

One of the most common gates is the “OR” gate, which requires a minimum of two inputs. When used, the outcome of the gate occurs if any of the inputs occur. In other words, the “OR” gate is represented as a Boolean union. In

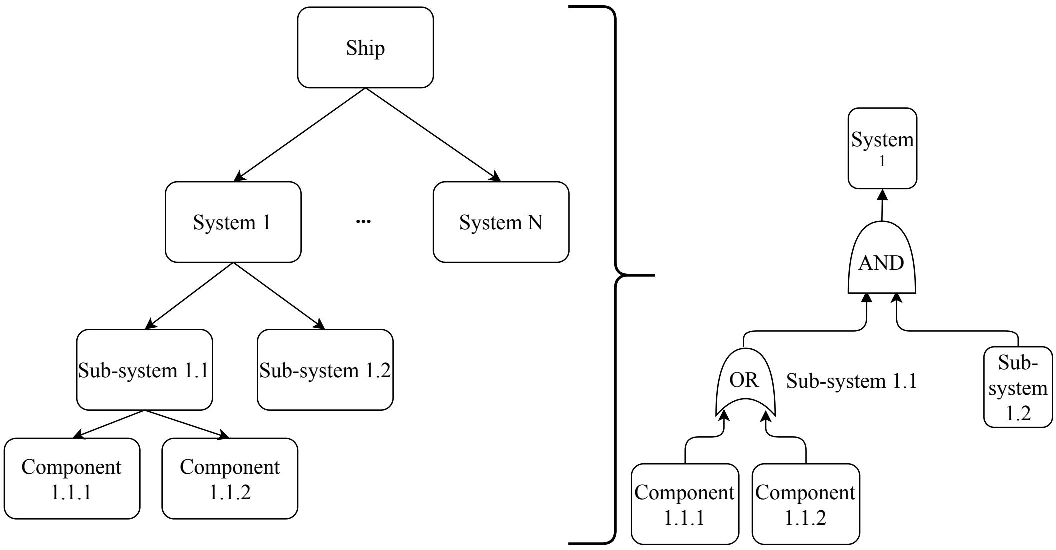

Figure 3.3: Depiction of the FT structure, as created from the ship systems analysis

engineering systems, "OR" gates are used to represents systems and sub-systems which are prone to failures and have limited fail-safe capabilities. Assuming an examined output A with a probability of occurrence $P(A)$, connect through an "OR" gate with n inputs $A_1, A_2 ... A_n$, then $P(A)$ is obtained by Equation 3.2 (Relex Software Corporation 2003).

$$P(A) = P(A_1) \cdots P(A_n) \tag{3.1}$$

Another very common gate is the "AND" gate, which also requires a minimum of two inputs. If only one input is given to an "AND" gate, the gate's logic is negated as there are not enough inputs for comparison and the output of the gate is conditional only to the single input. In other words, single-input "AND" gates behave like "OR" gates. The outcome of an "AND" gate occurs only if all the inputs occur at the same time. In terms of Boolean logic, "AND" gates are represented as sets intersection. In engineering systems, "AND" gates are used to model systems and sub-systems which are less prone to single-point failures, commonly by having redundant components. Assuming a different examined output A with a probability of occurrence $P(A)$, connect through an "AND" gate with different n inputs $A_1, A_2 ... A_n$, then $P(A)$ is obtained by Equation 3.1 (Relex Software Corporation 2003).

$$P(A) = 1 - [1 - P(A_1)][1 - P(A_2)] \cdots [1 - P(A_n)] \tag{3.2}$$

The "VOTING" gate represents another widely used way of modelling systems and sub-systems with partial fail-safe capabilities. In engineering systems, "VOTING" gates are used to model systems which are tolerant to single-point failures but are not as robust as the systems modelled with "AND" gates. The output of a "VOTING" gate occurs when a predefined number, J, of the Y inputs occur. When $J = 1$ the "VOTING" gate behaves like an "OR" gate, whereas when $J = Y$ the "VOTING" gates acts like an "AND gate". Assuming an examined output A with a probability of occurrence $P(A)$, connect through a "VOTING" gate requiring two of the three inputs A_1, A_2, A_3, then $P(A)$ is obtained by Equation 3.3 (Relex Software Corporation 2003).

$$P(A) = P(A_1 \cap A_2) \cup P(A_1 \cap A_3) \cup P(A_2 \cap A_3) \tag{3.3}$$

The identified components are represented as "BASIC" events. These events are located at the lowest level of the FT structure, and they represent software, hardware and component failures. "BASIC" events are the most common way of representing component-based failures and have the widest applicability (PTC Windchill 2019). The "BASIC" events are quantified by using failure statistics for the respective components. This information is supplied prior to the initiation of the analysis, and they are in the form of MTBFs, failure rates or probabilities of failures (Relex Software Corporation 2003). During this work, the events are quantified using the MTBFs as they are obtained from the collected maintenance schedule. More information on the available gates and events is available in Appendix A.

3.4.4.2 Qualitative Analysis

As soon as the structure of the FT is specified and the "BASIC" events are populated with their MTBFs, the main analysis initiates. The analysis can be performed both qualitatively and quantitatively, depending on the application and the availability of data.

Quantitative analysis is based on Minimal Cut-Sets (MCS), which are obtained by leveraging gate logic (Ruilin and Lowndes 2010). A cut-set is a set of "BASIC" events, the occurrence of which can cause the top-event to occur. The use of cut-sets allows for the identification of weak points in large and complex systems and is based solely on gate logic. In other words, cut-sets can order and prioritise the examination of different events. A basic event that belongs in a cut-set can provide information regarding single point of failures. An MCS is the smallest set of events which must co-occur for the top-event to occur (Lazakis, Raptodimos, and Varelas 2018b). In general, MCS can be used as a starting point for the analysis of the examined system. Assuming a rudimentary FT with a single "OR" gate and inputs the events A_1, A_2, A_3, then three MCS are obtain. The first is C_1 which includes event A_1, the second one is C_2 which includes event A_2 and the third one is C_3 which includes event A_3. Lastly, cut-sets can be organised in terms of their order, indicating the number of events in each cut-set. In general, cut-sets of lower order are more important and which also reflects to the individual events in them (Shafiee, Enjema, and Kolios 2019).

3.4.4.3 Quantitative Analysis

Quantitative analysis can be performed when all the "BASIC" events are populated with their respective failure statistics. In quantitative analysis, there are different calculation methods available. Each calculation method influences how the probabilities of the different gates are calculated.

The first option is the use of simulations by using Monte Carlo models. Simulation models are intuitively easy to understand, but they can be time-consuming (Relex Software Corporation 2003). Simulations generate random numbers associated with each event and then determine whether that event has occurred or not. Based on that, the status of the top-event is calculated. Simulation models are robust in their performance; however, they are time-consuming, and their performance may be comparable with less expensive models (PTC Windchill 2019).

Another approach for performing the reliability calculations of different gates is the cut-set summation method. The reliability calculations for each gate are obtained by adding the probabilities of the cut-sets of that gate (Relex Software Corporation 2003). In more detail, the probabilities of each cut-set are calculated as the product of the respective events. This approach is fast and accurate; however, its use is only recommended in FTs with low failure rates quantifying the "BASIC" events (Lazakis 2011).

Another calculation approach based on cut-sets information is the Esary-Proschan (EP) method. This method performs the reliability calculations for the top-event by defining an upper and lower reliability limit (Relex Software Corporation 2003). Since the EP method is based on the cut-sets, it has reduced computational times. Nonetheless, the application of this method is based on the assumption that each failure is the result of a gradual degradation (PTC Windchill 2019). As a result, failures affected by external influences cannot be modelled. Also, this method requires that every "BASIC" event appears at least in one MCS (Lazakis 2011).

Another calculation method that is based on cut-sets is the cross-product approach, which is very similar to the cut-set summation method (Relex Software

Corporation 2003). This approach performs the reliability calculations by using the summation and product terms of the cut-set probabilities of the FT(Lazakis 2011). Since the cross-product is based on cut-sets, it has reduced computational time. However, it is based on the assumption that the simultaneous occurrence of multiple cut-sets is not probable (PTC Windchill 2019).

Finally, the exact calculation method is examined, which is purely based on gate-logic and does not use cut-sets information (Relex Software Corporation 2003). This approach performs the reliability calculations in all the gates on the FT. The main advantage of this approach is its accuracy due to the limited assumptions; however, this comes at the expense of the required computational time (PTC Windchill 2019).

From the presented quantitative calculation methods, the latter is applied. The main benefit of the exact calculation method is the minimal assumptions it uses and its accurate performance. Also, since this work did not have strict time constraints, the increased computational time of this method was not a concern.

3.4.4.4 Importance Measures (IMs)

The reliability IMs represent another useful functionality of FTA. Unlike the quantitative calculation methods, which examine the reliability of the top and intermediate gates, and the MCS which group different events based on the influence to the top-gate, the IMs examine each of the event individually. The main goal of the IMs is to identify the events whose improvement will have the most positive influence on the top-event and the intermediate gates. In other words, IMs can identify the critical components by ranking the different “BASIC” events in the FTA. In the present thesis, the I^B, I^{CR} and I^{FV} are examined.

The I^B was first introduced in 1969 as a method of numerically ranking the importance of a system’s components and remains as one of the most widely used IMs. The I^B measures the probability of a component (event) being reliable from the failure of its system. It must be clarified that the Birnbaum IM of a component is not a function of the reliability of the components. The I^B measures the rate of change of the probability of the top-gate as a function of the availability of the examined “BASIC” event. The result of the Birnbaum IM is a ranking of events which can be used to decide which end-events need to be improved (Lazakis, Turan, and Aksu 2010b). Assuming a top-gate X and a "BASIC" event A, the I^B for A can be calculated as the difference of the probability of X given that the event A did occur minus the probability of X given that the event A did not occur (Equation 3.4).

$$I^B(A) = P(X|A) - P(X|A^{'}) \tag{3.4}$$

The criticality IM is another method for ranking the events of an FT. The goal of the ranking process is to assess how much the failure of an event influences the gate they participate in. The I^{CR} examines the global probability of the top-gate occurring due to the occurrence of the considered event. In other words, the I^{CR} calculates the probability that an examined event is critical for the entire system and will occur if the top-gate occurs. Assuming a top-gate X and a “BASIC” event A, the I^{CR} for A can be calculated according to Equation 3.5.

$$I^{CR}(A) = P(X|A) - P(X|A^{'})\frac{P(A)}{P(X)} \tag{3.5}$$

As can be seen from Equation 3.4 and Equation 3.5, the criticality IM is a modified version of the Birnbaum IM, as it is adjusted for the relative probability of the basic event A. This is done to reflect the possibility of occurrence of event A and at the same time how possible it is to improve it. Consequently, in contradiction with the Birnbaum IM, the criticality IM focuses only on the link between the event A and its gate. It is not necessarily tied with the failure of the top event, even though the occurrence of A may affect it (Lazakis, Turan, and Aksu 2010b).

The last importance measure that is considered is the I^{FV}, which measures the overall percent contribution of cut sets containing an event of interest to the top-gate failure. The event under consideration is not the most critical one; however, it can cause the entire system to fail. The Fussell-Vesely IM is expressed as the ratio of the probability of occurrence of any cut sets containing the event A and the probability of the top-gate. The I^{FV} is calculated based on Equation 3.6

$$I_i^{FV}(A) = \frac{1 - \cap_{j=1}^{m}[1 - P(M_j(t))]}{1 - R_s[r(t)]} \tag{3.6}$$

where:

m_i: the number of MCS containing i

$\cap_{j=1}^{m}$: a MCS

$M_j(t)$: the j^{th} MCS of those containing i, at a time t

R_s: the system reliability

$r(t)$: an end event occurring at time t

As briefly mentioned in Section 4.4.1, the selected clustering algorithm is restricted to three dimensions, to preserve the model's practical application, visual interpretability, while controlling the model's complexity. Therefore, from the calculated IMs, two of them are selected and combined with the repair costs for the clustering analysis. The use of two IMs provides a more detailed understanding of the criticality of each component, compared with the use of only one IM. The selection of the IMs is based on the theoretical background of each IM. A disadvantage of the I^{FV}, compared with the other ones, is its usage of MCS. Even though MCS offer good qualitative results, they do not take into account the failure statistics of each component. On the contrary, the I^B and I^{CR} are not based on MCS and instead take into account the failure statistics of each event. Even though this process may increase the required computational time, it can have a positive influence on the accuracy of the analysis. As a result, from the presented IMs, the I^B and I^{CR} propagate to the clustering analysis.

3.4.5 Clustering Analysis

The clustering analysis is the final step of the critical equipment selection. As mentioned above, the critical equipment are identified based on cut-sets, the selected IMs and the repair costs for the components modelled in the FTA. To control the complexity of the clustering analysis, while maintaining the visual interpretability, the analysis is restricted to three dimensions. In that way, the selected components are items with both high criticality and high repair costs. The failure of these items would cost the most, both in terms of their replacement and the resulting unavailability of the system.

The clustering analysis uses three inputs, two of the calculated IMs and the repair costs for the components. The resulting three-dimensional plot is used to identify the cluster whose centroid has the biggest distance from the origin of the axes. The components in that cluster are identified as critical. This visual representation of the critical components creates a model that is easy to interpret.

For that purpose, the k-means clustering algorithm is used, which is one of the most popular unsupervised ML algorithms. The k-means algorithm has the widest applicability of all the clustering algorithms due to its performance and simplicity (Yu et al. 2018). This clustering algorithm is optimum when the data are divided into distinct groups. This assumption is present in this methodology since the components can be divided based on their ranging criticality (Dikis and Lazakis 2019). Lastly, the k-means algorithm was selected as it is the most common option when dealing with non-oddly shaped data (Müller and Guido 2015).

K-means groups similar points together by looking for a fixed number of k clusters in the data. This algorithm iterative assigns the data into the best suited of the k clusters (Wu 2012). The aim of k-means is to minimise the intra-cluster variance of the data, as seen in Equation 3.7, where k is the number of clusters,

μ_i is the mean values of the i^{th} cluster and x_j is the j^{th} data-point.

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} \|x_j - \mu_i\|^2 \tag{3.7}$$

To initiate this algorithm, the number of clusters, k, is selected. Then, k points are randomly selected to act as μ_i for the first iteration of the algorithm. All the data-points are then assigned to a cluster, based on their proximity to the clusters' centroids (Equations 3.7). Lastly, the new centroids of the k clusters are calculated according to Equation 3.8, where S_i is the set of all the points assigned to the i^{ith} cluster.

$$\mu_i = \frac{1}{|S_i|} \sum_{x_i \in S_i} x_i \tag{3.8}$$

This process is repeated, until there is no change in the data-points assigned in each clusters in consecutive iterations of the algorithm.

3.5 Data Preparation

Once the critical equipment selection methodology is developed, the data preparation methodology of the proposed framework follows. This methodology is developed independently and as explained in Section 5.3, is tested on a different case study with different data. This part of the proposed novel framework, includes the development of a novel hybrid imputation method based on data-driven efforts and FP knowledge, as discussed in Section 3.8.1. The data preparation methodology ensures that the data used in the subsequent FD and diagnostic tasks are pre-treated and have reached their full knowledge-extracting potential. This mainly includes the imputation of any missing data, together with the necessary pre-and post-imputation steps. In the maritime industry, and especially regarding PdM, missing data can cause many problems. Notably, missing data can lead to inaccurate maintenance scheduling, which can cause machinery failures and possibly accidents. Data collection sensors, in shipboard systems, are prone to generating missing values due to a plethora of factors. Such factors can include the loss of calibration of the sensors due to external influences, sensor anomalies, the loss of sensors' connectivity, and the difficulty to replace failed sensors due to environmental complications. Consequently, the preparation of data and the imputation of the missing values is of paramount importance in PdM frameworks.

3.5.1 Overview

The data preparation methodology is initiated with the data collection step, which differs from the previous methodology. As with the critical equipment methodology, the data collection step ensures that the required data for the development of the methodology are available. The next step is the preliminary analysis of the gathered data. This step includes four processes which are designed to prepare the collected data for imputation. These four processes include the form handling, synchronisation, filtering and correlation examination of the data. Once the preliminary analysis is completed, the imputation process, which is the main focus of the data preparation methodology, takes place. The imputation process includes the imputation of missing values through the use of the novel hybrid method based on kNN and MICE. Moreover, the imputation performance of the novel hybrid method is assessed through the use of the Mean Absolute Percentage Error (MAPE), Absolute Percentage Error (APE) and standard deviation (σ) and compared with the kNN and MICE imputation methods. Once the novel hybrid imputation method is established, the operational analysis step concludes the data preparation methodology. The data preparation methodology of the proposed framework is demonstrated in Figure 3.4.

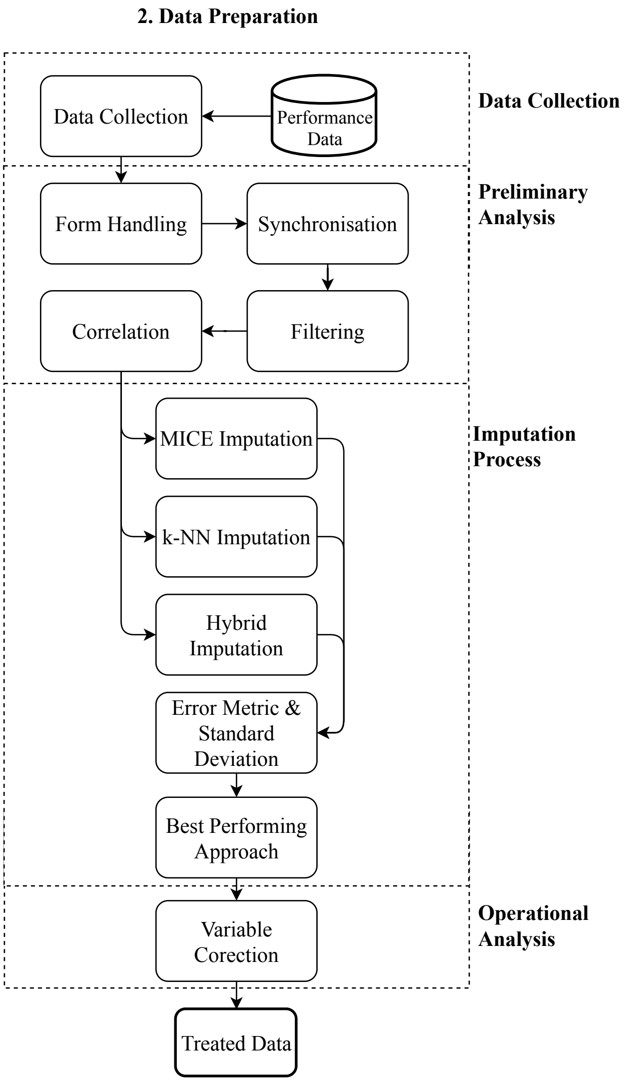

Figure 3.4: Layout of the data preparation methodology of the proposed framework, demonstrating the main steps and process.

3.5.2 Data Collection

The data collection step encompasses the necessary actions to collect the data used in the methodology. For that purpose, a commercial Data Acquisition (DAQ) system installed on board a merchant navy vessel was used. The data collected during the data preparation methodology differ from the similar step of the critical equipment selection methodology. In detail and as seen in Figure 3.1, instead of collecting repair costs and MTBFs, ship system performance data were gathered. The collected data are used to test the performance of the developed novel hybrid imputation tool. Lastly, performance data are collected, as similar research efforts are tested on performance data from their respective systems (Martinez-Luengo, Shafiee, and Kolios 2019).

3.5.3 Preliminary Analysis

The preliminary analysis is the step that follows the data collection step. The preliminary analysis serves the essential task of preparing the collected data for the imputation process. The four processes of this step are the form handling, synchronisation, filtering and correlation examination of the collected data and variables.

As seen in Figure 3.4, the first process is the form handling of the data. Form handling is a simple starting point for the preliminary analysis, yet its importance is paramount. This process ensures that the collected data are in tabulated form, ready for the next step of the methodology. Form handling is a process that is often the starting point of data-driven research efforts that contain unstructured data, collected from various sources.

As soon as the collected data are in a clear and tabulated format, the data synchronisation process takes place. Data synchronisation is needed as the different variables from the collected data may not be recorded uniformly. This may occur for two main reasons: a) the data collection sensors may not have the same sampling rate, and b) not all data collection sensors begin recording at the same time. Consequently, the synchronisation of the data warrants the consistency and the harmonisation of the data over time. Having all the variables synchronised over time can be very useful, especially when using similarity-based imputation approaches, or when trying to correlate variables for FD and diagnostic purposes. For the synchronisation of a variable, a timestamp is selected, and then, the timestamps before and after the selected one are also used. The synchronisation of the data is based on linear interpolation and is performed according to Equation 3.9

$$y_2 = \frac{(x_2 - x_1)(y_3 - y_1)}{(x_3 - x_1)} + y_1 \tag{3.9}$$

where:

x_1: the time before the timestamp of the synchronisation

x_2: the timestamp of the synchronisation

x_3: the time after the timestamp of the synchronisation

y_1: the variable before the timestamp of the synchronisation

y_2: the variable at the timestamp of the synchronisation

y_3: the variable after the timestamp of the synchronisation

The next process of the preliminary analysis step is the data filtering. This process is used to identify the points that need to be imputed, by determining if a sensor reading is missing, or it has an illogical value. The assessment of whether a recorded value is logical, or not, depends on the engineering knowledge of the variable being measured. As discussed in Section 3.6.2, domain knowledge is used to identify points that do not conform to an expected behaviour. The working process of the data filtering phase is shown in Algorithm 1.

Algorithm 1 Data filtering working process

Require: the upper limit (UL) and lower limit(LL) for each variable (v) in the collected data

```
for v in variables do
    for i in v do
        if i is NaN then
            Flag i as a missing reading
        else if i > UL or i < LL then
            Flag i as illogical
        end if
    end for
end for
```

Lastly, the final process of the preliminary analysis is the examination of the correlation of the variables. This is a common step in most data-driven research efforts, as it helps with the examination of the data. The identification of the correlation between the variables from the collected data helps with imparting FP knowledge during the imputation process. The correlation between the collected variables was examined by using the Pearson correlation coefficient, as seen in Han, Kamber, and Pei (2012), and cross-referencing the results with FP domain knowledge. The Pearson correlation coefficient ranges between -1 (perfect negative linear correlation) and 1 (perfect positive linear correlation) while 0 denotes no linear correlation.

3.5.4 Imputation Process

Following the completion of the four processes of the preliminary analysis step, the imputation of the missing data takes place. This step includes the implementation of the novel hybrid imputation method. Specifically, the novelty includes the comparison of the state-of-the-art MICE against the widely used kNN imputation algorithms and the combination of these two methods in a single, new, imputation method. The comparison of the hybrid, kNN and MICE imputation algorithms include their application to the points identified during the data filtering process of the preliminary analysis. Finally, their imputation performance is assessed by using the APE, MAPE and σ error metrics.

The kNN algorithm is a very popular ML tool with widespread applicability in imputation applications. The popularity of this tool is due to its easy learning curve and ability to produce accurate results (Zhang 2012; Huang et al. 2017; Zhang et al. 2018). As also presented in Section 3.6.2.2, kNN does not require an explicit training phase, which increases its overall efficiency. Lastly, kNN is very easy to integrate into hybrid models. Similarly, the MICE imputation algorithm is also a very useful tool in predicting values in multivariate datasets, albeit it is relatively new compared to the more traditional imputation approaches. Nonetheless, the MICE algorithm has the advantage of incorporating the benefits of MI with regression-based imputation. As also discussed in Section 3.6.2.2, MICE can easily be incorporated into hybrid models. The novel hybrid imputation method that is proposed combines the benefits of the kNN and MICE imputation algorithms while avoiding their respective shortcomings. In more detail, the benefits of the hybrid imputation method are listed below:

1. Provides realistic imputations due to the use of the kNN algorithm
2. Provides easy incorporation of FP knowledge due to the use of the kNN algorithm
3. Is based on the widely accepted kNN algorithm
4. Takes advantage of the non-artificial replication of values offered by MICE
5. Takes advantage of the flexible implementation of MICE

MICE is a flexible and state-of-the-art imputation algorithm that works by fitting a series of regression models in the data (Shah et al. 2014). As previously mentioned, MICE is used to assess the effectiveness of the hybrid imputation method. This approach is considered as an implementation of MI which uses linear regressions to help in the estimate of the missing values. For the rest of the section, assume two random variables Y and K with observed (Y_{obs}, K_{obs}) and missing points (Y_{miss}, K_{miss}). Also, assume a set of complete variables Z with Z_{obs} and Z_{miss} corresponding to the observed and missing points of Y and K. MICE uses a Bayesian approach to calculate the missing points by updating the prior distributions of the random variables. The steps for the application of MICE are the following:

1. Impute all the missing points of Y and K with the averages of the Y_{obs} and K_{obs} (Equation 3.11 and 3.10). In addition, n_{Yobs} and n_{Kobs} represent the

total number of observations for the Y and K variables respectively.

$$\hat{Y}_{miss,i} = \frac{\sum Y_{obs,i}}{n_{Yobs}} \tag{3.10}$$

$$\hat{K}_{miss,i} = \frac{\sum K_{obs,i}}{n_{Kobs}} \tag{3.11}$$

The initial estimates ($\hat{Y}_{miss,i}$, $\hat{K}_{miss,i}$) are placeholders and are only used to initiate the process.

2. Set the placeholders of one of the variables (e.g. $\hat{Y}_{miss,i}$) back to missing.

3. Fit a linear regression model (Equation 3.12) between the observed points of the target variable (e.g. Y_{obs}) and the appropriate independent variables (either all, or a subset of Z).

$$\hat{Y}_{miss,i} = \theta^T Z \tag{3.12}$$

In equation 3.12, Z is a column vector of the independent variables and θ is row vector of the regression parameters. The $\hat{Y}_{miss,i}$ parameter represents the imputation estimates produced by the regression model, to replace the original placeholders.

4. Find the row vector θ by minimising the mean squared error (Equation 3.13).

$$MSE = \frac{1}{n_{Yobs}} \sum_{i=1}^{n_{Yobs}} (Y_{obs,i} - \hat{Y}_{obs,i})^2 \tag{3.13}$$

The row vector θ can be calculated based on two different approaches. If the dataset is large, then an optimasation approach can be used (e.g. gradient decent) to fit the regression model and find the row vector θ. However, due to the size of the dataset used, an algebraic method was employed to fit the regression model and find the row vector θ. Generally, if the dataset is relatively small algebraic methods can be used, as they offer greater simplicity. As the size of the dataset increases, optimisation approaches are used as they offer a significant reduction in the required computational time.

5. Having found θ, use Equation 3.12 to impute the missing points of the Y variable (Y_{miss}).

6. Repeat steps 2, 3, 4, and 5 for every variable with missing points in the dataset

7. Reaching step 6 is one cycle. The entire process is repeated for a predetermined number of cycles (usually 10 repetitions is an empirically accepted number).

To summarise, MICE uses linear regression in an iterative manner. The process initiates by using mean (vertical) imputation. Every variable with missing values is used in a regression model to update the initial mean imputation.

Apart from MICE, kNN is also used individually to examine the effectiveness of the proposed novel hybrid imputation method. In kNN, k represents a user-defined number of instances (i.e. nearest neighbours) that are considered for the hot-deck imputation. This is a non-parametric and lazy algorithm as it does not take into account the distribution of the data in the examined vectors, and it has no explicit training phase, as presented in Zhang and Zhou (2007). As with any hot-deck approach, kNN is based on the similarity between features, which is assessed by the Minkowski distance (Equation 3.14).

$$D = (\sum_{i=1}^{n} \mid x_i - y_i \mid^{p})^{1/p} \tag{3.14}$$

In equation 3.14 the p hyperparameter is set to 2, which transforms D to the Euclidean distance. The Euclidean distance is the most common and widely used distance metric, with implementations in many different applications (Groenen and Jajuga 2001; Dikis and Lazakis 2019). Similarly, x_i and y_i represent the examined instances. In addition to the distance metric, a weight is also assigned to each possible donor based on its distance. By doing so, closer neighbouring points (i.e. similar and most recent operating conditions) have a more considerable influence over the instance to be predicted. This is a vital feature as it allows taking into account the actual operation of the system under examination. The number for the k hyperparameter is not standardised. It depends on the field of application, and its selection lies with the researcher. In general, a small k will restrict the algorithm to a small region of the data, and as a result, it will produce results with low bias and high variance. A very small value for k (e.g. $k = 1$) can create models sensitive to outliers, noise and anomalous data, as the model is overfitted and not generalised enough for use in out-of-sample data. On the other hand, a high k (e.g. $k = 30$) can create overgeneralised models, as it averages more possible donors, generating results with low variance and an increased bias.

Lastly, the hybrid approach integrating kNN and MICE is applied and assessed against the previously discussed algorithms. The kNN component of the hybrid approach is based on FP knowledge. This approach initiates with the correlation analysis, where the systemic correlations between the collected variables are determined. In the hybrid approach, each vector in the dataset is examined in turn. When an instance with a missing value is identified, the kNN imputation algorithm is used. However, kNN looks for possible donors only in correlated variables; as determined during the correlation analysis. This has the following two benefits:

- The imputation process is expedited as only certain vectors of the dataset are examined.
- The predictive power of the model is improved as only correlated variables

are used to predict missing points.

This process is repeated until no further changes occur to the data set. In this case, the suspension of the kNN algorithm signifies its inability to impute any more missing points, as points from the correlated vectors may be missing simultaneously. Therefore, the remaining missing points are predicted using the aforementioned MICE approach. The structure of the proposed novel hybrid methodology is demonstrated in Algorithm 2 (Cheliotis et al. 2019).

Algorithm 2 Hybrid novel imputation method using a combination of kNN and MICE

```
Require: filtered dataset x of dimension m × n
  modify_flag ← 1
  while modify_flag == 1 do
    modify_flag ← 0 {Check x was updated in prev. loop}
    for i = 1, 2 ... n do
      temp_column ← i^th columnofx
      corr_columns ← columns correlated with temp_column
      for j = 1, 2 ... n do
        if j^th element of temp_column does not exist then
          if j^th element of corr_columns exists then
            j^th element of temp_column ← kNN imputation
            modify_flag ← 1
          end if
          i^th column of x ← temp_column
        end if
      end for
    end for
  end while
  x ← MICE imputation
  return x
```

For the comparison of the mentioned imputation tools the APE (Equation 3.15), MAPE (Equation 3.16) and σ (Equation 3.17) are used. The aim is to choose the imputation approach with minimum MAPE and σ. The MAPE is selected as it is a popular and easy to understand metric for the evaluation of the model's imputation performance (Byrne 2012). Moreover, MAPE has widespread applicability for predictive models and is commonly used in imputation (Martinez-Luengo, Shafiee, and Kolios 2019; Cheliotis et al. 2019). The MAPE is expressed as the percentage difference between an actual and forecast value. The standard deviation of the error is used to evaluate the sparsity of the errors and to determine the possibility of introducing outliers within the predictions. In the following equations, x_i and $\hat{x}_i$ represent the actual value of the variable and the predicted value, respectively.

$$APE = \mid \frac{x_i - \hat{x}_i}{x_i} \mid \tag{3.15}$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} APE \tag{3.16}$$

$$\sigma = \sqrt{\frac{\sum (APE_i - MAPE)^2}{n}} \tag{3.17}$$

In summary, three different approaches are implemented, compared and assessed. The first one is MICE, which is applied to the entire dataset until no missing points were left. The second approach that is tried is the kNN. This approach is applied to the entire dataset, without taking into consideration any systemic correlations, until all the missing points in the dataset are imputed. Lastly, the hybrid approach is tested, which combines kNN with FP analysis and MICE. The kNN algorithm is deployed by taking into account systemic interdependencies between variables. Then, the MICE algorithm is used to impute any missing points that the kNN cannot predict. These three approaches are verified by testing them in the collected data. A sample of the data are removed and the approaches are evaluated in their ability to predict the removed values, simulating the imputation of missing data, as detailed in Section 5.3.2.

3.5.5 Operational Analysis

The data preparation methodology concludes with the operational analysis. This step includes the correction of the variables to account for ambient conditions and ensures that the data are prepared for the following FD and diagnostic tasks. To account for the ambient conditions, various sources are taken into consideration, including international standards and the manufacturers' recommendations. Accounting for ambient conditions is a common step in many applications, as it ensures that the affected variables are adjusted accordingly.

3.6 Fault Detection (FD)

After the preparation of the data, the FD methodology of the framework follows. The FD methodology includes the novel combination of data checking steps, with regression-based EB modelling and the use of EWMA control charts for FD in ship systems. Moreover, the types of the different predictor variables are investigated, as mentioned in Section 3.8.1. The FD methodology ensures that developing faults are captured in a timely manner. In more detail, this methodology examines the detection of faults that result from gradual degradation of components. Such faults can include fouling, corrosion and wear-and-tear of components. Faults that are caused by a sudden shock or breakage are not considered. By developing the proposed methodology, the ability to capture previously unseen anomalies based on an EB model is enhanced. Besides, there is also the advantage of examining how signals evolve in real-time, based on contributing factors and uncoupled from operating conditions, due to the use of an EB approach. Also, the use of the EWMA control charts allows for the accurate detection of developing faults. Similarly, the superior performance of EWMA control charts in filtering-out noise compared to traditional control charts (e.g. Hotelling's T2 statistic), as seen in Cheliotis, Lazakis, and Theotokatos (2020), is also beneficial. For clarification, noise is considered as systematic unwanted disturbances to the signal occurring from the system's interference with the environment. This is contrary to faults resulting from degradation which have measurable and observable trends (Guo et al. 2018).

3.6.1 Overview

As with the previous methodologies of the framework, the FD methodology initiates with its data collection step, as seen in Figure 3.5. As discussed in Section 5.4, the FD methodology is developed individually, and it uses different data from the previous methodologies. This step gathers data from multiple sources, including operating companies and data banks, to enable the development of this methodology. Once the data are collected, the data checking step follows, a step which prepares the collected data for subsequent FD steps. The data checking steps includes the application of the DBSCAN algorithm for outlier detection, and data filtering for the isolation of non-operational data points. Then, the model development step follows, which is based on historic ProMon data and shop tests and yields the developed EB model. During this step, the feasibility of different regression techniques and predictor variables is assessed in terms of their suitability for an EB model. Once this model is established, it is used for a comparison between the recorded and the expected values of a target variable, generating the residuals. In detail, once the predictor variables from the incoming data are checked, they are used as input to the EB model to produce the expected values of the target variables. These values are compared with the target variable from the incoming data, as demonstrated by the dotted lines of Figure 3.5. Thereupon, the obtained residuals are assessed in an EWMA control chart for FD.

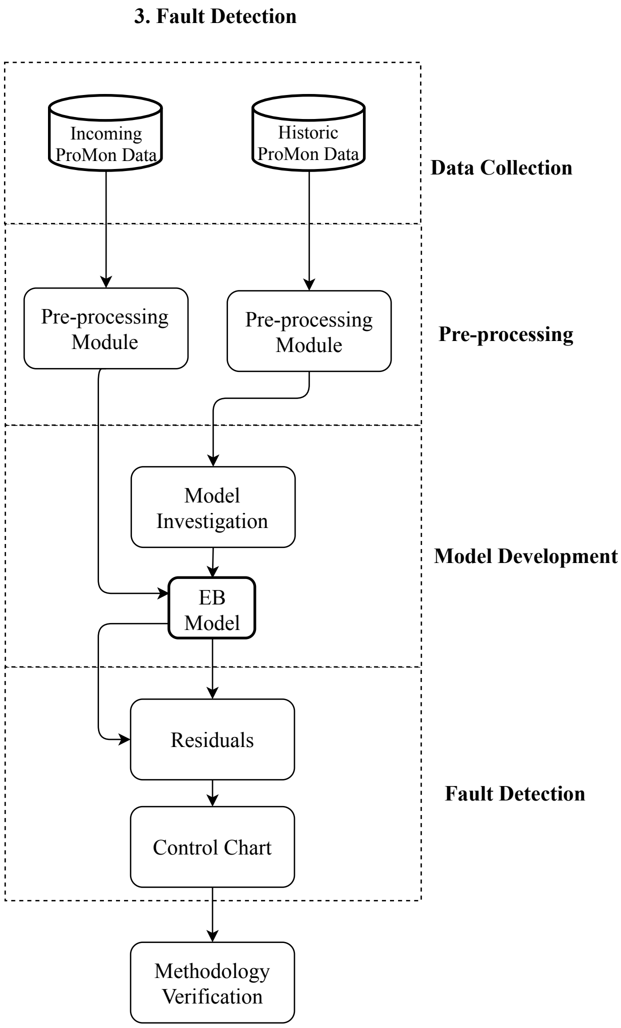

Figure 3.5: Layout of the fault detection methodology of the proposed framework presenting the main steps and process.

3.6.2 Data Collection

The data collection is the first of the FD methodology. The output of the data collection step is the creation of a database with historical information, which is used for both model development and methodology verification purposes. As also seen in Figure 3.5, data collection includes the gathering of three different types of information. Initially, the shop tests of the ship's main engine are collected. The shop tests are machinery tests and represent a form of benchmark and commissioning test. Even though shop tests are widely used in the maritime industry, their role in condition monitoring and PdM is limited. This is caused, as the actual operating conditions of the ship change throughout its life and differ from the conditions during the shop tests. Nonetheless, shop tests can be used to obtain initial estimates on limits of operation. Then, a DAQ system installed on board a merchant vessel is employed to gather historic ProMon data, The same system is also used to collect incoming ProMon data which are used to simulate different faults to evaluate the capabilities of the FD and diagnostic methodologies. Since the historic and incoming ProMon data are obtained from the same DAQ system, both of these datasets have the same sampling characteristics. In addition, any required pre-processing is the same between the two datasets. Typically, DAQ signals for FD tasks of engineering systems include power output, rotational speed, injection and scavenging pressure and EG, cooling medium, and LO temperature. Due to the nature of the FD methodology and unlike the data preparation methodology, the selected data must meet specific criteria regarding their diagnostic powers. In detail, developing faults must be able to manifest through the behaviour of the collected variables. Lastly, the data frequency usually ranges from one sample per second to one sample per five minutes, depending on the application.

3.6.3 Data Checking

Data checking is the next step following data collection and is concerned with ensuring that the collected datasets reach their full knowledge-extracting potential. Data checking, including the removal of outliers, is a standard step in most data-driven research efforts (Martinez-Guerra and Luis Mata-Machuca 2013; Sari 2013; Sayed-Mouchaweh 2018). The output of the data checking step is the creation of a checked dataset, ready for model development. There are four processes that are included in this step.

The first process is a data formatting step, where the units of the collected data are checked, and their form is altered if needed. By doing so, it is ensured that the data are tabulated and placed in a suitable format for the next steps of the methodology. This process is very similar to the preliminary analysis, discussed in Section 4.4.3.

In the next process, the DBSCAN algorithm is used to identify and remove outliers and transient states of operation, which are out of scope in the present work. As mentioned in Section 3.6.2, outliers are considered as sparse data points with significantly different values from the rest of the instances of the same variables. They are often caused by sensor errors and other instrumental faults and are not part of a fault indicative pattern. For instance, negative EG temperatures and power output above an engine's rated power are considered as outliers. Thus, outliers can be considered as data "anomalies", and if they are not removed, they can have a negative impact on the developed models.

DBSCAN algorithm is very effective in detecting outliers and does not rely on domain knowledge, which offers several advantages. It is a density-based spatial algorithm that works by examining each point in the dataset and identifying dense areas of points (clusters). The DBSCAN algorithm requires the use of the user-defined $minP$ hyperparameter. The $minP$ defines the minimum number of points that are required to form a cluster. The $minP$ is simple to specify as it is a function of the dimensionality of the dataset. Larger values are preferable, with an exclusive global lower bound of 3 (Schubert et al. 2017). Lastly, the value $minP$ should be close to the number of dimensions of the dataset (Chen and Li 2011; Ester et al. 1996). As suggested in the literature, the $minP$ hyperparameter is selected by combining the above restrictions with domain knowledge (Thang and Kim 2011; Schubert et al. 2017). Also, the ϵ hyperparameter is required, which defines the maximum distance between points for them to be considered to be in the same cluster. If ϵ is too small, the majority of the data points will be clustered as noise, whereas if it is too big, all the data points will be in the same cluster. In general, smaller values are preferred. An approach for calculating the ϵ hyperparameter is by considering the rate of change of the distance of each point to the nearest neighbour (k-nearest neighbour graph), as shown in the relevant literature (Rahmah and Sitanggang 2016; Gaonkar and Sawant 2013). However, this approach is not usable when using space data (i.e. time-series with constant sampling rate) evenly. As a result, the value of ϵ is obtained after iterative attempts.

Given these hyperparameters, the data are categorised in three groups. Core points are considered as data points with more than $minP$ points within a radius of ϵ. Border points are defined as data points with fewer than $minP$ points within a radius of ϵ. The remaining points are considered as outliers or noise. Moreover, a point q is directly density-reachable from a point p, if p is a core point and q is within a radius ϵ from p. Assuming another point q_1 which is directly density-reachable from point q only, it is said that points p and q_1 are indirectly density-reachable (Thang and Kim 2011; Chen and Li 2011; Çelik, Dadaşer-Çelik, and Dokuz 2011). The working process of the DBSCAN algorithm, as used in this methodology is shown below:

1. Find all core points
2. Assign all points that are directly density-reachable and indirectly density-reachable in the same cluster
3. Mark any unassigned points as outliers.

Following the removal of the transients and outliers, the data filtering process takes place. Specifically, the data are filtered to retain the points that represent operational periods. Since the data collection took place over an extended period, some points could have been recorded when the ship and its main engine were not operational. The data filtering is performed by using a value-based approach.

Therefore, this process removes non-operational points while retaining the rest. The last process of the data checking step is the correction of the data to reference conditions, according to the ISO 3046-1:2002 international standards and the original engine's manufacturer recommendations, as also discussed in Section 4.4.5.

3.6.4 Model Development

The model development step follows the data checking step and uses as input the checked data, as seen in Figure 3.6. The aim is the development of an EB model that can predict the ideal (expected) behaviour of a selected variable of a system based on appropriately selected inputs. EB models are often used in for FD tasks, as they can model the expected behaviour of a variable subject to changing operating conditions. As discussed in Section 3.6.3.1, EB models are also ideal in the absence of faulty labelled data, as they can detect developing faults by defining a range of normal operation. The output of this step is the developed EB model which is in turn used for the FD step. It should be noted that the model development step includes iterations for the identification of the optimal predictor variables. Throughout this step, the used data are divided for training, validation and testing, based on empirical rules and common practices. The training sample of the data is used to fit the different models. It is said amongst practitioners, that the models "see" and "learns" for the training data. The validation sample of the data is then used to tune the models' hyperparameters. The validation set is withheld from the models during the training phase, but it can still affect the models' performance, albeit in a more limited manner than training. Ultimately, the appropriate model is selected based on its performance on the validation set. Lastly, the test sample of the data is used to evaluate the overall performance of the selected model, after they are trained, and their hyperparameters are tuned. The test sample is also withheld from the models during both training and validation.

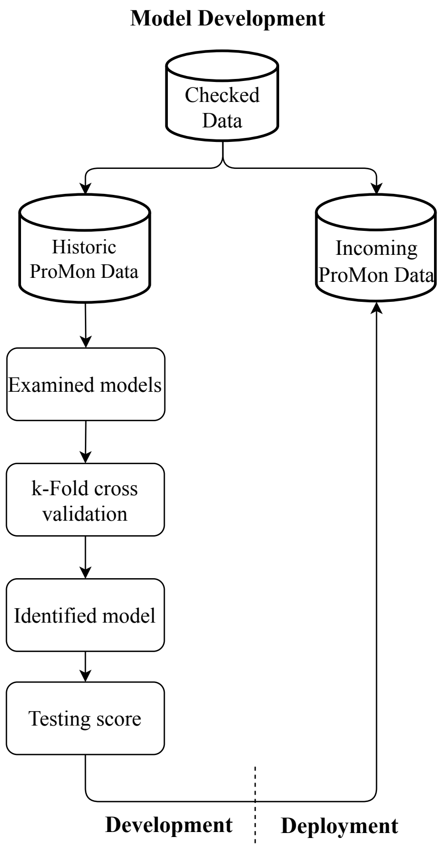

Figure 3.6: Working process of the model development step, demonstrating the different process, including the selection of the different predictor variables.

3.6.4.1 Training and Validation

The training and validation process is used to fit and fine-tune the different models and is structured around the use of historic ProMon data collected during the ship's operation. The aim is to use a training set to fit the different models, and a validation set to fine-tune and ultimately select the best performing model, prior to the evaluation of its generalisation capabilities in a test set. This process uses training and validation datasets, which are a portion of the historic ProMon data. Finally, it must be stressed, that the recorded ProMon data represent "healthy" ship operation, as established by the ship's operators.

During the EB model development, four regression models are generated including Ordinary Least Squares (OLS) single linear regression, multiple linear ridge regression, OLS single polynomial regression and Multiple polynomial ridge regression. As discussed in Section 3.6.3.1, regression-based EB models do not depend on extremely large training datasets and offer greater flexibility in imparting domain knowledge, as they are not black-box approaches. This is achieved by the selection of the inputs and by observing and influencing the weight each input has (i.e. the coefficients) on the output. These models are used to produce an estimated output for a selected target variable by relying on the use of appropriately selected inputs (predictor variables). The examined EB models are trained and validated, using the R^2 metric, for both the shop tests and the historical data. Linear and polynomial regression models are developed to examine the best type of fit, given the acquired data. There are several advantages for each type of model; however, the selection is application-specific and a function of the available data, as discussed by Müller and Guido (2015). Single-input OLS regression models, both linear and polynomial, are produced as a basis for comparison with the more accurate ridge regression models, as seen through the work of Lepore et al. (2017), Erto et al. (2015), Naik, Bisoi, and Dash (2018), and Assaf, Tsionas, and Tasiopoulos (2019). Lastly, the specific inputs (i.e. the used predictor variables) for the EB models are investigated separately.

In general, the developed linear regression models have a form as shown in Equation 3.18, where $\hat{y}$ represents an estimate for the target variable, w_0 to w_p are the regression coefficients, b is the axis intercept and x_0 to x_p represent the p different predictors (inputs).

$$\hat{y} = w_0 x_0 + \ldots w_p x_p + b = \sum_{i=0}^{p} w_i x_i + b \tag{3.18}$$

On the other hand, the developed polynomial regression models have a form as shown below. This equation represents the general form of k^{th} order polynomial based on two predictors (x_1,x_2) and including the interaction terms between the predictors (Bowerman, O'Connell, and Murphree 2015; Olive 2005).

$$\hat{y} = w_0 x_1 + w_1 x_2 + w_2 x_1 x_2 + \ldots w_p x_1^k + w_p x_2^k + b \tag{3.19}$$

During the training phase, sets of known predictors (x_0 to x_p) and target variables (y) are used as input in either the linear or polynomial regression models to obtain $\hat{y}$. Then, the objective functions in either Equation 3.20 (OLS regression) or Equation 3.21 (ridge regression) are minimised. As a result, the estimates for the coefficients (w) and intercept (b) are obtained.

When OLS regression is used, the coefficients and intercept are estimated by minimising the sum of the squared difference between the predicted and the actual values of the target variable (residuals). The minimisation of this objective function is enabled since both y and $\hat{y}$ are available during the training phase.

$$OLS : \|\hat{y} - y\|_2^2 \tag{3.20}$$

When ridge regression is used, the coefficients and intercept are estimated by minimising an objective function similar to the OLS. In addition to the sum of the squared residuals, an additional term is included. The additional term is called $L2$ regularisation and limits the magnitude of the coefficients. $L2$ regularisation explicitly restricts the model to avoid overfitting. The limiting capability of the regularisation term is attributed by the user-specified hyperparameter α. This hyperparameter limits the influence of the predictors to the target, given that α is appropriately selected. When α is equal to zero, the objective function becomes OLS, and on the other hand, if α is very large, the model will underfit the data. During this research effort, k-fold cross-validation was used to estimate the optimal α value (Olive 2005; Bowerman, O'Connell, and Murphree 2015;

Bishop 2006).

$$Ridge : \|\hat{y} - y\|_2^2 + \alpha \|w\|_2^2 \quad with \quad \alpha \in [0, \infty) \tag{3.21}$$

K-fold cross-validation is a process which iteratively trains and validates the examined models by using all the possible combinations of training and validating sets. The working principle of this process is demonstrated in Figure 3.7, which is a common example with $k = 3$ folds. In essence, the k-fold cross validation is

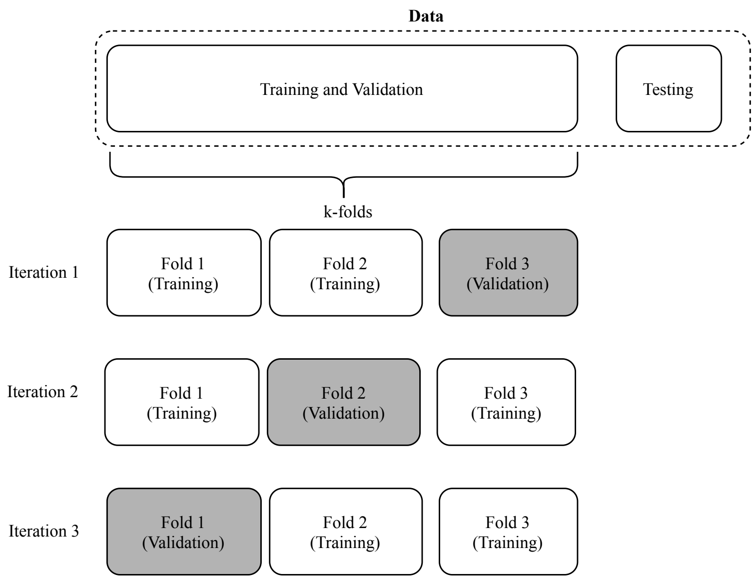

Figure 3.7: Training and validation process using k-fold cross validation, with $k = 3$ folds.

used to evaluate the performance of the trained models and select the best performing approach for testing. This process trains and validates as many models as there are different combinations of model hyperparameters. The different hyperparameters included in this work are parameters of the learning methods (e.g. α regularization term), and the different inputs used (e.g. predictor variables). The k-fold cross-validation partitions the data in k different folds. Each fold is set aside once, and the examined models are trained on the remaining $k-1$ folds. Then, the fold withheld from training is used, to obtain the validation score the trained models. This sequence is repeated until every fold is used for validation once. For each model, the mean validation score is calculated, and the model with the highest mean score is selected. Finally, the identified model is trained with all the training and validation data before its generalisation capabilities are assessed in the test set.

Moreover, the general working process that is followed as part of the development of the EB model is shown in Algorithm 3. Algorithm 3 requires as input the predictor (X) and target (Y) variables. Also, it requires the number of folds (k) for the k-fold cross-validation and the size of the test set. Lastly, the set of the considered values for the model's hyperparameters is given. Algorithm 3 represents the generalised process for the development of the supervised model, including the optimisation of the α hyperparameter.

Algorithm 3 Model development and hyperparameter optimisation

Require: X, Y, k and a list of hyperparameters h_i for i between 1 and n
  $X_{polynomial} \leftarrow$ derive the polynomial features of X
  Augment X with $X_{polynomial}$
  $X_{TrainValidate}, X_{Test}, Y_{TrainValidate}, Y_{Test} \leftarrow$ Split and normalise X and Y based on $TrainingSet$
  $Best\_score \leftarrow 0$
  $Best\_parameter \leftarrow 0$
  for $i = 1 \ldots n$ **do**
    Model $\leftarrow$ model with h_i hyperparameter
    Scores $\leftarrow$ k-fold cross-val. scores using $X_{TrainValidate}$, $Y_{TrainValidate}$, Model
    Score $\leftarrow$ average of Scores for the i^{it} iteration
    if Score $> Best\_score$ **then**
      $Best\_score \leftarrow$ Score
      $Best\_parameter \leftarrow h_i$
    end if
  end for
  Model $\leftarrow$ model with $Best\_parameter$
  return Model

3.6.4.2 Testing

As mentioned above, four different types of regression models are used, namely OLS single linear regression, multiple linear ridge regression, OLS single polynomial regression and multiple polynomial ridge regression. Also, during the training and validation, the value of α, the different predictor variables are assessed in the required cased. After the k-fold cross-validation, the mean validation score for each examined model is obtained. The validation performance is assessed using the R^2 score, and the model with the highest R^2 is selected for testing.

The model selected for testing is fully defined in terms of the regression type, the predictor variables and the value of α. That model is then retrained using the training and validation datasets, and its testing performance is evaluated using the R^2 score. Once the testing performance of the selected model is analysed the model is finalised (Figure 3.6).

3.6.5 Fault Detection

Following the selection of the ideal regression model and the identification of the optimum predictor variables, the FD step ensues. The output of the EB model is a prediction (for the EB) of a specifically selected variable of an engineering system. To facilitate fault detection, the aim is to monitor specific variables (y) and gauge any deviations from their expected value ($\hat{y}$), as produced by the EB model. Moreover, any deviations are assessed as a function of the ship's operational profile. As shown in Figure 3.5, the fault detection process has two inputs. It uses incoming, previously unseen data and the EB estimate from the model for the monitored variable.

For each instance of the incoming database, the residuals (r) between the expected value and the recorded value is calculated according to Equation 3.22.

$$r_k = \hat{y_k} - y_k \quad for \quad k = 1, \dots N \tag{3.22}$$

Analysing the residuals is an effective method for detecting faults in engineering systems, as the comparison between the actual and the expected behaviour can uncover developing faults at an early stage. The residuals quantify the deviation of a variable from its expected value, given an operating profile (Harrou et al. 2015; Awad, AlHamaydeh, and Faris 2018; Holmes and Mergen 2000).

After the residuals are calculated, the EWMA control chart is constructed, which allows for the creation of visual models that enable the accurate detection of developing faults in their early stages. In Equation 3.23, z refers to the EWMA statistic, which is calculated for all of the k instances. For the particular case of z_0, the mean value of the variable in the incoming data is used. The smoothing effect of the EWMA is attributed to the user-defined smoothing parameter, λ. The smoothing parameter is defined according to common practices. Lastly, the residual at each instance (r_k) is used.

$$\begin{aligned} z_k &= \lambda r_k + (1-\lambda) z_{k-1} \\ for &\quad k = 1 \\ and &\quad \lambda \in [0, 1) \end{aligned} \tag{3.23}$$

A crucial component of the EWMA fault detection is the Upper Control Limit (UCL) and Lower Control Limit (LCL). These two limits provide the basis for the detection of faults, as any point above the UCL or below the LCL signifies faults. These limits are calculated according to the following Equations 3.24 and 3.25.

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{2-\lambda}[1-(1-\lambda)^{2i}]} \tag{3.24}$$

$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{2-\lambda}[1-(1-\lambda)^{2i}]} \tag{3.25}$$

In these equations, μ_0 is the mean value of the variable in the incoming data and σ is the standard deviation. Lastly, L represents the width of the control chart, and its value is assigned based on the application, discussed in more detail in Section 6.4. In essence, the UCL and LCL form the envelope of normal operations for the selected variable. As the choice of L affects this envelope, it must be appropriately selected so that it can correctly classify normal and faulty operating points. If the recorded data represent "healthy" operating points, the resulting UCL and LCL envelope must fully encase all the data points. On the other hand, if a known fault exists in the data, the ULC or LCL must be exceed at the point of the failure. If the resulting envelope does not exhibit this behaviour, the value of L must be altered. Consequently, assigning L, its value can be an iterative process.

3.7 Diagnostics

The diagnosis of faults is the concluding step of the methodology. The aim is to propagate the evidence of developing faults in a diagnostic network that allows the determination of the root cause of the detected fault. Consequently, any diagnostic efforts must utilise to some degree, a fault detection methodology. Moreover, the diagnostic methodology can be used to summarise the condition of the ship effectively. This part of the framework focuses on the creation of a knowledge-based diagnostic network which is integrated with the FD methodology described in the previous section. In more detail, the integration of the knowledge-based diagnostic network with the ML-driven EB-based FD model is novel. The use of the knowledge-based diagnostic offers several advantages compared to the physics-based and data-driven alternatives. As discussed in Section

3.6.4, knowledge-based diagnostics offer accurate performance without requiring lengthy set-up times or a large amount of data for training. Besides, they are modular and easier to expand in multiple engineering systems.

3.7.1 Overview

The diagnostics methodology commences with the collection of the appropriate data, as seen in Figure 3.8. During this part of the framework, operating manuals from the ME's manufacturer are collected together with failure statistics from reliability data banks. Also, ProMon data collected during the FD methodology are used in this part of the framework too. This is due to the lack of additional required data, as explained further in Section 5.4. Once the required data are gathered, the fault mapping, which is of paramount importance to this diagnostic methodology, is developed. Fault mapping is a process that pairs certain faults with the variables they can affect. Moreover, the behaviour of the affected variables is also described. Then, the results from the FD step, mainly from the EWMA control chart, are aggregated. The objective of the aggregation is to classify the condition of the described system in its appropriate operational state. The FD and diagnostic steps are closely developed, as the trigger for the diagnostic tasks is a function of the output of the FD step. The next process is the set-up of the diagnostic network. In this work, a BN is employed due to the advantages detailed in Section 3.6.4. The BN integrates the results of the FD with the identification of the root cause of the detected faults. The structure of the network is specified by combining the results of the fault-mapping process with engineering knowledge of the examined system. At this stage, the failure statistics collected from data banks are used to quantify part of the BN. Once the structure of the BN is specified, the BN is used to combine the results from FD, with inputs from the data banks to pinpoint the root-causes of specific faults. Also, the final BN can be used to summarise the condition of a ship, quantifying the probabilities of different faults and summarising the condition of each cylinder.

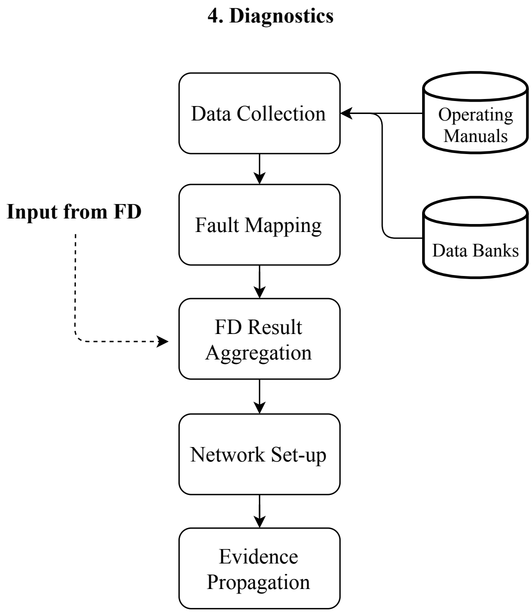

Figure 3.8: Layout of the diagnostic methodology of the proposed framework showing the different steps and demonstrating the input from the FD methodology

3.7.2 Data Collection

The data collection step of the diagnostic methodology supplements the data collected in the previous parts of the framework. Due to limited access to additional sources for the required ProMon data, the data gathered in the FD methodology are also used for the diagnostics. These data are supplemented with the operating manuals of a ME of a merchant ship together with detailed failure statistics from data banks. The operating manuals are collected from ship operators and include details regarding the baseline operation, maintenance and troubleshooting of the ship's ME. To that end, these manuals include alarm limits for various variables at different operating points and include detailed accounts of functional dependencies between different systems. However, the alarm limits in the operating manuals are single points and represent hard limits aimed at preventing very severe equipment damages. The overall aim of the FD and diagnostic methodology is to detect ship degradation or the development of a fault before the alarm limits are reached. Data banks, on the other hand, offers failure statistic for a plethora of shipboard equipment. They can include the failure rates of all the possible failure modes for shipboard systems, sub-systems and components.

3.7.3 Diagnostic Set-Up

Diagnostic set-up is the next phase of the methodology and follows the data collection. There are three processes that form the diagnostic set-up step. These processes include the mapping of faults, the aggregation of the results from the FD and finally, the network set-up. The goal of this phase is the ability to use real-time information to produce accurate probabilities, of different faults, occurring in the selected system.

3.7.3.1 Fault Mapping

Fault mapping is a crucial task as it identifies the potential faults that can be diagnosed in a selected system, together with the variables required for their diagnosis. Therefore, this step examines the diagnostic potential of the ProMon data gathered during the FD. This step essentially justifies the variables that are monitored in the EWMA control chart. Alongside with the required variables, the acceptable range of operation and the behaviour of each variable are specified. Lastly, any additional tests required for the diagnosis of specific faults are specified in this phase. Fault mapping is based on domain knowledge and by taking into consideration the operating manuals of the selected systems, provided after personal communications with the ship operator.

3.7.3.2 FD Results Aggregation

The first examined process of the diagnostic set-up step is the aggregation of the results from the FD step. The goal of this process is to classify the condition of a system to its appropriate operation state (i.e. normal, degraded, failed) based on the behaviour of an appropriate variable. The behaviour of the variable is assessed in the FD step and mainly during the EWMA control chart.

As discussed in Section 4.5.5, the EWMA makes use of the L hyperparameter, which forms the envelope of normal operation. Any data points positioned outside of that envelope represent a fault. Moreover, Equations 3.26 and 3.27 are used to define the UCL_{deg} and LCL_{deg} which define the envelope of degraded operation. Similarly, any points between the failed and degraded envelopes represent degraded operations. The degraded limits use the L_d hypeparameter, such that $L > L_d$. Laslty, any other points represent normal operations.

$$UCL_{deg} = \mu_0 + L_d \sigma \sqrt{\frac{\lambda}{2-\lambda}[1-(1-\lambda)^{2i}]} \tag{3.26}$$

$$LCL_{deg} = \mu_0 - L_d \sigma \sqrt{\frac{\lambda}{2-\lambda}[1-(1-\lambda)^{2i}]} \tag{3.27}$$

3.7.3.3 Network Set-up

Once the pairing between monitored variables and corresponding faults is completed, the structure of the diagnostic knowledge-based BN is determined. As discussed in Section 3.6.4, knowledge-based diagnostic models have the advantage of mimicking the reasoning of a specialist, while avoiding the restrictions of black-box approaches. Similarly, diagnostic BNs have high modularity and are easier to set-up and interpret, compared to the alternative knowledge-based approaches. The identified faults are represented in the primary and secondary fault nodes of the network. Depending on the application, the states of these nodes can vary between Normal and Abnormal, Working and Failed, etc. The variables required for the monitoring are used in the observable nodes. These variables are selected so that the primary and secondary faults can manifest through the behaviour of these variables. Also depending on the application, the states of the observable nodes can vary between Normal, Degraded, and Failed. Any additional tests required for the investigation of a fault are inserted in the test nodes. The states of the tests nodes can vary between Pass and Fail, Normal and Abnormal, etc. Lastly, any other nodes concerned with the inner-workings of the diagnostic tool can be inserted in the control nodes section (Figure 3.9). The states of the control nodes can very between True and False, Pass and Fail, etc.

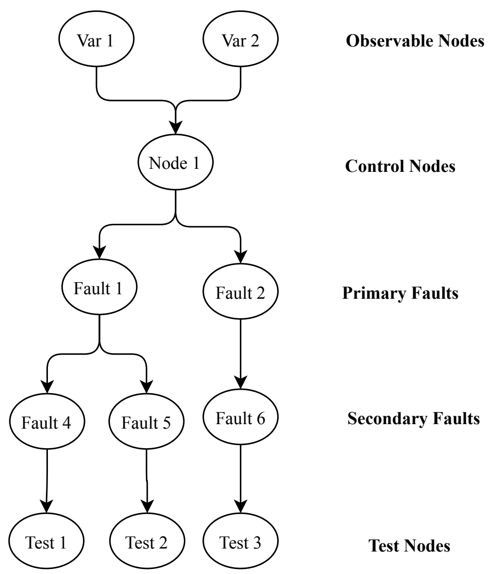

Figure 3.9: General diagnostic network structure

BNs represent a joint probability distribution of a set of random variables. They consist of a qualitative part and a quantitative part. The qualitative part is defined by a probabilistic Directed Acyclic Graphical (DAG) model, where each variable is depicted as a node. The qualitative part also includes directed links between the nodes to define a causal relationship. Similarly, the quantitative part is defined by the conditional probability distribution in the Conditional Probability Table (CPT) of each node (variable) (Ruggeri, Faltin, and Kenett 2007). The observable nodes of Figure 3.9 are the parent nodes of the control nodes. The control nodes can also be called the child nodes of the observable nodes. Moreover, leaf nodes are defined as nodes with parent nodes and no child nodes (e.g. test nodes), whereas root nodes have child nodes but no parent nodes (e.g. observable nodes) (Pearl 1985). BNs are based on Baye's theorem, with the goal of calculating the posterior conditional probability distribution of a fault given some observable evidence, as shown in Equation 3.28 (Langseth and Portinale 2007; Horný 2014; Cai, Huang, and Xie 2017b).

$$\begin{aligned} P(A|B) &= \frac{P(B|A)P(A)}{P(B)} \iff \\ P(fault|evidence) &= \frac{P(evidence|fault)P(fault)}{P(evidence)} \end{aligned} \tag{3.28}$$

Assuming a set (U) of n random variables $U = (X_1, \dots X_j, \dots X_n)$, a BN with n-nodes can be constructed. Moreover, X_j represents the j^{th} variable. The BN for the n variables can be represented by Equation 3.29, where $pa(X_j)$ denotes all the parent nodes of X_j.

$$P(X_1, X_2, \dots X_j, \dots X_n) = \prod_{j=1}^{n} P(X_j|pa(X_j)) \tag{3.29}$$

For example, the case of a simple network is considered in Figure 3.10.

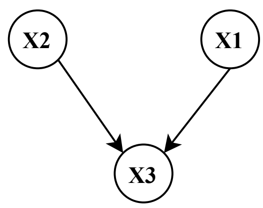

Figure 3.10: sample of a basic BN

In that network, we assume that each variable (X_1, X_2, X_3) has only two states, True (t) and False (f). Therefore, Equation 3.29 takes the form of Equation 3.30, by using the chain rule of probabilities and a conditional independence assumption. The conditional independence assumption dictates that a child node (X_j) is statistically dependent only to its parents $(pa(X_j))$.

$$P(X_1, X_2, X_3) = P(X_1)P(X_2)P(X_3|X_1, X_2) \tag{3.30}$$

Therefore, the probability $P(X_3 = t)$ is represented in Equation 3.31, which is also referred to as the prior probability of X_3.

$$P(X_3 = t) = P(X_3 = t, X_1, X_2) = P(X_1)P(X_2)P(X_3 = t|X_1, X_2) \tag{3.31}$$

In addition, assuming that X_3 is observed to be at its True state, then the probability of X_2 occurring $(P(X_2 = t|X_3 = t))$ can be found by using Equation 3.32.

$$\begin{gathered} P(X_2 = t|X_3 = t) = P(X_2 = t, X_1|X_3 = t) = \\ \frac{P(X_3 = t|X_2 = t, X_1)P(X_2 = t)}{P(X_3 = t)} P(X_1) \end{gathered} \tag{3.32}$$

Equation 3.32 is also referred to as the posterior probability, and the first part of the product is due to Equation 3.28, while the second term i due to the joint probability distribution (Pearl 1988).

For this study, two types of evidence were used, namely Hard Evidence (HE) and Virtual Evidence (VE). HE represent the traditional type of evidence used in BNs. They are used to dictate the value or state of a variable. For example, HE shows that a variable X$_j$ has a value x_j, with mathematical certainty, or that the variable $X_1 = True$. Under the premise of this thesis, HE was used for strict diagnostic tasks, to obtain the probabilities of examined faults based on monitored variables. However, HE can introduce troublesome assumptions, especially when the value of a variable is very close to a state's decision boundary. In other words, when the value of X_j is such that the variable could be in either of its states. To counter this issue, and to extend the capabilities of the diagnostic network, VE was used. VE represent evidence with uncertainty and was used to also obtain the fault profiles of the examined faults (Bilmes 2004; Korb and Nicholson 2010; Mrad et al. 2012). For instance, $X_1 = 0.7\ True$ is considered as VE and represents that X_1 is almost in its true state. For instance, VE can be used to describe the deteriorating state of a variable.

The fully defined diagnostic BN can be used for two main applications. Initially, it is used to carry-out "pure" diagnostic tasks, following the detection of a developed fault. Once the aggregated results from FD indicate the presence of a fault, HEs are used in the appropriate nodes (observable and tests nodes). As a result, the probabilities of different faults are investigated until the root cause of the detected fault is identified. In addition, the BN can be used to summarise the condition of the modelled system by characterising the condition of the observable nodes and assessing the probabilities of different faults developing. This process is also performed aggregating results from the FD and by using Equations 3.26 and 3.27. In this application, the BN is used proactively, as it does not relly on a detected fault, rather than the overall condition of the observable nodes.

3.8 Chapter Summary

This chapter presented the proposed framework, together with its novel methodological components. This includes the novel combination of FTA with k-means clustering for the identification of critical components, the novel hybrid imputation method based on MICE and kNN, the novel EB and EWMA-based FD model and the novel combination of an ML-driven FD with a BN-based diagnostic network. The framework targets the concept of maritime predictive maintenance in a complete and holistic way while generating novelty in all of its methodological components. The framework initiates with the critical components identification methodology, which is based on the used of FTA and the k-means clustering algorithm. Then, the data preparation methodology is presented, which aims at controlling the impact of missing values in the data. As a result, an imputation methodology is developed by combining the benefits of kNN and MICE imputation algorithms. Subsequently, the FD methodology is presented, which aims at developing models for the detection of developing faults in ship systems. The FD methodology includes the application of the DBSCAN clustering algorithm for the identification of outliers. Afterwards, an EB model is developed by examining the use of different regression models and assessing different predictor variables and training datasets. Once the EB model is developed, it is used to obtain the residuals, which are finally analysed in an EWMA control chart for FD tasks. Finally, the diagnostics methodology is developed. This methodology uses as input the evidence of developing faults, using the FD methodology, and tries to identify their root cause. This diagnostic task is performed in a BN, which is developed by combing the results of a fault mapping process with engineering knowledge. In conclusion, this chapter established the theoretical background of the proposed framework, which is required prior to the presentation of the different case studies.

Chapter 4

Case Studies

4.1 Chapter Overview

Following the presentation of the novel maritime predictive maintenance framework, this chapter aims at presenting the case studies used. The case studies give a description of the systems and data used for the application of each part of the framework and they present the necessary inputs. As a result, the case studies describe the technical details of the application of each methodological component.

In total, three different vessels were used for the case studies. The use of three different vessels for the different parts of the framework is justified based on three main reasons. Firstly, the different parts of the framework are developed independently. Secondly, each part of the framework has different data requirements and therefore, different sources of data and information are used. Lastly, it is not practical to find a single source that can fulfil the data requirements of all the parts of the framework.

Despite the three different case studies, the developed methodologies can be evaluated as a single framework in a unique case study. To that end, it should be clarified that the evaluation of the methodologies in a single case study does not negate their verification, as achieved by the individual case studies. Instead, the single case study can act supplementary to showcase further the developed methodologies. However, for this to be achieved, all the data requirements, discussed in the following sections, must be met by a single vessel. Initially, the maintenance schedule and repair costs would need to be collected. From that point, the ship systems analysis would take place to identify the main systems of the ship. This step would be performed with assistance from the vessel's operator. Then, the remaining steps of the critical equipment selection would be performed to identify the critical equipment. Subsequently, parameters from the critical equipment would be collected. Once they are identified and collected, the data preparation methodology would be deployed to identify and impute missing data. As soon as the missing values are treated, the FD and diagnostic methodologies would be applied. However, the fault mapping process and the diagnostic network would be a function of the available data and the identified critical equipment.

Initially, the case study applied for the selection of the critical equipment is given. Afterwards, the case study for the data preparation methodology is presented. Lastly, the case study for the FD and diagnostic methodologies is shown. Even though the FD and diagnostic methodologies are developed separately, they are applied in the same system of the same vessel, due to limitations of the required data. Despite this, both methodologies focus on different goals and they are evaluated independently.

4.2 Critical Equipment Selection

This section describes the case study in which the critical equipment selection methodology is applied. In more detail, this section gives general information on the type of ship used, the collection of the required data, the analysis of the ship systems and the resulting FT structure This methodology was applied in a case study of a Liquefied Natural Gas (LNG) carrier. The LNG carrier was selected for the case study due to the availability of the required data, obtained by the ship's operating company.

4.2.1 Data Collection

The collection of the required data is the first step of the critical equipment selection methodology. As seen in Figure 3.2, the methodology requires a maintenance schedule and a list of repair costs, both representing the same equipment and components of the LNG carrier. The maintenance schedule is used to obtain the numerical inputs for the FTA, in the form of MTBF for different components. On the other hand, the repair costs are used to identify the cluster of critical components.

The vessel studied in this part of the framework is an electric powered LNG carrier, referred to as vessel "A". Vessel "A" is a 162000 m^3 carrier with a continuous deck, sunken stern, bulbous bow, transom stern, single rudder and single screw propeller. The cargo area has a double deck, double hull and double bottom with cofferdams between each cargo tank. It also has four cargo tanks with the GTT MARK III membrane system directly supported on the inner hull. Vessel "A" has four Main Generating Engines (MGEs) in two different generating sets, providing propulsive and ship service power. Two main propulsion motors connected via a single output gearbox drive the propeller. The main features of vessel "A" are shown in the following table.

For the maintenance schedule, the PMS of the examined LNG carrier, supplied by the ship's operator, was used. The PMS details the different tasks that need to be performed, while identifying various parameters, requirements and constrains. In detail, each task from the collected PMS included the following: task identification information (number, code, creator), involved components, tasks description, type of action (inspection, testing, maintenance), calendar related

Table 4.1: Main features of vessel "A"

Characteristic	**Value**	**Unit**
L_{BP}	275	m
L_{OA}	289	m
B_{MLD}	45.6	m
D_{MLD}	33.2	m
T_{DESIGN}	11.2	m
$V_{SERVICE}$	19.5	knots
Capacity	163700	m^3
DWT	81000	tons
2 MGEs - 12V50DF	11700@514	kW, rpm
2 MGEs - 8L50DF	7800@514	kW, rpm

information (start date, finish date, task frequency, last performed date), responsibility related information (responsible department and position) and other identifiers. After careful examination only the following information were kept for each task: involved component, type of action, task description and details and frequency of task. The selection was based on the usefulness of the information and its applicability for the quantification of the Fault Tree. Table 4.2 is a sample of the used PMS, providing information for some of the components of the examined LNG carrier. The information obtained from the PMS is found in Appendix C.

Table 4.2: Sample of the PMS of vessel "A"

Involved Component	**Type of Action**	**Task Description and Details**	**Frequency**	**Unit**
Main Engine No.1 High Temperature Air Cooler	Maintenance	1)Clean the charge air coolers. 2)Perform the pressure test. 3)Look for corrosion. 4)Measure the pressure difference over the charge air cooler before and after cleaning.	4000	Hours
Main Generator Engine No.1 High Temperature Circulating Pump	Maintenance	1)Carry out external inspection (check for vibration, bearing temperature, performance of the pump and obvious defects). 2)Grease bearings as per maker's intervals. 3)Check that holding-down and end-cover bolts are correctly tightened. 4)Check starter/control box. 5)Check coupling wear/backlash. 6)Clean suction filter if necessary and possible.	3	Months

Continued on next page

Table 4.2 – *Continued from previous page*

Involved Component	**Type of Action**	**Task Description and Details**	**Frequency**	**Unit**
Main Engine No.1 Lubricating Oil Purifier Feed Pump	Maintenance	1)Carry out external inspection (check for vibration, bearing temperature, performance of the pump and obvious defects). 2)Grease bearings as per maker's intervals. 3)Check that holding-down and end-cover bolts are correctly tightened. 4)Check starter/control box. 5)Check coupling wear/backlash. 6)Clean suction filter if necessary and possible.	3	Months
Main Generator Engine No.1 Connecting Rod and Big End Bearing	Overhauling	1)Inspect big end bearing, one/bank 2)Dismantle the big end bearing 3)Inspect the mating surfaces, if defects are found open all big end bearings and renew bearing shells if necessary 4)Check small end bearing and piston pin, one/bank. If defects are found, open all and renew if needed.	12000	Hours

After this preliminary screening of the PMS, the frequency of the different tasks is formatted in different units. Since the PMS represents the frequency of the tasks either in hours, months or years, a common unit must be selected. Consequently, all the frequencies are converted to operational hours, to ensure uniformity and compatibility with the FTA (PTC Windchill 2019).

Apart from the PMS, cost information regarding various ship components are obtained. This information includes the repair costs of the components presented in the PMS. A sample table containing the used repair costs is shown in Table 4.3. The table with all the costs used is located in Appendix B.

Table 4.3: Table of repair costs of components shown in Table 4.2

Component	**Repair Cost (US Dollars)**
Main Engine No.1 High Temperature Air Cooler	15000
Main Engine No.1 High Temperature Circulating Pump	5000
Main Engine No.1 Lub Oil Purifier Feed Pump	2500
Main Engine No.1 Connecting Rod and Big End Bearing	2500

4.2.2 Ship System Analysis

The ship system analysis follows the data collection and its main aim is the examination of the case study vessel in terms of its systems, sub-systems and components. Moreover, the ship system analysis assists with the specification of the structure of the FTA.

After examining the specifications and engineering drawings of vessel “A”, the main systems of the vessel are identified. Moreover, the systems were identified with supplementary meetings and interactions with the superintendent engineer of vessel “A”. Figure 4.1 shows the main identified systems, as identified in five main groups. The essential machinery group includes the MGEs, the steering gear and the steam generation system. The fuel group includes the Fuel Oil (FO) transfer system, the FO purification system, the FO feed system for the MGEs and the gas fuel system. Also, the Lubricating Oil (LO) group covers the LO services system and the LO purification system. Moreover, the cooling group describes the central cooling system for the MGEs and the auxiliary cooling system. Finally, the various group encompasses the inter gas generation system, the LNG cargo equipment and the bilge, fire and ballast system.

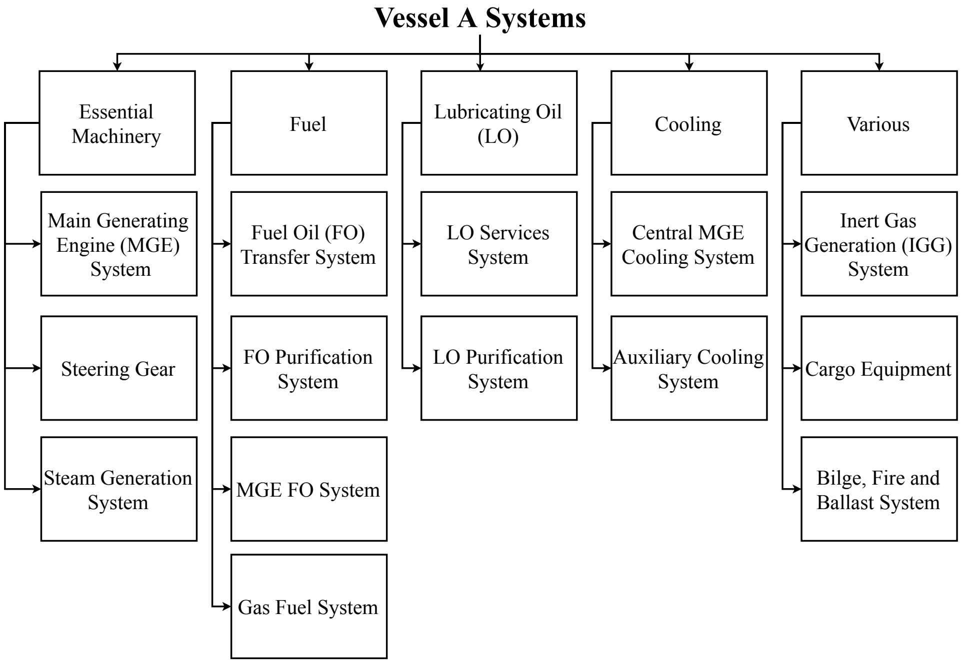

Figure 4.1: Identified systems for the studied vessel

4.2.2.1 Essential Machinery

The essential machinery group includes the most essential machinery of vessel "A". The MGE system includes the two 12V50DF and the two 8L50DF engines. These engines are Dual Fuel (DF) and as such they can burn both FO and gas fuel. These engines are used to generate the required electric output to cover all the electric loads of the vessel. The steering gear covers the equipment needed to steer the vessel along predefined routes. Lastly, the steam generation system includes the two auxiliary boilers that are responsible for generating the steam required for the various heaters and heat-exchangers.

4.2.2.2 Fuel

The fuel group includes the various oil and gas systems within the vessel. The FO transfer system includes various pumps which ensure that the different FO tanks are properly supplied. The FO purification system comprises of different pumps and purifiers that clean (purify) the FO onboard prior to its use in the various consumers. The MGE FO system consists of several pumps tasked with delivering purified FO to the MGEs. Lastly, the gas fuel system uses various different components (pumps, compressors, heaters) to deliver gas from the ship's cargo tanks to the DF MGEs for consumption.

4.2.2.3 Lubricating Oil (LO)

The LO group includes two main systems, the LO services and the LO purification systems. The former system includes different pumps tasked with delivering LO to various components in the ship, including the MGEs and the reduction gearboxes. The latter system includes pumps and purifiers which clean (purify) the LO prior to consumption.

4.2.2.4 Cooling

The cooling group includes the central cooling system for the MGEs and the auxiliary cooling system. The central MGE cooling system has Sea Water (SW) cooling pumps which transfer cooling SW to the central coolers. From the central coolers the cooled Fresh Water (FW) is circulated in the required components. The auxiliary cooling systems SW cooling pumps which transfer cooling water to auxiliary coolers. From there, the cooled FW is circulated to the various locations through different circulating and booster pumps.

4.2.2.5 Various

The last identified group includes the remaining systems of the vessel. One of these systems is the Inert Gas Generation (IGG) system, which creates and distributes inert gas to void and cargo spaces. This is done for safety reasons to mitigate the risks of fire and explosions. Another system listed in this group is the cargo equipment of the ship. The cargo equipment includes various pumps, heaters and compressors. The main aim of this system is to handle the loading and unloading of the cargo, as well as maintain it during passages. The last identified system is the bilge, fire and ballast system, which has several different pumps (ballast, bilge and fire), firefighting equipment and a ballast water treatment facility.

4.2.3 Fault Tree Analysis

To perform a FTA, the structure of the FT first needs to be identified. This process is based on the results of the ship systems analysis, and is a necessary step in order to obtain the required reliability IMs.

As identified in the previous section, the five main machinery groups are the essential machinery, fuel system, LO system, cooling system and the various remaining systems. In the following figures, each gate examines the failure of the modelled system. For the purpose of this work, a failure is considered the loss of a system's function, similarly with the failures considered in Lazakis, Turan, and Aksu (2010a). All the gates, apart from the top event, do not state this explicitly for simplicity reasons. Moreover, transfer gates (denoted as blue triangles) are used to group together extensive parts of the FT. These gates are used for representation reasons only and are not related with any calculations. The gates at the lower levels, and the events are identified by taking into account the results of the ship systems analysis and input from the operating company of vessel “A”, creating the ideal FT structure. However, certain basic events may be omitted in case of failure data limitations.

The resulting FT structure is shown in Figure 4.2, where the failure of vessel “A” is modelled as an “OR” gate (top event). In this structure, the systems in essential machinery group are modelled together under the common “essential machinery” gate and form an input to the top event. Also, the remaining systems (i.e. fuel, LO, cooling and various) are modelled under the common “auxiliary” gate and form the final input to the top event. The systems in the essential machinery group are modelled under the same gate, as they represent systems that are crucial for the operation of the vessel. Similarly, the auxiliary gate represents a larger set of systems that collectively have a high criticality for the vessel. Finally, the top event is modelled as an “OR” gate, as a loss of function in either the essential machinery, or the auxiliary gate will cause the ship to loss its functionality.

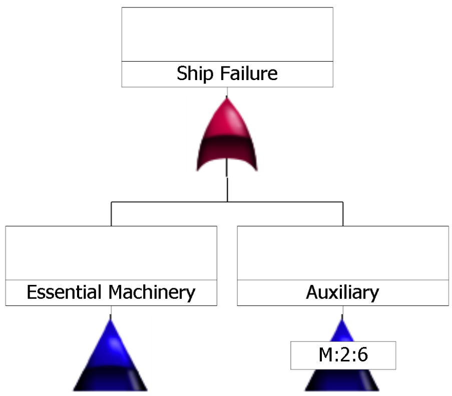

Figure 4.2: FTA representation of the systems of vessel “A”

Figure 4.3 shows the structure of the FT which models the essential machinery group. The failure of the essential machinery group is represented with an “OR” gate, having as input the steering gear, generating engines and steam generation systems. The "OR" gate is selected as a failure in any of the three input systems will cause the failure of the essential machinery group and will cascade, triggering the "ship failure" gate.

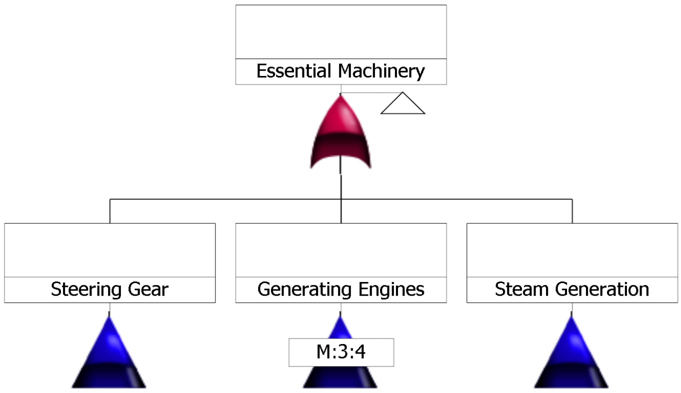

Figure 4.3: FTA representation of the essential machinery group

Similarly, Figure 4.4 shows the FT structure for the fuel, LO, cooling and various systems represented as inputs to the These systems are connected through a "VOTING" gate, which requires two of the six inputs to occur for the"auxiliary" gate to fail. The use of the "VOTING" gate represents a set of systems that are less likely to cause the entire ship to fail. In more detail, the "VOTING" gates is used as the failure of the cargo equipment would not cause the ship to stop its operation if the ship was sailing without cargo.

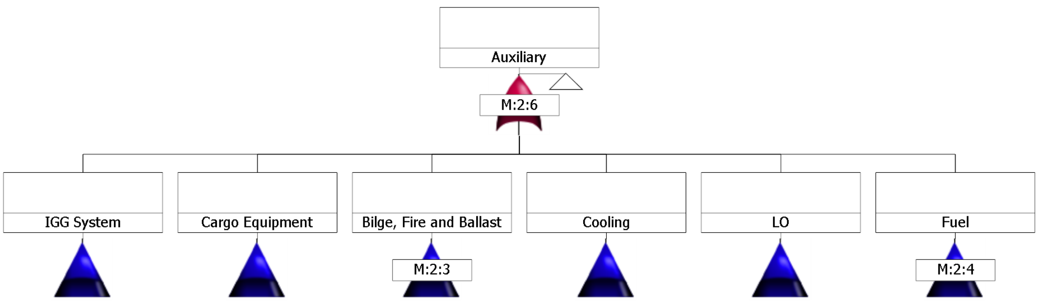

Figure 4.4: FTA representation of the remaining machinery groups

Figure 4.5 represents the FT structure that models the steering gear system.

This section of the FT has as inputs the machinery components and the control components of the system. The failure of the steering gear system is modelled with an “OR” gate, as any failures in either the machinery, or control components can cause the system to cease operating.

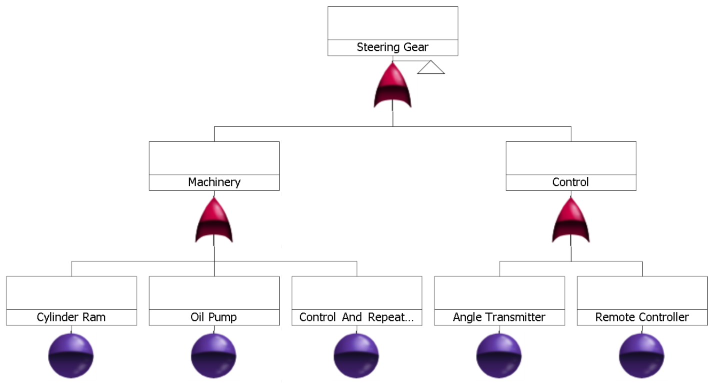

Figure 4.5: FTA representation of steering gear system

Figure 4.6 represents the FT structure of one of the four MGEs. Each MGE has as inputs the assembly of the engine (cylinders, liners, etc.) and the supporting systems of the engine (FO, LO and cooling system). The failure of each MGE is modelled with an “OR” gate, as a failure in either the assembly or the supporting systems will cause the engine to stop operating. As can be inferred from Figure 4.3, the system of the generating engines is modelled with a “VOTING” gate. The four MGEs offer a higher degree of redundancy and consequently, the vessel can still operate, albeit with a reduced performance, with only one MGE.

Figure 4.7 shows the FT structure for the steam generation system. This system includes the fuel and feed-water systems together with the internal components as inputs. The steam generation system comprises of two boilers, resulting in enhanced operability. The steam generation system is modelled as an “OR” gate, as any failure in its sub-system will stop steam generation.

Figure 4.8 shows the FT structure for the IGG system, comprising of the blowers and the various other sub-systems. The IGG system is also modelled

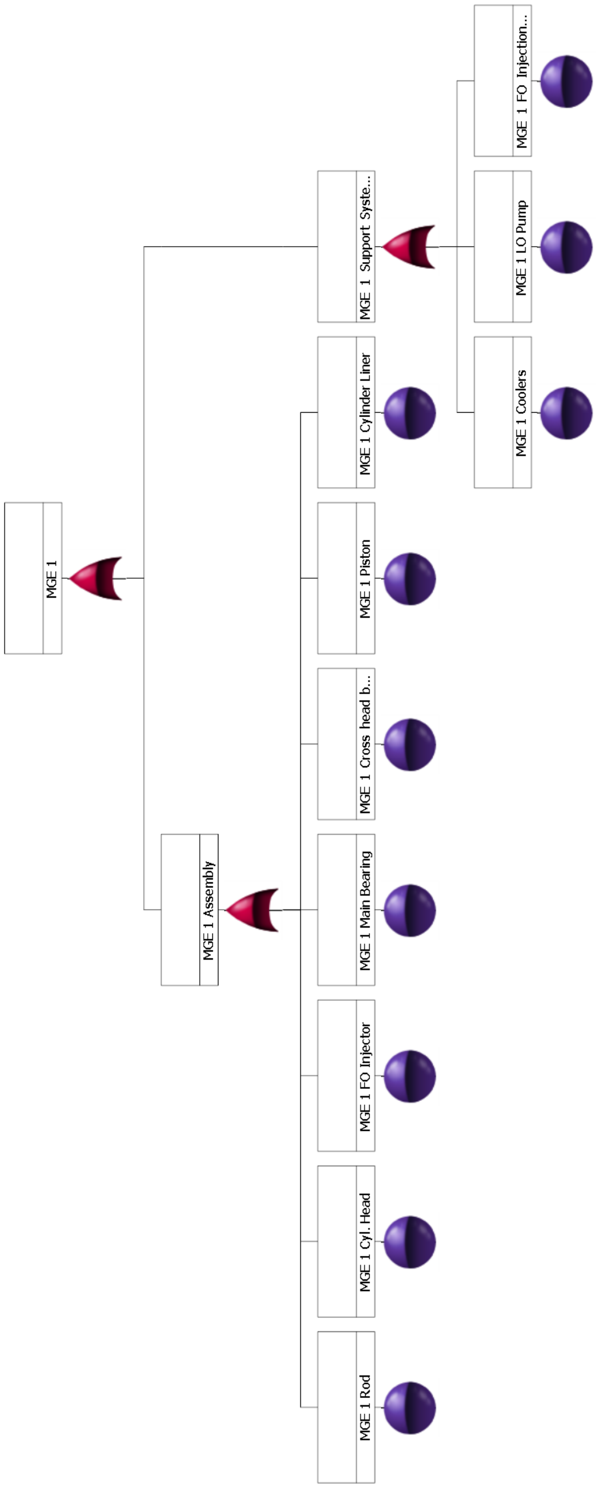

Figure 4.6: FTA representation of one of the four MGEs

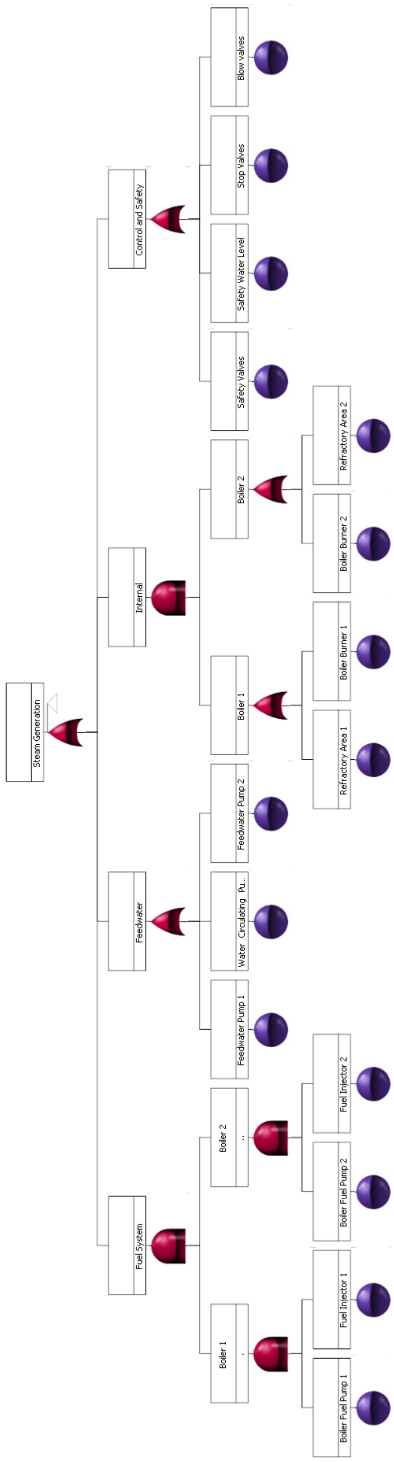

Figure 4.7: FTA representation of the steam generation system

with an “OR” gate, as it is sensitive to failures.

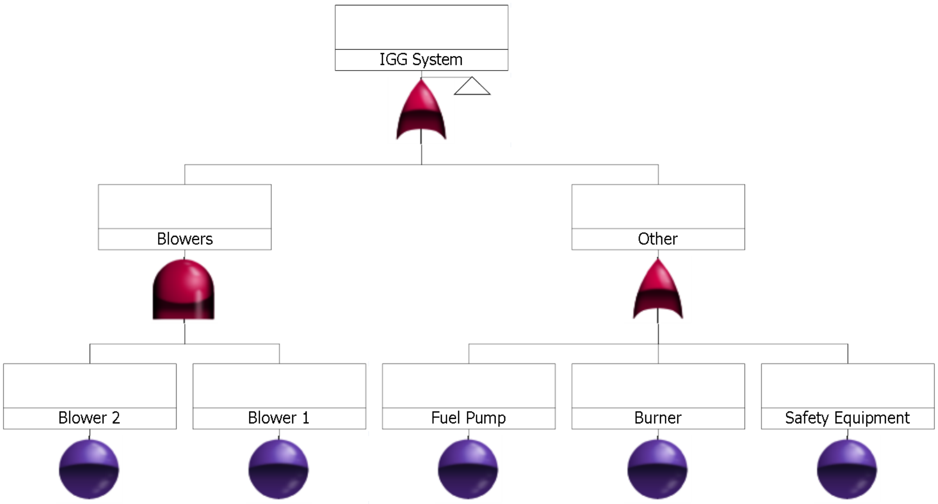

Figure 4.8: FTA representation of the IGG system

Also, Figure 4.9 shows the FT representation for the cargo equipment system. This system has as input the cargo spray pumps, high duty compressors and the other various components. As with the previous cases, the cargo equipment system is modelled with an “OR” gate, as it sensitive to failures.

Next, Figure 4.10 presents the FT representation of the bilge, fire and ballast system. This system comprises mainly of pumps, a water treatment system and various firefighting systems. Due to its nature, the bilge, fire and ballast system has high redundancy and each of the respective sub-systems has multiple redundant pumps which increase the system’s operability. For instance, the duties of a failed bilge pump can be replaced by a ballast pump. Even though this functional relationship exists, modelling it in FTA is a challenge. This is due, as the representation of multiple functional dependencies between different systems is an inherent limitation of FTA (Vesely 2002). As a result the bilge, fire and ballast system is modelled with a “VOTING” gate, failing when either two of the bilge, fire and ballast systems fail.

Figure 4.11 shows the FT representation of the cooling system. As can be

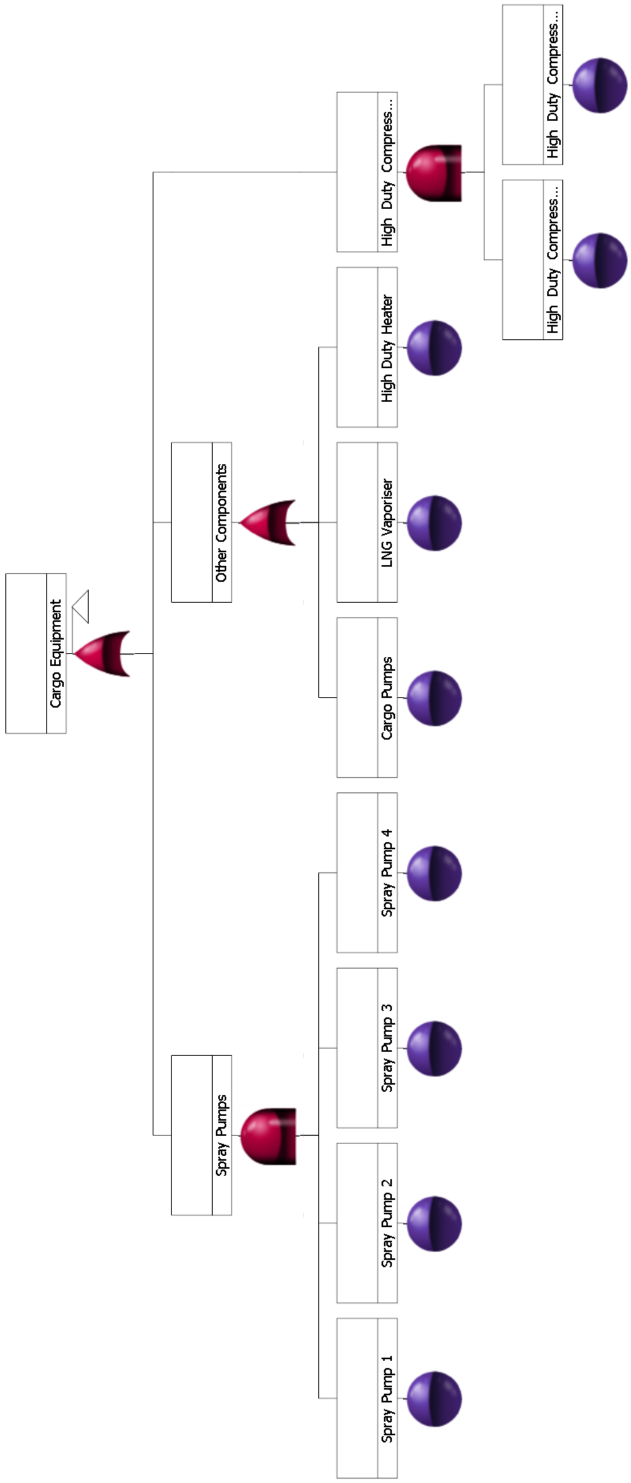

Figure 4.9: FTA representation of the cargo equipment

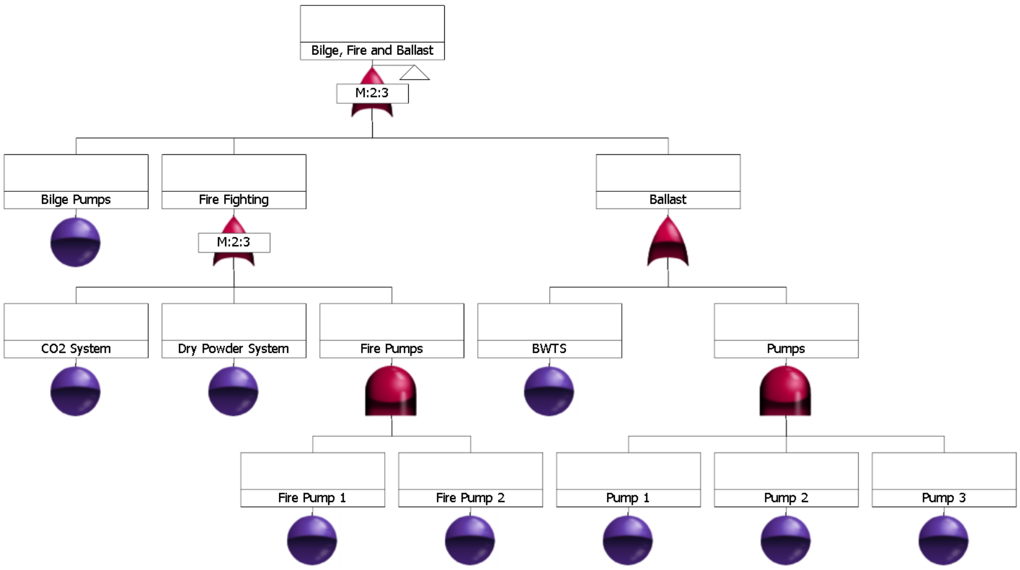

Figure 4.10: FTA representation of the bilge, fire and ballast systems

seen, this system comprises of the auxiliary cooling and the central MGE cooling sub-systems, shown in Figure 4.12 and Figure 4.13 respectively. The cooling system is modelled with an “OR” gate, as a failure in either of the inputs will cascade.

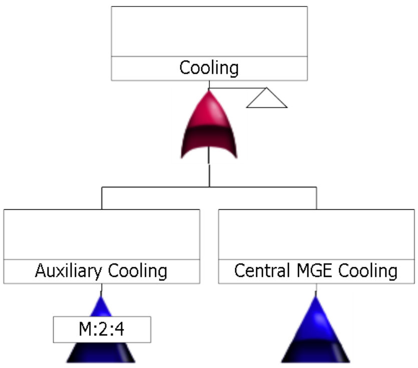

Figure 4.11: FTA representation of the cooling system and the two sub-systems

Similarly, Figure 4.14 shows the LO system, as modelled in a FT. This system comprises of the LO purification and the LO services systems, as seen in Figure 4.15 and Figure 4.16 respectively. The LO system is modelled using an “OR”

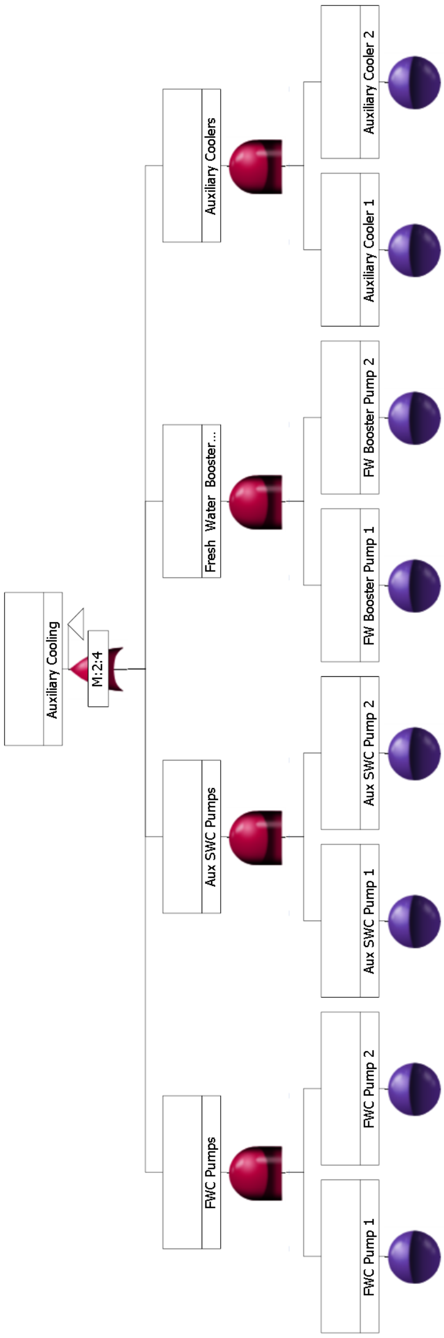

Figure 4.12: FTA representation of the auxiliary cooling systems

gate, as it will fail if either of its inputs fail.

Lastly, Figure 4.17 shows the FT representation of the fuel system. This system has four inputs (sub-systems) including, the gas fuel, MGE FO, FO pu-

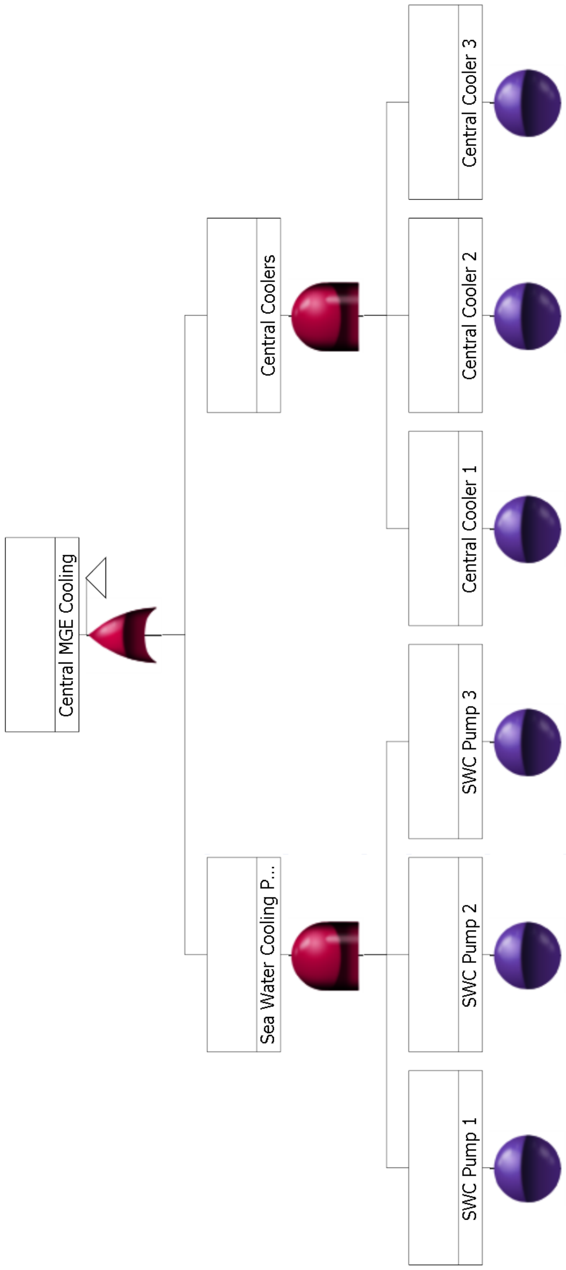

Figure 4.13: FTA representation of the central MGE cooling system

rification and the FO transfer systems. The fuel system is modelled with a "VOTING" gate requiring two of the four inputs to fail. This due to the fact that the vessel may be able to operate even if the gas fuel system fails, since the MGE

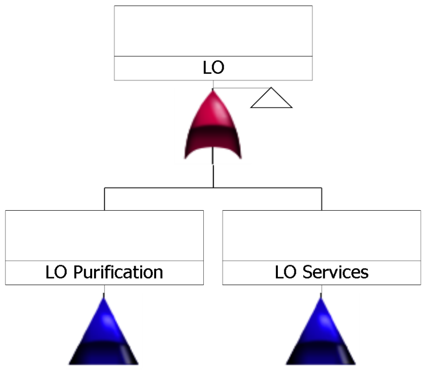

Figure 4.14: FTA representation of the LO systems

can operate with FO only (dual fuel). However, the use of this "VOTING" gate represents the best possible representation of the system, without increasing the model's complexity which is limited by the available computational power. For instance, the FO purification and FO transfer systems may fail and the system could still be operational for a while, due to the existing fuel in the service tanks. Nonetheless, this may not always be the case, as purified oil may be required when the service tanks are almost depleted. Therefore, the ability to model such cases is traded for a more manageable model.

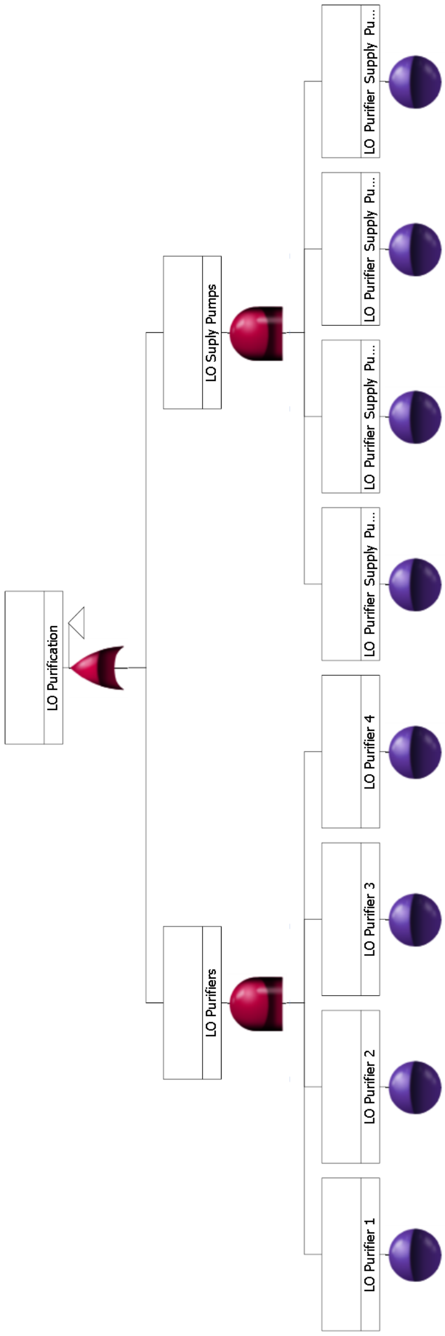

Figure 4.15: FTA representation of the LO purification systems

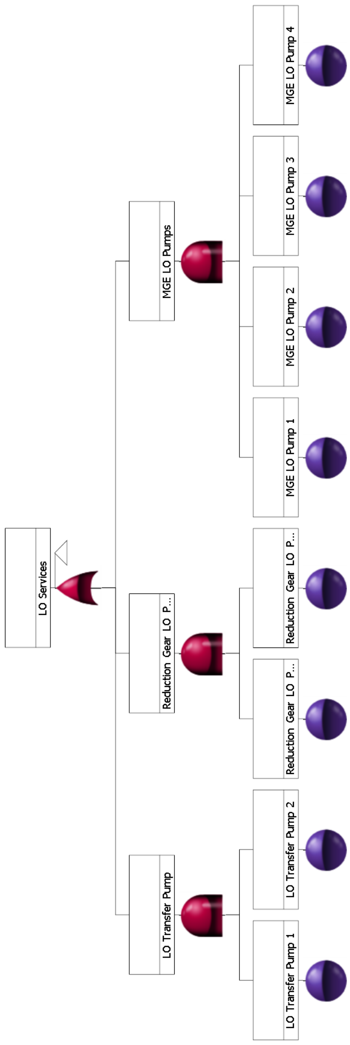

Figure 4.16: FTA representation of the LO services system

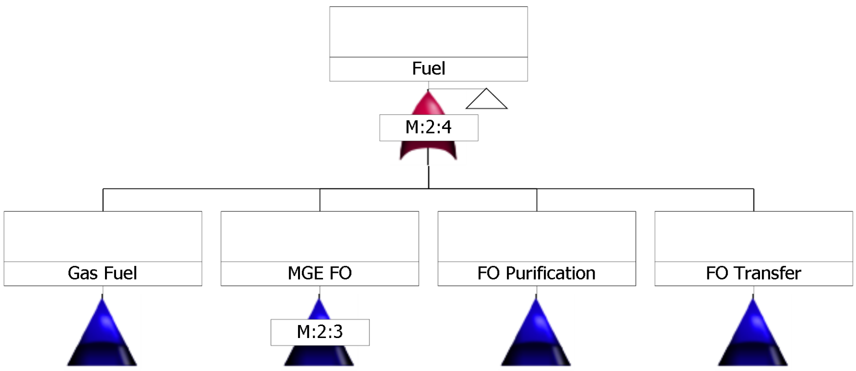

Figure 4.17: FTA representation of the fuel systems

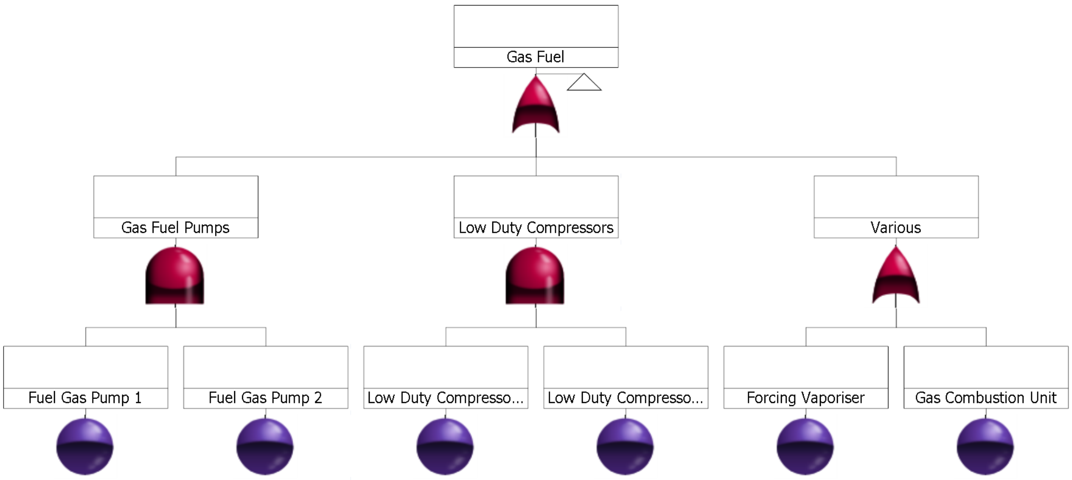

Figure 4.18: FTA representation of the gas fuel system

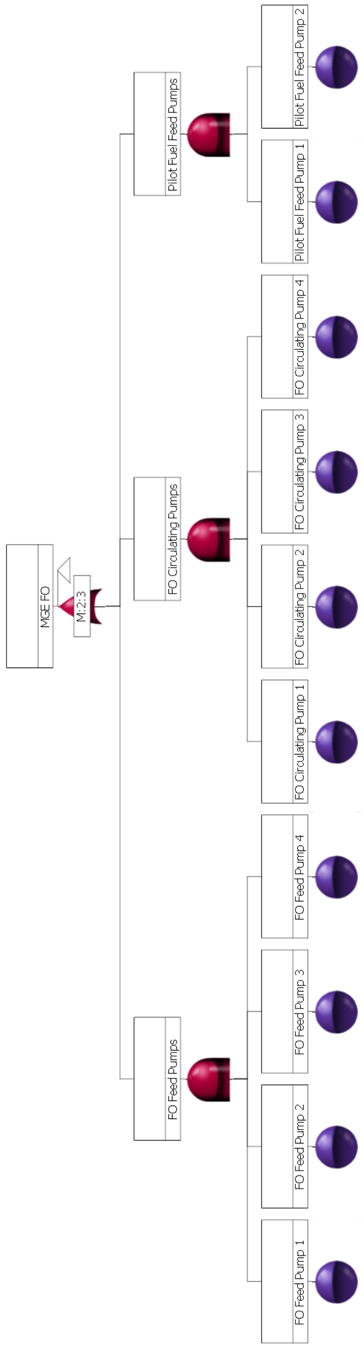

Figure 4.19: FTA representation of the MGE FO system

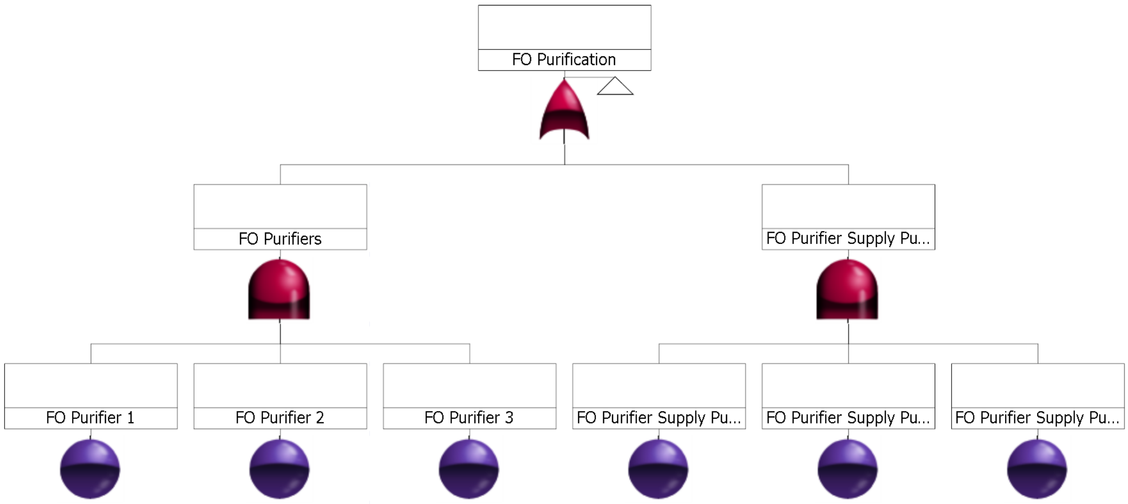

Figure 4.20: FTA representation of the FO purification systems

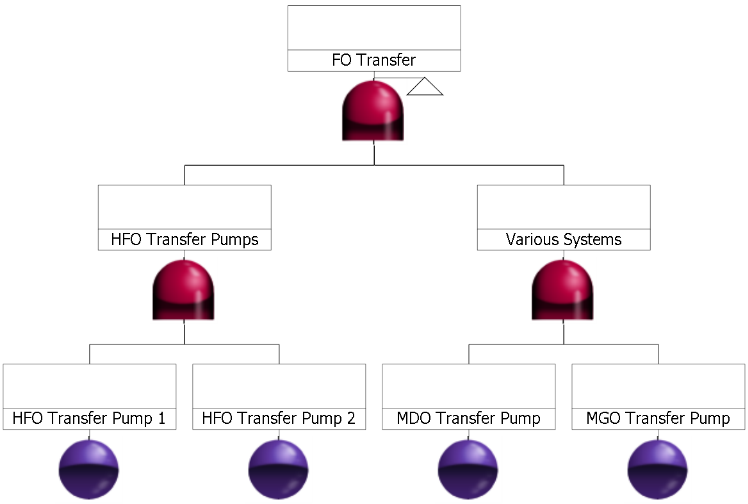

Figure 4.21: FTA representation of the FO transfer system

4.3 Data Preparation

This section describes the case study in which the data preparation methodology is applied. Consequently, the vessel and the data used for the application of the data preparation methodology are described. Since the operating company for the LNG carrier was only able to provide the PMS and repair costs of the vessel, alternative sources were sought. Instead of vessel "A", this methodology is applied in the case of a chemical tanker. Consequently, the operator of the chemical tanker was able to provide general information about the vessel, together with the required performance and process describing data.

As discussed in Section 4.1, the implementation of the data preparation methodology would be slightly altered if a single case study is used to evaluate all the methodologies. In detail, this methodology would be applied to parameters collected from the critical equipment, before they are used in the FD and diagnostic methodologies.

The vessel used in this case study is a diesel powered chemical tanker, referred to as vessel "B". Vessel "B" is a 38396 tons carrier with a continuous deck, bulbous bow, transom stern, single rudder and single screw propeller. This vessel is also double hulled and has five pure epoxy coated cargo tanks. Vessel "B" has a single ME for the generation of propulsive power and three diesel-powered generating sets for electric services. The main features of this vessel are summarised in Table 4.4.

4.3.1 Data Collection

Data collection is the first step of the data preparation methodology, as presented in Section 4.4. As shown in Figure 3.4, this methodology is structured on the use of performance data and on various operational limits from vessel "B". This case study is applied in the TC and ME system of vessel "B", a selection based

Table 4.4: Main features of vessel "B"

Characteristic	Value	Unit
L_{BP}	173	m
L_{OA}	183	m
B_{MLD}	27	m
D_{MLD}	16.8	m
T_{DESIGN}	11.6	m
$V_{SERVICE}$	10.0	knots
DWT	38396	tons
ME - 6S50MC	9611@127	kW, rpm

on the criticality and overall importance of the system (Theotokatos et al. 2018; Baldi, Theotokatos, and Andersson 2015), together with the input of the vessel's operator. A schematic of the studied system, together with the various available parameters is shown in Figure 4.22.

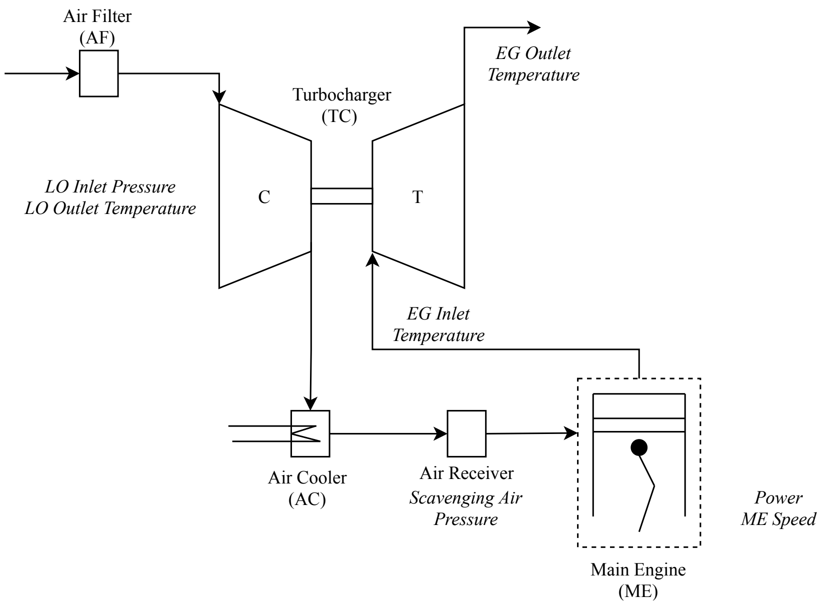

Figure 4.22: Diagram of a Main Engine (ME) system showing the physical interconnections between the measured parameters (the compressor is represented with C and the turbine with T)

The required performance data are collected from a DAQ system installed onboard vessel "B". The installed DAQ system records one sample every ten minutes from the ME power, ME speed, ME scavenging air pressure, TC EG inlet temperature, TC EG outlet temperature, TC LO inlet pressure, TC LO outlet temperature and the TC speed. These variables are recorded for nine days during the first two weeks of February of 2018, resulting in 1336 instances per variable. The descriptive statistics of these variables are shown in Figure 4.5.

Table 4.5: Descriptive statistics of the collected dataset used in the data preparation methodology

	ME Power (kW)	**ME Speed (rpm)**	**ME Scav. Air Press. (bar)**	**TC EG Inlet Temp. (^{o}C)**	**TC EG Outlet Temp. (^{o}C)**	**TC LO Inlet Press. (bar)**	**TC LO Outlet Temp. (^{o}C)**	**TC Speed (rpm)**
count	1336.0	1336.0	1336.0	1336.0	1336.0	1336.0	1336.00	1336.0
mean	4029.0	98.0	0.9	325.0	290.0	2.0	55.0	9494.0
std	1004.0	13.3	0.3	32.0	26.0	0.1	4.0	1995.0
min	9.0	5.0	0.0	54.0	142.0	1.6	35.0	68.0
25%	3810.0	96.8	0.7	319.0	279.0	1.9	53.00	9088.0
50%	4264.0	102.0	0.9	334.0	293.0	2.1	55.0	9879.0
75%	4680.20	105.0	1.2	340.0	305.0	2.2	59.0	10897.0
max	5876.0	126.0	1.6	365.0	346.0	2.8	63.00	12258.0

Moreover, the aforementioned operational limits are aggregated from various sources including the shop tests (commissioning tests) of the ME and technical information from the Original Equipment Manufacturers (OEM) of the ship's equipment, as seen in Table 4.6. The operational limits define the range of plausible operating values for the collected variables on Table 4.5. The operational limits are used to scan and filter the data to determine the points for imputation, as described in Section 4.4.3.

Table 4.6: Ship system parameter limits used in the data preparation methodology

Parameter	**Units**	**Lower Limit**	**Upper Limit**	**Source**
ME Power	kW	0	10600	100% load from ME shop test
ME Speed	rpm	0	131	100% load from ME shop test
ME Scav. Air Press.	bar	0	3.14	100% load from ME shop test
TC EG Inlet Temp.	^{o}C	35	650	From ambient temperature and 130% of the TC OEM limit
TC EG Outlet Temp.	^{o}C	35	650	From ambient temperature and 130% of the TC OEM limit
TC LO Inlet Press.	bar	0	3.6	150% of the ME shop test
TC LO Outlet Temp.	^{o}C	35	123	130% of the TC OEM limit
TC Speed	rpm	0	17600	110% of the TC OEM limit

4.4 Fault Detection (FD) and Diagnostics

This section describes the case study in which the FD and diagnostics methodologies are applied. Even though these two methodologies are independent, they are applied in the same vessel and systems, due to restricted accesses to additional required data. Since the operator of vessel “A” could not supply any ProMon data, and the operator of vessel “B” could not provide the needed parameters for meaningful FD and diagnostics, an additional ship operator was selected. As a result, the FD and diagnostic methodologies are applied in a case study of a bulk carrier.

The ship used is a 64000 tons bulk carrier, referred to as vessel “C”. Vessel “C” is a diesel-powered and self-loading carrier with a continuous deck, bulbous bow, transom stern, single rudder and single screw propeller. This ship has five cargo holds and four cranes for the loading and unloading of its cargo. Lastly, vessel “C” has a double-bottom, a single ME for the generation of propulsive power and three diesel-powered generating sets for electric services. The main features of this vessel are presented in Table 4.7.

Table 4.7: Main features of vessel "C"

Characteristic	**Value**	**Unit**
L_{BP}	194.5	m
L_{OA}	199.9	m
B_{MLD}	32.26	m
D_{MLD}	18.5	m
T_{DESIGN}	11.3	m
$V_{SERVICE}$	13.2	knots
DWT	64000	tons
ME - 5S60ME	8050@89	kW, rpm

Both of the methodologies are applied in the ME and TC system of vessel "C". Similarly to Section 5.3.1, the selection of this system was based on its overall importance, criticality and the input the ship's operator. The schematic of the studied system, depicting the various components and measurable variables is shown in Figure 4.23.

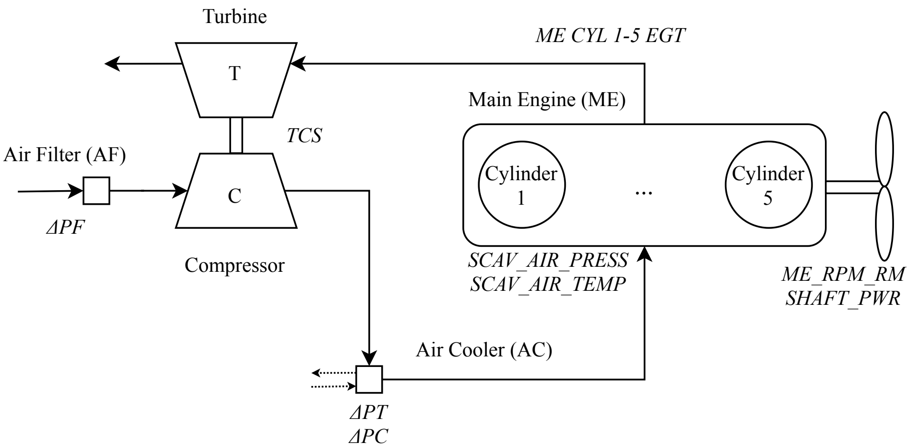

Figure 4.23: Diagram of a Main Engine (ME) system showing the physical interconnections between the measured parameters (the compressor is represented with C and the turbine with T)

There are numerous monitored parameters in the selected system, including pressure and temperature drop across the Air Filter (AF) and Air Cooler (AC), speed of the TC, scavenging air temperature and pressure for the ME, power and rotational speed of the ME and EG temperature from each cylinder of the

ME, as seen in Table 4.8. From these parameters, the EG temperature of each cylinder of the ME is monitored and used for FD. This selection was based on the variables importance in performance and process monitoring. In detail, monitoring the ME cylinder EG temperature can help a) control the ME's emissions, b) understand the cylinders' combustion performance c) identify underlying and developing faults. More specifically, faults in the AC, TC and gas passages of the ME can manifest through the ME EG temperature, as further described in Chapter 6 (Woodyard 2009; MAN B&W 20017). Apart from the ME cylinder EG temperature, the ME speed, power, scavenging air temperature and pressure are used as predictor variables and also for the identification of the root-cause of detected faults, as further described in Chapter 6. Also, the pressure and temperature drop across the AF and AC and the speed of the TC are used for the identification of the root-cause of detected faults.

4.4.1 Data Collection

The application of the FD and diagnostic methodologies in this case study requires the collection of several different types of data. As shown in Figure 3.5 and Figure 3.8 these methodologies require the use of historic and incoming ProMon data from vessel "C", information from the vessel's ME shop tests, the ship's ME operating manual and information from data banks.

4.4.1.1 Historic Process Monitoring (ProMon) Data

Historic ProMon data from the vessel's system are used in both methodologies. In more detail, they are employed to train, validate and test the developed EB model used for FD. Moreover, since the same FD model triggers the diagnostic methodology (i.e. the diagnostic tasks initiate after the detection of a fault), the historic ProMon data influence the diagnostic methodology. These data are collected from the beginning April of 2017 until the end of June of 2017, with a

Table 4.8: Information for the variables used in the FD and diagnostics methodologies

Variable Name	Description	Units	System	Role
ME CYL 1 EGT	ME cylinder 1 EG temperature	^oC	Main Engine (ME)	Target variable
ME CYL 2 EGT	ME cylinder 2 EG temperature	^oC	Main Engine (ME)	Target variable
ME CYL 3 EGT	ME cylinder 3 EG temperature	^oC	Main Engine (ME)	Target variable
ME CYL 4 EGT	ME cylinder 4 EG temperature	^oC	Main Engine (ME)	Target variable
ME CYL 5 EGT	ME cylinder 5 EG temperature	^oC	Main Engine (ME)	Target variable
SHAFT_PWR	ME shaft power	kW	Main Engine (ME)	Diagnostic and Predictor
ME_RPM_TM	ME shaft speed	rpm	Main Engine (ME)	Diagnostic and Predictor
SCAV_AIR_PRESS	ME scavenging air pressure	bar	Main Engine (ME)	Diagnostic and Predictor
SCAV_AIR_TEMP	ME scavenging air temperature	bar	Main Engine (ME)	Diagnostic and Predictor
ΔPC	Scavenging air pressure drop across air cooler	mmWC	Air Cooler (AC)	Diagnostic Test
ΔPT	Temperature difference between air cooler air outlet and air cooler water inlet	^oC	Air Cooler (AC)	Diagnostic Test
TCS	Turbocharger speed	rpm	Turbocharger (TC)	Diagnostic Test
ΔPF	Pressure drop across turbocharger air filter	mmWC	Air Filter (AF)	Diagnostic Test

5-minutes sampling rate and their descriptive statistics are shown in Table 4.9. Lastly, these data are randomly split into 80% for training and validation and 20% for testing, according to common practices and empirical knowledge.

4.4.1.2 Incoming Process Monitoring (ProMon) Data

Once the EB-based FD model is established through the use of the historic ProMon data, incoming ProMon data are used to simulate different faults to evaluate the capabilities of the FD and diagnostic methodologies. As mention in

Table 4.9: Descriptive statistics of the historic ProMon data used in the FD and diagnostic methodologies

	SCAV AIR TEMP (^{o}C)	**SCAV AIR PRESS (bar)**	**SHAFT PWR (kW)**	**ME RPM TM (rpm)**	**ME CYL 1 EGT (^{o}C)**	**ME CYL 2 EGT (^{o}C)**	**ME CYL 3 EGT (^{o}C)**	**ME CYL 4 EGT (^{o}C)**	**ME CYL 5 EGT (^{o}C)**
count	26205	26205	26205	26205	26205	26205	26205	26205	26205
mean	44.9	0.8	2750.0	279.0	212.0	197.0	211.0	210.0	220.0
std	3.1	0.7	3066.0	2783.0	112.0	100.0	109.0	108.0	114.0
min	0	0	0	0	0	0	0	0	0
25%	41.5	0	0	0	51.8	52.2	52.7	54.1	53.3
50%	43.7	0.7	2710	59.8	285.0	261.0	280.0	280.0	294.0
75%	46.0	1.5	4624	74.9	296.0	271.0	295.0	292.0	304.0
max	55.3	2.6	32768	65509	364.0	336.0	357.0	354.0	360.0

the previous section, the historic data were supplied first. Once they were analysed and used for model development, additional data were requested from the operating company. However, only data from before April 2017 were available, and to avoid unnecessary repetitions of the work, they were used for the faults simulation. Therefore, before the newly supplied, incoming data, were used for the simulated faults different checks had to be performed. This was necessary due to the unconventional chronological order of the data sets. To avoid issues, the distributions of the two datasets were checked to ensure their similarity. As a result, it was observed that both datasets have similar distributions, validating their order of use. The accurate results from the verification of the methodologies also verify that the chronological order did not have a negative impact.

The use of simulated fault is necessary due to the fault-free nature of the used data, which is a very common problem in applications from merchant vessels. The maritime industry can be reluctant in sharing performance and condition datasets, even more so when they contain faulty data. Even though the same incoming ProMon data are used for the evaluation of the two methodologies, each methodology is assessed in different faults. These data are recorded from the beginning of January of 2017 until the end of March of 2017 and they are recorded with a 5-minutes sampling rate. The descriptive statistics of the incoming ProMon data are shown in Table 4.10

Table 4.10: Descriptive statistics of the incoming ProMon data used in FD and diagnostic methodologies

	SCAV AIR TEMP (^{o}C)	**SCAV AIR PRESS (bar)**	**SHAFT PWR (kW)**	**ME RPM TM (rpm)**	**ME CYL 1 EGT (^{o}C)**	**ME CYL 2 EGT (^{o}C)**	**ME CYL 3 EGT (^{o}C)**	**ME CYL 4 EGT (^{o}C)**	**ME CYL 5 EGT (^{o}C)**
count	9960	9960	9960	9960	9960	9960	9960	9960	9960
mean	40.8	0.7	2876.0	64.8	292.0	272.0	286.0	285.0	282.0
std	1.0	0.1	140.0	0.7	6.3	7.6	4.7	5.9	17.7
min	39.3	0.6	2474.0	58.2	256.0	235.0	255.0	247.0	247.0
25%	40.4	0.7	2794.0	64.5	288.0	267.0	283.0	282.0	269.0
50%	40.8	0.7	2852.0	64.7	292.0	274.0	286.0	286.0	277.0
75%	41.1	0.7	2928.0	64.9	296.0	277.0	288.0	289.0	299.0
max	49.9	1.3	4101.0	72.3	310.0	287.0	298.0	303.0	314.0

4.4.1.3 Main Engine (ME) Shop Tests

The ME shop tests represent another source of data used during the development (training, validation and testing) of the EB-based FD model. The shop tests are machinery tests and represent a form of benchmark and commissioning test, which is widely used in the maritime industry for setting the standards of normal operations for each ship. During these tests, the ME operates at different pre-defined loads and several parameters are recorded. Since these tests are performed at the manufacturer's facilities, the recorded values are intended to represent a baseline for normal operations. A sample of the shop tests of the ME of vessel "C" is shown in Table 4.11

Table 4.11: Shop test sample for the ME of vessel "C"

ME Power(kW)	**ME Speed (rpm)**	**EG Temperature (^{o}C)**	**ME Scavenging Air Pressure (bar)**	**ME Scavenging Air Temperature (^{o}C)**
2013	56.1	215.0	0.4	34
4025	70.6	246.0	1.2	30
6038	80.9	281.0	2.1	32
6843	84.3	308.0	2.5	34
8050	89	346.0	3.0	36
8855	91.9	364.0	3.3	38

4.4.1.4 Data Banks

The last source of information that was used during this case study is the OREDA data bank. In the context of reliability and PdM, data banks are repositories that contain failure information that is difficult, or too detailed, to obtain from other sources (e.g.ship operators).

OREDA is a major data bank that originated from the offshore oil and gas sector after the collaboration of major industrial stakeholder. It contains a plethora of failure information for most shipboard systems, including mechanical and electrical components. Moreover, it is one of the most extensive and detailed data banks for machinery and is commonly employed in PdM and reliability related projects (Goble, Bukowski, and Loren 2016).

In OREDA, each of the examined systems (e.g. generating engines) is divided in sub-systems and components and the failure rate of each component is given. Moreover, OREDA specifies the different failure rates for the various failure modes of each subsystem and component. Failure rates of the different components were used to quantify the BN that was developed for the diagnostic methodology, as further discussed in Chapter 6.

4.4.2 Chapter Summary

This chapter presented the different case studies of the methodological components of the proposed framework. The main goal was to describe the different inputs required for the developed methodologies. In more detail, the critical equipment selection methodology is applied in the case study of an LNG carrier, as allowed by the access to the ship's maintenance schedule and repair costs. Then, a chemical tanker is used for the case study of the data preparation methodology. This is facilitated through the use of the available information from the OEM and from access to data collected from a DAQ system. Lastly, the case study of the

FD and diagnostic methodologies is shown. These methodologies are applied in the same case study, but are developed and assessed independently. This required access to different ProMon data, the ME's shop tests and information from data banks.

Chapter 5

Case Studies Results

5.1 Chapter Overview

This chapter describes the results of the novel maritime PdM framework as applied in different case studies. Initially, the results from the critical equipment selection methodology, applied in the case study of an LNG carrier (vessel "A"), are presented. These results include the FTA and the resulting IMs, together with the application of k-means for the clustering analysis. Subsequently, the results from the data preparation methodology are presented, as applied in the case study of a chemical tanker (vessel "B"). The results include the preliminary analysis, the imputation process and the operational analysis. Finally, the results of the FD and diagnostics methodologies are presented, which originate from the bulk carrier case study (vessel "C"). The results from these two methodologies include data checking, model development, FD and diagnostic network set-up and use.

5.2 Critical Equipment Selection

The selection of critical equipment is the initiating methodology of the proposed novel predictive maintenance framework. This process of the framework is performed through the developed methodology presented in Section 4.4. The main aim of the critical equipment selection methodology is to enhance maritime predictive maintenance by establishing of a novel methodology for the identification systems with high functional and economic risk. To quantify the functional risks, the I^B and I^{CR} for each component are used. Similarly, the economic risks are gauged by using the repair and replacement costs for the modelled components As outlined in Figure 3.2, this methodology initiates with the data collection, ship system analysis and FT structure specification; steps which are applied in vessel "A', as earlier presented in Section 5.2. The IMs, together with the repair costs, are then clustered using the k-means algorithm, to identify the cluster with the critical equipment.

5.2.1 Reliability Importance Measures (IM)

After the structure of the FT is specified, as seen in Figures 4.2-4.21, the modelled "BASIC" events are quantified using MTBFs. Table 5.1 shows a sample of the MTBFs used for the bilge, fire and ballast system. The particular MTBFs used for each "BASIC" event are detailed in Appendix C.

Table 5.1: Table of MTBFs used for the bilge, fire and ballast systems

Bilge, Fire and Ballast	
Component	**MTBF (Hours)**
Ballast Pumps	2190
BWTS	6048
Fire Pumps	2190
Bilge Pumps	2190
CO2 System	6132
Dry Powder System	6132

Once all the "BASIC" events are quantified, the exact calculation method is specified, as described in Section 4.4.4.3, and the analysis is performed. In this work, the output of the FTA is the calculation of the I^B and I^{CR} IMs. The calculated IMs measure how the failure of each "BASIC" event influences the occurrence of the modelled top-event. As discussed in Section 4.4.4.4, the I^B measures the probability of a component being reliable for the occurrence of the top-event, without taking into account the component's reliability. Similarly, the I^{CR} evaluates the probability of the top-event occurring due to the failure of an examined component.

A sample of events with the highest I^B is shown in Table 5.2. The I^B for all of these components, show the probability of the component being reliable for the occurrence of the top-event, by only taking into account functional and systemic dependencies.

Table 5.2: Sample of the obtained I^B for vessel "A"

Component	I^B **(Probability)**
MGE 4 Cylinder Head	3.0307
MGE 1 FO Injector	2.0
FO Feed Pump 1	2.7061
MGE 3 LO Pump	2.02

As observed, the MGE Cylinder Head of vessel "A" has a very high I^B. Consequently, the MGE Cylinder Head has the biggest influence on the rate of change of the probability of the top-event. From a practical point of view, the failure of a cylinder head could cause either a slow-down or a shut-down of the MGE of the ship, crippling the operation of the vessel. Likewise, a failure in either a FO Injector or a FO Feed Pump could restrict the supply of FO to the engine, negatively influencing the ship's operation. The same adverse effects can be caused by a failure in an MGE LO pump, as the absence of LO can be disastrous for an engine. The I^B for all the modelled components can be found in Appendix C.

Table 5.3 gives a sample of the events with the highest I^{CR}. The I^{CR} measures how critical each component is to the system, by also taking into consideration its reliability. Therefore, as it can be observed, the events in Table 5.3 are different from those in Table 5.2. This originates from the different formula each IM has, showcases their difference and further solidifies the need to examine both of them for the selection of the critical equipment. Therefore, the MGE FO Injection Pump and MGE FO Injector have the highest probability of causing a ship-wide failure. This is followed by the MGE LO Pump and the FO Feed Pump. The I^{CR} for all the modelled components can be found in Appendix C.

Table 5.3: Sample of the obtained I^{CR} for vessel "A"

Component	I^{CR} **(Probability)**
MGE 2 FO Injection Pump	0.18
MGE 3 FO Injector	0.15
MGE 1 LO Pump	0.13
FO Feed Pump	0.0874

By observing Tables 5.2 and 5.3, it is becoming apparent that even though both of the examined IMs assess the importance of components, the results can be different. For instance, according to the I^B, the most important is the MGE Cylinder Head. However, the most critical component, according to the I^{CR}, is the MGE FO Injection Pump. Also, this discrepancy between the ranked components is repeated. Therefore, additional analysis is required to select the most critical equipment of the modelled systems subjectively.

5.2.2 Clustering Analysis

The clustering analysis is the final step of the critical equipment selection methodology, developed as an integral part of the proposed novel predictive maintenance framework. During this step, the obtained IMs and repair costs are clustered together, using the k-means algorithm. Combining both of the obtained IMs with the repair costs allows for a more systematic selection of critical equipment.

Before the initiation of the clustering analysis, the k hyperparameter of the k-means algorithm must be specified. As discussed in Section 4.4.5, the k hyperparameter controls the ultimate number of the clusters; in this work is assumed that $k = 3$. As a result, the clustering algorithm will group components, based on their functional and economic risks, in three groups. In this work, it is assumed that the overall criticality of the equipment ranges. Therefore, the equipment can be divided into critical, partially critical and not critical components. The value of k is also a function of the shape of the data. In detail, the selected k value must correspond with distinct groups of the dataset. If the value of $k = 3$ doe not correspond to the number of groups in the data, its value should be reduced.

Figure 5.1 shows the modelled components in a three-dimensional scatter plot, including the obtained IMs and repair costs detailed in Section 5.2.1 (data-space). The left plot of this Figure presents the modelled components in the examined data-space (IMs and repair costs). As also observed, the k value fits the shape of the data-space. In addition, the used axes are scaled, in accordance with standard practices, and to create an unbiased model. In this work, the common min-max scaling approach is used, as described in Necoara et al. (2008) , resulting in a dimensionless analysis. All of the axes range from 0 to 1, with 0 denoting the smallest value of the respective axis prior to the scaling and 1 indicating the largest values prior to the scaling. The right plot of this Figure shows the result of the k-means algorithm. In that plot, the different clusters are marked with green, blue and orange colours. Moreover, the centroids of the different clustered are denoted with an x-mark.

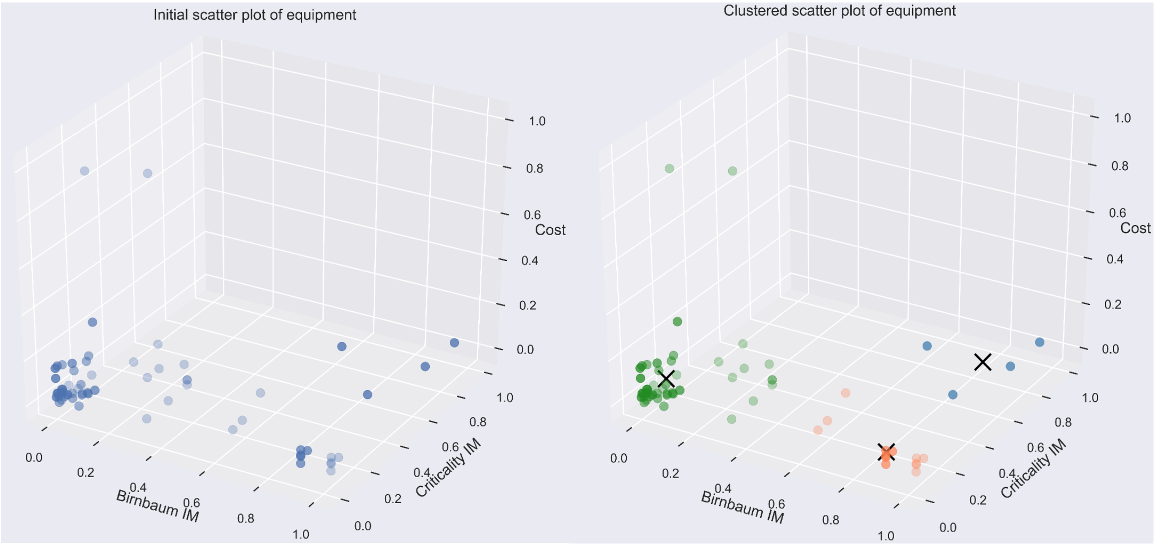

Figure 5.1: Three dimensional scatter plot showing the initial data-space (left) and the results of the k-mean algorithm (right).

As mentioned in Section 4.5.5, the critical equipment is defined as the components that belong in the cluster, which has the greatest distance from the beginning of the axes. That cluster contains components that have high I^B, I^{CR} and repair costs. As a result, the identified critical equipment has all of the following characteristics:

- They have the biggest influence on the rate of change of the probability of a ship failure, due to systemic dependencies.
- They are the most critical in the modelled system, by also considering the components' reliability and failure rate.
- They are the most costly to maintain after a failure, as they have the highest repair and replacement costs.

The cluster that contains the critical equipment is coloured in orange and is shown in Figure 5.2. On the other hand the green cluster in Figure 5.2 contains the least critical (i.e. safest) components.

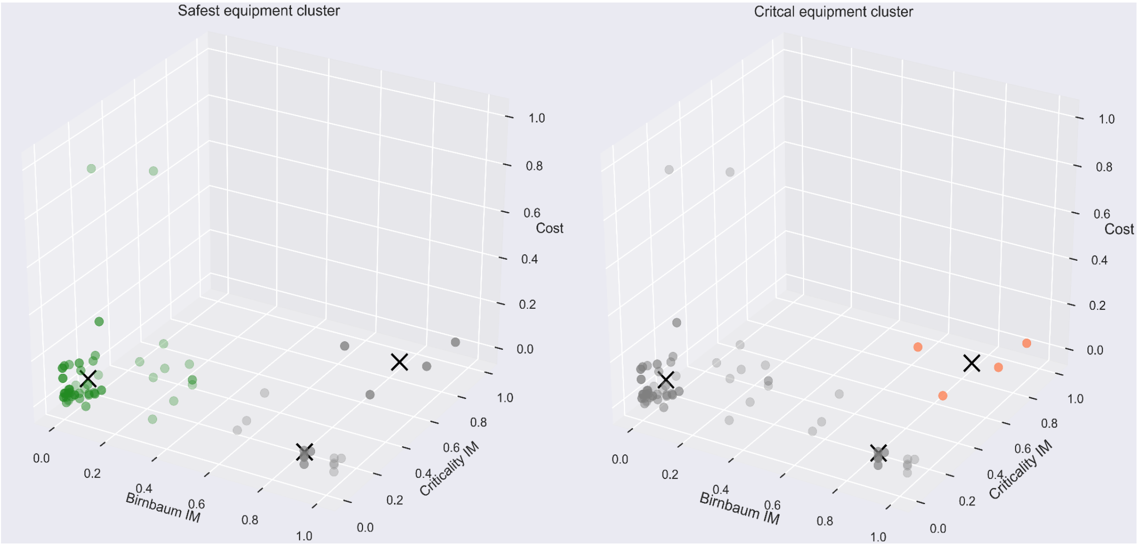

Figure 5.2: Three dimensional scatter plot showing the least critical components (left) and the most critical components (right).

It is interesting to note that the green cluster includes the two most expensive components, including the BWTS and the CO_2 fire containment system. Especially in the case of the later, there are safety barriers and redundant systems in place (e.g. localised fire fighting systems), which reduce the overall risk of the system. On the other hand, it is observed that the orange cluster contains components with high IMs and relatively small costs.

In detail, the identified critical components are FO Feed Pump 1, FO Feed Pump 2, FO Feed Pump 3, FO Feed Pump 4, MGE 1 FO Injection Pump, MGE 2 FO Injection Pump, MGE 3 FO Injection Pump, MGE 4 FO Injection Pump, MGE 1 Injector, MGE 2 Injector, MGE 3 Injector, MGE 4 Injector, MGE 1 LO Pump, MGE 2 LO Pump, MGE 3 LO Pump and MGE 4 LO Pump. The I^B and I^{CR} of the identified critical equipment are shown in Figure 5.3 and Figure 5.4 respectively. Interestingly, even though the FO Feed Pumps and MGE FO Injectors have a relatively low I^{CR} they are included in the critical equipment. As previously discussed, the presented critical components belong in low order cut-sets (i.e. the smallest set of events that can lead to a failure). This justifies the absence of main engine components from the critical equipment, as these belong in cut-sets of higher order (i.e. more events required for a failure). Also, the failure statistics used to quantify the FT (provided by the ship operator) may have affected this outcome. This demonstrates the need for considering more than one IMs and taking into account both systemic interdependencies and individual failure statistics. Lastly, Figure 5.5 shows the Euclidean distance of

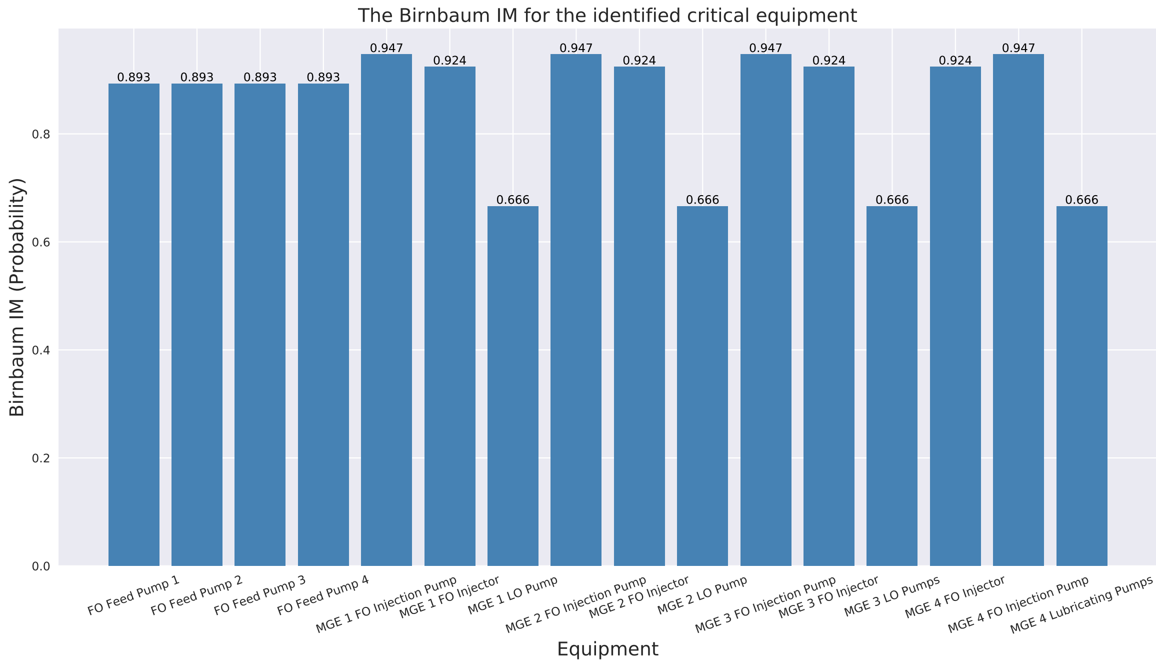

Figure 5.3: Bar chart showing the I^B of the identified critical equipment.

the critical equipment to the origin of the axes. This distance can consolidate and quantify the overall performance of the critical equipment in the used data-space. Figure 5.5 also shows for reference, denoted with a dotted line, the distance of the centroid of the critical equipment cluster.

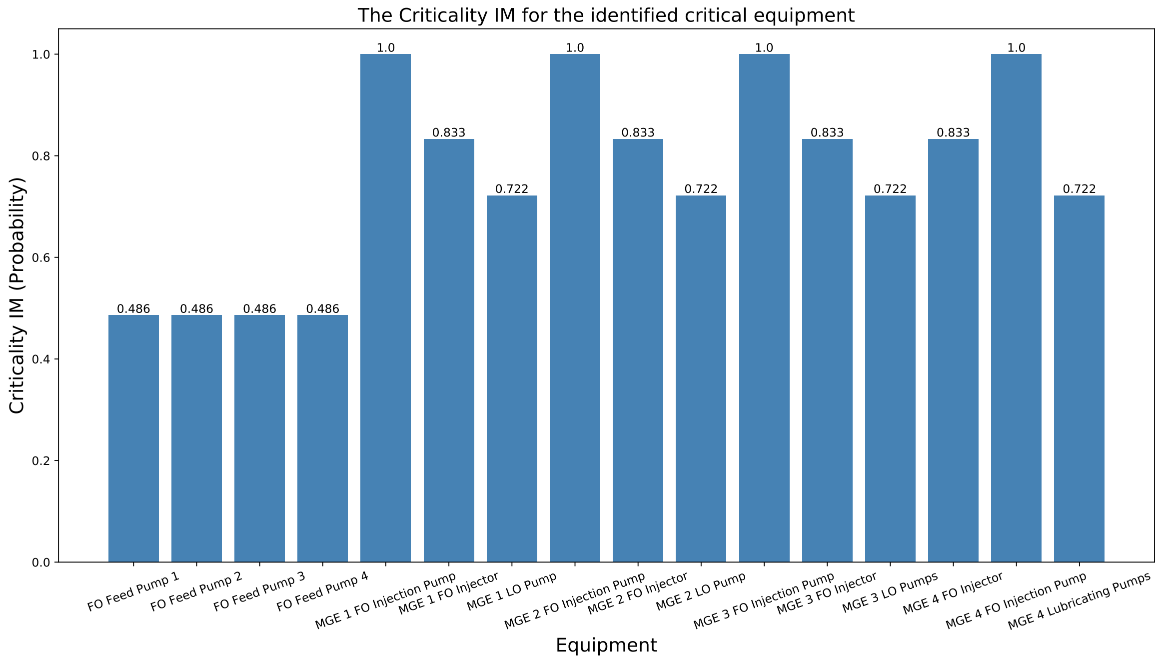

Figure 5.4: Bar chart showing the I^{CR} of the identified critical equipment.

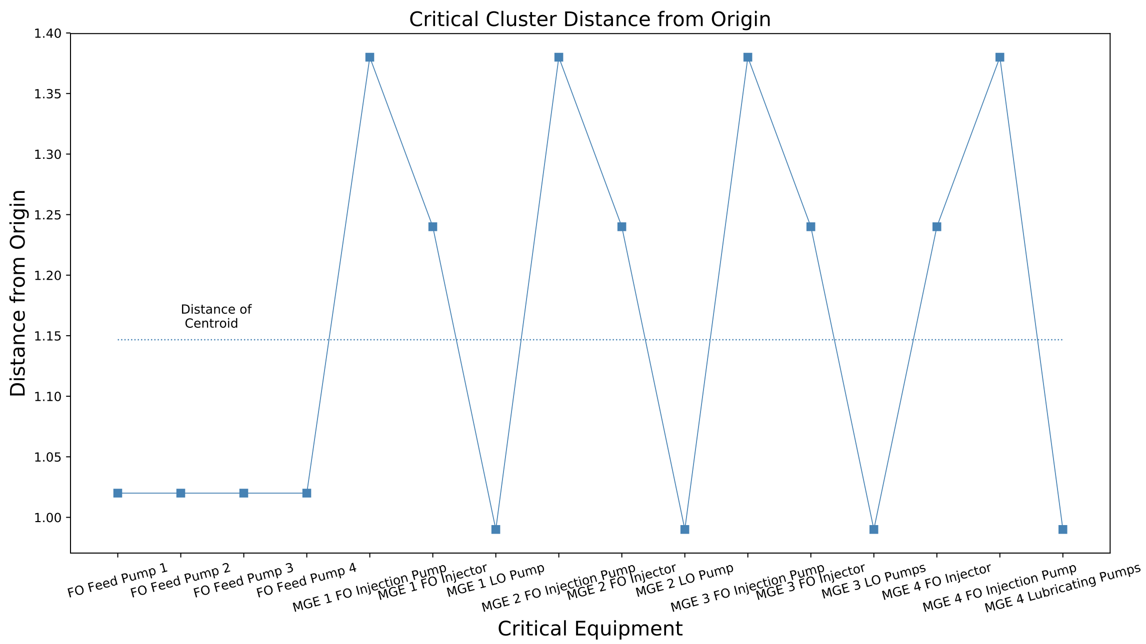

Figure 5.5: Distance of critical equipment to the origin of the axes

5.3 Data Preparation

Following the completion of the critical equipment selection methodology, the proposed predictive maintenance framework addresses the issue of data preparation. The data preparation part of the proposed framework is performed through the methodology presented in Section 4.5. The main aim of the data preparation methodology is to enhance maritime predictive maintenance by establishing a systematic and novel approach that ensures datasets reach their full knowledge-extracting potential. This is achieved by identifying and filtering-out missing and illogical values and subsequently using imputation to replace them. As outlined in Figure 3.4, this methodology initiates with the collection data from vessel “B”, as described in Section 5.3. Following the data collection, the preliminary analysis follows, which includes the form handling, data synchronisation, data filtering and correlation examination processes. Then, the imputation step is performed, which includes the implementation of a novel imputation method and its comparison with other prominent algorithms. Lastly, an operational analysis is applied, which adjusts variables to account for ambient conditions.

5.3.1 Preliminary Analysis

The first process in the preliminary analysis is the form handling of the data, which ensures that data are in tabulated formats. Afterwards, the tabulated data are synchronised according to Equation 3.9 and filtered according to Algorithm 1. The final process of the preliminary analysis is the correlation examination of the variables. For that reason, the Pearson correlation coefficient is used. The Pearson correlation coefficient is selected due to its simplicity and universal applicability (Hastie, Tibshirani, and Friedman 2006). Figure 5.6 shows a heat-map of the correlation coefficient between the examined variables. Finally, the results of the Figure 5.6 are cross-referenced with the engineering knowledge of the ME and TC systems.

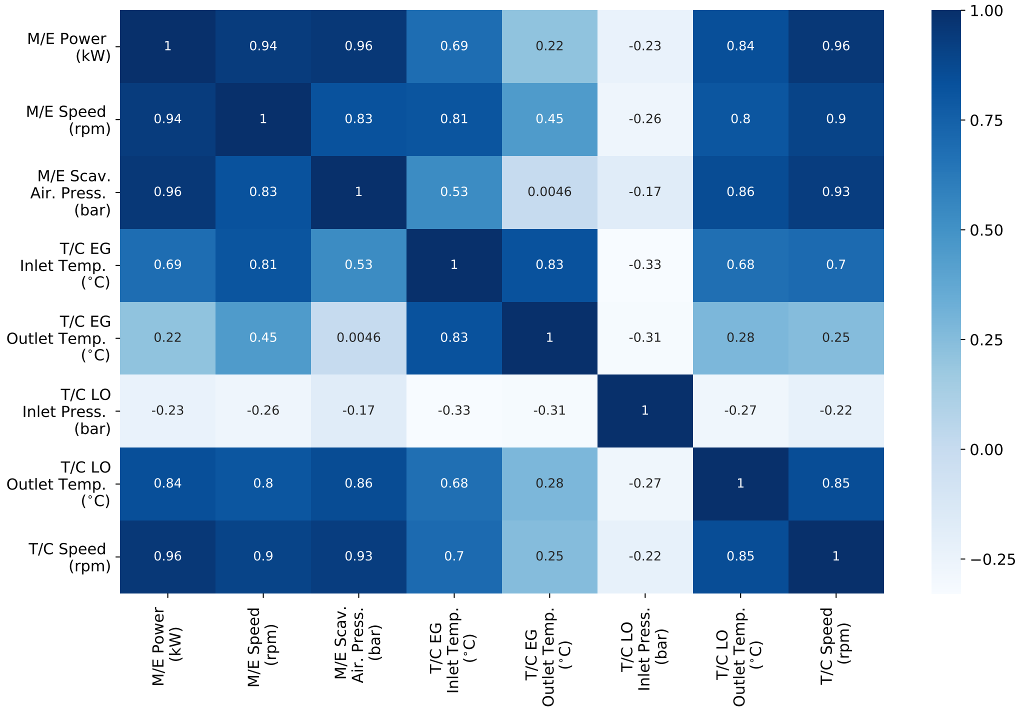

Figure 5.6: Heat-map showing the Pearson correlation coefficient of the ME and TC variables.

From an engineering point of view, it is known that the TC LO inlet pressure and TC LO outlet temperature are amongst the uncorrelated variables. This is due to the fact that the TC LO system is independent and does not come in contact with areas of the ME or the TC where the ignition processes occurs. On the other hand, the TC speed and the ME power have the largest correlation. More specifically, the TC speed is influenced by many factors. It is correlated with the temperature drop of the exhaust gases in the TC. The TC speed is also correlated with the ME power and ME speed, which in turn influences the temperature of the exhaust gases. It should be noted that there are other variables that influence the TC speed, ME power and the temperature of the exhaust gases. For example, such variables are the combustion pressure and the back-pressure of the TC. The combustion pressure influences the power output and subsequently, the temperature of the exhaust gases. On the other hand, the back-pressure of the TC can affect (reduce) the TC speed, as the back-pressure can restrict the flow of the gases (Hountalas et al. 2014; Guan, Theotokatos, and Chen 2015). Even though these parameters are identified for their importance, they are not included in the selected dataset for the analysis. This is due to the fact that the DAQ used for the measuring of the parameters is not capable of recording them. Comparing the results from Figure 5.6 and the engineering knowledge of the ME and TC systems, the final correlation between variables is obtained. (Table 5.4). Table 5.4 presents in a concise manner the presence of correlation

Table 5.4: Resulting correlation based on the integration of the data-driven Pearson coefficient and the first-principle domain knowledge.

	Main Engine parameters			**TC parameters**				
	Power (kW)	**Speed (rpm)**	**Scav. air press. (bar)**	**EG inlet temp. (°C)**	**EG outlet temp. (°C)**	**LO inlet press. (bar)**	**LO outlet temp. (°C)**	**Speed (rpm)**
ME Power (kW)		✓	✓	✓	✗	✗	✗	✓
ME Speed (rpm)	✓		✗	✓	✗	✗	✗	✓
ME Scav. air press. (bar)	✓	✗		✗	✗	✗	✗	✓
TC EG inlet temp. (°C)	✓	✓	✗		✓	✗	✗	✗
TC EG outlet temp. (°C)	✗	✗	✗	✓		✗	✗	✓
TC LO inlet press. (bar)	✗	✗	✗	✗	✗		✗	✗
TC LO outlet temp. (°C)	✗	✗	✗	✗	✗	✗		✗
TC Speed (rpm)	✓	✓	✓	✓	✓	✗	✗	

between the collected variables (Cheliotis et al. 2019). This Table is also used in the application of the novel hybrid imputation approach, as described in the following sections.

5.3.2 Imputation Process

Following the completion of the preliminary analysis, the imputation process takes place. The filtered values from each of the collected variables from vessel "B", are replaced with predictions obtained by applying the MICE, and the kNN algorithms and the hybrid novel imputation approach. The imputation performance of the different algorithms is assessed with simulated missing values. More specifically, random points from the used dataset (150 instances) are removed and the imputation algorithms predict the missing (removed) value. As a result, the comparison of the removed values with the predicted values evaluates the different algorithms (Cheliotis et al. 2019). The results from the discussed imputation approaches are presented in Figures 5.7-5.14. To evaluate the performance of the different imputation approaches and according to common practices of similar research, two graphs are generated for each variable. Initially, a scatter plot is provided, which presents the performance of each prediction. The x-axes of each scatter plot show the actual values of each prediction, whereas the y-axis shows the predicted values. Lastly, each scatter plot includes a dashed $y = x$ line, which represents perfect accuracy and is provided to help determine the performance of each prediction. Also, a histogram is supplemented, which depicts the APE of each prediction. The histogram enumerates the APE of each prediction (distance from $y = x$) and is used to visualise the performance of each imputation approach. This representation of the results offers and concise and descriptive way of visualising the performance of the different imputation algorithms. These two graphs include the information that would be presented in a simple table format, however, they create a more engaging visualisation.

Figure 5.7 shows the imputed (predicted) values and APE for the TC LO inlet pressure. Observing the histogram, it is noted that all the imputation approaches produce equally good predictions. Also from the histogram, it is observed that the approaches produce predictions with APE ranging from 0-35%. This is a large range for the APE, indicating the probability of a model predicting inaccurate values. Through the scatter plot, it is observed that the kNN algorithm produces the results with the biggest standard deviation (sparsity), which can introduce outliers in the dataset. As aforementioned, all three approaches produce results with errors. This behaviour is attributed to the fact that TC LO inlet pressure does not have a substantial correlation with the other variables, as discussed in the previous section, and all of the imputation approaches are correlation-based. The errors produced are justified, as the TC LO inlet pressure is a variable with low correlation (Figure 5.6).

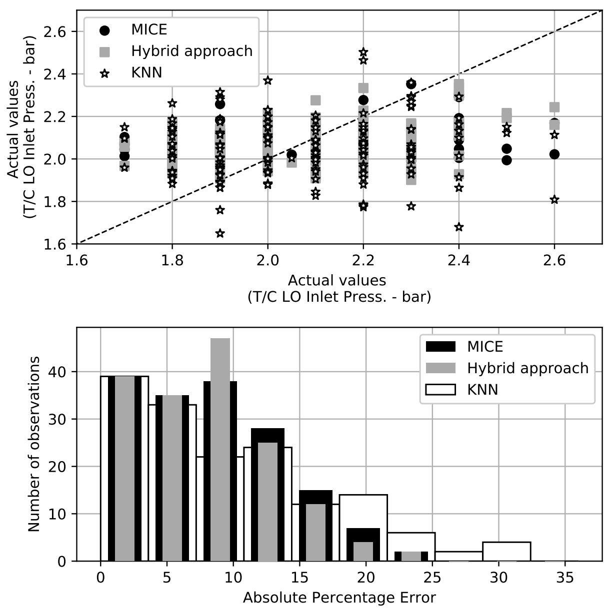

Figure 5.7: TC LO inlet pressure imputation performance comparing the MICE, kNN and hybrid methods.

Figure 5.8 shows the imputed values and APE for the TC LO outlet temperature. Observing the histogram, it is noted that the hybrid method has the best performance, as the majority of the predictions have less than 1% APE. The low APE of the hybrid method demonstrates its consistency in predicting very accurate results. Also from the histogram, it is observed that all the approaches produce predictions with APE ranging from 0-8%. This range of the APE indicates the relatively low probability of a model making inaccurate predictions. Through the scatter plot, it is observed that both kNN and MICE algorithms produce results with large sparsity, which can introduce outliers in the dataset. The hybrid approach performs the best, as it closely follows the $y = x$ line.

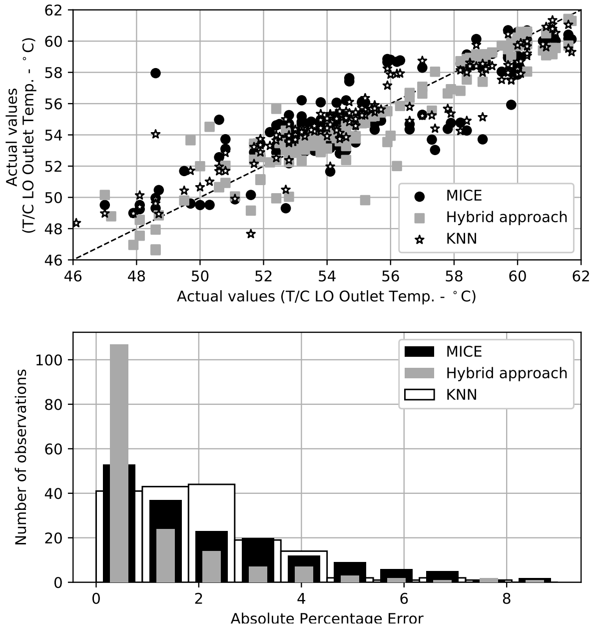

Figure 5.8: TC LO outlet temperature imputation performance comparing the MICE, kNN and hybrid methods.

Figure 5.9 shows the imputed values and APE for the ME power. Observing the histogram, it is noted that the hybrid method has the best performance with the majority of the predictions having less than 1% APE. The low APE of the hybrid method demonstrates its consistency in predicting very accurate results. Also from the histogram, it is observed that all the approaches produce predictions with APE ranging from 0-12%. This range of the APE indicates the relatively low probability of a model making inaccurate predictions. Through the scatter plot, it is observed that the MICE algorithm produces results with large sparsity, which can introduce outliers in the dataset. It is observed that the hybrid approach performs the best, as it closely follows the $y = x$ line. As the ME power is a highly correlated variable, the FP component of the hybrid method contributes to its overall positive performance.

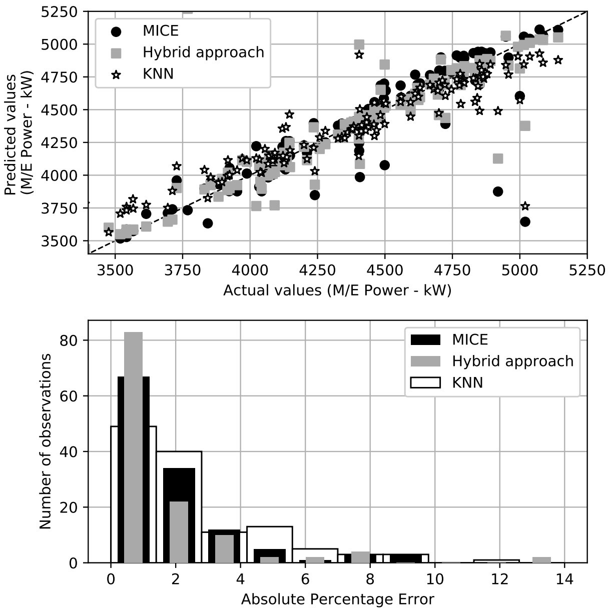

Figure 5.9: ME Power imputation performance comparing the MICE, kNN and hybrid methods.

Figure 5.10 shows the imputed values and APE for the ME speed. Observing the histogram, it is noted that the hybrid method has the best performance with the majority of the predictions having less than 1% APE. The low APE of the hybrid method demonstrates its consistency in making very accurate predictions. Also from the histogram, it is observed that all the approaches produce predictions with APE ranging from 0-8%. This range of the APE indicates the low probability of a model making inaccurate predictions. Through the scatter plot, we observe that the MICE algorithm produces results with large sparsity, which can introduce outliers in the dataset. It is observed that all the tools produce more accurate predictions from 100 rpm and above. At lower speeds, many of the predictions are relatively inaccurate, with the MICE tool predicting possible outliers. As with the previous cases, the hybrid approach follows the $y = x$ line the closest. Since the ME speed is also a highly correlated variable, the FP component of the hybrid approach has a positive effect.

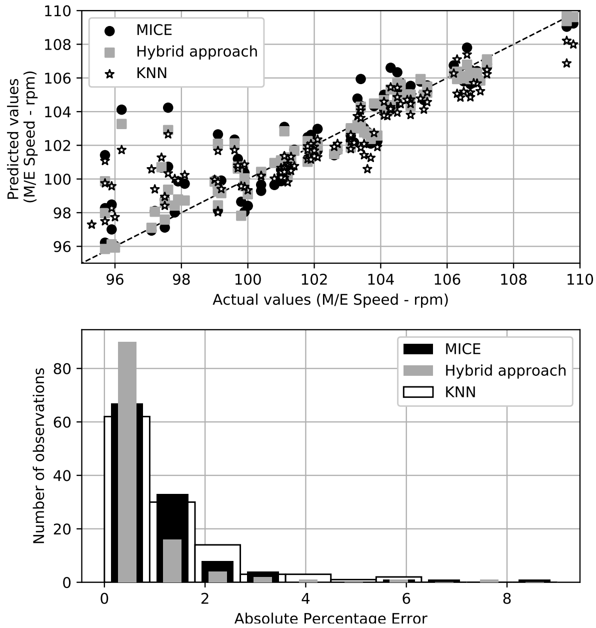

Figure 5.10: ME Speed imputation performance comparing the MICE, kNN and hybrid methods.

Figure 5.11 show the imputed values and APE for the ME scavenging air pressure. Observing the histogram, it is noted that the hybrid method has the best performance with the majority of the predictions having less than 1% APE. The low APE of the hybrid method demonstrates its consistency in making very accurate predictions. Also from the histogram, it is observed that all the approaches produce predictions with APE ranging from 0-35%. This is a large range for the APE, indicating the probability of a model making inaccurate predictions. Interestingly, the ME scavenging air pressure and TC LO inlet pressure have the largest range for APE. This is attributed to the uncorrelated nature of the TC LO inlet pressure and the poor performance of the kNN algorithm. Through the scatter plot, it is noted that the kNN algorithm produces results with large sparsity, which can introduce outliers in the dataset. In this variable, all of the imputation methods produce results very close to the actual values. It is also observed that both the MICE algorithm and the hybrid approach have comparable performance and both follow the $y = x$ line closely.

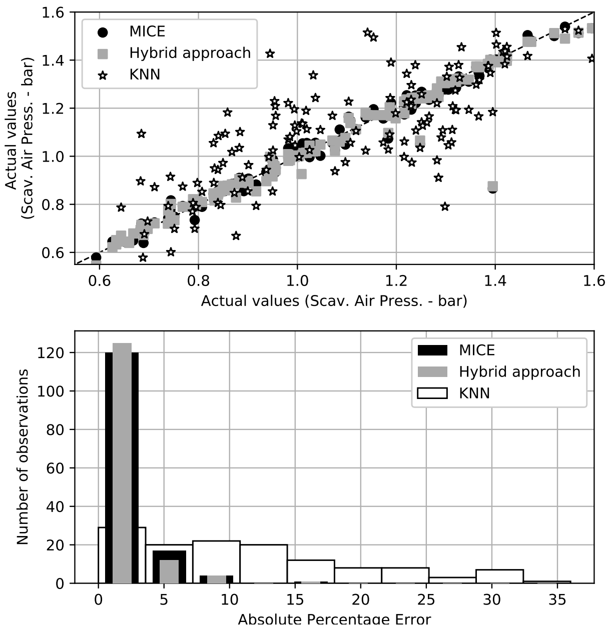

Figure 5.11: ME scavenging air pressure imputation performance comparing the ME, kNN and hybrid methods.

Figure 5.12 shows the imputed values and APE for the TC EG inlet temperature. Observing the histogram, it is noted that the hybrid method has the best performance with the majority of the predictions having less than 1% APE. The low APE of the hybrid method demonstrates its consistency in making very accurate predictions. Also from the histogram, it is observed that all the approaches produce predictions with APE ranging from 0-10%. This range of the APE indicates the relatively low probability of a model making inaccurate predictions. Through the scatter plot, it is observed that the Multiple Imputation by Chained Equations (MICE) algorithm produces results with large sparsity, which can introduce outliers in the dataset. The TC EG inlet temperature exhibits similar behaviour with the ME Speed. The predictions of all the tools are relatively inaccurate at lower temperatures. However, this behaviour is reverted at higher temperatures, with the hybrid method following the $y = x$ line the closest.

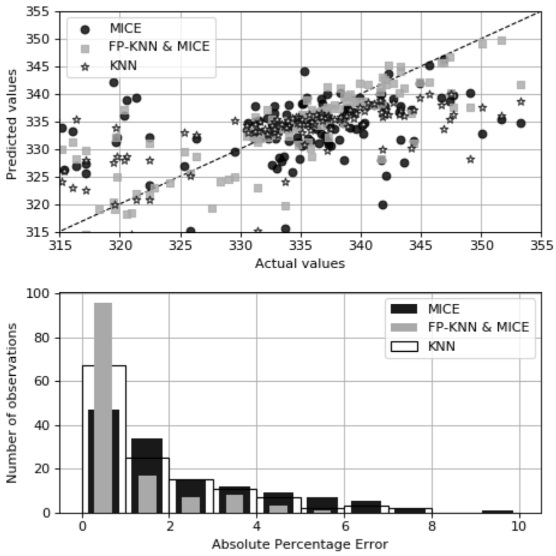

Figure 5.12: TC EG inlet temperature imputation performance comparing the MICE, kNN and hybrid methods.

Figure 5.13 shows the imputed values and APE for the TC EG outlet temperature. Observing the histogram, it is noted that the hybrid method has the best performance with the majority of the predictions having less than 1% APE. The low APE of the hybrid method demonstrates its consistency in making very accurate predictions. Also from the histogram, it is observed that the approaches produce predictions with APE ranging from 0-10%. This range of the APE indicates the relatively low probability of a model making inaccurate predictions. Through the scatter plot, it is noted that the MICE algorithm produces results with large sparsity, which can introduce outliers in the dataset. In general, the hybrid method displays consistently good predictions in the temperature range following the $y = x$ line the closest.

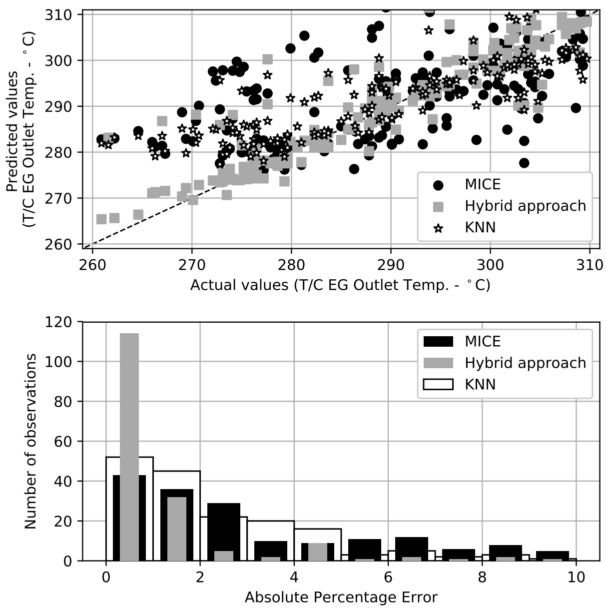

Figure 5.13: TC EG outlet temperature imputation performance comparing the MICE, kNN and hybrid method.

Finally, Figure 5.14 shows the imputed values and APE for the TC speed. Observing the histogram, it is noted that the hybrid method has the best performance with the majority of the predictions having less than 1% APE. The low APE of the hybrid method demonstrates its consistency in making very accurate predictions. Also from the histogram, it is observed that all the approaches produce predictions with APE ranging from 0-18%. This range of the APE indicates the moderate probability of a model making inaccurate predictions. Through the scatter plot, it is noted that the MICE algorithm produces results with large sparsity, which can introduce outliers in the dataset. Similarly with the previous cases, the hybrid method displays consistently good predictions in the speed range following the $y = x$ line closely.

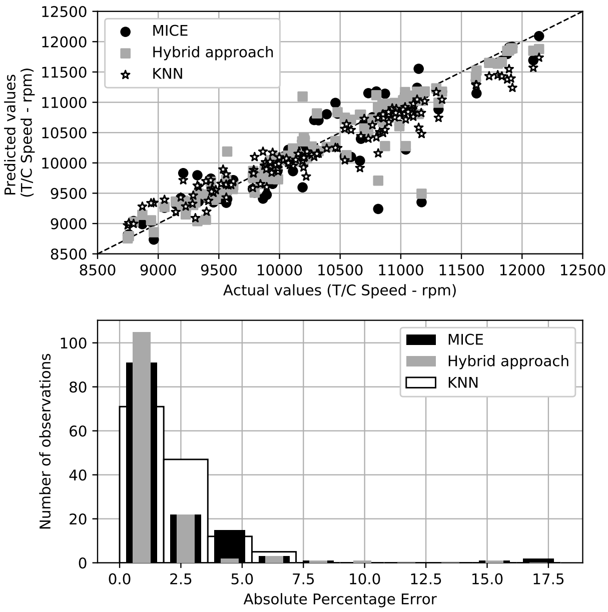

Figure 5.14: TC Speed imputation performance comparing the MICE, kNN and hybrid methods.

Summarising the above, Table 5.5 encapsulates the overall performance of the three imputation approaches for the examined variables. Table 5.5 shows the MAPE and mean σ for each approach and for each variable. Also, an overall MAPE and mean σ are shown to summarise the general performance of each approach. As it is observed, even though the MICE and kNN approaches perform relatively well, the hybrid method outperforms them. It has the lowest overall mean error of 2.21% and the smallest overall σ of 2.64%. The hybrid tool makes accurate predictions without running the risk of generating outliers. The worst performing tool is the kNN with an overall mean error of 5.55% and an overall σ of 8.9%. In addition, Figure 5.15 provides a graphical representation of the MAPE and mean σ of the different approaches across the examined variables. As visually confirmed, the hybrid approach tends to have the lowest error metrics (MAPE, mean σ). Observing the results, it becomes clear that in correlated variables (ME power, ME speed, TC speed, TC EG inlet temperature, TC EG outlet temperature, ME scavenging air pressure, TC LO outlet temperature) the novel imputation method has superior performance. It is observed that the FP component of the hybrid model makes a positive influence on the prediction. By understanding the systemic interdependencies of the system under examination, the performance of the predictions is enhanced. Therefore, the integration of the knowledge of the system to any predictive effort is encouraged and should be preferred to purely data driven approaches.

Table 5.5: Summary table of imputation approaches performance

Case	**MAPE**			**Mean σ**		
	kNN	MICE	Hybrid	kNN	MICE	Hybrid
ME Power	3.16%	2.44%	2.29%	5.48%	4.06%	4.98%
ME Speed	1.15%	1.02%	0.65%	1.12%	1.23%	1.05%
ME Scav. Air Press.	17.15%	2.34%	1.92%	23.72%	3.63%	3.60%
ME TC EG Inlet Temp.	1.63%	2.15%	0.92%	1.69%	1.96%	1.16%
TC EG Outlet Temp.	2.25%	3.08%	1.19%	1.96%	2.60%	1.64%
TC LO Inlet Press.	14.92%	8.46%	7.97%	32.11%	5.24%	4.96%
TC LO Outlet Temp.	2.25%	2.33%	1.29%	3.65%	2.31%	1.73%
TC Speed	1.96%	1.92%	1.42%	1.49%	2.61%	1.97%
Average	**5.55%**	**2.97%**	**2.21%**	**8.9%**	**2.96%**	**2.64%**

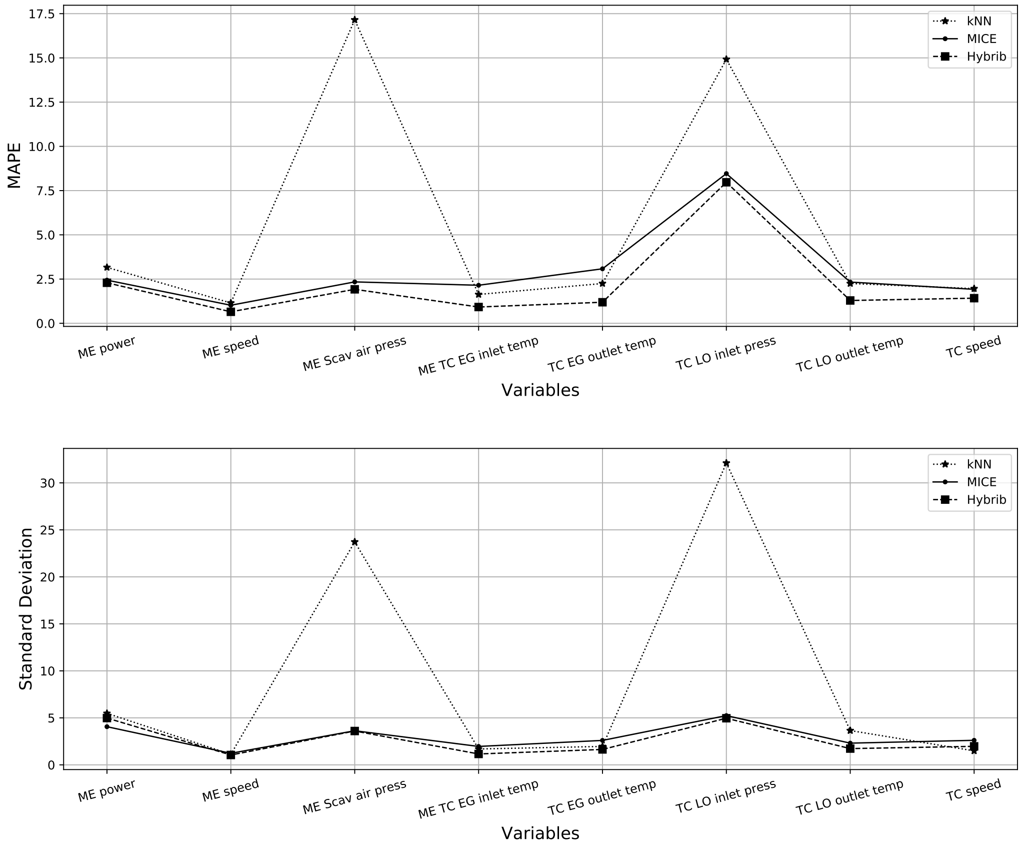

Figure 5.15: Summary plot of imputation approaches performance

5.3.3 Operational Analysis

Following the imputation process step, the resulting dataset is adjusted to account for the influence of the environmental conditions. As also mentioned in Section 3.5.5, this is a common step in similar research efforts as it accounts for the influence ambient conditions have on the collected data. In general, accounting for ambient conditions improves the accuracy of the subsequent developed models (Sodré and Soares n.d.). For that reason, the TC speed, ME scavenging air pressure and the TC EG inlet temperature were corrected (MAN B&W 2014; Tsitsilonis and Theotokatos 2018) according to the manufactures guides and the ISO 3046-1:2002 standards (ISO 2008). The measured ME scavenging air pressure, P_{scav}, was adjusted to its corrected figure, $P_{scav,corr}$ according to Equation 5.1. In Equations 5.1, 5.2 and 5.3 K, F_1 and F_2 are correction constants, while T_{air} and T_{sea} are the ambient temperatures of the air and the sea respectively.

$$P_{scav,corr} = P_{scva} + (T_{air} - 25)F_1(K + P_{scav}) + (T_{sea} - 25)F_2(K + P_{scav}) \quad (5.1)$$

The measured TC speed, N, was adjusted to its corrected value, N_{corr} according to equation 5.2.

$$N_{corr} = \frac{N}{\sqrt{\frac{(K+T_{air})}{(K+25)}}} \quad (5.2)$$

The measured TC EG inlet temperature, T_{egin}, was adjusted to its corrected value, $T_{egin,corr}$ according to equation 5.3.

$$T_{egin,corr} = T_{egin} + (T_{air} - 25)F_1(K + T_{egin}) + (T_{sea} - 25)F_2(K + T_{egin}) \quad (5.3)$$

5.4 Fault Detection (FD)

Following the completion of the data preparation methodology, the proposed predictive maintenance framework addresses the issue of FD. The FD part of the proposed framework is performed through the methodology presented in Section 4.6. The FD methodology aims to enhance maritime predictive maintenance by establishing a novel approach for the early detection of developing faults. During this work, the considered faults are the result of gradual degradation and wear-and-tear. In other words, sudden breakages and shock loads are not considered. As outlined in Figure 3.5, the FD methodology initiates with data collection, described in Section 5.4. Then, it proceeds with the development of a regression-based EB model, which uses as input the pre-processed historic ProMon data. The selected model is the optimal result from a systematic model evaluation process, which examines different regression types, model inputs and model hyperparameters. Once the generalisation performance of the selected model is evaluated, the fault detection steps proceeds, utilising the pre-processed incoming ProMon data. For FD, the residuals between the predicted values and the actual values of the target variable (ME EG temperature of each cylinder) are assessed in an EWMA control chart. Lastly, as discussed in Section 5.4.1, the performance of the FD process is evaluated using simulated faults. The simulated faults are divided into four different cases, with each case representing groups of different possible faults.

5.4.1 Data Checking

The first process of the data checking step is to ensure that the units of the data are in the correct form and that the dataset is in a tabulated form. Following that, the DBSCAN algorithm is deployed to remove transient states of operation and outliers from each variable.

The application of the DBSCAN algorithm requires the specification of the ϵ and $minP$ hyperparameters. The ϵ hyperparameter dictates the maximum distance between points for them to be considered in the same cluster. Also, the $minP$ hyperparameter controls the number of neighbouring points required to form a cluster. As discussed in Section 4.6.3, the value of ϵ is determined after iterative attempts. Different values are iteratively used until the transient states are removed, and consequently, the outliers are filtered out. Finally, the selected value was $\epsilon = 0.25$. Considering the dataset used in the FD methodology has 9 dimensions, as seen in Table 4.9, and keeping in mind the restrictions suggested by Chen and Li (2011) the final value for $minP$ was determined to by 9. As the sampling rate of the data is 1 recording per 5 minutes and $minP = 9$, samples from 45 minutes are required to form a cluster. This is realistic and reasonable time-frame for the operation of the ME when the ship in on voyage, as confirmed by the operators of vessel "B".

The last process of the data checking step is to filter-out any points collected when the ship was not operational. For that purpose a simple value-based filter was created, as seen in Equation 5.4.

$$Power_{ME} > 10kW \tag{5.4}$$

Figure 5.16 shows two plots depicting the initial state and the result of the data checking process for the ME shaft power and ME shaft speed variables respectively. In each of the two plots, the top graph represents the "checked data", whereas the bottom graph represents the "raw" data, as supplied by the DAQ system of vessel "C". As observed, the spikes and dips int the "raw" data graph are filtered out by the DBSCAN clustering algorithm, while the flat-lines are removed by Equation 5.4. The data checking results for all the variables of vessel "C' ' are shown in Appendix D.

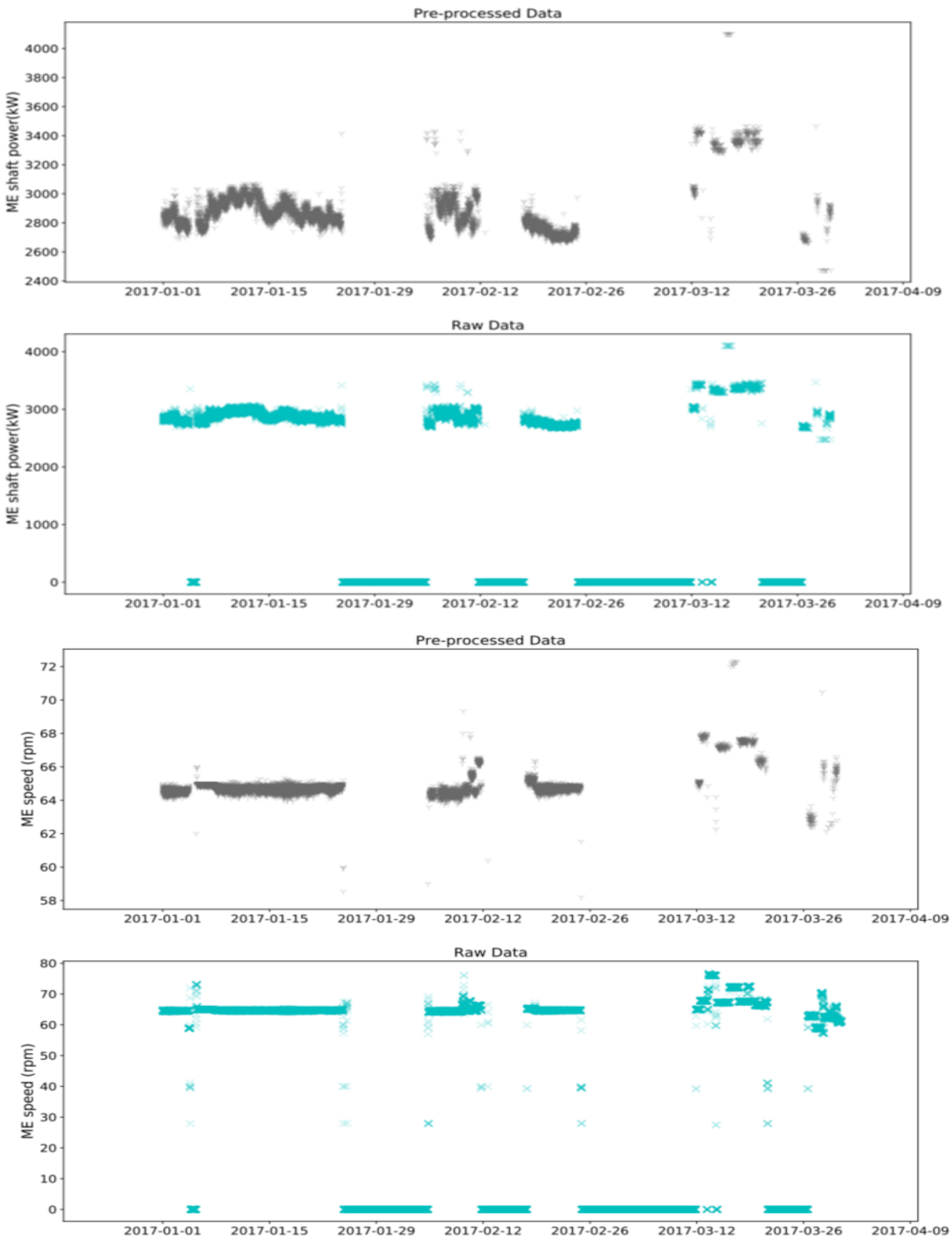

Figure 5.16: Data checking result for ME shaft power (top) and ME shaft speed (bottom)

5.4.2 Model Development

The purpose of model development is to identify the optimum EB model, which is then used to predict the ideal behaviour of a selected target variable. The target variable that is used in this part of the methodology is the ME EG temperature for each cylinder. This variable was selected due to its great importance in performance and process monitoring. Monitoring the ME cylinder EG temperature can help 1) control the ME's emissions, 2) understand the cylinders' combustion performance 2) identify underlying and developing faults. In more detail, faults in the air cooler, turbocharger and gas passages of the ME can manifest through the ME EG temperature.

During the model development, the available historical data are divided into a training and validation set and a testing set. The former is used to fit the different models, tune the different hyperparameters, compare and ultimately select the best performing model. The best model is selected by primarily assessing the validation score and taking into account the standard deviation (σ) of the prediction errors. Once the best performing model is selected, its generalisation capabilities are assessed in the training set.

In total, four different types of regression models are examined, including OLS single linear regression, multiple linear ridge regression, OLS single polynomial regression and multiple polynomial ridge regression, discussed in Section 4.6.4. Apart from the different types of models, different inputs (predictor variables) are considered for each model. For each of the ridge regression models, the α hyperparameter ranges from 0.1 to 0.6. Also, the examined polynomial models are assumed to be of 6^{th} order. The value of α and the order of the polynomial models depends purely on each application, and there is no standard guide on their selection. Instead, different ranges of α and different values for the polynomial order can be examined. In case none of the models exhibits good behaviour with the selected α and order, these values are changed, and the analysis is repeated.

The various resulting models are detailed in Tables 5.6-5.8. These tables detail the different models with their IDs together with the inputs used in each case. The inputs refer to the predictor variables used in each model and can include the ME power, ME speed, scavenging air pressure and scavenging air temperature. Table 5.6 contains the different models based on multiple linear ridge regression and Table 5.7 contains the models based on multiple polynomial ridge regression. For instance, model M1 uses as predictors the ME power, ME speed, scavenging air pressure and scavenging air temperature and has the α hyperparameter ranging from 0.1 to 0.6 with 0.1 increments. Consequently, model M16 has the predictors of model M1, and the α hyperparameter has a value of 0.6. Lastly, Table 5.8 has the single input OLS models that are used as a benchmark.

Table 5.6: List of examined multiple linear ridge regression models.

Multiple Linear Ridge Regression	
Variables	**Model ID**
Power, Pressure, Temperature, Speed	M1
Power, Pressure, Temperature	M2
Speed, Pressure, Temperature	M3
Speed, Power, Temperature	M4
Power, Pressure, Speed	M5
Power, Pressure	M6
Pressure, Temperature	M7
Power, Temperature	M8
Speed, Temperature	M9
Speed, Power	M10
Speed Pressure	M11

Table 5.7: List of examined multiple polynomial ridge regression models

Multiple Polynomial Ridge Regression	
Variables	**Model ID**
Power, Pressure, Temperature Speed	N1
Power, Pressure, Temperature	N2
Speed, Pressure, Temperature	N3
Speed, Power, Temperature	N4
Power, Pressure, Speed	N5
Power, Pressure	N6
Pressure, Temperature	N7
Power, Temperature	N8
Speed, Temperature	N9
Speed, Power	N10
Speed Pressure	N11

Table 5.8: List of examined single regression models

Remaining Models	
Mode	**Model ID**
OLS Single Linear Regression	L
OLS Single Polynomial Regression	P

5.4.2.1 Training and Validation

From the historic ProMon data, 80% of them are randomly selected for training and validation, according to empirical knowledge and common practices. The different models need a substantial amount of the collected data (e.g. 80%) in order to identify patterns and develop good generalisation capabilities. The random selection of the data controls the variance of the model, and it enhances its generalisation capabilities, as during the training, data from the entirety of the operational profile are used (Kirk 2017).

During this stage, k-fold cross-validation is used to train and validate the different models discussed above. For this work, the value of $k = 7$ was assumed. Similarly with the previous hyperparameters (e.g. α), the selection of k was based on empirical knowledge, as its value is application-specific. Consequently, each model is trained and validated 7 times, each time using a different segment of the data for validation. The validation performance of each model is then assessed by averaging the 7 different validation scores resulting from the 7-fold cross-validation.

Figure 5.17 shows the validation performance of the different models in terms of their average R^2 score during the k-fold cross-validation. This Figure examines different regression models and with varying inputs and ranging α values. The upper bar chart examines the average score of each model (multiple linear ridge regression) shown in Table 5.6. To further evaluate the performance of the different models, the maximum score is shown as a dashed blue line. Similarly, the performance of the single OLS linear regression, using the ME power as an input, is shown as a solid black line. Models M11, M12 and M13 which use as inputs the ME power, speed, scavenging air temperature and pressure with $\alpha = 0.1$, $\alpha = 0.2$ and $\alpha = 0.3$ respectively have the best validation score of nearly 0.93. The performance of the OLS linear regression is lower than the other multiple linear ridge regression models. The lower bar chart examines the average score of each model (multiple polynomial ridge regression) shown in Table 5.7. The maximum score and the performance of the OLS single polynomial regression are also shown as a dashed and a solid line respectively. Models N53, N54, N55 and N56 which use as inputs ME power, speed, scavenging air pressure with $\alpha = 0.3$, $\alpha = 0.4$, $\alpha = 0.5$ and $\alpha = 0.6$ respectively have the best validation score of nearly 0.96. Interestingly, the performance of the OLS single polynomial regression is preferable to most of the multiple polynomial ridge regression models, as seen by the high R^2 score. Finally, it is observed that the polynomial models have a superior performance in terms of the mean validation score. As summarised in Table 5.9, the polynomial models have a higher mean validation score and a smaller range compared to the linear models.

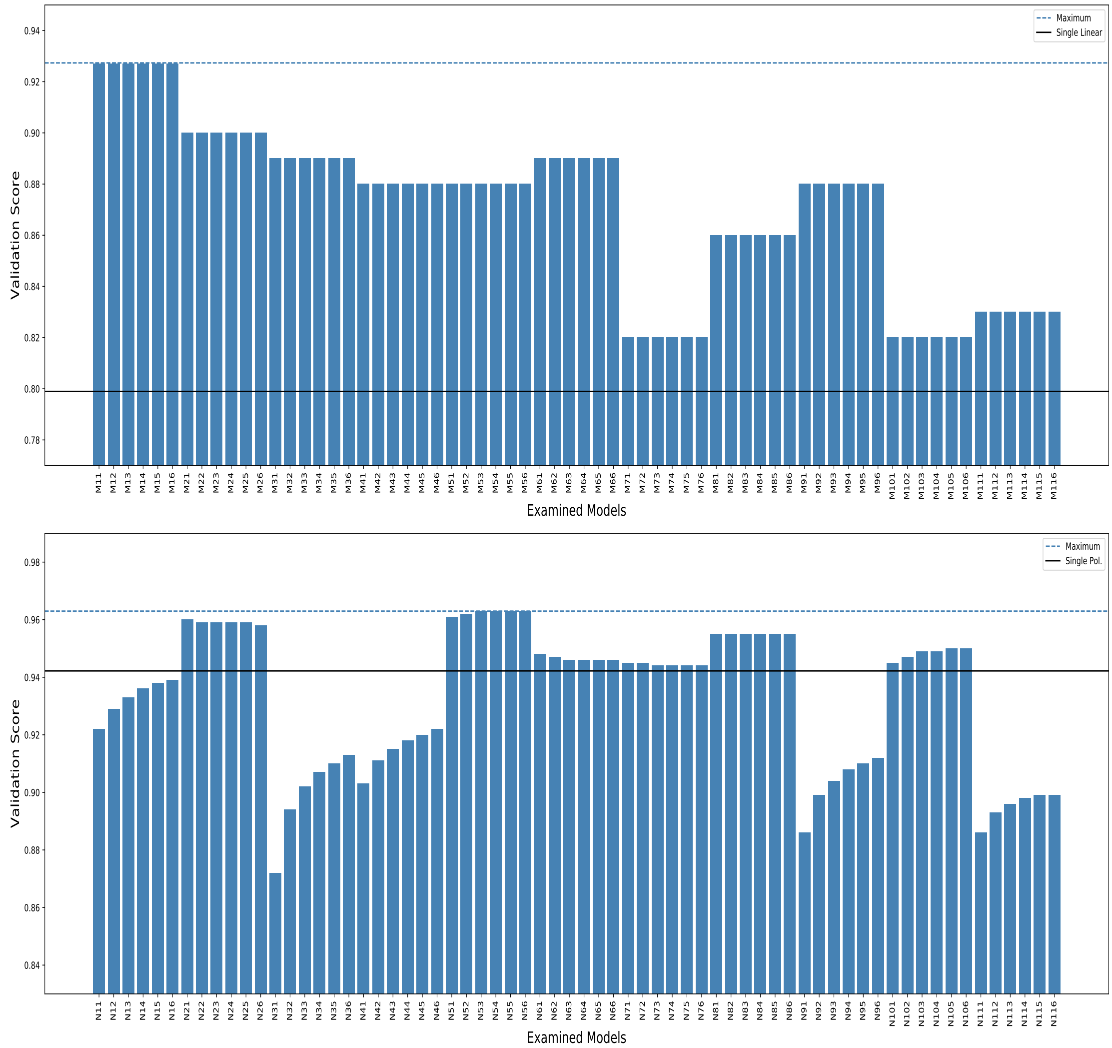

Figure 5.17: R^2 validation performance of the linear (upper chart) and polynomial models (lower chart)

Table 5.9: Performance of linear and polynomial models in terms of R^2

	Linear Models	**Polynomial Models**
Mean Validation Score	0.83	0.94
Validation Score Range	0.11	0.091

Figure 5.18 shows the validation performance of the different models in terms of the standard deviation (σ) of the average R^2 scores during the k-fold cross-validation. This Figure examines the same models as Figure 5.17 and is sup-

plementary for the evaluation of the different models. Similarly, the minimum σ of the average R^2 scores is shown as a solid line and the σ of the R^2 scores from the single linear and single polynomial models are shown as dashed lines. The standard deviation of the validation performance describes the consistency of each model in their predictions during the k-fold cross-validation. It is observed that the linear models have a superior performance in terms of the σ of the mean validation score. As summarised in Table 5.10, the linear models have a lower mean σ and a smaller range compared to the polynomial models.

Table 5.10: Performance of linear and polynomial models in terms of σ

	Linear Models	**Polynomial Models**
σ **of Mean Validation Score**	0.046	0.07
σ **of Mean Validation Score Range**	0.07	0.24

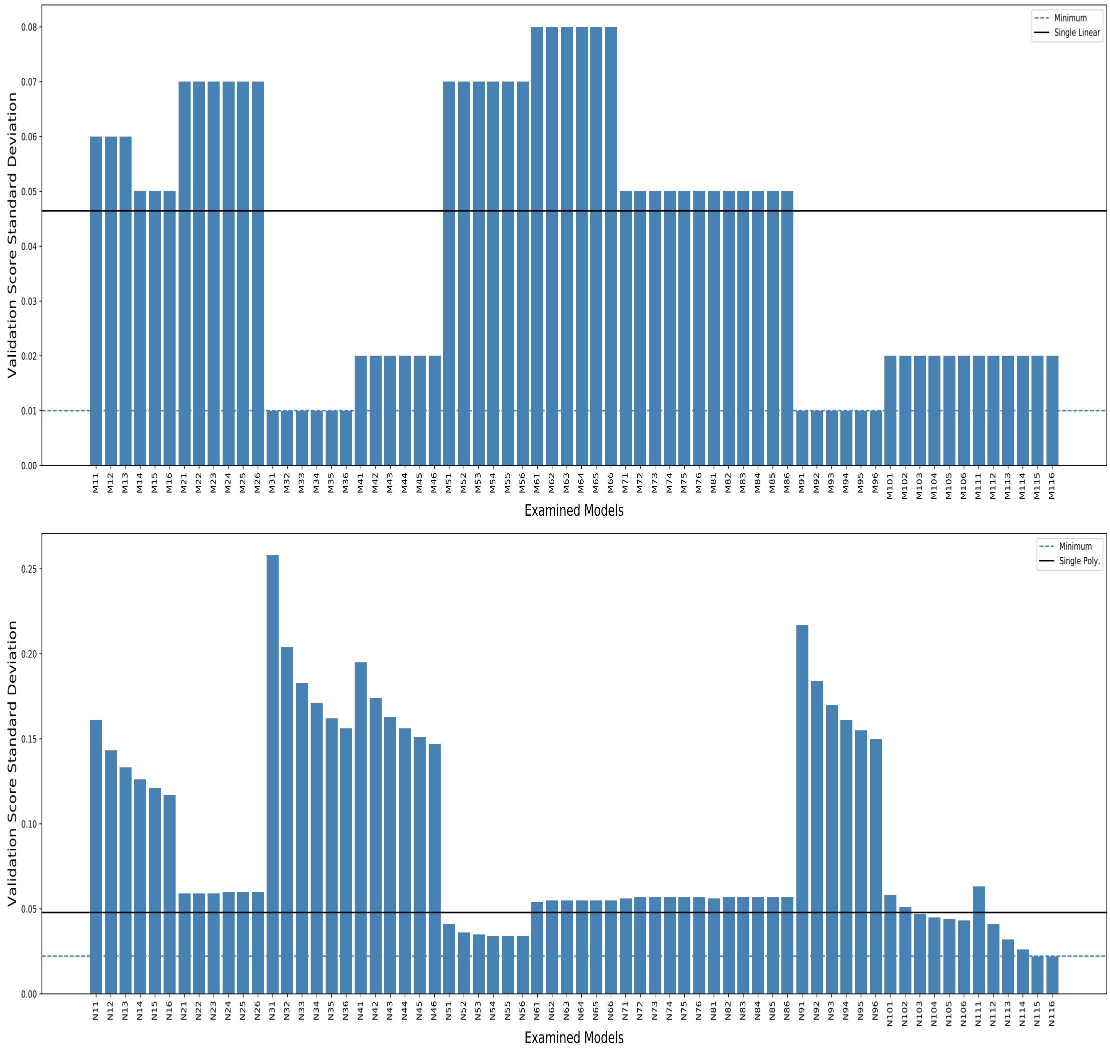

Figure 5.18: σ of the performance of the linear (upper chart) and polynomial models (lower chart)

As previously discussed, the model development aims to identify the model with the highest R^2 and a small σ. For that reason, the models with the highest R^2 and the models with the lowest σ are identified and compared. The identified models are presented in Table 5.11. As highlighted in the Table, model N54 has the best mean validation R^2 and a σ comparable with the remaining models and for these reasons is identified as the optimum choice. In summary model N54 uses multiple polynomial ridge regression has $\alpha = 0.4$ and uses as input the ME

Power, pressure, and speed.

Table 5.11: Performance of models with the highest R^2 and performance of models with lowest σ

	Mean Validation R^2	**σ of Mean Validation R^2**
N54	0.96	0.03
M31	0.89	0.01
M32	0.89	0.01
M33	0.89	0.01
M34	0.89	0.01
M35	0.89	0.01
M36	0.89	0.01
M91	0.88	0.01
M92	0.88	0.01
M93	0.88	0.01
M94	0.88	0.01
M95	0.88	0.01
M96	0.88	0.01

Finally, Figure 5.19 shows the learning curves of model N54 having as target variable the EG temperature of the cylinders of the ME and the average EG temperature of all the cylinders of the ME. These curves show the training (red) and validation (black) scores for each case as a function of the number of folds in k-fold cross-validation. In effect, increasing the number of folds also increases the training data. Thus, the learning curves aim to evaluate if the model is either overfitting or underfitting the data. In other words, the learning curves are used to gauge the model's generalisation capabilities. In Figure 5.19, across all the graphs, as the number of fold increases the training performance reaches a plateau, indicating that the training performance can no longer improve by increasing the amount of training data. Similarly, the validation score increases, indicating that the generalisation capabilities of the model are satisfactory. In general, the convergence of the training and validation learning curves indicate the presence of a model with a good fit on the data. For example, the upper left chart of Figure 5.19 shows the learning curves for the model predicting the average EG temperature of all the cylinders of the ME. As seen, the training score reaches a plateau of around 0.977, and the validation score reaches a maximum value of nearly 0.968.

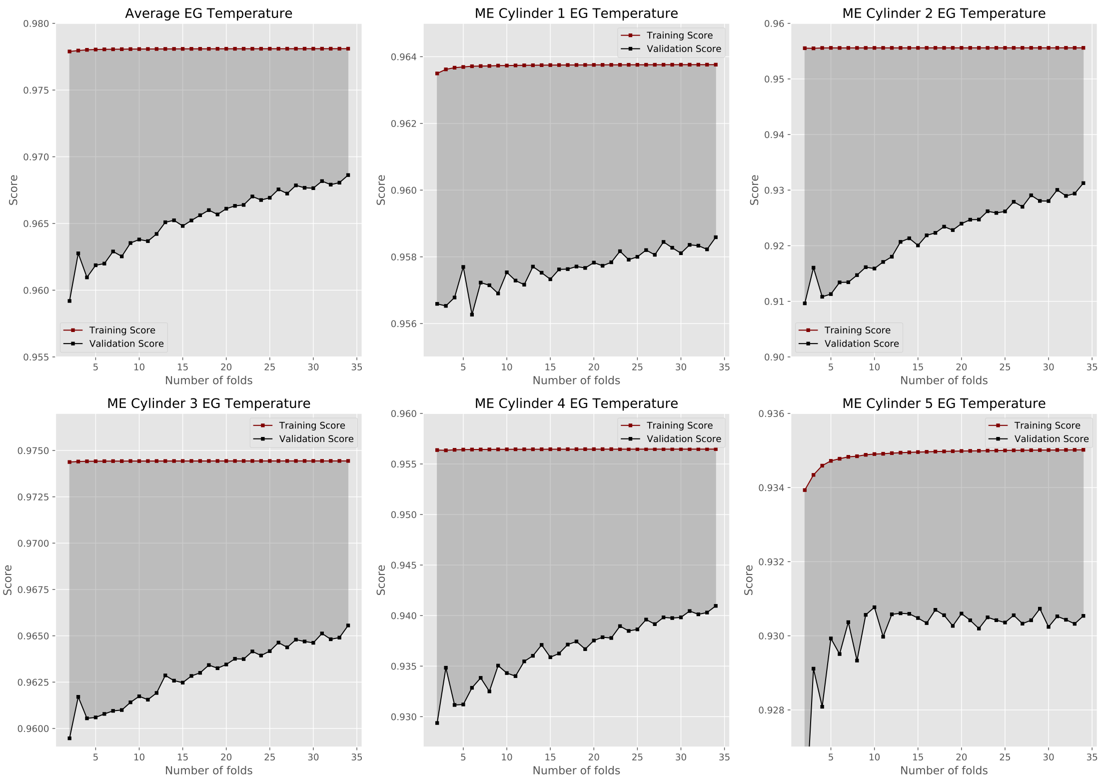

Figure 5.19: Learning curves of model N54 showing the training and validation scores as a function of increasing folds during the cross-validation process

5.4.2.2 Testing

Model N54 is identified as the optimal and fully defined choice for the prediction of the EG temperature of the cylinders of the ME. Following the completion of the training and validation process, model N54 is trained using the whole training set (no validation set is used). The trained model is then evaluated on the previously unseen test set. Figure 5.20 shows the training and testing scores of this process. As observed, the testing performance is satisfactory as the R^2 ranges from 0.93 to 0.966.

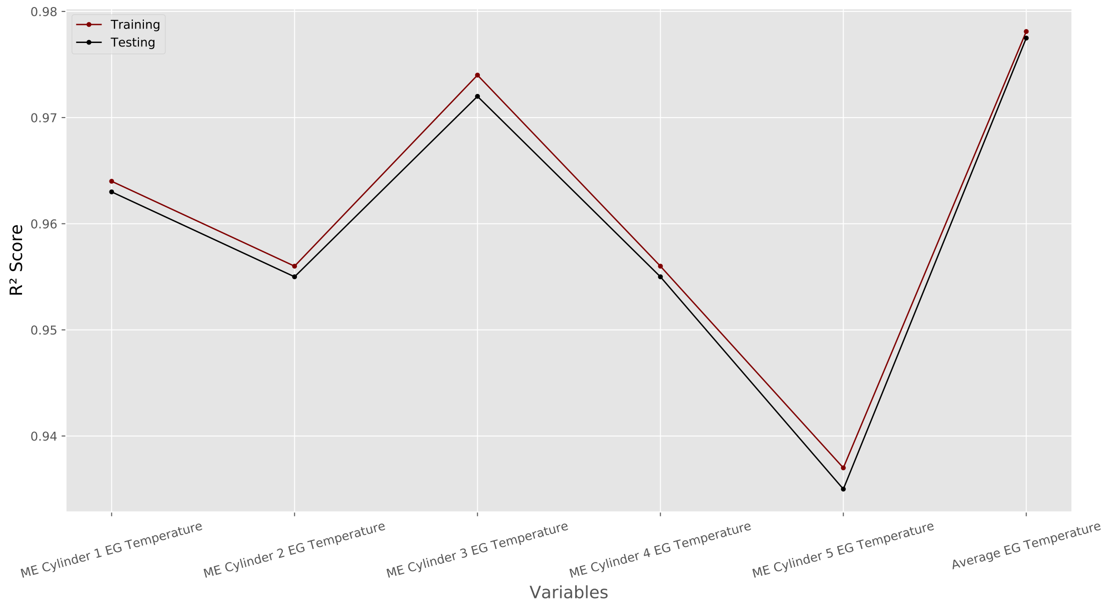

Figure 5.20: Final training and testing scores of the selected model

5.4.3 Fault Detection

This step of the methodology uses the incoming ProMon data, which are checked according to the process described in Section 4.6.3. The identified and evaluated model (N54) is used to obtain the expected (predicted) values for the ME EG temperature of each cylinder of vessel "C". Once these values are calculated, they are compared with the actual EG temperature from the incoming ProMon data, resulting in the residuals.

Once the calculation of the residuals is completed, the EWMA control chart is constructed, which requires the specification of the λ and L hyperparameters. The former is the smoothing parameter and is obtained according to common practices. In this work, it is assumed that $\lambda = 0.3$, according to Badodkar and Dwarakanath (2017). On the other hand, the L hyperparameter controls the width of the control chart (distance between UCL and LCL), and its value is assigned after iterations. As discussed in Section 5.4.1, the incoming data represent healthy operating conditions, as confirmed by the operator of vessel "C". Therefore, the value of L was selected so that the residuals on the control chart do not exceed the UCL and LCL. Figure 5.21 shows the residuals of the average EG temperature of cylinders of the ME of vessel "C", plotted in an EWMA control chart. The average EG temperature is used for simplicity reasons, as it summarises the behaviour of the individual cylinders. In this Figure, the obtained residuals are shown with grey, and the EWMA statistic for each residual is shown as blue. Lastly, the UCL, LCL and the Center Line (CL) are also shown. In Figure 5.21, $L = 3$ was used, since the resulting EWMA statistic for the residuals lie between UCL and LCL. It should be specified that $L = 3$ is the first value correctly classifying the EWMA residuals.

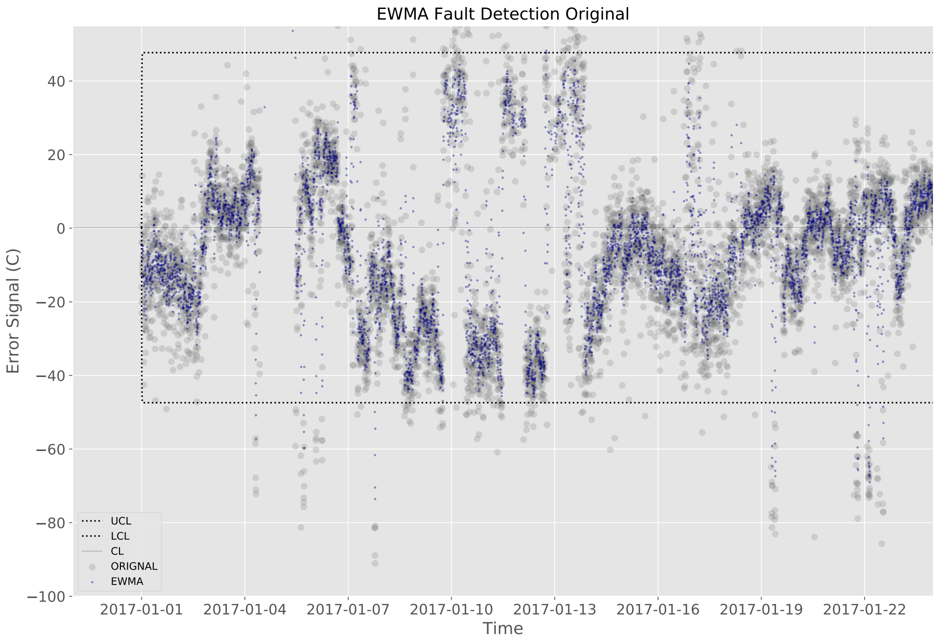

Figure 5.21: EWMA control chart for the selection of the L hyperparameter

The evaluation of the methodology transpires by using the developed EB model and analysing the residuals in an EWMA chart for fault detection. To examine the detection capabilities of the methodology, and by considering the fault-free nature of the available data, four different fault cases are examined through simulated data in the form of a sensitivity analysis (Law 2009; Saltelli 2004)

These four cases are presented in Table 5.12 and represent failure modes that can affect the target variable. In detail, according to domain knowledge and by considering the publications from Hountalas (2000) and Theotokatos and Tzelepis (2015), the examined cases represent specific failure modes in a ship, further explained in the remaining section. In addition, the limits presented in Table 5.12 are selected from the ME manufacturer guide (MAN B&W 20017) and represent the alarm limits set by the manufacturer. In each case, the appropriate variables in the incoming ProMon data are adjusted linearly, to reach and exceed the presented limits, simulating the faulty conditions.

Table 5.12: Verification cases description

Case ID	**Variable**	**Alteration**	**Limit**	**Value**
Case 1	ME scavenging air pressure	Increased	Upper	3.3 bar
Case 2	ME scavenging air pressure	Decreased	Lower	0.4 bar
Case 3	ME cylinder EG temperature	Increased	Upper	420 ^{o}C
Case 4	ME cylinder EG temperature	Decreased	Lower	214 ^{o}C

These adjustments take place, across all cases, from 10/01/2017 to 11/01/2017 and is assumed that after this period, rectifying actions take place. Figures 5.22 -5.25 show the EWMA fault detection results for case 1 to case 4 respectively. All cases show the residuals of the average EG temperature across all the cylinders. This is due to simplicity reasons, as the examples of the examined faults affect the EG temperature of all the cylinders.

Figure 5.22 shows the EWMA smoothed residuals signal for case 1. As it can be observed, the points from the first few days have residuals with an error close to 0^{o}C. However, from the 10/01/2017 the residuals begin to increase and reach more than 200^{o}C. This surge is attributed to the increase of the ME scavenging air pressure to more than 3.20 bar. The residuals (as defined in Equation 3.22) increase, as the expected value of the target variable, increases with a higher rate. As it can be observed, the simulated fault is successfully detected as the EWMA exceeds the UCL. A typical example of a fault described in case 1 is the overloading of the ME caused by fouling of the ship's hull.

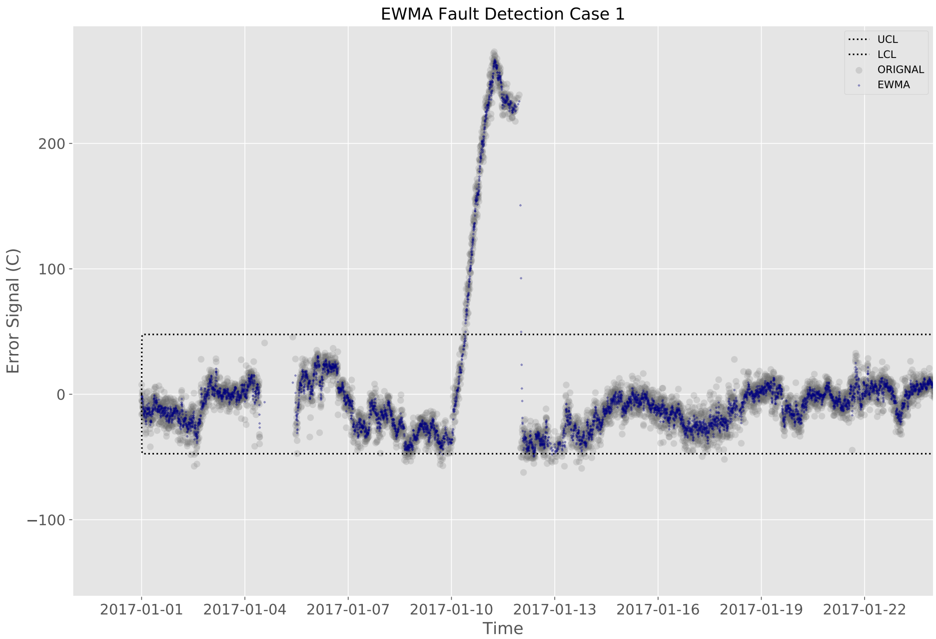

Figure 5.22: EWMA control chart of the average EG temperature for case 1

Figure 5.23 shows the EWMA smoothed residuals signal for case 2. Similarly with the previous case, the residuals from the first few days fluctuate around 0^oC. However, from 10/01/2017 the residuals begin to drop and reach a value of more than -350^oC. This decrease is attributed to the controlled drop of the ME scavenging air pressure to nearly 0.20bar. In this case, the residuals drop, as the expected value of the target variable declines with a sharper rate. As it can be observed, the simulated fault is successfully detected by the LCL. For instance, such behaviour can be attributed to fouling and corrosion in the TC of the ship, and fouling and corrosion in the nozzle ring of the TC.

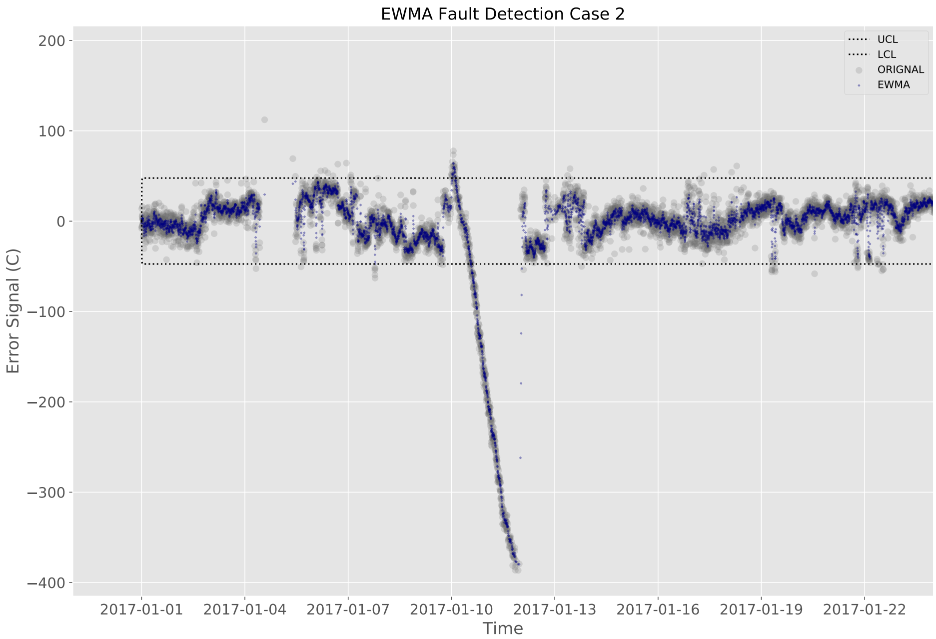

Figure 5.23: EWMA control chart of the average EG temperature for case 2

Figure 5.24 shows the EWMA smoothed residuals signal for case 3. As it can be observed, the points from the first few days fluctuate around 0^{o}C. However, from 10/01/2017 the residuals begin to decrease and reach a value of approximately 150^{o}C. This drop is attributed to the simulated rise in the ME cylinder EG temperature to nearly 420^{o}C. The residuals in case 3 decline, as the actual value of the EG temperature drops decoupled from the expected value. As it can be observed, the simulated fault is successfully detected, as the LCL is successfully exceeded. Typical examples of fault described in case 3 include the fouling of the main cooler of the ship and fouling in the AC of the ME (both air and water sides).

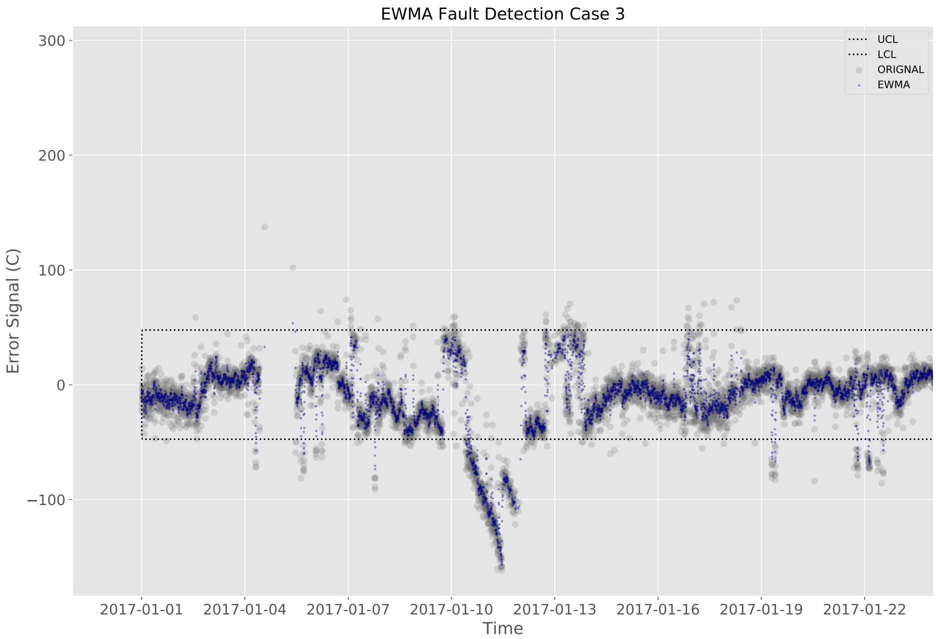

Figure 5.24: EWMA control chart of the average EG temperature for case 3

Figure 5.25 shows the EWMA smoothed residuals signal for case 4. As it can be observed, the points from the first few days fluctuate around 0^{o}C. However, from 10/01/2017 the residuals begin to increase and exceed the value of approximately 200^{o}C. This surge is attributed to the simulated drop in the ME cylinder EG temperature to nearly 214^{o}C. Following the same underlying reasoning as case 3, the decoupled decrease of the actual values of the target variable increases the residuals. As it can be observed, the simulated fault is successfully detected by the UCL. A typical example of a fault described in case 4 includes the improperly maintained or improperly configured engine room conditions.

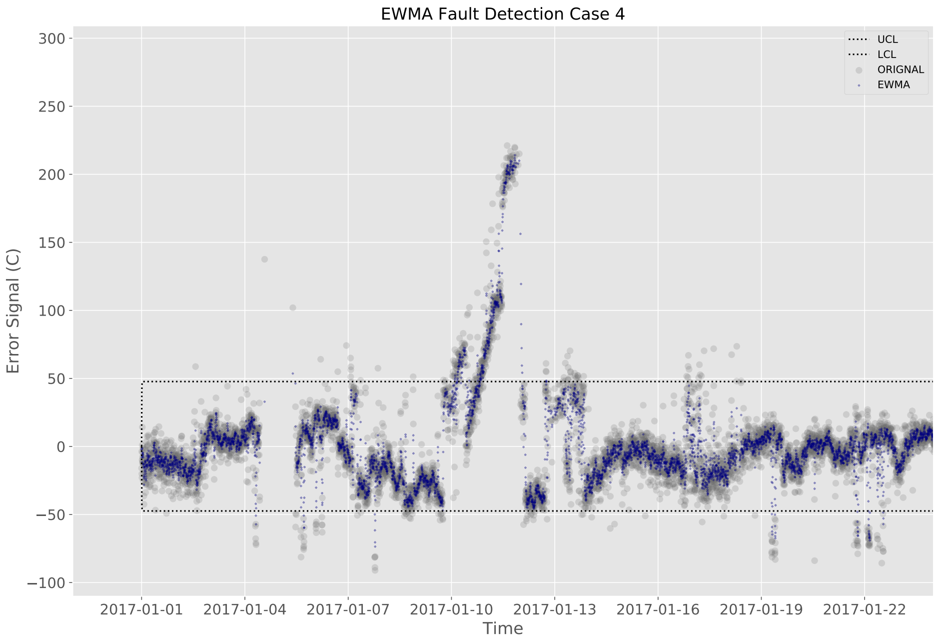

Figure 5.25: EWMA control chart of the average EG temperature for case 4

5.5 Diagnostics

Following the completion of the FD methodology, the proposed predictive maintenance framework addresses the issue of diagnostics. The diagnostics part of the proposed framework is performed through the methodology presented in Section 4.7. The diagnostics methodology aims to enhance maritime predictive maintenance by developing a novel approach to pinpoint the root cause of certain detected fault. More specifically, this methodology includes the novel integration of an ML-based EB model (multiple polynomial ridge regression) for FD with a knowledge-based BN for diagnostics. As discussed in Section 5.4, the diagnostic methodology uses the same data as the FD methodology, due to restrictions in obtaining additional required data. The FD and the diagnostics methodologies were developed sequentially, as any diagnostic efforts must initiate after the detection of a fault. As a result, the diagnostic methodology uses the identified EB model (model N54) as input. As outlined in Figure 3.8, the diagnostics methodology initiates with data collection, described in Section 5.4. The next step includes the fault mapping process, which allows the determination of the different possible causes of the faults identified with model N54. Then, model N54 is used to detect developing faults, and the results are subsequently aggregated. After the different fault causes are identified, the structure of the BN is determined, and the resulting network is used for diagnostic tasks.

5.5.1 Diagnostic Set-up

The diagnostic set-up is the primary step of this methodology and forms the link between the FD and the diagnostics methodologies. This step includes the fault mapping, the FD results aggregation process and the network set-up.

5.5.1.1 Fault Mapping

Fault mapping is a crucial task as it identifies the potential faults that can be diagnosed in a selected system, together with the variables required for their diagnosis. During this step, faults are paired-up with incoming ProMon variables and also with additional required tests. The monitored variables are selected so that any deviations indicate the development of a specific fault.

As previously discussed, the main monitored variables are the ME CYL 1-6 EGT (Table 4.8) The behaviour of these variables is accessed in terms of any abnormal increments in all of the cylinders simultaneously. Such behaviour indicates faults in the supporting systems of the ME, namely the AC and Air and Gas (AG) handling system. Table 5.13 shows the outcome of the fault mapping process, assuming a simultaneous increase in the EG temperature of all the cylinders.

Table 5.13: Mapped faults for increases in EG temperature in all cylinders, adapted from (MAN B&W 20017)

Primary Fault	**Secondary Fault**	**Diagnostic Parameters**	**Diagnostic Test**
AC	AC air-side fouling	ΔPC, $SCAV\_AIR\_PRESS$	Pressure drop test
AC	AC water-side fouling	ΔPT, $SCAV\_AIR\_PRESS$	Temperature drop test
AG handling system	AF fouling	ΔPF, $SCAV\_AIR\_PRESS$	Pressure drop test
AG handling system	Corroded TC mechanical components	TCS, $SCAV\_AIR\_PRESS$	Speed drop test
AG handling system	TC Fouling	$SHAFT\_PWR$, $SCAV\_AIR\_PRESS$	Scavenge air pressure drop test

The faults in Table 5.13 are divided into primary and secondary. The primary faults refer to the system in which a fault is developing. The secondary faults refer to the specific components of a system in which the fault is developing. Moreover, each fault is given a specific diagnostic test to assist with its identification. The diagnostic tests are used once a simultaneous abnormal increase in the EG temperature is detected, in order to pinpoint the specific root cause of the detected fault. The fault-mapping process and the diagnostic tests were identified by taking into account the operating manuals of the ME (MAN B&W 20017; Woodyard 2009). The diagnostic tests are shown in Figures 5.26 - 5.30. Figure 5.26 shows the diagnostic test (chart) used to identify fouling in the air-side of the AC. The ΔPC is examined in terms of the $SCAV\_AIR\_PRESS$, and if its value is beyond the highlighted envelope, the test is failed. If this tests fails and all the cylinders have increased EG temperature fouling in the air-side of the AC is detected.

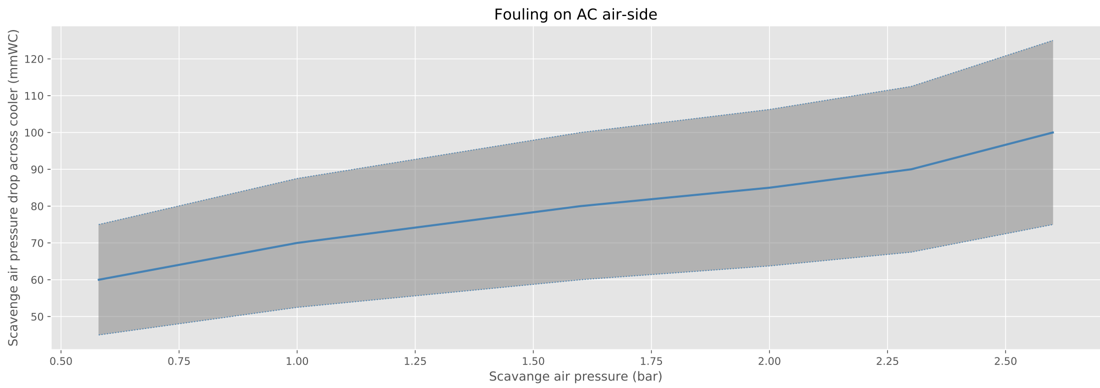

Figure 5.26: Diagnostic test for the detection of AC air-side fouling

Similarly, Figure 5.27 shows the diagnostic test identified from the ME manufacturer, used to identify fouling in the water-side of the AC. The ΔPT is examined in terms of the $SCAV\_AIR\_PRESS$, and if its value is beyond the highlighted envelope, the test is failed. If this tests fails and all the cylinders have increased EG temperature fouling in the water-side of the AC is detected.

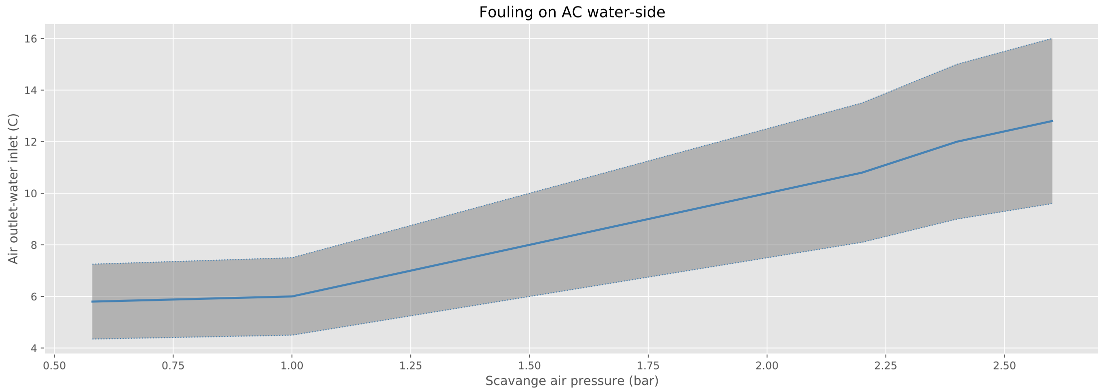

Figure 5.27: Diagnostic test the detection of AC water-side fouling

Likewise, Figure 5.28 shows the diagnostic test (chart) used to identify fouling in the AF of the ME. The ΔPF is examined in terms of the $SCAV\_AIR\_PRESS$, and if its value is beyond the highlighted envelope, the test is failed. If this tests fails and all the cylinders have increased EG temperature fouling in the AF of the ME is detected.

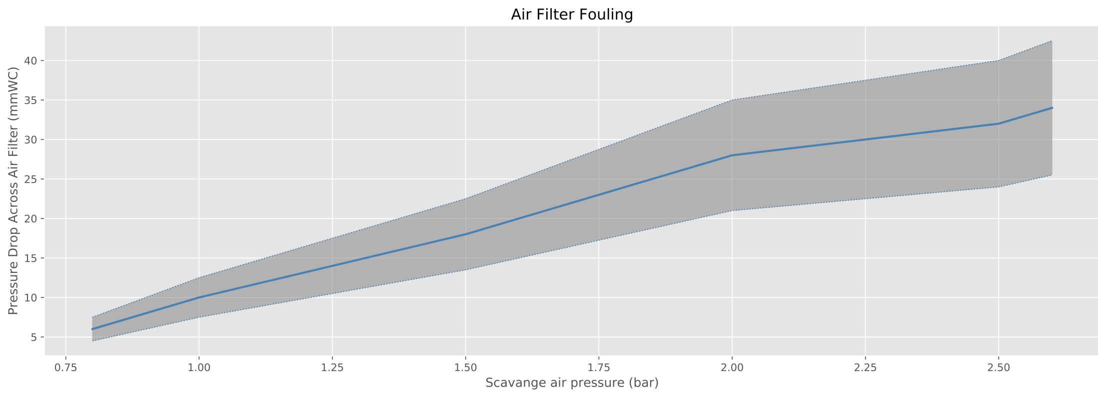

Figure 5.28: Diagnostic test for the detection of ME AF fouling

Figure 5.29 shows the diagnostic chart used to identify fouling in the mechanical components of the TC (turbine blades, nozzle ring). The TCS is examined in terms of the $SCAV\_AIR\_PRESS$, and if its value is beyond the highlighted envelope, the test is failed. If this test fails and all the cylinders have increased EG temperature fouling in the turbine blades, or nozzle ring of the TC is detected.

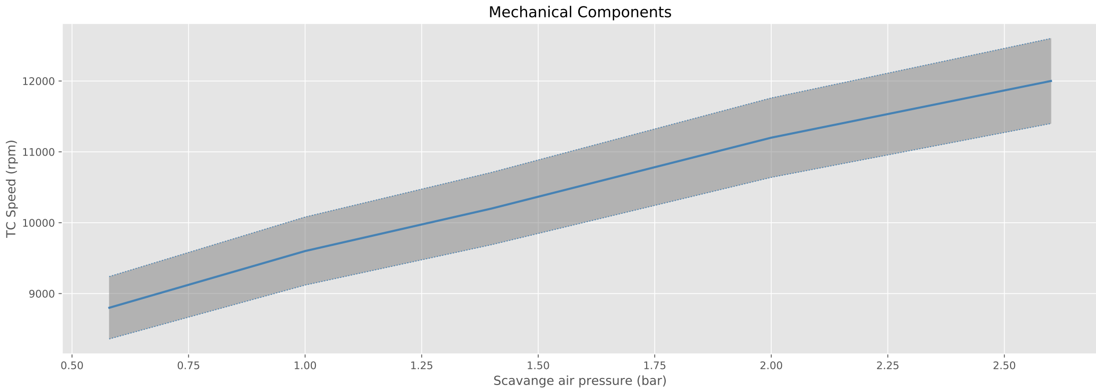

Figure 5.29: Diagnostic test for the detection of fouling in the mechanical components of the TC

Lastly, Figure 5.30 provides the diagnostic chart used to identify fouling in the turbine or compressor of the TC. The $SCAV\_AIR\_PRESS$ is examined in terms of the ME power, and if its value is beyond the highlighted envelope, the test is failed. If this tests fails and all the cylinders have increased EG temperature fouling in either the compressor,or the turbine is detected.

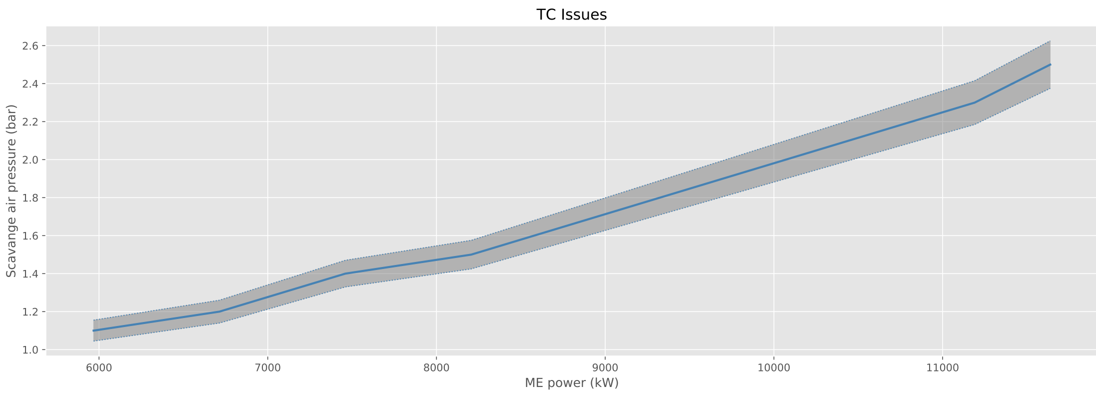

Figure 5.30: Diagnostic test for the fouling in the turbine or compressor of the TC

Apart from the simultaneous increase in the EG temperature in all the cylinders, it is possible to observe increased EGs in only one cylinder. This behaviour alters the fault-mapping shown in Table 5.13 and instead the faults in Table 5.14

are investigated. An isolated increase in the EG temperature indicates the presence of faults within that specific cylinder, as demonstrated by the primary and secondary faults in Table 5.14.

Table 5.14: Mapped faults for increase in EG temperature of one cylinder, adapted from (MAN B&W 20017)

Primary Fault	**Secondary Fault**	**Diagnostic Parameters**	**Diagnostic Test**
Cylinder head	Leaking Exhaust Gas Valve (EGV)	$SHAFT\_PWR$, P_{max}	Power drop and P_{max} drop
Cylinder head	Blocked fuel valve or fuel injector	$SHAFT\_PWR$, P_{max}	Power drop and P_{max} drop
Combustion chamber	Chamber blow-by	P_{comp}, P_{max}, $SCAV\_AIR\_TEMP$	P_{comp} drop, P_{max} drop and $SCAV\_AIR\_TEMP$ increase

For instance, to investigate whether an isolated EG temperature increase is caused by a leaking Exhaust Gas Valve (EGV), the power output and the maximum combustion pressure (P_{max}) of the suspected cylinder are examined. If the power output and P_{max} are reduced, a leak in the EGV of the cylinder is possible (Papagiannakis and Hountalas 2004). However, the same behaviour can be observed when the temperature rise is caused by a blocked fuel valve or fuel injector. It is often challenging to distinguish these two faults without visually inspecting the cylinders. However, the drops in the power output and P_{max} are more prominent in the former cases (Hountalas 2000). Lastly, the case of a blow-by, as defined by (Mobley, Higgins, and Wikoff 2008), is mapped. If the P_{max} and compression pressure P_{comp} are reduced, and the $SCAV\_AIR\_TEMP$ is increased, the presence of a blow-by is detected (Woodyard 2009).

Based on the above, it is becoming apparent the faults diagnostics are heavily reliant on a variety of data. To successfully identify the faults mapped in Tables 5.13 and 5.14, both ProMon and PeMon data are required. Since the DAQ system installed onboard vessel "C" is not able to record PeMon data, only the faults shown in Tables 5.13 are pursued.

5.5.1.2 FD Results Aggregation

Once the fault-mapping process is completed, the results from the FD are aggregated to summarise the condition of each cylinder. During this step, the incoming ProMon data are used, together with the residuals obtained by using model N54 (described in Section 6.4.3). To evaluate the diagnostic capabilities of the developed methodology and since the incoming ProMon data represent fault-free operations, artificial faults are also used. The artificial fault is introduced in terms of increased residuals for each cylinder, which are caused by a gradual increase in the ME scavenging air pressure (predictor variable) until the alarm limit (3.30 bar) for the variable is exceeded (Table 5.12).

The FD results aggregation aims to introduce the necessary artificial faults, reflected on each cylinder. Then, the residuals of each cylinder are plotted in an EWMA control chart, covering in duration up until the end of the introduced fault. Once the EWMA control chart is plotted, the states of each cylinder are summarised (aggregated) in Failed, Degraded and Normal states. In detail, points situated above the UCL, or below the LCL, contribute to the Failed state. Point between the UCL_{deg} and UCL, or between the LCL and LCL_{deg} (Section 4.7.3.1), contribute to the Degraded state. The remaining points contribute to the Normal state.

Figures 5.31 - 5.35 show the resulting EWMA control charts for the introduced faults, for all the cylinders (cylinder 1 - cylinder 5). From these figures, it is observed that the artificial faults that are introduced on the 18th of January 2017 are successfully detected, as the EWMA of the residuals for all cylinders exceed the UCLs. Similarly, Figure 5.36 shows the produced aggregated results, in terms of Normal, Degraded and Failed states for each cylinder.

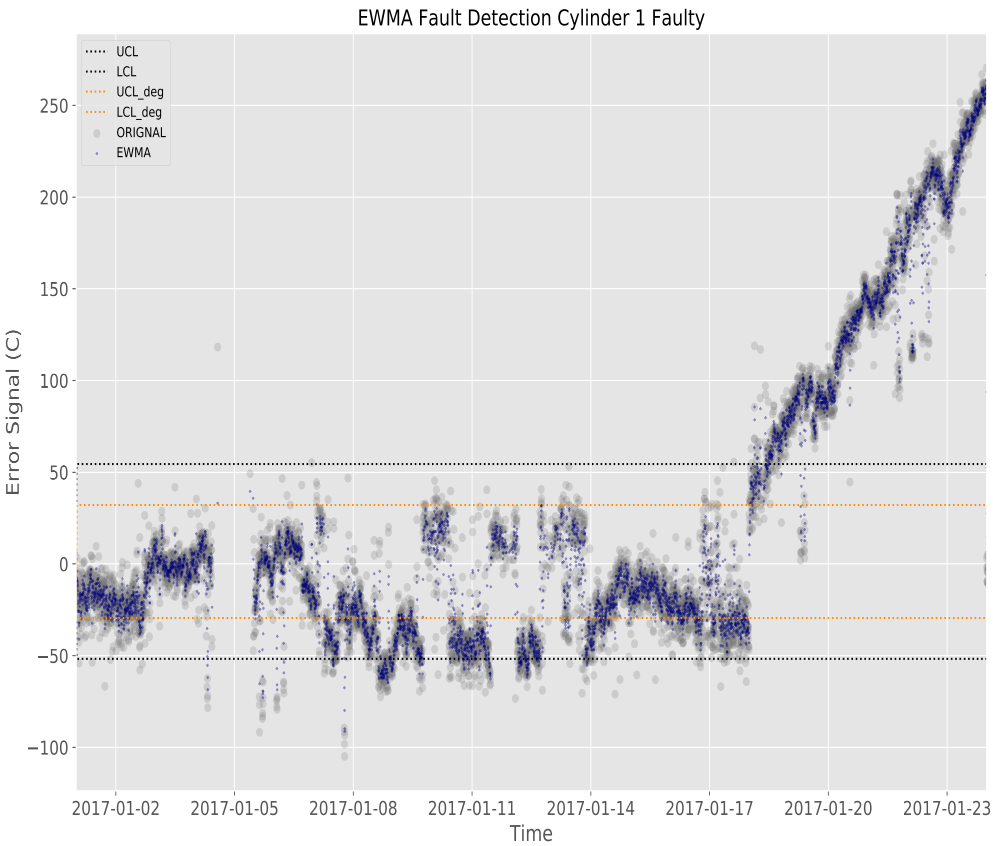

Figure 5.31: EWMA control chart for Cylinder 1 during the simulated fault

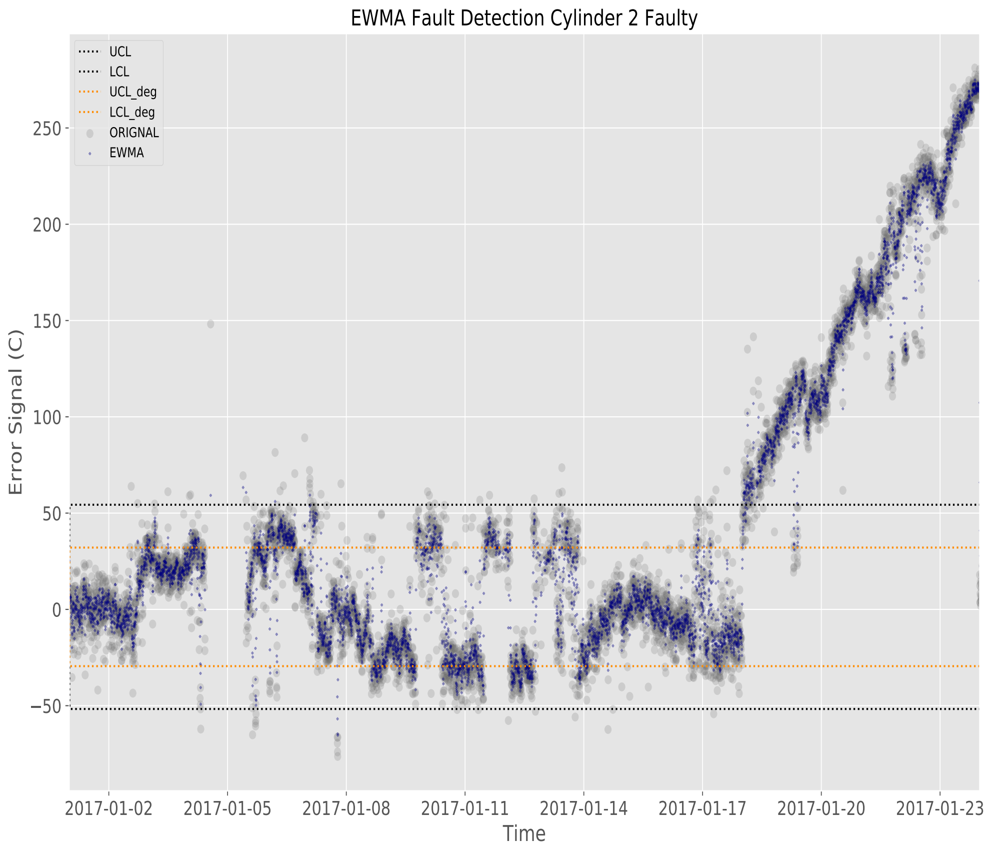

Figure 5.32: EWMA control chart for Cylinder 2 during the simulated fault

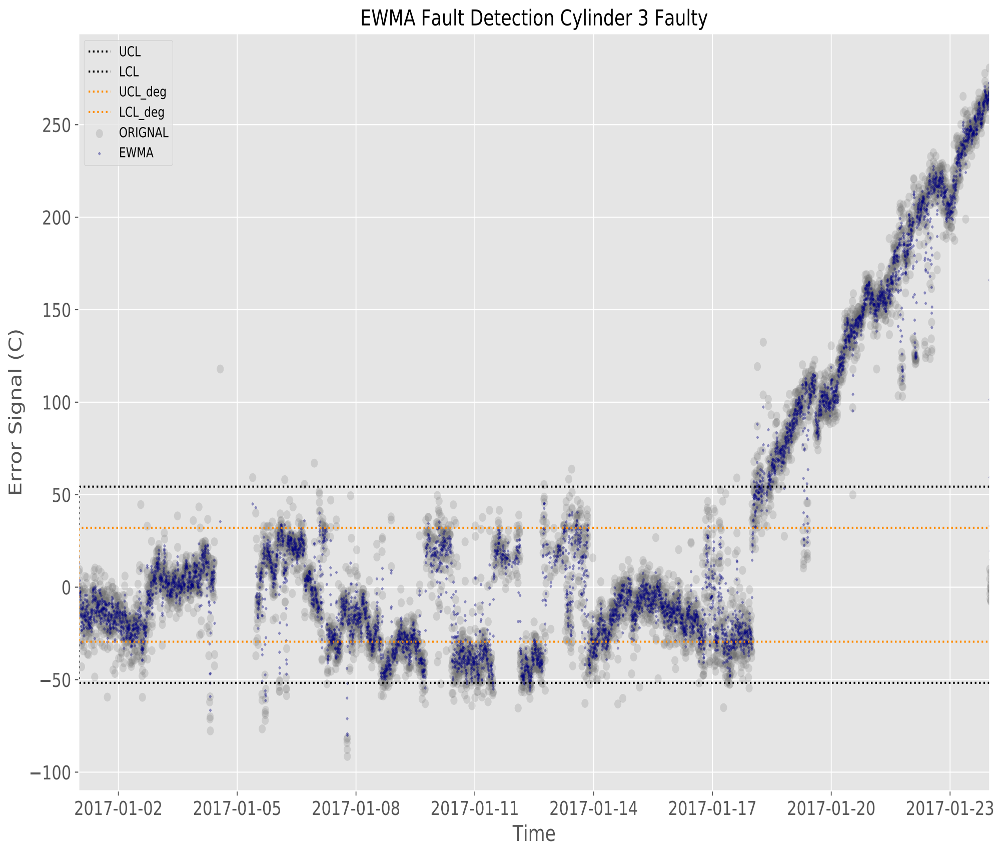

Figure 5.33: EWMA control chart for Cylinder 3 during the simulated fault

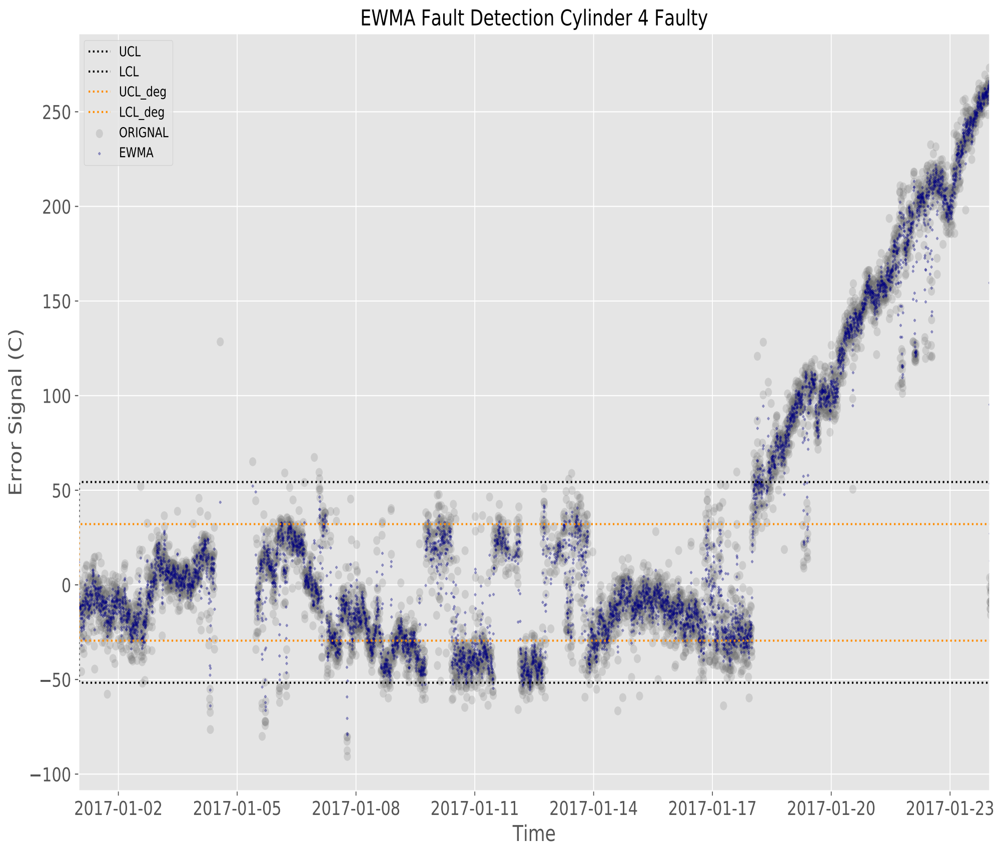

Figure 5.34: EWMA control chart for Cylinder 4 during the simulated fault

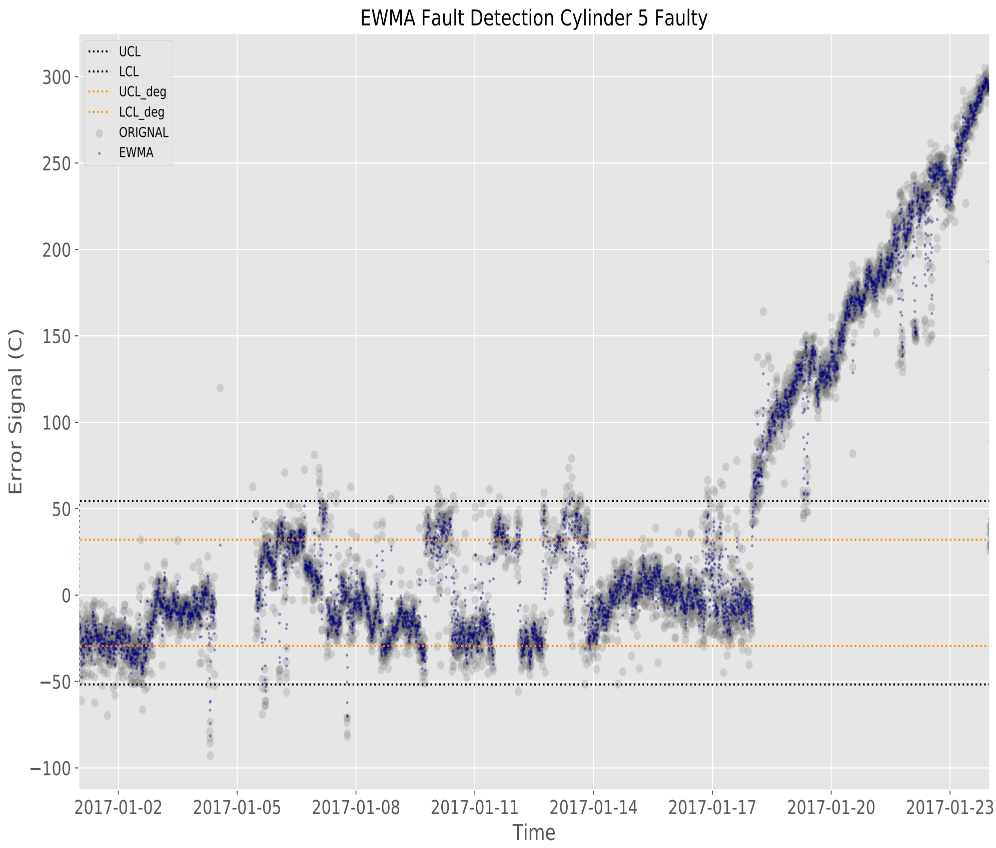

Figure 5.35: EWMA control chart for Cylinder 5 during the simulated fault

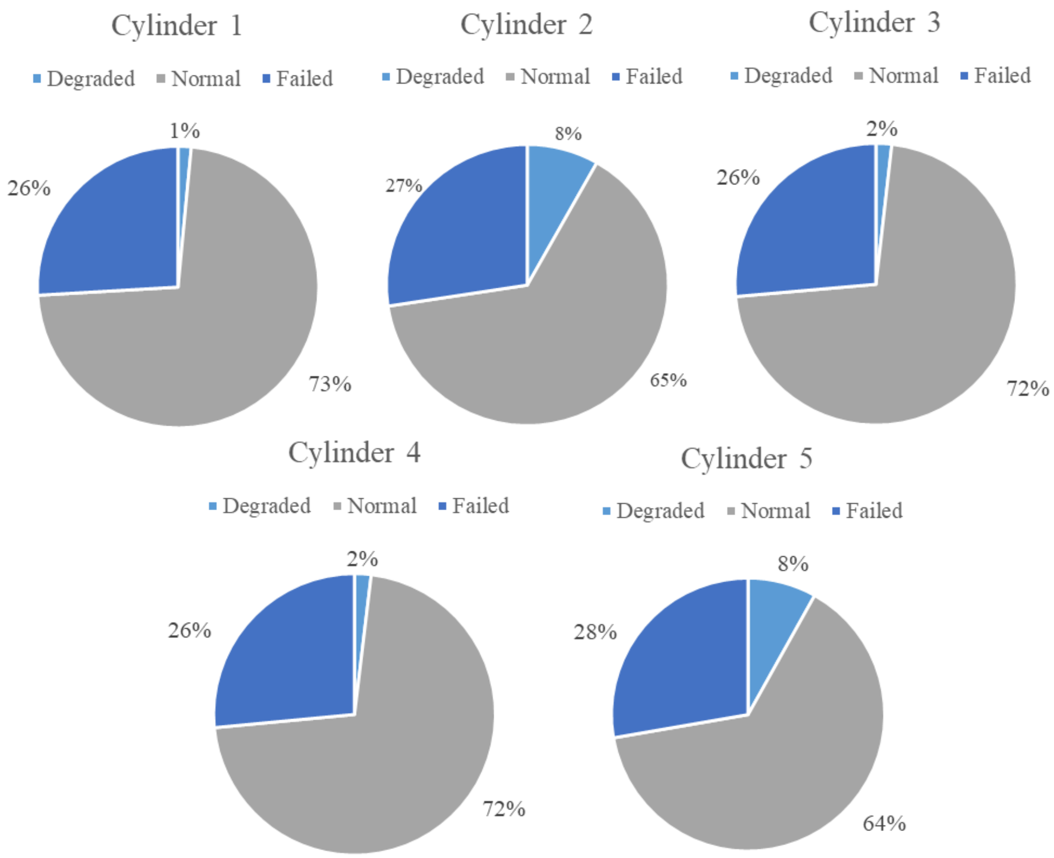

Figure 5.36: Aggregated results during the simulated fault for the ME cylinders

5.5.1.3 Network Set-Up

Once the fault-mapping is concluded and the aggregated results for each cylinder (under the effects of the introduced faults) are obtained, the network set-up process takes place. The network set-up includes the specification of the structure of the BN, as discussed in Section 4.7.3.3, and the quantification of the BN using the aggregated results for each cylinder. For the period of interest, the CPTs of the network are populated. Afterwards, evidence (VE and HE) regarding the states of the observable and test nodes are used as input, and the probabilities of the primary and secondary faults, together with the profile of each fault are obtained.

In Figure 5.37, the resulting layout of the diagnostic BN is shown. The top nodes (i.e. Cyl 1- Cyl 5) represent the state of each cylinder (Failed, Degraded, Normal), based on the residuals' location in the EWMA control chart for that cylinder. For example, during the period of interest the condition of cylinder 1 is summarised as 26% in the Failed state, 2% in the Degraded state and 73% in the Normal state, as also summarised in the upper left chart of Figure 5.36. The nodes representing the cylinders are the observable nodes, as discussed in Section 4.7.3.3. The next layer represents the control nodes, which are tasked with accessing if a simultaneous increase in the ME EGT of all the cylinders takes place. The state of these nodes is binary (True or False) and their purpose is to propagate and evaluate the information from the observable nodes. The next two layers represent the primary and secondary fault nodes, each of which has a Normal or Abnormal state. Lastly, the lowest layer represents the test nodes which help to quantify the probability of a specific fault occurring and have Pass or Fail states. The CPTs of the test and the control nodes are populated based on logical rules depicting functional dependencies in the network. Lastly, the CPTs of the primary and secondary nodes are populated by obtaining failure statistics from the OREDA data-bank and using logical rules. For instance, using the OREDA statistics and without using evidence in the test nodes, it is observed that the AC function is 97% normal. The 3% abnormal state of the AC is attributed to the propagation of the increased Failed state of the cylinders, demonstrating the network's ability in evaluating the condition of certain ship systems. The structure of the BN in Figure 5.37 corresponds to output of the fault-mapping process shown in Table 5.13 As can be observed, the BN in Figure

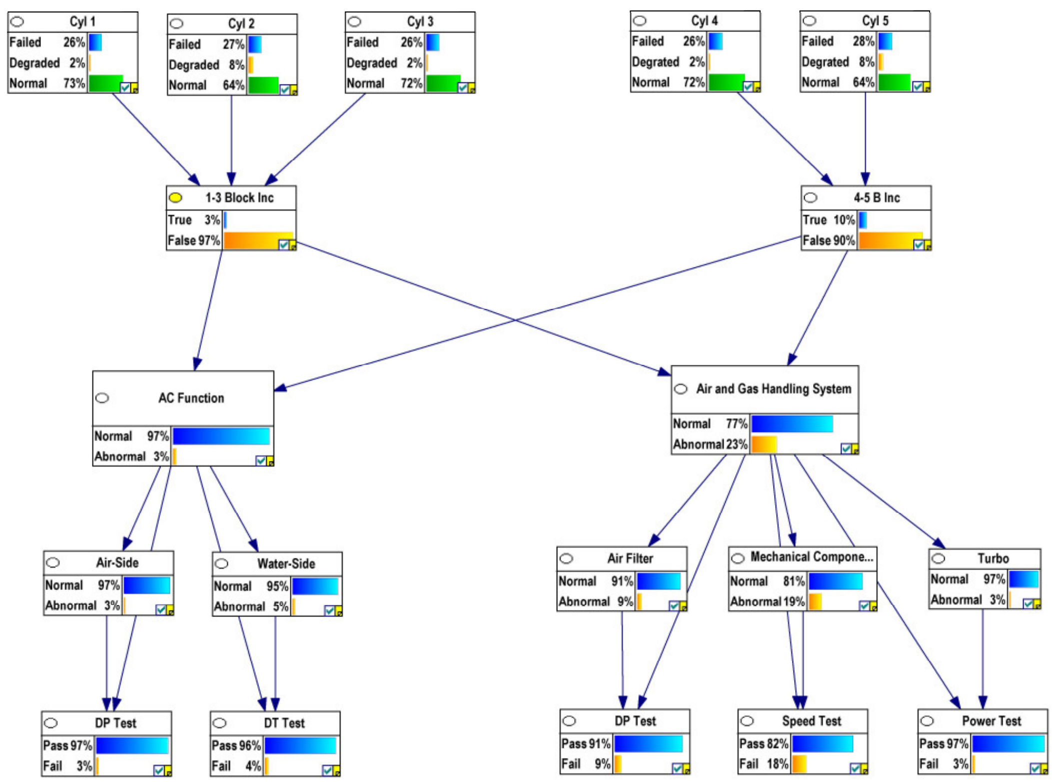

Figure 5.37: Initial diagnostic BN

5.37 creates a visual model summarising the condition of the vessel. This graph covers the period up until the end of the introduced artificial fault. Without using evidence to specify the presence of a fault, the condition of the cylinders is shown in the observable nodes. Each cylinder has a high percentage in the Failed state, which is attributed to the presence of the artificial fault.

However, on the 23rd of January 2017, the EWMA control charts indicate that the ME cylinders are on the "Failed" state, as presented in Figures 5.31 - 5.35, due to the presence of the simulated fault. Consequently, HEs are used to specify the Failed state in each observable (cylinder) node. As a result, each cylinder is 100% at the failed state. Comparing Figures 5.37 and 5.38, this has a great effect in the probabilities of primary and secondary fault nodes. For example, using the information from above and without utilising the test nodes the abnormal state of the AC increases to 20%.

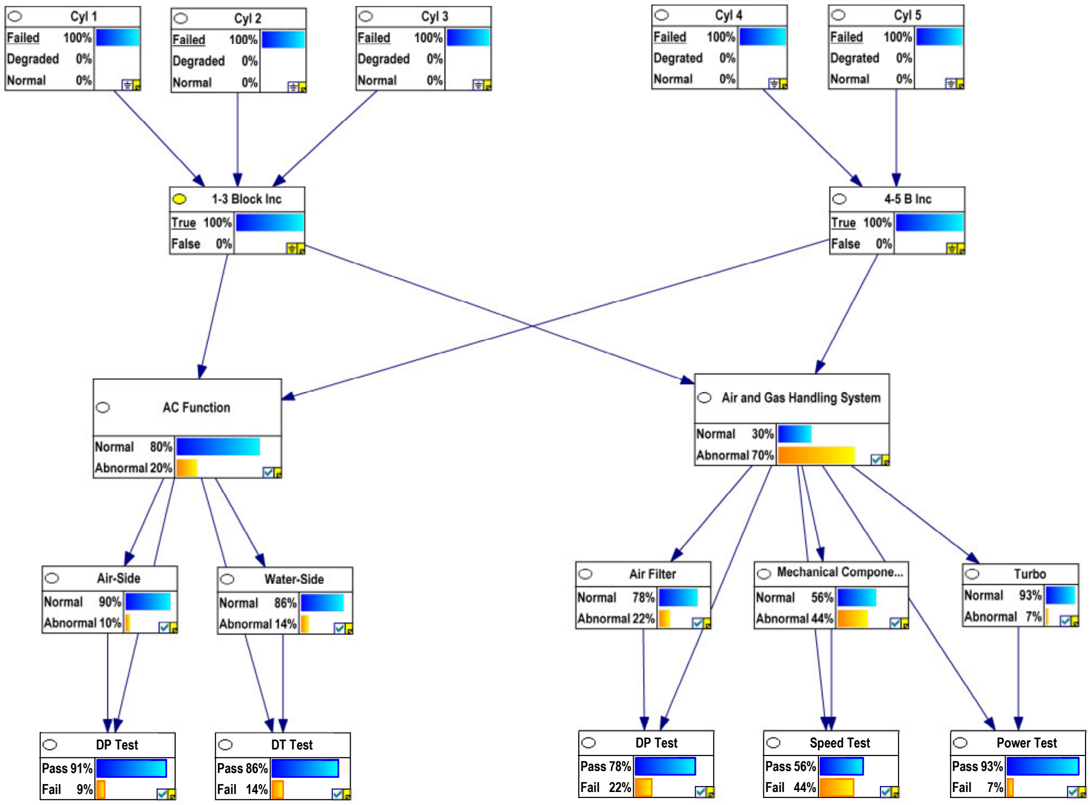

Figure 5.38: Diagnostic BN with with observable nodes at Failed state

To investigate the root-cause of the detected fault, the diagnostic tests must be performed and their outcomes used as input in the test nodes. Assuming a simultaneous increase in the EG temperature and a failed pressure drop test (Table 5.13) in the AC, fouling in the air-side of the AC is detected (Figure 5.39).

Using HE, the state of the DP test node is specified at 100% Failed. Therefore, the

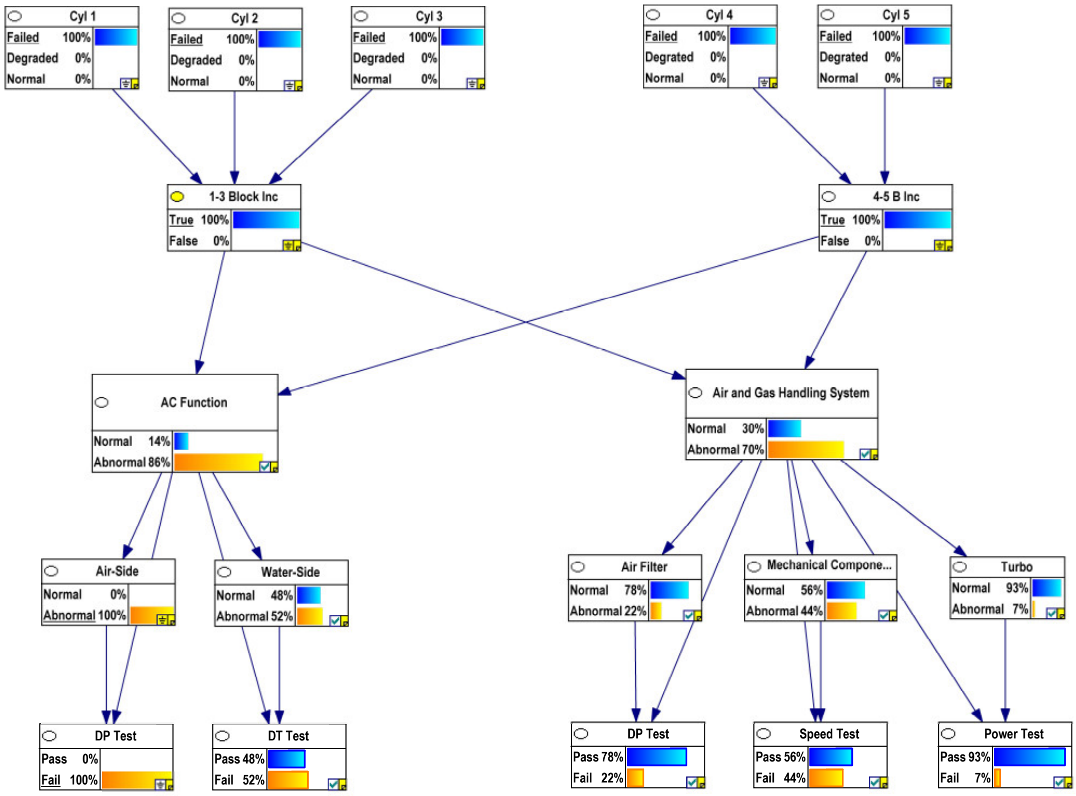

Figure 5.39: Fully investigated diagnostic BN

network identifies that the air-side of the AC is at 100% Abnormal state, whilst also increasing the abnormal state of the AC to 86% Abnormal, identifying the root-cause of the abnormal simultaneous increase in the EG temperature.

To further investigate the behaviour of the mapped faults (fault profile), the gradual transitions between each state of the observable and test nodes take place. The gradual transition between states is represented using VE, whereas the fully observed states are described using HE. This transition concludes at the Failed state in all the observable nodes and the Fail state in the test nodes. In more detail, HEs are used to demonstrate the ability of the BN to calculate the probability of each fault. To achieve this, the following two conditions are met: a) the observable nodes are at the Failed state, due to the artificial fault and b)

Table 5.15: Failure modes summary for the primary faults

Case Number	Failure Modes
AC Fault 1	AC Water-side fouling
AC Fault 2	AC Air-side fouling
AC Fault 3	AC Air-side fouling and AC Water-side fouling
AG Handling System Fault 1	AF Fouling
AG Handling System Fault 2	Corroded TC mechanical components
AG Handling System Fault 3	TC fouling
AG Handling System Fault 4	AF Fouling Corroded and TC mechanical components and TC fouling
AG Handling System Fault 5	AF Fouling and Corroded TC mechanical components
AG Handling System Fault 6	Corroded TC mechanical components and TC fouling
AG Handling System Fault 7	AF Fouling and TC fouling

appropriate test nodes are set to the Fail state which simulates the cause for the artificial fault. The application of the VE follows the same principle, but their use allows to capture the profile of each fault and examine the rate with which it develops.

The resulting fault profiles for the primary and secondary faults are shown in Figure 5.40 and Figure 5.42 respectively. Moreover, the primary faults are examined in terms of all the different failure modes. These failure modes are shown in Table 5.15, and represent different combinations which can cause either the AC or the AG handling systems to fail.

Regarding the primary faults, Figure 5.40 shows their fault profiles based on all the possible causing combinations (failure modes), as detailed in Table 5.15. In this case, the lower three lines represent failure modes of the AC, whereas the remaining represent the failure modes of the AG handling system. As it can be observed, the failure of the AG handling system is more likely than the failure of the AC. As a consequence, any simultaneous deviation in the ME EG temperature is more likely to be caused by a fault in the AG handling system. In particular, the most likely failure mode corresponds to the simultaneous failure of all the components of the AG handling system. Figure 5.41 shows the average rate of change of the primary faults. In that plot the y-axis denotes the average rate of change of the probability of a fault and the x-axis shows the considered faults. The faults of the AC are colour-coded in teal and the faults of the AG handling system in blue. From that chart, it is observed that the simultaneous fouling in both the air-side and the water-side of the AC has the largest rate of increase and therefore can develop the quickest.

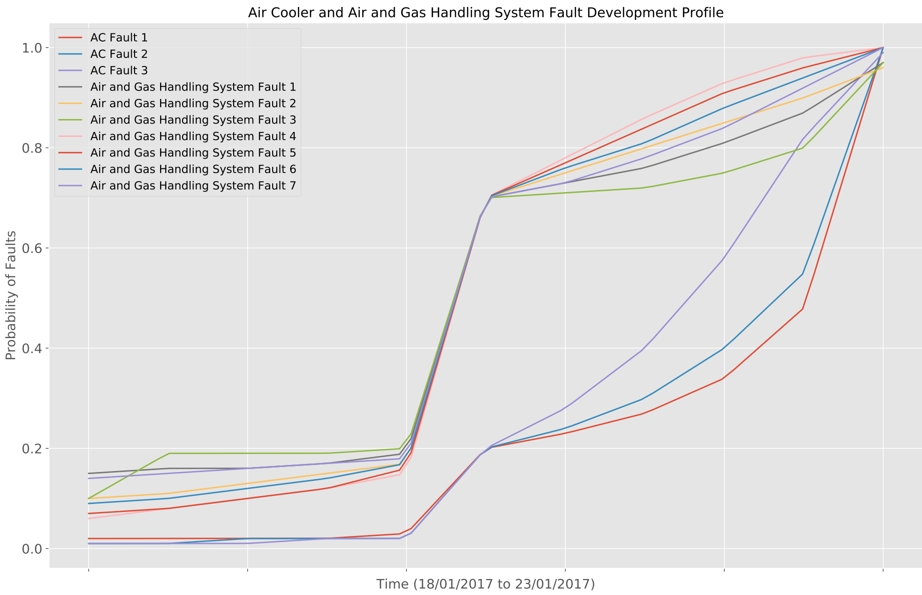

Figure 5.40: Fault profiles for the primary faults

In Figure 5.42, the fault profiles for the secondary faults are shown. In that case, it can be observed that the highest fault profiles belongs to the corroded TC mechanical components, which is then followed by the AF fouling. Therefore, the most likely secondary fault is the corrosion in the mechanical components of the TC. Consequently, any faults manifested through the simultaneous increase of the ME EGT, are most likely attributed to the corrosion of the mechanical components of the TC. Figure 5.43 shows the average rate of change of the sec-

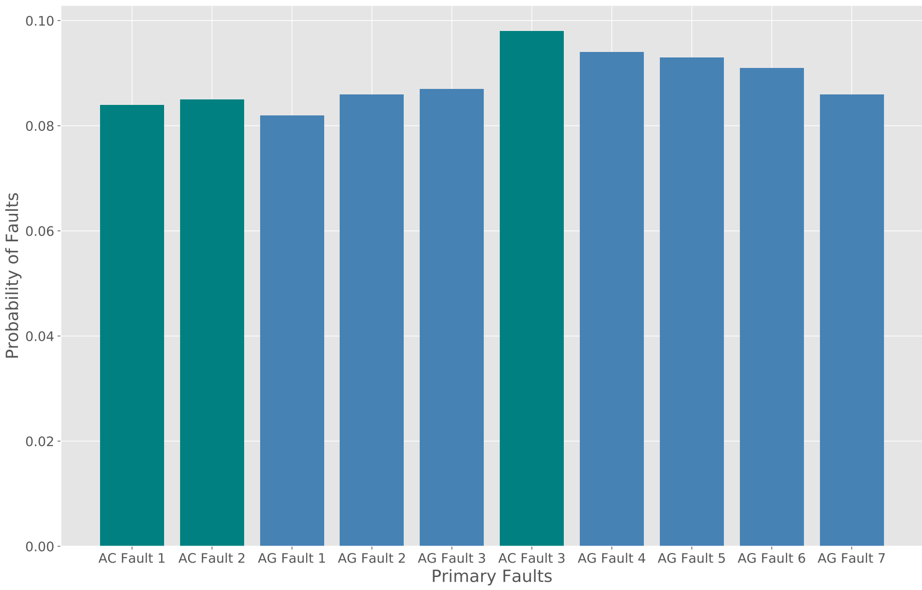

Figure 5.41: Average rate of change of primary faults

ondary faults. From that chart, it is observed that the corrosion of the mechanical components of the TC has the largest rate of increase and therefore, can develop the quickest.

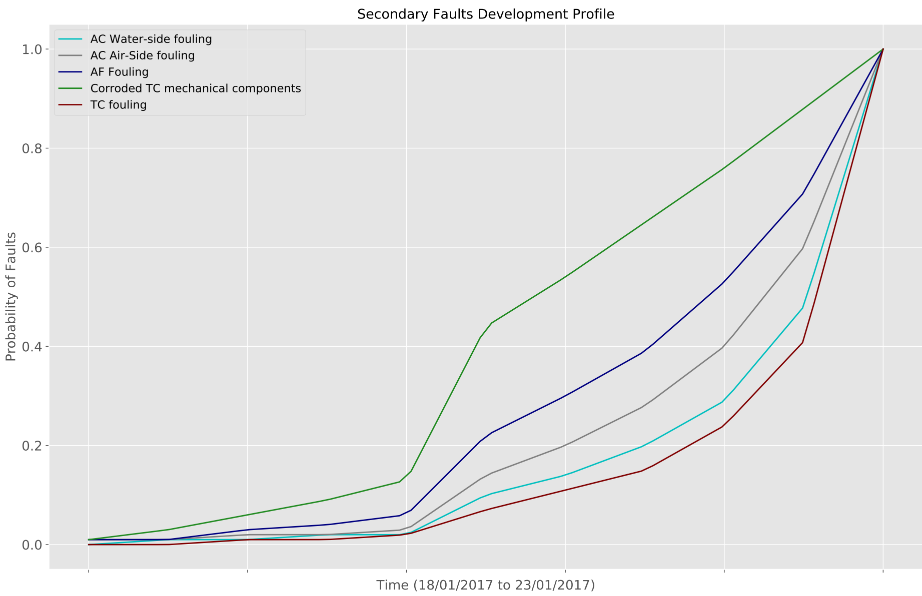

Figure 5.42: Fault profiles for the secondary faults

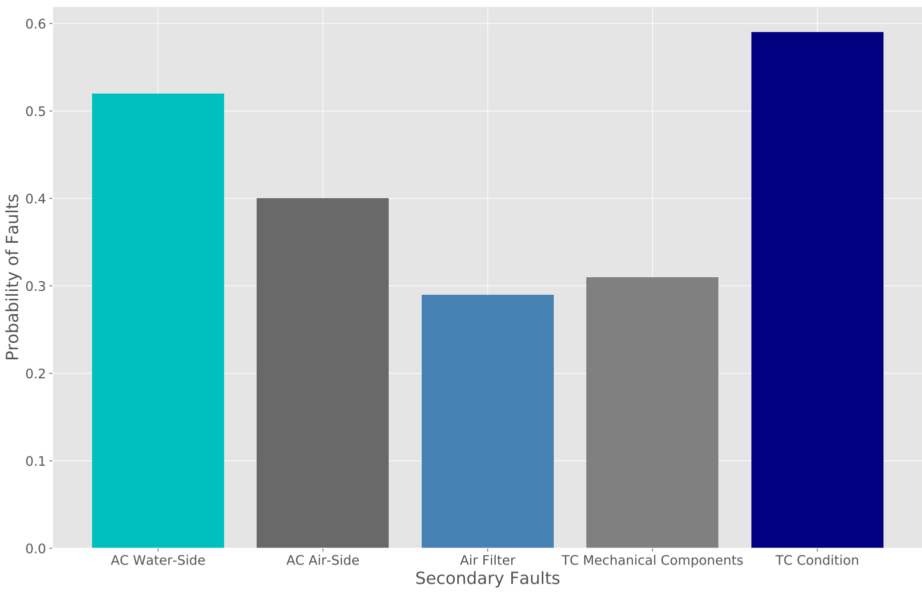

Figure 5.43: Average rate of change of secondary faults

5.6 Discussion of Results

This section aims to summarise the primary outcomes of the case studies and discuss the impact of the proposed framework. The different methodologies of the proposed predictive maintenance framework are applied in different case-studies, each aiming at demonstrating the effectiveness of the different parts of the framework.

The proposed predictive maintenance framework enhances maritime maintenance by combining reliability-based and data-driven tools in a novel way. The proposed framework examines the areas of critical equipment selection, data preparation, FD and diagnostics in unique methodologies, assessed in the presented case studies.

The first case study that is considered is the critical equipment selection part of the framework, which is applied in vessel “A”. During this case study, a ship system analysis is performed, which creates a useful base for the implementation of the FTA. Translating the ship systems analysis in an FT structure creates a visual model demonstrating various functional and systemic interdependencies. Quantifying the resulting FT structure and using the exact calculation method, the I^B and I^{CR} are obtained, which allow the ranking of the modelled components based on two different metrics. Calculating both the I^B and the I^{CR} enables the criticality examination of the components both in terms of their reliability and in terms of their functional dependencies.

By combining the obtained IMs with the repair costs of the modelled components, an initial scatter plot of the data-space is created. Then, the use of the k-means clustering algorithm allows for the segmentation of plotted components in three groups, including a) critical components, b) medium criticality components and c) safest components. The critical components are located in the cluster whose centroid has the biggest distance from the beginning of the axes.

Based on the above, it is suggested that the maintenance actions are focused on the critical components, as they have the following characteristics. They have the biggest influence on the rate of change of the probability of a ship failure, due to systemic dependencies. Also, they are the most critical in the modelled system, by considering the components' reliability and failure rate. Lastly, they are the most costly to maintain after a failure, as they have the highest repair and replacement costs. Focusing maintenance actions on the critical components have a positive effect on the daily operations of ships, by improving their overall availability and reliability. Similarly, this part of the framework can be used as a maintenance prioritisation tool for ship owners and operators.

Once the critical equipment is identified, the case study of the data preparation methodology of the proposed framework is applied. This part of the framework focuses on imputations from a holistic view, including all the necessary pre- and post-imputation steps. The drive of the data preparation methodology of the framework is to improve the quality and knowledge extracting potential of data.

The data preparation methodology establishes a hybrid imputation approach based on the MICE and kNN imputation algorithms. The superior performance of the proposed novel imputation method is compared against the existing kNN and MICE methods. It is demonstrated in the case of a ME and TC system of vessel "B". In total, eight variables are examined including the ME power, ME speed, ME scavenging air pressure, TC EG inlet temperature, TC EG outlet temperature, TC LO outlet temperature, TC LO inlet pressure and TC speed.

A key outcome of this case study is the investigative comparison between the kNN, MICE and the proposed hybrid method for imputation purposes, which exhibits superior performance. In detail, the proposed approach has a mean error of 2.21% compared to the MICE, kNN algorithms with errors of 3.3% and 5.6%, respectively, highlighting that the small error of the proposed hybrid method improves the quality of data. Since the proposed approach is based on a combination of data-driven tools and FP knowledge, the small error of the method highlights the importance of using FP knowledge in the prediction of measurements from an engineering system, compared to pure data-driven approaches.

The use of the data preparation methodology of the developed framework can enhance the accuracy of maritime predictive maintenance. Ensuring the quality of data, while maximising their knowledge extracting potential can improve various aspects of ship operation. It can improve maintenance planning by providing accurate estimates for the condition of the vessel, which also has a positive effect on ship safety.

Following the data preparation case study, the results FD part of the framework applied on vessel "C" are presented. This case study provides an application for an ML and data-driven FD methodology, based on EB modelling and EWMA control charts. The ultimate goal of the FD is to allow for preemptive rectifying actions and maintenance scheduling. The EB modelling approach is used to predict the EB of the ME cylinder EG temperature. The ME EG temperature is selected, as several faults in the ME's supporting systems can manifest through this variable. Then, the residuals between the expected and recorded ME cylinder EG temperature are analysed in an EWMA control chart to detect developing faults by means of the UCL and LCL.

During the development of the EB model, several regression models are examined, and the optimal model is selected, using k-fold cross-validation. In more detail, multiple linear ridge regression and multiple polynomial ridge regression models are compared. In addition to that, the optimal value of the α hyperparameter is examined, together with different predictor variables, including the ME power, speed, scavenging air pressure and scavenging air temperature. From the analysis, it is seen that on average, the polynomial models have mean validation R^2 score of 0.94 and linear models have a mean validation R^2 of 0.83. Lastly, the identified optimal model is based on multiple polynomial ridge regression with

$\alpha = 0.4$ and inputs the ME power, speed and scavenging air pressure.

The identified model is used to obtain the residuals of the target variable, which are then analysed in an EWMA control chart. Healthy operating data are used to fine-tune the L hyperparameter of the control chart before 4 different artificial faults are simulated to assess the detection capabilities of the proposed method.

The use of the FD methodology of the developed framework can improve maritime predictive maintenance. The early detection of developing faults has a profound effect on the safety of vessels, their availability and operational efficiency. By identifying faults, extensive failures are avoided while allowing for efficient maintenance planning. Also, this part of the framework can mitigate the risk of inefficient ship operations, as degraded machinery operations are detected.

The last case study that is presented is on the developed diagnostics methodology of the proposed framework. This part of the framework is also applied on vessel "C". The developed methodology combines the use of ML for FD and BNs for diagnostics. As seen in this case study, the diagnostic network uses the evidence of detected faults in the ME cylinders and seeks possible root-causes in the AC and AG handling system of the ME.

The diagnostics case study demonstrated the creation of a practical diagnostic network which allows for the real-time assessment of operational data to compute accurate probabilities of different faults. Moreover, fault probabilities are used to better understand the operation state of the ME cylinders, ME AC and ME AG handling system.

The case study of the diagnostics frameworks results that the fastest developing faults (largest mean rate of change) are the simultaneous fouling in both the air-side and the water-side of the AC and the corrosion of the mechanical components of the TC. Similarly, the most likely faults are the simultaneous failure of all the components of the AG handling system and the corrosion in the mechanical components of the TC.

The use of the diagnostics methodology of the developed framework can augment maritime predictive maintenance. The diagnostics of developing faults has a positive effect on the operational efficiency of ships. By identifying the root-cause of a fault, targeted maintenance actions are enabled, reducing the downtime of ship systems. Also, this part of the framework can mitigate the risk of inefficient ship operations, as degraded machinery operations are detected.

5.7 Chapter Summary

This chapter discusses the main results of the novel predictive maintenance framework applied in the cases studies of vessels “A”, “B” and “C”. Initially, the results of the critical equipment selection methodology are presented. This methodology is applied in vessel “A”, and combines FTA with k-means clustering. In more detail, the methodology integrates reliability IMs repair costs to select critical components systematically. Then, the outcomes of the data preparation methodology are presented. This methodology is applied in the case of vessel “B” and showcases the effectiveness of a hybrid imputation method, based on MICE and kNN, in predicting values from missing instances. The results from the FD methodology then follow, which are obtained from vessel “C”. The FD methodology combines the DBSCAN algorithm for data checking, with a regression-based EB model and the use of EWMA control charts for FD. This methodology includes the systematic investigation for the optimal regression model, which results in a multiple polynomial ridge regression model using as inputs the ME power, speed and scavenging air pressure. Lastly, the results of the diagnostic methodology are shown. This methodology is also applied in vessel “C” and demonstrates the integration of ML-based FD with BN diagnostics.

Chapter 6

Discussion and Conclusions

6.1 Chapter Overview

This is the final chapter of this thesis and discusses the conclusions drawn from the establishment of the novel predictive maintenance framework. The fulfilment of the aim and objectives is deliberated first, before presenting the generated novelty. Then, the concluding remarks and reflections are presented, followed by recommendations for future work and the discussion of the main assumptions and challenges.

6.2 Fulfilment of Aim and Objectives

The main drive of this research is to enrich, in a practical and theoretical manner, the area of maritime predictive maintenance for ship machinery systems. This was accomplished by focusing on the research question presented in Section 2. As a result, this work was directed towards developing a framework encompassing the areas of critical equipment selection, data preparation, detection and diagnostics of developing faults. In detail, the set objectives of this work and how they were fulfilled are discussed in depth in this Section.

Objective 1: The investigation of the relevant literature regarding maintenance strategies, reliability assessment and data-drive predictive modelling in a factual and critical manner, in order to identify gaps and direct the novelty of the present research. This objective was achieved through the factual and critical review of the relevant literature, presented in Section 3, and the generation of the novelties, detailed in Section 4.2 and summarised in Section 7.3. The review of the literature identified several gaps in the maritime industry regarding the applications of PdM. It was uncovered that there is a gap in addressing the topics of critical equipment selection, data imputation, FD and diagnostics in a single research effort. In more detail, maintenance concepts and frameworks are examined. Then, the different categories of tools used in predictive maintenance are presented, including reliability assessment and data-driven approaches. Based on the identified tools, the resulting predictive maintenance process are explored, which are aligned with the remaining objectives. Lastly, by comparing the predictive maintenance status quo between the maritime sector and other industries, several gaps are identified. These gaps are presented in detail in Section 3.9 and stem from the limitations of the maritime predictive maintenance process, in terms of data preparation, fault detection and diagnostics. Moreover, the main identified gap is the absence of a complete predictive maintenance framework taking into account the particular needs of the maritime industry and providing data-driven and knowledge-based solutions. The identified gaps are subsequently used to direct the novelty of this research.

Objective 2: The proposal of a novel, data-driven and reliability-based predictive maintenance framework, tailor-made for the needs of the maritime industry. The completion of the objective was based on the development of the novel compound framework, together with its methodological components. The novel framework is presented in Section 4, and its flow is illustrated in Figure 3.1. The development of this novel framework addresses the gap for a complete predictive maintenance framework taking into account the particular needs of the maritime industry. In more detail, it includes the novel integration critical selection, data preparation, fault detection and diagnostic methodologies in a single framework. From a holistic point of view, this work initiates by identifying high-risk (functional and economical) ship equipment, which can be used as a starting point for predictive maintenance framework. Then, the data preparation methodology improves the quality and knowledge extracting potential of the data used in the fault detection and diagnostic tasks. Lastly, the fault detection and diagnostic methodologies identify developing anomalies, together with their root causes, by using treated data from specially identified equipment.

Objective 3: The development of a novel methodology for the identification of the critical equipment of ship systems, aimed at prioritising maintenance efforts. This objective was completed by developing a novel methodology for the identification and selection of critical equipment and components of ship systems. Through this objective, it was uncovered that it is necessary to combine different reliability metrics for the identification of critical components, as the same items rank differently with different metrics. Also, reliability metrics must be combined with cost information for practical maintenance prioritisation. Moreover, this objective highlighted the importance of clustering different components as it can effectively group and summarise them based on their importance. This methodology is detailed in Section 4.4 and illustrated in Figure 3.2. The novelty of this part of the frameworks stems from addressing the gap of combining data-driven and reliability-based tools for the identification of critical components. Similarly, it also stems from addressing the gap in combining cost aspects with reliability characteristics for identifying critical components. Following the collection maintenance and repair cost data, this methodology performs a ship systems analysis which leads to a fault tree analysis. The results from the fault tree analysis are combined with additional cost information in a clustering analysis which leads to the identification and selection of the critical equipment. The creation of a methodology able to identify high-risk ship equipment allows for targeted and efficient maintenance prioritisation.

Objective 4: The establishment of a novel data preparation methodology, concerned explicitly with handling missing values from data sets used on condition monitoring tasks. The completion of the objective was based on the development of a novel data preparation methodology, aiming at improving the quality and value of data. This objective uncovered that the performance of the developed hybrid imputation approach (2.2% mean error) is superior compared against the state-of-the-art MICE (3.3% mean error) and widely used kNN (5.6% mean error) algorithms. Also, it was concluded that imputation methods that take into account the correlation between variable perform better. Moreover, a major advantage of the developed imputation approach is that it can be used as a virtual sensor enhancing the accuracy of data-driven models and preserving otherwise lost information from DAQ systems. This methodology is detailed in Section 4.5 and illustrated in Figure 3.4. The novelty of this part of the framework originates from establishing a formalised data preparation approach for the maritime industry. Also, the novelty of this part of the framework stems from the novel combination of data-driven solutions with domain knowledge for the imputation of missing values. The starting point of this methodology is the form handling, synchronisation and filtering of the data. Then, a new imputation approach is used to predict missing values from the dataset. The effectiveness of the new imputation approach is established through the comparison with prominent MICE and kNN imputations algorithms. Enhancing the quality of data can have a positive effect on the resulting predictive maintenance framework, as misdirecting information are removed and missing trend-describing points are restored.

Objective 5: The development of a novel fault detection methodology, lessening the amount of data-associated assumptions, and tailored to the needs of the mar-

itime industry. This objective was completed by establishing an innovative fault detection methodology by modelling and monitoring the expected behaviour of systems. This objective resulted in the creation of an FD model that can allow for preemptive rectifying actions and maintenance scheduling, greatly improving ship operations. Also, another benefit for the created model is that the selected monitored parameter (ME EG temperature) can be used to detect various faults from different systems. Similarly, the completion of this objective required the investigation of the optimal regression EB model, resulting in an optimised multiple polynomial ridge regression model with a testing R^2 score of 0.96. This methodology is detailed in Section 4.6 and illustrated in Figure 3.5 and Figure 3.6. The novelty of this part of the framework stems from addressing the gap of the application of an FD model taking into account the particular needs of the maritime industry and addressing the limitations imposed by the available data. The fault detection process starts with a supplementary data filtering and outlier detection process, exploiting the benefits of application-agnostic tools. Then, the optimal expected-behaviour model is identified through a structured comparison of different regression models, under the effect of different inputs. The resulting model is used to gauge the deviation between the expected behaviour of a selected signal and its recorder behaviour from an incoming dataset. To facilitate this comparison, a signal-smoothing control chart is used. The early detection of developing faults can significantly enhance safety and operational efficiency, through monitoring specially selected signals with fault indicative potential.

Objective 6: The establishment of a diagnostic methodology combining in a novel way, machine learning applications with domain knowledge for practical applications of ship systems. This objective is accomplished by developing a novel diagnostic methodology, integrated with a fault detection module, for practical applications of ship systems. This objective resulted in one of the few diagnostic models that are integrated with ML-based FD for ship applications. Another benefit is that the resulting model uses evidence of developed faults to identify potential root-cause, thus improving ship operations This results in a practical network that allows for the real-time assessment of the condition of specific systems. Also, this objective examined the rate of change of the probabilities of different faults, proving insight on how certain faults develop. This methodology is detailed in Section 4.7 and is illustrated in Figure 3.8. The novelty of this part of the framework originates from addressing the gap in the application of a diagnostic module combining ML-based FD, with knowledge-based BN diagnostics. A detrimental step in this methodology is the fault-mapping process, in which monitored variables are paired with potential faults that can manifest through trends in their signal. Once the monitored signals are paired with potential faults, the method for summarising the results from the FD step is developed. The last step of the diagnostic methodology is the specification of a diagnostic network, which draws as input the outcome of the fault-mapping process. The creation of the diagnostic network allows for the creation of a visual model that is easy to interpret. It provides with the capability of assessing in real-time the operational status of the examined model.

Objective 7: The demonstration and validation of the effectiveness of the proposed predictive maintenance framework through different case studies, such as the main engine of a bulk carrier. The requirements of this objective are met by evaluating the performance of the different methodologies in different case studies. These case studies are described in Section 5, and their outcomes are presented in detail throughout Section 6. The different case studies relate to various vessels, but in each case, they are mainly structured around the main engine of the respective ship. Moreover, all the case studies aim at showcasing the capabilities of the different methodologies by also taking into account potential limitations during development. In detail, the case studies evaluate the framework's capabilities in a) identifying critical equipment, b) adequately preparing data for subsequent analysis, c) detecting in a timely manner developing faults and d) identifying the root-cause of detected faults. The case study for the critical equipment selection is described in Section 5.2, expanded in Section 6.2 and applied in an 81000 DWT LNG carrier. During this case study, maintenance information is used to quantify the developed fault tree. The obtained reliability IMs together with repair costs are clustered together to identify the critical equipment. The case study for the data preparation is described in Section 5.3, expanded in Section 6.3 and is applied in a 38000 DWT chemical tanker. During this case study operating parameters from the vessel's ME are used to develop an imputation approach and compare it against common practices. The developed approach, based on domain knowledge and data-driven approaches, can predict missing values with the biggest accuracy and consistency. The fault detection case study is described in Section 5.4, detailed in Section 6.4 and is applied in a 64000 DWT bulk carrier. Throughout this case study, variables from the vessel's ME are used. The collected variables are used to develop and select the optimal regression model, from a pool of compared models. The selected model is used to produce the expected behaviour of a selected variable, which is then compared with its recorded behaviour. Analysing the deviation between these two values, a signal-smoothing control chart allows for the detection of developing faults. Lastly, the case study for the diagnostics is described in Section 5.5, detailed in Section 6.5 and is applied in the same 64000 DWT bulk carrier. In this case study, variables from the vessel's ME are also used. Combing domain knowledge with information for the ship's ME manufacturer a fault mapping process is carried, which heavily influences the developed Bayesian diagnostic network. The developed diagnostic network is used to evaluate in real-time the condition of the ship by examining the probabilities of different faults in the supporting systems of the ME.

Objective 8: The discussion of the main outcomes of the developed framework *together with suggestions for future work.* This objective is fulfilled in the current chapter, which outlines the generated novelty, provides the main reflections and conclusions of this research and directs any potential future work.

6.3 Generated Novelty

The novelty of the present research stems from the development of the compound maritime predictive maintenance framework. Keeping in line with the stated research aim, the research and development related objectives are summarised in four distinct categories, including critical equipment selection, data preparation, fault detection, and diagnostics. The established maritime predictive maintenance framework introduces novel aspects in the areas of critical equipment selection of ship systems, data preparation for maritime applications, and fault detection and diagnostics of ship systems and components. Similarly, the established framework combines, in a novel manner, reliability-based and data-driven models. The novel combination of these tools is innovative and address practical problems of the maritime industry. Due to the use of established reliability tools, the developed framework benefits in terms of robustness. Similarly, the data-driven aspects incorporate innovative applications which future-proof the developed framework. The data-driven methodologies of the proposed framework can be implemented in a variety of different settings. They can be integrated with different applications due to the inherent interoperable nature of these tools.

A novel aspect of this work is the combination of fault tree analysis with k-means clustering for the identification of critical components. This methodology uses as input maintenance information from vessel "A" to obtain reliability IMs, by performing a fault tree analysis. Then, the obtained IMs are clustered together with cost information to identify critical equipment. This methodology combines in a novel manner the use of fault tree analysis with k-means clustering. Moreover, the consideration of cost information for the identification of critical equipment is ship systems is also novel. In general, the application of this methodology in LNG ship systems represents a novel application. Apart from the generated novelties, this methodology has a practical impact on the shipping industry. It can be used to prioritise maintenance actions in high-risk equipment, improving the ship's availability and mitigating the risks of breakdowns. From a similar standpoint, this framework can be used to optimise the procurement and distribution of spare parts, to reduce the risks of breakdowns further. Lastly, this methodology can provide a starting point for more in-depth reliability analysis of ship systems.

Another novel part of the present research is the implementation of a hybrid imputation approach, developed as a part of the data preparation methodology. This methodology uses as input performance and process variables from vessel's "B" ME. The collected data pass through a basic pre-processing step before they are used to develop the hybrid imputation tool, which is based on the MICE and kNN algorithms. Using these two algorithms enables the combination of data-driven solutions with domain knowledge in a single approach. Once the hybrid imputation approach is developed, its performance is evaluated against the MICE and kNN imputation algorithms. This methodology integrates in a novel way the MICE and kNN imputation algorithms in an approach with superior performance. From a theoretical point of view, this methodology includes the novel combination of data-driven models with domain knowledge in a single imputation approach. Moreover, the application of this methodology in ship systems is also novel. Apart from the discussed novel aspects, this methodology has practical significance in shipping. Initially, it can be used as a virtual sensor, ensuring the continuous collection of required data. It enriches the literature and addresses a practical problem encounter by maintenance planners. This methodology can be used to improve the quality of data sets used in predictive maintenance, enhancing the accuracy of subsequent models. As a result, decision-making processes are more accurate and lead to more effective actions.

Another novel aspect of this work is the combination of regression-based expected behaviour modelling with the exponential moving average control chart for fault detection. This particular combination allows for the creation accurate regression models that are not depend on very large training sets and detect developing faults while filtering out noise (Cheliotis, Lazakis, and Theotokatos 2020). This part of the framework considers the use of performance and process variables from vessel's "C" ME. The DBSCAN algorithm is deployed to remove outliers from the dataset before the data are used to train and validate different regression models. Once the optimal model is selected and tested, the residuals of a chosen variable are obtained and analysed in the exponential moving average control chart for fault detection. This methodology combines in a novel way the investigation of different regression models for expected behaviour modelling with control charts for fault detection. Moreover, the use of the DBSCAN algorithm for outlier detection, coupled with the presented fault detection approach for ship applications is also novel. The expected behaviour approach has the distinct advantage of detecting faulty operating conditions without requiring scarce faulty labelled data for model training. Also, this approach has enhanced applicability when compared with traditional classification approaches. This is due to the time-series output of the expected behaviour approach, which is more useful and interpretable. From a practical point of view, this model can be used to improve the safety of ship systems and to reduce the number of breakdowns.

The final novel part of this research is the combination of machine learning-based fault detection with a Bayesian diagnostic network. This part of the framework also uses as input performance and process variables from vessel's "C" ME. By aggregating the results from fault detection and by carrying out a fault-mapping process, the structure of the Bayesian diagnostic network is specified. This methodology includes the novel combination of a machine learning-based fault detection module with a Bayesian diagnostic network, in a novel application for ship systems. From a theoretical point of view, this methodology combines in a novel manner, data-driven approaches with knowledge-based models in an integrated diagnostics application. The use of this methodology has several practical benefits for the maritime industry. It can enable ship operators to get a real-time assessment of the condition of their vessels. As a result, better maintenance planning is allowed, which increase the safety of ships and ship systems.

6.4 Reflections

The following statements contain the concluding reflections of this work:

- The presented framework is established through the examination of the relevant literature investigating trends and common practices of predictive maintenance in the maritime and other sectors. The established requirements for a holistic framework encompassing the individual methodologies strengthen the framework presented in this work.

- In line with the above, this thesis presented a reliability-based and data-driven framework addressing a multitude of issues of predictive maintenance. The resulting framework combines different data-driven and reliability based tools in a practical schema with proven accuracy. Maritime predictive maintenance issues can be tackled by either using the framework as a stand-alone solution or by employing the individual methodologies.

- The developed maritime predictive maintenance framework initiates with the critical equipment selection methodology. The methodology includes a ship system analysis, fault tree analysis, reliability IMs assessment and data clustering. It is possible to identify critical equipment systematically, using objective criteria and incorporating various aspects. This methodology enhances the manner in which critical components are identified by combining reliability indices with cost information. The use of additional criteria is enabled by using easy to expanded partitioning algorithms. As a result, ship operators can identify critical components in a tailor-made manner, by including parameters and metrics based on their requirements and goals.

- The data preparation methodology is the subsequent step in tackling maritime predictive maintenance. The steps of this methodology include data form handling and synchronisation, data filtering, imputation of missing values and correction to ambient conditions. The development of the data preparation methodology enriches the relevant literature, which is very limited for maritime applications. Imputation in shipping is overlooked, but it remains essential. This is particularly true with the increasing application of machine learning algorithms, which are sensitive to missing values. In essence, the proposed imputation approach acts as a virtual sensor, ensuring the uninterrupted collection of required data. From the developed methodology, it is observed that when attempting to predict missing values from highly correlated variables, imparting domain knowledge in data-driven modes can have a positive effect. On the other hand, when performing imputation of uncorrelated values, increasing the model's complexity can have a limited influence.

- The fault detection methodology is the following step in addressing maritime predictive maintenance. This methodology incorporates the investigation of the optimum expected behaviour model, the evaluation of the identified model, the calculation of the residuals of a target variable, and the analysis of the residuals in a signal-smoothing control chart. The developed methodology allows for the prediction of faults without requiring faulty labelled data during model training. However, the selection of the model's inputs should be thoroughly and systematically investigated. This expedites the developing process, resulting in models that are quicker to deploy and can offer accurate predictions decoupled from operating conditions. By detection faults using an expected behaviour approach, the need for traditional one-class classifiers is bypassed. This increases flexibility and eases the model's integration with subsequent diagnostic tasks. Due to the reduced number of assumptions, the developed methodology can be expanded and implemented in different engineering systems, increasing the framework's impact on safety.

- The developed diagnostics methodology is the final step of maritime predictive maintenance framework. The steps of this methodology are, the aggregation of the results from fault detection, the fault mapping structure, the specification of the structure of the diagnostic network, and the investigation of different faults. This methodology demonstrates the integration of a machine learning-based fault detection module, with a knowledge-based diagnostic network. As a result, this methodology enriches limited maritime literature regarding integrated fault detection and diagnostics. The developed network is also expandable and can be used to model additional systems; however, this process depends heavily on additional failure statistics which can be hard to obtain. Shipowners and operators can use the developed diagnostic network in order to improve their understanding, in real-time, in terms of the condition of their vessels.

6.5 Recommendation for future work

The developed framework, together with the different methodologies contained within, contribute to the area of maritime predictive maintenance. Future research directions that can further enhance the impact of this work are presented below. These directions reflect both to the individual methodologies and the framework as a whole:

- The fault tree structure developed for the critical equipment selection can be expanded to account for greater modelling detail and include dynamic gates. These gates can model with greater accuracy the dynamic dependencies between components. Moreover, additional gates and events can be used to model with greater accuracy the ship systems, by incorporating additional components, currently omitted for simplicity reasons. However, this process should always be a function of the available computational power.

- The reliability and cost criteria used to identify the critical equipment can be expanded to include additional information, both from a practical and from a theoretical standpoint. For example, the availability of spares could be factored in order to provide application-specific maintenance prioritisation.

- Additional clustering algorithms can be explored when partitioning the critical equipment data-space. The used k-means algorithm creates hard clusters, where each component has a binary membership in each cluster. Exploring algorithms which create soft clusters, where each component has a gradual membership in different clusters could be beneficial. For instance, the c-means clustering algorithm can be used to improve the representation of components which are currently located near the boundary of each cluster.

- To further establish the effectiveness of the developed imputation approach, it would be beneficial to compare it with additional imputation methods, apart from the MICE and kNN algorithms. For instance, vertical imputation approaches, or additional machine learning tools (e.g. random forests) can provide an extended basis for comparison. Similarly, the effectiveness of the developed approach can be evaluated through the use of additional variables during the comparison of the different imputation approaches.

- The data filtering process used during the data preparation methodology can be replaced with application-agnostic tools. For example, instead of using a value-based filter, the DBSCAN algorithm, or other similar algorithms, could be employed.

- Regarding the data preparation methodology, it would be beneficial to holistically assess its impact on ship condition monitoring (e.g. fault detection, diagnostics). In more detail, this would involve performing condition monitoring tasks with treated and untreated datasets and evaluating the obtained results.

- The fault detection methodology could be enhanced by exploring additional expected behaviour models. Even though the selected expected behaviour model obtained excellent training, validation and testing scores, its performance could be compared with random forest, or support vector machine regression models.

- The outlier detection algorithm used during the fault detection methodology (DBSCAN) could be compared with additional density-based clustering techniques (e.g. OPTICS algorithm).

- Since the aim of the expected behaviour models is to classify each point in terms of its state, a direct comparison between this approach and the traditional classification approach would be beneficial. For example, comparing the regression-based expected behaviour model with a one-class classifier (e.g. support vector machine) would offer an insight into the performance of these two approaches.

- The effectiveness of the expected behaviour model could be expanded in predicting additional signals (e.g. ME speed).
- The effectiveness of the exponentially weighted moving average in analysing the residuals, during fault detection, could be compared with additional control charts (e.g. cumulative sum charts).
- The structure of the diagnostic Bayesian Network can be expanded in future research to include additional observable nodes (e.g. ME speed and ME power). However, this process is a function of the available data.
- Future research efforts could also compare the performance of the developed diagnostic network with alternative knowledge-based approaches.
- Future research efforts could bypass the use of data banks for the non-observable nodes. Instead, combining reliability tools with Monte Carlo simulations could be used as an alternative.
- Finally, future research efforts could examine the overall effectiveness of the developed framework in a single, continuous, case study.

6.6 Assumptions and Challenges

To meet the main research objectives and establish the novelties of this thesis, several assumptions were made, and different challenges had to be overcome. These two topics are presented and discussed in this Section.

The main assumptions of this thesis represent the basic premises based on which this work is developed. The first assumption reflects the manner in which the various methodologies of the framework are evaluated. Due to the data limitations discussed in Section 5, different case studies are used to evaluate the capabilities of the individual parts of the framework. Also, the individual methodologies of the proposed framework were not developed simultaneously. Regarding the critical equipment selection aspect of the framework, it is assumed that the maintenance schedule of the examined vessel is used to obtain information for the quantification of the FT structure. Similarly, regarding the data preparation part of the framework, operating manual supplied for ship operators are used for data filtering. The main assumption of the FD methodology of the proposed framework is based on the retraining of the EB models after major modifications and repairs on the examined vessel. Lastly, the diagnostics methodology is based on the assumption that data banks can be used for failure statistics in the absence of required data.

The majority of the challenges of this thesis are relating to the required resources. Initially, there was an absence of a single dataset containing all the required information necessary to develop and evaluate the different components of the framework in a single case study. Moreover, some of the individual datasets were still missing some information, resulting in the use of alternative sources (e.g. data banks). Lastly, the size of the analysis is some parts of the framework (e.g. during the FTA) was restricted due to the limited computational power.

6.7 Chapter Summary

This chapter presented concluding remarks and reflections for the established predictive maintenance framework. Initially, the fulfilment of the main aim and objectives is elaborated. Then, the novelty generated from this work is summarised and outlined before presenting concluding reflections and remarks. Lastly, this chapter presented recommendations and directions for future work and discussed the main assumptions and challenges. List of references and appendices are provided next, supplementing this work.

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Appendix A

FTA Gates and Events

A.1 FTA Gates

AND Gate

The AND gate is used to indicate that the output occurs if and only if all the input events occur. The output of an AND gate can be the top event or any intermediate event. The input events can be basic events, intermediate events (outputs of other gates) or a combination of both (PTC Windchill 2019).

OR Gate

The OR gate is used to indicate that the output occurs if and only if at least one of the input events occur. The output of an OR gate can be the top event or any intermediate event. The input events can be basic events, intermediate events or a combination of both. There should be at least two inputs to an OR gate (PTC Windchill 2019).

Voting Gate

The Voting (M/n) gate is used to indicate that the output occurs if and only if M out of the n input events occur. The output occurs when at least m input events occur. When M = 1, the Voting gate behaves like an OR gate. The output of a Voting gate can be a top event or an intermediate event. The input events can be basic events, intermediate events or a combination of both (PTC Windchill 2019).

Inhibit Gate

The Inhibit gate is used to indicate that the output occurs when the input events (l1 and l2) occur and the input condition (C) is satisfied. The output of an Inhibit gate can be a top event or an intermediate event. The input events can be basic events, intermediate events or a combination of both (PTC Windchill 2019).

Exclusive OR Gate

The Exclusive OR (XOR) gate is used to indicate that the output occurs if and only if one of the two input events occurs and the other input event does not occur. An XOR gate can only have two inputs. The output of an Exclusive OR gate can be the top event or an intermediate event. The input events can be basic events, intermediate events or a combination of both. The presence of an XOR gate may give rise to non-coherent trees, where the non-occurrence of an event causes the top event to occur (PTC Windchill 2019).

NOT Gate

The NOT gate is used to indicate that the output occurs when the input event does not occur. The presence of a NOT gate may give rise to non-coherent trees, where the non-occurrence of an event causes the top event to occur. There is only one input to a NOT gate (PTC Windchill 2019).

NOR Gate

The NOR gate functions like a combination of an OR gate and a NOT gate. The NOR gate is used to indicate that the output occurs when all the input events are absent. The output of a NOR gate can be the top event or an intermediate event. The input events can be basic events, intermediate events or a combination of both. The presence of a NOR gate may give rise to non-coherent trees, where the lack of one or more events causes the top event to occur (PTC Windchill 2019).

NAND Gate

The NAND gate functions like a combination of an AND gate and a NOT gate. The NAND gate is used to indicate that the output occurs when at least one of the input events is absent. The output of a NAND gate can be the top event or an intermediate event. The input events can be basic events, intermediate events or a combination of both. The presence of a NAND gate may give rise to non-coherent trees, where the non-occurrence of an event causes the top event to occur (PTC Windchill 2019).

Priority AND Gate

The Priority AND (PAND) gate is used to indicate that the output occurs if and only if all input events occur in a particular order. The order is the same as that in which the inputs events are connected to the PAND gate from left to right. The PAND gate is a dynamic gate, which means that the order of the occurrence of input events is important to determining the output.

The output of a PAND gate can be the top event or an intermediate event. The inputs can be basic events or outputs of any AND gate, OR gate, or dynamic gate, which includes the SPARE gate, PAND gate, sequence-enforcing (SEQ) gate and functional dependency (FDEP) gate. (These gates should have the inputs from basic events or other AND gates and OR gates.) The items that enter a PAND gate need to fail in temporal order from left to right to trigger the event. The PAND gate also supports a single input. When only a single input exists, then occurrence of that input will trigger the event (PTC Windchill 2019).

Functional Dependency Gate

The Functional Dependency (FDEP) gate is used to indicate that all dependent basic events are forced to occur whenever the trigger event occurs. The separate occurrence of any of the dependent basic events has no effect on the trigger event. The FDEP gate has one trigger event and can have one or more dependent events. All dependent events are either basic events or spare events. The trigger event can be a terminal event or output of any AND gate, OR gate or dynamic gate, which includes the SPARE gate, PAND gate, Sequence-Enforcing gate (SEQ) and FDEP gate.

Dependent events are repeated events that are present in other parts of the fault tree. The FDEP gate is a dynamic gate, which means the temporal order of the occurrence of events is important to analyse this gate. Generally, the output of the FDEP gate is not that important; however, it is equivalent to the status of its trigger event.

The FDEP gate can also be used to set the priorities for SPARE gates. For example, if multiple spares are connected to a FDEP gate, after the occurrence of the trigger event, all spares that are connected to the FDEP gate will fail. Upon failure of these spares, the next available good spares in those SPARE gates will replace the failed spares. If there exists a conflict in choosing the next available spare between multiple SPARE gates, the priority will be based on the order of the connection of these spares in the FDEP gate from left to right (PTC Windchill 2019).

Sequence Enforcing Gate

The Sequence-Enforcing (SEQ) gate forces events to occur in a particular order.

The input events are constrained to occur in the left-to-right order in which they appear under the gate. That means that the left-most event must occur before the event on its immediate right, which must occur before the event on its immediate right is allowed to occur. The SEQ gate is used to indicate that the output occurs if and only if all input events occurs, when the input events are constraint to occur in a particular order.

The SEQ gate is a dynamic gate, which means the occurrence of the inputs follows a sequential order. In other words, an event connected to a SEQ gate will be initiated immediately after occurrence of its immediate left event. Therefore, if the left-most input is a basic event, then the SEQ gate works like a cold SPARE gate. The SEQ gate can be contrasted with the PAND gate in that the PAND gate detects whether events occur in a particular order (but the events can occur in any order), whereas the SEQ gate allows the events to occur only in the specified order. The first input (left-most input) to a SEQ gate can be a terminal event or outputs of any AND gate, OR gate or dynamic gate, which includes the SPARE gate, PAND gate, FDEP gate or SEQ gate). Only basic events are allowed for all other inputs (PTC Windchill 2019).

SPARE Gate

The SPARE gate is used to model the behaviour of spares in the system. The SPARE gate is used to indicate that the output occurs if and only if all input spare events occur. All inputs of a SPARE gate are spare events. A SPARE gate can have multiple inputs. The first event (left-most event) is known as the primary input, and all other inputs are known as alternative inputs. The primary event is the one that is initially powered on, and the alternative inputs and are initially in standby mode.

After a failure, the active/powered unit that is the first available spare from left to right will be chosen to be active. If all units are failed, then the spare will be considered as failed (output occurred). Depending on the dormancy factor of spares, spares can fail even in standby mode.

If the dormancy factor of all spares connected to a SPARE gate are 0, then the spare acts like a cold spare. If the dormancy factor of all spares connected to a SPARE gate is 1, then the spare acts like a hot spare. If the dormancy factor of all spares connected to a SPARE gate are the same (and are between 0 and 1), then the spare acts like a warm spare. If the dormancy factors of its inputs are different, then it handles generalised situations. The SPARE gate is a dynamic gate, which means the temporal order of the occurrence of events is important to analyse this gate (PTC Windchill 2019).

A.2 FTA Events

Basic Event

A basic event is either a component level event that is not further resolved. A basic event is at the lowest level in a tree branch and terminates a fault tree path. Component level events can include hardware or software failures, human errors and sub-system failures (PTC Windchill 2019).

House Event

A house event is used to represent an event that is normally expected to occur. A house event can be turned on or off. When a house event is turned on (TRUE), that event is presumed to have occurred, and the probability of that event is set to 1. When a house event is turned off (FALSE), that event is presumed not to have occurred, and the probability is set to 0. House events are useful in making parts of a fault tree functional or non-functional. House events are also referred to as trigger events or switching events (PTC Windchill 2019).

House Event

A conditional event is used to indicate specific conditions or restrictions that apply to any logic gate, although they are most often used with Inhibit gates (PTC Windchill 2019).

Undeveloped Event

An undeveloped event is used if further resolution of that event does not improve the understanding of the problem or if further resolution is not necessary for proper evaluation of the fault tree. It is similar to a basic event, but is shown as a different symbol to signify that it could be developed further but that the analysis has not yet been done or need not be done for the sake of the analysis in question. Undeveloped events may changed to some other event type and broken down into associated gates and events if it is later deemed necessary (PTC Windchill 2019).

Spare Event

A spare event is used to specify spares in dynamic fault trees. Spare events are similar to basic events in functionality; however, they allow only rates as inputs. The dormancy factor of the spare indicates the ratio of failure rate in the spare mode and the failure rate in the operational mode. Spare events can have a spares pool, which represents the number of identical instances of that event. For example, if a spares pool of an event is two, there are two identical spare components of that spare event. Spare events are restricted to use as either spares to SPARE gates or as dependent events to Functional Dependency gates (PTC Windchill 2019).

Appendix B

Ship Components Cost

B.1 Costs

Table B.1: Repair and replacement costs for the components of vessel "A"

Component	**Cost (US Dollars)**
BWTS	90000
CO2 System	90000
Central Cooler 1	30000
Central Cooler 2	30000
Central Cooler 3	30000
High Duty Compressor 1	17000
High Duty Compressor 2	17000
Auxiliary Cooler 1	15000
Auxiliary Cooler 2	15000
Cargo Pumps	15000
FO Purifier 1	15000
FO Purifier 2	15000
FO Purifier 3	15000

Continued on next page

Table B.1 – *Continued from previous page*

Component	**Cost (US Dollars)**
Low Duty Compressor 1	15000
Low Duty Compressor 2	15000
Ballast Pump 1	15000
Ballast Pump 2	15000
Ballast Pump 3	15000
LO Purifier 1	14000
LO Purifier 2	14000
LO Purifier 3	14000
LO Purifier 4	14000
Bilge Pumps	12000
Steering Gear Cylinder Ram	12000
Dry Powder System	12000
Fire Pump 1	12000
Fire Pump 2	12000
MGE LO Pump 1	10000
MGE LO Pump 2	10000
MGE LO Pump 3	10000
MGE LO Pump 4	10000
Boiler Burner 1	8000
Boiler Burner 2	8000
IGG Burner	8000
Gas Combustion Unit	8000
MGE 1 LO Pump	6500
MGE 2 LO Pump	6500
MGE 3 LO Pumps	6500

Continued on next page

Table B.1 – *Continued from previous page*

Component	Cost (US Dollars)
MGE 4 Lubricating Pumps	6500
Blower 1	6000
Blower 2	6000
MGE 1 Cyl. Head	5500
MGE 2 Cylinder Head	8000
MGE 3 Cylinder Head	8000
MGE 4 Cylinder Head	12000
Boiler Feedwater Pump 1	5000
Boiler Feedwater Pump 2	5000
FO Feed Pump 1	5000
FO Feed Pump 2	5000
FO Feed Pump 3	5000
FO Feed Pump 4	5000
High Duty Heater	5000
LNG Vaporiser	5000
Reduction Gear LO Pump 1	5000
Reduction Gear LO Pump 2	5000
FO Circulating Pump 1	4000
FO Circulating Pump 2	4000
FO Circulating Pump 3	4000
FO Circulating Pump 4	4000
Forcing Vaporiser	4000
Fuel Gas Pump 1	4000
Fuel Gas Pump 2	4000
IGG Fuel Pump	4000

Continued on next page

Table B.1 – *Continued from previous page*

Component	**Cost (US Dollars)**
HFO Transfer Pump 1	4000
HFO Transfer Pump 2	4000
MGE 1 Coolers	4000
MGE 3 Coolers	4000
MGE 4 Coolers	4000
MGE 2 Coolers	4000
Pilot Fuel Feed Pump 1	4000
Pilot Fuel Feed Pump 2	4000
MGE 1 Rod	3500
MGE 2 Rod	3500
MGE 3 Rod	3500
MGE 4 Rod	3500
FW Booster Pump 1	3000
FW Booster Pump 2	3000
LO Transfer Pump 1	3000
LO Transfer Pump 2	3000
MGE 1 Cylinder Liner	3000
MGE 1 Piston	3000
MGE 2 Cylinder Liner	3500
MGE 2 Piston	3000
MGE 3 Cylinder Liner	3500
MGE 3 Pistons	3000
MGE 4 Cylinder Liner	3000
MGE 4 Piston	3000
SWC Pump 1	3000

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Table B.1 – *Continued from previous page*

Component	**Cost (US Dollars)**
SWC Pump 2	3000
SWC Pump 3	3000
Boiler Water Circulating Pumps	3000
Aux SWC Pump 1	2500
Aux SWC Pump 2	2500
Boiler Fuel Pump 1	2500
Boiler Fuel Pump 2	2500
FWC Pump 1	2500
FWC Pump 2	2500
LO Purifier Supply Pump 1	2500
LO Purifier Supply Pump 2	2500
LO Purifier Supply Pump 3	2500
LO Purifier Supply Pump 4	2500
MDO Transfer Pump	2500
MGE 1 FO Injection Pump	2500
MGE 2 FO Injection Pump	2500
MGE 3 FO Injection Pump	2500
MGE 4 FO Injection Pump	2500
MGO Transfer Pump	2500
Steering Gear Oil Pump	2500
Spray Pump 1	2500
Spray Pump 2	2500
Spray Pump 3	2500
Spray Pump 4	2500
Steering Gear Control And Repeat Back Leaver	2000

Continued on next page

Table B.1 – *Continued from previous page*

Component	**Cost (US Dollars)**
FO Purifier Supply Pump 1	2000
FO Purifier Supply Pump 2	2000
FO Purifier Supply Pump 3	2000
Steering Gear Remote Controller	2000
Steering Gear Angle Transmitter	1500
IGG Safety Equipment	1000
Fuel Injector 1	300
Fuel Injector 2	300
MGE 1 Main Bearing	200
MGE 2 Main Bearing	200
MGE 3 Main Bearing	200
MGE 4 Main Bearing	200
Boiler Refractory Area 1	200
Boiler Refractory Area 2	200
MGE 1 FO Injector	150
MGE 2 FO Injector	300
MGE 3 FO Injector	300
MGE 4 FO Injector	150

Appendix C

Critical Equipment Selection

C.1 MTBFs

Table C.1: Table of MTBFs used for the inert gas generation system

Inert Gas Generation	
Component	**MTBF (Hours)**
Blower	30240
Fuel Pump	12264
Burner	6132
Safety Equipment	15120

Table C.2: Table of MTBFs used for the cargo equipment system

Cargo Equipment	
Component	**MTBF (Hours)**
Cargo Pumps	1540
Spray Pumps	1540
LNG Vaporiser	1512
High Duty Compressor	2190
High Duty Heater	2190

Table C.3: Table of MTBFs used for the bilge, fire and ballast systems

Bilge, Fire and Ballast	
Component	**MTBF (Hours)**
Ballast Pumps	2190
BWTS	6048
Fire Pumps	2190
Bilge Pumps	2190
CO2 System	6132
Dry Powder System	6132

Table C.4: Table of MTBFs used for the steering gear system

Steering Gear	
Component	**MTBF (Hours)**
Cylinder Ram	61320
Oil Pump	12264
Control and Repeat Back Lever	30660
Angle Transmitter	18396
Remote Controller	18396

Table C.5: Table of MTBFs used for the steam generation system

Steam Generation	
Component	**MTBF (Hours)**
Pilot Fuel Injector	3100
Fuel Pump	3100
Water Circulating Pump	3000
Feed-water Pump	3000
Burner	6132
Refractory Area	1226

Table C.6: Table of MTBFs used for the main generating engines system

Main Generating Engines	
Component	**MTBF (Hours)**
Piston Rod	61320
Cylinder Head	61320
Fuel Oil Injector	12264
Main Bearing	61320
Cylinder Liner	61320
Piston	30660
Cooling Pumps	3000
Coolers	2190
Lubricating Pumps	12264
Fuel Oil Injection Pumps	2200

Table C.7: Table of MTBFs used for the gas fuel system

Gas Fuel	
Component	**MTBF (Hours)**
Fuel Gas Pumps	3100
Low Duty Compressor	2190
Forcing Vaporiser	1512
Gas Combustion Unit	12264

Table C.8: Table of MTBFs used for the fuel oil feed system

Fuel Oil Feed	
Component	**MTBF (Hours)**
Fuel Oil Feed Pump	2200
Fuel Oil Circulating Pump	2200
Pilot Fuel Feed Pump	3100

Table C.9: Table of MTBFs used for the fuel oil purification system

Fuel Oil Purification	
Component	**MTBF (Hours)**
Fuel Oil Purifiers	8400
Fuel Oil Purifiers Supply Pump	2200

Table C.10: Table of MTBFs used for the fuel oil transfer system

Fuel Oil Transfer	
Component	**MTBF (Hours)**
Heavy Fuel Oil Transfer Pumps	2200
Marine Diesel Oil Transfer Pumps	3100
Marine Gas Oil Transfer Pumps	3100

Table C.11: Table of MTBFs used for the lubricating oil purification system

Lubricating Oil Purification	
Component	**MTBF (Hours)**
Lubricating Oil Purifiers	12000
Lubricating Oil Purifier Supply Pumps	12264

Table C.12: Table of MTBFs used for the lubricating oil service system

Lubricating Oil Service	
Component	**MTBF (Hours)**
Lubricating Oil Transfer Pumps	12264
Reduction Gear Lubricating Oil Pumps	12264
MGE Lubricating Oil Pumps	12264

Table C.13: Table of MTBFs used for the central MGE cooling system

Central MGE Cooling	
Component	**MTBF (Hours)**
Sea Water Cooling Pumps	2190
Central Cooler	2190

Table C.14: Table of MTBFs used for the auxiliary cooling system

Auxiliary Cooling	
Component	**MTBF (Hours)**
Fresh Water Cooling Pumps	3000
Sea Water Cooling Pumps	2190
Fresh Water Booster Pumps	3000
Auxiliary Cooler	2190

C.2 IMs

Table C.15: Obtained I^B for the components of vessel "A"

Component	I^B
MGE 4 Cylinder Head	3.0307
MGE 4 Cylinder Liner	3.0307
MGE 4 Main Bearing	3.0307
MGE 4 Piston	3.0307
MGE 4 Rod	3.0307
MGE 1 FO Injection Pump	2.8700
MGE 2 FO Injection Pump	2.8700
MGE 3 FO Injection Pump	2.8700
MGE 4 FO Injection Pump	2.8700
MGE 1 FO Injector	2.8000
MGE 2 FO Injector	2.8000
MGE 3 FO Injector	2.8000
MGE 4 FO Injector	2.8000
FO Feed Pump 1	2.7061
FO Feed Pump 2	2.7061
FO Feed Pump 3	2.7061
FO Feed Pump 4	2.7061
MGE 1 Cyl. Head	2.7061
MGE 1 Cylinder Liner	2.7061
MGE 1 Main Bearing	2.7061
MGE 1 Piston	2.7061
MGE 1 Rod	2.7061
MGE 2 Cylinder Head	2.7061

Continued on next page

Table C.15 – *Continued from previous page*

Component	I^B
MGE 2 Cylinder Liner	2.7061
MGE 2 Main Bearing	2.7061
MGE 2 Piston	2.7061
MGE 2 Rod	2.7061
MGE 3 Cylinder Head	2.7061
MGE 3 Cylinder Liner	2.7061
MGE 3 Main Bearing	2.7061
MGE 3 Pistons	2.7061
MGE 3 Rod	2.7061
MGE 1 LO Pump	2.0200
MGE 2 LO Pump	2.0200
MGE 3 LO Pumps	2.0200
MGE 4 Lubricating Pumps	2.0200
IGG Burner	1.8525
IGG Fuel Pump	1.8525
IGG Safety Equipment	1.8525
Steering Gear Control And Repeat Back Leaver	1.0000
Steering Gear Cylinder Ram	1.0000
Boiler Feedwater Pump 1	1.0000
Boiler Feedwater Pump 2	1.0000
Steering Gear Oil Pump	1.0000
Boiler Water Circulating Pumps	1.0000
BWTS	0.8750
Cargo Pumps	0.6318
High Duty Heater	0.6318

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Table C.15 – *Continued from previous page*

Component	I^B
LNG Vaporiser	0.6318
Bilge Pumps	0.5392
CO2 System	0.3296
Dry Powder System	0.3296
Central Cooler 1	0.2661
Central Cooler 2	0.2661
Central Cooler 3	0.2661
SWC Pump 1	0.2661
SWC Pump 2	0.2661
SWC Pump 3	0.2661
High Duty Compressor 1	0.2316
High Duty Compressor 2	0.2316
Boiler Burner 1	0.2288
Boiler Burner 2	0.2288
Boiler Refractory Area 1	0.2288
Boiler Refractory Area 2	0.2288
FO Purifier Supply Pump 1	0.2198
FO Purifier Supply Pump 2	0.2198
FO Purifier Supply Pump 3	0.2198
Aux SWC Pump 1	0.2142
Aux SWC Pump 2	0.2142
Auxiliary Cooler 1	0.2142
Auxiliary Cooler 2	0.2142
FW Booster Pump 1	0.1960
FW Booster Pump 2	0.1960

Continued on next page

Table C.15 – *Continued from previous page*

Component	I^B
FWC Pump 1	0.1960
FWC Pump 2	0.1960
LO Transfer Pump 1	0.1671
LO Transfer Pump 2	0.1671
Reduction Gear LO Pump 1	0.1671
Reduction Gear LO Pump 2	0.1671
Forcing Vaporiser	0.1327
Gas Combustion Unit	0.1327
Fire Pump 1	0.1277
Fire Pump 2	0.1277
Ballast Pump 1	0.1176
Ballast Pump 2	0.1176
Ballast Pump 3	0.1176
Spray Pump 1	0.0688
Spray Pump 2	0.0688
Spray Pump 3	0.0688
Spray Pump 4	0.0688
MDO Transfer Pump	0.0637
MGO Transfer Pump	0.0637
Blower 1	0.0603
Blower 2	0.0603
Steering Gear Angle Transmitter	0.0529
Steering Gear Remote Controller	0.0529
Low Duty Compressor 1	0.0487
Low Duty Compressor 2	0.0487

Continued on next page

Table C.15 – *Continued from previous page*

Component	I^B
HFO Transfer Pump 1	0.0481
HFO Transfer Pump 2	0.0481
Fuel Gas Pump 1	0.0366
Fuel Gas Pump 2	0.0366
Boiler Fuel Pump 1	0.0210
Boiler Fuel Pump 2	0.0210
Fuel Injector 1	0.0210
Fuel Injector 2	0.0210
FO Purifier 1	0.0208
FO Purifier 2	0.0208
FO Purifier 3	0.0208
Pilot Fuel Feed Pump 1	0.0171
Pilot Fuel Feed Pump 2	0.0171
FO Circulating Pump 1	0.0080
FO Circulating Pump 2	0.0080
FO Circulating Pump 3	0.0080
FO Circulating Pump 4	0.0080
MGE 1 Coolers	0.0050
MGE 3 Coolers	0.0050
MGE 4 Coolers	0.0050
MGE 2 Coolers	0.0050
LO Purifier 1	0.0011
LO Purifier 2	0.0011
LO Purifier 3	0.0011
LO Purifier 4	0.0011

Continued on next page

Table C.15 – *Continued from previous page*

Component	I^B
LO Purifier Supply Pump 1	0.0010
LO Purifier Supply Pump 2	0.0010
LO Purifier Supply Pump 3	0.0010
LO Purifier Supply Pump 4	0.0010
MGE LO Pump 1	0.0010
MGE LO Pump 2	0.0010
MGE LO Pump 3	0.0010
MGE LO Pump 4	0.0010

Table C.16: Obtained I^{CR} for the components of vessel “A”

Component	I^{CR}
MGE 1 FO Injection Pump	0.1800
MGE 2 FO Injection Pump	0.1800
MGE 3 FO Injection Pump	0.1800
MGE 4 FO Injection Pump	0.1800
MGE 1 FO Injector	0.1500
MGE 2 FO Injector	0.1500
MGE 3 FO Injector	0.1500
MGE 4 FO Injector	0.1500
MGE 1 LO Pump	0.1300
MGE 2 LO Pump	0.1300
MGE 3 LO Pumps	0.1300
MGE 4 Lubricating Pumps	0.1300

Continued on next page

Table C.16 – *Continued from previous page*

Component	I^{ICR}
FO Feed Pump 1	0.0874
FO Feed Pump 2	0.0874
FO Feed Pump 3	0.0874
FO Feed Pump 4	0.0874
LNG Vaporiser	0.0545
Cargo Pumps	0.0538
Boiler Feedwater Pump 1	0.0505
Boiler Feedwater Pump 2	0.0505
Boiler Water Circulating Pumps	0.0505
IGG Burner	0.0497
Steering Gear Cylinder Ram	0.0475
High Duty Heater	0.0413
Bilge Pumps	0.0352
Steering Gear Oil Pump	0.0290
IGG Fuel Pump	0.0259
BWTS	0.0238
IGG Safety Equipment	0.0211
Central Cooler 1	0.0174
Central Cooler 2	0.0174
Central Cooler 3	0.0174
SWC Pump 1	0.0174
SWC Pump 2	0.0174
SWC Pump 3	0.0174
MGE 4 Cylinder Liner	0.0173
MGE 1 Piston	0.0155

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Table C.16 – *Continued from previous page*

Component	I^{ICR}
MGE 2 Cylinder Liner	0.0155
MGE 3 Cylinder Liner	0.0155
High Duty Compressor 1	0.0151
High Duty Compressor 2	0.0151
FO Purifier Supply Pump 1	0.0143
FO Purifier Supply Pump 2	0.0143
FO Purifier Supply Pump 3	0.0143
Aux SWC Pump 1	0.0140
Aux SWC Pump 2	0.0140
Auxiliary Cooler 1	0.0140
Auxiliary Cooler 2	0.0140
Forcing Vaporiser	0.0115
FW Booster Pump 1	0.0099
FW Booster Pump 2	0.0099
FWC Pump 1	0.0099
FWC Pump 2	0.0099
CO2 System	0.0088
Dry Powder System	0.0088
MGE 4 Cylinder Head	0.0087
MGE 4 Main Bearing	0.0087
MGE 4 Piston	0.0087
MGE 4 Rod	0.0087
Fire Pump 1	0.0083
Fire Pump 2	0.0083
MGE 1 Cyl. Head	0.0078

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Table C.16 – *Continued from previous page*

Component	I^{ICR}
MGE 1 Cylinder Liner	0.0078
MGE 1 Main Bearing	0.0078
MGE 1 Rod	0.0078
MGE 2 Cylinder Head	0.0078
MGE 2 Main Bearing	0.0078
MGE 2 Piston	0.0078
MGE 2 Rod	0.0078
MGE 3 Cylinder Head	0.0078
MGE 3 Main Bearing	0.0078
MGE 3 Pistons	0.0078
MGE 3 Rod	0.0078
Ballast Pump 1	0.0077
Ballast Pump 2	0.0077
Ballast Pump 3	0.0077
MGE 1 Coolers	0.0062
MGE 3 Coolers	0.0062
MGE 4 Coolers	0.0062
MGE 2 Coolers	0.0062
Boiler Burner 1	0.0061
Boiler Burner 2	0.0061
Spray Pump 1	0.0059
Spray Pump 2	0.0059
Spray Pump 3	0.0059
Spray Pump 4	0.0059
Steering Gear Control And Repeat Back Leaver	0.0050

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Table C.16 – *Continued from previous page*

Component	I^{ICR}
Boiler Refractory Area 1	0.0032
Boiler Refractory Area 2	0.0032
Low Duty Compressor 1	0.0032
Low Duty Compressor 2	0.0032
HFO Transfer Pump 1	0.0031
HFO Transfer Pump 2	0.0031
MDO Transfer Pump	0.0031
MGO Transfer Pump	0.0031
LO Transfer Pump 1	0.0023
LO Transfer Pump 2	0.0023
Reduction Gear LO Pump 1	0.0023
Reduction Gear LO Pump 2	0.0023
Gas Combustion Unit	0.0019
Fuel Gas Pump 1	0.0018
Fuel Gas Pump 2	0.0018
Boiler Fuel Pump 1	0.0010
Boiler Fuel Pump 2	0.0010
Fuel Injector 1	0.0010
Fuel Injector 2	0.0010
Pilot Fuel Feed Pump 1	0.0008
Pilot Fuel Feed Pump 2	0.0008
FO Circulating Pump 1	0.0005
FO Circulating Pump 2	0.0005
FO Circulating Pump 3	0.0005
FO Circulating Pump 4	0.0005

Continued on next page

Table C.16 – *Continued from previous page*

Component	I^{ICR}
Steering Gear Angle Transmitter	0.0005
Steering Gear Remote Controller	0.0005
FO Purifier 1	0.0004
FO Purifier 2	0.0004
FO Purifier 3	0.0004
Blower 1	0.0003
Blower 2	0.0003
LO Purifier 1	0.0000
LO Purifier 2	0.0000
LO Purifier 3	0.0000
LO Purifier 4	0.0000
LO Purifier Supply Pump 1	0.0000
LO Purifier Supply Pump 2	0.0000
LO Purifier Supply Pump 3	0.0000
LO Purifier Supply Pump 4	0.0000
MGE LO Pump 1	0.0000
MGE LO Pump 2	0.0000
MGE LO Pump 3	0.0000
MGE LO Pump 4	0.0000

Appendix D

Fault Detection

D.1 Data Checking Results

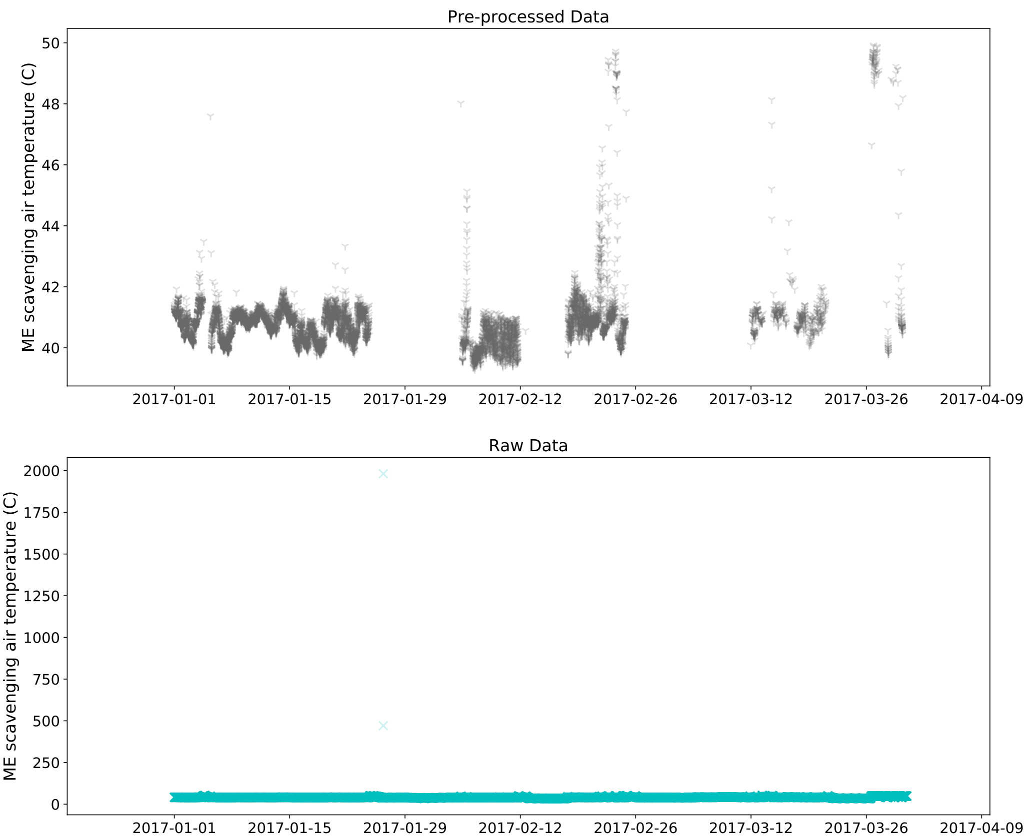

Figure D.1: Data checking result for ME scavenging air temperature

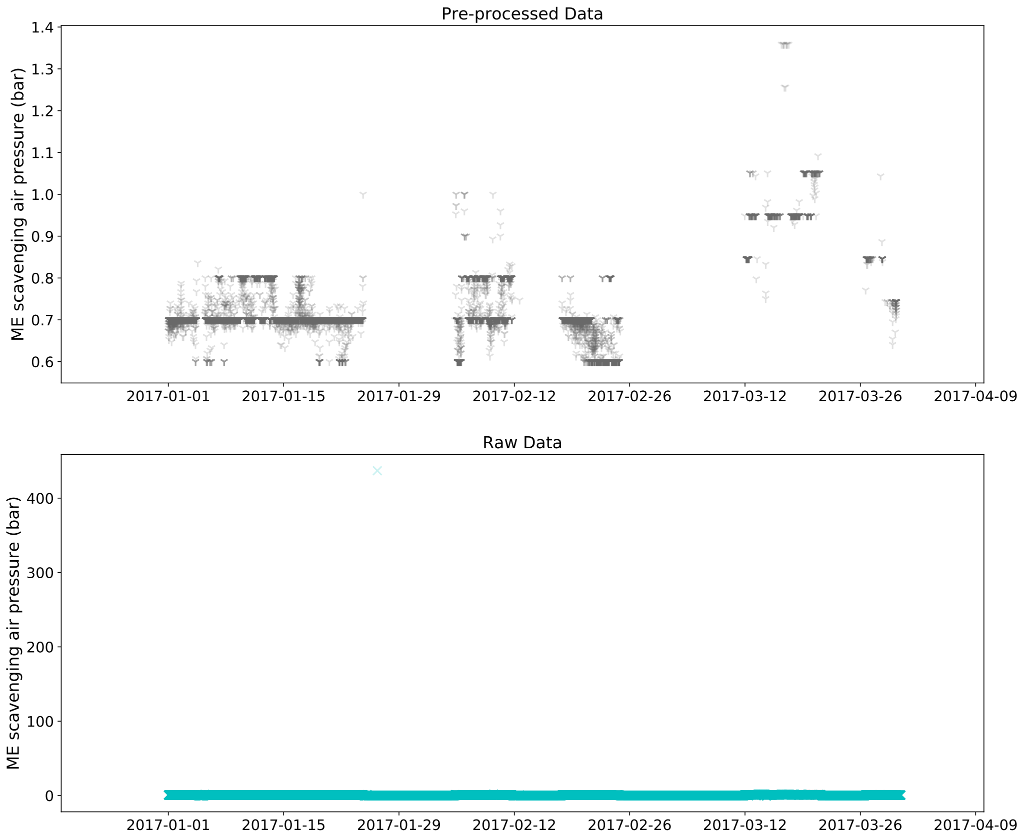

Figure D.2: Data checking result for ME scavenging air pressure

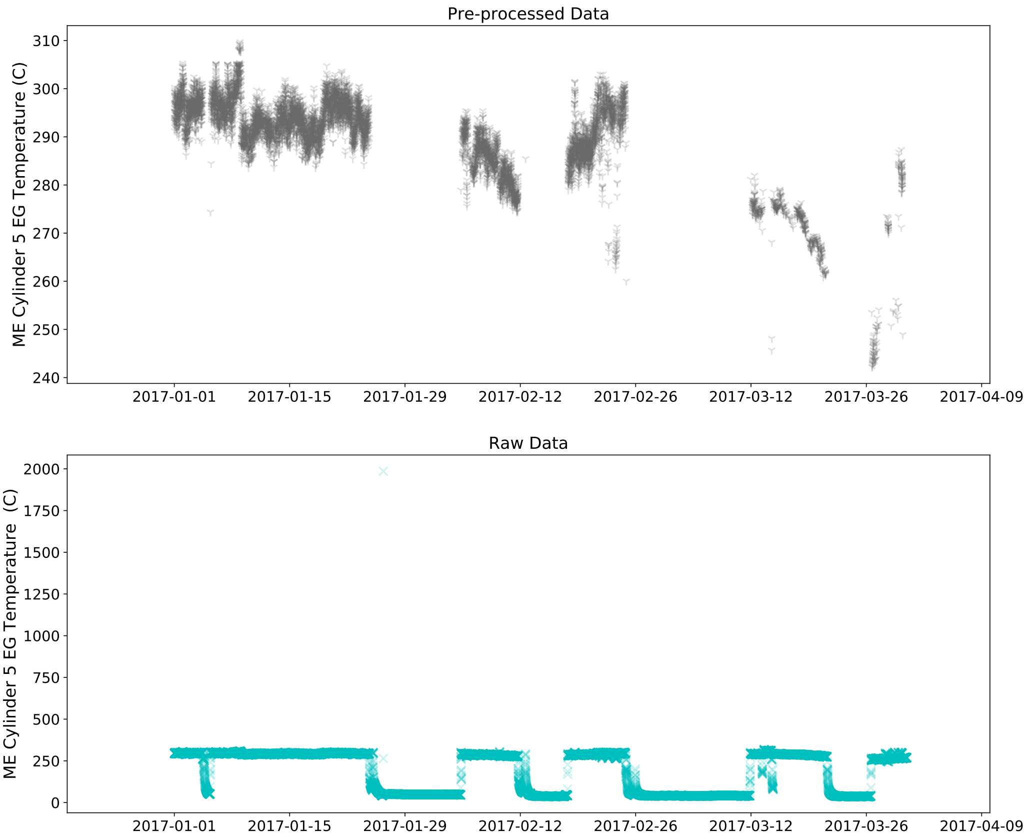

Figure D.3: Data checking result for ME cylinder 1 EG temperature

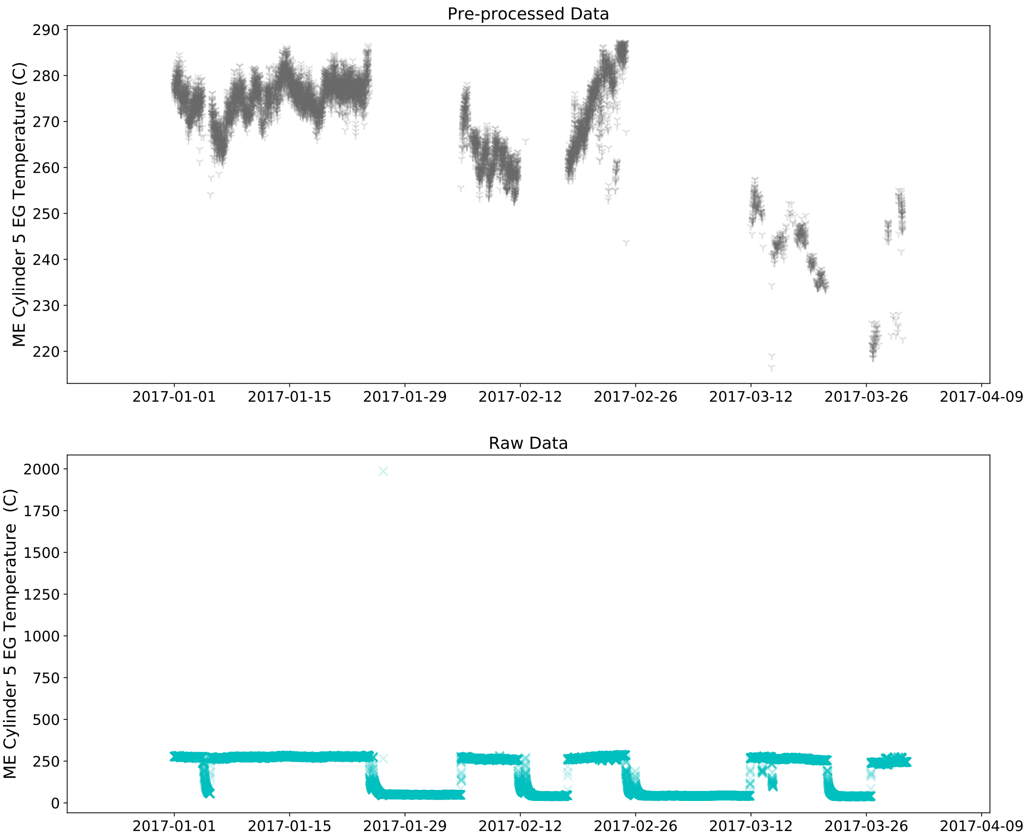

Figure D.4: Data checking result for ME cylinder 2 EG temperature

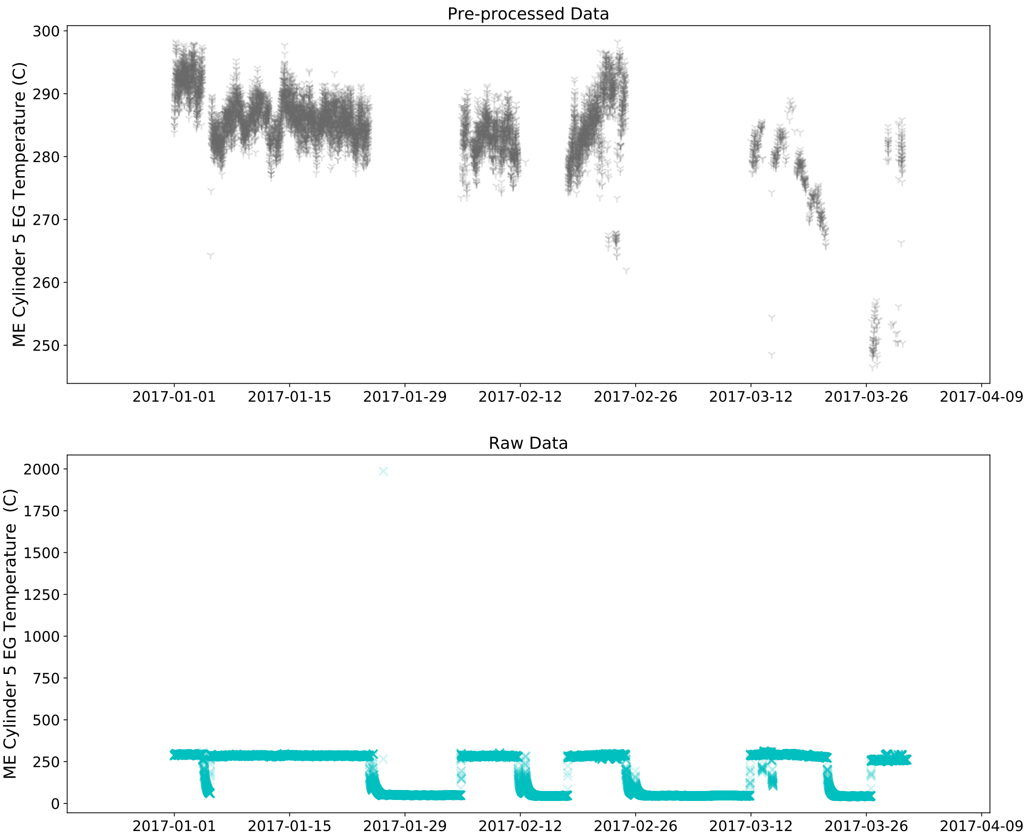

Figure D.5: Data checking result for ME cylinder 3 EG temperature

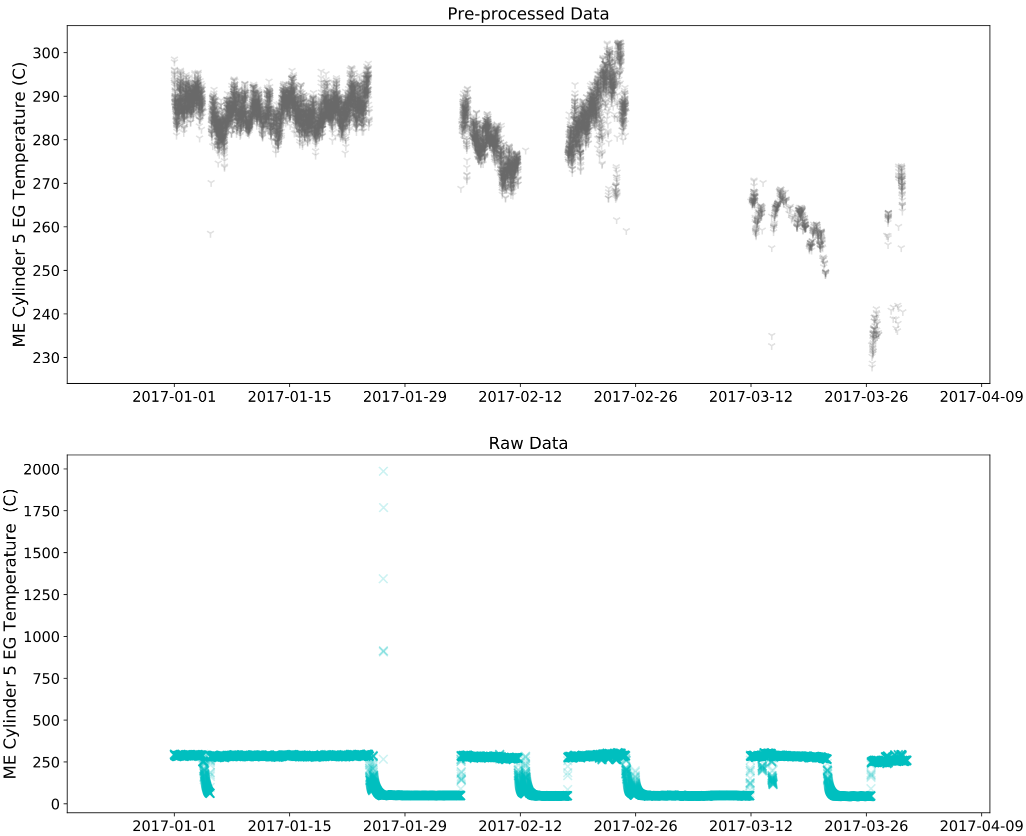

Figure D.6: Data checking result for ME cylinder 4 EG temperature

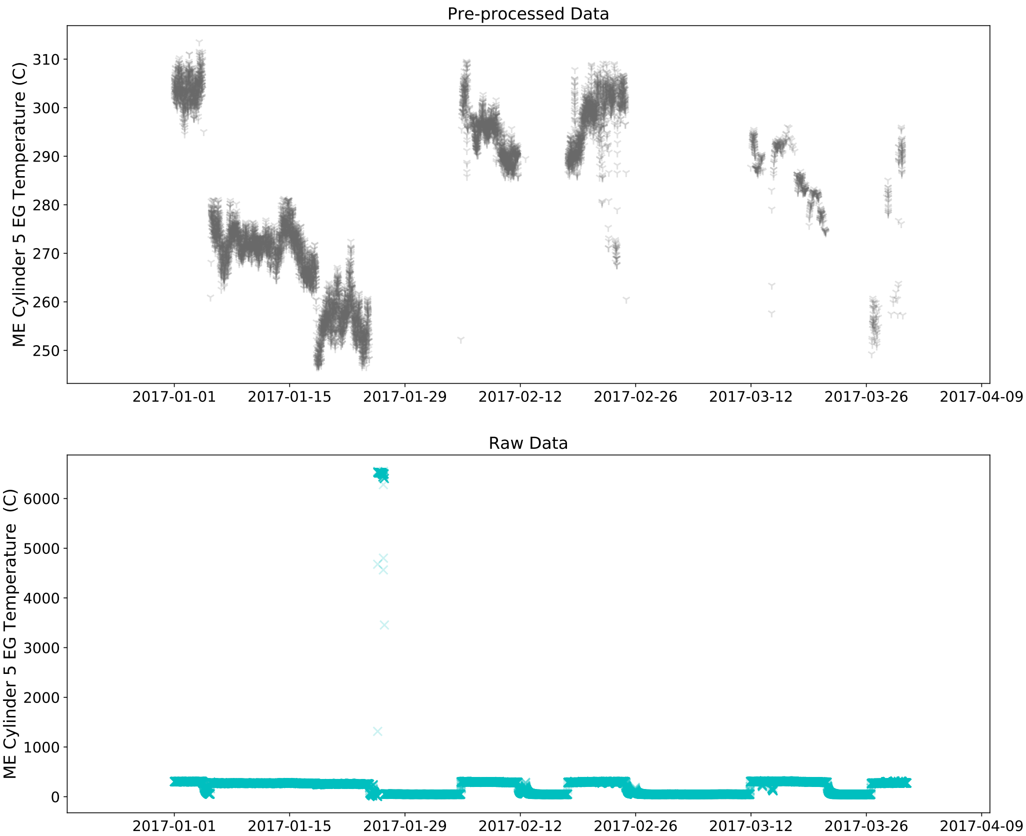

Figure D.7: Data checking result for ME cylinder 5 EG temperature