University of Strathclyde

Department of Naval Architecture, Ocean and Marine Engineering

Establishment of a novel predictive reliability assessment strategy for ship machinery

by

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A thesis presented in fulfilment of the requirements for the degree of Doctor of Philosophy

Glasgow, UK

2017

Declaration of Authenticity and Author's Rights

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: Konstantinos Dikis Date: 02 May 2017

The quotes below express lessons learnt through this trip to knowledge.

Hoping to motivate.

'Πάντα κατ' αριθμόν γίγνονται.' (Πυθαγόρας, 580-490 π.Χ., αρχαίος Έλληνας φιλόσοφος)

μετάφραση: Τα πάντα γίνονται σύμφωνα με αριθμούς.

'Number rules the universe.' (Pythagoras, 580-490 BC, ancient Greek philosopher)

'ἓν μόνον ἀγαθὸν εἶναι, τὴν ἐπιστήμην, καὶ ἓν μόνον κακόν, τὴν ἀμαθίαν.' (Σωκράτης, 470-399 π.Χ., αρχαίος Έλληνας φιλόσοφος)

μετάφραση: Υπάρχει ένα μόνο καλό , η γνώση και ένα κακό, η αμάθεια.

'There is only one good, knowledge and one evil, ignorance.' (Socrates, 470-399 BC, classical Greek philosopher)

'Ανέχου και απέχου.' (Επίκτητος, 50-138 μ.Χ., Έλληνας φιλόσοφος)

μετάφραση: να έχεις υπομονή και αντοχή.

'Well thriveth that well suffereth.' (Epictetus, 55 – 138 AD, Greek philosopher)

ACKNOWLEDGEMENTS

This great journey of research gave me the opportunity to collaborate with valuable colleagues, excellent co-researchers and create strong friendships. In my turn, I would like to express my special appreciation and thanks to all these.

Firstly, I would like to express my sincere gratitude to my supervisor Dr Iraklis Lazakis for the continuous support of my PhD study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis.

Besides my supervisor, I would like to thank and express my great honour to Dr Hany Elosta, for assisting and motivating me to start this research and development trip to knowledge as well as introducing me to my PhD thesis supervisor. My sincere gratefulness also goes to Mrs Thelma Will and all the administrative personnel of the department of NAOME for assisting me with the day-to-day details of my work at the University of Strathclyde.

Special thanks and appreciation to my family such as my mother Eleni, my father Nikos, and my brother Victor. Words cannot express how grateful I am to my mother and father for all of the sacrifices that you have made on my behalf. Your prayer for me was what sustained me thus far.

Additionally, I would like to take the opportunity to thank researchers/colleagues and friends who have supported me through the everyday struggle of my research work Elif Oguz, Yalcin Dalgic, Yigit Kemal Demirel, Sefer Anil Gunbeyaz, Kurt Mizzi, Yiannis Raptodimos, Christos Gkerekos, Christos Pollalis, Sotiris Chouliaras, Alexandros Priftis, George Deskas, and George Pitiris.

Finally yet importantly the present research work and PhD thesis could not have been accomplished without the support of the EU FP7 funded INCASS project as well as the department of NAOME loyalty studentship.

RESEARCH OUTPUTS

The outcomes of this research dissertation are associated to both research and industrial/commercial practices. Hence, during this exploration and development multiple dissemination activities are considered and taken place such as journal articles, conference proceedings and European Union reports and workshops. A sample of these dissemination activities has been listed below.

Journal publications

Dikis, K. & Lazakis, I. 2016. Dynamic Risk Assessment for Enhanced Ship Machinery Safety. Special issue, Journal of Ocean Engineering: Maritime Safety and Operations.

Lazakis, I., Dikis, K., Michala, A. L. & Theotokatos, G. 2016. Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. Transportation Research Procedia, 14, 1679-1688.

Conference publications

Dikis, K. & Lazakis, I. 2016. Dynamic Risk Assessment for Enhanced Ship Machinery Safety. In: Lazakis, I. Theotokatos, G., ed. Proceedings of MSO2016, International Conference on Maritime Safety and Operations (MSO2016), 13-14 October 2016 Glasgow, United Kingdom.

Dikis, K., Lazakis, I. & Michala, A. L. 2016. Dynamic risk and reliability assessment of ship machinery for decision making. European Safety and Reliability (ESREL2016). 25-29 September 2016 Glasgow, United Kingdom.

Lazakis, I., Dikis, K. & Michala, A. L. 2016. Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. Practical design of ships and other floating structures (PRADS2016). 4-8 September 2016 Copenhagen, Denmark.

Dikis, K. Lazakis, I. 2016. Dynamic Risk and Reliability Assessment of Ship Machinery and Equipment. International Society of Offshore and Polar Engineers (ISOPE2016). 26 June – 02 July 2016 Rhodes (Rodos), Greece.

Lazakis, I., Dikis, K., Michala, A. L. & Theotokatos, G. 2016. Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. 6th Transport Research Arena (TRA2016). 18-21 April 2016 Warsaw, Poland.

Dikis, K., Lazakis, I., Theotokatos, G. & Tanneberger, K. 2015. Increasing Ship Machinery Energy Efficiency by Dynamic Condition Monitoring Maintenance Strategy. Shipping in Changing Climates (SCC2016). 24-26 November 2015 Glasgow, United Kingdom.

Lazakis, I., Dikis, K. & Theotokatos, G. 2015. Inspection and Maintenance Platform for Enhanced Ship Safety. World Maritime Technology Conference (WMTC2015). 3-7 November 2015 Providence, Rhode Island, USA.

Dikis, K., Lazakis, I. & Theotokatos, G. 2015. Dynamic Reliability Analysis Tool for Ship Machinery Maintenance. International Maritime Association of the Mediterranean (IMAM2015). 21-24 September 2015 Pula, Croatia.

Lazakis, I., Theotokatos, G., Barltrop, N. & Dikis, K. 2015. Inspection Capabilities for Enhanced Ship Safety. International Maritime Association of the Mediterranean (IMAM2015). 21-24 September 2015 Pula, Croatia.

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ABBREVIATIONS

ABS	American Bureau of Shipping
AE	Acoustic Emissions
AI	Artificial Intelligence
ALARP	As Low As Reasonable Practicable
AM	Asset Management
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
AWT	Analytic Wavelet Transform
BBN	Bayesian Belief Network
BIP	Bayesian-Inference-based Probability
BS/ISO	British Standards / International Standards Organisation
BV	Bureau Veritas
CAP	Condition Assessment Programs
CAS	Condition Assessment Scheme
CBA	Cost Benefit Analysis
CBM	Condition Based Maintenance
CIM	Computer Integrated Manufacturing
CM	Condition Monitoring
CMMS	Computerised Maintenance Management Systems
CW	Cooling Water
CWT	Continuous Wavelet Transform
D/G	Diesel Generator
DAG	Direct Acyclic Graph
DBBN	Dynamic Bayesian Belief Networks
DFTA	Dynamic Fault Tree Analysis
DNV-GL	Det Norske Veritas - Germanischer Lloyd

DSS	Decision Support System
DTMC	Discrete Time Markov Chain
DWT	Discrete Wavelet Transform
E/R	Engine Room
EA	Evolutionary Algorithm
EM	Expectation Maximisation algorithm
ES	Expert Systems
ETA	Event Tree Analysis
FDD	Fault Detection and Diagnosis
FFT	Fast Fourier Transform
FL	Fuzzy Linguistic
FM	Failure Mode
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes, Effects and Criticality Analysis
FO	Fuel Oil
FPSO	Floating Production Storage Offloading
FR	Failure Rate
FrFT	Fractional Fourier Transform
FSA	Formal Safety Assessment
GA	Genetic Algorithms
GMM	Gaussian Mixture Model
GT	Gross Tonnage
GUI	Graphical User Interface
HAZID	Hazard Identification
HAZOP	Hazard and Operability study
HMM	Hidden Markov Model
HSE	Health Safety Executive
I/O	Input/Output
IACS	International Association of Classification Societies
ICE	Internal Combustion Engines
IDE	Integrated Development Environment
IMO	International Maritime Organization

INCASS	Inspection Capabilities for Enhanced Ship Safety
IR	Infrared
ISM code	International Safety Management code
ISO	International Standards Organisation
IT	Information Technology
IUMI	International Union of Marine Insurance
IVI	Internal Visual Inspection
JCFW	Jacket Cooling Fresh Water
JIT	Just-In-Time
KDD	Knowledge Discovery in Databases
KPI	Key Performance Indicator
LAD	Logical Analysis of Data
LO	Lube Oil
LR	Lloyd's Register
LSE	Least Squares Estimate
M/E	Main Engine
MC	Markov Chains
MCDM	Multiple Criteria Decision Making
MINOAS	Marine Inspection Robotic Assistant System
MoD	Ministry of Defence
MRA	Machinery Risk/Reliability Analysis
MTBF	Mean Time Before Failure
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
NII	Non-Instructive Inspection
NKK	Nippon Kaiji Kyokai
NN	Neural Networks
O&M	Organisation and Maintenance
OCIMF	Oil Companies International Marine Forum
OEM	Original Equipment Manufacturer
OOP	Object Oriented Programming
OREDA	Offshore Reliability Database

OS	Operating System
PDCA	Plan, Do, Correct and Act
PDF	Probability Density Function
PdM	Predictive Maintenance
PHM	Prognostics and Health Management
PM	Preventive Maintenance
PMRA	Probabilistic Machinery Reliability Assessment
PMS	Planned Maintenance Systems
PoF	Probability of Failure
PoO	Probability of Occurrence
PoW	Probability of Working
PRA	Probabilistic Risk Assessment
PSA	Probabilistic Safety Analysis
PSV	Pressure Safety Valves
QRA	Quantitative Risk Analysis
R&D	Research and Development
RAMS	Reliability Availability Maintenance and Safety
RBI	Risk Based Inspection
RBM	Risk Based Maintenance
RCM	Reliability Centred Maintenance
RIMAP	Risk-Based Inspection and Maintenance for European Industries
RISPECT	Risk Based Expert System for Through-Life Ship Structural Inspection and Maintenance and New-Build Ship Structural Design
RPM	Revolutions Per Minute
RS	Rough Set
RUL	Remaining Useful Life
SQL	Structured Query Language
STFT	Short-Time Fourier Transform
SVM	Support Vector Machines
SWIFT	Structured What-If Technique

T/C	Turbocharger
TCI	Technical Condition Index
TEI	Total Employee Involvement
TMSA	Tanker Management Self-Assessment
TPM	Total Productive Maintenance
TQC	Total Quality Control
TQM	Total Quality Management
TTF	Time To Failure
UK	United Kingdom
USD	United States Dollar
UTM	Ultrasonic Thickness Measurements
VBM	Vibration Based Maintenance
WPT	Wavelet Packet Transform
WVD	Wigner-Ville Distribution
XML	Extensible Mark-up Language

NOMENCLATURE

C_1, C_2, C_n	Component involved in reliability assessment
e_1, e_2, e_n	Event involved in reliability assessment (failure)
t	time
ds	dataset
i	position of object in ds
n	maximum number of total recorded objects
μ_{ds}	mean value of ds
σ_{ds}	standard deviation of ds
k	number of clusters
ds_1	data set of cluster 1
ds_2	data set of cluster 2
μ_{ds1L}	data set ds, cluster 1, lower mean value
μ_{ds1H}	data set ds, cluster 1, higher mean value
μ_{ds2L}	data set ds, cluster 2, lower mean value
μ_{ds2H}	data set ds, cluster 2, higher mean value
$P_{ds}(w_t)$	Probability of working state for dataset ds at t timeframe
$P_{ds}(f_t)$	Probability of failing state for dataset ds at t timeframe
j	total number of clusters
$c_i^{(j)}$	clustered data point i belonging to j^{th} cluster
e_{n1}	event involved due to parameter of first node n_1
T	component lifetime
λ	failure rate function
fm	failure mode
m	maximum number of components
fm_{iSUM}	summarised percentage of occurrence of each failure mode (including all involved components)

c_{ij}	failure rate index per component
p_{cij}	recorded failure proportion per component per total failure rate of each mode
fm_{iOP}	failure mode in relation to system aggregated time t
c_{jSUM}	component's failure rate proportion out of all involved components in a subsystem
λ_{ij}	failure rate of component per failure mode in aggregated time t
ds_j	data set clusters (j: 1, 2) for cluster 1 and 2
d^2_{dsj}	distance calculated utilising squared Euclidean formula for both involved clusters
α	proportion of clustered observations

ABSTRACT

There is no doubt that recent years, maritime industry is moving forward to novel and sophisticated inspection and maintenance practices. Nowadays maintenance is encountered as an operational method, which can be employed both as a profit generating process and a cost reduction budget centre through an enhanced Operation and Maintenance (O&M) strategy. In the first place, a flexible framework to be applicable on complex system level of machinery can be introduced towards ship maintenance scheduling of systems, subsystems and components. This holistic inspection and maintenance notion should be implemented by integrating different strategies, methodologies, technologies and tools, suitably selected by fulfilling the requirements of the selected ship systems. In this thesis, an innovative maintenance strategy for ship machinery is proposed, namely the Probabilistic Machinery Reliability Assessment (PMRA) strategy focusing towards the reliability and safety enhancement of main systems, subsystems and maintainable units and components. In this respect, the combination of a data mining method (k-means), the manufacturer safety aspects, the dynamic state modelling (Markov Chains), the probabilistic predictive reliability assessment (Bayesian Belief Networks) and the qualitative decision making (Failure Modes and Effects Analysis) is employed encompassing the benefits of qualitative and quantitative reliability assessment. PMRA has been clearly demonstrated in two case studies applied on offshore platform oil and gas and selected ship machinery. The results are used to identify the most unreliability systems, subsystems and components, while advising suitable practical inspection and maintenance activities. The proposed PMRA strategy is also tested in a flexible sensitivity analysis scheme.

Keywords: Maintenance, maritime industry, reliability, dynamic state modelling, data mining, Bayesian Belief Network (BBN)

1. INTRODUCTION

1.1. Chapter outline

In this Chapter, the dissertation background is demonstrated. Initially, a brief introduction into the shipping industry is presented and crucial notion definitions are identified. Furthermore, the maritime transportation challenges are presented. This Chapter layouts the content and the research structure introducing the reader into the essence of the thesis.

1.2. The background of maritime industry

For hundreds of years, shipping serves the global economy by transporting goods all over the world. Nowadays, shipping provides a sophisticated transportation mode to every part of the globe. Maritime industry incorporates complex technical, operational and economic aspects through a competitive international trade.

Historical records of the world fleet are suitable for identifying the past and current shipping industry growth through time. Furthermore, historical records can be utilised in order to scrutinise and examine future prospects of the industry. Therefore, International Union of Marine Insurance (IUMI, 2016b) presents recent records of the average age of the world fleet considering the tanker, bulk carrier, container and gas carrier ship types.

The reported figures for the period of 2000-2015 as well as the predictions for 2016-2018 reveal an increase of the average age of the world fleet with respect to container and tanker ship types. Nevertheless, bulk carrier and liquid ship types declare a decrease of the average age of these vessel types. On the other hand, the overall world fleet average age shows an almost stable ship lifecycle of approximately 20 years.

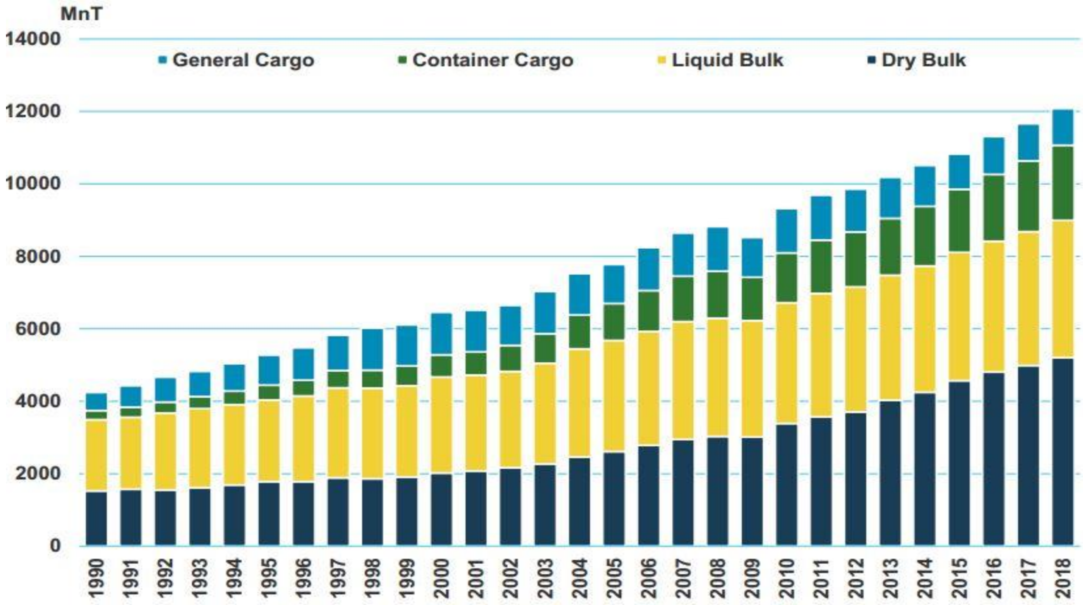

Figure 1.1 Seaborne trade demand for transport (IUMI, 2016a)

Notwithstanding the almost stable average age of the world fleet, historical figures and statistical predictions confirm the raise of the global seaborne tonnage demand (IUMI, 2016a). This increased trade demand verifies the consecutive global seaborne growth, while ensuring the shipping market progress and development. Additionally, the expansion of tonnage demand assures the maritime industry stability through time, especially for merchant ships such as dry bulk, liquid bulk and container as shown in Figure 1.1. The greatest tonnage increase demand since 1990s is recorded and forecasted for dry and container cargos respectively. However, the second largest seaborne trade demand for transportation is recorded for liquid bulk, while the demand expansion seems almost steady over the past decades. Hence, the overall merchant ship tonnage demand increased through the past years, especially the former decade. All of the above records, and their continuous increase, clearly indicate that shipping plays a significant role in the transportation of commodities worldwide.

Moreover, the world fleet has to be examined with respect to the available gross tonnage by ship type. In other words, the worldwide ship supply has to be assessed and integrated with the historical records and predictions of the seaborne trade demand. The combination of these two sources, such as seaborne trade supply and demand, will provide a respectful indication of existing and future market growth expectations. According to recent statistical data (Equasis, 2014), 80% of the world gross tonnage of ships consists of bulk carriers (35.9%), oil and chemical tankers (25.7%) and container ships (18.4%). The remaining 20% of world fleet in gross tonnage includes gas tankers, Ro-Ro cargo, general cargo, offshore vessels and passenger ship types. These historical recorded figures, integrated with the seaborne trade demand for transportation, demonstrate the global commodity trade and the ship type market growth. As the maritime industry growth and expansion is proven on specific ship types such as bulk carrier, tanker and container ships, this historical research sets the grounds for operational and functional concern investigation.

As stated by Hunt (1995), making decisions under conditions of risk and uncertainty has always been the shipowners' challenge. Expanding this statement, the author's belief is that risk and control of uncertainty as well as safety awareness is the responsibility of all involved maritime stakeholders contributing actively towards safety enhancement. As a matter of fact, the development and establishment of safety regulatory frameworks in the maritime industry is led by lessons learnt from hazardous incidents and accidents. Several marine and offshore casualties took place in the last decades such as Titanic (1911), Derbyshire (1980), Herald of Free Enterprise (1987), Piper Alpha (1988), Exxon Valdez (1989), Scandinavian Star (1991), Estonia (1994), Petrobras P-36 (2001), Star Princess (2006), Deepwater Horizon (2010), Costa Concordia (2012), among others.

The most recent casualty statistics for the period 2000-2014, published by the International Union of Marine Insurance (IUMI, 2015), present that the causes leading towards total or serious losses are listed as weather, grounding, fire/explosion, collision/contact, hull damage and machinery failure. The dominant causes triggering serious losses are recorded among machinery damage, grounding and collision/contact (Figure 1.2). Especially, machinery failure reports over 35% of all losses for the period. Hence, more than one third of the losses caused due to machinery failure. It is worth noting than the losses since 2000-2004 period are negligibly reduced by approximately 1%.

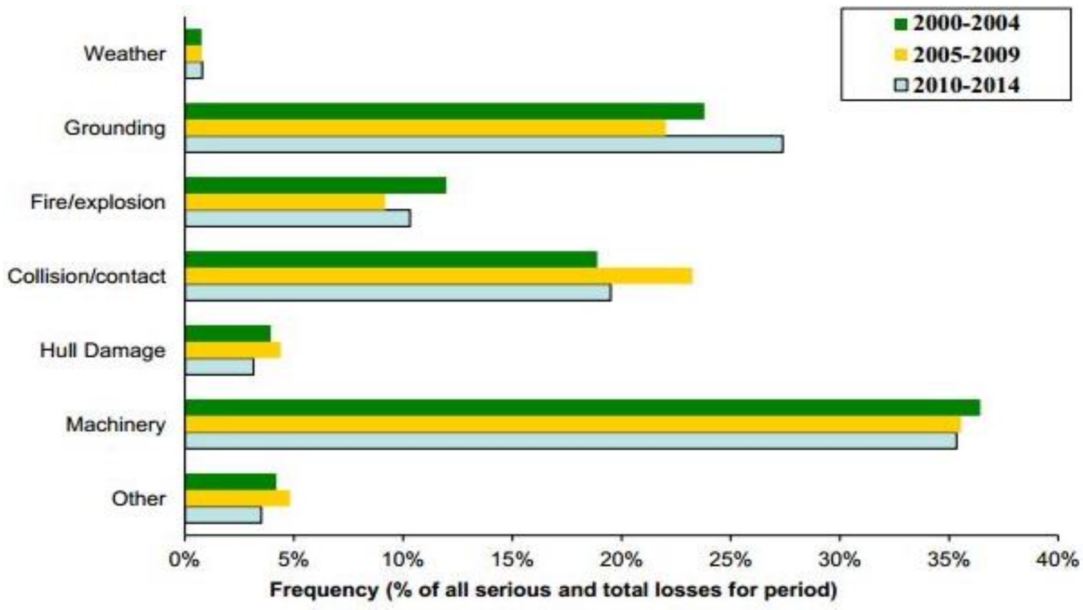

Figure 1.2 Ship serious losses by cause for all vessel types 2000-2014 vessels 500 GT and above (IUMI, 2015)

On the other hand, IUMI (2016b) published the latest casualty and world fleet statistics. The causes of total ship losses for vessels larger than 500 GT list weather, grounding, fire/explosion, collision/contact and hull and machinery damage as shown in Figure 1.3.

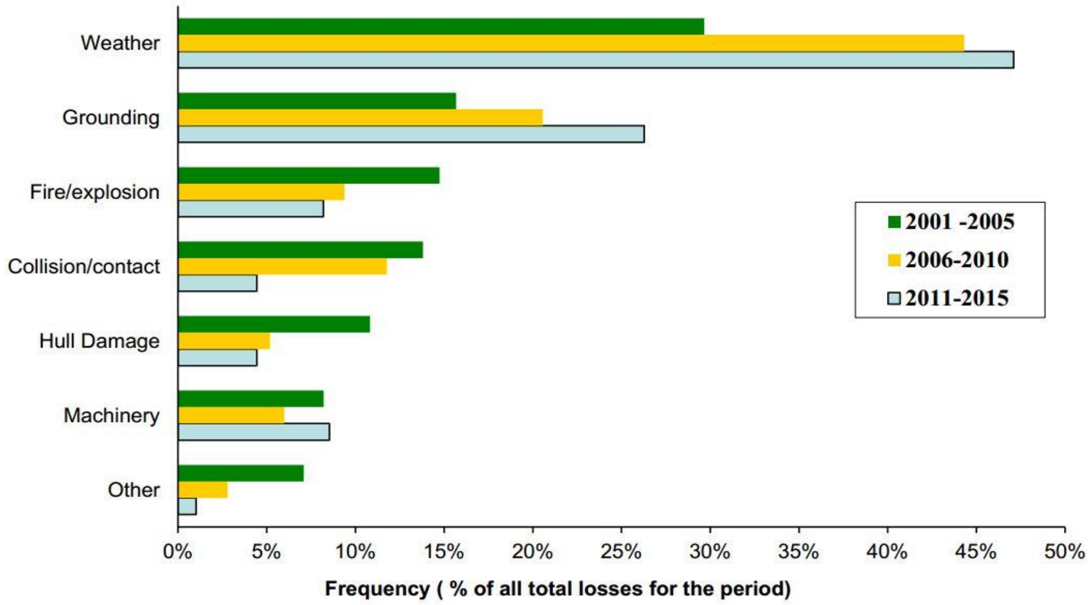

Figure 1.3 Ship total losses by cause for all vessel types 2000-2014 vessels 500 GT and above (IUMI, 2016b)

Hence, ship machinery and systems are vital and leading reason for serious ship losses as shown from the latest records. It is crucial to highlight that machinery failures causing total ship loss are enormously less compared to serious ship losses, however they present an increase the last 5 years. Additionally, Allianz (2015) publishes that major cause of loss leading to marine claims higher than €1.0m is related to machinery damage and breakdowns. In the UK alone of all hull and machinery claims, 60% is caused due to machinery damage, with the majority of these attributed due to human negligence.

Specifically oriented towards the causes of oil spills, as these affect the environment as well as humans' lives, International Maritime Organization (IMO) reports that most spills from tanker ships are a result of routine operations and human errors such as loading, discharging and bunkering (IMO, 2012). Furthermore, IMO clarifies that the major reasons, causing oil spills, are related to machinery failures, hull failures, groundings, collisions and explosions respectively. The existing brief research reveals that the majority of incidents or accidents occurred due to machinery failure and/or human errors in the onboard operations. Hence, the necessity of establishing inspection and maintenance standardisation methods that can effectively control the risk of machinery failure is needed. Furthermore, automation in shipping operational applications and onboard functionalities targeting human error elimination should be considered as leading goal.

Before exploring the latest inspection and maintenance methodologies and applications in maritime industry, it is crucial to identify the functionality of maintenance. In this respect, several definitions are provided by various authors, summarising the notion that maintenance is a set of technical, administrative and managerial actions targeting to retain or restore the state of a system to function as required (Dikis et al., 2014). Furthermore, appropriately selected inspection and maintenance practices will enhance ship machinery reliability and availability by ensuring safety and functionality. Especially focused towards safety, maintenace impact affects the environment, humans such as crew members and passengers as well as assets, the ship herself and third parties' properties.

Moreover, parametres such as reliability, availability, risk of failure, uncertainty and machinery downtime also affect operational expenses. Hence, control of technical, managerial and costs aspects, through selected inspection and maintenance activities, contributes towards enhancement of business reputation by providing smooth transportation of commodities services and eliminating commercial penalties. In further, nowadays maintenance is encountered as an operational method, which can be employed both as a profit generating process and a cost reduction budget centre through an enhanced Operation and Maintenance (O&M) strategy.

Inspection and maintenance implementation in industry takes place at different levels, considering multiple aspects, functionalities and requirements. Practices are established through strategies and methodologies. Their applicability and implementation is illustrated through technologies and tools. Furthermore, the necessity for standardisation of inspection and maintenance practices is proven through the continuous development towards maintenance guidelines and regulations. These standardisation guidelines are introduced by British and European Standards (BS) and International Organisation for Standardisation (ISO) and regulations established by regulatory bodies such as International Maritime Organization (IMO) and International Association of Classification Societies (IACS).

As identified in literature, inspection and maintenance activities have been reformed from reactive to proactive. Hence, the notion of failure prevention and risk control is introduced. Specifically in shipping industry, where vessel availability and accessibility are vital. This maintenance reformation is achieved through maintenance strategies such as corrective, preventive and most recent predictive strategy. The implementation strategies in industry takes place by utilising multiple maintenance methodologies. The most known can be classified among Reliability Centred Maintenance (RCM), Total Productive Maintenance (TPM), Total Quality Management (TQM), Maintenance Risk Based Methodologies for Inspection and Maintenance (i.e. RBI and RBM respectively) as well as Asset Management (AM) and Computerised Maintenance Management System (CMMS). The maintenance methodologies' investigation leads to the latest one Condition Based Maintenance (CBM). The investigation of inspection and maintenance practices is performed by assessing research and applications from multiple industries and transportation modes. These involve aviation, nuclear, offshore energy and oil and gas, manufacturing, rail and automotive.

Inspection and maintenance practices are developed through time by introducing and enabling control and assessment of factors such as reliability, criticality with respect to operational priorities, production and quality. The notion of risk assessment is implemented in both inspection and maintenance. Likewise, inspection automation and computerised approaches are introduced targeting on-condition assessment in the latest CBM methodology.

The up-to-date inspection and maintenance approaches are the result of decades of experience and efforts of a number of stakeholders such as ship owners, operators, service providers, classification societies, shipyards and manufacturers. Additionally, stakeholders such as insurers, flag states, ports, cargo owners, charterers as well as research developers and academics contributed in this effort by introducing solid and innovative inspection practices.

Moreover, collaborations of various maritime stakeholders focusing towards inspection and maintenance automation and safety enhancement are introduced through multiple European funded research projects such as MINOAS (2012), RISPECT (2013) and INCASS (2014a). Hence, research and development, concerning ship operations' automation, inspection and maintenance practices and safety enhancement, is under continuous investigation and novel practices are assessed.

On the other hand, market competition has grown gradually due to continuous increase in production demand, resulting in the implementation of mechanised and automated systems. This enhances targeted appropriate delivery time, quality and quantity of supply. The automation of operational processes and equipment mechanisation forces the development and implementation of maintenance functions and Asset Management (AM) control in order to manage failure uncertainty, reduce risk and enhance safety.

Nowadays, in maritime industry, maintenance structure is transformed from budget gain perspective to investment for continuous and reliable asset service. It is commonly found that inspection and maintenance departments in shipping companies are the largest in work force and expense. Hence, there is available potential for development of new inspection and maintenance practices.

Safety requirements, operational demand and inspection and maintenance concerns have to be considered as prerequisites ensuring the ultimate performance. A unified , robust and flexible risk-based approach has not been introduced yet in the maritime field for identifying inspection and maintenance schedules and activities by ensuring safety of personnel, environment and property (Rizzo and Nigro, 2008). International Safety Management (ISM) Code from International Maritime Organisation (IMO) and Tanker Management and Self-Assessment (TMSA) from Oil Companies International Marine Forum (OCIMF) are risk-based practices offering international standards for the safe management and operation of ships and for pollution prevention, however they provide minimum requirements.

Furthermore, it is the author's opinion that innovative and automated unified risk-based practices should be established in maritime transportation mode, aiming at safety enhancement, unavailability reduction and control of uncertainty, which leads to hazardous consequences. Moreover, by applying the appropriate maintenance sequence onboard a ship, cost reduction of inspection, maintenance and operational expenses can be achieved.

This research study contributes within the major vessel fleet including merchant ships, passenger vessels and general service vessels. Ships utilise similar installed machinery onboard enabling the implementation of unified inspection and maintenance framework. These functional and practical similarities set the grounds for introducing a flexible framework for tackling the challenges concerning inspection and maintenance practices of selected machinery. The dissertation Chapter layout is shown in the next section that will introduce the major research areas and achievements.

1.3. Dissertation layout

The present thesis consists of ten Chapters as outlined in Figure 1.4. Each chapter is included in the outline below allowing the reader to identify what can be expected from each chapter, by introducing key information. Each chapter includes a summary section highlighting key achievements and novelties. The thesis layout is shown in Figure 1.4 below.

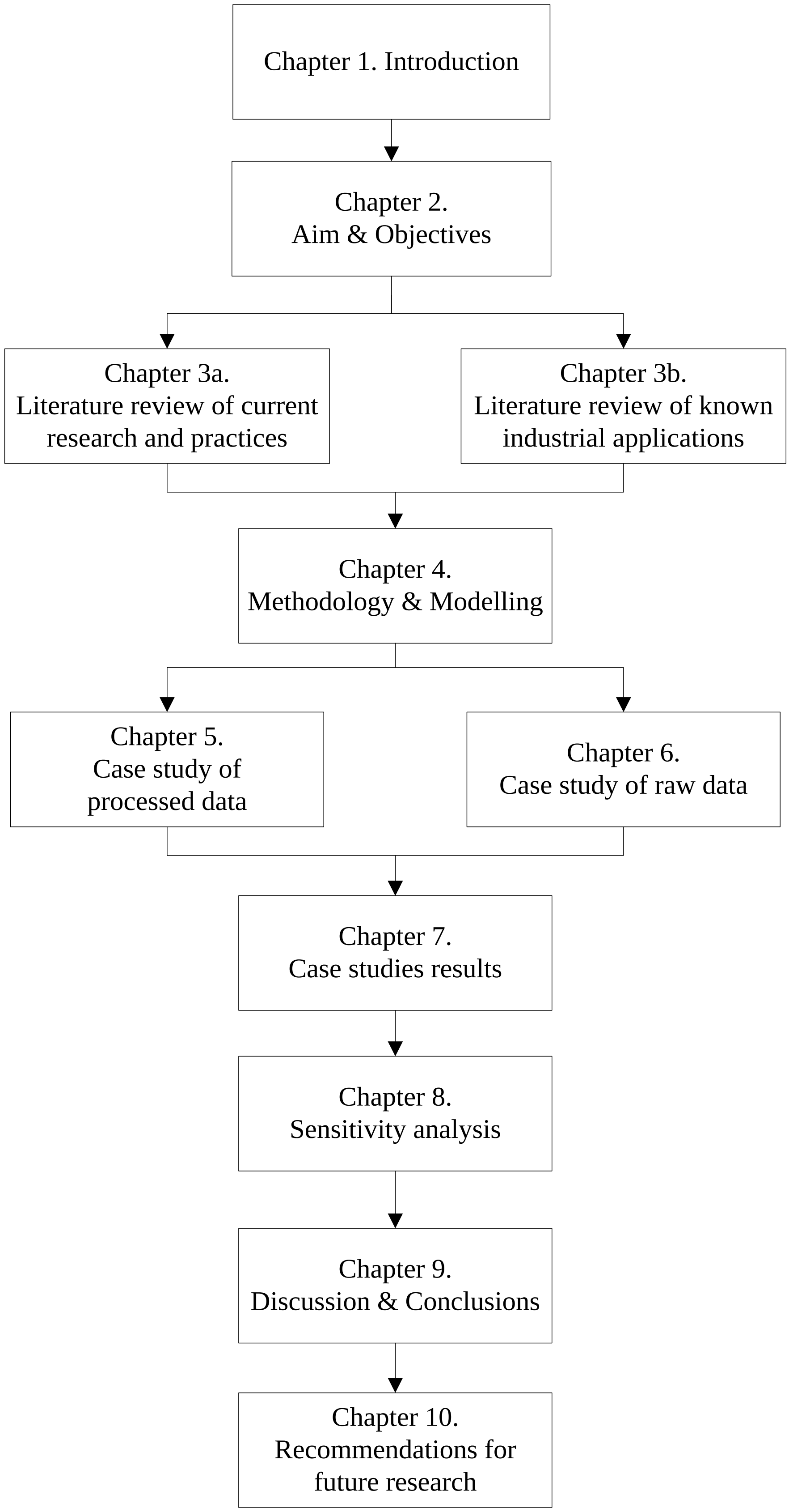

Figure 1.4 Chapters of thesis layout

Chapter 1. Introduction

The first chapter sets out the essence of the thesis by introducing the background as well as the motivation for this proposed and developed research work. This chapter briefly introduces the shipping industry by exposing its growth through time, operational and decision challenges and concerns to be taken into account.

Chapter 2. Aim & objectives

This chapter sets the main aim that will be achieved through the performed research. The objectives present the major challenging achievements reflecting the foremost study aim.

Chapter 3. Literature review

The research background through an extensive literature review is presented in Chapter 3. This chapter reviews the latest literature on maintenance strategies, methodologies and technologies of ship's main and auxiliary machinery systems oriented towards research and industrial applications. The research considers European standards, industry guidelines as well as the International Maritime Organization (IMO) regulatory framework. The review aims to present the significance of maintenance and Asset Management (AM). It assesses technologies and optimization research approaches by identifying research gaps and motivating further improvement. The investigation takes place in maintenance industrial implementation timeline focused on research optimization tools of diagnostics and the latest prognostics for Condition Monitoring (CM) technologies.

Chapter 4. Methodology and modelling

As the evaluation of the existing novel literature review led to the identifying of research gaps, this chapter is focused towards the theoretical framework. The considered and developed tools and methods are demonstrated by introducing the modelling principles. The functionality and novelties of the methodology are explained in depth by clarifying design assumptions.

Chapter 5. Case study of processed data

The fifth chapter evaluates the proposed and developed reliability assessment methodology through multiple systems applied in a case study. The implementation involves multiple marine machinery units such as a marine diesel engine, turbocharger and various electrically and steam powered driven pumps. This chapter's target is to evaluate the risk analysis tool's ability of predicting the reliability performance on system, subsystem and component levels. Processed input data are sourced by the Offshore Reliability Database (OREDA).

Chapter 6. Case study of raw recorded input data

Complementing the applicability of the previous chapter, this chapter aims to assess the overall developed research methodology through an application including statistical data clustering and classification, Probabilistic Risk Assessment (PRA) and decision making. The predictive reliability assessment framework utilises raw onboard collected input data. This chapter establishes the overall risk and reliability framework as well as the decision support system by introducing innovative achievements, considerations, challenges and key assumptions.

Chapter 7. Case studies results

In this chapter, particular focus is given to the case studies results. An in depth analysis takes place assessing the outcomes of each part of the proposed methodology as an independent tool as well as integrated within the demonstrated framework. The results and their assessment aim to present and validate the applicability and accuracy of the reliability assessment methodology.

Chapter 8. Sensitivity analysis

The sensitivity analysis explores and proves that the suggested maintenance strategy performs efficiently under different operating conditions, which are also important for the testing process of the developed methodology.

Chapter 9. Conclusions

An in depth summary of the key learning points of this research is presented in conclusions chapter. Furthermore, the contribution to knowledge and science through theoretical and practical aspects is demonstrated by highlighting the research novelty and its results.

Chapter 10. Recommendations for future research

The performed research contributes directly to science as well as to industry. In this respect, this chapter highlights future research suggestions setting the ground and motivating researchers and professionals for further research work. These recommendations provide observations and considerations for further research and development in both scientific and industrial features.

1.4. Chapter summary

In this Chapter, the introductory section presents the potential of further growth and expansion of maritime industry and world trade demand respectively. Furthermore, this Chapter highlights the importance of inspection and maintenance operations by ensuring safety onboard and ship machinery availability, hence, profitable business functioning. The various challenges in shipping industry are also demonstrated and this dissertation aims to bring solutions at some points of these difficulties. Thereafter, the Chapter thesis outline is provided, allowing the reader to identify what to expect from each Chapter. The Chapter allocation is structured in such a way to be smooth for the reader and introduce the topic. Lastly, dissemination activities performed during the development of this research are listed.

2. AIM & OBJECTIVES

2.1. Chapter outline

The second Chapter presents the identified main aim and objectives of the present thesis. The planned research and development tasks are listed and described next.

2.2. Aim & objectives

The main aim of this thesis is to tackle the issue of optimal ship machinery maintenance strategy by establishing a novel dynamic, predictive, probabilistic reliability assessment strategy. The objectives related to the above mentioned aim are given below:

1. Investigate and critically review the existing maintenance strategies, methodologies and applied approaches in literature by assessing the state-of-the-art of Research and Development (R&D) and industrial/commercial applications and define similarities, advantages, limitations and research gaps.
2. Propose an innovative maintenance strategy for ship machinery by establishing novel data analysis methods as well as forecasting reliability assessment modelling.
3. Develop an innovative and adaptable predictive reliability assessment tool for processed data.
4. Propose a methodology for raw input data analysis to transform data into probabilistic measures that can be utilised by the developed reliability tool proposed above.
5. Demonstrate the applicability of the developed tools on selected ship machinery by utilising processed as well as raw onboard recorded input data.

6. Verify and test the suggested strategy through a Sensitivity Analysis (SA) scheme.

2.3. Chapter summary

In this Chapter, the research aim and the related objectives are identified by setting the principles of the planned work tasks and expected achievements. The specified thesis aim and objectives will be addressed in the forthcoming Chapters. Hence, the next Chapter demonstrates the literature and critical review that has taken place for this study identifying existing research practices, industrial applications and research gaps.

3. CRITICAL LITERATURE REVIEW

3.1. Chapter outline

In this Chapter, the literature review is demonstrated incorporating research background considerations and tendencies. The research topic of this dissertation is oriented towards inspection and maintenance strategies and practices for ship machinery. Hence, the present research and development awareness contributes in research science as well as industry and commercial applications. This Chapter examines inspection and maintenance field with respect to strategies, guidelines and regulations, methodologies, recent condition monitoring technologies as well as maintenance optimisation tools. Therefore, it refers to efforts demonstrating the evolution and reformation of maintenance from corrective to preventive and then to latest predictive strategy. In parallel, the significance of inspection and maintenance operations is ensured by revising up-to-date guidelines and regulatory bodies' standardisation frameworks. Furthermore, major inspection and maintenance methodologies are assessed taking into account factors such as reliability, production control, quality assurance, risk based and on-condition assessment as well as automation and computerised asset management. Furthermore, this Chapter, as shown in Figure 3.1, clarifies research gaps related to the latest tendencies of machinery maintenance condition monitoring. It identifies data mining methods, well known and innovative reliability assessment tools by leading to decision making and prioritisation tools. Moreover, the second section outlines in a generic form the pillar of the research methodology. All of the above performed research targets to obtain a clear perception of the existing inspection and maintenance practices by identifying existing gaps and introducing the innovative maintenance framework suggested in this thesis.

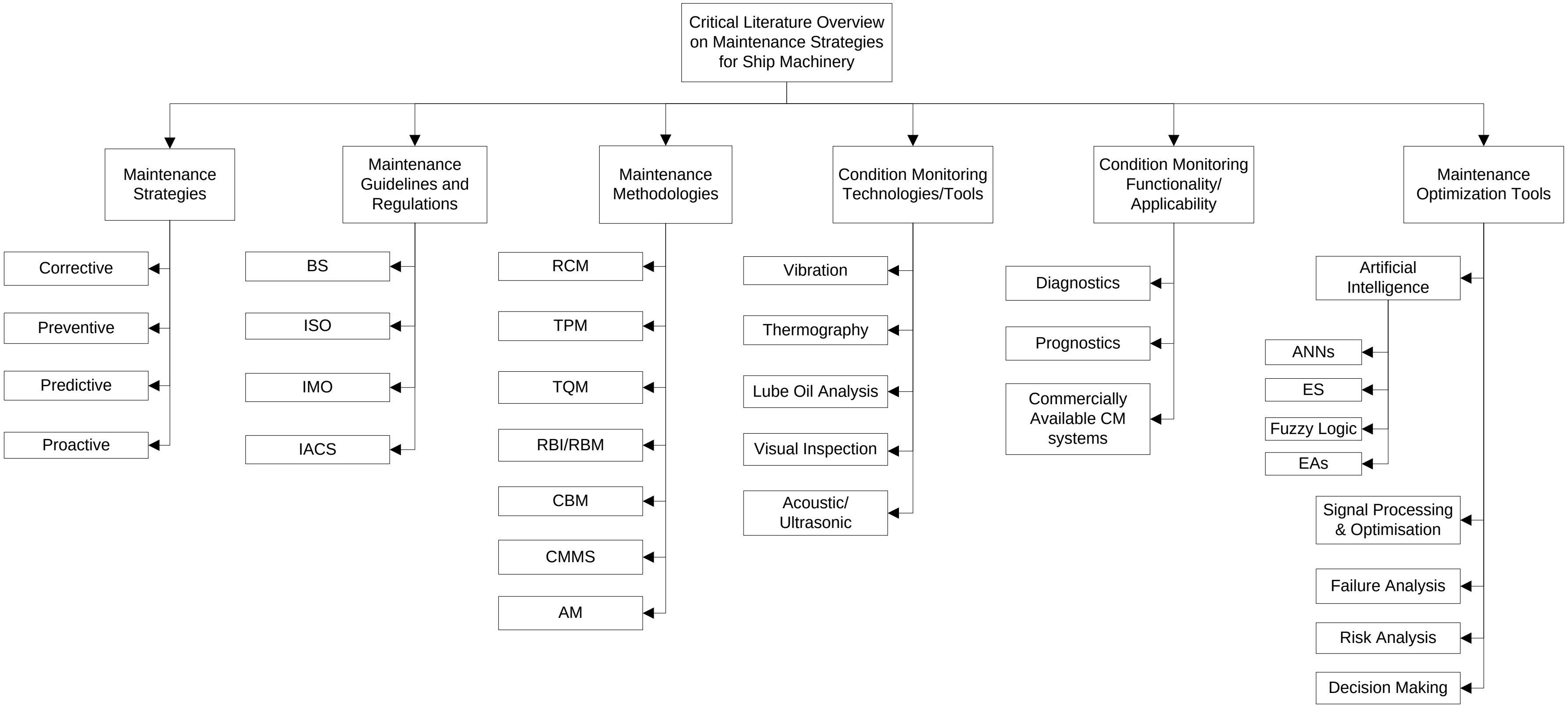

Figure 3.1 Literature on maintenance strategies of marine engineering systems

Abbreviations: BS: British Standards, ISO: International Standards Organisation, IMO: International Maritime Organisation, IACS: International Association of Classification Societies, RCM: Reliability Centred Maintenance, TPM: Total Productive Maintenance, TQM: Total Quality Management, RBI/RBM: Reliability Based Inspection/Maintenance, CBM: Condition Based Maintenance, CMMS: Computerised Maintenance Management System, AM: Asset Management, CM: Condition Monitoring, ANNs: Artificial Neural Networks, ES: Expert Systems, EAs: Evolutionary Algorithms

3.2. Maintenance strategies

Recent studies show that competition in the shipping market is influenced by factors such as cost, flexibility, quality, priorities and product's capabilities (Pinjala et al., 2006). On the other hand, Madu (2000) supports that business' competition incorporates time, price, technology, innovation, quality, reliability and information management. Hence, the necessity of retaining business competitive profile introduces the prerequisite of well-planned and controlled maintenance policy. This business policy approach is known as maintenance strategy.

Literature indicates that maintenance strategies are classified differently by various researchers. Garg and Deshmukh (2006), Ahuja and Khamba (2008), and Dowlatshahi (2008) combine maintenance strategies and techniques by identifying them with respect to their applicability and characteristics. On the other hand, Wang (2002) approaches maintenance in the commonly cited types of corrective and preventive strategies. This section classifies the maintenance strategies between corrective, preventive, predictive and proactive maintenance.

3.2.1. Corrective maintenance

The most fundamental maintenance strategy is known as corrective maintenance (Shreve, 2003), (Arunraj and Maiti, 2007). This strategy has been implemented in industry since the beginning of industrial revolution and is often described as "fix it when it breaks" expressing its reactive side (Kobbacy and Murthy, 2008). It is routine maintenance strategy, oriented on the replacement of components after failure. An exploration of published material shows that the recent applications are limited, because this strategy leads to expensive component replacement solutions instead of proactive maintenance actions. Mobley et al. (2008) explain the unpopularity of corrective maintenance by presenting the major limitations of corrective maintenance as poor planning and incomplete repair resulting in the repair of obvious failures while ignoring the root cause of the failure. The combination of both limitations causes a significant increase in repair expenditures, up to three to four times more, compared with a well-planned strategy.

In shipping industry, leading factors influencing vessels' smooth functioning are availability and sailing trustworthiness. Corrective maintenance strategy does not seem to be suitable to the marine industry's challenging characteristics due to high risk of machinery uncontrolled failures, which will consequently lead to unavailability of the ship. However, Fedele (2011) asserts that corrective maintenance is suitable for non-critical, inexpensive and easily replaced components that their replacement will not affect the efficiency of a plant's operation. Hence, specified components can be selected to be stocked onboard the ship's inventory for immediate use if required.

3.2.2. Preventive maintenance

This maintenance strategy is identified as a second generation policy (Shreve, 2003). Preventive Maintenance (PM) is introduced in industry at the beginning of 1950s classified as Time Based Maintenance (TBM) or the first time-driven management program (Arunraj and Maiti, 2007). Similarly, Márquez (2007) outlines this strategy as an operation arranged in predefined periods satisfying given criteria in order to reduce the likelihood of failure or the affection of critical functions due to equipment degradation. Correspondingly, Mobley et al. (2008) identify PM as specific task approach, which aims to avoid corrective actions by extending the useful life of capital and supplementary assets. More specifically, Kobbacy and Murthy (2008) define PM as the strategy which tends to replace, overhaul or remanufacture components at predetermined intervals regardless of its condition at the time.

A demanding research and development task related to PM is the specification of the inspection and maintenance intervals. Multiple explorations are offered in literature, while failure rate measures are assessed and maintenance activities are considered for risk prevention. Regarding the establishment of the interval maintenance periods, Fedele (2011) and Yi et al. (2012) present the bathtub curve, verifying three regions within the operational life cycle of equipment. The first period named 'infant mortality' associates with failures that may occur due to possible design, planning or installation errors. The next phase is the 'steady state' in which the failure rate is constant within time, while in the last 'wear out' period, failures are expected and replacement should be carried out.

Preventive maintenance has wide applicability in industry contributing in technical and economic aspects as well. Therefore, a PM planning approach is presented by Oke and Charles-Owaba (2006) redefining the maintenance intervals related to cost function considering vessels' design and technical characteristics from recorded data. The dynamic state modelling notion (i.e. consideration of time dependency) as well as the multi-component concept are integrated in a PM model assessing maintenance from the value perspective (Liu et al., 2014). PM strategy is the foundation of the well-known and widely applied Planned Maintenance Systems (PMS), where maintenance actions are applied according to defined operational hours.

Summarising the characteristics of this maintenance approach, PM enables higher risk control and uncertainty assessment compared to corrective maintenance by utilising predefined inspection and maintenance interval activities. Nonetheless, due to ignorance of the system's condition, components' replacement could take place earlier or later than required, leading to loss of money or unexpected failures respectively.

3.2.3. Predictive maintenance

This is the third generation of maintenance strategies introduced into market between 1960s and 1970s (Shreve, 2003) and (Arunraj and Maiti, 2007). This maintenance strategy is characterised by the non-destructive reactive mode of testing a system, determining the condition of equipment and subsequently considering the maintenance plan. Fedele (2011) supports that Predictive Maintenance (PdM) is on-condition assessment of assets, employing real time programming by avoiding unnecessary downtime, inspections, and reactive failures due to human mistakes. Specifically, he states that the majority of failures take place due to gradual deterioration rather than due to sudden break down, and specifies that condition measures result in output data, sourced from visual inspection, non-destructive controls and functional tests without disassembling the system.

Similarly, Mobley et al. (2008) present PdM as total production performance management program and regular condition-driven monitoring of mechanical state of equipment. An alternative view is presented by Márquez (2007). He classifies this strategy as division of PM, categorising the latter one as predetermined and Condition Based Maintenance (CBM). Despite this, CBM is considered as diagnostic and predictive maintenance concept due to the forecasting and evaluating factors, which are linked to the system's degradation. A more technical definition is given by Kobbacy and Murthy (2008) specifying PdM as integration of data, information and processes combining diagnostic and performance data from various sources leading to successful PdM implementation.

A prominent concept of PdM is presented by Gossling and Wollschlaeger (2007). They integrated a wide range of information sources setting a flexible framework. This attempt introduced a strategy for scheduling maintenance actions before failure takes place and not far earlier than required, which will signify inefficient planning. This consideration of setting the appropriate time for maintenance leads to the concept of Condition Monitoring (CM). Comparatively, ABB (2012a) presents predictive maintenance as 30-40% more cost efficient than corrective maintenance and 8-12% than preventive maintenance.

3.2.4. Proactive maintenance

As already defined, PdM is the latest strategy oriented towards the on-condition-driven concept of providing alert signals through data collection, aiming to schedule the correct maintenance actions. Fedele (2011) extends PdM by presenting proactive maintenance. This maintenance notion considers the pre-alert actions discovered from system's performance malfunctions that may lead to machinery's deterioration. This strategy analyses the root causes of breakdown events setting the acceptable operational limits of the predetermined factors. In addition, Shreve (2003) presents proactive strategy as a tool focused on failure modes of equipment intending to reduce maintenance costs by involving proactive skills and technologies. PdM strategy plays a key role in this thesis by selecting and developing innovative diagnostic and predictive functionalities within the proposed maintenance strategy.

3.3. Maintenance guidelines and regulations

The complexity of machinery installed onboard ships nowadays, combined with the environmental and operational safety awareness and the market competitiveness generate the need for standardisation of the inspection techniques and maintenance practices. This section demonstrates guidelines and regulations provided by competent bodies setting the basis for standardised inspection and maintenance framework regulations.

The concept of integrated and unified regulatory framework is confirmed in maritime industry and specifically with respect to safety aspects. However, the implementation of risk assessment in ship machinery is limited. An initial attempt is performed by IMO and IACS. They proposed a structured risk analysis process named Formal Safety Assessment (FSA) to assess the risk of failure in occasions that may lead to catastrophic consequences (Devanney, 2009a). Moreover, International Safety Management (ISM) code ensures safety at sea, prevention of human injury or loss of life, and avoidance of damage to the environment, in particular to the marine environment and to property (Maritime Coastguard Agency, 2015).

3.3.1. British Standards (BS) and ISO

The key role of British Standards (BS) and International Organization for Standardization (ISO) is to set up criteria for controlling risk and quality of goods and services. A research on standards, related to inspection and maintenance practices of machinery, provides a series of criteria that identify condition monitoring parameters for signal measurement, data collection and analysis.

The significance of machinery maintenance is assessed by BS/ISO 13613 (2011) emphasising on the reduction of risk and ensuring ship propulsion and manoeuvrability. Specific standardisation effort on container ships' machinery is given by BS/ISO 17905 (2014) identifying the requirements for installation, inspection and maintenance of container securing devices.

The material, lubrication and operational assessment of rotating machinery such as bearings, gears and rotors is examined by multiple BS and ISO reports. This assessment involves the employment of vibration analysis condition monitoring technique. Current effort on BS and ISO reports determines the vibration data gathering equipment (i.e. sensors), the unit of raw data collection and the suitable operating speed that these sensors can be employed ensuring accurate analysis.

Therefore, BS/ISO 7919 (1996) provides guidelines on vibration measurement and assessment of rotating shafts. It considers signal changes and monitors the radial clearance between components. The second sub-section of this BS report guides for radial shaft vibration measurement of bearings for large steam turbines and generators. The vibration's magnitude and its changes are identified by specifying warning alarms of vibration limits by detecting the magnitude after which malfunctions may occur.

Similarly, the third sub-section of BS/ISO 7919 (1996) provides instructions for transverse shaft vibration data acquisition. This standard is applied in fluid-film bearings utilised in steam turbines, turbocompressors, turbogenerators, turbofans, electric drives and gears and turbo pumps. The fourth sub-section is applied on radial vibration measurement collection of the shaft axis for heavy-duty gas turbines with fluid-film bearings. It describes on output higher than 3 MW and operating speed between 3,000 and 30,000 rev/min.

On the other hand, guideline and regulation effort through BS and ISO is given on input unification by integrating technical measures. Multiple input data parametres are considered leading to condition monitoring diagnostics. Hence, BS/ISO 17359 (2011) outlines the foundation of input data integration measuring machinery vibration, temperature, flow rates, contamination, power and speed, evaluating equipment performance and quality of operation. In further detail, BS/ISO 13379 (2012) sets the baseline parameters and data interpretation for indicators, alarm values and malfunction determination on turbines, compressors, pumps, generators, electrical motors, blowers, gearboxes and fans.

Lastly, the consideration of an overall standardisation framework is provided by BS/ISO 13381 (2015) allowing users to consider vital data and characteristics for efficient malfunction prognosis. It also outlines optimum prognostic method development and introduces various conceptions for future systems and their training.

3.3.2. International Maritime Organisation (IMO)

The International Maritime Organisation (IMO) is the United Nations specialized agency with responsibility for the safety and security of shipping and the prevention of marine accidents. As safety being the agent of the United Nations, IMO plays significant role in the global standardisation effort. IMO's active contribution aims to enhance safety, security and environmental performance of international shipping. This framework aims to set standards in multiple functional levels so ship operators cannot enforce cost reductions by compromising safety, security and environmental performance. Major areas that IMO dedicates effort include safety of environment and humans, fire prevention, lifesaving appliances, navigation systems and radio communication.

As mentioned above, the development and establishment of safety regulatory frameworks in maritime industry is led by lessons learned from hazardous incidents and accidents. Extending this perception, Devanney (2009b) expresses the problems of non-controlled records of ship casualty data. The creation of a consortium of port states is recommended, which will provide freely available ship casualty data. The data is suggested to be categorised among collision, contact, grounding, fire, explosion and Non-Accidental Structural Failure (NASF). Furthermore, flexible event identification is deliberated as sequence of the classified incidents and accidents may lead to catastrophic consequences, instead of single independent event examination.

In addition, Devanney (2009a) presents Formal Safety Assessment (FSA), a process through which regulations from IMO have to be assessed. FSA determines quantitative ranking considering safety measurements, while ensuring safety assessment objectiveness and cost-effectiveness respectively. Likewise, IMO (2006) illustrates FSA as presented by IACS in MSC 75. FSA consists of multiple identification and assessment levels. This framework involves hazard identification, risk analysis by employing risk control options. FSA examines performance by utilising Cost Benefit

Analysis (CBA) and leads to decision-making activity suggestions. In order to perform risk assessment and achieve the desired risk/safety level, the Health and Safety Executive's (HSE) framework demonstrates the As Low As Reasonable Practicable (ALARP) concept. ALARP comprises of three regions the unacceptable, tolerable and broadly acceptable (HSE, 2001b). This risk assessment tool enables the investigation of current practice's risk and targets to lowest reasonable practicable.

3.3.3. International Association of Classification Societies (IACS)

This section examines the contribution in safety and risk assessment of the International Association of Classification Societies (IACS). This is a regulatory member dedicated to safety on ships and protected environment. IACS contributes to maritime safety and regulation through technical support and research and development performed by Classification Societies (also known classes). These members lead a global network of well qualified surveyors' providing feedback of technical data, generating an internationally suitable management system.

According to historical records of each IACS member, classes identify safety importance and system criticality prioritisation with respect to their available records. Furthermore, the classes focus their interest on operational accuracy by certifying safety and functionality. Due to the fact of maintenance transformation from reactive to proactive strategies (i.e. corrective, preventive, predictive), classes through research and development develop standardisation guides and regulations following the market and industrial requirements.

For instance, ABS (2013) specifies critical areas such as the main machinery and shafting system. On the first place, these systems ensure the ship's functionality and secondly they can be affected by operational vibrations along the length generated by the propeller. With respect to data collection for condition monitoring applications, DNV-GL (2008) distinguishes the measurement sampling methods as fixed and portable by employing periodic sampling.

Targeting to establish automated inspection and maintenance methods, where technical, managerial, practical and economic aspects are considered, classes outline condition monitoring among specific assessment phases. Hence, the assessment takes into account the system functional description, quantitative measures identification, data gathering methods to be applied, data handling and data analysis. Along these lines, classes such as ClassNK (2014), LR (2014) and DNV-GL (2014) have also introduced Condition Assessment Programs (CAP) for surveying machinery and cargo systems on oil tankers, chemical carriers and bulk carriers.

Moreover, MARPOL 73/78 Condition Assessment Scheme (CAS) provides international standard to meet the requirements of regulations of the International Convention for the Prevention of Pollution from Ships (LMA, 2005). Additionally, Oil Companies International Marine Forum (OCIMF) introduces the Tanker Management and Self-Assessment (TMSA) framework. The TMSA programme is based on different elements of management practice. These elements involve management and accountability, reliability and maintenance standards, navigation safety, cargo, ballast and mooring operations, safety and environmental management and emergency planning, measurement analysis and improvement (OCIMF, 2008).

Concluding, international associations, authorities and regulatory bodies introduce frameworks and programs aiming to enhance safety of personnel, environment and assets. The reviewed sources aim to tackle the issue of risk in ship operations by considering standardisation measures and practices. Moreover, the proposed frameworks establish elements such as management, economics, reliability, maintenance, navigation as well as safety and emergency planning. However, these elements are assessed on an independent basis. Consequently, the integration and relation of these elements is proposed by connecting input and results among them through an overall unified framework.

3.4. Maintenance methodologies

By focusing towards the applicability of maintenance strategies, methodologies enable their implementation in industry. Maintenance methodologies are empowered with specific features that will be evaluated in this section, pointing out the elements they are contributing. Fedele (2011) identifies these methodologies as policies indicating the entire business orientation. An extended research shows the classification of maintenance methodologies as presented by various researchers. This section targets to explore the most-known and widely applied Reliability Centred Maintenance (RCM), Total Productive Maintenance (TPM) and Total Quality Management (TQM). Furthermore, the risk assessment notion is introduced in inspection and maintenance field through Risk Based methodologies (RBI and RBM respectively). Finally, the most recent Condition-Based Maintenance (CBM) methodology scrutinises the on-condition assessment of systems providing valuable input to Computerized Maintenance Management Systems (CMMS) and contributing towards the overall concept of Asset Management (AM).

3.4.1. Reliability Centred Maintenance (RCM)

One of the most applicable and widely explored maintenance frameworks is Reliability Centred Maintenance (RCM). This framework was introduced in the beginning of 1970s by a maintenance steering group of commercial airline company (United Airlines) and applied on the newly introduced at that time Boeing 747 aircraft. The major target of this methodology is the reduction of downtime due to maintenance. Furthermore, RCM aims the reduction of operational expenses, while enhancing flight safety. According to Deshpande and Modak (2002b), RCM offers the greatest available technique for preventive maintenance optimisation and provides identification of system's failure modes.

Vital notions of risk and reliability are utilised by Nowlan and Heap (1978), Sandtorv and Rausand (1992) and Moubray (1997) stating that RCM employs failure and risk analysis for prioritisation of maintenance actions. Expanding this observation, Moubray (1997) asserts that by gaining reliability assessment control using RCM, the failure consequences can be examined as well. The implementation of integrating risk and reliability assessment tools is presented by Eisinger and Rakowsky (2001). Two primary tools are employed in order to specify uncertainty that may lead to non-optimum maintenance strategies. These tools are Failure Mode, Effects and Criticality Analysis (FMECA) and RCM advancing of both qualitative and quantitative analysis aspects, respectively. The proposed integration encompasses multiple assessment and stages. Firstly, the required data are collected, followed by evaluation of criticality through FMECA and risk analysis using RCM. The integration of outcomes from FMECA and RCM is exploited for decision-making and maintenance strategy suggestion. The overall methodology proposal is confirmed through the implementation of feedback for performance comparison.

Literature offers a wide range of applications, where reliability assessment is introduced in inspection and maintenance regime especially in maritime and offshore oil and gas industries. A practical identification of this methodology is given by Deshpande and Modak (2002a) declaring that RCM maintains system's functionality by preventing failures and collapses. This is achieved by considering minor activities, compared to risk of failure, such as inspections and replacements in various failure modes. The inspection and maintenance movement from preventive actions of RCM to on-condition assessment is attempted in offshore industry and especially on subsea oil pipelines (Castanier and Rausand, 2006). Systematic condition measurements are generated in predefined intervals aiming to check the quality of the internal pipe coating.

Providing a flexible RCM framework, Cheng et al. (2008) suggest the Intelligent RCM Analysis (IRCMA), led by processes established on Case-Based Reasoning. The proposed model identifies the appropriate PM program for the specific equipment. The input of this framework is the description of equipment demanding RCM analysis, whilst the output is the PM requirements of the machinery. On the other hand, Lazakis et al. (2010) introduce a novel holistic maintenance management approach by referring in the appraisal of the reliability and criticality characteristics of a vessel. Well-known tools are used such as FMECA and Fault Tree Analysis (FTA). The developed maintenance management approach is applied on the machinery space of a cruise ship. Concluding, Reliability and Criticality Based Maintenance (RCBM) framework is verified on Diving Support Vessels (DSV). This methodology optimises the maintenance regimes onboard DSVs. The maintenance optimisation method investigates the reliability and criticality of selected systems such as propulsion, lifting, anchoring & hauling and diving systems using RCBM (Lazakis et al., 2012).

The validation of this methodology is achieved through the time-dependent risk assessment tool of Dynamic FTA (DFTA).

3.4.2. Total Productive Maintenance (TPM)

Total Productive Maintenance (TPM) is one of the core maintenance frameworks that is centred to maintenance regime and is applied in various industries and cases worldwide. TPM was introduced in the Toyota, a Japanese car manufacturer in the 1970s. The definition of this methodology reflects in three critical functional statements as zero defects, zero accidents and zero breakdowns (Nakajima, 1988), (Hartmann, 1992) and (Willmott, 1994). Hence, TPM involves practices with respect to humans as well as technology in scheming and eliminating failures, incidents and accidents.

According to Kennedy (2006), this methodology integrates Total Quality Control (TQC), Just-In-Time (JIT) and Total Employee Involvement (TEI) practices. Hence, TPM confirms the fusion of quality assessment in different phases of the production, ensuring in time delivery of goods or services and active involvement of all employees, in all industrial and production levels. TPM is developed concept of Total Quality Management (TQM) that will be examined next and targets zero production defects applied on critical equipment, involving highly top management support, sense of ownership and responsibility of operators and maintenance workers (Tajiri and Gotoh, 1992). Comparing the already introduced RCM with TPM, the first one can be considered as a maintenance improvement strategy. On the contrast, TPM is implemented on a holistic level to ensure productivity and defects' control without assessing technical aspects into the detail of reliability improvement. An application of TPM by Waeyenbergh and Pintelon (2004) proves that successfully implemented TPM increased machineries' productivity by 83%.

As can be seen above, TPM is defined from various authors, distinguishing aspects and advantages. However, a research gap is found in implementing guidelines aiding continuous improvement in plants. In addition, the main obstacles of TPM as presented by Bakerjan (1994) and Davis (1997) are the absence of management support and understanding, insufficient training and failure to allow adequate time for evolution. Concluding the considerations for future investigation, further effort should be invested in the human aspects at any level of production and involvement by gaining out of employs' expert judgment.

3.4.3. Total Quality Management (TQM)

As previously stated, Total Quality Management (TQM) is predecessor of TPM. Outlining TQM, Hellsten and Klefsjö (2000) define it as a managerial system combining values, techniques and tools for enhancement of customer satisfaction and minimisation of resources. According to Hackman and Wageman (1995) and Powell (1995), TQM aims customer satisfaction through continuous improvement of operational processes by sustaining quality through management, workforce and suppliers. A research on TQM, JIT and TPM is presented by Cua et al. (2001) stating that TQM incorporates cross-functional product design, process management, supplier quality management and customer involvement, reducing defects and rework by developing quality and product delivery. However, JIT involves set-up time reduction, schedule observance and delivery control by minimising inadequate inventory and flow time (Brown and Mitchell, 1991).

From the drawbacks side, the most reported interventions are these of TQM and Business Process Reengineering (BPR) (Hipkin and De Cock, 2000). The limitations are showing difficulties of implementation, lack of guidance on procedures, inadequate training, difficult measures of performance and lack of top management support. In conclusion so far RCM, TPM and TQM frameworks are presented and assessed. All methodologies consist of qualitative and quantitative assessment measures focusing on technical and managerial features. However, RCM is mathematical-based approach allowing the reliability assessment by involving mostly objective measures. In contrast, TPM and TQM enable the overall production evaluation involving human performance and production quality. These two subjective parameters require further determination and guidance in introducing analytical implementation techniques by considering human training and retaining practices.

3.4.4. *Risk based Inspection / Maintenance (RBI and RBM)*

This section introduces the most significant parameter, which affects safety, system operational efficiency, control of functioning and business profitability and it is known as risk. This parameter is widely explored and assessed in literature. Risk is defined by Hecht and An (2004) as the product of Probability of Failure (PoF) and its consequences, whilst by Arunraj and Maiti (2007) as the expected loss or damage associated with the occurrence of a possible undesired event.

Literature as well as industry examine the risk of occurrence of incidence independently for inspection and maintenance. From the Classification Societies perspective (DNV-GL, 2002), RBI is split in qualitative and quantitative analysis. The first one involves assessment scales, whereas the latter involves quantitative information measurements of probability of failure by taking into account their consequences as well. In a similar manner, Ablitt and Speck (2005) define Risk Based Inspection/Maintenance (RBI/RBM respectively) as a monitoring technique involved in inspection, maintenance, operations and safety, forming the most accurate quantitative probabilistic assessment tool. Summarising the definition assessment, ABS (2003), HSE (2001a) and Biasotto and Rouhan (2004) state that RBI aims to minimise the risk at network level, optimise the inspection resources and efforts, oriented towards critical areas or identification of suitable inspection methods.

Literature offers a wide range of risk based applications, for instance, the development of Risk Based Life Management (RBLM) presented by Jovanovic (2003). RBLM compared to RBI evaluates and plans pre-inspection processes. Furthermore, it contributes in reducing operational expenses by minimising or eliminating unnecessary inspections actions such as overhauling. A novel risk-based model is developed by Thodi et al. (2013) scheduling the replacement of offshore components by utilising the likelihood of failure and its consequences. The time-driven risk assessment of system degradation is taken place utilising the Bayesian theorem, whereas the consequences are expressed in monetary values and cost of resources.

In a similar manner, Hecht and An (2004) utilise the failure likelihood as a function of inspection frequency and effectiveness. The developed model is verified on a cargo vessel. An alternative study on Integral Risk-Based Inspection (IRBI) is presented by (Goyet et al., 2004). This study is focused on the risk acceptance criteria regarding risk to personnel, environmental and economic considerations for an FPSO by involving critical, recorded information on repair strategies, which can subsequently lead to the estimation of failures. On the other hand, (Chien et al., 2009) develop a semi-quantitative RBI strategy performing Plan, Do, Correct and Act (PDCA) cycle, utilising test data and statistical analysis of aging conditions for Pressure Safety Valves (PSVs) in lubricant process units. On the contrast of the presented RBI machinery practices, one of the latest implementations (Moura et al., 2015) combines RBI with a Multi-Objective Genetic Algorithm (MOGA). The model achieves avoidance of users' requirement to specify risk, reducing the estimation of consequences of failures and controllable inspection expenditures. In addition, the model provides control on efficient inspection of budget management. The evaluation of the proposed model involves an oil and gas separator vessel affected by internal and external corrosion.

Involvement in risk assessment is also discovered in EU funded research projects. An instance of this input is Risk-Based Inspection and Maintenance for European Industries 'RIMAP' EU project (Kauer et al., 2004). The project suggests a generic model widely acceptable by the European industry which exploits existing risk methods, tools and standards proving its significant role and setting the ground for Risk Based Maintenance (RBM).

In the manner of enhancing RBI with maintenance aspects, Arunraj and Maiti (2007) considered the risk of all probable failure modes by developing a maintenance strategy for minimisation of occurrence of critical failures. RBM implementation consists of phases such as hazard analysis, likelihood of failure and consequence assessment, risk estimation, and maintenance planning. Khan and Haddara (2003) propose an RBM planning method, setting accurate risk factors related to the harmfulness of consequences and accuracy of estimates of probability of failures. The method combines failure analysis by considering consequences and risk evaluation, involving the As Low As Reasonable Practicable (ALARP) approach. In addition, the integration of financial and reliability levels through a model is proposed by Garbatov and Guedes Soares (2001) quantifying repair costs, which affect RBM strategies.

3.4.5. *Condition Based Maintenance (CBM)*

The most recent methodology offering control of risk and uncertainty is known as Condition Based Maintenance (CBM). The fundamental idea of this framework is the on-condition assessment of systems or structures by considering specified record measurements that will potentially lead to risk or reliability state identification. This state identification is separated into two major areas of on-condition assessment the diagnostics and prognostics. In the first place, diagnostics allow the identification of occurred failure modes, whereas, in the second case prognostics aim to forecast the future risk performance. CBM is broadly utilised in various industries including maritime as well. However, leading literature provides techniques sourced from high risk applications such as aviation, offshore oil and gas and nuclear power stations.

The scope of CBM and fault diagnosis as defined by Mechefske (2005) is to detect the upcoming failure before even incipient failures take place, aiming to enhance machinery's availability, reliability, efficiency and safety, by reducing maintenance costs through controlled spare part inventories. A survey (Prajapati et al., 2012) on CBM applications highlights the key aspects as data collection, artificial intelligence, and statistics allow intelligent maintenance and prediction of consequences using past and current data.

A subsection of CBM is the data gathering and assessment of vibration signal, collected mostly from rotating machinery. This technique is known Vibration Based Maintenance (VBM). This on-condition assessment technique offers an extensive range of research and applications. Major scope of published VBM practices is the enhancement of diagnostic accuracy though sophisticated vibration signal analysis. In this respect, a practical application on CBM strategy is presented by Al-Najjar (1996) integrating vibration and age-based maintenance oriented towards quality control and environmental condition.

In the industrial domain, SKF, a leading global product, services and technology provider, supports that CBM aims to identify risks and predetermination of strategic actions (SKF, 2012a). Hence, implementation of CBM should lead to reliability enhancement and cost reduction by integrating information and management of critical components for time reduction of expensive and challenging maintenance phases such as dry-docking. With respect to critical component and system selection for on-condition assessment, SKF (2009) states that the criticality of onboard equipment depends on the type of ship and its operation. However, according to SKF's historical records, the most critical systems that should be under on-condition assessment are listed among gearboxes, turbochargers, thrusters and propulsion steam turbines.

In order to layout CBM and the processes that consists of; Tsang et al. (2006) suggest a data structure leading to decision analysis according to machinery's condition, proposing a method for data-driven CBM achieving data preparation, model assessment, decision-making and sensitivity analysis. Similarly, as highlighted by Kyrtatos (1989), an improved CBM model for ship propulsion management should consist of condition and performance monitoring, fault diagnosis as well as maintenance optimisation modules. In conclusion, Shreve (2003) presents the difficulties and requirements of implementing CBM, supporting that the major reason of lack of applicability is based on managers' weak training. Moreover, the integration of latest and most complex technology creates the need for skilled and well-trained personnel as well as business investment in terms of equipment and training.

3.4.6. Computerised Maintenance Management Systems (CMMS)

As equipment onboard the ships becomes more complex and the market gets more competitive, the need for implementation of automated maintenance management systems is presented. Computerised Maintenance Management Systems (CMMS) is the latest framework which allows machinery functionality, reliability and availability enhancement and uncertainty control by employing computerised, flexible tools for managing critical assets.

According to Shreve (2003), CMMS suggests maintenance planning as it assists using critical data for equipment, workforce and recorded conditions. Fernandez et al. (2003) present the functionality of CMMS in order to gain information from raw data and enhance decision-making by automating existing iterative assessment processes. On the other hand, Monostori et al. (2006) state by summarising mobile solutions for maintenance applications that CMMS employs continuous connectivity including active data management, web-based interaction, access to knowledge and information and enhancement of communication systems.

In contrast, Chryssolouris et al. (2004) explore the difficulties arising from the integration of partners' heterogeneous/incompatible IT systems on ship repair industry by presenting a solution for connectivity of various modern IT systems. This applicability is achieved through the implementation of neutral data format provided by the Extensible Mark-up Language (XML). On the other hand, a conceptual IT maintenance management model is proposed by Kans (2008). It determines the business goals and current state of maintenance by identifying possible improvements and IT requirements. In addition, Hamada et al. (2002) outline inspection data under various conditions integrated with a Computer Integrated Manufacturing (CIM) system for ship's structural information; calculating the damage-finding probability and generating damage and inspection state.

As stated by Sherwin (2000), maintenance has to be considered as key factor within the business as changes in its processes affect various interrelated functions. Originated from this view, Kans and Ingwald (2008) present the benefits of an integrated database and the significant role of maintenance performance in economic improvement. One step further, Gabbar et al. (2003) propose the integration of RCM process with CMMS motivated by the major difficulties arising from involving vast amount of resources.

3.4.7. Asset Management (AM)

An innovative and widely applicable methodology spread over in the maintenance evolution is Asset Management (AM). This practice targets the business oriented implementation by concentrating on the overall asset performance. AM is extensively assessed and introduced into multiple industries and nowadays successfully in maritime by leading machinery manufacturers. AM integrates notions, tools and features from risk based assessment methods, CBM and CMMS as already presented.

Through a literature review focusing on the cost benefits of maintenance strategies and methodologies, (Eti et al., 2006) summarises that maintenance and AM can achieve growth of profile by decreasing running costs and increasing capability and availability. ABB is a global leader in power and automation technologies (ABB, 2010) proposing the basis of an ultimate AM tool integrating CMMS with real-time CM which collects data from various sources and alerts on failure detection. Furthermore, Asset Health Centre (AHC) is presented by ABB as well (ABB, 2012b). AHC performs as an entire business asset supervision system utilising reliability, performance, prioritising maintenance actions, and minimising Operations and Maintenance (O&M) expenditures. AHC's innovation is the integration of Operation Technology (OT) and Information Technology (IT) by enhancing decision-making on asset's existing condition.

On the other hand, Emmanouilidis et al. (2009) extend the AM notion and flexibility of data access by presenting the advantages of wireless solutions for engineering asset and maintenance management processes. AM offers solutions for remote management of complex and high risk capital intensive assets. Hence, Emmanouilidis et al. (2008) highlight that smart transducers enable capabilities for self-identification, self-description, self-diagnosis, self-calibration, location-awareness, time-awareness, data processing, reasoning, data fusion, alert notification (warnings), standard-based data formats, and communication protocols, supported by the so called TEDS (Transducer Electronic Data Sheets). The current research work and the proposed methodology target to explore and develop some of these aspects. This thesis is oriented towards innovative methods by accomplishing capabilities beyond the presented diagnostics, hence considering working state risk and reliability prognostics of ship machinery.

This section reviewed applications of different maintenance methodologies. Each methodology is oriented towards elements such as reliability, criticality, production, quality and condition as well as risk in inspection and maintenance levels of machinery. A methodology transition from assessing specific elements to holistic view of resources is initially introduced through AM. The complexity of systems and technology expansion led to the introduction of computerised automated systems (i.e. CMMS) as well as the on condition assessment (i.e. CBM). Hence, vast amount of recorded data per system and components has to be handled and processed by utilising different methodologies and analysis techniques. In other words, the systems' complication and technological growth require the integration of different methodologies by employing and incorporating necessary elements for the creation of flexible and efficient inspection and maintenance frameworks and tools advancing features from all above examined methodologies.

3.5. Condition Monitoring (CM) technologies and tools

As already defined, CBM is the latest maintenance methodology, which assesses machinery and equipment risk of failure performance, while functioning. In this case, Condition Monitoring introduces technologies and tools that are employed for the on-condition assessment. CM technology is applied through various tools, recording and evaluating measurable parameters that will be reviewed in this section. These measured parameters comprise the signal gathering, from which several data processing methods can be considered with respect to machinery recorded input data. Precisely, Eder (2012) defines health assessment as method measuring wear and system performance.

CM is identified by Delvecchio (2012) in steps such as data acquisition, signal processing and feature extraction, signal analysis and fault detection, leading to decision-making and failure prognostics. Moreover, Jiang and Yan (2008) present the most popular CM tools as lubrication oil testing, vibration and Acoustic Emissions (AE). Expanding CM concept, Hall and Llinas (1997), Al-Najjar (2000b) and Brotherton et al. (2002) propose the integration of various techniques detecting faults that is difficult to be achieved from a single sensor. They utilise Artificial Intelligence (AI), pattern recognition and statistical estimation by enhancing effectiveness and accuracy of decision-making. This subsection evaluates the most-known and broadly applicable CM technologies such as vibration monitoring, thermography, lubrication oil analysis, visual inspection and acoustic/ultrasonic monitoring. Furthermore, monitoring diagnostic and prognostic applications are demonstrated by taking into account research and commercially available condition monitoring systems.

3.5.1. Vibration monitoring

This is the most known and well applied technique. Vibration-Based Maintenance (VBM) methodology offers early indication of machinery malfunctions involving parameters as rotational speed, loading frequency, and material state (Al-Najjar, 1996). These parameters can be measured and evaluated by employing different data gathering equipment (sensors) such as displacement, velocity and acceleration sensors. Displacement transducers are sensitive in lower frequency range; velocity transducers which are ideal for optimised sensitivity over the frequency range; and accelerometers which are more sensitive in higher frequency range (Mechefske, 2005).

Representative application of VBM allows fault detection of electric motors. Lamim et al. (2007) integrate the advances of motor monitoring with electric current, vibration monitoring of bearings leading to malfunction and failure diagnostics. The assessment of causes of cracking sourced from vibration modes for diesel engine's alternator set is presented by Clarke et al. (2011) using Operational Modal Analysis (OMA) tool. Data are collected during start-up, shutdown and running conditions at various power levels.

In addition, the vibration modes of cracked shaft detection and diagnostic techniques are classified by Sabnavis et al. (2004) between crack initiation stage, crack propagation and failure stage. An alternative view on rotating machinery is presented by Sassi et al. (2007) simulating the dynamic performance of ball bearings by localising surface defects, considering bearing rotation, load distribution, material elasticity and oil film characteristics.

Expanding CM diagnostic notion into the forecast field, Paris' law contributes for prediction of residual fatigue life. Xu et al. (2012) present the relationship between the machinery's condition values of vibration signals and the variable in Paris equation which describes the health of machine. Al-Najjar (2000a) examines the relation of bearing failure modes to the recorded vibration spectra and their development patterns over the bearings' lifecycle.

Due to deficiency of shaft speed measurement, vibration signals can be weak in quality to detect malfunction and material deterioration. Hence, Cardona-Morales et al. (2013) introduce a novel Order Tracking (OT) system, established on the state space model, which avoids speed reference signals. Similarly, Sundstrom (2013) states that CM of rotating bearings at lower speeds than 100 rpm is challenging because of lack of useful signals produced from spalls and cracks as they are indicated from low energy content. Sundstrom (2013) proposes a method, allowing the analysis of speeds within the 1-20,000 rpm range using high performance low-noise electronic components and extensive signal processing which allows malfunction detection even on well lubricated bearings.

3.5.2. Thermography

Thermography in CM is a technique, applicable to both electrical and mechanical equipment, and is deployed to identify hot and cold spots providing early signs of equipment failure. As claimed by Bagavathiappan et al. (2013), Infrared Thermography (IRT) is one of the most accepted CM tools. Due to the non-contact function is suitable for detecting structural, machinery, electrical and material malfunctions. The key advantage of IRT compared to other CM tools is the real-time representation of pseudo colour coded image.

Presenting machinery defects, Budweg (2012) reveals that uncontrolled heat can be generated due to reasons as overloading, phase imbalance, power factors, corrosion and poor electrical connections and this is a warning of loss of energy. Moreover, heat is a parameter that can shorten machinery’s lifecycle up to 85%. The suitable CM technique presented for electrical circuits is thermal imaging snapshots through Infrared (IR) inspection under full load. This technique can capture the degradation conditions in a quick and limited data set manner.

Nevertheless, in line with various professionals the ideal monitoring solution is under continuous inspection, unfortunately the lack of trends seems to be a barrier for this application. The main disadvantages of this monitoring technology, as indicated by Chandroth (2003), are the influence of accuracy due to high humidity and ambient temperatures and that electric circuits have to be loaded in order malfunctions to be detected. Hence, an integrated CM system considering vibration, lubrication of oil, and thermographic images seems to enhance the dimension of information and accuracy of measured factors compared to independent technological selections.

3.5.3. Lubrication oil analysis

Oil analysis is achieved through laboratory concentration investigation in lubricant, known as debris analysis, which deals with shape, size, composition of wear particles and lubricant degradation analysis for physical and chemical characteristics (Jiang and Yan, 2008). Lubricants' monitoring seems to be the most efficient diagnostic tool as from a small amount of fluids the condition of the entire lubricant in each machinery can be determined. Typical tests of lubricants are divided into phases such as visual testing, viscosity at 40°C and pH value, supplementary dealing with viscosity at 100°C, and optional counting particles. Each test phase has to take place twice to achieve higher accuracy.

However, the existing oil analysis of lubricants requires the integration of lab-based filtration methods involving reagent, solvent costs, testers and time-consuming work with hazardous chemicals. Integrating oil analysis and computerised technologies, Casale et al. (1993) analyse the key aspects of monitoring marine lubricants through a computerised Expert System (ES) named EXXCARE. This system deals with the efficiency of lubricants in diesel engines and related machinery. In a manner of solving this limitation, Walsh (2013) presents FluidScan Q1000, a handheld IR spectrometer, which measures parameters such as lubrication contamination, degradation and cross-contamination at the point of use. This device achieves analysis and completion of test results in 2.5 minutes at the machinery's location leading to accurate and repeatable process and reducing cost of manpower by 25% and cost of analysis by 75%. Lastly by setting the ground for further analysis and presenting the lack of publications in performance analysis of steam turbine generators, Beebe (2003) promotes that vibration and oil debris analysis can show efficiency and output reduction such as deposits on blades and erosion of internal clearances.

3.5.4. *Visual inspection*

This inspection method is the simplest option, employing human senses on assessing machinery. DNV-GL (2007) presents the applicability of Non-Instructive Inspection (NII) in comparison with the existing Internal Visual Inspection (IVI) on pressure vessels and pressure systems, which require periodic testing ensuring their continuous safe and reliable operation. According to this analysis, NII decreases employees' access, initiation of possible hazardous occasions, shutting down the entire operation and allows inspection when potential problem is identified. Furthermore, visual inspection allows the employment of expert judgement as well as immediate additional examination if required. In contrast, human visual inspection relies on the human's subjective criticism, which may mislead to overestimation or underestimation of the examined case. In other words, expensive unnecessary activities may take place or vital inspection and maintenance actions may be ignored leading to hazardous failures.

3.5.5. *Acoustic and ultrasonic monitoring*

The applicability and efficiency of ultrasonic condition monitoring is confirmed by IACS as this technique is authorised from Classification Societies for surveys and certifications. Specifically, acoustic and ultrasonic monitoring is utilised in the well-known Ultrasonic Thickness Measurements (UTM) (IACS, 2004), (IACS, 2006).

In practice, Kim and Lee (2009) propose a real-time diagnostic system for high speed Acoustic Emission (AE) signal analysis assessing wear condition of cylinder liners in marine large two-stroke diesel engines. Furthermore, Mirhadizadeh and Mba (2009) focus on understanding the relation between speed and load generated of hydrodynamic bearings by monitoring AE. The results indicate that increase of operating speed produces higher AE activity compared to the increase in bearing load due to power losses from shearing of lubrication film. The innovative implementation in recording AE data for the connection of piston rings and cylinder liners in diesel engines is presented (Douglas et al., 2006), considering lubricant flow and blowby obtained from tests. Input data is gathered using a small HSDI diesel engine and large 2-stroke marine diesel engines. Similarly, the wear level of cylinder liners in marine diesel engines is studied by Kim and Lee (2009) as well, developing a real-time diagnostic system for analysis of high speed AE signals.

Expanding AE applicability, Vervloesem (2013) explores the user-friendliness and accessibility of ultrasounds on non-rotational equipment breakdowns that exist onboard ships by advancing the ease of manual data collection and the direct sourced result. However, an unknown aspect of this CM tool compared to traditional vibration analysis is discovered the ability of performing on high and slow speed rotating machinery as low as 0.25 RPM.

On the other hand, SKF (2012b) researching on AE enveloping develops a solution in order to detect the lubrication problem in bearings by achieving early alarm signs before damage arises extending the warning time to failure. Whereas, Carlton and Rogers (2008) review that during 1990s AE was implemented for structural integrity assessment of offshore applications and corrosion studies for water ballasting arrangements aiming failure detection. Finally, development of this method results in using it on rolling bearing failures of POD propulsion systems.

3.6. Condition Monitoring (CM) functionality and applicability

On-condition assessment targets to evaluate the state of degraded ship machinery and equipment. This subsection identifies and examines the major Condition Monitoring (CM) functionalities and the available commercial applications. The CM functionalities are classified among diagnostics and prognostics, whereas, leading software applications and industrial solutions are reviewed.

3.6.1. Condition Monitoring (CM) diagnostics

As already defined, CM is the technology of assessing the state of machinery without interrupting the operation. Presenting the CM layout, it consists of phases as data gathering utilising sensors (on-line or off-line devices), data analysis, whilst leading to decision-making. The systematic automation in industry, the need for safety enhancement and control of risk enforced the implementation of monitoring diagnostics which aim to determine and specify the fault type as well as the reasoning that led to this failure.

In line with Delvecchio (2012), fault diagnosis is severe requiring the determination of type, size, location and time of detected faults. Supporting the importance of accurate and early fault diagnosis, Refocus (2005) states that a specific maintenance issue can be the replacement of a $5,000 bearing turning into a $220,000 project concerning cranes, service crew and power loss. A typical example (Mortada et al., 2011) of rotating machinery diagnostics, hence feature extraction from frequency and time-based signals, assesses the performance of a supervised method called Logical Analysis of Data (LAD). LAD identifies malfunctions in rotating machinery by using VBM targeting decision function enhancement. According to SKF (2012b), an important factor of managing marine online data for diagnostics is the input data categorisation to be arranged in load groups for similar trend comparison. In other words, the data classification should be considered in correlation to the machinery's operational load.

On the practical side of diagnostics, various models suitable for marine diesel engines are developed. A thermodynamic modelling approach is proposed for Internal Combustion Engines (ICE), involving components such as filters and compressor modules (Barelli et al., 2013). The developed model simulates the performance degradation while taking into account the effect of compensation and assessing failures using Mamdani fuzzy inference. Similarly, Watzenig et al. (2009) introduce two thermodynamic models detecting common failures as increased blowby and compression ratio failures of large diesel engines.

On the other hand, a diagnostic method for diesel engines is proposed by Wang et al. (2013). The methodology integrates Adaptive Wavelet Threshold (AWT) de-noising, Ensemble Mode Decomposition (EEMD) and Correlation Dimension (CD) for non-stationary vibration signals. Artificial Intelligence is employed by Logan et al. (2002) introducing Neural Networks (NNs) for real-time machine learning. The proposed methodology is known as Cerebellar Model Articulation Controller (CMAC) and tested on a normal and faulty engine simulator

Chandroth (2004) integrates data from independent sources in order to implement a unified robust diagnostic system for diesel engines. Data is gained from cylinder pressures and vibrations. Different ANNs classifiers are improved and statistical models are applied for evaluating the diversity within the methodologies creating these classifiers. Additionally, Logan (2005) reviews intelligent real-time diagnostic software agents serving onboard vessels for gas turbines and diesel machinery plants by utilising NN diagnostic inference and short-term prognostics. In conclusion, according to Rattenbury (2008), while a ship engine operates beyond the recommended continuous power output range (extreme engine load conditions), careful analysis should be carried out. In order to ensure engine's reliability performance, various parameters have to be taken into account such as fuel quality, lubricating oil consumption and power/speed conditions. This statement sets the grounds for critical measurement considerations enabling further research, development and in practice implementation.

3.6.2. Condition Monitoring (CM) prognostics

An innovative and newly introduced maintenance concept on CM technology expansion of diagnostics is the prognostics. This notion scopes to predict, whether a failure will occur by considering the Remaining Useful Life (RUL) of systems. As defined by Lee et al. (2013), Prognostics and Health Management (PHM) combines health condition and RUL prediction for an overall system and its associated components. On-condition assessment of systems typically use fault detection and diagnostic technologies, which extend from single thresholding to rule-based algorithms (Byington et al., 2002). Additional prognostic approaches involve experienced-based modelling and physics-based also known as first principle analysis prognostics. Prognostics offer limited literature, as they are recently established. However, different forecasting techniques are already developed.

A methodology predicting the RUL of natural gas export compressor is proposed by Nystad and Rasmussen (2010) integrating Technical Condition Index (TCI) parameters, historical data with PHM and the general maximum-possibility theory. The performance of diesel engine prediction simulation is presented by Benvenuto and

Campora (2007) employing a two-zone cylinder combustion outline, calculating the thermodynamic processes inside the cylinders and considering the performance of the turbocharger, intercooler, manifolds and fuel pump. Furthermore, Hountalas (2000) develops a simulation model for prediction of marine diesel engine performance considering different faults and applies it successfully on a slow speed two stroke marine diesel engine. On the contrary, Zhang et al. (2003) present the Unequal Interval Revised Grey Model (UIRGM) based on grey system theory, which allows to determine whether the information for wear prediction studies is known or unknown. The model is designed for prediction element collection and tested diesel engine.

The requirement for an improved prognostic CM maintenance concept develops the multi-component modelling. This notion incorporates the risk assessment of different components of a system by allowing an overall performance monitoring compared to independent evaluation. Therefore, Liu et al. (2012) expand the prediction concept by proposing an innovative data-fusion prognostic framework. This concept improves the accuracy of long term condition forecasting by combining the advantages of data-driven prognostic method and the model-based particle filtering approach in system state prediction.

Similarly, Niu and Yang (2010) propose an intelligent CM prognostics method based on data-fusion strategy. The algorithm consists of stages such as vibration signal collection and trend feature extraction, feature normalization and use of NN for feature-level fusion, data de-noising and wavelet decomposition for reduction of fluctuation and selection of trend information. Likewise, Kacprzynski et al. (2001) develop a prognostic model on naval gas turbines using standard instrumentation combining probabilistic analysis of fouling test outputs. The prognostic section forecasts the compressor performance degradation rate resulted from salt deposit ingestion, while determining the optimal time for online waterwashing or crank washing according to cost benefit parameters.

As data fusion for multi-component applications is under continuous development, Tian and Liao (2011) propose a multi-component system by utilising CBM policy and employing Proportional Hazards Model (PHM). A numerical algorithm is developed exacting cost evaluation of the PHM based multi-component CBM policy. On the other hand, Niu and Yang (2010) suggest an intelligent CM and prognostics system based on data-fusion strategy. The prognostic module is initiated and time-series prediction is performed by employing multi-nonlinear regression models once degradation curve crosses the determined alarm threshold. In further analysis, Niu et al. (2010) integrate the features of a novel CBM system with RCM mechanism, optimising maintenance costs, achieving health assessment and prognostics by employing data fusion strategy. An innovative bearing fault diagnostic method is presented by Safizadeh and Latifi (2014) which employs the fusion of accelerometer and load cell sensors. The condition-based monitoring system is built on six phases such as sensing, signal processing, feature extraction, classification, high-level fusion and decision-making.

As the prognostics scope is to forecast future states of machinery, CBM combined with DSS aims to propose maintenance actions for components and systems life extension. A research on probabilistic prognostics is presented by Dikis et al. (2014). The probabilistic risk assessment of CM for marine diesel engines is assessed by utilising Bayesian Belief Networks (BBNs). Latest research from Ramírez and Utne (2015) proposes a dynamic Bayesian network which examines the life extension of repairable systems. The model's applicability is oriented towards decision-making related to system's maintenance by utilising historical data. Finally, data-driven prognostics are researched by (Xi et al., 2014) through a method which involves offline training and online prediction processes. The first one (offline) is built by structuring a statistical relationship between the failure time and the recognition time, while the online prediction forecasts the probable failure times for online testing based on the offline statistical model.

3.6.3. Commercially available condition monitoring systems

Condition monitoring systems are widely spread in maritime industry and they are under continuous investigation and development focusing on the market and business competence factors concerning environmental, maintenance, operational and financial considerations. Commercially, various developers and providers offer in market CM software tools such as machinery and equipment manufacturers, Classification

Societies, operators and service providers. Each of these maritime stakeholders suggests and offers CM applications, which target to fulfil specific requirements identified with respect to their priorities and necessities.

Firstly by investigating engine manufacturers, MAN (2012a) presents Engine Management Concept (EMC) for operation and maintenance of main and auxiliary engines. EMC enhances availability, scheduling, quality and cost commitment at optimum performance by substituting shipowners' technical management function with MAN Diesel & Turbo. Furthermore, MAN (2012b) provides the Intelligent Remote Diagnostic System (IRDS) to increase the operating reliability. IRDS manages data collection and transition periodically (approximately 10MB/day), while analysing and presenting automatically or manually impending faults at an early stage.

On the other hand, Wartsila presents Dynamic Maintenance Plan (DMP), a CM system which integrates the data collected from equipment using sensors and crew members. DMP reports in unscheduled manner, when required, and input data is collected within scheduled inspections (Klockars et al., 2010). In addition, the same manufacturer introduces one more system the Wartsila Intelligent Combustion Monitoring (ICM) (Rolle and Wiesmann, 2011). Wartsila ICM system assesses firing and compression cylinder pressure data. The innovation of this system is the consideration and integration with the Fuel Quality Setting (FQS) system, which assesses the fuel quality combined with the cylinder performance.

Another example from Wartsila is the Propulsion Condition Monitoring Service (PCMS), a real-time solution on engine and thruster monitoring. PCMS involves database storing and transmission features as well as information gathered from vibration, hydraulic pressure and temperature sensors integrating operational conditions such as vessel's pitch, speed, rate of turn and draught (Pakarinen R., 2011). A system combining monitoring and control services is introduced by Rolls-Royce (2012), called Synchro Autotrawl. This system is designed to manipulate and monitor winches onboard by offering alarm warnings, monitoring control and automatic communication, with net sensors as well as graphical and dynamic representation of gears.

Kongsberg is an international technology corporation that supplies reliable, advanced technological solutions that improve the reliability, safety and efficiency of complex operations and under extreme conditions. Hence, Kongsberg (2014) presents Engine Monitoring Systems (EMS) built on K-Chief hardware and software. K-Chief comprises of elements such as bearing material wear and bearing temperature monitoring of crank-train bearings, water in oil, cylinder liner temperature and shaft power monitoring. On the other hand, Katsikas et al. (2014) present a monitoring system, named LAROS. The system is flexible, adaptable, scalable and easily installed. According to the authors, LAROS is the only system of this kind available in the global market for shipping and especially for monitoring ship's engines.

Concluding this section, the significant points have to be highlighted leading to commercially available application gaps. The majority of onboard ships machinery and equipment manufacturers provide appropriate in-house developed CM tools for the systems they produce and provide. Furthermore, it is noticeable that manufacturers offer different independent software CM tools suitable for their functionalities, priorities and offered equipment. Hence, independent diagnostic monitoring tools examine the systems' performance without taking into account the machinery interdependencies. This ship Engine Room (ER) leads to condition monitoring management system inefficiency, because the systems' interaction and influence in functioning is not considered so far in research and proposed applications. On the other hand, multiple CM software interactions may lead to compatibility issues, fault alarm disruption and delay of data manipulation. An available solution could be the creation of larger flexible monitoring systems customised and installed to each client.

Lastly, through this research is identified that Classification Societies and international safety agents are mostly interested in structural monitoring systems development. An uncontrolled incident of machinery break down can lead to structural collapse and significant failures, which are harmful for humans, environment and property. An analytical list of commercially available condition monitoring systems is presented in Appendix A.1. Well-known applications are examined with respect to latest features, functions and specifications.

3.7. Maintenance input data optimisation tools

As already analysed, there are different CM technologies suitably introduced on ship machinery and equipment associated with the functional operation and the type of considered measured parameters. In this subsection, review will be carried out for the maintenance optimisation tools, signal processing, failure and risk analysis as well as decision-making methods from various researchers highlighting strengths and weaknesses to develop accurate CM strategy tools.

Presenting the layout of maintenance optimisation models, Garg and Deshmukh (2006) outline Bayesian approach, Mixed Integer Linear Programming (MILP) formulation, Multiple Criteria Decision Making (MCDM), Fuzzy Linguistic (FL), Markovian probabilistic models, Analytic Hierarchy Process (AHP) and maintenance organisation modelling, whilst integrating business aspects with engineering asset management. In contrast, Sikorska et al. (2011) summarise the available prognostic modelling options for RUL estimation between knowledge-based (ES and fuzzy), life expectancy (stochastic and statistical) Artificial Neural Networks (ANNs) and physical or first principle cases.

3.7.1. Artificial Intelligent (AI) approaches

According to Fiippetti and Vas (1998), AI assists equipment degradation assessment, statistical failure analysis, prognostics and intelligent diagnosis for CM tasks and fault detection. Al-Najjar and Alsyouf (2000) state that Intelligent Monitoring (IM) system matching with human monitoring actions should have indirect sensing, signal conditioning, parallel processing of information and knowledge learning in order to make precise decisions. Henceforth, most of the input data analysis and optimisation tools are integrated in literature. The major reason is the need to establish flexible and accurate CM tools, aiming the greatest achievable performance of failure recognition and system state prognostics. The foremost AI and associated approaches investigated in this study involve the Artificial Neural Networks (ANNs), Expert Systems (ES), fuzzy logic and Evolutionary Algorithms (EAs).

A. Artificial Neural Networks (ANNs)

According to Sinha et al. (2000) most of research on ANNs is oriented towards static Feedforward Neural Networks (FNNs) operating directly without considering time delay causes. A solution motivated from neurobiology field recommends the development of Dynamic NNs (DNNs) offering better computational capabilities in comparison with the static networks. On the other hand, an analytical model by Lei et al. (2008) proposes an intelligent fault diagnosis by integrating statistical analysis, evaluating distance technique and Adaptive Network-based Fuzzy Inference System (ANFIS). It consists of three stages, the first stage is dealing with time-domain, frequency domain statistics and Empirical Mode Decomposition (EMD), gaining detailed fault information. The second stage comprises the most superior features from an initial feature set and in third and final stage, these selected features are imported into ANFIS for identification of malfunctions. The outcome is utilised on bearings for fault diagnosis which shows its reliability on fault categorisation and severity recognition. Mizutani and Jang (1995) develop Co-Active Neuro-Fuzzy Inference System (CANFIS) merging Fuzzy Systems (FSs) as an expanded case of ANFIS by utilising multiple input and output pairs.

B. Expert Systems (ES)

The second approach of AI under investigation is ES, involved in CM. In line with Al-Najjar and Alsyouf (2000), ES consists of three key elements, a knowledge base, an inference engine and a database. An integration of tools is aspired by Yimin and Nezu (1995) developing an AI, which combines ES with the Degree of Creditability of Parameter value Variations (DCPV factor) aiming to face the difficulties of online monitoring of bearings affected by intrusive vibration signals. The results show a practical system with superior potential, being quick and flexible to build up.

C. Fuzzy logic systems

Expanding the capabilities of Boolean logic, fuzzy logic handles the concept of partial truth values ranging between the complete truth and false (0 or 1). According to Dmitry and Dmitry (2004), data mining can be handled by introducing fuzzy logic in control systems for applications in the domain of pattern recognition. However, the state-of-the-art technique is neuro-fuzzy approach to automate the problem of selecting fuzzy sets and appropriate rules due to experts' difficulties of controlling it. Various methods are presented for this problem such as, Genetic Algorithms (GAs) and data clustering.

An alternative study by Khan et al. (2004) challenges the problem of variation in the results sourced from different inspection agencies. The study outlines an RBI maintenance methodology and employs fuzzy logic integrated with the probability of occurrence and consequence estimating the risk. The method focused on the risk aspects and decision support involving semi-quantitative and quality parameters employing fuzzy logic for translation of qualitative data into numerical readings. The study presents the construction and evaluation of a scheme assessing the probability of failure by eliminating the adaption of assumptions.

D. Evolutionary Algorithms (EAs)

Recently, ship maintenance scheduling is considered by Deris et al. (1999) through Constraint Satisfaction Problem (CSP) perspective for the needs of Royal Malaysian Navy by utilising effective Genetic Algorithms (GAs). CSP parameters involve start times and its domain values the initiation and horizon of the schedule. The methodology of solving this maintenance scheduling takes into account Constraint-Based Reasoning (CBR), which involves start times of initial activities of maintenance cycles. Moreover, the study suggests further exploration of estimating the time between planned and actual maintenance cycles reinforcing maintenance planning by adjusting delays and maintenance activities which are postponed until resources are available. Rafiul Hassan et al. (2012) propose the integration of tools such as Hidden Markov Model (HMM), fuzzy logic and multi-objective Evolutionary Algorithm (EA) for estimation of non-linear time series data. Multi-objective EA scopes to find a range of optimal solutions between the number of fuzzy rules and the prediction accuracy. However, experimental results accomplish reduction of fuzzy rules by achieving equivalent efficiency with the existing fuzzy models.

3.7.2. *Signal processing and optimisation methods*

This subsection is focused towards rotational machinery and mostly vibration signal analysis. One of the most critical stages within the CM framework arrangement is signal processing. This stage is mostly responsible for the accuracy of the failure detection as it consists of signal de-noising processes, through which collected data are analysed and unnecessary information is removed from them. This processing level allows accurate filtering and preparation of the signal for the upcoming feature extraction process (i.e. pattern recognition form of dimensionality reduction). Various optimisation methods are proposed and tested in literature and their applicability varies due to signal type specification and output requirements. Wu and Chen (2006) summarise Short-Time Fourier Transforms (STFT), Wigner-Ville Distributions (WVD) and Continuous Wavelet Transforms (CWT) as widely used methods for detection of fault conditions and practical fault diagnosis of rotational machineries.

An application is developed by Halim et al. (2008) proposing Time Domain Averaging across all Scales (TDAS) by combining time averaging and Wavelet Transforms (WT), extracting noisy vibration signals from various periodic waveform scales. The results present successful noise clean up and detection of local and distributed faults identifying gear missing and chipping tooth as large peak and peak with parallel side at the meshing frequency respectively. On the other hand, Estocq et al. (2006) present the importance of de-noising vibration signals gathered from ball bearings by spectral subtraction in different frequency bands which improves sensitivity of the temporal indicators and enhancing the reliability and diagnosis efficiency. In the analysis of the de-noised signal results, Lin et al. (2004) express that existing wavelet de-noising methods use orthogonal wavelets, causing problematic matching with information on the impulse. A different technique implements Morlet wavelet as basic wavelet corresponding to impulse by using maximum likelihood estimation and utilising prior information on the probability density of the impulse. This technique shows ultimate performance with low signal to noise ratio.

Alternatively, Utsumi et al. (2001) present a novel model of ferrographic analysis to diagnose bearings through local spatial frequency analysis using WT. Gabor function is selected as main function of WT as it is effective in distinguishing particles along the magnetic force lines on the ferrogram particles. Fuzzy system theory is applied to classify the particles and present the effectiveness of the proposed method. An integration for transient vibration signal fault detection method is proposed by Zhu et al. (2009) which combines CWT in time-scale plane representation and Kolmogorov-Smirnov (K-S) test for detection of equipment failure which is applied on gearbox. The method is tested on vibration signals of cone bearings with fault detection in the inner, outer race and rolling elements.

Bearing performance degradation is assessed by Pan et al. (2010) based on lifting wavelet packet decomposition and fuzzy c-means clustering method. Normal and failure data is used for training, developing model's degradation indication. Finally, Shi et al. (2004) propose an Adaptive Time-Frequency Decomposition (ATFD) method which analyses vibration measurements. This method clarifies accurately complex signals using different time-frequency analysis tools. ATFD's results show accuracy and efficiency in monitoring rotating machinery by identifying critical speed and accelerating rates during stable operation, run up and shut down phases.

3.7.3. Risk of failure identification and analysis methods

In the previous sections, AI and signal processing methods are examined. According to Russell and Norvig (2003), AI is a flexible rational mediator that observes the operational environment and takes actions that maximize its chance of success at an arbitrary goal. Similarly, signal processing is an enabling technology that transfers information contained in different formats designated as signals (Moura, 2009). In this section, the information gained from AI, signal processing or data mining methods is examined with respect to risk and reliability assessment and failure identification.

Risk, failure and uncertainty are crucial factors influencing the functionality of ship machinery, and systems, hence businesses by affecting the environment, humans and assets. The risk of failure identification and analysis can be examined through qualitative and quantitative approaches. Each of these offers different features, advantages and limitations. This subsection identifies and examines well-known and applied failure identification and analysis methods.

Backlund and Hannu (2002) highlight the importance of maintenance by focusing on market competition. One of the parameters ensuring that a plant succeeds this challenge is to handle maintenance costs efficiently. A major tool that decision makers use to prioritise planning inspection and maintenance actions is risk analysis. According to Tuzku et al. (2006), risk assessment is a process comprising statistics and historical data. Nevertheless, in conditions that statistical data does not exist or they are inadequate, information is gained by using expert judgement. On the other hand, a summative research by Tixier et al. (2002) reviews various risk analysis methodologies by separating them in identification, evaluation and hierarchisation.

According to Delia and Rafael (2008), system degradation should be included in the risk analysis models, due to the fact that systems, while they operate, deteriorate. Furthermore, various failure types have to be considered and evaluated independently as well as dependently leading to sequential failure reasoning assessment. Expanding this idea, Devanney (2006) states that the difference between hull and machinery failures is oriented in the function. In the case of the hull, failure can arise due to an independent cause, whereas in the machinery case, failures take place due to influences from more dependent factors.

A comparative research by Aksu et al. (2006) and Aksu et al. (2007) presents the risk and reliability assessment methodology on four-pod propulsion system. It utilises Failure Mode and Effect Analysis (FMEA) for qualitative analysis, which provides a valuable foundation for quantitative reliability and availability analyses. Fault Tree Analysis (FTA) is employed for qualitative and quantitative information, allowing the examination of multiple failures and Markov Analysis (MA) by solving Dynamic FTA (DFTA) capturing sequences and combining events. Another proposed model by Čepin and Mavko (2002) extends FTA with time requirements proving that DFTA reduces system unavailability by expanding and upgrading knowledge gained from probabilistic safety assessment including time dependent information.

FMEA is also employed by Cicek and Celik (2013) to determine the maintenance time, achieve cost reduction and reliability enhancement to prevent crankcase explosion failure on board. In addition, Carmignani (2009) extends FMEA to an advanced expression of Failure Mode, Effects and Criticality Analysis (FMECA) model considering the factor of the corrective action cost. Priority-Cost FMECA (PC-FMECA) allows the calculation of a new Risk Priority Number (RPN) by introducing the concept of profitability related to action cost.

A predictive maintenance strategy utilising FMECA and FTA is presented by Lazakis et al. (2010) to achieve the upgrade of the existing ship maintenance regime to an overall strategy including technological advances and DSS by combining existing ship operational and maintenance tasks with the advances stemming from new applied techniques. On the other hand, Turan et al. (2011) develop maintenance strategy based on criticality and reliability assessment using DFTA. An alternative line is proposed by Gamidov et al. (2009) to assess the reliability of marine diesel engines using a mathematical model on Markov Chains (MC), which allows reliability estimation of components and systems, and the likelihood of effective operation at specific time. In a similar manner, Xu et al. (2006) propose a dynamic mathematical model for marine main engine systems, which improves operation through fault tolerant control system by employing ANN. The advantages of user modelling from multi-sensor information sources are presented by Oliver and Horvitz (2005), where Dynamic Bayesian Networks (DBN) and Hidden Markov Model (HMM) are assessed leading to crucial differences and benefits of each modelling approach.

In addition to mathematical modelling, material analysis is used by Hassan and Alam (2010) to identify the root cause of failure of gearbox and clutch shaft from a marine engine by employing metallurgical failure analysis and assessing the surface fracture. The study presents that the gearbox shaft affected by rotational bending, while the clutch shaft is affected by torsional and corrosion. The RUL of bearings is predicted through a proposed model by Kim et al. (2012). This model uses health state probability estimations and historical data. Support Vector Machine (SVM) classifier is employed for condition probability estimation of machine’s degradation process providing long-term predictions. Jardine et al. (1997) present a parametric approach using Weibull hazard function and time-dependent stochastic covariates by combining monitoring data in systems' reliability through Proportional Hazard Modelling (PHM). Markov model is used by Artana and Ishida (2002) as well. They set reliability and availability as constants to determine the optimal maintenance and failure frequency stating that it is applicable to systems having constant hazard rate, while the transition probability between two states remains constant (discrete time-dependencies).

Alternatively, Rougé et al. (2014) link for first time viability and reliability. Hence, proving that time-variant reliability and stochastic viability focus on same problems from different perspective. The connection of these two terms is expressed by describing reliability as the evaluation of probability of failure with regards to uncertainty and stochasticity. Viability scopes to maintain and control the systems dynamically within specified functional levels. In line with the notion and motivation of authors' viewpoint, Fiondella and Xing (2015) present a method to consider reliability of systems by involving identically correlated components. Discrete and continuous models are developed and explored through a series of examples.

Furthermore, Yu (2013) develops a Generative Topographic Mapping (GTM) and contribution analysis-based method for health degradation assessment of turbine engine's bearings utilising Bayesian-Inference-based Probability (BIP) for failure likelihood consideration. Moreover, an alternative arrangement for probabilistic analysis is emphasized. According to Kaplan and Garrick (1981), five steps have to be followed for Probabilistic Risk Assessment (PRA) including the expansion of various scenarios, improvement of models, estimation of factors, ranges and uncertainties, performance calculations and clarification of outputs.

Lastly, INCASS (Inspection Capabilities for Enhanced Ship Safety) project introduces a probabilistic multi-component prognostic CM model for ship machinery inspection and maintenance scheduling known as Machinery Reliability Analysis (MRA). Part the present thesis research work has been utilised in INCASS project. INCASS integrates MRA with a DSS for critical ship machinery by taking into account technical as well as economic parameters (INCASS, 2014a), (INCASS, 2014b) and (INCASS, 2014c).

3.7.4. Decision making methods

Decision-making is the final stage of the CM framework. This phase aims to suggest inspection and maintenance actions by prioritising critical systems, subsystems and components. The scope of this decision-making stage is to assist professionals by automating operational and functional processes.

A Decision Support System (DSS) is presented by De Boer et al. (1997) to improve the process and capacity planning of large repair projects supported by the Royal Netherlands Navy Dockyard, which performs repairs, overhaul and modification projects for several classes of navy ships. Andersen and Rasmussen (1999) present a basic cost-risk model sourced from technical health information for short-term maintenance scheduling by deliberating costs of postponed PM. An intelligent CBM/DSS for maintenance deficiency on planning issues is developed by utilising fuzzy sets for diagnostic modelling and machine reasoning through expert knowledge (Du et al., 2012). On the other hand, Lazakis and Olcer (2015) introduce an overall novel Reliability and Criticality Based Maintenance strategy by employing an existing fuzzy multiple attributive group decision-making technique, which is further enhanced with the employment of Analytical Hierarchy Process (AHP). The outcome of this study indicates that preventive maintenance is ideal approach closely followed by predictive maintenance, hence, avoiding the ship corrective maintenance framework and increasing overall ship reliability and availability.

Multiple difficulties arise in handling large database sources from continuous CM activities. Hence, Gento (2004) presents decision techniques through Rough Set (RS) theory scoping to extract knowledge from these information and establish decision rules for maintenance processes achieving reduction of unnecessary data. Similarly, Pawlak (1982) supports that RS theory extracts rules, reduces data and increases the effectiveness of maintenance department. However, the implementation of RS theory technique requires great amount of input data and extensive time for development. On the other hand, Al-Najjar and Kans (2006) analyse the construction of database by mapping technical and financial effectiveness of production for cost-effective maintenance decisions. From this exploration, a generic guideline shows that there is a connection between technical and economic associated factors, such as productivity, performance efficiency, quality rate, availability and production cost as well as the strategic level expressed by the company's profit and competitiveness. Additional decision making

A review by Hofmann (2011) presents commercial and under development DSS, oriented on operation and maintenance planning of offshore wind farms. However the major limitations are discovered similarly with the maritime industry on the absence of models covering the entire life cycle of equipment. Through an exploration of research and commercial applications, Juuso and Lahdelma (2013) combine maintenance and operation by integrating process and condition monitoring data with performance measures. The key result of this approach is that control, condition, maintenance and performance monitoring interact in closed loops (feedback) arrangement. Lastly, Dikis et al. (2016) presents the development of Machinery Risk and Reliability Assessment Decision Support System (MRA-DSS) as part of INCASS FP7 EU funded project (INCASS, 2015b). MRA DSS analysis demonstrates failure predictions through a user-friendly Graphical User Interface (GUI). The user has available information related to cost analysis, maintenance actions, reliability performance predictions and symptoms due to reliability loss.

3.8. Identification of research and development direction

This Chapter assesses existing literature with respect to inspection and maintenance strategies, methodologies, guidelines, regulations and standardisation policies/rules. Hence, this literature review identifies the research and development tendency for ship machinery inspection and maintenance. Critical outcomes of this review are summarised in this section and utilised for structuring the proposed Probabilistic Machinery Reliability Assessment (PMRA) maintenance strategy, targeting to accomplish this research aim and objectives.

First of all, the need for an overall adaptable inspection and maintenance framework is identified. Hence, a framework to be applicable on complex system level of machinery can be introduced towards maintenance scheduling of systems, subsystems and components. This holistic inspection and maintenance notion should be implemented by integrating different strategies, methodologies, technologies and tools, suitably selected, as the requirements per system may vary. Specifically, the implementation of maintenance strategies in industry as well as the research interest is aligned with the lately established predictive and proactive maintenance strategies. Henceforward, inspection and maintenance challenges are conformed to operational and failure diagnostics, prognostics and failure forecasting as well as the root cause analysis of malfunctions and abnormal functioning.

Along these lines, multiple guidelines, regulations and policies are established by different standardisation and regulatory bodies. Fundamental guidelines that support the structure of the proposed research methodology of this dissertation are correlated to BS/ISO 17359 (2011) and BS/ISO 13381 (2015). The first general guideline sets the grounds for machinery Condition Monitoring (CM) with respect to diagnostics. On the other hand, the second guideline introduces general rules and procedures for machinery CM diagnostics and prognostics. These two BS/ISO standards are employed for guiding generic aspects of the proposed maintenance strategy procedure flow.

With regards to the maintenance methodologies, the research awareness is oriented towards the latest on-condition assessment through non-distractive inspection methods. Hence, Condition Based Maintenance (CBM) is currently the state-of-the-art, especially the integration of Condition Monitoring (CM) technologies and tools. This on-condition assessment through automated procedures generates the requirement for multiple data/information source management and analysis. In other words, features from Computerised Maintenance Management Systems (CMMS) are incorporated with CBM. Additionally, the newly-introduced holistic viewpoint of the overall system inspection and maintenance scheduling enables the consideration of technical, economic and managerial assessment aspects. Therefore, CBM characteristics are integrated with Asset Management (AM).

Considering these research findings with respect to the generic maintenance strategies' tendency, it is vital to highlight specific technical research gaps. Summarising, fundamental research issues remain the development of an inspection and maintenance strategy for accurate Condition Monitoring (CM) prognostics. Current methods solve the failure prediction problems of single components, however performance assessment and degradation prediction is needed. Hence, specific single component diagnostic and prognostic approaches exist in industry and research. However, a generic adaptable prognostic methodology for complex ship machinery is required. On the other hand, the integration of CM techniques with cost-effective applications should be combined for complex ship machinery. This flexible CM framework should aim of forecasting accurate failure warnings (alarms) before a fault reaches specific critical operational levels, schedule repairs and plan inspection and maintenance actions as well as control the fault tolerance.

Additionally, except of the failure prediction, ship machinery health degradation can be examined integrated with failure modes. This performance degradation assessment will allow the performance loss identification through time, before failures or signs of malfunctions appear. Along these lines, the sooner the abnormal functioning is identified the more available time to plan the maintenance actions and the more financial efficient solution can be obtained. Therefore, predictive maintenance can incorporate both Time-to-Failure (TTF) and the Probability of Failure (PoF) in future time. TTF is a random evaluation measure of systems' reliability. This value arises out of performance measurements, operational conditions as well as information out of the functioning environment, so the inspection and maintenance decision should be risk-based.

In particular, risk-based assessment, evaluating the PoF of systems for failure interaction, is missing from literature. In other words, the examination of the systems, subsystems and components operational interdependencies should be introduced, in order the failure and malfunction root cause analysis to be identified. From a technical perspective, the working state reliability performance estimation should be introduced integrating multiple p-step-before filtering methods with multiple p-step-ahead forecasting for prediction accuracy enhancement.

Lastly, the state-of-the-art in inspection and maintenance of ship machinery reflects the establishment of performance degradation assessment. Currently, the failure prediction issue is tried to be solved on specific component level. However, tools for system performance assessment and degradation prediction are not well addressed. Henceforward, ship system holistic view by integrating CM with equipment performance monitoring is required for accurate and reliable risk assessment.

In conclusion summarising the key findings of this literature review and setting the ground for the proposed methodology, PMRA establishes an adaptable ship machinery methodology for complex systems. Probabilistic Machinery Reliability Assessment (PMRA) introduces multiple level assessment on system, subsystem and component analysis. Moreover, PMRA considers operational interdependencies among systems, subsystems and components targeting the failure root cause assessment. Furthermore, PMRA methodology structure complies with BS/ISO 17359 (2011) and BS/ISO 13381 (2015) guidelines fulfilling requirements of already certified standards.

PMRA methodology directs towards holistic perspective of ship machinery inspection and maintenance by incorporating fundamental aspects of Asset Management (AM). Additionally, PMRA examines the reliability degradation of ship machinery through time before warnings and failures appear. Last of all, a research gap that PMRA will examine and try to cover is related to p-step-before assessment and multiple p-step-ahead reliability prediction, expecting to enhance prediction accuracy.

3.9. Chapter summary

In this Chapter, the literature review of this dissertation has been presented. Firstly, the overview of the maintenance classification has been identified as implemented in industry including corrective, preventive, predictive and proactive maintenance strategies. The research interest is mostly oriented towards the latest introduced predictive and proactive strategies. This Chapter introduces guidelines and regulations provided by competent bodies setting the basis for standardised inspection and maintenance framework regulations. These regulatory bodies include British Standards (BS) and International Standards Organisation (ISO), International Maritime Organization (IMO) regulations and guidelines from the International Association of Classification Societies (IACS). The implementation of various maintenance methodologies is assessed by identifying advantages and limitations. The considered methodologies include Reliability Centred Maintenance (CBM), Total Productive Maintenance (TPM), Total Quality Management (TQM), Risk Based Inspection/Maintenance (RBI and RBM respectively) Condition Based Maintenance (CBM), Computerised Maintenance Management System (CMMS) and Asset Management (AM). The latter three (i.e. CBM, CMMS and AM) set the grounds for system inspection and maintenance automation by taking into account computerised approaches. Hence, further research on the on-condition inspection and maintenance methods is undertaken by investigating widely applied and novel Condition Monitoring (CM) technologies and tools such as vibration monitoring, thermography, lubrication oil analysis, visual inspection and acoustic and ultrasonic monitoring. Moreover, the main CM functionalities are presented such as the fault detection and diagnostics and the state-of-the-art prognostics, which targets the time-to-failure forecasting before failure occurs. On-condition assessment has wide applicability in industry. Hence, the presented literature review considers well-known commercially available CM systems. Lastly, maintenance input data optimisation tools are examined and demonstrated considering Artificial Intelligence (AI) approaches, signal processing methods, risk of failure identification and analysis methods and decision making tools. Concluding, as this Chapter aims to specify research and development tendencies and gaps, a sample of this comparative investigation can be found in Appendix A.2. This input evaluates multiple sources and specifies the current research gaps that the proposed dissertation methodology will examine and try to cover. Hence, the most critical sample of publications has been placed in Appendix A.2, which led to decisions taken for the methodology structure, data processing and reliability modelling method selection. Also these publications guided for listing the future research work. Additionally, the table added in Appendix A.2 intends to guide researchers and professionals in an efficient way of identifying research gaps and evaluating recent research. The proposed methodology will be presented in Chapter 4 demonstrating Probabilistic Machinery Reliability Assessment (PMRA).

4. PROPOSED PREDICTIVE INSPECTION AND MAINTENANCE STRATEGY FOR SHIP MACHINERY

4.1. Chapter outline

In the previous Chapters, the maritime transportation challenges were presented by specifying the comprehensive goals of shipping. Additionally, the identification of research gaps and development direction with respect to undistracted inspection and maintenance of ship machinery was demonstrated setting the foundations for this Chapter. The proposed Probabilistic Machinery Reliability Assessment (PMRA) strategy is established in this Chapter by introducing novel predictive methods and data analysis techniques. It is essential to highlight that PMRA strategy is capable and suitable for providing reliability predictions of both processed and raw data. An introduction into data mining field takes place outlining methods, which allow to extract information from a dataset and transform it into an understandable structure for further use. Multiple data clustering practices are assessed leading to the utilised k-means algorithm, also referred as Lloyd's algorithm, which is based on the generalised form of Expectation-Maximisation (EM) algorithm. Next, the implementation of specific operational safety thresholds set the limits for acceptable functioning. These safety thresholds combined with the output from the utilised data clustering algorithm (k-means) transform the gathered raw input data into probabilistic indices. Subsequently, these indices are fed into Bayesian Belief Networks (BBN). Furthermore, time-dependency is considered and BBN is integrated with the adaptable process of Markov Chains (MC), which introduces the dynamic aspects allowing predictive transitions from one state to another on a state space. Lastly, Decision Making (DM) has been achieved employing expert judgement and the qualitative tool of Failure Modes and Effects Analysis (FMEA).

4.2. Introduction of the PMRA strategy

4.2.1. Research gaps in maintenance practices on ship machinery

Chapter 3 examined different maintenance methodologies and practices as presented in literature and in industry. These practices aim to bridge the distance between the theoretical development of maintenance and its applications. Nevertheless, multiple research and development gaps are identified through this critical literature review. This section demonstrates the research gaps that the proposed Probabilistic Machinery Reliability Assessment (PMRA) strategy will try to tackle.

First of all with respect to maintenance strategies, corrective and preventive share wide applicability. The first one is carried out after a failure occurs. Hence, this leads to impractical and costly inspection and maintenance solutions by increasing the risk of unexpected failures. On the other hand, preventive maintenance is applied through planned maintenance activities in predefined time intervals. This strategy allows safer ship machinery to corrective maintenance. However, preventive maintenance may lead to over-maintained equipment by premature component replacement or unexpected failures, before planned maintenance actions take place, due to extreme operational conditions. Consequently, if the maintenance time-interval can be specified according to the ship machinery condition, the maintenance plan will lead to optimum solutions. Therefore, on-condition assessment is the optimal practice that will allow maintenance activities to take place when decided by experts or suggested by integrated Decision Support Systems (DSS).

Critical literature review, demonstrated in the previous Chapter, shows that on-condition assessment for equipment and components involves failure or abnormal functioning diagnostics and prognostics. Current literature provides a wide range of sources, methodologies and practices for single component diagnostics and more limited for single component prognostics. Furthermore, literature on condition monitoring assessment on multiple components and multiple equipment prognostics does not exist. CM diagnostic and prognostic assessment examines the occurrence of failure, Time-to-Failure (TTF) and Remaining Useful Life (RUL). However, all of these estimations remain challenging tasks for data analysts and engineers. An innovative equipment and component assessment can establish the reliability performance and degradation evaluation leading to accurate forecasting before operational safety thresholds are exceeded or failures occur.

Moreover, an overall holistic methodology of assessing multiple complex ship machinery should be introduced. This methodology can integrate accurate CM diagnostics and prognostics as well as performance monitoring by evaluating degradation through time. According to the latest critical literature review, fundamental issues in CM prognostics remain the accurate failure predictions, performance assessment and degradation forecasting. Specific component and equipment prognostic approaches exist, however a generic adaptable CM prognostic framework is required as research presents space for further investigation and development.

The implementation of CM of multiple complex ship machinery generates the necessity for further research and development on data fusion gathered from various sensors and sources. Existing practices perform CM diagnostics and prognostics of components whilst single input data is processed and analysed. The innovative aspects of data fusion enable flexibility in risk assessment, enhancement of accuracy in predictions and integration of different methodologies and tools. On the other hand, the assessment of multiple complex systems combined with the data fusion features will allow the investigation of failure interaction among different systems, subsystems and components.

Additionally, the establishment of practices integrating data of various ship machinery empower the necessity for automated data management systems such as Computerised Maintenance Management Systems (CMMS). This CMMS practice can facilitate management of data such as raw gathered data, expert information, historical input, event occurrence, diagnostic and predictive features and descriptions targeting the formation of long-term asset data file. Concluding, the core research gaps on inspection and maintenance, a scalable and adaptable predictive methodology (toolbox) applicable on various ship machinery should be introduced enabling monitoring of multiple systems, while taking into account past, current and forecasted operational states. According to the latest critical literature review, the present thesis contribution is focused towards the establishment of an efficient maintenance strategy for machinery fulfilling the following requirements:

- Scalable and adaptable structure of maintenance strategy facilitating multiple different ship machinery by integrating accurate Condition Monitoring (CM) diagnostics and prognostics.
- Integration of Condition Monitoring (CM) aspects should incorporate raw data processing, predictive reliability analysis, degradation drop and economic impact further than the technical concerns.
- Essential CM prognostic features should involve raw data analytics and feature extraction utilising novel data mining methods. These methods introduce diagnostic features into the methodology.
- Risk and reliability assessment should take place on system, subsystem, component levels targeting root cause analysis of failures.
- Consideration of system, subsystem and component operational dependence as degradation or failure of one can lead to failure of multiple others (failure interaction).
- Effective, practical and reliable input data fusion leading to accurate and robust CM diagnostics and prognostics.
- Multiple sources of input data should be considered gaining information from various sources (i.e. historical data, expert judgement, raw sensor data) enhancing the predictive aspects such as accuracy, efficiency and diagnostic precision.
- Integration of different input data processing methods and combination of various diagnostic and prognostic practices can enhance the overall target of flexibility and prediction accuracy.

4.3. PMRA strategy framework

In the previous section, core research gaps in maintenance practices on ship machinery are identified setting the prerequisites for the proposed strategy. The suggested Probabilistic Machinery Reliability Assessment (PMRA) strategy aims to enhance ship machinery reliability by offering accurate reliability predictions. These predictions enable the suggestion and scheduling of maintenance actions at the right time at the right place. Having the above gaps and requirements in mind, this section presents the overall PMRA strategy framework as this can be applied in the maritime sector. The proposed PMRA strategy will be demonstrated in two stages as shown in Figure 4.1.

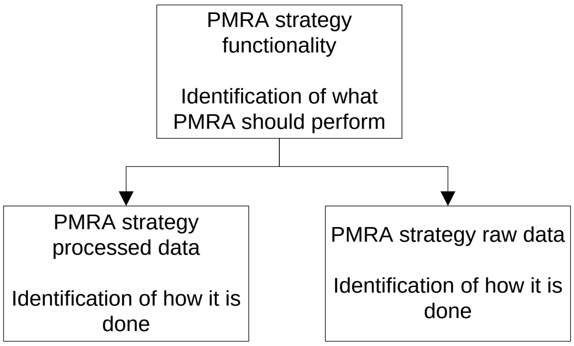

Figure 4.1 Stages of PMRA strategy implementation

At the first stage, the fundamental aspects of PMRA are identified setting the grounds for further analysis. This first stage of assessment involves the identification of the major PMRA strategy features. PMRA has been oriented towards a predictive reliability assessment capable of utilising the processed and raw data. In this Chapter, the PMRA strategy framework is presented classifying the processes for analysing processed and raw data targeting dynamic predictive reliability assessment.

The processed data assessment introduces the fundamental aspects fulfilling main gaps of the latest literature presented in Chapter 3. At the second stage, the principle considered methods are classified and the suitable methods and tools are selected for utilising raw data. Lastly, the proposed PMRA strategy will be established demonstrating specific selected algorithms and methods. Moreover, the stages represented in Figure 4.1 refer to the implementation of the predictive reliability assessment tools as well as the innovative solutions introduced through PMRA in each involved stage that will be presented next. It is essential to clarify in advance that PMRA strategy embeds flexible technical aspects integrating features for predictive reliability assessment based on processed and raw data. This decision has been made, because shipping stakeholders utilise their data in one of these two data types (i.e.

processed or raw). Therefore, applicability and flexibility is a leading characteristic of the novel PMRA strategy framework.

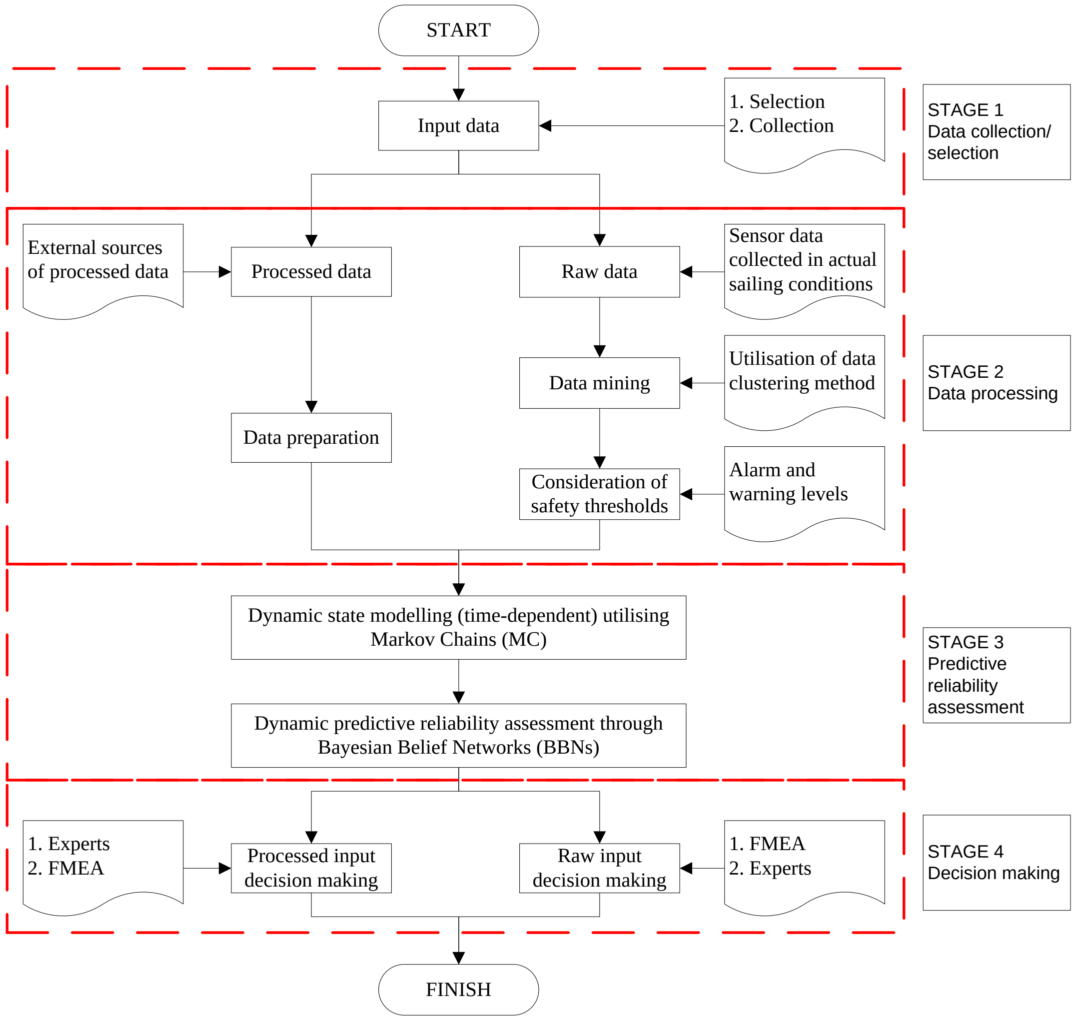

Figure 4.2 PMRA strategy framework

The overall PMRA strategy framework consists of four stages such as the data collection, data processing, predictive reliability assessment and decision making. These stages refer to both processed and raw data implementation. In the following sections, the PMRA strategy framework is demonstrated analytically for both data type cases (processed and raw). The fundamental aspects of PMRA strategy framework will be presented next and in the following sections each data type and processing method will be demonstrated analytically.

STAGE 1: Data collection

This stage refers to data gathering from any data source such as sensors, which provide raw data or databases and particular shipping stakeholders (i.e. service providers, ship owners and operators, Classification Societies etc.) for providing processed data. In this stage, the selected input data has been identified regarding the type and collection interval. The gathered data has been fed into the following level of data processing.

STAGE 2: Data processing

The second stage of PMRA strategy framework takes into account data processing techniques. These have been separated between processed and raw data approaches. The first data type has been already processed by external data developers such as shipping companies, Classification Societies and stakeholders, which provide or share data and records in percentages such as failure rates. The latter data type is raw and PMRA strategy incorporates an innovative data mining method for processing and extracting useful information. Once the raw data has been transformed into percentages figures (which is compatible to the following reliability assessment tool), these are fed into the dynamic predictive reliability assessment stage.

STAGE 3: Predictive reliability assessment

The reliability assessment stage takes into account figures in the format of percentage, which are processed for providing dynamic reliability predictions. This particular stage employs the dynamic state modelling aspects (time-dependencies) and reliability assessment through the appropriate network arrangement. The predictive reliability assessment stage is common in structure, and functionality for both processed and raw data. The scope of this processing stage is to obtain the predicted reliability states on system, subsystem and component. Once these figures have been acquired decision making actions can be proposed.

STAGE 4: Decision making

This is the latter stage of the PMRA strategy framework. It involves practical features offering inspection and maintenance action suggestions, by taking into account the current and predicted reliability performance as acquired by the previous processing stage. Overall, decision making has been developed into a qualitative manner by incorporating expert judgment of ship owners, service providers, Classification Societies, chief crew members and chartered engineers and valuable contribution from Original Equipment Manufacturers (OEMs) manuals and reports. A qualitative risk assessment tool known as Failure Modes and Effects Analysis (FMEA) has been introduced in guiding the user for identification of failure modes, effects, damaged equipment and components and appropriate failure causes.

Summarising, PMRA strategy framework is capable in providing reliability performance predictions for processed and raw input data. It is essential to highlight that processed data PMRA strategy is simpler in structure and method arrangement. The main reason is based on the fact that data processing has been taken place by external developers and data providers. Therefore, the processed data has already formatted in percentage figures, which is prerequisite for the predictive dynamic reliability assessment.

4.4. PMRA strategy for processed data

Data processing of PMRA strategy is demonstrated in the flow diagram shown in Figure 4.2. These stages are associated in hierarchical order, whilst each process feeds data the following with the required input. The referred processes are analytically presented in the following subsection. Overall, PMRA strategy for processed data has been initiated by selecting the required input data in processed form.

This processed data has been provided by external databases or data and process providers such as ship owners, operators, service providers, and Classification Societies. The following procedure involves the data processing. In this stage, the provided input data is transformed in figures that fulfil the requirements of the predictive reliability assessment stage, which takes place next. The third stage of PMRA strategy integrates innovative solutions for the dynamic state modelling (time-dependencies) and the predictive reliability assessment. Lastly, the acquired predictions from the previous stage have been combined with the qualitative decision making functionality of expert judgement and FMEA tool.

4.4.1. *Input Data Selection & Collection*

The first processing stage involves the selection of the required input data types. Overall, PMRA strategy merges historical data, expert judgment, and raw/real-time sensor data. However, the processed data PMRA strategy implements historical processed data (instead of raw) for the appropriate machinery. This historical data incorporates failure rates, and number of failures per component and failure mode. Additionally, at this state, the selection of the optimal source (i.e. experts and professionals, sensor type etc.) has to be considered. Data collection should deliberate in advance all the necessities and requests for the overall Condition Monitoring (CM) PMRA strategy up to the latest stage of maintenance actions suggestion.

4.4.2. *Data Processing and Preparation*

The second stage of PMRA strategy regarding the processed data is simpler in structure and functionality compared to raw data case. The reason behind this simplicity is described by the fact that external data providers have been already processed the data. Therefore, the data mining method developed for the PMRA strategy has not been employed in the processed data case. However, data preparation can be required, which can be specified once the processed data is known. This stage aims to set the grounds for the input data in order to fulfil the requirements of the following predictive reliability assessment tool. Analytical data preparation of processed data has been discussed in Chapter 5.

4.4.3. *Machinery Risk & Reliability Assessment*

Ship functioning encompasses high level of uncertainty due to operation of multiple complex machinery and equipment (i.e. main engine, diesel generators, various pumps, purifiers, boilers among others) in different weather, sea state, ship sailing, cargo loading and engine load conditions. Machinery reliability evaluation, with respect to risk of failure and abnormal functioning, can be tackled by concerning first principle assessment or probabilistic reliability assessment practices. The first approach involves fundamental laws of science and engineering such as mathematics, physics, fluid mechanics, thermodynamics and material science in order to assess the reliable operation of ship machinery. First principles assessment is time-consuming, may requiring enormous amount of man-months (depending on the detail level), including programming, automation and other challenging tasks.

On the other hand, the complexity and variety of the involved parameters, as listed above (i.e. multiple complex machinery, weather, sea state, sailing, cargo loading and engine load), lead to operational parametric assumptions. These assumptions reduce the risk and reliability assessment flexibility by examining specific conditions. Furthermore, operational and conditional parametric assumptions limit the ability of system reliability assessment over a holistic/overall viewpoint, which is the fundamental idea of the proposed PMRA strategy.

Therefore, the PMRA strategy is oriented towards the selection and implementation of a novel probabilistic reliability assessment tool. This research domain is known as Probabilistic Risk Analysis (PRA) also called Quantitative Risk Analysis (QRA) or Probabilistic Safety Analysis (PSA) is a supportive tool for management and decision making, establishing a new domain in risk management (Bedford and Cooke, 2001).

Various risk and reliability assessment tools are demonstrated in literature as shown in Chapter 3. These tools tackle risk and reliability assessment in qualitative and quantitative manner. In the first place, well-known qualitative tools are listed among HAZID, HAZOP, SWIFT, FMEA and FMECA. On the other hand, quantitative risk and reliability assessment includes ETA, FTA and BBNs tools among others. Each of these risk and reliability assessment tools contributes towards operational evaluation from a different perspective. However, qualitative tools provide subjective output, whereas, quantitative tools are objective by employing specific measurable indices.

Hence, PMRA strategy is oriented towards objective practices, where specific input data can be recorded, processed and evaluated through an accurate, flexible and robust approach. Therefore, PMRA strategy integrates qualitative and quantitative aspects for accomplishing the CM, input data processing, information extraction, predictive reliability performance and decision making tasks.

4.4.4. PMRA Decision Making

The outcomes of the machinery predictive reliability assessment process level will be integrated with historical data from external reliability data sources and expert judgment, where required, providing technical input to the following PMRA decision making. At this level of analysis, the reliability predictions, delivered by the previous machinery reliability assessment process (above), are utilised in order to suggest maintenance activities. The suggested maintenance actions aim to enhance ship safety and machinery reliability. This historical and expert data has been used as well in creating a qualitative risk assessment tool known as Failure Modes and Effects Analysis (FMEA).

4.5. PMRA strategy raw data

At this stage of analysis and evaluation, while structuring the raw data PMRA strategy, the available data mining, safety thresholds and reliability assessment tools are compared and the selected ones are demonstrated. PMRA strategy incorporates various procedures, methods and tools for accomplishing the required CM predictive features as shown in the flow diagram of Figure 4.3. First of all, the raw input data is gathered, followed by the recorded raw data mining. The latter is split among recorded input dataset clustering and the applied k-means algorithm, established in literature as Lloyd’s algorithm (MacQueen, 1967).

In the following level of analysis, the safety thresholds are identified for each of the selected raw sensor data. The machinery reliability assessment integrates the benefits of Markov Chains (MC) with the advantages of Dynamic Bayesian Belief Networks (DBBNs) in order to provide reliability performance predictions. Lastly, the forecasted reliability performance is combined with historical data and expert judgment providing decision-making maintenance suggestions.

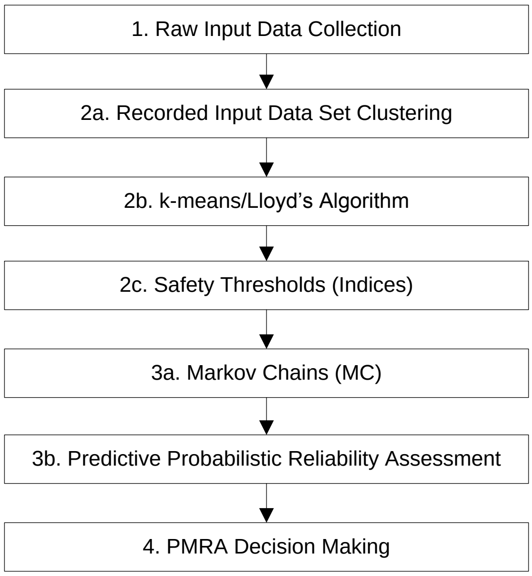

Figure 4.3 PMRA strategy method and tool selection flow diagram for raw data

4.5.1. Raw Input Data Collection

The collected input data consists of three data types such as historical, expert, raw/real-time sensor data. The historical input includes information such as inspection and maintenance actions, maintenance intervals, Plant Maintenance System (PMS) reports, drawings and layouts of each deck of the Engine Room (E/R), survey reports and specific logbook records, voyage reports as well as booklets and manufacturers' manuals with information related to machinery. Historical data is supplementary in Condition Monitoring (CM) methods providing additional information related to current inspection and maintenance practices. For instance, PMS reports are valuable source of input as they provide information related to frequency of inspection and maintenance actions (the smaller the time interval, the higher importance of action) on component level per machinery.

On the other hand, expert data involves failures and related measures including consequences, technical and economic impact sources by Classification Societies' reports, inspection findings by crewmembers, ship operators and superintendents. Specifically, expert data utilises Failure Rates (FR) per system, subsystem and components, data such as incidents per ship and Mean Time To Fail (MTTF).

Additionally, expert data contribution incorporates personal judgment, operational difficulties and knowledge gained through experience.

The third and critical data group is the raw/real-time monitoring data type corresponding to onboard measurements and records gathered while the vessel operates. Parameters that can be recorded onboard the vessel vary including operational parameters per trip, ship sailing condition parameters, environmental parameters per day, and ship machinery condition monitoring measurements. In the case of operational parameters, multiple records can be collected such as date, time in port, voyage time (port-to-port), ship sailing time, manoeuvring time and last dry dock date among others. Ship sailing data consists of parameters such as vessel speed, direction and position, rudder angle and draft (fore/aft). On the other hand, environmental records can include weather, wind speed and direction, sea state, current speed, current direction, and ambient temperature and pressure. The last and more crucial raw input data group involves ship machinery condition monitoring parameters. These parameters consist of performance measurements such as temperature and pressure in various locations on the ship as well as flow rates of fuel oil, lube oil, and water supply, vibration measurements, thermography, lube oil analysis and noise records (INCASS, 2014c).

Probabilistic Machinery Reliability Assessment (PMRA) strategy is oriented towards raw sensor data. Specifically, PMRA utilises raw performance measurements of ship machinery such as pressure and temperature parameters. These are valuable input sources of indicating the reliable operation of ship machinery and providing data for analysis and evaluation.

4.5.2. Recorded Input Dataset Clustering

The second level of processing takes into account the raw sensor gathered data. At this stage, selected data mining methods aim to extract hidden information from the recorded datasets and transform it into useful and understandable structure for further elaboration (Witten et al., 2011). In other words, data mining is the practice of investigating patterns such as similarities and differences in collected data. From the perspective of scientific research, data mining is a relatively new notion in marine engineering that has been imported from studies in other fields such as computing, statistics, and data analytics (Giudici, 2005). Henceforth, the newly introduced and innovative "big data" notion is considered in maritime industry by PMRA strategy as well enabling large datasets to be analysed computationally revealing patterns and trends.

As stated above, data mining consists of processes aiming to extract hidden information from the recorded datasets and transform it into useful information. Data mining is a step in Knowledge Discovery in Databases (KDD) procedure that incorporates data analysis and information extraction algorithms generating particular enumeration of patterns over the gathered data (Fayyad et al., 1996b).

Data mining algorithms in practice achieve prediction (forecasting future values) and performance description (finding patterns of describing the dataset) of the collected data. The two targets of data mining such as prediction and description can be achieved utilising different methods. Literature presents a wide range of data mining methods such as classification, regression, clustering, summarisation, dependency modelling and change and deviation detection as shown in Figure 4.4 MacQueen (1967), Fayyad et al. (1996a), Estivill-Castro (2002) and Gerardo et al. (2005).

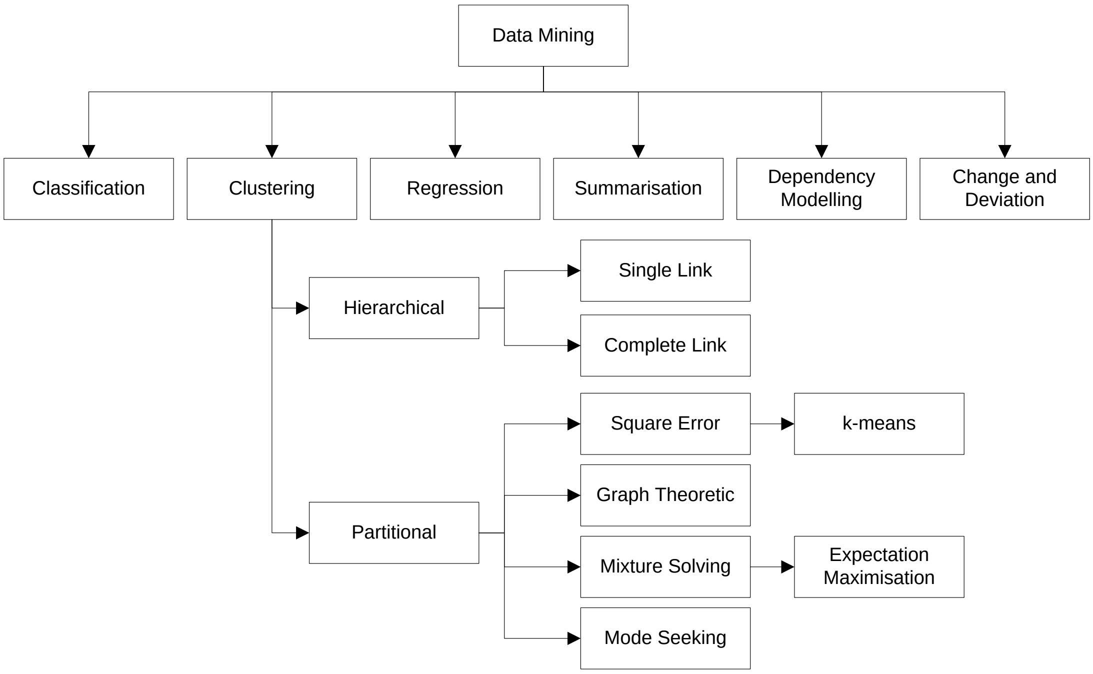

Figure 4.4 Data mining taxonomy

- **Dependency modelling**

Evaluating each of the available data mining methods, dependency modelling investigates the relationships between variables (Fayyad et al., 1996b). In other words, it examines the input data interdependencies. This is a valuable and innovative consideration because this modelling approach allows the assessment of the effects on failure interaction. PMRA strategy considers these dependencies and their evaluation will take place in the following probabilistic predictive reliability assessment level by utilising the appropriate reliability tool. On ship machinery, data dependencies are already known, because machinery interacts while functioning. Therefore, these input data dependencies do not require a tool in order to be investigated. However, they require evaluation that PMRA strategy fulfils through the reliability assessment tool that will be presented next.

- **Summarisation modelling**

Summarisation data mining method provides a compact representation of the recorded dataset or a subpopulation of each set. Typical examples of summarisation methods involve parameters to represent the dataset or subsets such as mean and standard deviations. In maritime industry, the availability of raw sensor data is limited, thus, out of inadequate or incomplete data sources summarisation (attempting to compact information) does not seem reasonable tool to extract information.

- **Regression modelling**

Additionally, regression modelling is separated in linear and nonlinear. Regression methods depend on making initial parameter assumptions (Freedman, 2009). However, these assumptions can be tested, if sufficient quantity of data is provided. Regression methods are beneficial even in cases that unsuccessful assumptions are taken place, however, they may not perform optimally and provide misleading outcomes (Cook and Weisberg, 1982). Therefore, the limited source of raw sensor data in maritime industry causes practical difficulties in testing and verifying the assumptions of regression data mining methods.

- **Change and deviation detection modelling**

Change and deviation (also known anomaly) detection data mining method addresses the identification of observation that do not comply to an expected pattern of the recorded dataset (Chandola et al., 2009). These anomalies are associated with noise, deviations and exceptions and they are recorded from the operational environment of the ship machinery and equipment (Hodge and Austin, 2004). In contrast to the remaining data mining methods, various change and deviation practices exist such as unsupervised, supervised and semi-supervised. Furthermore, popular change and deviation techniques include density-based techniques, Support Vector Machines (SVMs), Neural Networks (NNs) and fuzzy logic. Literature offers a wide range of applications and practices involving these techniques, thus, anomaly detection is placed a potential option for further development and investigation or comparison involved in PMRA strategy Demetgul et al. (2009), Chen and Vachtsevanos (2012) and Fazlollahtabar et al. (2015).

- **Data classification and clustering modelling methods**

These methods involve various groups of algorithms. Estivill-Castro (2002) states that there is no objective decision making process of selecting the correct classification or clustering algorithm, because each dataset may require different classification or clustering method for feature identification or information mining. The decision of selection is related to the developer's opinion satisfying specific requirements of the input data.

Data classification and clustering aim to separate (i.e. classify and cluster respectively) in groups (subpopulations such as classifiers or clusters) of similar statistical features and characteristics the recorded observations (parameters) and members of a dataset. In the case of data classification, the algorithms are known as supervised, whereas, in the case of data clustering as unsupervised. Supervised data classification algorithms require a training phase before data mining takes place for the recorded datasets. In this training procedure, a sample of the recorded dataset will perform the algorithm in order to create the structure of the subpopulation/classification groups (classifiers), where observations/indices of the actual dataset will be allocated accordingly. Hence, the training phase of supervised classification algorithms imposes the existence of extensive and large amount of input data observations in order to satisfy the training and classification requirements.

On the other hand, data clustering algorithms are simpler in structuring the required clusters compared to data classification practices. Data clustering is the general task to be solved placing observations in the appropriate cluster as defined by the characteristics of each cluster. In addition, Jung et al. (2014) highlights that clustering is an important unsupervised learning problem, as this method intends to structure the separation of unlabelled data. Furthermore, data clustering incorporates notions of clusters including subpopulations with small distances among the observations, dense areas of the data space and intervals or particular statistical distributions. Vital point is stated by Witten et al. (2011) that clustering methods are utilised when the instances of the gathered datasets are divided into natural groups.

Summarising with respect to the selection of data mining methods, PMRA strategy is oriented towards data clustering (also known automatic classification). Various reasons led to this decision. First of all, data mining does not require training procedure as it relies on unsupervised algorithms. This is critical point as in maritime industry large raw input datasets (i.e. long term records) cannot be easily provided to others by shipping companies, owners, operators, service providers or Classification Societies due to confidentiality issues. Hence, the simplicity and flexibility that data clustering offers for information extraction out of limited data sources place data clustering a valuable tool to be employed. On the other hand, the implementation of clusters upon decision of the developer enables flexibility in implementation according to the format and characteristics of the utilised input data types. Therefore, input data inclination and deviation clusters can be implemented, where clusters can be identified out of acceptable and warning operational levels.

- **Data clustering characteristics and criteria of selection**

Essentially, Giudici (2005) specifies that cluster analysis aims n gathered observations to be allocated into k subpopulations (with $k<n$). Hence, data clustering algorithms regulate the allocation of these observations into the clusters, the number of clusters involved in this process as well as the characteristics of the clusters in separating these observations. In order to identify and select the suitable data clustering algorithm, it is necessary to classify them according to fundamental functional features.

Data clustering algorithms can be distinguished among multiple criteria and the appropriate descriptions are provided next. First of all, clusters can be divided in hard and soft clustering techniques. The first one allows elements or observations of the dataset to belong to one specific cluster or not, whereas, soft (also known fuzzy clustering) allows each element to belong to each cluster to a certain degree. Hence in soft clustering, characteristics of an observation can be inherited to more than one clusters. PMRA strategy is oriented towards hard clustering as the observations of the recorded raw sensor data (i.e. pressure and temperature) are classified in specific clusters such as acceptable and warnings. Additional information and reasons related to this decision are provided in the safety threshold process of PMRA strategy (see Figure 4.3).

Another functional criterion of data clustering methods involves the agglomerative and divisive aspects. Agglomerative practice initiates clustering with each data pattern in a distinct cluster and then progressively merges clusters until a specified criterion is met. Alternatively, divisive practice splits the patterns until a criterion is satisfied.

Additionally, monothetic and polythetic aspects affect the decision of selecting data clustering algorithm. A monothetic algorithm considers features sequentially (one by one) dividing the provided dataset of patterns. On the other hand, most algorithms are polythetic, where features analysed according to calculated distances between patterns and these computations take place simultaneously (Jain and Dubes, 1988). Moreover, data clustering methods are classified according to incremental or non-incremental features. Since datasets get larger through technological development and analysis requirements increase as well, constraints on execution with respect to time or computational memory space affect the architecture of the algorithm.

- **Data clustering: Hierarchical vs. Partitional**

Data clustering methods are classified among hierarchical and partitional (also known non-hierarchical) as demonstrated in Figure 4.4. Hierarchical clustering is characterised by nested sequence of partitions, whereas, partitional clustering performs a single partition. A feature of hierarchical clustering is the graphical representation through a dendrogram, which enables the visual assessment of the merged objects into clusters. Hierarchical data clustering methods are mostly popular in biological, social and human behavioural sciences due to the fact of constructing taxonomies.

On the other hand, partitional methods are employed in engineering practices where single partitions are required (Jain and Dubes, 1988). Furthermore, experimental studies show that hierarchical clustering (dendrograms) is impractical to large datasets and complicated patterns. Conversely, partitional clustering methods are suitable for representation and compression of large datasets.

Therefore, PMRA strategy is oriented towards partitional (non-hierarchical) data clustering methods as they are suitable for engineering applications. Moreover, the ability of partitional clustering methods to compress and represent large datasets provides flexibility in case excessive quantity of data is provided. As shown in Figure 4.4, partitional data clustering methods consist of squared error, graph theoretic, mixture solving and mode seeking algorithms.

- **Square error and graph theoretic algorithms**

Squared error algorithms are most intuitive and frequently utilised as they perform well with isolated and compact clusters. The most-known representative is the k-means as it is the simplest satisfying a squared error criterion (MacQueen, 1967). According to Jain and Dubes (1988), different geometric structures and graphs established useful algorithms for examining multidimensional patters. Graph theory is applicable in both hierarchical and partitional (non-hierarchical) data clustering methods. Graph theoretic practice involves arrangements of nodes and edges. The nodes represent the patterns to be clustered, whereas, the edges correspond to the relations between the nodes (Jain and Dubes, 1988). Hence, graph theory in data representation has direct applicability in k-means data clustering method.

- **Mixture-solving and mode-seeking algorithms**

On the other hand, mixture-solving and mode-seeking algorithms rely on the assumption that the patterns are clustered utilising one of several probability distributions. The majority of the published work assumes that individual components are drawn using Gaussian distribution. Therefore, the process aims to identify the individual Gaussians. Expectation Maximisation (EM) algorithm, stems from Gaussian Mixture Model (GMM), is established for missing-data problems and estimation of the Gaussian parameters. In other words, EM algorithm estimates through the patterns the parameters of the component densities.

- **k-means vs. Expectation Maximisation algorithms**

Two well-known algorithms and widely applied in different research fields are the k-means and EM algorithm. They share common aspects such as the iterative clustering procedure of guessing parameters targeting convergence according to predefined criteria. However, the main differences among k-means and EM algorithm are related to the clustering practice and the calculation of the distances. Firstly, k-means employs hard clustering, whereas, EM soft. Furthermore, k-means method implements the Euclidean distance while calculating the distance between items, whereas, EM utilises statistical methods (Jung et al., 2014). On the other hand, EM algorithm assigns the points in the clusters, when convergence is reached, whereas, k-means reallocates them at each point until convergence (Hand et al., 2001). A comparative research study between k-means and EM algorithm performed by Jung et al. (2014) shows that k-means provides more accurate data clustering, especially when the number of clusters is small (Williams and Simoff, 2006), whereas, EM algorithm is faster in processing. Estivill-Castro (2002) comments that "the nature of clustering is exploratory than confirmatory", highlighting that "one person's noise could be another person's signal" (Han et al., 2011).

Concluding, in this section multiple considerations and aspects of the examined data clustering methods are demonstrated. Due to accuracy, efficiency, simplicity and flexibility, k-means method will be utilised by the PMRA strategy in order to partition the recorded observations provided by the onboard sensors. Summarising, k-means algorithm offers the following advantages that will benefit the raw sensor data processing of PMRA strategy:

- Unsupervised data mining method, that does not require supplementary input data for training and classification
- Partitional method employed in engineering practices where single partitions are required
- Hard data clustering (not overlapping) simplifies calculation processes as each observation belongs to one cluster or not
- Suitable for excessive data quantity (if available) as it is easily programmed
- Computational efficiency when number of clusters is small

4.5.3. k-means/Lloyd's Algorithm

In this part of the second stage of PMRA strategy, the employed k-means data-clustering algorithm is demonstrated. The method of k-means partitioning belongs to square error, partitional data clustering. This method separates data into clusters creating strong association among members of the same cluster and weak between different clusters (Gerardo et al., 2005). In other words, it creates definite association of the data point to the particular cluster, where it shares statistical characteristics only with the remaining members of the same cluster.

Data clustering of k-means was firstly used by MacQueen (1967). Moreover, the clustering procedure was examined and presented by various authors such as Jain et al. (1999), Gerardo et al. (2005), and (Williams and Simoff, 2006) among others. Hence, k-means input data clustering uses of the following steps:

- Identify number of k clusters.
- Initiate the calculation of means from μ_1 until μ_k of k clusters.
- Generate random selection of objects.
- Assign each pattern to the closest cluster centre. If the data point is closest to its own cluster centroid, proceed to the following data point. If not, move it into the closest cluster.
- Calculate minimum Euclidean distance determining the membership for the respective clusters.
- Determine the membership and assign each point to corresponding cluster.
- Iterate until the criterion function converges. During iteration process recalculation of μ_1-μ_k is taken place until there is no change in the value of mean.

4.5.4. Safety Thresholds (Indices)

The following process level introduces the safety thresholds. These are values, which aim to set operational warning/alarm thresholds. These thresholds classify the recorded input data among acceptable and abnormal functioning levels. In maritime industry, safety and warning thresholds can be assigned by various stakeholders and experts such as ship machinery and equipment manufacturers, ship owners, operators and service providers as well as Classification Societies. Safety thresholds are utilised as reference points in order to compare the recorded, the predicted and the safety levels.

In this selection, the physical measurements' thresholds are classified and selected. In other words, the safety indices are considered in order to set acceptable operational levels (reference points). These safety levels identify the acceptable and warning limits of the physical measurements that the system should function. Various stakeholders in maritime industry can contribute in order to provide valuable input in setting the appropriate safety/warning operational levels such as ship machinery and equipment manufacturers (manuals), Classification Societies (standards), ship owners, operators and service providers (reports, requirements, and expert judgment).

Due to the fact that input from Classification Societies, ship owners, operators and service providers requires expert judgment and subjective decision making, the establishment of safety thresholds from these stakeholders may lead to technical assumptions. Therefore, in the case of PMRA, the safety thresholds (i.e. safety indices) are identified through the machinery manufacturer's manual and the sea trials reports. These safety indices are selected as they fulfil the manufacturer's requirements and sea trials provide the ideal available reference points for the required comparison. The establishment of safety levels in the PMRA strategy triggers the identification and assessment of the tendency the recorded input to downgrade and lead to alarm/warning levels before failures or malfunctions appear.

The integration of the data clustering analysis (previous process level) with the identification of the safety thresholds introduces the probability of occurrence the observed (recorded) input data to perform within the predefined acceptable functional levels. This probabilistic measure in percentage generates the input for the following Markov Chain (MC) process and Dynamic Bayesian Belief Networks (DBBNs).

4.5.5. Markov Chains (MC)

Having in mind as fundamental notion that systems functioning degrade, the data processing level of PMRA examines different states of reliability assessment. These states are classified among static and dynamic modelling. In the first place, static modelling practice considers reliability input as fixed input that remains unchanged within the timeline. This modelling approach is simple and suitable to provide an initial indication of the ship machinery reliability performance.

However, static state reliability modelling opposes the fundamental statement that degradation takes place almost continuously while systems operate. Therefore, a multiple-state assessment has to be introduced examining the variation of reliability within time. This type of assessment is known as dynamic or time dependent.

A well-known and widely applied process, established by Andrey Markov, is the Markov Chain (MC) or Discrete-Time Markov chain (DTMC) (Norris, 1998), which examines the state variation into a discretised timeline. MC is a flexible process that relies on memoryless Markovian state space analysis as it requires little information under simple hypothesis (Fort et al., 2015). According to Ghahramani (2001), MC model is tool for representing probability distributions over sequences of recorded data points denoting the observation at time t and the variable Y_t.

In the case of dynamic modelling, the time dependencies and state division of the reliability input are developed in parallel with the reliability assessment tool that will be presented next. Regarding the dynamic state modelling, PMRA strategy employs the mathematical tool of First-order Markov Chains (MC) (Yan et al., 2011), (Fort et al., 2015). First-order MC is mathematical system that undergoes transitions from one state to another within the state space. Furthermore, MC is selected, as it is flexible to set up by allowing different levels of state sequence complexity. In order to represent this dynamic modelling practice, a schematic diagram is shown in Figure 4.5.

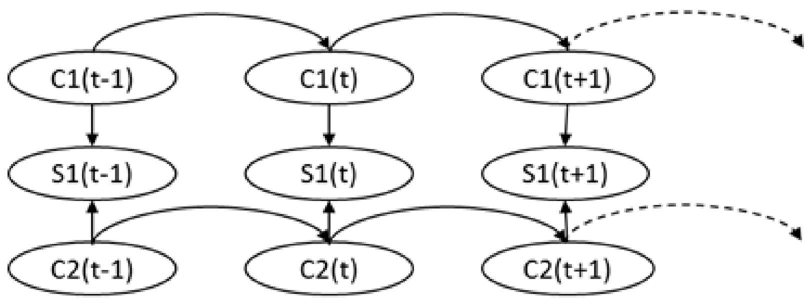

Figure 4.5 Dynamic probabilistic network arrangement

In Figure 4.5, a risk assessment network is represented, where specific technical and practical details of this will be provided in the following PMRA level. This arrangement demonstrates the simplest network structure consisting of three nodes in each time step such as C_1 corresponding to component 1, C_2 for component 2, and S_1 for subsystem 1. The presented subsystem network arrangement includes in total three states within the timeline. Firstly, processed input data (i.e. reliability indices) from the previous time slice is provided shown as *t-1*. The current state *t* is calculated, whereas the predictive state is shown as future state *t+1*. As shown in Figure 4.5, each time slice (*t-1*, *t*, *t+1*) in first-order MC depends only on the previous state. This single state transition from past to present and then to forecasted future is known as Markov property.

First-order MC process is utilised in PMRA strategy in order to connect the results acquired by k-means data clustering method and the implementation of safety thresholds with the following dynamic reliability assessment tool. Therefore, k-means clustering and safety indices specify the normality of functioning by transforming the recorded input data into probabilistic indices (i.e. percentages). These values are fed into the first-order Markov Chain (MC) process in order to generate the time dependencies, state transition of the predefined intervals, within the timeline. The sequence of MC outcomes (i.e. past, present, future) is then utilised in the following reliability assessment tool.

4.5.6. Predictive Probabilistic Reliability Assessment

In this process level of the second stage of PMRA strategy, the available in literature reliability assessment tools are demonstrated and evaluated leading to the selected one. PMRA strategy is oriented towards quantitative assessment as offers subjective judgement without involving objective decision making, which may lead to insufficient or problematic solutions. Before evaluating these tools, it is crucial to define two principal terms such as reliability. Firstly, risk is defined by Nieuwhof (1985) as the expected loss or damage associated with the occurrence of a possible undesired event. More precisely, the International Electrotechnical Commission (ICE) outlines risk as the combination of frequency or probability of occurrence and the consequence of a specified hazardous event (IEC 60300, 1995). On the other hand, Fazlollahtabar et al. (2015) define reliability as the probability that a system works until time *t*. therefore, if a ship machinery or equipment breaks down, it can be dealt as failure. A desired level of reliability can be achieved by regulating the Probability of Failure (PoF). This approach of controlling reliability is known as the method of chance constraints in the context of mathematical programming.

Literature presents various failure, risk and reliability analysis methods that will be presented next. The majority of these methods visualize failure occurrence as independent event for each considered component of a system. The most known, well-applied and capable quantitative risk and reliability modelling tools involve the Event Tree Analysis (ETA), Fault Tree Analysis (FTA) and the lately introduced in the engineering regime Bayesian Belief Networks (BBNs). FTA and BBNs present dynamic state modelling practices as well, such as DFTA and DBBNs respectively, taking into account time dependencies of risk and reliability variation.

- **Fault Tree Analysis (FTA)**

Fault Tree Analysis (FTA) is a well-known reliability tool used in various research studies for different applications since its original introduction in reliability analysis in the '60s and '70s. A Fault Tree is a detailed and organised structure consisting of a top event (or in technical terms top gate), intermediate gates/events and basic events showing the dependability steps and process under which the latter (basic events or causal factors) lead to the failure of a top event. The Fault Tree structure identifies all the independent factors, which influence the occurrence of the top event/gate and consequently the reliability of the top event/system under investigation.

According to Bedford and Cooke (2001), FTA is a modelling tool employed as part of quantitative analysis of systems. It is basic tool in system analysis, which allows pictorial representation of statement in Boolean logic (i.e. 0 or 1, yes or no etc.). A FTA develops a deterministic description of the occurrence of an event (the top event). Fault Trees analyse the component failure which contributes towards system failure. Furthermore, FTA most usually employs the Boolean operations (also known as logical gates) *AND*, *OR* and *NOT* among others (Kumamoto and Henley, 1996). The most-known logical gates are the *AND* and *OR* and they are described as shown in equations (4.1) to (4.4) (Lazakis, 2011):

$$P_{ANDgate}(t) = P\left\{C_1 \bigcap C_2 \bigcap C_3 \dots \bigcap C_n\right\} = P(C_1)P(C_2)\dots P(C_n) \tag{4.1}$$

$$P_{ANDgate}(t) = P(e_1)P(e_2)\dots P(e_n) \tag{4.2}$$

$$P_{ORgate}(t) = P\left\{C_1 \bigcup C_2 \dots \bigcup C_n\right\} \\ = 1 - [1 - P(C_1)][1 - P(C_2)] \dots [1 - P(C_n)] \tag{4.3}$$

$$P_{ORgate}(t) = 1 - [1 - P(e_1)][1 - P(e_2)] \dots [1 - P(e_n)] \tag{4.4}$$

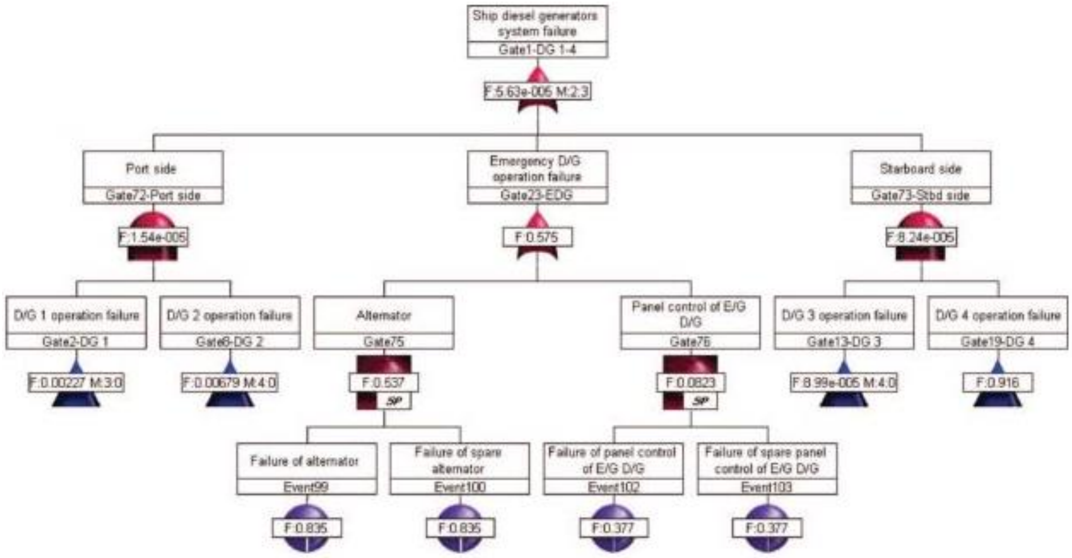

Figure 4.6 Sample of Fault Tree structure (Lazakis, 2011)

In Figure 4.6, a typical Fault Tree structure is presented. The arrangement is developed from top to bottom, while the calculations of the failure case scenarios are generated from the bottom basic events determining the failure of the top event. The sequence of events is built by logic gates. Furthermore, the possible routes of failing events are named ‘cut sets’. The failure scenario that involves the least of components’ failures in order the top event to fail is known as ‘minimal cut set’.

In the case of Dynamic Fault Tree Analysis (DFTA), Probability of Working (PoW) input is updated continuously by changing their condition and value through time. In other words, time dependencies of the operational conditions are introduced. Moreover, the dynamic risk modelling of FTA employs dynamic logic gates. These gates utilise continuously new values of the considered reliability input, while they are calculated the updated results according to the constantly developed system state.

FTA and DFTA are capable risk and reliability assessment tools, however potential limitations in the use of FTA include the requirement of specific knowledge of the system under investigation. Expert's knowledge on modelling is essential leading to subjective assessment. Furthermore, FT structure examines the failure occurrence of a single main/top event each time, hence, multiple top events need to be examined separately in the FT modelling structure.

- **Event Tree Analysis (ETA)**

Event Tree Analysis (ETA) is used for the identification of risks originating especially in the case of technical systems. In contrast with FTA, ETA utilises 'forward logic' structure and assessment as shows in Figure 4.7. Hence, it begins by considering an initiating event (i.e. non-standard functional case) and propagates this event through the system by considering all possible routes/options that can affect the behaviour of the system (Bedford and Cooke, 2001).

Therefore, ETA is modelled starting from an initial undesired event/failure (shown on the left side) and then proceeds with the description of several branches denoting the failure possibilities (shown on the right side), most usually in a binary manner. Eventually, conditional probability values are assigned to each of the branches created with the summation of all the values of each branch (success and failure) being one or 100%. In order to calculate the probability values for the end-events of the Event Tree, multiplication of all the intermediate values takes place, with the summation of all the values of all outcomes being one as well.

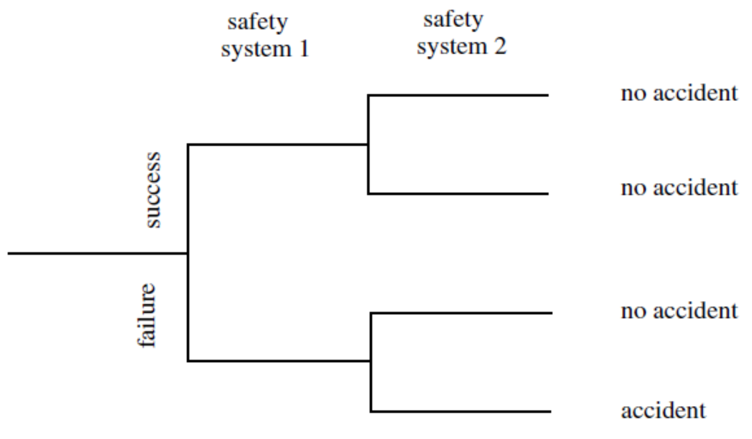

Figure 4.7 Sample of event tree structure (Bedford and Cooke, 2001)

FTA and ETA tools are fundamental quantitative modelling tools which allow the risk study of fault or event occurrence. Both tools are suitable for risk analysis of simple systems by allowing minimum data and structured failure case scenarios. However, PMRA strategy aims to assess the risk and reliability performance through time of complex multicomponent ship machinery and equipment. Hence, the implementation of a flexible risk tool is required, which can model various systems, subsystems and components.

- **Bayesian Belief Networks (BBNs)**

The third and most critical under consideration quantitative risk tool is the Bayesian Belief Networks (BBNs). A Bayesian Belief Network (BBN) is represented as a Direct Acyclic Graph (DAG), which consists of nodes (variables) showing the different system states and a given set of arrows (edges), which represent the probabilistic dependence among the variables and interconnect the nodes. Various features of this risk and reliability assessment tool render BBNs the most suitable tool fulfilling PMRA strategy requirements. The main advantage of this tool is the flexible arrangement of the involved systems, subsystems and components as well as the considered real time input data (or failure modes) represented by different nodes (Dikis et al., 2014).

BBNs allow the adjustment of size, shape and connections (links or arrows) by introducing more systems, subsystems, components, input sources and failure modes or removing them if required without reconsidering the remaining structure of the model (Figure 4.8). Moreover, network arrangement allows the innovative notion of interconnections among different systems, subsystems and components by introducing and assessing functional dependences. Furthermore, they can simulate real models by satisfying the condition that systems and components, while they operate, affect each other. Additionally, BBNs combine technical, economic and decision-making features by introducing functions of cost and decision through utility nodes.

An example of a BBN model is presented in Figure 4.8 for a diesel Main Engine (M/E). This model demonstrates an extract of a case study designed and performed, while PMRA strategy was initially developed. In this extract, various groups of nodes can be recognised representing the M/E and two subsystems such as the engine internal components and the engine external components. Moreover, multiple components are involved such as cylinders, injectors, exhaust (valve and receiver combined failure rate), pistons, bearings etc. as well as various failure modes and consequences (i.e. overheating, noise, vibration etc.).

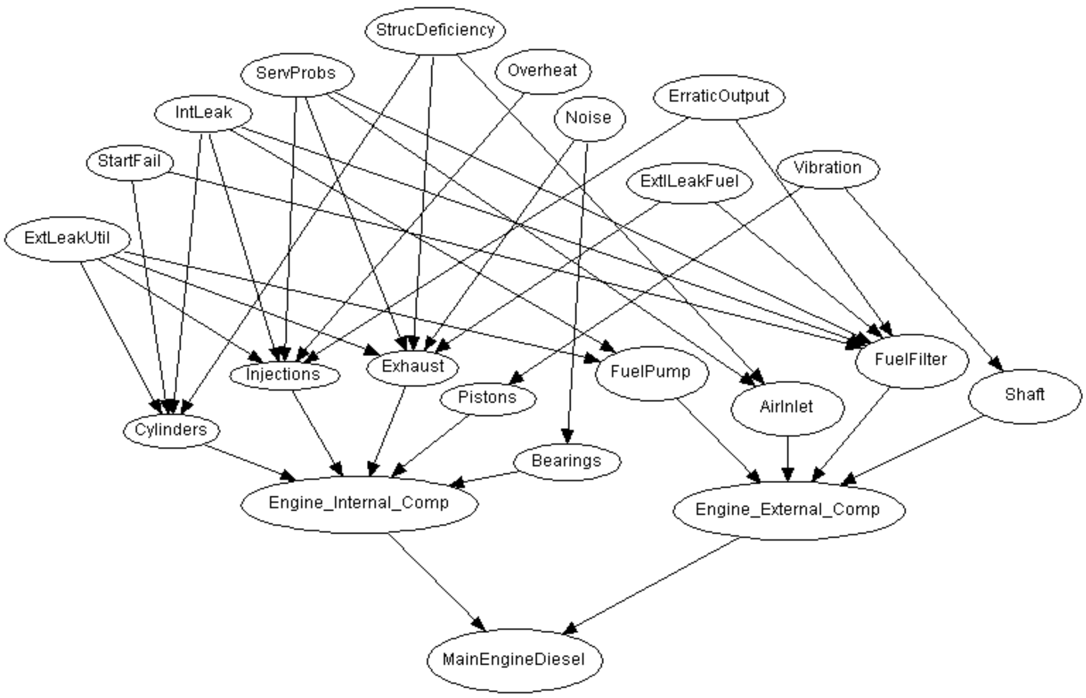

Figure 4.8 Sample of Bayesian Belief Network (BBN) structure (Dikis et al., 2014)

The involved members (units) of this network are presented in nodes demonstrating the input gates. On the other hand, the arrows present the connections between the failure modes and the components/subsystems and main system. Hence in the graphical representation of BBNs in Figure 4.8, the nodes from which an arrow originates are called the ‘parent’ nodes (e.g. Cylinder is the ‘parent’ node of engine internal components) while for the ones to which the arrow ends are called the ‘child’ nodes (e.g. Main Engine Diesel node is ‘child’ of Engine Internal Components). Lastly, ‘root’ nodes signify that there are no arrows leading to them (e.g. top nodes representing the involved failure modes).

4.5.7. *Overall PMRA strategy for raw data*

In the previous section, PMRA strategy development was presented in two stages of implementation as shown in Figure 4.1. Firstly, the principle aspects of PMRA were presented fulfilling research gaps investigated in the latest literature. In the second stage of the strategy implementation, the selected PMRA methods and tools were demonstrated focusing towards the advantages and innovation achieved through the proposed inspection and maintenance strategy. Therefore, in this section, PMRA strategy structure is proposed combining all involved methods and tools as applied and programmed.

This section is mainly focused towards the overall PMRA strategy with respect to processing algorithms, methods applied and tools utilised. It is essential to highlight that two levels of procedures for input data selection and collection of processed and raw data are taken place as demonstrated in Figure 4.2 and Figure 4.3 respectively. These data considerations and related procedures will be discussed in the case study Chapters (5 & 6 respectively), where specific offshore oil and gas platform and ship machinery are employed for testing the proposed PMRA strategy.

Therefore, Figure 4.9 presents the analytical PMRA strategy for ship machinery for raw input data. The proposed strategy consists of four distinct stages, which form the core of PMRA. These stages involve the (1) data processing, (2) data transformation, (3) dynamic predictive risk assessment and (4) decision-making. It is essential to highlight that this stage arrangement fulfils requirements and guidelines of European standardisation regulatory bodies such as British Standards (BS) and International Standards Organisation (ISO). More specifically, PMRA strategy is developed guided by BS/ISO 17359 (2011) and BS/ISO 13381 (2015), where the processing flowcharts of these guidelines can be found analytically in Appendix B confirming the appropriate similarities.

At first place, data processing stage utilises the recorded real time input data in order to mine information with respect to ship machinery functioning. This process stage allows the identification of performance trend and pattern recognition (i.e. degradation, measurement variation etc.). The data transformation process is followed, which performs a transition from natural measurements (i.e. temperature and pressure) to reliability input values (i.e. percentage). This second stage connects the raw input data information extraction with the benefits of probabilistic reliability assessment. The third stage involves risk assessment, where dynamic state modelling is integrated with a flexible reliability assessment tool. The latter combines information from various sources providing predictions with respect to reliability performance on system, subsystem and component levels.

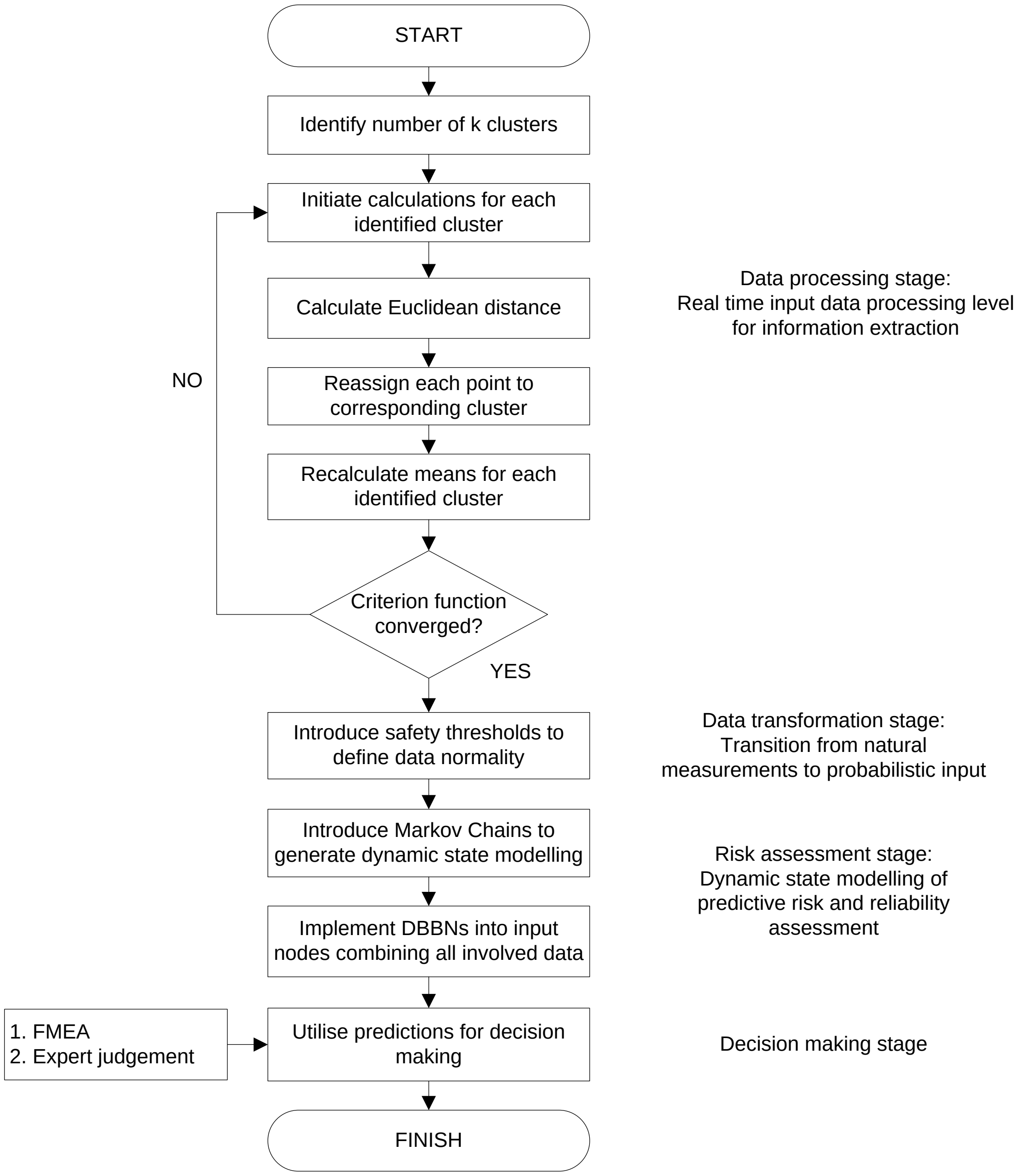

Figure 4.9 Suggested PMRA strategy for raw ship machinery data

- **Data processing stage**

Assuming that raw input sensor data (e.g. temperature and pressure datasets) is collected from various sources, the PMRA strategy is initiated by utilising the data processing stage. PRMA strategy employs k-means data clustering algorithm. The three major operational phases of k-means involve initialisation, transfer evaluation and repetition of the previous two phases until a predefined criterion is met.

PMRA strategy assesses the reliability performance of ship machinery, hence, the predefined clusters categorise the recorded objects by monitoring the increase or decrease of performance inclination. The data mining method of k-means will perform for PMRA strategy consisting of 2 clusters (k=2). This decision enables higher accuracy and clustering performance when the number of clusters is small (Williams and Simoff, 2006). The involved clusters separate recorded data in decreasing and increasing segments/groups considering as their performance origin the overall gathered input dataset.

Therefore, k-means data clustering algorithm for PMRA strategy requires an initiation dataset referred as *ds*. Dataset *ds* includes *n* number of total recorded objects known as indices *i* (*i* refers to the particular position of an object in *ds*, initiated at index number 1 and reaches the maximum number *n*). The overall *ds* has mean value μ_{ds} and calculated as shown in equation (4.5).

$$\mu_{ds} = \frac{\sum_{i=1}^{n} ds}{n} \tag{4.5}$$

Furthermore, initialisation phase requires the calculation of dataset *ds* standard deviation referred as σ_{ds}. Firstly, the squared deviation *D* of each data point *i* has to be calculated known as D_i as show in equation (4.6).

$$D_{i \to n} = (ds_{i \to n} - \mu_{ds})^2 \tag{4.6}$$

The calculation of standard deviation σ_{ds} requires the implementation of variance σ^2 for dataset *ds* known as σ_{ds}^2 shown in equation (4.7).

$$\sigma_{ds}^2 = \frac{\sum_{i=1}^{n} D}{n} \tag{4.7}$$

When in fact as shown in equation (4.8), the standard deviation (σ_{ds}) is equal to the square root of variance (σ_{ds}^2).

$$\sigma_{ds} = \sqrt{\sigma_{ds}^2} \tag{4.8}$$

In the first place, dataset *ds* consists of *n* observations, where, the mean (μ_{ds}) and standard deviation (σ_{ds}) are calculated as reference points related to the initial gathered information. Dataset *ds* is separated in two almost equal initial in index size clusters. If *n* is even number, then clusters (i.e. *k*=1 and *k*=2) will be equal in size (included number of observations), else initial arrangement of cluster *k*=1 will include one more observation (data point) compared to *k*=2. The initial arrangement of clusters will be updated once k-means first iteration takes place. Therefore, out of dataset *ds*, two clusters are created such as ds_1 and ds_2 corresponding to cluster 1 and 2, respectively.

The indices (data points) of each of these clusters ds_1 and ds_2 are classified in two groups according to predefined criteria. The first classification criterion identifies data points of ds_1 that $i \leq \mu_{ds}$ (or $i < \mu_{ds}$), whereas the second criterion data points where $i > \mu_{ds}$ (or $i \geq \mu_{ds}$). This data point classification takes place for the second dataset ds_2 as well.

$$\mu_{ds1L} = \frac{\sum_{i=1}^{n_{ds1}} (i \in ds_1 < \mu_{ds})}{n_{ds1L}} \tag{4.9}$$

$$\mu_{ds1H} = \frac{\sum_{i=1}^{n_{ds1}} (i \in ds_1 \geq \mu_{ds})}{n_{ds1H}} \tag{4.10}$$

$$\mu_{ds1L} = \frac{\sum_{i=1}^{n_{ds1}} (i \in ds_1 \leq \mu_{ds})}{n_{ds1L}} \tag{4.11}$$

$$\mu_{ds1H} = \frac{\sum_{i=1}^{n_{ds1}} (i \in ds_1 > \mu_{ds})}{n_{ds1H}} \tag{4.12}$$

Hence, equations (4.9) and (4.10) are utilised, when the measurements under data clustering analysis have upper warning limits (not exceeding the defined threshold), whereas equations (4.11) and (4.12) are employed in the case of lower warning limits dataset clustering (not dropping below the defined limit). Additionally, μ_{ds1L} denotes the mean value of ds_1 for the data points having magnitude lower *L* than μ_{ds}. Similarly,

μ_{ds1H} represents the mean value of *ds₁* for the data points having magnitude higher *H* than μ_{ds}.

According to ship machinery manufactures and guide manuals (further details will be provided in the following section and the case study chapter), a group of performance measurements utilise upper safety threshold limit (i.e. alarms and warnings) such as not exceeding a particular value during operation. On the other hand, another group of measurements employs lower safety limits. PMRA strategy prognostic features are oriented towards the examination and evaluation of ship machinery reliability degradation. Consequently, performance increase and decrease are vital indications of anticipated malfunctions or abnormal functioning. Furthermore, PMRA strategy aims to evaluate measurement deviation before reaching or exceeding the predefined acceptable operational levels (i.e. alarm/warning levels).

$$\mu_{ds2L} = \frac{\sum_{i=1}^{n_{ds2}} (i \in ds_2 < \mu_{ds})}{n_{ds2L}} \tag{4.13}$$

$$\mu_{ds2H} = \frac{\sum_{i=1}^{n_{ds2}} (i \in ds_2 \geq \mu_{ds})}{n_{ds2H}} \tag{4.14}$$

$$\mu_{ds2L} = \frac{\sum_{i=1}^{n_{ds2}} (i \in ds_2 \leq \mu_{ds})}{n_{ds2L}} \tag{4.15}$$

$$\mu_{ds2H} = \frac{\sum_{i=1}^{n_{ds2}} (i \in ds_2 > \mu_{ds})}{n_{ds2H}} \tag{4.16}$$

In a similar manner, equations (4.13) and (4.14) refer to mean calculation (ds_2) for upper threshold limits and equations (4.15) and (4.16) to mean values (ds_2) for lower threshold limits. In order to calculate the distance between the observations (data points) and the centroids of the groups, PMRA strategy and k-means algorithm utilise the squared Euclidean distance as shown in equation (4.17) (Gerardo et al., 2005), (Hand et al., 2001).

$$d_{dsj}^2 = \sum_{j=1}^{k} \sum_{i=1}^{n_j} \left\| c_i^{(j)} - \mu_{dsjg} \right\|^2 \tag{4.17}$$

The squared Euclidean distance is calculated by taking into account the involved clusters j, the included clustered data points $c_i^{(j)}$ belonging to the j^{th} cluster and the relevant selected mean value (centroid) per cluster *j* (cluster 1 or 2) and segment/group g (lower L than μ_{ds} and higher H than μ_{ds}) as denoted in equations from (4.9) to (4.16) (Jain et al., 1999). The calculation procedure takes place iteratively until no observations are reassigned to another cluster. Hence, convergence is achieved and *ds* is clustered accordingly. Additional information and the iterative process of the utilised data clustering method is provided in Appendix C.

- **Data transformation stage**

This section demonstrates the data transformation stage through which raw sensor data is expressed in probabilistic indices. Data transformation stage is utilised to generate input indices for the following dynamic reliability assessment tool. Therefore, the clustered groups of observations within the appropriate clusters are employed in order to identify the probability of occurrence of data points exceeding the acceptable operational levels. As stated in the PMRA strategy method and tool selection development phase, the alarm functioning levels are identified by employing ship machinery manufacturers' manuals as well as the ship trial report.

PMRA strategy considers as raw sensor input data performance measurements. Henceforth in particular cases, the predefined safety threshold (i.e. alarm/warning limit) refers to the highest acceptable operational level (not exceeding), whereas in other cases, it sets the lowest satisfactory. Data transformation stage utilises the results of k-means data clustering method and the predefined safety thresholds. Through these input sources, the normality of each cluster is identified with respect to the reference point that is set for each measurement. Hence, the proportion of healthy data in a dataset is identified compared to the selected reference point. In the case of PMRA strategy, OEMs have been selected for identification of alarm levels. In other words, the number of clustered observations is considered within the acceptable limits and out of these. A ratio (percentage), among these, is created demonstrating the level of satisfactory and warning operation through the entire real time sensor dataset *ds* as shown in equations (4.18) and (4.19).

$$P_{ds}(w_t) = 100\frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j}(c_i^{(j)} < l)}{m_j} \tag{4.18}$$

$$P_{ds}(f_t) = 100\frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j}(c_i^{(j)} \geq l)}{m_j} \tag{4.19}$$

Equation (4.18) presents the probability of working state (occurrence of acceptable indices/measurements) for dataset *ds* at *t* timeframe $P_{ds}(w_t)$, in case of upper threshold limit selection. On the other hand, equation (4.19) demonstrates the probability of failing state (occurrence of measurements exceeding the limits). In these mathematical expressions, $c_i^{(j)}$ denotes the clustered input data point, result of k-means, *l* represents the predefined limits (i.e. safety thresholds) and m_j the entire number clustered indices.

$$P_{ds}(w_t) = 100\frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j}(c_i^{(j)} > l)}{m_j} \tag{4.20}$$

$$P_{ds}(f_t) = 100\frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j}(c_i^{(j)} \leq l)}{m_j} \tag{4.21}$$

In a similar manner, equations (4.20) and (4.21) present the probability of working and failing states respectively, in the case of lower threshold selection (not acceptable drop lower than particular point) considering the relations with the selected limits *l*.

- **Risk assessment stage**

This section demonstrates the dynamic (time dependent) state modelling aspects and the probabilistic reliability assessment of PMRA strategy. The risk assessment stage incorporates the time dependent modelling by employing the MC process and implements the Dynamic Bayesian Belief Networks (DBBNs) for the reliability assessment. Risk assessment stage of PMRA strategy utilises the final converged results of data transformation stage such as $P_{ds}(w_t)$ and $P_{ds}(f_t)$ from equations (4.18) to (4.22).

Therefore, regarding the time dependencies, PMRA strategy employs the MC process. This is a mathematical procedure which undergoes transitions from one state to another on a state space (Dikis et al., 2015a). MC performs single state transitions, hence, each time slice depends only on the previous one. This single state transition from past to present and then to forecasted future is known as Markov property. The time-homogeneous MC (or stationary MC) are processed utilising equation (4.23).

$$P(X_{n+1} = x \,|X_n = y) = P(X_n = x \,|X_{n-1} = y) \tag{4.23}$$

In MC sequential arrangement of random variables X = (X_1, X_2, …, X_n) a joint distribution is specified by the conditionals P(X_i | X_{i-1}, X_{i-2}, …, X_1) (Fosler-Lussier, 1998). As Markov property states in the simplest form of MC, the dependency of current variable is associated explicitly only to previous variable. Moreover, Blake et al. (2011) highlights that the dependency of current state is also linked inherently to all previous states. This is the first-order MC model arrangement as shown in equation (4.24) Blake et al. (2011).

$$P(X_i|X_{i-1}, X_{i-2}, \dots, X_1) = P(X_i|X_{i-1}) \tag{4.24}$$

$$P(X_0 = x_0, \dots, X_n = x_n) = P(X_0 = x_0)\prod_{t=1}^{n} P(X_t = x_t|X_{t-1} = x_{t-1}, \dots, X_0 = x_0) \tag{4.25}$$

Therefore, a generalised form of MC of order *m* (m stands for memory), is process satisfying:

$$P(X_n = x_n|X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_1 = x_1)$$

$$=P(X_n = x_n|X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_{n-m} = x_{n-m}) \tag{4.26}$$

for n>m

Major and innovative benefit of DBBNs involves the consideration of system, subsystem and component interdependencies. Therefore, interconnections among any nodes can be considered (acyclic). This key feature of DBBNs is significant and innovative, compared to the remaining quantitative risk and reliability methods (i.e. FTA, ETA etc.), as it allows the simulation of functions and operations on actual modelling environment. The BBN is defined as probabilistic graphical model as shown in equation (4.27) involving conditional dependencies arranged into Directed Acyclic Graphs (DAG) and it is expressed as presented in (Dikis et al., 2015b).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{4.28}$$

Where P(A) and P(B) are the probabilities of events A and B, while A given B and B given A are conditional probabilities. Furthermore, innovative features of BBNs involve the utilization of decision-making and cost functions.

Each system, subsystem and component, hence each node such as parent or child (not root nodes), is linked with a certain number of events or failure modes that varies per node. Therefore, multiple probabilistic failure case scenarios are formed among the associated nodes. Assuming that a child node has *k* parent nodes receiving input from, the generated number of probabilistic failure case scenarios is demonstrated in equation (4.29).

$$m = 2^k \tag{4.29}$$

The simplest form expressing the probabilistic event case scenarios is presented in (4.30*)*. In this expression, P_1 denotes the Probability of Survival (PoS) due to one event scenario, where *w* presents the Probability of Working (PoW) state and *f* the Probability of Failure (PoF). On the other hand, e_{n1} denotes the event *e* due to the involved parent node 1 n_1 (subscript indication).

$$P_1 = \begin{cases} w: 100 - e_{n1} \\ f: \qquad e_{n1} \end{cases}; \tag{4.30}$$

$$P_2 = \begin{cases} w: 100 - e_{n2} \\ f: \qquad e_{n2} \end{cases}; \tag{4.31}$$

$$P_3 = \begin{cases} w: 100 - (e_{n1}\, e_{n2}) \\ f: \qquad (e_{n1}\, e_{n2}) \end{cases}; \tag{4.32}$$

$$P_m = (e_{n1}\, e_{n2}\, e_{n3}\, \dots\, e_{nk}) \tag{4.33}$$

$$f = 100 - w \tag{4.34}$$

Similarly, equation (4.31) demonstrates another probability event scenario (P_2) by involving a different parent node e_{n2}. Accordingly, in equation (4.32), the combination of two event scenarios is demonstrated such as e_{n1} and e_{n2}. Assuming that k=2, hence, two parent nodes are involved, the overall number of probabilistic case scenarios is four by utilising equation (4.29). Comparing BBNs with the closest competitor of FTA and the utilised logical gates (i.e. AND, OR, NOT etc.) (Lazakis, 2011), BBNs enable the calculation of multiple events considering simultaneously both AND and OR logical gates. Equations (4.30) and (4.31) refer to OR gate such as participation of one event in order the failure event of child node to take place, whereas, equation (4.32) acts as AND logical gate by involving both events. Therefore, this network arrangement of DBBNs is flexible and capable of modelling multiple operations and failure or malfunction events effectively. It is crucial to highlight that in case of k=2, the fourth probabilistic event scenario does not involve any failure or any event to take place. This event case mathematically is not provided as it equals to probability 100%.

Moreover, equation (4.33) presents the generic form of event case scenario implementation. In this mathematical expression, m denotes the total number of case scenarios considered, while k refers to the total number of parent nodes linked. The relation of working and failing states performance w and f respectively is shown in equation (4.34).

In addition to the analytical expression of equations (4.30) to (4.33), (Ghahramani (2001)) considers four random variables such as W, X, Y, and Z. From fundamental probability theory, the joint probability is known as the product of conditional probabilities shown in equation (4.35).

$$P(W,X,Y,Z) = P(W)P(X|W)P(Y|W,X)P(Z|W,X,Y) \tag{4.36}$$

- **Decision making stage**

The final stage of PMRA strategy involves the decision making process. This stage offers inspection and maintenance suggestions by utilising the prediction results sourced from the risk assessment stage. Overall PMRA strategy examines the working state reliability performance of ship machinery on system, subsystem and component level. This approach aims to examine the root cause of failures or abnormal functioning. The establishment of working state reliability predictions on component level allows to introduce inspection and maintenance action recommendations. These suggestions are integrated in the qualitative risk and reliability tool known as Failure Mode and Effects Analysis (FMEA) by employing information sourced by expert judgement and manufacturers' manuals.

FMEA is a valuable qualitative assessment tool, which will actively contribute towards decision making in PMRA strategy. It integrates essential information, knowledge and expertise sourced from machinery manuals, engine operators' handbooks, onboard crewmembers, superintendents, engineers, ship operators, service providers and Classification Societies. This technical information has been collected as part of PMRA strategy, while various technical meetings with experts have been taken place. Therefore, the FMEA tool provides manually professional and expert level of information on inspection and maintenance action suggestions. The FMEA is structured from the perspective of the considered and collected input data. Hence, if deviation is noticed on the predicted reliability performance, the FMEA correlates forecasted figures with the failure mode and the related effect on system and component level.

4.6. PMRA strategy features in development

Condition Monitoring (CM) applications are newly introduced in maritime industry as investigation in academic research and commercial practices show. PMRA strategy introduces innovative solutions in this field considering processes from the very initial data acquisition point up to reliability assessment enhanced with practical decision making recommendations. The fundamental idea is to establish PMRA strategy without employing commercial software for the development. Therefore, the entire development takes place in-house by utilising Java Object Oriented Programming (OOP) language.

Java language is chosen due to combination of different aspects and features. The language's popularity offers a wide range of well-established program developers to publish functional and tested codes and tools for Java programming. An example of these Java code developers is the APACHE software foundation, which provides software for the public good (APACHE, 2016). These codes are known as libraries can contribute towards PMRA accuracy and efficiency in programming. On the other hand, Java language is cross platform performing on different Operating Systems (OS) such as Windows, Macintosh, Linux distributors and smart/handheld devices such as Android, iOS and tablets. Hence, compatibility features enable development, implementation and functionality among any system.

PMRA strategy is programmed in order automated raw input data to be imported and results to be exported. Therefore, Input/Output (I/O) file processing and exchange is performed on an independent level supporting separate files for input and output utilising platforms such as Microsoft Excel (.xlsx) and text (.txt). Additionally, executable files (i.e. .exe and .dmg) have been created and PMRA strategy has been tested on both Windows and Macintosh Operating Systems (OS) satisfying the initial consideration of compatibility.

Tree structure programming is applied on the method and tool development for the data processing, dynamic state modelling and the reliability assessment tool. Moreover, tree structure arrangement is considered on the case study as well performing programming on system, subsystem and component level allowing flexible and efficient adjustments of the particular reliability assessment tool. This decision enables to adopt changes on the methodology for further development as well as on the Dynamic Bayesian Belief Networks (DBBNs) by adjusting components, subsystems and systems. Further description on the source code development can be found in Appendix D.

4.7. Chapter summary

In this Chapter, the suggested PMRA strategy for ship machinery is presented. First of all, research gaps are identified through the literature in maintenance of ship machinery. The establishment of PMRA strategy takes place in two stages. The principle aspects of PMRA strategy are presented first, followed by the method and tools selection. In the second stage, a structured analysis of data mining taxonomy examines core categories of data analysis and information extraction algorithms leading to the most suitable (k-means data clustering method) for the PMRA requirements. On the other hand, various quantitative risk and reliability assessment tools are evaluated leading to the use of flexible Bayesian Belief Networks (BBNs) capable in modelling complex ship machinery systems. BBNs allow dynamic state modelling (time dependent), system, subsystem and component level of reliability evaluation by considering interdependencies and failure interaction. The proposed PMRA strategy consists of data selection and acquisition phase, data clustering, dynamic state modelling and reliability assessment. The suggested methodology is supported by additional information included in Appendices B, C and D, where core areas of BS/ISO 17359 and BS/ISO 13381 guidelines, the structure of data clustering pseudocode and the Java source code structure analysis are placed respectively.

5. CASE STUDY OF PROCESSED DATA

5.1. Chapter outline

In the previous Chapter, the development of the research methodology and the overall proposed Probabilistic Machinery Reliability Assessment (PMRA) strategy were demonstrated. In this Chapter, the initial application and some technical aspects of the PMRA strategy are presented. This application includes the demonstration of a case study of the primary developed dynamic reliability assessment tool as part of PMRA strategy. Therefore, this case study introduces the Markov Chain (MC) time dependences (i.e. dynamic state modelling) and establish the Dynamic Bayesian Belief Networks (DBBNs). Multiple independent main systems are considered such as the diesel generator (D/G), turboexpander and various electric powered pumps such as the seawater lift, oil export, cooling water, water firefighting and the crude oil handling. This study examines the dynamic reliability performance on main system, subsystem and component levels by incorporating various recorded failure modes. The involved data acquisition source employs, at this initial implementation stage of PMRA strategy, the Offshore Reliability Database (OREDA), which is oriented towards processed input data. This case study examines the dynamic state modelling as well as the selected reliability assessment tool. Additionally, this case study contributes towards the research and development of the network arrangement and the features and techniques of program design flexibly and efficiently in Java Object Oriented Programming (OOP) language setting the grounds for the overall PMRA strategy. Moreover, expert information is gained through OREDA source related to frequent failures, failure modes and critical systems, which is evaluated and considered further in PMRA strategy.

5.2. PMRA strategy case study arrangement

The Probabilistic Machinery Reliability Assessment (PMRA) strategy consists of multiple analysis levels such data mining, transformation, time-dependent state modelling, and predictive reliability assessment. PMRA incorporates phases such as data acquisition, data clustering method for information extraction, dynamic state modelling, reliability assessment and initial implementation of decision making for maintenance action suggestions. The application of PMRA strategy takes place in two stages through case studies. Each stage of implementation examines different technical aspects of the PMRA strategy. In the first place, multiple systems are performed utilising processed input, sourced by Offshore Reliability Database (OREDA, 2002). At the second stage of implementation, raw sensor data is utilised testing the overall performance of PMRA strategy.

The benefits of OREDA-based case study include critical points as follows:

- Development of networks considering multiple complex systems, subsystems, various components and failure modes.
- Development and testing of dynamic state modelling.
- Implementation of the selected dynamic reliability assessment tool as demonstrated in Chapter 4 ‘Proposed Maintenance Strategy for Ship Machinery’.
- Expert information extraction of a leading reliability analysis records source in maritime and offshore sectors.
- Establishment of automation in the suggested methodology through programming Markov Chain (MC) process and Dynamic Bayesian Belief Network (DBBN) in Java programming language.

The second stage of implementation of the PMRA strategy application utilises raw sensor data. This case study benefits the PMRA strategy development as follows:

- Utilisation of raw actual sensor gathered data.
- Acquire PMRA predictions on real data by testing the overall performance of the entire suggested methodology.

- Examine the procedure of the selected data clustering method.
- Establish fully in-house developed reliability assessment networks by considering system, subsystem and component functional dependencies and independencies.
- Investigate the applicability and performance of the dynamic state modelling integrated within the reliability assessment tool.
- Coding the entire PMRA strategy in Java language by considering Input/Output (I/O) features, data exchange characteristics and programming optimisation.
- Integration of PMRA strategy programmed application with the commercial platform of Danaos one for data acquisition.

5.3. Case study systems selection

As examined in Chapter 4, demonstrated in Appendix B and in accordance to BS/ISO 17359 (2011), one of the initial stages of Condition Monitoring (CM) procedures involves the equipment audit. Hence, this critical stage identifies machinery that CM practices are applied on. The performed case study involves critical complex machinery systems such as the diesel generator (D/G), turboexpander and multiple electric powered pumps such as seawater lift, oil export, cooling water, water firefighting and the crude oil handling pump.

The considered criteria, which led to the selection of these systems, involve technical, managerial/business, economic and safety aspects. Additionally, these aspects employ parameters related to continuous ship operation (i.e. operational hours), environment, property and the ship herself, cost of inspection and maintenance in case of malfunction or failure, redundancy and impact to commercial reputation (i.e. delay of cargo delivery in case of failure). Each system takes into account different components and failure modes as recorded by OREDA. Therefore, each system demonstrates different reliability performance.

5.4. Input data source

In an attempt to initiate the development and programming of PMRA strategy process, input data is required to feed and test the designed methodology. The first step of the PMRA strategy development encompasses the dynamic state modelling and the reliability assessment tool. These processes require input data in the form of percentage (%) because the overall assessment takes place in probabilistic format. A valuable and trustworthy, initial source of input data in this format is Offshore Reliability Database (OREDA) for reasons that will be explained next. In this section, the utilised input data gathering source of OREDA and method of implementation are demonstrated. These set the grounds for the case study and the analysis undertaken related to Markov Chain (MC) process and Dynamic Bayesian Belief Networks (DBBNs).

5.4.1. What is OREDA?

OREDA stands for Offshore Reliability Database and is utilised as initial source of processed input data for PMRA strategy. OREDA is developed under the contribution of leading oil and gas companies such as Total, Statoil, Shell, Pretrobras, Engie, Gassco, ENI and BP.

This source of information includes Reliability, Availability, Maintenance and Safety (RAMS) indices of offshore oil and gas machinery such as machinery, electric and mechanical equipment, control and safety equipment and subsea systems. Furthermore, the equipment classes incorporated by the OREDA database include rotating machinery, static equipment, additional topside systems, miscellaneous and subsea equipment (i.e. pipelines, manifolds etc.) as shown in Appendix E. RAMS provide a valuable foundation for decision making actions in offshore engineering and will be employed as initial quantitative input data in PMRA case study implementation. Characteristics of the utilised information include the record of data while machinery operate in steady-state time period (OREDA, 2002).

The equipment data is classified among topside and subsea systems. PMRA strategy processed input data case study extracts information from the topside systems as they share similarities in functioning. Each OREDA-based considered topside unit is presented followed by information such as:

- Boundary definition drawing.
- Subdivision in subunits the maintainable items.
- List of recorded failure modes.
- Observed number of failures for each failure mode.
- The aggregated observed time in service for the equipment unit, identified as calendar and operational time.
- Repair time estimate.
- Supplementary information such as number of items and installations.
- A cross-tabulation of maintainable items versus failure modes.

In contrast to the published handbook, the released detailed information is demonstrated in a generic form anonymously rendered. So far, OREDA project publishes failure data strictly collected on hardware systems and components. Information related to human errors and interaction has not been considered yet. However, it is unknown if component failures are caused due to human error and implicitly these are included in the recorded failure rates.

The mathematical definition of failure rate function (λ) (also known as hazard rate or force of mortality) is provided by OREDA (2002) and shown in equation (5.1). This definition states that failure rate is equivalent to the probability that the item will fail in the time interval (t, $t + \Delta t$), while the component is still operating at time t. Additionally, failure rate is identified as the probability that the component that has reached the age t will fail in the following interval, defined as (t, $t + \Delta t$).

$$\lambda(t)\Delta t \approx \Pr(t < T \leq t + \Delta t \mid T > t) \tag{5.1}$$

It is crucial to highlight that the life of a component or item is split into three regions of expected failure behaviour known as burn-in (or infant mortality) phase, useful life and wear-out phase. These three phases are demonstrated in a curve known as bath-tub shape, which represents the failure rate function through time.

5.4.2. Data acquisition and preparation

As identified above, the source of processed input data for the initial PMRA application is OREDA. However, an input data preparation process is undertaken prior to the implementation. In this section, this data process is demonstrated which generates input for the dynamic state modelling process and the reliability assessment tool. This input data preparation phase utilises indices and data records as shown in Appendix E and the extracted table samples of OREDA.

Each system involves various identified and recorded failure modes fm (from i=1 to n), where n denotes the maximum number of failure modes each topside system has been affected. On the other hand, each system consists of maintainable components c (from j=1 to m), where m indicates the maximum number of components each topside system consists of (according to recorded failures). Each failure mode holds a specific proportion out of the overall recorded modes per system and a different proportion per component (as each component may fail due to different failure modes) in relation to the likelihood of occurrence. The summarised percentage of occurrence of each failure mode fm_{iSUM}, by considering figures of every involved recorded component, is shown in equation (5.2) below:

$$fm_{iSUM} = \sum_{j=1}^{m} c^{i} \tag{5.2}$$

If c_{ij} denotes the failure rate index of component c_j involving failure mode i (see Appendix E), then the recorded failure proportion p_{cij} per component per total failure rate of each mode is expressed by equation (5.3).

$$p_{cij} = \frac{c_{ij}}{fm_{iSUM}} \tag{5.3}$$

On the other hand, each failure mode fm_{iOP} is expressed in relation to the system aggregated time in service t, the mean failure rate index of failure mode i denoted as μ_{fri} and the total component's failure rate proportion out of all involved components in the system c_{jSUM}. The mathematical relation is shown in equation (5.4).

$$fm_{iOP} = \frac{c_{jSUM}^{i}\,\mu_{fri}}{t} \tag{5.4}$$

Therefore, the failure rate of each component per failure mode by taking into account the aggregated time *t* is denoted as λ_{ij} as shown in equation (5.5). Moreover, the failure rate of each component, by considering all failure modes that the particular unit can fail, is expressed in equation (5.6).

$$\lambda_{ij} = p_{cij}\, fm_{iOP}\, 100 \tag{5.5}$$

$$\lambda_J = \sum_{i=1}^{n} \lambda_{ij} \tag{5.6}$$

This section combined with supplementary information attached in Appendix E demonstrates the processed data preparation of figures mined from the OREDA database. The results of this process set the grounds for system, subsystem and component level failure rate to be utilised by the dynamic state modelling process and the reliability assessment tool. These results take into account the proportion of failure rates per failure mode and the involved maintainable components.

5.5. Case study network development

In the previous section, the processed input data preparation phase was demonstrated which employs reliability figures and records from OREDA database. This section presents the Bayesian Belief Network (BBN) layout as structured in system, subsystem and component level by considering various failure modes. In total seven main systems are utilised for this case study such as the 4-stroke diesel generator (D/G), turboexpander and multiple pumps such as the seawater lift, oil export, cooling water, water firefighting, and the crude oil handling.

5.5.1. Diesel Generator (D/G) system

In this section, the diesel generator (D/G) case study is presented. This system is modelled to examine its reliability performance, as it is complex and its functioning is crucial. It is essential to clarify in advance that OREDA database involves 4-stroke diesel engines (known as diesel generators) for energy supply requirements, whereas large ships are equipped with larger 2-stroke diesel engines for their propulsion requirements. The common aspects of these power generators (i.e. 2-stroke and 4-stroke) create a fruitful ground for implementation of the initial application on 4-stroke diesel engines. Therefore, at this initial level of PMRA application, D/G are utilised, whereas ship application of PMRA, demonstrated next in Chapter 6, employs 2-stroke diesel engine. The D/G is vital in functioning system integrating a diesel engine with an electric generator to produce electrical energy. This application is oriented towards the diesel engine of the D/G as it shares common aspects and features with the 2-stroke marine diesel engines.

Suitable inspection and maintenance planning of the D/G can eliminate the risk of failures and malfunctions, which can be harmful for humans and dangerous for the environment. Hence, Figure 5.1 illustrates the different unit levels consisting of the main system, subsystems and maintainable components and units. The main system is the D/G, which includes subsystems such as the lubrication, starting, control and monitoring, engine internal and external components and the cooling system. Each of these subsystems consists of different maintainable components and items. For instance, the lubrication system includes the oil, cooler and pressure instrument. On the other hand, various Failure Modes (FM) are recorded and introduced that can affect these components/subsystems/systems.

The analytical list of failure modes is presented in Table 5.1 incorporating leakages of fluids, operational malfunctions, overhearing, noise, vibration and structural damage. These failure modes refer to recorded incidences as identified per maintainable unit or component. Furthermore, the D/G network arrangement includes multiple maintainable components among instruments, fuel items, cylinders, exhaust and bearings as listed in Table 5.2. Each of these components belongs into one of the consisted subsystems as shown in Table 5.3.

Overall, the identified subsystems consist of the lubrication, starting, control monitoring, engine internal and external components and the cooling. However, OREDA database arranges the involved components and maintainable units among starting, engine, control and monitoring, lubrication, and cooling subsystems. The major difference among these approaches involves the engine subsystem. In the OREDA arrangement, engine comprises of nine components and maintainable units. On the other hand, PMRA strategy divides these into two subsystems such as the engine internal and external components respectively. This is an attempt to optimise the calculation time, efficiency and programming effort. The mathematical explanation behind this decision has been provided in equation 4.27. In other words, the more the parent nodes feed input a child node, the greater the number of failure case scenarios will have to be developed.

During the research and development period, different technical meetings have been taken place with professionals such as ship owners, operators, Classification Societies, service providers, consultants, onboard personnel/crewmembers and captains. These meetings offered valuable information from professionals that is sourced from years of experience, knowledge and actual/practical operational conditions in the field. The node selection (as shown in Figure 5.1) is combined with criteria such as system redundancy, number of failures per component and involved failure modes extracted from external source (OREDA from previous case study), and practical impact in case of failure. Additionally, expert judgment has been extracted from resources such as OEMs, technical reports, sea and shop trials, maintenance reports and engine operational manuals. Therefore, the utilised expert information has been selected, while taking into account the lowest possible subjective judgement.

Furthermore, the dependencies of the provided network have been examined and validated by experts through the validation scheme obtained as part of the INCASS EU FP7 project (INCASS, 2014a). Lastly, it is essential to clarify that particular maintainable units and components have been congregated in single nodes such as injections, cylinders, pistons and radial bearings. OREDA database integrates gathered failure records of similar components and maintainable units and provides reliability figures into aggregated format. This decision of reliability representation is related to the input reliability figures OREDA provides. The failure records of OREDA have been collected by various oil and gas stakeholders summarising figures of similar or identical maintainable units and components (as listed above).

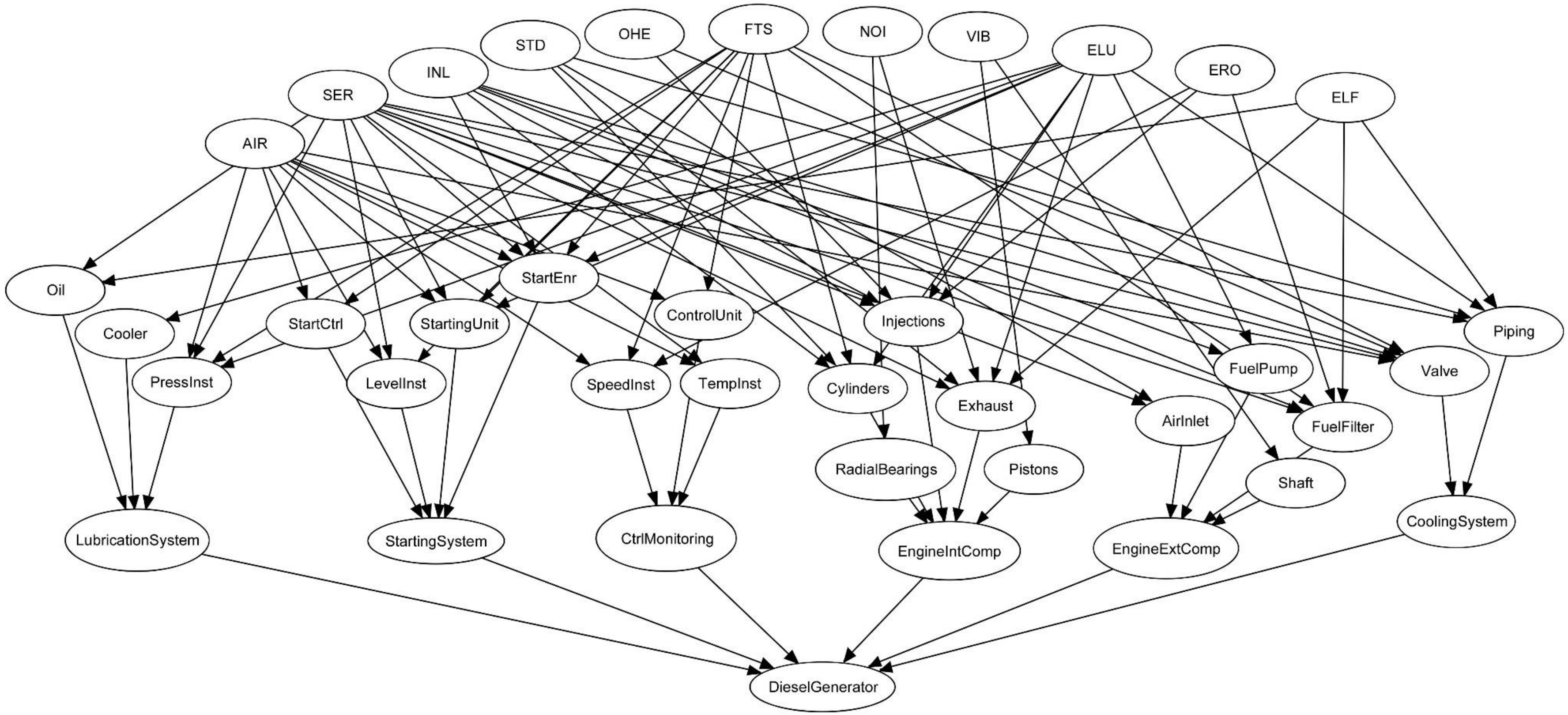

Figure 5.1 Diesel Generator (D/G) PMRA strategy network case study

Table 5.1 Failure mode list of PMRA strategy for D/G case study

Failure Mode Abbreviation	**Meaning**
AIR	Abnormal Instrument Reading
ERO	Erratic Output
ELF	External Leakage – Fuel
ELU	External Leakage – Utility Medium (i.e. lubricant, cooling water)
FTS	Fail to start on demand
INL	Internal Leakage
SER	Minor in-service problems
NOI	Noise
OHE	Overheating
STD	Structural Deficiency
VIB	Vibration

Table 5.2 Component list of PMRA strategy for D/G case study

Diesel Generator Component List	
Air Inlet	Pistons
Control Unit	Pressure Instrument
Cooler	Radial Bearing
Cylinders	Shaft
Exhaust	Speed Instrument
Fuel Filter	Start Control
Fuel Pump	Start Energy
Injections	Starting Unit
Level Instrument	Temperature Instrument
Oil	Valve
Piping	

Table 5.3 Subsystem list of PMRA strategy for D/G case study

Diesel Generator Subsystem List
Control & Monitoring
Cooling
Engine External Components
Engine Internal Components
Lubrication
Starting

5.5.2. Turboexpander system

The second case study involves the reliability assessment of the turboexpander. The reliability performance of this system is examined independently of the diesel generator (D/G) as this processed input data arrangement is provided according to the data source. The network arrangement is demonstrated in Figure 5.2. From top to bottom, turboexpander is structured into multiple nodes. Firstly, parent nodes of failure modes lead to components and maintainable units and these to subsystems.

This system is divided in four subsystems such as the expander and recompressor turbine, control and monitoring, lubrication and the shaft and seal as shown in Table 5.6. OREDA database separates expander turbine and recompressor subsystems. However, both subsystems are associated with five maintainable units and components and PMRA strategy combines them in this predictive reliability assessment. This decision has been made because the majority of the involved components (in expander-recompressor turbine subsystem) are instruments such as pressure, speed and temperature. As long as failure records have been gathered, their reliable performance is significant. However, applied CM practices (which is the research orientation of PMRA strategy) for instruments are impractical and PMRA strategy is not oriented towards these maintainable units and components.

Each of these subsystems consists of multiple related in function components and maintainable units such as instruments, oil, piping, seal, bearings and valves among others. Analytical list of turboexpander maintainable items and components is provided in Table 5.5. Lastly, eight failure modes are recorded to affect the optimal functioning of turboexpander as shown in Table 5.4. The presented BBN arrangement and particularly the node associations have been validated by academic experts on probabilistic risk assessment, chartered and onboard chief engineers from ship service providers and shipping companies, and Classification Societies. Similarly as in D/G case, the network arrangement has been validated by the INCASS FP7 EU project validation scheme. According to the feedback gained, the structure of the demonstrated network fulfils the practical/operational and research requirements.

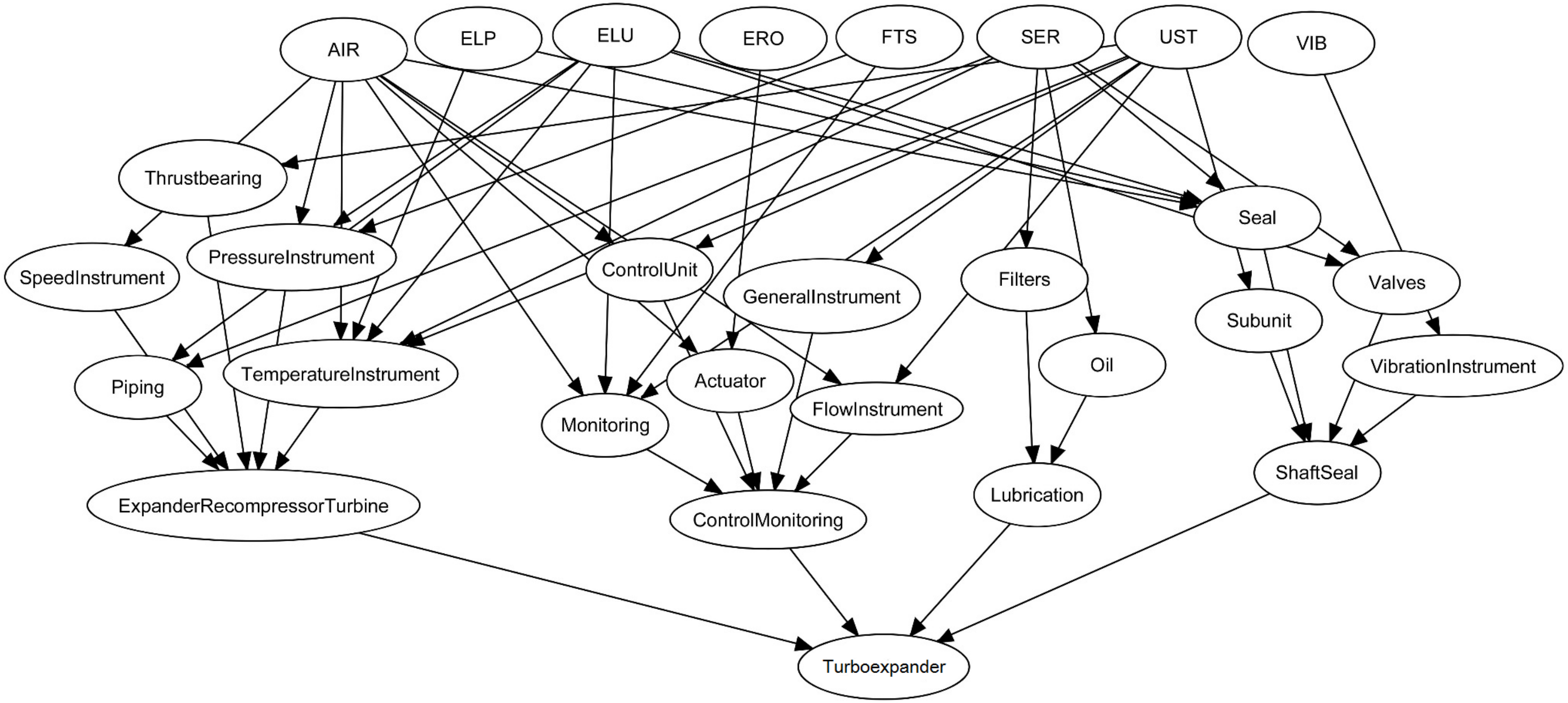

Figure 5.2 Turboexpander PMRA strategy network case study

Table 5.4 Failure mode list of PMRA strategy for turboexpander case study

Failure Mode Abbreviation	Meaning
AIR	Abnormal Instrument Reading
ERO	Erratic Output
ELP	External Leakage – Process Medium (i.e. oil, gas, condensate, water)
ELU	External Leakage – Utility Medium (i.e. lubricant, CW)
FTS	Fail to start on demand
SER	Minor in-service problems
UST	Spurious Stop
VIB	Vibration

Table 5.5 Component list of PMRA strategy for turboexpander case study

Turbocharger Component List	
Actuator	Pressure Instrument
Control Unit	Seal
Filters	Speed Instrument
Flow Instrument	Subunit
General Instrument	Temperature Instrument
Monitoring	Thrust Bearing
Oil	Valves
Piping	Vibration Instrument

Table 5.6 Subsystem list of PMRA strategy for turboexpander case study

Turbocharger Subsystem List
Control Monitoring
Expander Re-compressor
Turbine
Lubrication
Shaft & Seal

5.5.3. Seawater lift pump system

In this section, the working state reliability performance of the seawater lift pump is assessed. This system has been selected as it shares similarities in function and service as the ship ballast water pump. These systems' reliable performance is crucial as they ensure the appropriate conditions for stability control through seawater supply in the ship application case and water supply for the oil and gas platform practices. This pump type records thirteen occurred failure modes by involving seventeen components and maintainable items/units that have been associated with the failure modes. The failure modes and components are represented in the BBNs in nodes, while they are arranged in subsystems according to their function. In agreement with OREDA database, these components and maintainable units have been arranged in subsystems such as the controller, shell, cooling, couples and mechanical power.

Technical meetings, discussions and publications have been taken place as part of this research thesis. On the other hand, the validation scheme of INCASS FP7 EU project have contributed towards the testing of the present case study model. Hence, the represented structure, node and connections arrangement have been validated as well through the same procedure, experts and professionals as in the Diesel Generator (D/G) and Turbocharger cases. Therefore, chartered engineers and onboard crew members as well as engineers from Classification Societies have confirmed the seawater lift pump network structure. Additionally, the node structured fulfils the OREDA database structure ensuring accurate implementation. The network structure is demonstrated in Figure *5.3*. On the other hand, the analytical list of failure modes is shown in Table *5.7*, the components and maintainable items in Table *5.8* and the subsystems in Table *5.9*.

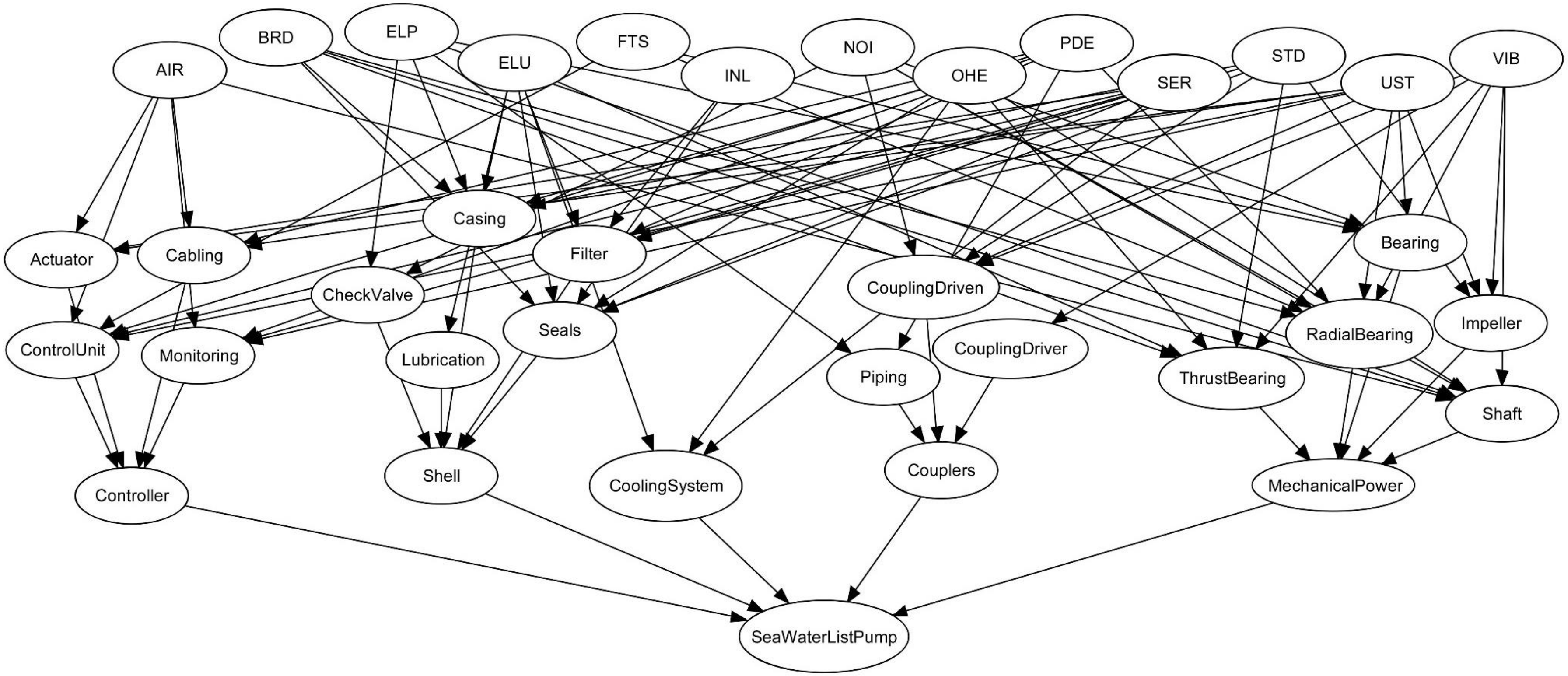

Figure 5.3 Seawater lift pump PMRA strategy network case study

Table 5.7 Failure mode list of PMRA strategy for seawater lift pump case study

Failure Mode Abbreviation	Meaning
AIR	Abnormal Instrument Reading
BRD	Breakdown
ELP	External Leakage – Process Medium (i.e. oil, gas, condensate, water)
ELU	External Leakage – Utility Medium (i.e. lubricant, cooling water)
FTS	Fail to start on demand
INL	Internal Leakage
NOI	Noise
OHE	Overhearing
PDE	Parametre Deviation
SER	Minor in-service problems
STD	Structural Deficiency
UST	Spurious Stop
VIB	Vibration

Table 5.8 Component list of PMRA strategy for seawater lift pump case study

Seawater Lift Pump Component List	
Actuator	Impeller
Bearing	Lubrication
Cabling	Monitoring
Casing	Piping
Check Valve	Radial Bearing
Control Unit	Seals
Coupling Driven	Shaft
Coupling Driver	Thrust Bearing
Filter	

Table 5.9 Subsystem list of PMRA strategy for seawater lift pump case study

Seawater Lift Pump Subsystem List
Controller
Shell
Cooling
Couplers
Mechanical Power

5.5.4. *Oil export pump system*

The following considered main system is the oil export pump and its reliability degradation is examined. This pump has been selected as it shares common functional aspects as the cargo pumps of the tanker ships. The purpose of the cargo pumps is to load and unload the cargo tanks, whereas the scope of oil export pumps is to discharge the tanks of the oil and gas platforms. The oil export pump type has been assessed as it is installed for similar operational requirements as the cargo pumps. However, it is vital to clarify that tanker ship cargo pumps are steam-powered, whereas the power requirements of the oil export pumps of OREDA database are not specified.

This system is selected in order to assess the working state reliability performance as its optimum functioning ensures safety on the platform as well as efficiency in discharging the oil storage tanks. Overall, the oil export pump consists of five subsystems such as the controller, shell, cooling, couplers and mechanical power. These subsystems involve vital in functioning maintainable units and components, where failures have been recorded. These components are associated with at least on failure mode. Similarly as in the D/G, turboexpander and seawater lift pump, the network arrangement and node modelling have been validated by leading maritime stakeholders and INCASS FP7 EU project research members. On the other hand, risk assessment academic experts have been validated the demonstrated structure, as well as experienced engineers.

Its network structure is illustrated in Figure *5.4*. Furthermore, Table *5.10* lists the involved failure modes recorded. Furthermore, sixteen components and maintainable items are recorded that has been failed as shown in Table *5.11*. These units belong to one of the arranged subsystems as listed in Table *5.12*. As long as various failures have been recorded by leading oil and gas stakeholders, there is research space for reliability and safety enhancement. This case study attempts to provide inspection and maintenance activity guidelines.

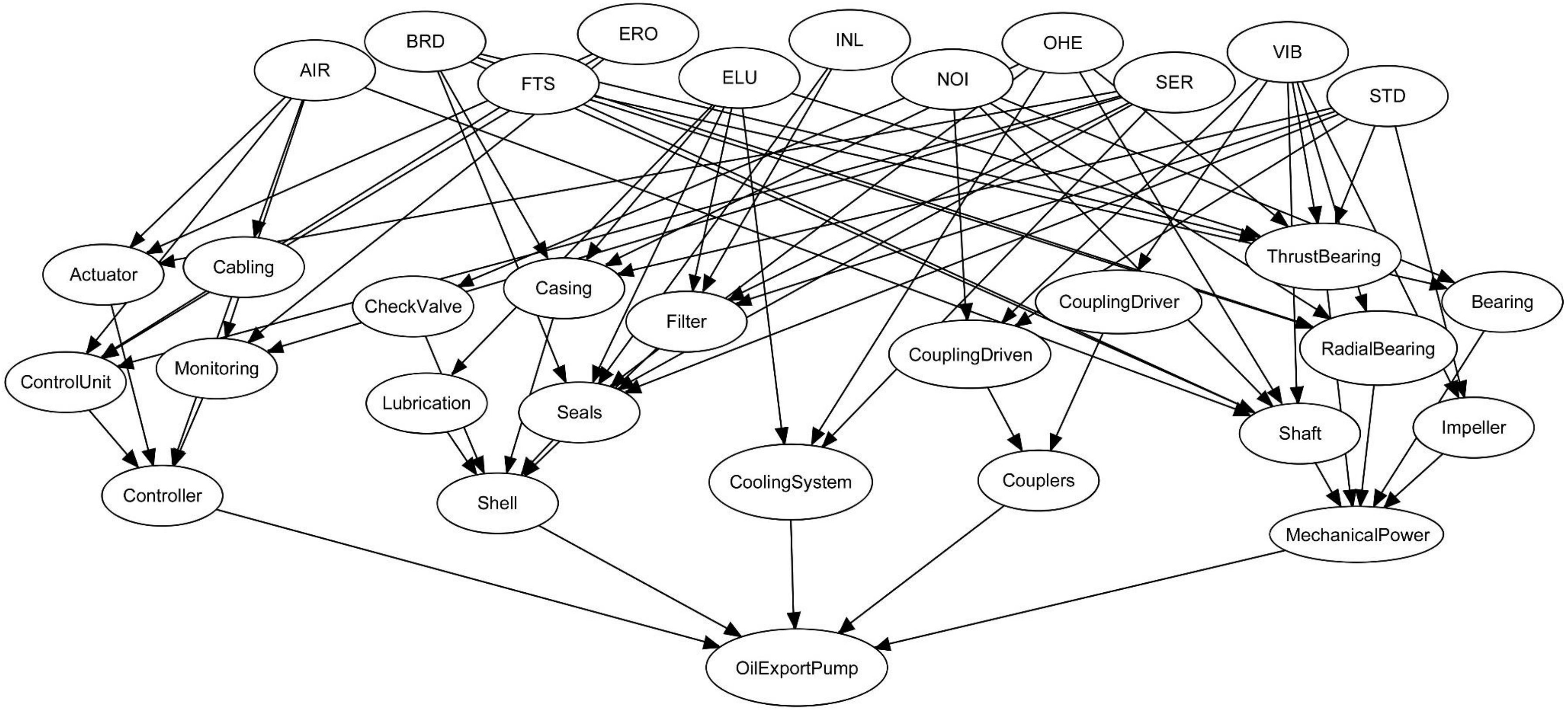

Figure 5.4 Oil export pump PMRA strategy network case study

Table 5.10 Failure mode list of PMRA strategy for oil export pump case study

Failure Mode Abbreviation	Meaning
AIR	Abnormal Instrument Reading
BRD	Breakdown
ELU	External Leakage – Utility Medium (i.e. lubricant, cooling water)
ERO	Erratic Output
FTS	Fail to start on demand
INL	Internal Leakage
NOI	Noise
OHE	Overhearing
SER	Minor in-service problems
STD	Structural Deficiency
VIB	Vibration

Table 5.11 Component list of PMRA strategy for oil export pump case study

Oil Export Pump Component List	
Actuator	Filter
Bearing	Impeller
Cabling	Lubrication
Casing	Monitoring
Check Valve	Radial Bearing
Control Unit	Seals
Coupling Driven	Shaft
Coupling Driver	Thrust Bearing

Table 5.12 Subsystem list of PMRA strategy for oil export pump case study

Oil Export Pump Subsystem List
Controller
Cooling System
Couplers
Mechanical Power
Shell

5.5.5. Cooling water pump system

This case study introduces the cooling water pump. This pump type is electrically powered and has the same functional purpose for both applications of offshore oil and gas platforms and ships. In Figure 5.5, the network arrangement is demonstrated, structured in nodes which denote the recorded failure modes, maintainable units and components, subsystems and the main system. As Figure 5.5 illustrates three failure modes are involved in this system, such as abnormal instrument reading, fail to start on demand and noise (Table *5.13*).

Therefore, cooling water pump demonstrates a narrowed range of failure modes compared to the previously presented seawater lift and oil export pumps. In total, seven maintainable units and components are recorded to be associated with failure modes as listed in Table *5.14*. Lastly, four nodes denote the subsystem level such as the controller, valve, coupling driven and mechanical power (Table *5.15*). Similarly, the cooling water pump network structure has been validated in regards to node arrangement and connections among them. The validation campaign of INCASS FP7 EU project has provided feedback for applying the PMRA strategy on the presented network below (Figure 5.5). Along the same lines, experts and professionals have validated the network arrangement of cooling water pump.

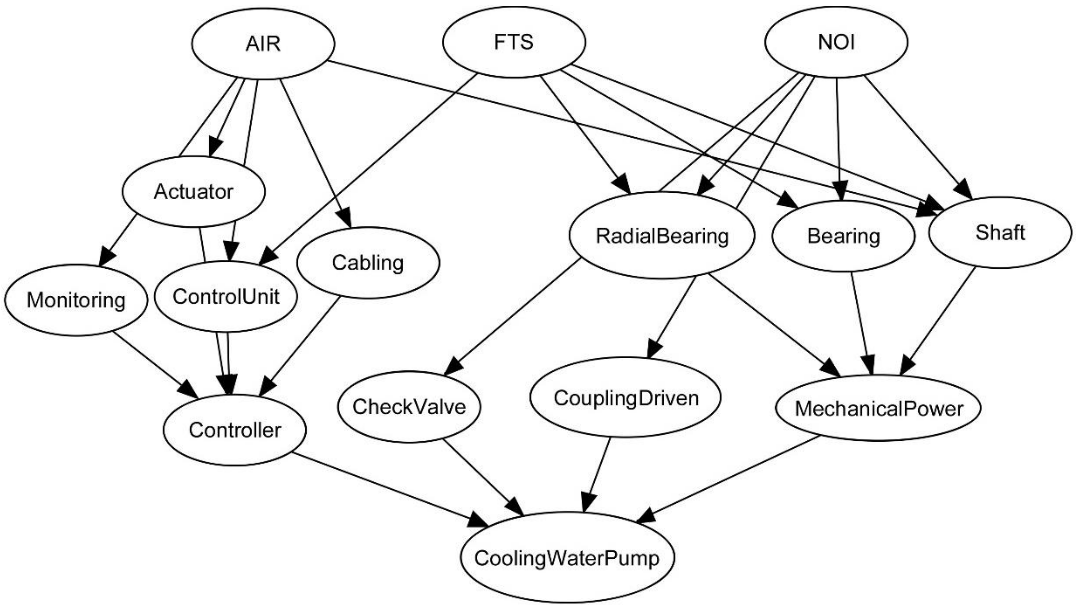

Figure 5.5 Cooling water pump PMRA strategy network case study

Table 5.13 Failure mode list of PMRA strategy for cooling water pump case study

Failure Mode Abbreviation	Meaning
AIR	Abnormal Instrument Reading
FTS	Fail to start on demand
NOI	Noise

Table 5.14 Component list of PMRA strategy for cooling water pump case study

Cooling Water Pump Component List
Actuator
Bearing
Cabling
Control Unit
Monitoring
Radial Bearing
Shaft

Table 5.15 Subsystem list of PMRA strategy for cooling water pump case study

Cooling Water Pump Subsystem List
Controller
Check Valve
Coupling Driven
Mechanical Power

5.5.6. Firefighting pump system

An important system which ensures safety onboard the offshore oil and gas platforms and ships is the water firefighting pump. It is crucial to be well-maintained and in functional condition for immediate operation if needed. Firefighting pumps have vital in safety duty, however they are operated seldom. Therefore, typical testing of these systems involves periodic switch-on check and infrequent overhauling.

Despite the fact that firefighting pumps are seldom to be operated, many and major failure modes have been recorded by oil and gas stakeholders in OREDA database. Therefore, the existing maintenance plan is inadequate to offer reliable condition for an important onboard system. This system's network structure (Figure *5.6*), as processed input data extracted from OREDA, shows poor reliability performance recording various failure modes, which are listed in Table 5.16. The affected, from these failure modes, maintainable units and components are analytically provided in Table 5.17 and the involved subsystems that these belong in Table 5.18.

According to existing practices and experts' judgment CM practices are impractical on water firefighting pumps. Because CM requires effort, equipment installation, data analysis, hence resources, on-condition assessment has not been applied. However, it is promising to examine the predicted reliability assessment of the OREDA database figures in regards to the firefighting pump. The forecasted result will indicate the most significant failure modes, the most frequent failed components and the involved subsystems.

In Figure 5.6, the network arrangement of the water firefighting pump has been presented. In a similar manner as the D/G, turboexpander, seawater lift, oil export and cooling water pumps, the firefighting pump's network structure has been validated in regards to node arrangement and involved associations. Therefore, various shipping stakeholders such as chartered and chief onboard engineering, Classification Societies, risk assessment academic experts and the INCASS FP7 EU projects have been assessed the present network arrangement.

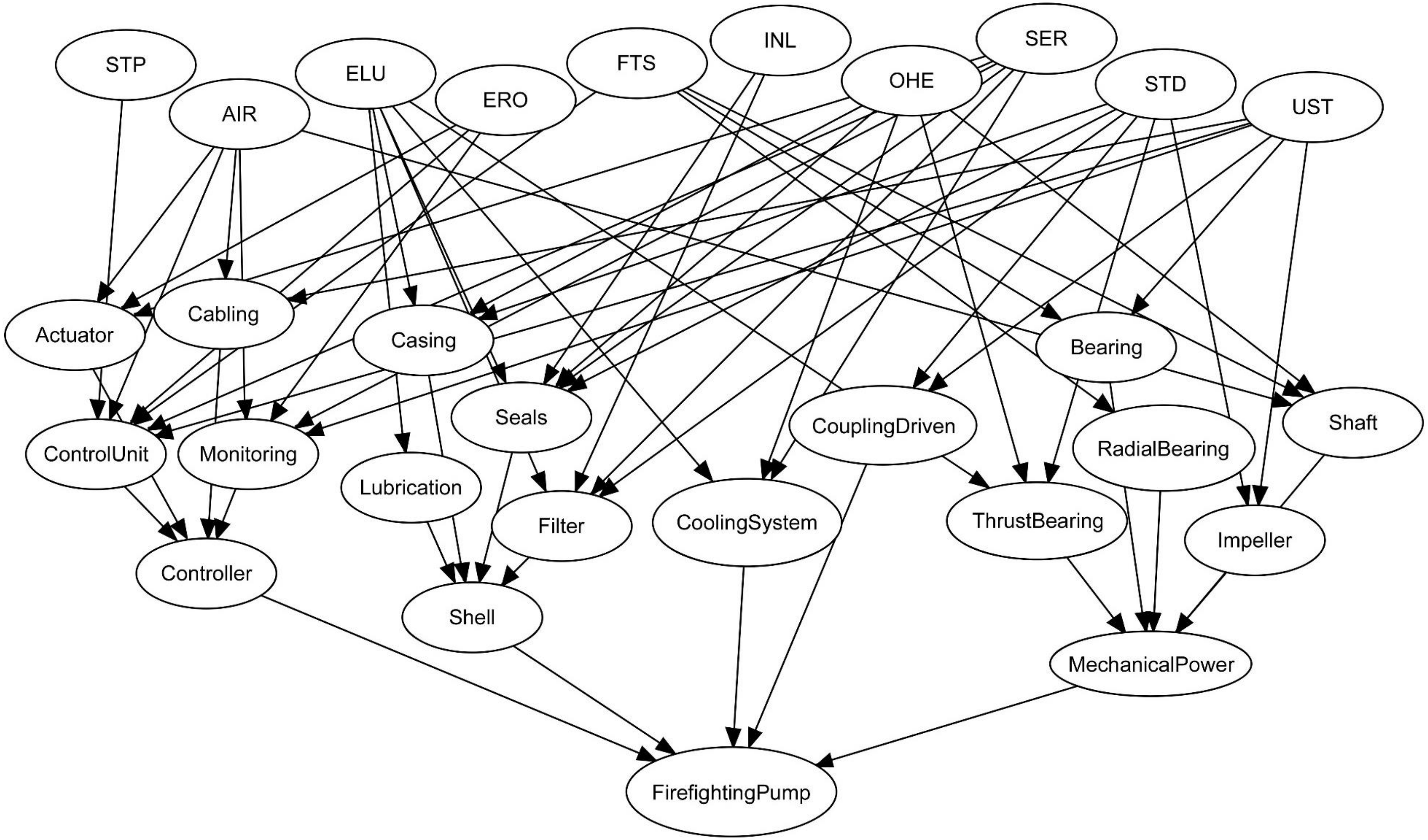

Figure 5.6 Firefighting pump PMRA strategy network case study

Table 5.16 Failure mode list of PMRA strategy for firefighting pump case study

Failure Mode Abbreviation	Meaning
AIR	Abnormal Instrument Reading
ELU	External Leakage – Utility Medium (i.e. lubricant, cooling water)
ERO	Erratic Output
FTS	Fail to start on demand
INL	Internal Leakage
OHE	Overhearing
SER	Minor in-service problems
STD	Structural Deficiency
STP	Fail to stop on demand
UST	Spurious Stop

Table 5.17 Component list of PMRA strategy for firefighting pump case study

Firefighting Pump Component List
Actuator
Bearing
Cabling
Casing
Control Unit
Filter
Impeller
Lubrication
Monitoring
Radial Bearing
Seals
Shaft
Thrust Bearing

Table 5.18 Subsystem list of PMRA strategy for firefighting pump case study

Firefighting Pump Subsystem List
Controller
Cooling
Coupling Driven
Mechanical Power
Shell

5.5.7. Crude oil handling pump system

Lastly, the crude oil handling pump is the final system for predictive reliability assessment at this initial level of the technical implementation of PMRA strategy. Crude oil handling pump is electrically powered and share common functional and structural aspects with the ship fuel oil pump. This system's reliable and efficient operation affects directly the crude oil and fuel oil supply respectively.

In a similar manner, reliability input figures have been provided by OREDA database by taking into account various failed maintainable units and components and occurred failure modes. These are structured into subsystems such as the controller, shell, cooling, couplers and mechanical power. In Figure 5.7, the network arrangement structure is demonstrated consisting of multiple nodes denoting the main system, the involved subsystems (Table 5.21) and various failed maintainable units and components (Table 5.20). On the other hand, the associated recorded failure modes are listed in Table 5.19.

The crude oil handling pump's network layout has been confirmed by maritime stakeholders such as engineers, the INCASS FP7 EU project validation scheme, as well as risk assessment academic experts. The received feedback confirms the presented structure for further development by applying the PMRA strategy.

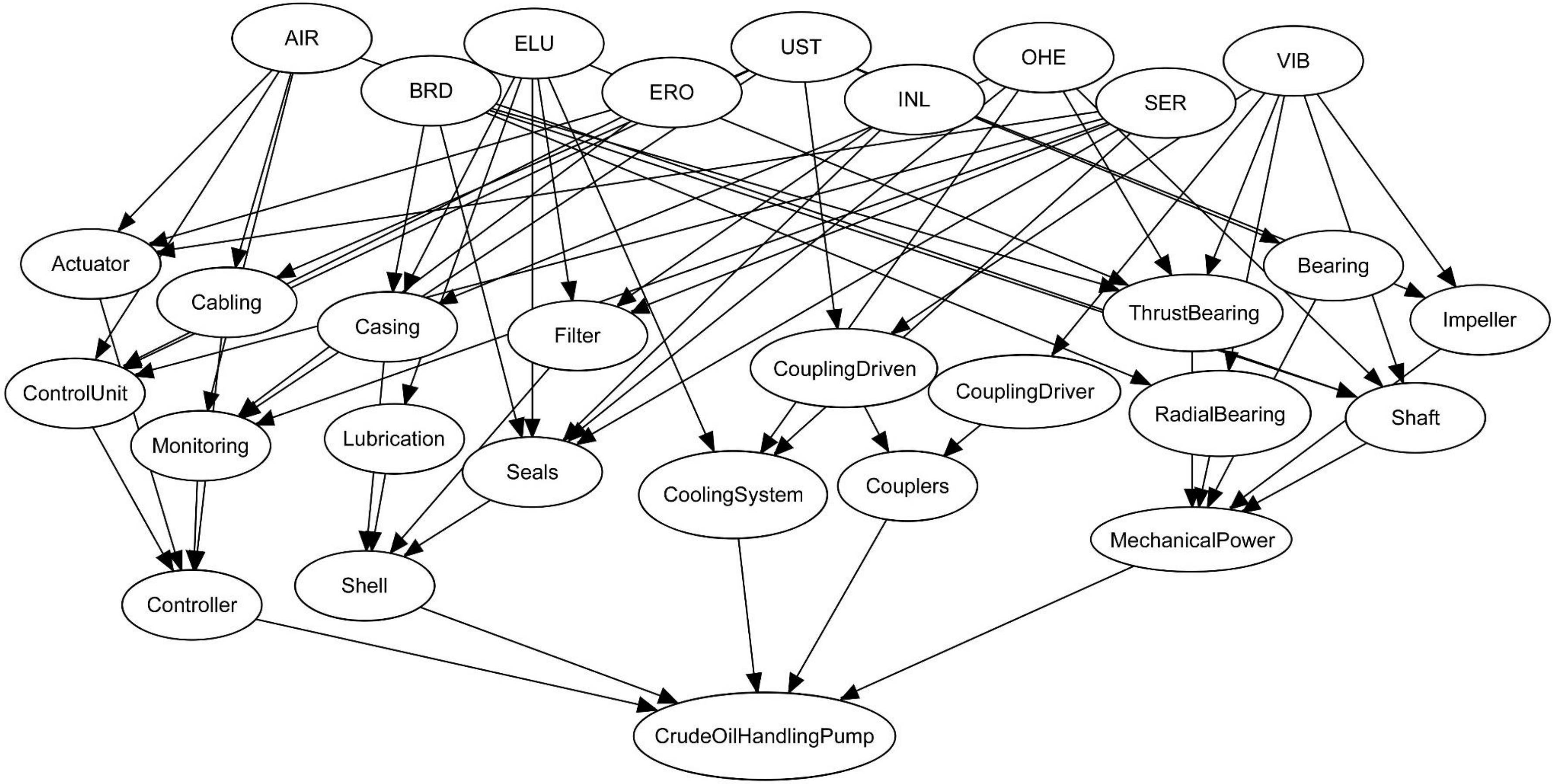

Figure 5.7 Crude oil handling pump PMRA strategy network case study

Table 5.19 Failure mode list of PMRA strategy for crude oil handling pump case study

Failure Mode Abbreviation	Meaning
AIR	Abnormal Instrument Reading
BRD	Breakdown
ELU	External Leakage – Utility Medium (i.e. lubricant, cooling water)
ERO	Erratic Output
INL	Internal Leakage
OHE	Overhearing
SER	Minor in-service problems
UST	Spurious Stop
VIB	Vibration

Table 5.20 Component list of PMRA strategy for crude oil handling pump case study

Crude Oil Handling Pump Component List
Actuator
Bearing
Cabling
Casing
Control Unit
Coupling Driven
Coupling Driver
Filter
Impeller
Lubrication
Monitoring
Radial Bearing
Seals
Shaft
Thrust Bearing

Table 5.21 Subsystem list of PMRA strategy for crude oil handling pump case study

Crude Oil Handling Pump Subsystem List
Controller
Cooling
Coupling Driven
Mechanical Power
Shell

5.6. Failure modes effects and analysis

As already discussed, the decision making stage of PMRA strategy takes into account qualitative input such as expert judgement from chief onboard crew members, chartered engineers, ship owners, operators, service providers and Classification Societies. Therefore, as part of the present PhD thesis, various technical meetings have been taken place in order to gather useful information from experts, professionals, and various stakeholders of maritime industry.

On the other hand, valuable input has been extracted by OEMs, and ship machinery manuals. This input is utilised for structuring a qualitative risk assessment tool known as Failure Modes and Effects Analysis (FMEA). Therefore, FMEA has been employed for providing essential guidelines regarding the defected subsystems, particular involved failure modes, effects of failure, damaged equipment and components as well as malfunctions and failure causes.

A sample of this FMEA tool has been demonstrated in Table 5.22, where particular maintainable units and components of the engine have been incorporated. More specifically, the camshaft bearings (aft and fore), thrust bearing and intermediate shaft bearings have been included. For each bearing, the operational temperature has been recorded listing failure modes, effects and probable damaged equipment and components in case of malfunction. Analytical representation of this FMEA including more systems and measurements has been attached in Appendix F.

Table 5.22 Sample of FMEA for PMRA strategy case study

Subsystem	Measurement	Parameter	Failure Mode	Effect of Failure	Damaged Equipment	Damaged Component	Malfunction/ Failure Cause
Engine	Camshaft Bearing (aft)	Temperature	Overheating of bearing	Engine damage	Camshaft	Bearings Camshaft	Wear & Tear
	Camshaft Bearing (fore)	Temperature	Overheating of bearing	Engine damage	Camshaft	Bearings Camshaft	Wear & Tear
	Thrust bearing LO outlet	Temperature	Improper lubrication	Engine damage	Thrust bearing	LO Piping	Leak
			Shaft malfunctioning	Engine slow down	Crankshaft	Thrust bearing	Wear & Tear
	Intermediate shaft bearing	Temperature	Overheating of bearing	Engine damage	Shaft	Bearing	Wear & Tear

5.7. Outcomes of processed data type case study

This section aims to summarise and present the key findings of the acquired results of the processed data type case study. The results are presented on system level by taking into account weaker subsystems, components and maintainable units and the relation to particular failure modes. Furthermore, this section provides recommendations with respect to inspection and maintenance actions according to the observed reliability performance predictions.

The summarised results of each main system are provided in significance order of the most probable subsystems, components and involved failure modes to cause malfunctions and failures. For instance as shown in Table 5.23, starting subsystem acquired results set this more probable to fail compared to engine internal. Similarly, starting energy is more probable to fail than level instrument. Additionally, starting energy's involved INL failure mode is predicted to be more likely to occur than FTS and the latter more likely than SER, AIR and ELU respectively. Hence, the subsystems, components and failure modes are placed in the tables below in probabilistic order to lead in failures as the results are acquired by the PMRA strategy.

Therefore, the summarised forecasted reliability performance results of the D/G place starting subsystem the most likely to fail followed by engine internal and external subsystems respectively. Starting subsystem's maintainable units' and components' predicted reliability performance show that the most likely component to fail is the starting energy followed by the level instrument, starting unit and lastly the starting control. The involved failure modes comprise of AIR, ELU, FTS, INL and SER. The majority of these failure modes such as AIR, FTS and SER do not provide a specific indication or information related to the failure observed.

However, ELU and INL are recorded due to leakages (i.e. fluids), which did not allow the sufficient pressure for initiating the D/G. Therefore, particular interest should be focused towards pressure measurements, which will allow the monitoring of the conditions required for starting the D/G.

Table 5.23 Summary of diesel generator (D/G) processed data type case study results

System	Subsystem	Component	Failure Mode
D/G	Starting	Starting Energy	INL, FTS, SER, AIR, ELU
		Level Inst.	SER, AIR, FTS
		Starting Unit	FTS, SER, ELU, AIR
		Starting Control	FTS, AIR
	Engine Internal	Injections	SER, INL, ELU, ERO, OHE
		Exhaust	SER, STD, ELF, NOI, ELU
		Cylinders	STD, FTS, INL, ELU
		Radial Bearings	NOI
		Pistons	VIB
	Engine External	Air Inlet	SER, STD
		Fuel Filter	SER, ERO, FTS, ELF, INL
		Fuel Pump	INL, ELU
		Shaft	VIB

Furthermore, the second in order subsystem as shown in Table 5.23, for occurrence of probable failures or malfunctions, is the engine internal components subsystem. In this case various components and maintainable units are involved such as the injections, exhaust, cylinders, radial bearings and pistons. The developed FMEA diagnostic qualitative table of PMRA strategy (Appendix F) provides description per failure mode, effect of failure, damaged equipment and component as well as cause of malfunction. In regards to fuel injection equipment, the probable causes of failure are associated to leakages and worn fuel pumps. The predicted leakages may take place due to damaged fuel valves. Hence, the valves should be checked visually or by pressure testing.

On the other hand, the malfunction or failure of exhaust system is more complex as it is associated to more complicated functions and operational conditions. Therefore, low output flow will lead to loss of performance and the indication is low temperature of exhaust gases. The fuel supply equipment will be affected and particular components such as the suction pipe or inlet valve. Alternatively, if increased exhaust gas temperature is identified then damage could occur in the fuel injectors, cylinder, air coolers and the turbocharger. Particular components damaged can either be piston rings or exhaust valves.

Cylinders can be investigated by monitoring the gas outlet temperature and liner pressure (i.e. worn) among others. In regards to cylinder JCFW, two measurement indices can be recorded the JCFW outlet temperature and the inlet pressure. In the first place, higher fresh water temperature may damage the engine due to failure or malfunction of the JCFW pump. Additionally, lower fresh water supply can lead to loss of redundancy due to the motor of the JCFW pump of the pump.

In the case of the bearings, the lubrication oil outlet temperature should be analysed, in order to identify increase before malfunctions occur. Furthermore, thermography can be introduced for monitoring the temperature of the entire bearing, which will allow the localisation of the temperature increase. Another option for the bearing's defect assessment is vibration analysis. This method is not considered in this PhD research thesis; however, vibration analysis benefits can be integrated with the advantages of lubrication oil temperature monitoring and thermography for optimising the predicted results. Lastly, the proper condition of the pistons can be recognised from the condition of piston rings and the piston crown (per cylinder). Measurements that sign improper condition of the piston rings and crown are the exhaust gas outlet temperature and the compression pressure.

The second main system under reliability assessment is the Turboexpander as shown in Table 5.24. In this case, the most likely subsystem to cause failures and abnormal functioning is the expander/recompressor turbine. More specifically, components such as the temperature and pressure instrument, piping, thrust bearing and the speed instrument acquired the lowest reliability performance.

Table 5.24 Summary of Turboexpander processed data type case study results

System	Subsystem	Component	Failure Mode
Turboexpander	Exp./Recomp. Turbine	Temperature Inst.	AIR, SER, ELP, UST, ELU
		Pressure Inst.	AIR, FTS, ELU
		Piping	SER, ELU
		Thrust Bearing	UST
		Speed Inst.	AIR

The instruments such as temperature, pressure and speed are devices utilised for data gathering. Therefore, implementation of condition monitoring practices will be financially inefficient and practically demanding for controlling and processing additional data. According to the developed FMEA (Appendix F), T/C can be monitored by analysing the exhaust gas temperature. The temperature increase will indicate fouling of the turbine or the compressor side.

Various pumps are installed onboard merchant ships. These ensure the optimum transfer of liquids such as sea and fresh water, fuel and lubrication oil among others for different functional requests. The processed input data type case study involves the seawater lift (SW), oil export (OE), cooling water (CW), water firefighting (FF) and the crude oil handling (CH) pump. Therefore, Table 5.25 demonstrates commonalities and differences in regards to the most probable, to cause failures and malfunctions, subsystems, maintainable units and components and involved failure modes. The summarised pump results are provided in significance order of the most probable units to cause malfunctions and failures.

Table 5.25 Summary of pumps processed data type case study results

System	Subsystem	Component	Failure Mode
SW	Shell	Seals	ELU, SER, INL, STD, OHE, BRD
		Casing	BRD, STD, ELP, ELU, OHE
		Filter	SER, PDE, ELU, STD, INL
		Lubrication	ELU
		Valve	NOI, ELP
OE	Shell	Casing	STD, BRD, ELU, OHE
		Seals	ELU, SER, STD, INL, BRD, OHE
		Filter	SER, ELU, STD, INL
		Lubrication	ELU
		Valve	NOI
CW	Couplers	Coupling Driven	NOI
FF	Controller	Control Unit	AIR, SER, STP, ERO, UST
		Monitoring	AIR, SER, ERO, STP
		Actuator	SER, AIR, ERO
		Cabling	AIR, UST
CO	Controller	Control Unit	AIR, ERO, UST, SER
		Monitoring	AIR, ERO, SER, UST
		Actuator	SER, AIR, ERO
		Cabling	AIR, UST

SW and OE acquired similar forecasted results on subsystem level. Hence, shell subsystem is expected as the most probable to cause malfunctions and failures, whereas involved components and maintainable units are seals, casing, filter, lubrication and valve. It is essential to clarify that in the SW case, seals are less reliable than casing, whereas in OE case, seals are more reliable than casing. The order of subsystems, maintainable units and components as well as the failure modes indicates the most likely to fail to the least.

In all discovered pump cases, seal damage can be identified by detecting low liquid supply (or no flow) by measuring the inlet pressure. Moreover, no flow or low supply can be also caused due to blockage of the filter. In both cases, loss of redundancy is expected. Furthermore, OHE can be detected by implementing thermography monitoring, especially in the particular case of the pump rotors. According to expert judgment and historical information gathered through technical discussions undertaken as part of this PhD research project, pumps are monitored by measuring the input/output flowrate, applying vibration monitoring for the bearings, thermography for the rotor and the pump and measuring the pump's rotor current by utilising ammeter (ampere-meter).

Concluding the outcomes of the processed input data type case study as part of the PMRA strategy development and implementation, there should be highlighted essential points related to the utilised input and its relationship to the acquired predictions. The acquired predicted reliability performance results illustrate result uniformity among similar systems such as the pumps. This uniformity can be described as data and reliability records are provided in a summarised format by combining measurements from various similar systems installed in different offshore applications.

In other words, OREDA database provides reliability records by combining input and historical measurements from various systems collected in certain period of data gathering. Furthermore, data records are integrated for similar components. Therefore, reliability figures for maintainable units and components (e.g. cylinders, pistons, bearings etc.) are provided for the entire historical record and not for single/independent items.

Additionally, the forecasted results present high reliability performance. In many of the failure cases, results exceed 99% of reliability. The reason is mainly focused towards the implementation of aggregated time in service, which is considered by OREDA at 10^6 hours. Moreover, accumulated reliability input records are provided by summarising the reliability performance on particular groups of similar systems and maintainable units. Therefore, the independent unit/component reliability performance is unknown according to the provided input. Lastly, many recorded failure modes direct to generic descriptive causes such as abnormal instrument reading, breakdown, minor in-service problems, and parameter deviation among others.

The scope of this case study is to indicate the most probable failure case scenarios by taking into account-recorded failure modes. The implementation of processed reliability input data enables the testing and programming of the initial technical aspects of PMRA strategy such as the dynamic state modelling and the reliability assessment tool of Bayesian Belief Networks (BBNs).

5.8. Chapter summary

In this Chapter, the initial technical implementation of the dynamic state modelling process and the reliability assessment tool as parts of the PMRA strategy is demonstrated in detail. The selection of seven main systems demonstrates the applicability of the above in terms of evaluating the reliability performance on system, subsystem and component levels. This initial technical implementation takes place by performing a case study on different offshore platform oil and gas systems. This study considers systems such as the diesel generator (D/G), turboexpander and various electric powered pumps among the seawater lift, oil export, cooling water, water firefighting and the crude oil handling pump. Moreover, initial input data is extracted from OREDA, which provides reliability figures on system and maintainable component/item level by taking into account various failure modes. This Chapter presents the OREDA handbooks features and structure as preliminary input data source of PMRA strategy. On the other hand, input data gathered from this source is processed in order to be suitable for the PMRA strategy requirements.

6. CASE STUDY OF RAW DATA

6.1. Chapter outline

In this Chapter, the second stage of PMRA strategy implementation takes place involving a holistic study of the entire suggested methodology. This case study considers all data processes, methods and techniques of PMRA strategy such as the data acquisition, data clustering and safety threshold implementation, reliability assessment and the initial aspects of decision-making. On the other hand, compared to the previous case study as presented in Chapter 5, the current study utilises raw input data such as temperature and pressure gathered from actual ship operational conditions. This decision of utilising raw input data has been made because of different reasons. The majority of the presented reliability assessment methods utilise reliability figures and failure records in the form of percentage without presenting the processing method. Hence, processed input data incorporates major assumptions. On the other hand, the input data source's processing methodology is unknown, leading to trust to the data provider. Secondly, the developed methodology relies on the input data source, which leads to dependence to external data processing developers. Therefore, this study intends to evaluate the entire PMRA strategy performing reliability performance predictions by employing raw input data. The structure of the developed PMRA strategy network consists of various nodes. These nodes denote the raw input data measurements, maintainable units and components, subsystems, and the main systems. Overall, the PMRA raw input case study takes into account systems such as the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and cylinders. It is essential to clarify that the entire PMRA strategy development has been taken place in Java Object Oriented Programming (OOP) language.

6.2. Input Data Acquisition and safety thresholds

As already mentioned, this case study utilises raw input data. The data has been gathered by the automatically created report of Danaos 1 data collection platform. It is important to highlight that the developed in Java language PMRA strategy is compatibly programmed in acquiring data directly from the automatic Danaos 1 platform generated report. Overall, different performance measurements have been gathered originating from a total of 37 temperature and pressure measurement locations of ship machinery.

The overall data collection period involves one month of operation from the 1-30 of April 2016. The condition monitoring and data acquisition process involve hourly collected data. Hence, input data observations are uniform in time step (interval) ensuring uniformity in the performed reliability performance predictions. The automatically created report by Danaos 1 platform provides some fundamental statistical figures of the acquired data incorporating values such as average, time integral, maximum increase and decrease rate, variance, deviation and minimum and maximum-recorded values. These values provide useful initial indication of the ship machinery condition; however, they are not enough in order to acquire time-dependent predictive reliability assessment.

Table 6.1 provides a sample of the raw input data gathered onboard. The demonstrated input denotes the lube oil outlet temperature (°C) of the thrust bearing. According to manufacturer’s manual and expert judgment, the optimum temperature range is 55-70 °C, whereas the alarm limit has been defined at 90 °C. As shown in Table 6.1 the provided raw input data sample shows almost steady temperature values within the suggested limits. More specifically, the temperature reaches the lowest acceptable limits. Additional provided information includes the precise time stamp at which each observation is collected.

Table 6.1 Sample of thrust bearing lube oil outlet temperature input data

Time	Thrust Bearing LO Outlet Temperature (°C)
01/04/2016 13:10:10	50.3
01/04/2016 14:10:10	50.2
01/04/2016 15:10:10	50.2
01/04/2016 16:10:10	50.2
01/04/2016 17:10:10	50.2
01/04/2016 18:10:10	50.1
01/04/2016 19:10:10	49.9
01/04/2016 20:10:10	49.9
01/04/2016 21:10:10	49.9
01/04/2016 22:10:10	50.0

With regards to the alarm point, the establishment of warning level at 90 °C ensures the safest possible functioning. Hence, this alarm limit prevents of overhearing caused by improper lubrication of the thrust bearing, which will lead to malfunctions, material wear and may cause failure (see Appendix F). Moreover, normal functioning of the bearing requires optimum lubrication of the moving parts. As the operational range is defined at 55-70 °C and the warning threshold at 90 °C, the latter defines the highest acceptable input measurement.

The identification of warning at higher exceeded levels of temperature, according to manufacturers and experts, prevents of failure or malfunctions. However according to the thesis author and ship onboard chief engineers and experts, the temperature records lower than 55 °C may indicate over-lubrication, which leads to expensive or financially inefficient solutions of retaining low operational temperature. In other words, warnings should be considered for the lowest band of data points as well. This research study intends to enhance safety onboard the ship through the suggested predictive reliability assessment. Therefore, the warnings and alarm limits that are implemented come in agreement to the manufacturer’s indications. Additional information related to gathered raw input data and their safety thresholds can be found in Appendix F.

6.3. BBN arrangement of case study

Ship machinery is complex in structure, functioning and maintenance consisting of multiple components, maintainable units, subsystems and main systems. Therefore, the structure of this network arrangement is challenging in order to demonstrate an actual/realistic model of the critically selected measurements and maintainable units. Furthermore due to this complexity, the list of units and components can be assumed as "unlimited", hence specific criteria are required in order to set the baseline of the network structure and the involved nodes.

First of all, Figure 6.1 demonstrates the overall PMRA strategy case study network arrangement. This network consists of groups of nodes denoting the raw sensor input data, the maintainable units and components, the subsystems that these units belong to and the overall reliability performance of PMRA case study model. The selection of raw input data measurements is identified according to information extracted from machinery manufacturers' reports and manuals.

As part of this thesis, various technical discussions and meetings have been taken place identifying essential ship machinery, maintainable units and components as well as key input data measurements. Professionals from different maritime stakeholders such as ship owners, operators, service providers, Classification Societies, onboard crew members and ship machinery condition monitoring experts contributed with their valuable knowledge and expertise in the field of marine engineering and inspection and maintenance practices. The gathered input from experts has been utilised in structuring the network arrangement as presented in Figure 6.1. Lastly, this case study network structure and arrangement is influenced by the knowledge and experience gained from the previously designed and performed OREDA-based case study (see Chapter 5).

PMRA strategy case study network model consists of six systems as shown in Figure 6.1. These systems clarify major functions that their reliable operation affects parameters such as safety onboard for humans and the environment, and economic and business reputation aspects. The considered systems are listed among fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and the cylinder as shown in

Table 6.2. Each of these systems has been considered to contribute to the overall PMRA strategy assessment equal percentage quantities. In other words, no weighting factors have been introduced into these subsystems.

It is important to highlight in advance, that the research assumptions incorporated in this thesis will be discussed analytically in Chapter 9. More specifically related to the BBN arrangement, as long as a child node has been associated to multiple parent nodes each input has equal contribution to the child node. For instance, in case a child node has two parent nodes affecting it, the contribution is 50% per input. This decision has been made as neutral (equal) weighting factors demonstrate the actual reliability degradation without the implementation of quantitative (subjective) factors. The idea behind PMRA strategy is to eliminate subjective judgment and this has been tried to be applied in all development aspects.

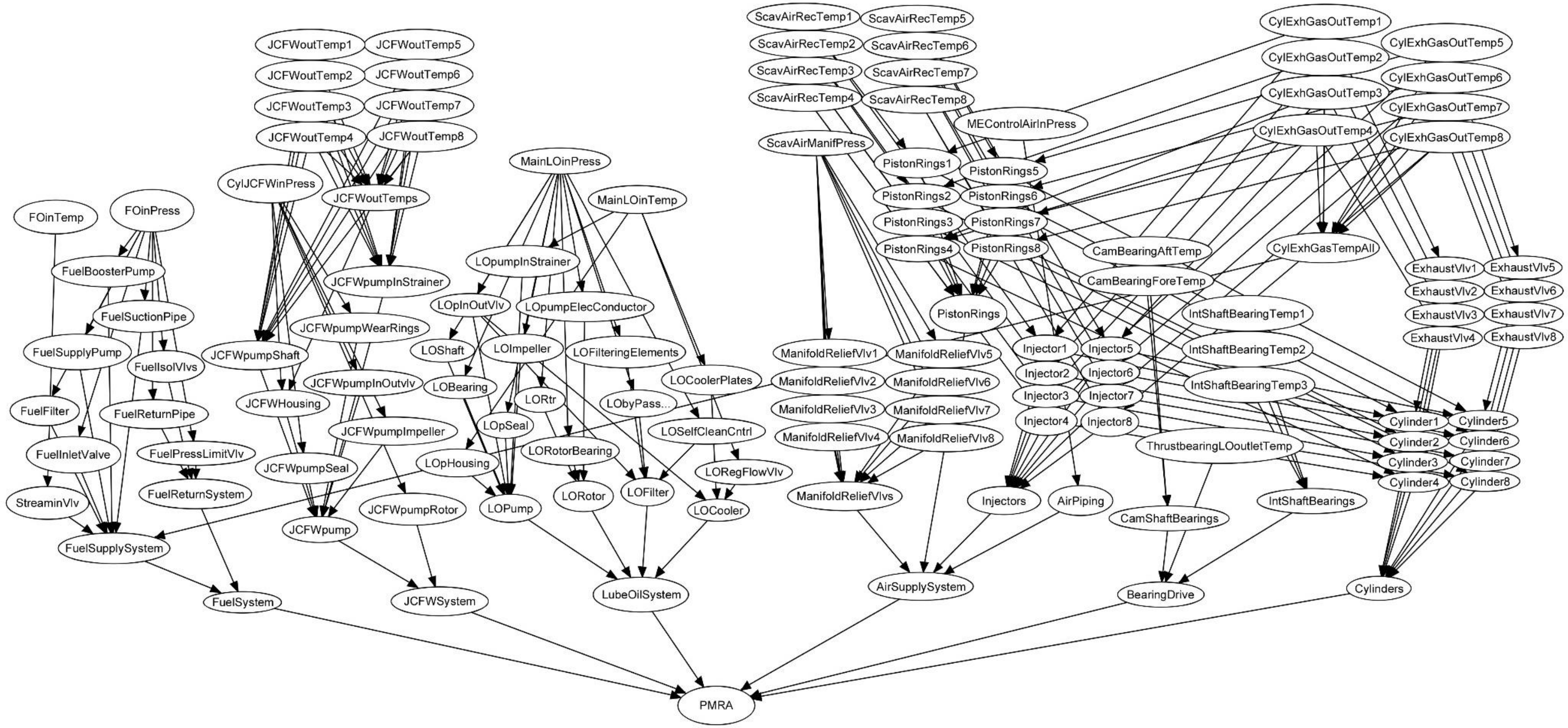

Figure 6.1 Overall PMRA strategy network case study

Table 6.2 PMRA strategy systems examined in case study

Systems
Fuel System
JCFW System
Lube Oil System
Air Supply System
Bearing Drive System
Cylinders System

PMRA strategy has been tested through this case study, while collecting input data from a Panamax container ship. The vessel has been equipment with an 8-cylinder 2-stroke slow speed marine diesel engine (MAN B&W 8K90MC-C). In Figure 6.1, the six systems combine various nodes, which denote the maintainable units and components and the raw input data. In this section, the systems' network arrangement will be demonstrated considering all involved nodes per system. It is important to clarify in advance that the demonstration of these systems takes place independently. However, the potential functional interdependencies among the raw input data measurements and the maintainable units are considered and will be identified and described as well. Therefore, PMRA strategy benefits from node interconnections as established by the Bayesian Belief Networks (BBNs) and they will be demonstrated in detail below.

6.3.1. Fuel system

First of all the fuel system (also known fuel oil system) manages the precisely designed fuel oil feeding process. The reliable functioning of this system will lead to financially, and technically efficient performance. This system's operation is directly linked to fuel consumption expenses and safety for crew and the environment. Hence, it is important to appreciate the processing involved before identifying the required raw input data and maintainable units (Taylor, 1996).

The fuel temperature has to be progressively increased reaching the appropriate viscosity before delivery to injectors and burners. Moreover, attention should be paid on the filters as cleanliness of fuel is essential. Therefore, specific treatment of fuel oils is required before reaching the engine. This treatment involves storage, heating and separation of water. Fine filtering and centrifuging utilising purifiers are necessary for removing solid particles and separating two liquids such as oil and water. The removal of solid particles and water from the fuel oil ensures efficiency and reduction of wear.

As defined above, the initial processes of fuel oil preparation involve centrifuges and heating oil. The clean heated fuel oil is pumped into the daily service tank. The oil is transferred to a mixing tank and flow meter records the fuel consumption. The booster pumps lead oil through the heaters, viscosity regulators and the engine-driven fuel pumps. Hence, the fuel pumps transfer high-pressure fuel to the appropriate injectors.

The fuel system is structured in two main subsystems the fuel supply and return as shown in Figure 6.2. The maintainable units and components that these subsystems consist, include valves, pipes, the fuel booster pump and the fuel filter. On other hand, the considered input data measurements involve the fuel oil inlet pressure and temperature and the cylinder exhaust gas outlet temperature. The latter raw measurement belongs to cylinder system and will be presented next. Therefore, this is the first introduced interconnection linking nodes of different systems (i.e. fuel and cylinder systems). Analytical lists of the input data requirements and the considered maintainable units and components can be found in Table *6.3* and Table *6.4*.

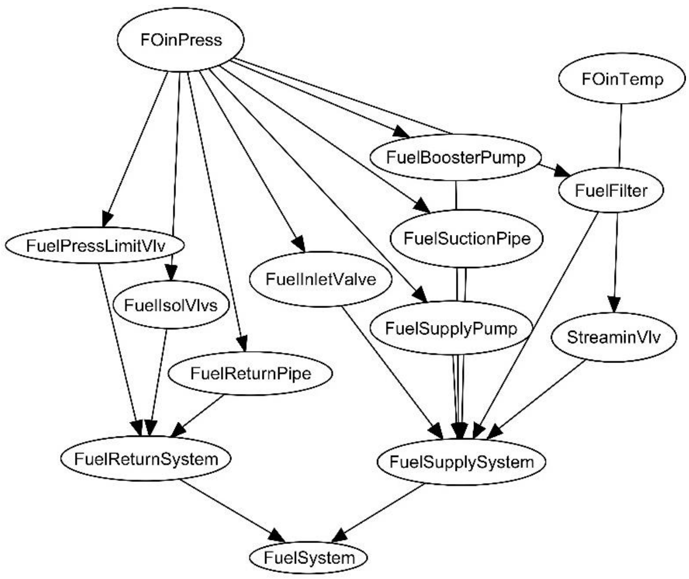

Figure 6.2 Fuel system of PMRA strategy network case study

Table 6.3 Fuel system input list of PMRA strategy case study

Fuel System Input
Fuel Oil Input Temperature
Fuel Oil Input Pressure
Cylinder Exhaust Gas Outlet Temperature

Table 6.4 Fuel system maintainable units list of PMRA strategy case study

Fuel System Maintainable Units	
Fuel Booster Pump	Fuel Inlet Valve
Fuel Supply Pump	Fuel Pressure Limit Valve
Fuel Suction Pipe	Stream Inlet Valve
Fuel Isolating Valves	Fuel Supply System
Fuel Filter	Fuel Return System
Fuel Return Pipe	

6.3.2. Jacket Cooling Fresh Water (JCFW) system

The second considered system is the Jacket Cooling Fresh Water (JCFW). It is responsible for retaining the required temperature of the cylinder jackets, the cylinder heads, turbo-blowers and cooling the pistons. According to Taylor (1996), a fresh water cooling system for a slow-speed diesel engine is split in two systems. The first system is responsible for cooling the cylinder jackets, heads and turbo-blowers, whereas the second system for cooling the pistons.

The cylinder jacket cooling fresh water is connected to a sea-water-circulation cooler and then into the jacket-water circulating pumps. The following process involves the cooling of the cylinder jackets, cylinder heads and turbo-blowers. A header tank expands and water is fed into the system. Vents release air from the cooling water. A heater facilitates in a warming of the engine before the starting process by circulating hot water. On the other hand, the piston cooling system uses similar components. The piston cooling system is separate to eliminate contamination from piston cooling glands to the piston cooling system.

The JCFW system network designed for the PMRA strategy case study is demonstrated in Figure 6.3. In total nine raw input data measurements are required such as the JCFW outlet temperature for cylinders 1 to 8 and the cylinder JCFW inlet pressure. The key maintainable unit considered is the JCFW pump and components that consists of such as the shaft, housing, rotor and impeller. Analytical lists of the raw input data and the maintainable units and components are demonstrated in Table 6.5 and Table 6.6.

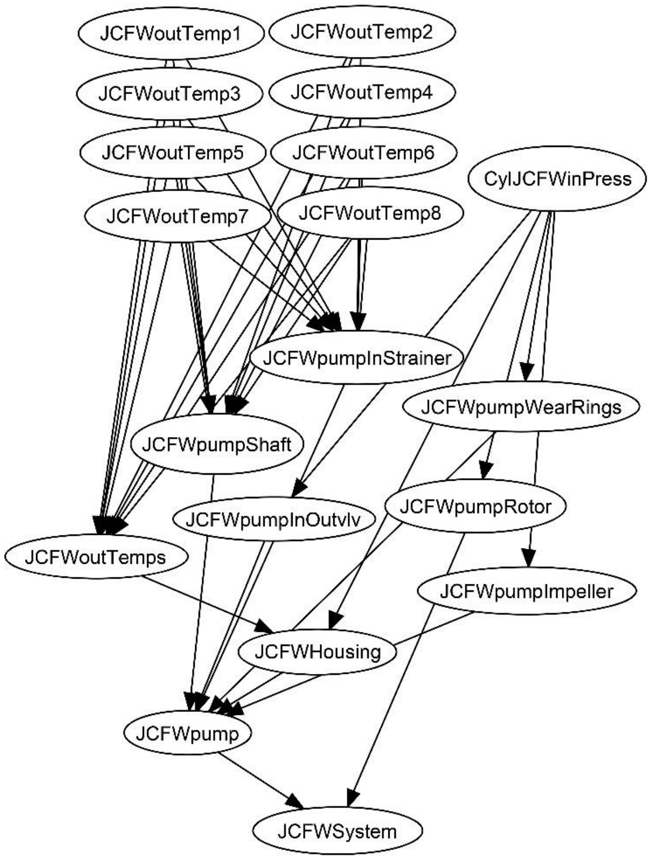

Figure 6.3 Jacket cooling fresh water system of PMRA strategy network case study

Table 6.5 Jacket cooling fresh water system input list of PMRA strategy case study

Jacket Cooling Fresh Water System Input
JCFW Outlet Temperature 1
JCFW Outlet Temperature 2
JCFW Outlet Temperature 3
JCFW Outlet Temperature 4
JCFW Outlet Temperature 5
JCFW Outlet Temperature 6
JCFW Outlet Temperature 7
JCFW Outlet Temperature 8
Cylinder JCFW Inlet Pressure

Table 6.6 Jacket cooling fresh water system maintainable units list of PMRA strategy case study

Jacket Cooling Fresh Water System Maintainable Units
JCFW Pump Inlet Strainer
JCFW Pump Wear Rings
JCFW Pump Shaft
JCFW Pump Inlet/Outlet Valve
JCFW Pump Housing
JCFW Pump Impeller
JCFW Pump Seal
JCFW Pump Rotor
JCFW Pump

6.3.3. Lube Oil (LO) system

An essential system onboard the ship is the lubrication one. This system provides a supply of lubricating oil to moving parts and components in the engine retaining temperature within the desired range. Lubrication oil's purpose is the creation of a film of oil between the moving parts. This lube oil film decreases friction and eliminates material wear. In some cases, lubrication oil is utilised as coolant.

First of all, the lubrication oil is placed in the bottom of the crankcase (sump) or in a drain tank. A lube oil pump inlet strainer drains oil from the tank to a pair of pumps and then to a pair of filters. The oil is led into a seawater cooler and then to the various branch pipes of the engine. The branch pipes pass lube oil to the main bearing of a particular cylinder, leading to a drilled port in the crankshaft to the bottom end bearing and then in the connecting rod gudgeon pin or the crosshead bearing. Moreover, an alarm system located at the end of the lube oil distribution pipe secures that the appropriate pressure is retained by the pump.

The pumps and filters are allocated in pairs allowing redundancy and standby use, while one is cleaned, the second can be operated. The lubrication system performs in closed-loop enabling re-use of the lube oil. Hence, after a lubrication cycle is completed the oil drains back to the sump or drain tank, where it is pumped again. A level instrument (gauge) provides readings of the available lubrication oil in the drain tank. On the other hand, a centrifuge ensures the lube oil cleanliness in the system and if required clean oil is fed from a storage tank. The seawater oil cooler operates at a lower pressure than the oil, therefore probable failure will lead to oil leak and not contamination of the lubrication circulation system by seawater. Lastly, if the engine has oil-cooled pistons, lube oil is provided from the system as well at higher pressure by employing booster pumps (e.g. Sulzer RTA engine) (Taylor, 1996).

The lubrication system of PMRA strategy case study is demonstrated in Figure 6.4. This system consists of four subsystems such as the lube oil pump and its rotor, the lube filter and the cooler. Each of these maintainable units includes various components as listed in Table 6.8 and these are linked to the considered and recorded raw input data as shown in Table 6.7.

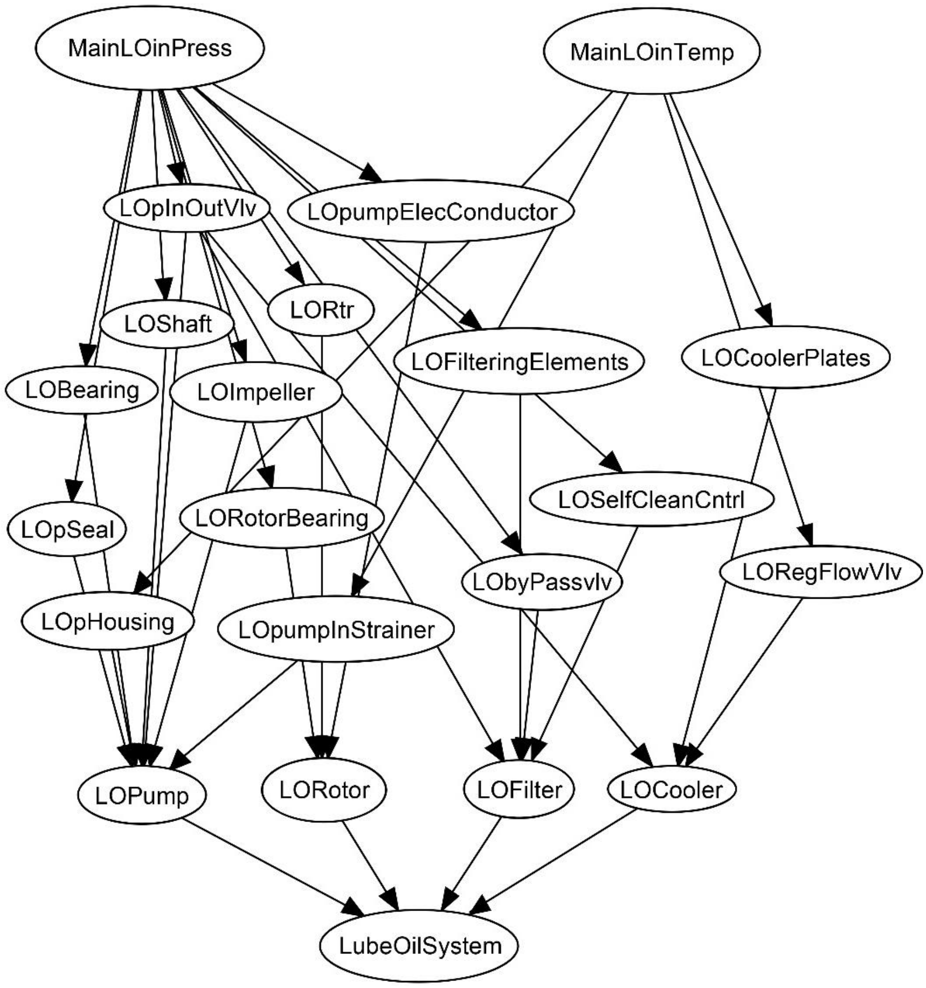

Figure 6.4 Lube oil system of PMRA strategy network case study

It is essential to highlight that large slow-speed diesel engines are installed with separate lubrication system for the cylinder liners. Oil is mechanically provided between the liner and the piston in each cylinder and the process is not recovered. However, PMRA strategy is oriented towards the model arrangement described above.

Table 6.7 Lube oil system input list of PMRA strategy case study

Lube Oil System Input
Main LO Inlet Pressure
Main LO Inlet Temperature

Table 6.8 Lube oil system maintainable units list of PMRA strategy case study

Lube Oil System Maintainable Units	
LO Pump Inlet Strainer	LO Cooler Plates
LO Pump Electric Conductor	LO by Pass Valve
LO Pump Shaft	LO Rotor Bearing
LO Pump Inlet/Outlet Valve	LO Self Cleaning Control
LO Pump Impeller	LO Regulation Flow Valve
LO Pump Bearing	LO Pump
LO Pump Rotor	LO Rotor
LO Pump Seal	LO Filter
LO Pump Housing	LO Cooler
LO Filtering Elements	

6.3.4. Air supply system

The most fundamental and important in efficiency functions of internal combustion engines are the supply of fresh air and the removal of exhaust gases. This cyclic process is known as gas exchange. The reliability assessment of the involved maintainable units and components involved in both of these functions are considered in the PMRA strategy case study. The separation of these two functions is challenging task and is taken place among the air supply system and the cylinders as shown in Figure 6.1.

However due to the cyclic process between air supply and gas removal, interdependencies of raw input measurements and maintainable units' reliability are utilised. This network arrangement allows in a flexible manner the implementation of connecting nodes of different systems. This technique of interconnections and integration of nodes of various systems produces an overlapping of information among the air supply and the cylinder systems, hence each section supplements the other. The removal of exhaust gases by blowing fresh air is known as scavenging. Modern engines have installed exhaust gas driven Turbochargers (T/C) for scavenging and supercharging processes (i.e. removal of exhaust gases and supply of fresh air for compression respectively).

Improper scavenging can cause collection of fuel oil in the scavenging space of the engine. Hence, unburned fuel may be blown into the scavenge space due to damaged piston rings, faulty timing or damaged injectors. This faulty incidence can lead to scavenge fire. Therefore, engine power will be reduced diagnosed from higher exhaust gas temperature at the affected cylinders. Further information related to defects, diagnostics and engine inspection and maintenance suggestions due to improper scavenging and increased exhaust gas temperature can be found in Appendix F.

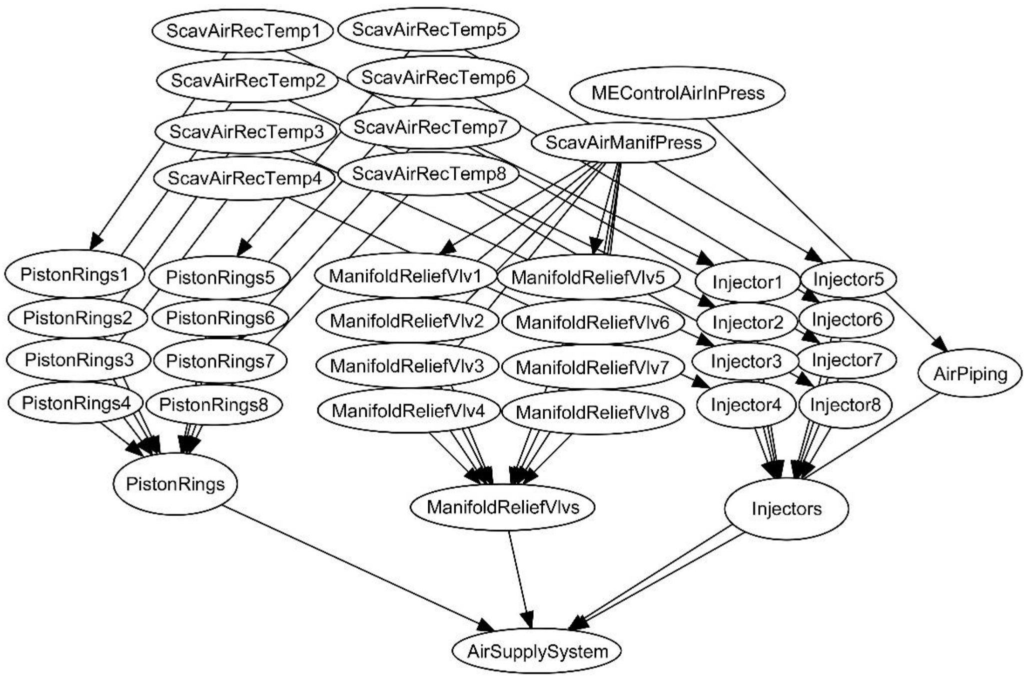

Figure 6.5 Air supply system of PMRA strategy network case study

As stated above, this section presents the air supply system reliability assessment. Its structure is demonstrated in Figure 6.5. This case study of PMRA strategy takes into account multiple raw input data measurements as listed in Table 6.9 integrating input data from both air supply and cylinder systems. On the other hand, the involved nodes which denote the considered maintainable units and components are listed in Table 6.10.

Table 6.9 Air supply system input list of PMRA strategy case study

Air Supply System Input	
Scavenging Air Receiver Temperature 1	Cyl. 1 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 2	Cyl. 2 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 3	Cyl. 3 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 4	Cyl. 4 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 5	Cyl. 5 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 6	Cyl. 6 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 7	Cyl. 7 Exhaust Gas Outlet Temperature
Scavenging Air Receiver Temperature 8	Cyl. 8 Exhaust Gas Outlet Temperature
Scavenging Air Manifold Pressure	Main Engine Control Air Inlet Pressure

Table 6.10 Air supply system maintainable units list of PMRA strategy case study

Air Supply System Maintainable Units	
Piston Rings 1	Manifold Relief Valve 1
Piston Rings 2	Manifold Relief Valve 2
Piston Rings 3	Manifold Relief Valve 3
Piston Rings 4	Manifold Relief Valve 4
Piston Rings 5	Manifold Relief Valve 5
Piston Rings 6	Manifold Relief Valve 6
Piston Rings 7	Manifold Relief Valve 7
Piston Rings 8	Manifold Relief Valve 8
Injector 1	Injector 5
Injector 2	Injector 6
Injector 3	Injector 7
Injector 4	Injector 8
Injectors	Manifold Relief Valves
Air Piping	

6.3.5. *Bearing drive system*

The following system presented in this section is the bearing drive, which ensures the appropriate functioning of the air supply and scavenging. Most of the moving parts are armed through bearings in order to transfer the generated kinetic energy to the shaft and the propeller. The probable failure or malfunction of bearings will lead to engine slow down (inefficiency) or damage, material wear or entire bearing collapse. Therefore, sufficient lubrication of the bearing's moving parts will ensure its functioning. The bearing drive network arrangement for the PMRA strategy case study is illustrated in Figure 6.6. Analytical list of the input data requirements is provided in Table 6.11, whereas the maintainable units and components are shown in Table 6.12.

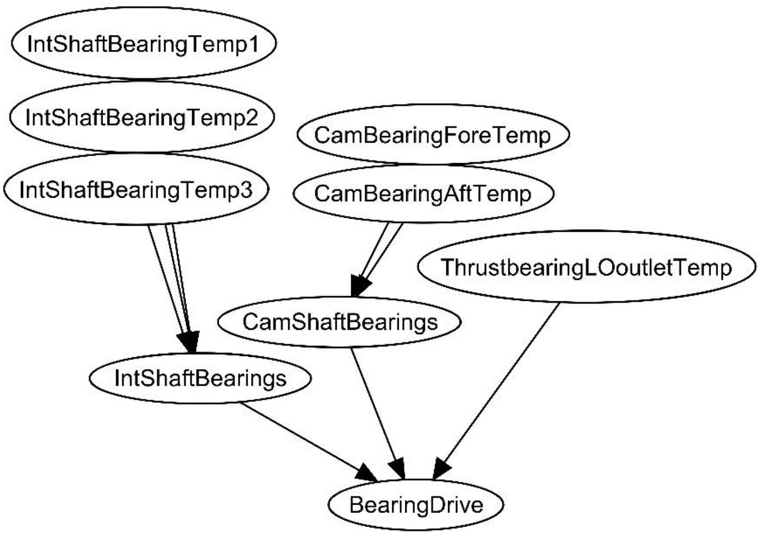

Figure 6.6 Bearing drive system of PMRA strategy network case study

Table 6.11 Bearing drive system input list of PMRA strategy case study

Bearing Drive System Input
Camshaft Bearing Aft Temperature
Camshaft Bearing Fore Temperature
Intermediate Shaft Bearing Temperature 1
Intermediate Shaft Bearing Temperature 2
Intermediate Shaft Bearing Temperature 3
Thrust bearing LO Outlet Temperature

Table 6.12 Bearing drive system maintainable units list of PMRA strategy case study

Bearing Drive Maintainable Units
Camshaft Bearings
Thrust Bearing
Intermediate Shaft Bearings

6.3.6. Cylinder system

The last system involved in the PMRA strategy case study is the cylinder. This network part collaborates with the air supply system, where both manage the required fresh air supply and the scavenging. Analytical description of this cyclic process is provided in the air supply system section above. However, it is necessary to highlight that the utilised engine is the MAN B&W 8K90MC-C. Therefore, eight cylinders are arranged in this study and reliability network arrangement.

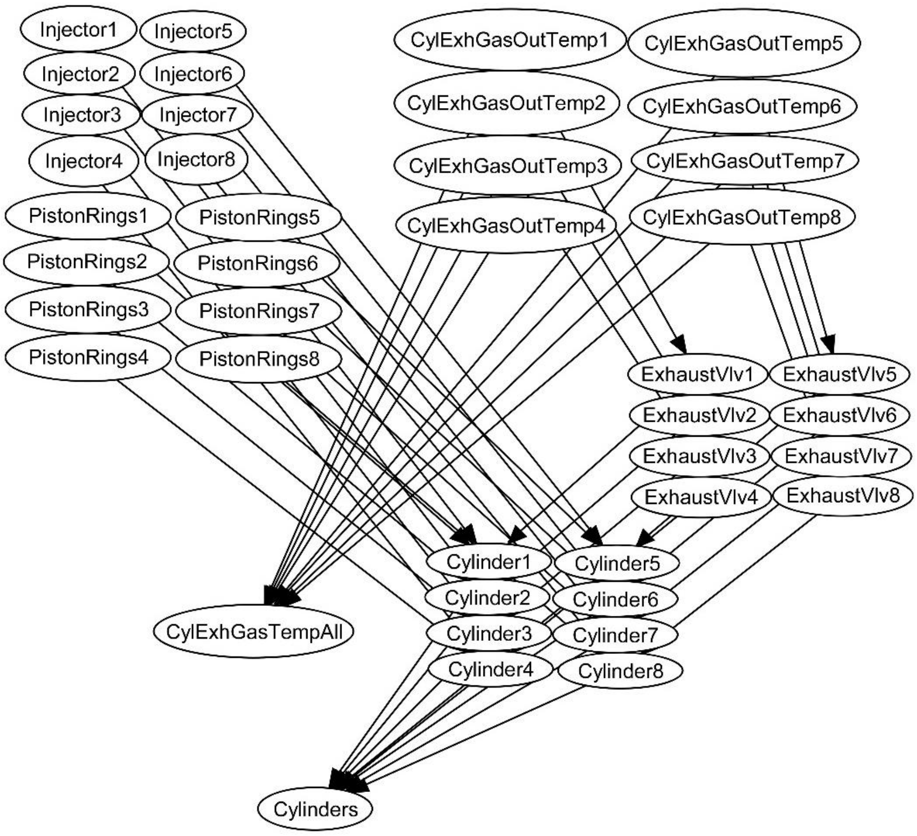

Figure 6.7 Cylinders of PMRA strategy network case study

The system's network structure is provided in Figure 6.7 incorporating maintainable units and components of the air supply system such as the piston rings and the injectors for cylinders 1-8. The overall involved cylinders' system input data requirements are listed in Table 6.13, whereas the considered maintainable units and components are provided in Table 6.14.

Table 6.13 Cylinder input list of PMRA strategy case study

Cylinders Input
Cyl. 1 Exhaust Gas Outlet Temperature
Cyl. 2 Exhaust Gas Outlet Temperature
Cyl. 3 Exhaust Gas Outlet Temperature
Cyl. 4 Exhaust Gas Outlet Temperature
Cyl. 5 Exhaust Gas Outlet Temperature
Cyl. 6 Exhaust Gas Outlet Temperature
Cyl. 7 Exhaust Gas Outlet Temperature
Cyl. 8 Exhaust Gas Outlet Temperature

Table 6.14 Cylinder maintainable units list of PMRA strategy case study

Cylinders Maintainable Units	
Exhaust Valve 1	Cylinder 1
Exhaust Valve 2	Cylinder 2
Exhaust Valve 3	Cylinder 3
Exhaust Valve 4	Cylinder 4
Exhaust Valve 5	Cylinder 5
Exhaust Valve 6	Cylinder 6
Exhaust Valve 7	Cylinder 7
Exhaust Valve 8	Cylinder 8
Piston Rings 1	Injector 1
Piston Rings 2	Injector 2
Piston Rings 3	Injector 3
Piston Rings 4	Injector 4
Piston Rings 5	Injector 5
Piston Rings 6	Injector 6
Piston Rings 7	Injector 7
Piston Rings 8	Injector 8

6.4. Raw data and effects assessment

As explained above and more analytically in Chapter 4, PMRA strategy consists of multiple processing levels such as the data selection and collection, data mining for information extraction and pattern recognition, safety threshold implementation, predictive reliability assessment and the fundamental aspects of decision making. This section demonstrates the developed qualitative risk and reliability assessment tool of Failure Modes and Effects Analysis (FMEA). The obtained FMEA aims to guide the decision making process and root cause analysis of the gained PMRA prediction results.

In other words, the reliability assessment tool provides forecasted reliability performance figures on system, subsystem and maintainable unit and component level. The predicted reliability values clarify the importance in introducing specific suggestions for maintenance activities. These suggestions have been identified by taking into account a wide range of sources, experts and professionals. The provided information in the FMEA is extracted from sources such as Pulkrabek (1997), McGeorge (1998), Taylor (1996), Anish (2016), INCASS (2014a), INCASS (2014b), INCASS (2014c), INCASS (2015a) and INCASS (2015b). Moreover, engine manufacturers' reports and manuals are utilised for information exploration and extraction including Kawasaki (2000), (Hyundai-MAN, 2010a) and (Hyundai-MAN, 2010b) among others such as results the report of sea trial testing.

The developed FMEA as demonstrated in Table 6.15 consists of information on subsystem level by taking into account the collected raw input measurement, parameter (i.e. temperature or pressure), failure mode, effect of failure, damaged equipment and component and the associated failure cause. This information has been manually linked to the developed FMEA strategy, when the predicted reliability performance on system, subsystem and component level has been obtained.

Table 6.15 Sample of FMEA for PMRA strategy case study

Subsystem	**Measurement**	**Parameter**	**Failure Mode**	**Effect of Failure**	**Damaged Equipment**	**Damaged Component**	**Malfunction/ Failure Cause**
Fuel Oil	FO Inlet	Pressure	Insufficient pumping	Engine stop	Fuel Supply	Suction pipe Fuel Supply Pump Fuel Booster Pump	Heavy leak Obstruction (particles)
			Damage of filter	Loss of redundancy	Fuel Supply	Filter	Blocking
			Lower output flow	Loss of performance, Low temperature exhaust gases	Fuel Supply	Suction pipe	Leak Obstruction (particles)
			Fuel leakage	Loss of performance		Inlet valve	Leak No Flow
			Higher fuel pressure	Lower performance to prevent failure	Fuel Return	Fuel self-pressure limiting valve	No Flow
						Isolating valves	No Flow
			Lower fuel pressure	Loss of performance	Fuel Return	Fuel pressure limiting valve	Leak
						Fuel return pipe	Leak
						Return isolating valve	Leak
		Temperature	Lower fuel temperature	Unexpected engine stop/ Loss of performance	Heating Tracers	Inlet valve	No Flow

6.5. Outcomes of raw data type case study

This section aims to summarise the outcomes of the raw data type case study performed as part of the PMRA strategy implementation. This case study examined the entire suggested methodology of Probabilistic Machinery Reliability Assessment (PMRA) strategy by utilising raw collected input data. This data is gathered in real operational environment, while a Panamax container ship was sailing. The reliability performance assessment is taken place by considering essential in functioning systems such as fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and cylinders.

Overall, this ship machinery is examined on system, subsystem and particular component or maintainable unit level. The reliability performance results are demonstrated in two segments of time such as the data gathering timeline (i.e. one month of hourly data collection) and the predicted period (i.e. following two and a half months). The results, as presented above, indicate reliable functioning of all systems and subsystems. The collected and predicted figures are found within the acceptable operational limits as they are predefined by the manufacturers' manuals. However, specific subsystems and maintainable units acquired lower reliability (still acceptable for functioning) as identified above. In this section, these particular subsystems are summarised per system by suggesting in advance (as results are forecasted) inspection and maintenance actions and activities extracted by the developed FMEA table attached in Appendix F.

The first ship machinery arrangement under consideration in the PMRA strategy application involves the fuel system. More specifically, the lowest reliability performance is brought by the fuel supply system, which has been mainly identified by the cylinder exhaust gas outlet temperature predicted figures. In regards to the fuel oil system in correlation with cylinder exhaust gas outlet temperature, the most probable case scenario of failure or malfunction is the worn fuel pumps. The fuel inlet valves have to be checked visually and by pressure testing control (monitoring). It is essential to clarify that in the particular examined case, the fuel supply system operates within the acceptable limits as the predictions show.

However, according to the manufacturer's instruction book for maintenance and expert judgment, there are four potential failure modes. In order to identify them, the cylinder exhaust gas outlet temperature and fuel oil inlet pressure are prerequisites, hence, both are considered in the case study above. The potential failure modes identified utilising the FO inlet pressure prediction involve inadequate pumping, loss of filter, reduced output flow (than required) and fuel leakage. In the first case of inadequate pumping, the effect will lead to stop the engine by affecting the fuel supply system. More specifically, components probably affected are the suction pipe, fuel supply pump and the fuel booster pump. In the case of loss of filter, the redundancy will be lost due to blockage. The reduced output flow of fuel oil will lead to derating engine or low temperature of exhaust gases, which are caused by leakage in suction pipe or obstruction in lines. Lastly, fuel leakage will affect the engine power due to damaged fuel oil inlet valve which can be caused due to leakage or no flow (excessive example).

The following under reliability assessment system is the jacket cooling fresh water (JCFW). According to the predicted results, the JCFW pump acquired the lowest reliability. On component level, the JCFW housing presents reliable and undistracted operation, however the lowest performance in the JCFW system (above 99%). At this performance level, there are not required any inspection and maintenance actions as the raw input data and their predictions vary within acceptable operational limits. Two input data sources are required such as the JCFW outlet temperature and the cylinder JCFW inlet pressure. The JCFW housing can be detected by identifying high temperature of fresh water and/or less flow of fresh water than expected due to pump's condition. The input data collected vary within safety functional limits, therefore there has not been expected malfunctions or failures. The reason identified for this lower reliability loss is related to the wider amplitude (not dense) of recorded data points within the dataset.

The third system examined by implementing PMRA strategy is lube oil, which incorporates maintainable units and components such as the lube oil pump, rotor, filter and the cooler. All associated subsystems and components retain high and acceptable reliability. Therefore, the involved raw measurements of main lube oil inlet pressure and temperature vary within the safety limits without reaching or exceeding the predefined alarm points. Moreover, the operation of lube oil system according to the recorded and predicted reliability figures ensure undistracted functioning. However, it is essential to identify the component with the lowest performance as it intends to cause malfunctions or failures first.

Among the involved lube oil subsystems and maintainable units and components, lube oil pump presents the lowest performance (over 97%). There are two cases taken place that clarify this minor (within acceptable limits) reliability loss. The first case is related to negligible lube oil inlet pressure drop and the second to minor lube oil inlet temperature increase, both inclinations are acceptable for ensuring regular functioning. There are overall three potential failure modes involved. In the case of lube oil inlet pressure, the probable scenarios implicate observation of no or low flow, whereas in the case of lube oil inlet temperature to be identified increased of the recorded indices.

In the excessive cases of no or low flow (pressure drop), the potential effect of failure is loss of redundancy. The LO pump's components affected are listed among impeller, seal, inlet/outlet valve, bearing and shaft, whereas the potential causes are related to shaft wear or seized bearing. On the other hand, if higher lube oil inlet temperature is observed, the engine power will be reduced (slow down), whereas the lube oil shaft or housing will be affected due to bent shaft or misalignment respectively.

The following system utilised as part of the PMRA strategy application is the air supply, which comprises components such as the piston rings, injector and the manifold relief valves. The maintainable units and components performing the lowest (however acceptable and safe) reliability are the injectors and pistons rings. Both units are associated with the scavenging air receiver temperature measurements per cylinder and the cylinder exhaust gas outlet temperature. In the first place, inclination of air receiver temperature denotes improper scavenging leading to loss of engine power and high exhaust gas outlet temperature at the affected cylinder. The defected components are the piston rings and injectors, whereas the potential causes are related to faulty timing, blow-by and unburned fuel.

Bearing drive system comprises of the camshaft (i.e. aft and fore), intermediate (i.e. 1 to 3) and thrust bearings. The acquired results confirm lowest performance by the second intermediate shaft bearing. This reliability drop indicates variation in the collected temperature measurements as in the predicted. Therefore, potential failure mode directs towards bearing overheating causing material wear and tear, which can lead to engine damage or failure.

Lastly, cylinders are considered as dependent system of the main engine, which has direct association with all the remaining systems of the PMRA strategy application. More specifically, cylinder exhaust gas outlet temperature measurements are connected with nodes such as subsystems and maintainable units and components of different systems. These are known as interconnections, which enable dependencies among any node/member of the developed network. The overall system acquired results fulfil the manufacturer's criteria and predefined acceptable levels ensuring further undistracted operation. However, cylinder exhaust gas outlet temperature is essential source of information for the entire combustion process as it affects various systems, subsystems and components. The increase of exhaust gas temperature affects ship systems and equipment such as the fuel injectors, cylinders, air coolers, turbocharger and the fuel oil system. In the particular case of cylinders, the piston rings are affected leading to blow-by effect. Typical guidelines and suggestions in regards to cylinders incorporate actions such as to compare the compression pressures from the indicator and draw diagrams, while during engine standstill carry out scavenging port inspection and check exhaust valve.

In conclusion, this section summarised the outcomes of raw input data case study performed as part of the PMRA strategy implementation. Overall, the reliability assessment of six main ship systems is demonstrated of the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and the cylinders. The acquired results ensure acceptable reliability performance levels allowing further undistracted operation without the consideration of any inspection or maintenance actions. It is essential to highlight that the utilised raw input data vary within the identified acceptable limits. Therefore, the forecasted predictions obtain high reliability performance. According to these forecasted figures, inspection and maintenance suggestions have been provided in regards to the subsystems and maintainable units and components that brought the lowest reliability performance.

6.6. Chapter summary

In this Chapter, the second stage of PMRA strategy application takes place involving a holistic case study of the entire suggested methodology. This case study considers all data processes, methods and techniques of PMRA strategy such as the data acquisition, data clustering and safety threshold implementation, predictive reliability assessment and the initial aspects of decision-making. The demonstrated case study utilises raw input data gathered from a Panamax container ship, while sailing in actual operating conditions. The vessel has been equipped with a two-stroke slow speed marine diesel engine (MAN B&W 8K90MC-C). The safety thresholds have been employed as reference points, which define the acceptable operating levels. For this crucial task, the manufacturer's engine manual and the sea trials have been exploited. The network arrangement is demonstrated structured among six functional systems such as the fuel oil, jacket cooling fresh water, lubrication, air supply, bearing drive and cylinder for scavenging. Various maintainable units and components are employed per system as well as the required raw input data. A novel aspect of the present thesis involves the subsystem, maintainable component and raw data interdependencies. This feature allows the interconnection, hence the transmission of input from any node to another. These interdependencies or interconnections are novel as they enable the connection of nodes that belong to different subsystems or systems. Furthermore, a qualitative assessment is demonstrated incorporating a Failure Modes and Effects Analysis (FMEA) research study followed by qualitative diagnostic input for the PMRA strategy case study. These two qualitative assessment sources of information aim to assist the final part of PMRA strategy providing the initial aspects of decision-making suggestions. Supplementary information and work performed for this Chapter is attached in Appendix F. This attachment incorporates information regarding the alarm and warning levels, the developed FMEA and diagnostic qualitative input for the implementation of the fundamental aspects of the decision making tool.

7. CASE STUDIES RESULTS

7.1. Chapter outline

In this Chapter, the results of the performed applications of the Probabilistic Machinery Reliability Assessment (PMRA) strategy in the maritime industry are demonstrated. These applications are structured among two groups of case studies involving different input data types, while testing the different data processing methods and tools of the predictive PMRA strategy. The first case study group of systems implements and assesses fundamental technical aspects of the PMRA strategy such as the dynamic state modelling and the predictive reliability assessment tool. These modelling tools involve the implementation of Markov Chain (MC) process and Dynamic Bayesian Belief Networks (DBBNs). The first application approach takes into account-processed data extracted from OREDA database. Multiple independent main systems are considered such as the diesel generator (D/G), turboexpander and pumps such as the seawater lift, oil export, cooling water, water firefighting and the crude oil handling. This case study through these systems initiated the development of the networks' arrangement. Flexible features and efficient programming techniques have been applied in Java Object Oriented Programming (OOP) language. The second case study involves the application of the entire suggested PMRA strategy by utilising various ship machinery such as the fuel system, the jacket cooling fresh water system, the lube oil system, air supply system, bearing drive and cylinders of an eight cylinder 2-stroke marine diesel engine installed on a Panamax container vessel. Raw input data such as temperature and pressure is gathered through actual operational conditions. Both groups of case studies provide results in the form of predictions of reliability performance.

7.2. Case study of processed data

As introduced above, this section demonstrates the results acquired by the case study applied on various systems, which performed as part of the Probabilistic Machinery Reliability Assessment (PMRA) strategy development. This case study involves offshore oil and gas platform machinery such as the diesel generator (D/G), turboexpander and pumps including the seawater lift, oil export, cooling water, water firefighting and the crude oil handling. The presented results provide predictions of the reliability performance on system, subsystem and component levels. Furthermore, the processed data reliability case study utilises input extracted by OREDA database.

It is crucial to highlight that the processed data reliability case study aims to assess some fundamental technical aspects of the PMRA strategy such as the dynamic state modelling and the reliability tool. In parallel to this technical development, practical aspects have been investigated involving features in programming the network reliability model, while optimising the node arrangement. The acquired experience and benefits from this case study set the grounds for the PMRA strategy raw input reliability application that will be demonstrated next.

OREDA stands for Offshore Reliability Database, hence reliability input data extracted from this source are related to machinery installed into offshore applications such as oil and gas platforms. Therefore, the system, subsystem and mainly component arrangement may differ compared to ship machinery. However, offshore systems through OREDA database can provide a valuable initial input for the PMRA strategy by involving similar systems and operational environment as in maritime industry. This input data source has been employed for the initial application of PMRA strategy due to scarcity of data at the time of development.

On the other hand, OREDA database provides static input data (i.e. single failure rate indices), where time of record or interval of the recording period has not been specified. Therefore, the calculated and provided reliability performance predictions are expressed into unitless time intervals. In other words, as long as the time record interval points are not known (for this processed data reliability case study), the predictions lie within a unitless timeline. OREDA provides failure records per occurred failure mode. Each failure mode holds a specific proportion out of the overall recorded modes per system and a different proportion per component (as each component may fail due to different failure modes) in relation to the likelihood of occurrence.

Initially, the summarised percentage of occurrence of each failure mode has been introduced, and then the recorded failure proportion per component per total failure rate of each mode has been calculated. Each failure mode is expressed in relation to aggregated time in service per system, the mean failure rate index of failure mode and the total component's failure rate proportion out of all involved components in the system. The involved failure rate of each component per failure mode by taking into account the aggregated time has been calculated and analytical calculation procedures can be found in Chapter 5. The failure rate of each component has been calculated by considering all failure modes that the particular unit can fail. Lastly, it is essential to clarify in advance the plotted curves in the processed data case study demonstrate both the existing and predictive reliability performance. Therefore, in each timeline, point 1 indicates the existing performance and points 2-5 the predicted ones.

7.2.1. Diesel Generator (D/G) case study

The first case study examines the reliability performance of the diesel generator (D/G) system. Offshore applications such as these incorporated into OREDA database involve for various facilities and energy requirements 4-stroke Diesel Generators (D/G). This case study employs processed data gathered from different D/G. This engine structure arrangement consists of subsystems such as the Lubrication (LUB), Starting (STR), Engine Internal Components (EIC), Engine External Components (EEC), Cooling (COO), and Control Monitoring (MON).

In Figure 7.1, the reliability performance for the considered subsystems of the D/G is demonstrated. According to the gathered reliability input data and the PMRA strategy, STR subsystem (85.7%) is the most likely to cause malfunctions and failures followed by the EIC (92.4%), COO (94.5%), LUB (98.2%), EEC (98.5%) and MON (99.3%). It is essential to clarify in advance that the first point in the timeline is the obtained reliability through the OREDA input data, whereas the points 2-5 are the predicted ones.

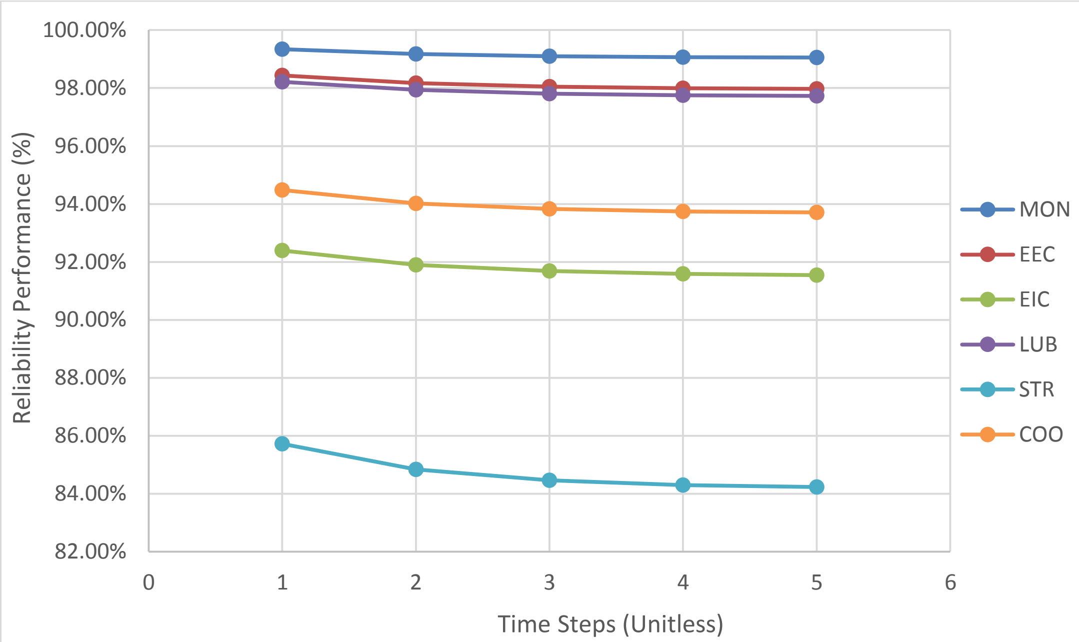

Figure 7.1 Reliability performance of diesel generator (D/G) subsystem level

The OREDA input data provides reliability records (failures) incorporating indices from various similar 4-stroke diesel engines. Therefore, this data contribution does not take into account operational conditions as well as past inspection and maintenance plans and actions. The obtained reliability prediction results are suitable for indicative utilisation by specifying particular unreliable subsystems and components According to the gathered failure records and the acquired predictions; STR subsystem causes major reliability instability.

However, particular components of other subsystems may have low reliability as well. Therefore, reliability performance analysis should be undertaken on component level for all of the considered subsystems of the D/G. More specifically, Figure 7.2 demonstrates the reliability performance (current and predicted) of failure case scenarios involving the recorded failure modes of Abnormal Instrument Reading (AIR) at 99.8%, External Leakage of Utility (ELU) (i.e. lubricant, cooling water) at 96.8% and Failure To Start on demand (FTS) and minor in-service problems (SER) at approximately similar probability of 94.6%. The first point in the timeline (position 1) denotes the current reliability performance, whereas the following four the predictions.

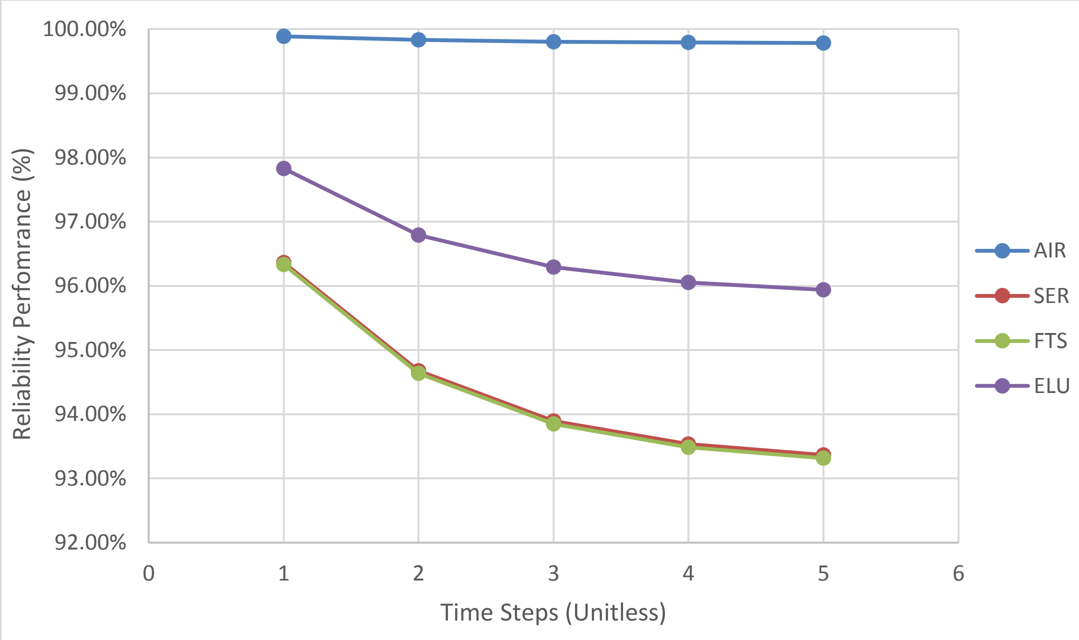

Figure 7.2 Reliability performance of diesel generator (D/G) starting unit

Therefore, the most probable failure modes that can lead to failure or malfunctions of the starting unit are the minor-service problems (SER) and the Failure To Start on demand (FTS). SER is an unspecified failure mode, hence particular inspection and maintenance solutions cannot be provided as the input data source does not provide further information related to this mode. However, assumptions can involve minor issues such as low electrical power or damaged cables. Hence, failures, where solutions, can be provided onboard. A detailed component assessment of the overall D/G system can provide valuable information related to the reasons (diagnostics) that the starting unit can be affected by FTS (component interaction leading to FTS). BBN has the ability to calculate any probable failure case scenario. As explained in Chapter 4, the more parent nodes feed input a child node the more the failure case scenarios to be calculated. In the case of starting unit, four failure modes have been recorded leading to 16 failure case scenarios, hence, these are attached in Appendix G.

The following D/G subsystem under investigation is the lubrication one (also known lube oil). According to the provided failure records, it consists of three maintainable units and components identified as the oil, cooler and the pressure instrument. The latter component is a device for collecting measurements of pressure. Therefore, this is not included as no interest in applying proactive condition monitoring techniques collecting performance data for an instrument. However, the instrument's reliability performance has been taken into account through this PMRA strategy case study.

On the other hand, oil and cooler are functional maintainable unit and component respectively, while their reliable operation is vital for ensuring the appropriate lubrication. Oil has been identified as maintainable unit by OREDA as it is a medium, which requires inspection and replacement (maintenance). In other words, because oil degrades through time, it has been considered as unit. Firstly, Figure 7.3 illustrates the reliability performance of oil. There are two failure modes involved in the oil reliability drop, the minor in-service problems (SER) at 96.3% and the External Leakage of Fuel Oil (ELF) at 93.7%. The case of leakage leads to failures or malfunctions due to improper lubrication, whereas minor in-service problems are unspecified and inspection and maintenance solutions cannot be provided. However, SER can be assumed as failures or malfunctions due to minor human error such as a closed valve, which led to low or no pressure. Therefore, there is no actual failure; however, an in-service distraction has been recorded.

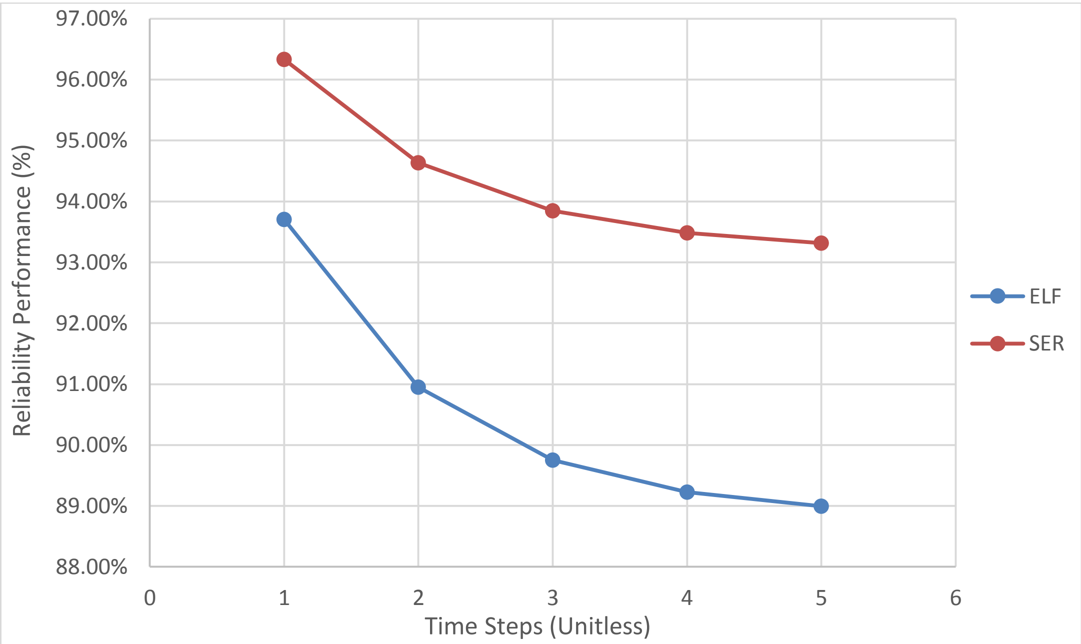

Figure 7.3 Reliability performance of Diesel Generator (D/G) oil

However, the most common measurement that signifies deterioration of the D/G or particular components (i.e. bearings) due to improper lubrication is the increase of operating temperature. Another option of monitoring the oil is the technique of lubrication oil analysis; which deals with the shape, size, composition of wear particles and lubricant degradation analysis for physical and chemical characteristics.

Cooler is the following maintainable unit considered in the lubrication subsystem. The recorded failure mode affecting its suitable operation is External Leakage of Utility Medium (ELU) such as lubricant or cooling water. Its reliability loss due to ELU can be identified by pressure drop in the lube-oil piping network. According to OREDA records and the obtained forecasted results, the cooler piping network has to be inspected occasionally in order to prevent leakages, which lead to pressure drop.

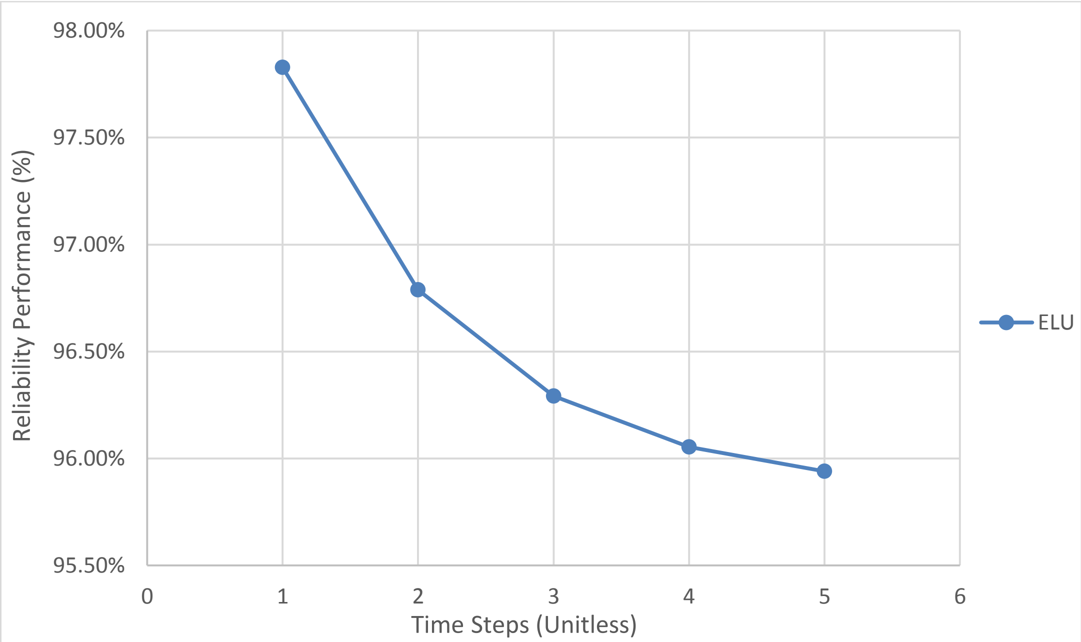

Figure 7.4 Reliability performance of Diesel Generator (D/G) cooler

The third subsystem considered for the reliability assessment of the D/G is the control monitoring. Three maintainable units are monitored the control unit and the speed and temperature instruments. The two measurement instruments are not considered for further condition monitoring as these are sensors and on-condition assessment is impractical and expensive. The third member of control and monitoring subsystem is the control unit. This maintainable unit is linked with the failure modes of AIR (94.7%)

and FTS (99%). There are not particular inspection and maintenance actions to be suggested as the provided failure modes illustrate generic/unspecified malfunctioning.

The following D/G components and maintainable units such as injections, cylinders, exhaust, pistons, radial bearings, fuel pump, air inlet, fuel filter and shaft are separated into two subsystems. These maintainable units form the engine internal and external components subsystems respectively. Engine internal components subsystem consists of maintainable units related to the main functioning of the combustion engine block, whereas external to the fuelling and propulsion.

More specifically, Engine Internal Components (EIC) subsystem consists of injections, cylinders, exhaust, radial bearings and pistons. The input data records failures and reliability indices providing reliability values per group of similar components and maintainable units. Hence, provided information does not represent the reliability of a single cylinder, bearing, piston or injection unit. However, summarised figures are provided for the entire reliability performance of all cylinders, bearings, pistons and injections recorded and processed by OREDA database. In other words, the reliability assessment of these components is oriented towards a holistic attempt to examine and analyse them as gathered through the operational timeline.

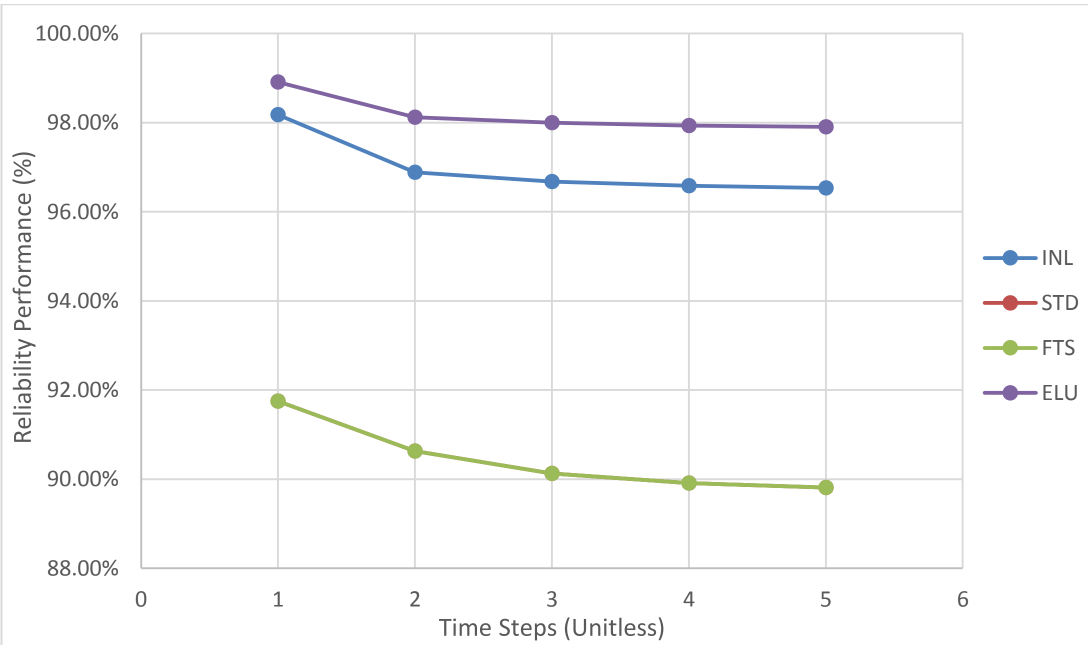

Figure 7.5 Reliability performance of Diesel Generator (D/G) cylinders

In Figure 7.5, the reliability performance predictions of D/G cylinders are presented related to failure modes such as Internal Leakage (INL) at 97.3%, Structural Deficiency (STD) and Fail To Start on demand (FTS) at 91.7% and External Leakage of Utility Medium (ELU) (i.e. lubricant, cooling water) at 98.4%. According to the acquired predicted results, STD and FTS are the most probable to occur and deteriorate the cylinders. In the case of FTS, cylinder can fail to start due to different reasons, as long as the reasons are unspecified by OREDA, assumption include failure to control system or malfunction of the starting system among others.

However, failure in the cylinders may lead to failure in starting the engine. On the other hand, STD is a significant failure mode as this can be caused due to improper lubrication, increase of temperature, material tear and wear among other reasons. Multiple measurements and performance indices can prevent the occurrence of this failure mode. More importantly, catastrophic consequences can be avoided by applying suitable condition monitoring methods. The most common and indicative measurements are the cylinder exhaust gas temperature, scavenging air receiver temperature and scavenging air manifold pressure. These measurements are analytically explained in Chapter 6.

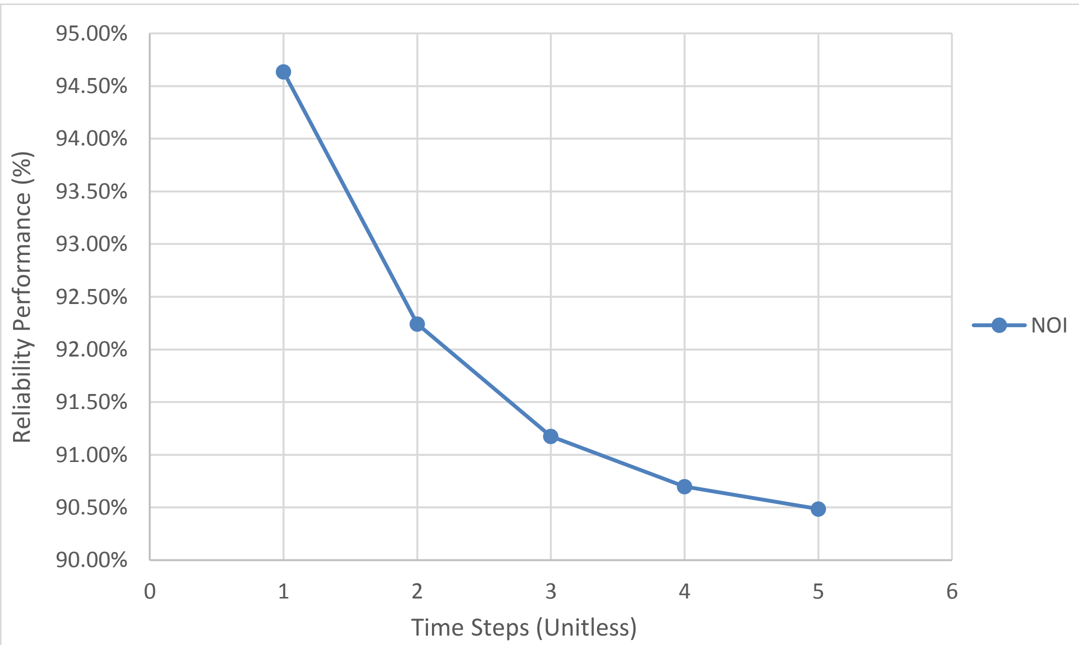

Figure 7.6 Reliability performance of Diesel Generator (D/G) radial bearings

Radial bearings are the following maintainable components of EIC subsystem. PMRA strategy provides reliability at 94.6% and predictions at 92.2% related to noise (NOI) failure mode. NOI can be caused due to improper bearing lubrication, which will lead to material tear and wear. Except of lubrication issues and malfunctions, material damage can be caused due to age of material, while heading towards the end of the lifecycle. According to preventive inspection and maintenance actions, in predefined intervals, bearings have to be overhauled for visual inspection of the internal components and its races. Predictive condition monitoring techniques can be applied in order to prevent and forecast malfunctions and failures while avoiding catastrophic collapse. Regarding the radial bearings, various condition monitoring of lube oil temperature will ensure the suitable lubrication of the bearing's moving parts. Additionally, in predefined intervals, normally once in six months, vibration monitoring can be applied in order to identify the material wear.

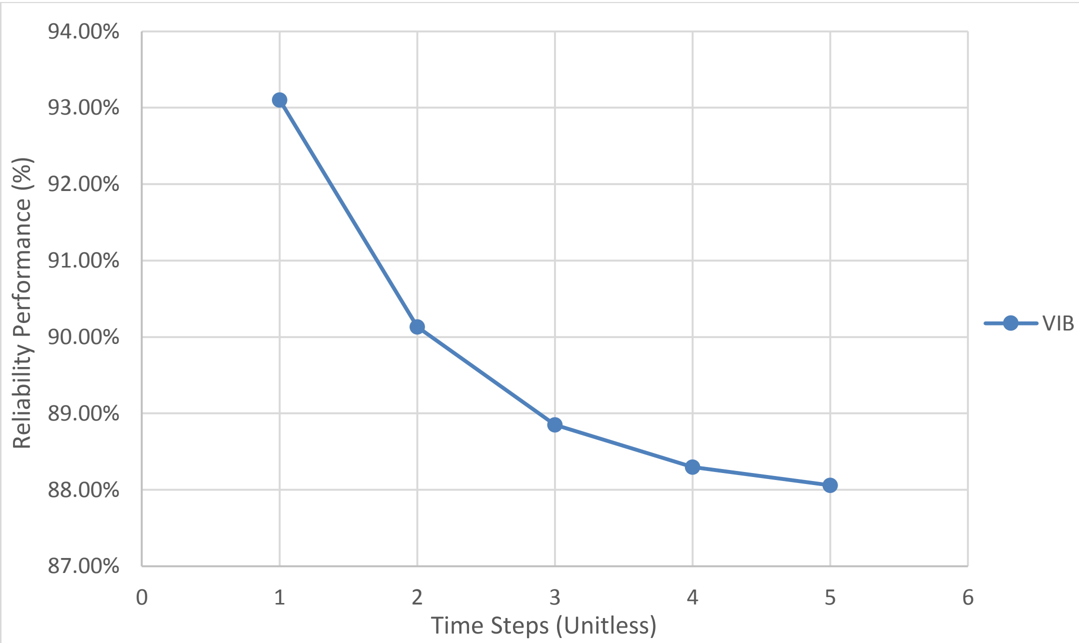

Figure 7.7 Reliability performance of Diesel Generator (D/G) pistons

Lastly for EIC subsystem, pistons are related to vibration failure mode. In the case of OREDA input data, pistons achieve predicted reliability at approximately 90%. Furthermore, pistons have a direct functional relation with the piston rings, cylinder liner, exhaust gases and combustion process as well as the lubrication and fuelling procedures. Diagnostics related to pistons, piston rings and piston crowns are attached analytically in Appendix F. However, it is essential to mention that the incorporated information involved CM approaches by taking into account measurements and indications such as the exhaust gas temperature, compression pressure and improper scavenging (due to high exhaust gas temperature).

The following subsystem structuring the reliability network of the D/G is the Engine External Components (EEC). This subsystem consists of the fuel pump, fuel filter, air inlet and the propulsion shaft. In Figure 7.8, the fuel filter predicted reliability performance is demonstrated involving failure modes such as ELF at 97.8%, INL at 96.8%, FTS and ERO at almost the same 94.6% and SER at almost 91%. SER is a generic failure mode expression, where the particular recorded minor in-service causes are not provided. Therefore, inspection and maintenance actions cannot be suggested. On the other hand, ERO and FTS gain reliability predictions at 94.6%. The major reason that fuel filter can fail due to ERO and FTS is due to blockage. Hence, flow rate measurements can be collected as well as pressure indices. In case of low flow rate, firstly the fuel filters have to be cleaned or replaced.

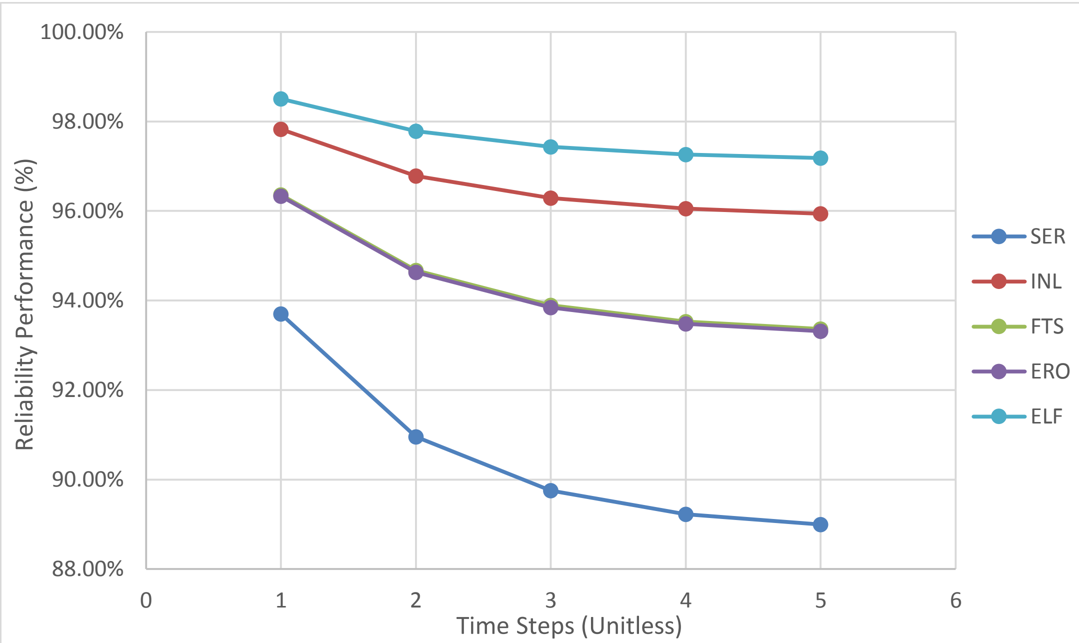

Figure 7.8 Reliability performance of Diesel Generator (D/G) fuel filter

7.2.2. *Turboexpander case study*

The second main system that PMRA strategy is employed for predicting the reliability performance on system, subsystem and component level is the Turboexpander. This system consists of four subsystems such as the expander/recompressor turbine (ERT), the control monitoring (CMN), the lubrication (LUB) and the shaft/seal (SHS). According to the recorded historical reliability input data and the predicted results of the PMRA strategy, ERT performs the lowest reliability at approximately 94.4% followed by the SHS at 98.6%, the CMN at 99% and the LUB at 100% as shown in Figure 7.9.

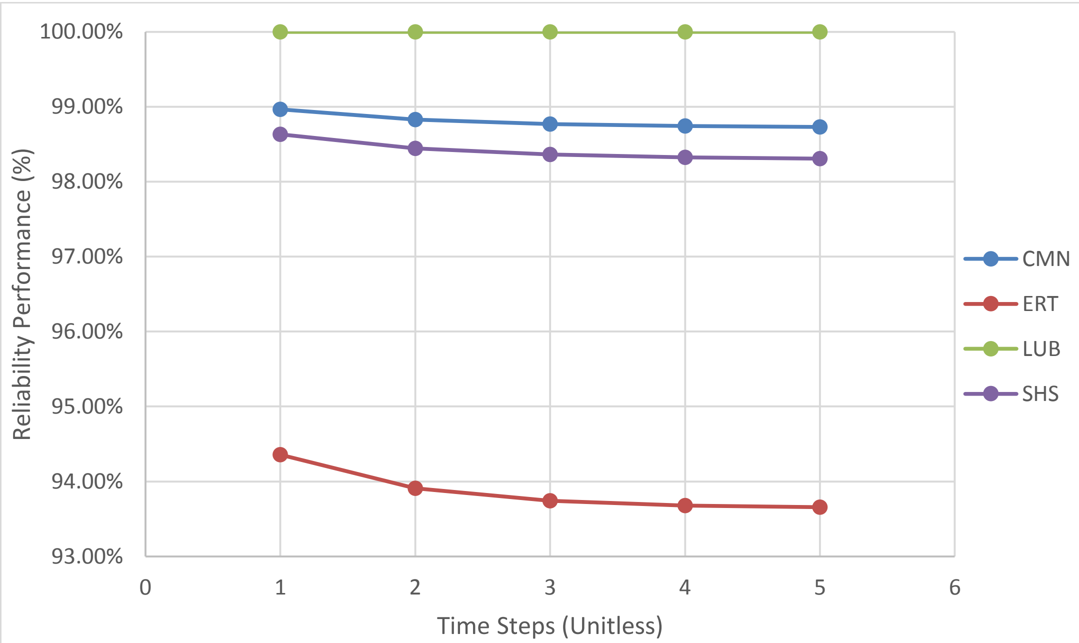

Figure 7.9 Reliability performance of Turboexpander subsystem level

The first subsystem is the ERT, which consists of the thrust bearing, the speed, pressure and temperature instruments and the piping. The most crucial in functioning component is the thrust bearing as it delivers and retains the rotational movement. Its failure may lead to overall turboexpander operation collapse and in specific cases to catastrophic consequences. According to OREDA, thrust bearing records negligible number of failures and its reliability is forecasted at almost 100%.

On the other hand, speed, pressure and temperature instruments are devices for gathering operational information. Sensor installation and probabilistic data analysis for instruments will lead to financially non-viable applications. In the case of ERT subsystem, the forecasted reliability performance of turboexpander piping involves predictions of ELU failure mode at 99.99% and SER at 99.97%. Summarising the ERT subsystem reliability performance, small number of failures are recorded and predicted related to thrust bearing and piping. However these failures can be dangerous and critical with respect to safety and functioning respectively such as the failure or malfunction of the thrust bearing or leakage of lube oil due to failure of the piping.

The second subsystem of the turboexpander network is the CMN, which consists of the control unit, general and flow instruments, actuator and turboexpander monitoring. The instruments/sonsors are not considered in the reliability assessment. Furthermore, the following maintainable unit involved in the failure records of OREDA related to turboexpander is the monitoring, which has been affected by AIR, ELU, FTS and UST. In all involved failure case scenarios, the reliability performance is greater than 99%.. According to the performed reliability predictions Figure 7.10, the most likely failure mode to cause failure or malfunctions is AIR, however the acquired results illustrate reliable performance and the probability of failure is negligible.

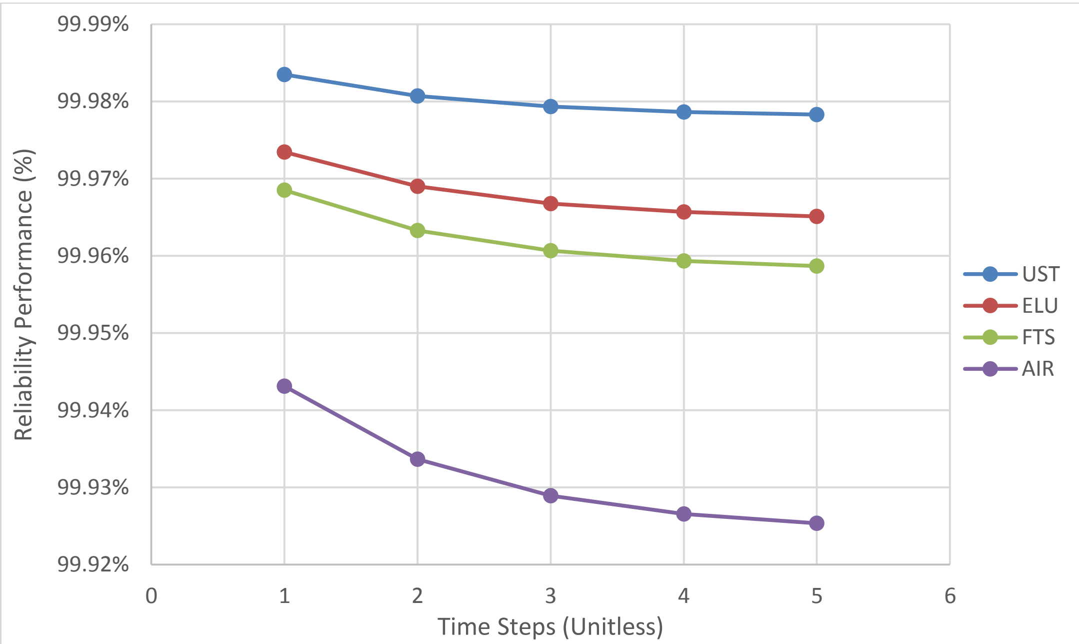

Figure 7.10 Reliability performance of Turboexpander monitoring

The third subsystem of turboexpander is the lubrication one. According to OREDA, two maintainable units have been failed due to SER failure mode, the filter and the lube oil (i.e. degradation of quality or minor leakage). The failure records of filter and lube oil are minor in amount, however they are critical for ensuring the required quality of turboexpander lubrication and functioning. Their quality is vital and one interacts with the other one (quality of oil to filter). The most suitable measurement that should be applied is the pressure control. If pressure drop has been identified then blockage of filter can lead to lose of itself.

Lastly, the fourth subsystem, structuring the relations among components and recorded failure modes, is the turboexpander shaft/seal (SHS). This subsystem consists of four components and maintainable units such as the seal, valves, subunit and the vibration instrument. The latter belongs to the measurement devices that PMRA strategy will not be applied for reasons explained above as in various other instruments (i.e. level, pressure, temperature instrument etc.).

In regards to the reliability assessment and failure mode predictions on component level of the turboexpander, seals are vital units on the turboexpander. Seals ensure optimal functioning while separating the compressor impeller from the thrust bearing and the turbine impeller from the shaft. If the seals and the thrust bearing retain acceptable condition, overhauling of the turboexpander can be avoided. Therefore, by avoiding overhauling, human errors can be prevented such as undesired assembly mistakes. According to Figure 7.11, seals are recorded to be affected by AIR, ELP, ELU and SER failure modes. All reliability predictions reach high level of performance. More specifically, ELU achieves 99.98%, ELP at 99.99%, SER at 99.97% and AIR at 99.94%.

AIR refers to misleading instrument reading due to malfunctioning of the seals. On the other hand, ELP and ELU are failure modes related to leakages due to process medium (i.e. gas, condensate, water) and utility medium (i.e. lubricant, CW) respectively. It is crucial to highlight that most of the recorded failure modes, in case of occurrence require overhauling of the turboexpander and reassembly. This traditional visual inspection technique is risky for causing damages due to human error, they require great amount of downtime and may lead to expensive mistakes.

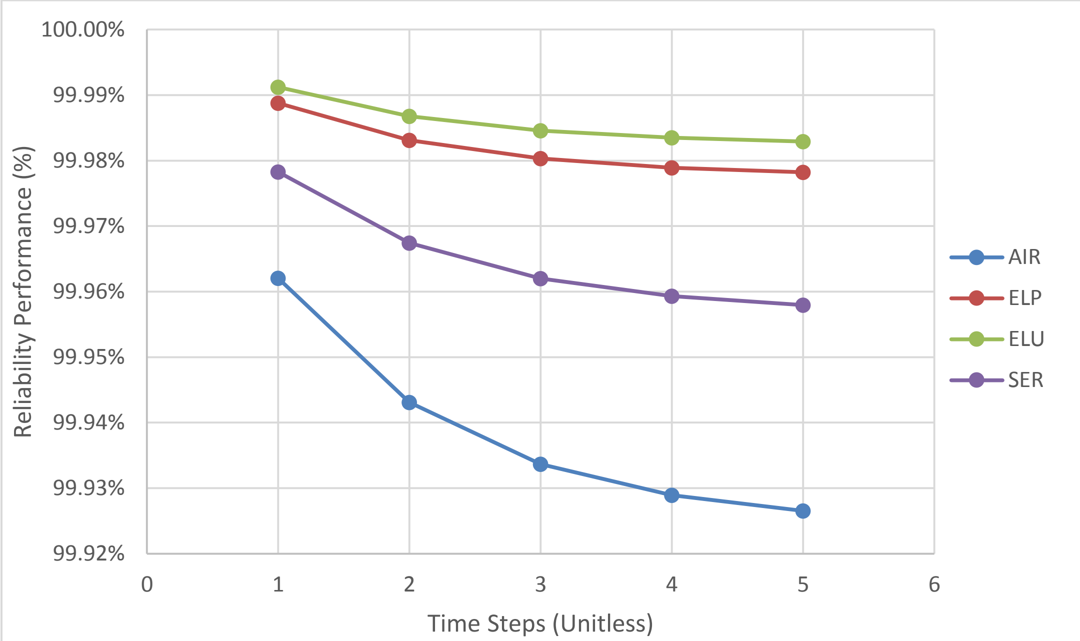

Figure 7.11 Reliability performance of Turboexpander seals

The following maintainable component of turboexpander SHS subsystem is the pressure valve. According to records, associated failure modes affecting these valves are ELU and SER. Both failure case scenarios are forecasted performing almost 100% reliability. However, valves' failures and malfunctions are recorded in past, hence they are involved in the reliability assessment. According to the current and the predicted reliability performance, SER demonstrated a faster reliability drop (in decimal places), which is negligible as it retains values greater than 99.9%. However, SER obtains greater proportion of pressure valve component to the overall occurrence of SER compared to the proportion of pressure valve recorded for the ELU case.

7.2.3. Seawater lift pump case study

OREDA database provides a wide variation of pumps and amount of reliability input data related to pumps. The first pump type that PMRA processed input data case study is oriented towards is the seawater lift pump. The network arrangement of this pump type involves five subsystems such as the controller (CTL), shell (SHL), cooling (COO), couplers (COU) and the mechanical power (MEC). Each of these subsystems consists of various components and their reliability performance predictions will be presented in this section next. Furthermore, the failure cause assessment is taken place by investigating particular failure modes that led to failure or malfunctions these components. Firstly, on subsystem level, COU has reached predicted reliability performance at 99.99%, MEC at 99.65%, COO at 98.0%, CTL at 98.4% and SHL at 97.4%. As seen in Figure 7.12, all of the involved subsystems accomplish high level of reliability. However, it is crucial to explore and identify particular components and specific failure modes that are probable to cause potential malfunctions.

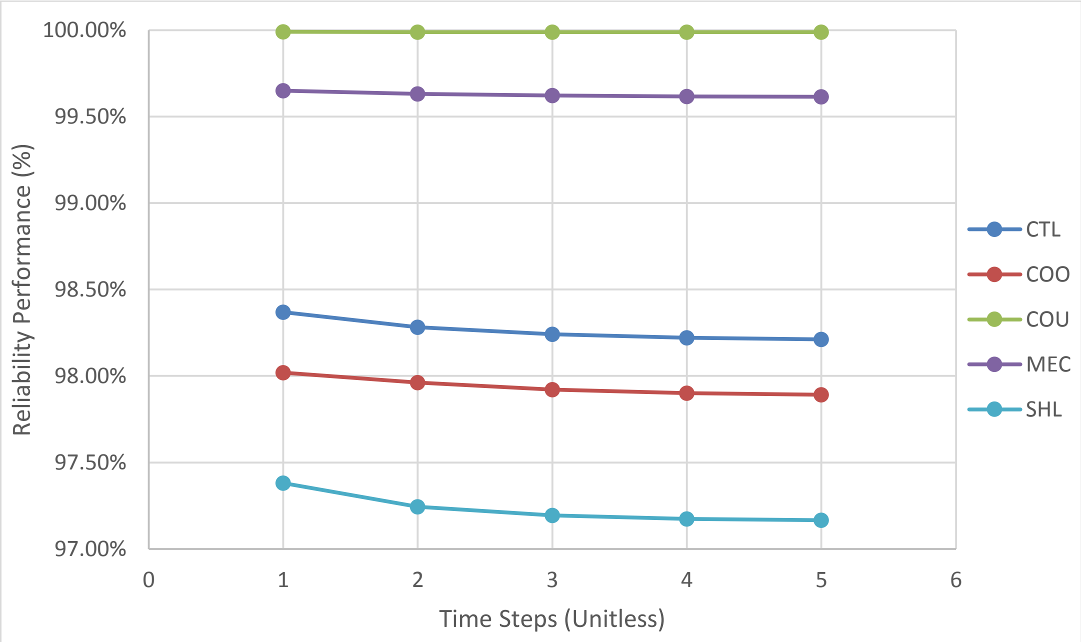

Figure 7.12 Reliability performance of seawater lift pump subsystem level

The first subsystem of the seawater lift pump under reliability assessment is CTL, which consists of components and maintainable units such as the actuator, cabling, control unit and the monitoring. In Figure 7.13, the reliability performance of the actuator is demonstrated. In total, three failure modes are recorded for this maintainable unit such as AIR, SER and UST achieving predicted reliability greater than 99.9%.

It is essential to highlight that UST presents the lowest reliability performance and the faster drop as well. This is explained because the mean failure rate index of SER is greater than AIR and UST and the proportion of actuator in SER is greater as well than in AIR and UST failure modes.

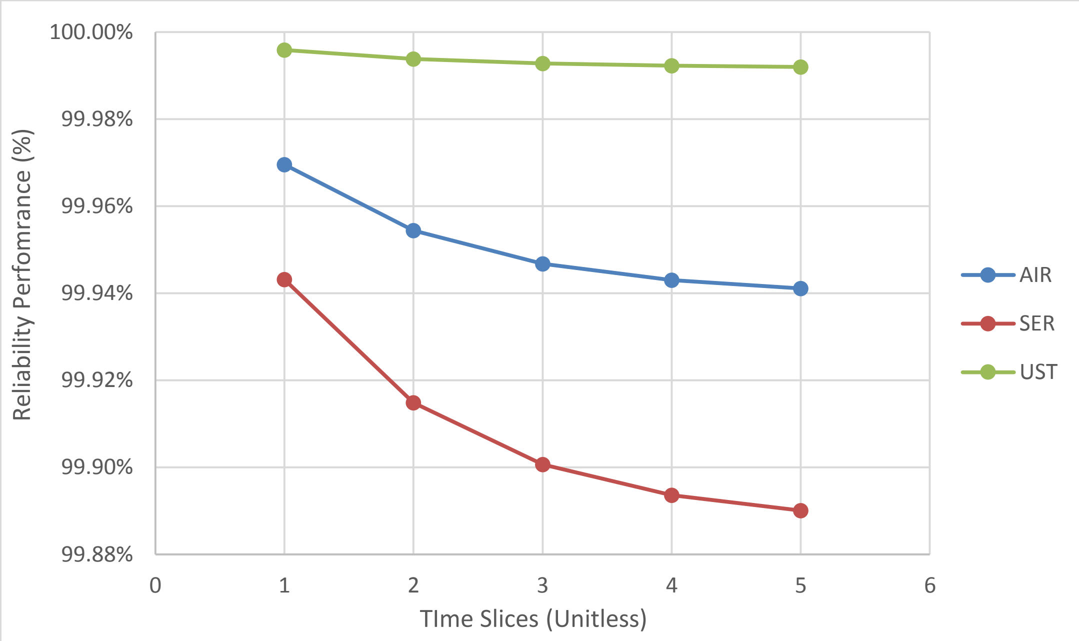

Figure 7.13 Reliability performance of seawater lift pump actuator

Control unit is another maintainable unit of CT. It reaches similar reliability performance as the actuator, however, more FM are associated with this component. The FMs probable to cause malfunctions are AIR, FTS, PDE, SER and UST. AIR presents the lowest reliability performance, followed by FTS. FTS can be caused due to power loss of the control unit. The FMs PDE, SER and UST perform higher reliability, declining slower compared to AIR and FTS. Therefore, PDE, SER and UST have smaller mean FR index and smaller proportion per FM for the control unit.

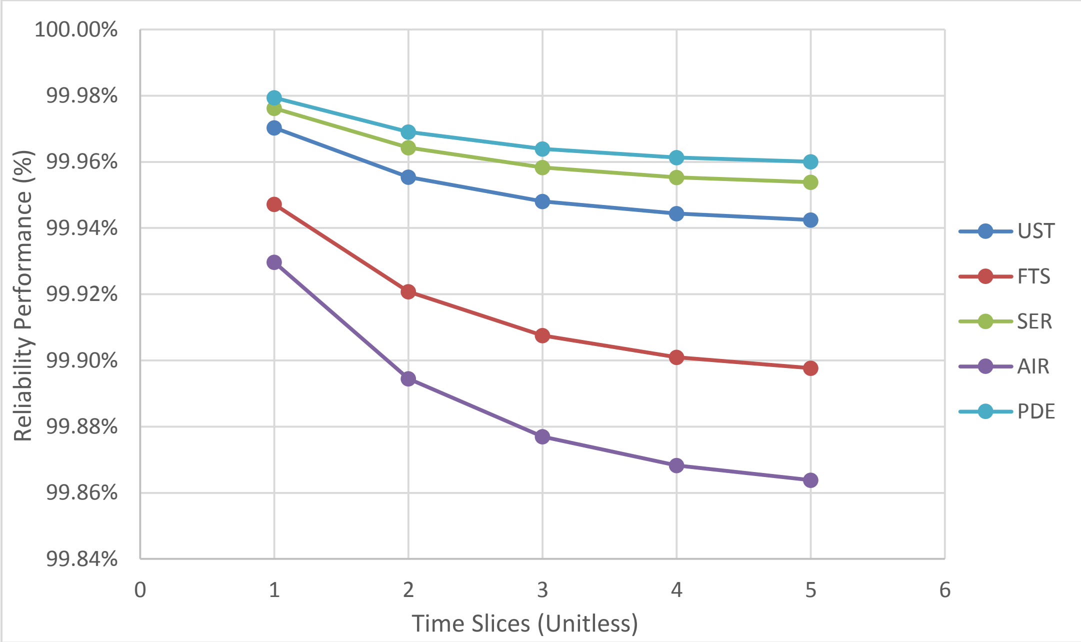

Figure 7.14 Reliability performance of seawater lift pump control unit

It is important to highlight that STD, ELP and ELU present similar reliability drop on different reliability performance levels. This similarity in pattern has been occurred because the mean failure rate index of these failure modes is almost the same (negligible variation). However, the proportion (weighting factor) of each of these modes to casing component differs, therefore they achieve different reliability performance levels. The lowest among them is ELP. Pump filter is component, which requires high quality or replacement if required for reliable operation of the system. OREDA database failure records involve various failure modes such as ELU, INL, PDE, SER and STD.

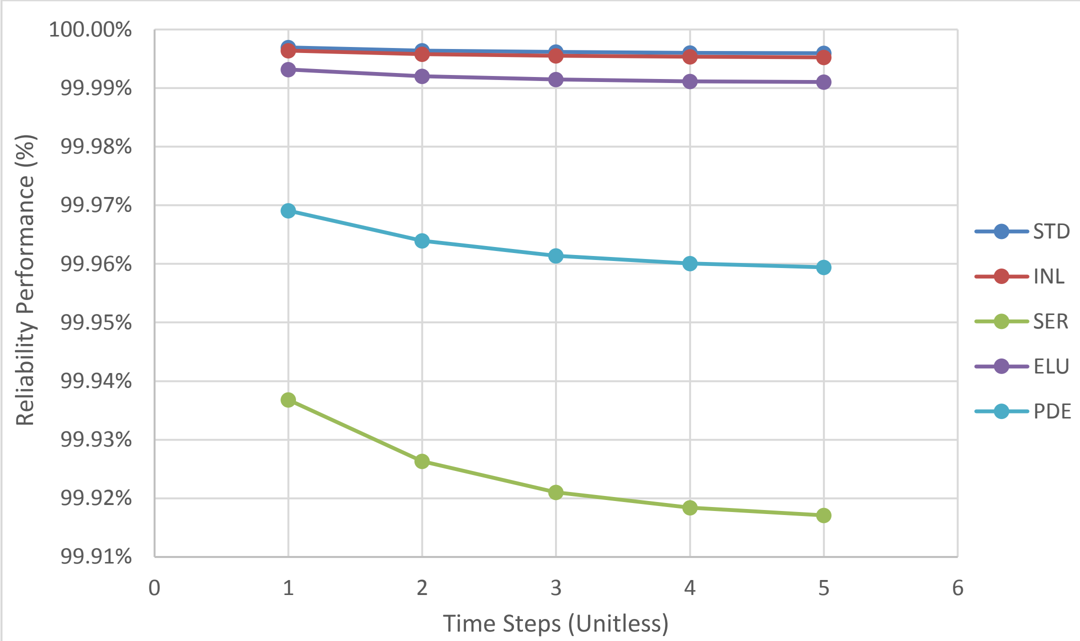

Figure 7.15 Reliability performance of seawater lift pump filter

First of all, STD and INL present the highest reliability performance, where it is almost steady. Therefore, these failure modes employ almost the same mean failure rate indices and proportion (weighting factor) per failure mode for the pump filter. In the case of seawater lift pump filter, the reliability performance predictions reach 99.9%. It is import to highlight that STD, INL and ELU perform almost steady reliability forecasts, whereas in case of SER and PDE a drop is expected in the next period of time. The generic definition of SER and PDE failure modes does not allow to provide specific maintenance solutions for preventing failures and malfunctions as well as achieving slower reliability drop through time. The highest mean failure rate and weighting factor has been shown regarding SER failure mode. SER is unspecified failure mode, however it is assumed that these minor in-service issues have been occurred due to negligible blockage.

The seawater lift pump couplers (COU) subsystem is responsible for the movement transmission involving two maintainable components, which cooperate for achieving this function. These components are the coupling driver and the coupling driven. The predicted reliability performance of the latter involves failure modes such as VIB, STD, UST and NOI. All of these failure modes denote component's material deficiency due to inefficient lubrication and material tear and wear. Further reliability drop can be prevented by monitoring the operating temperature of the pump and its lube oil as well as the operating pressure.

The final subsystem of seawater lift pump is mechanical power (MEC). This subsystem involves the moving parts, which retain the functioning of the system such bearings (i.e. radial and thrust bearings), impeller and the shaft. Firstly, the predicted reliability performance of the impeller and the shaft is taken into consideration as both components cooperate while are attached to each other. Therefore, common failure modes and causes of malfunctions and failures are expected.

Shaft's failure mode list consists of AIR, BRD, NOI, OHE and VIB. All of these modes achieve high reliability due to low failure rate records, however, the lowest performed failure mode is the unspecified breakdown (BRD). In a similar manner, the impeller presents the forecasted reliability performance of impeller maintainable component. The recorded failure modes consist of STD, UST and VIB. Additional reliability predictions, components and involved failure modes of MEC components (i.e. bearings) are attached in Appendix G, because they present similarly high reliability performance.

7.2.4. Oil export pump case study

In this section, the second pump type of processed input data case study of PMRA strategy is presented. This system involves the oil export pump, an essential equipment for offshore applications and tank ships, which unloads the crude oil cargo from the cargo/storage tanks. The reliability input data utilised for this study is gathered from the OREDA database.

The network arrangement of the oil export pump takes into account five subsystems such as the controller (CTL), shell (SHL), cooling (COO), couplers (COU) and mechanical power (MEC). Each of these subsystems consists of various maintainable units and these are associated to at least one or multiple recorded failure modes. The forecasted reliability performance on subsystem level is demonstrated in Figure 7.16. Overall, SHL is the least reliable subsystem performing 97.1% reliability followed by the COO at 98.5%, CTL at 98.8%, MEC at 99.8% and almost 100% for COU.

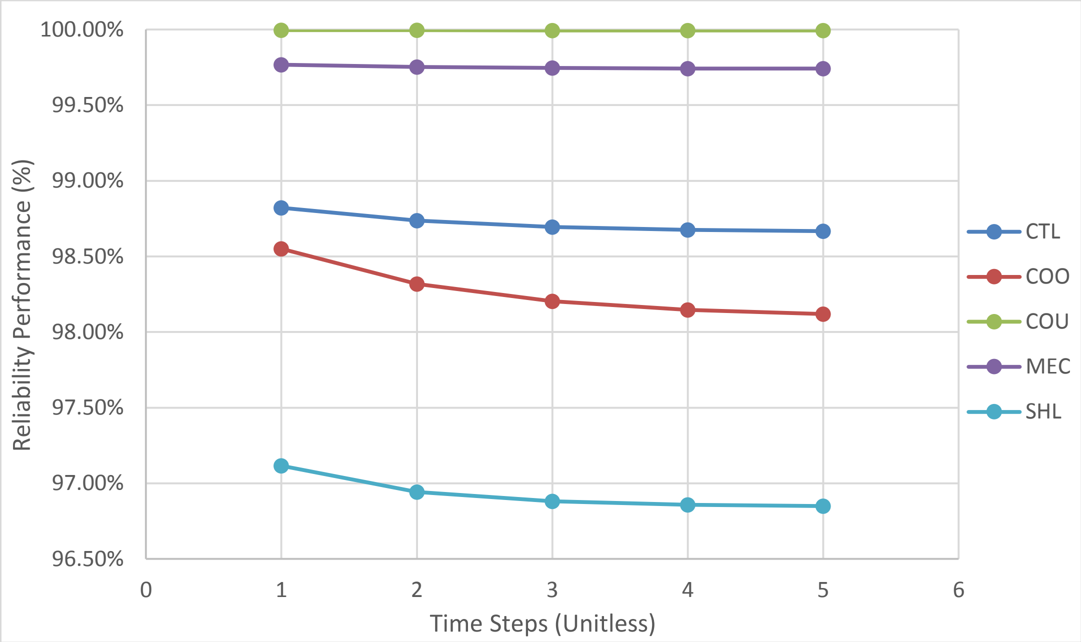

Figure 7.16 Reliability performance of oil export pump subsystem level

The first subsystem of oil export pump under reliability assessment is the controller. It consists of four maintainable components such as the actuator (ACT), cabling (CAB), control unit (CTL) and monitoring (MON). The lowest forecasted reliability performance is presented by CTL followed by MON, ACT and CAB.

More specifically, Figure 7.17 presents the reliability performance of control unit (point 1 current, points 2-5 predicted in the timeline). This maintainable unit is associated to four failure modes such as AIR, ERO, FTS and SER. All failure case scenarios achieve high reliability (i.e. greater than 99.4%), however AIR failure mode performs the least reliable by presenting the fastest reliability loss within the timeline. This failure mode is associated to failure or malfunction of an instrument. Additional results on component level related to COO subsystem are attached in Appendix G providing a better picture of the overall reliability performance.

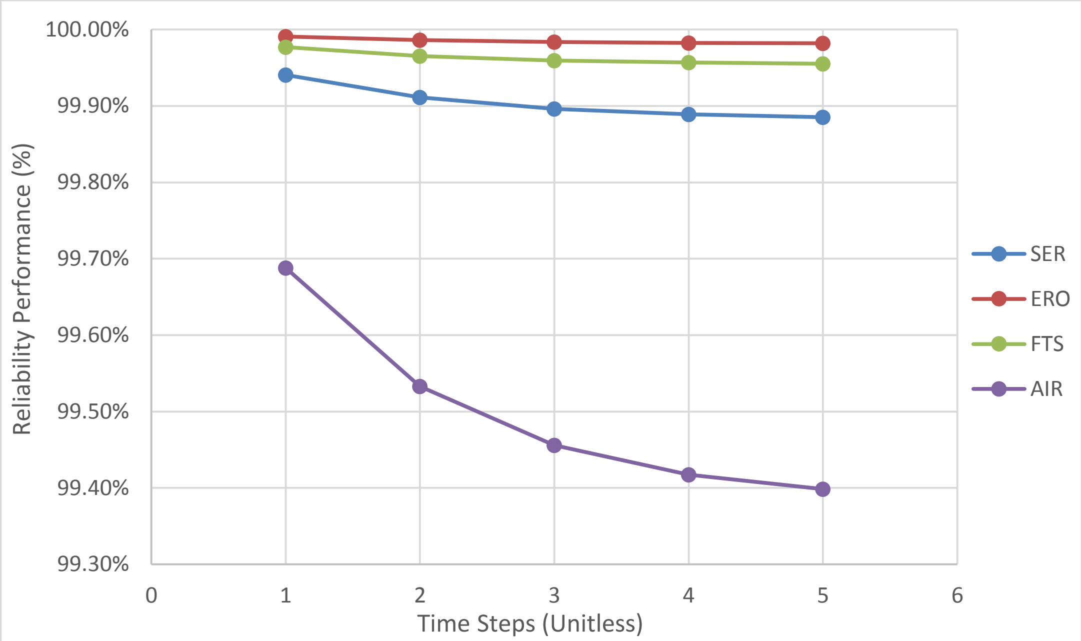

Figure 7.17 Reliability performance of oil export pump control unit

The following oil export pump subsystem is SHL, which consists of five maintainable units such as the casing, valve, filter, lubrication and the seals. The most indicative maintainable units of this subsystem are the filter, lubrication and seals. For instance Figure 7.18 presents the reliability performance predictions of seals, where various failure modes have been recorded such as STD, SER, ELU, INL, OHE and BRD.

According to the forecasted reliability performance the most likely failure mode leading to failure or malfunction is ELU, hence, external leakage of utility medium. This failure mode can be identified to material tear and wear, which leads to damage and consequently to leakage. SHL subsystem involves various components and maintainable units. Therefore, multiple failure case scenarios can provided in-depth reliability assessment. Additional reliability prediction results related to oil export pump filter and lubrication can be found in Appendix G.

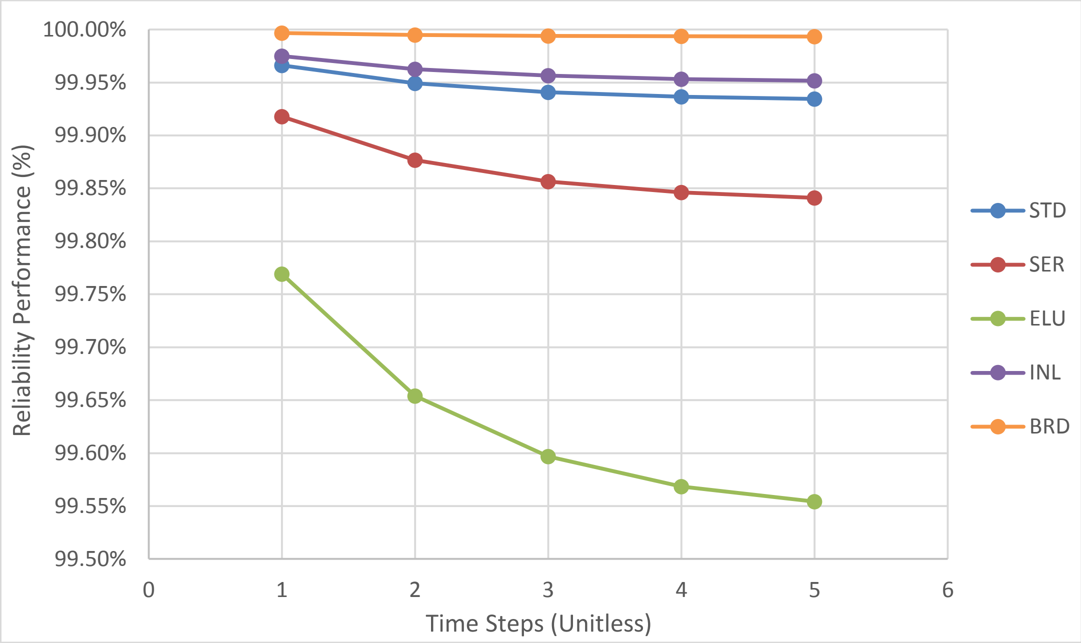

Figure 7.18 Reliability performance of oil export pump seals

Progressing towards the reliability assessment of the oil export pump on subsystem, component and failure mode levels, the couplers subsystem consists of coupling driven and coupling driver (as explained in seawater lift pump case study). As shown in Figure 7.19, coupling driven has been diagnosed in past with failure mode records such as noise (NOI), structural deficiency (STD) and vibration (VIB). According to predictions, STD is the most probable failure mode to cause failures or malfunctions. This failure mode utilises the lowest mean failure rate index and the higher proportion (weighting factor) among the involved modes. STD has not been specified by OREDA, however it can be assumed that occurred due to material damage.

However, noise (NOI) and vibration (VIB) are failure modes that should be identified before STD occurs. Therefore, if active and efficient condition monitoring applications are established on the most likely to fail components of the selected, under assessment systems, malfunctions can be forecasted and failures will be avoided.

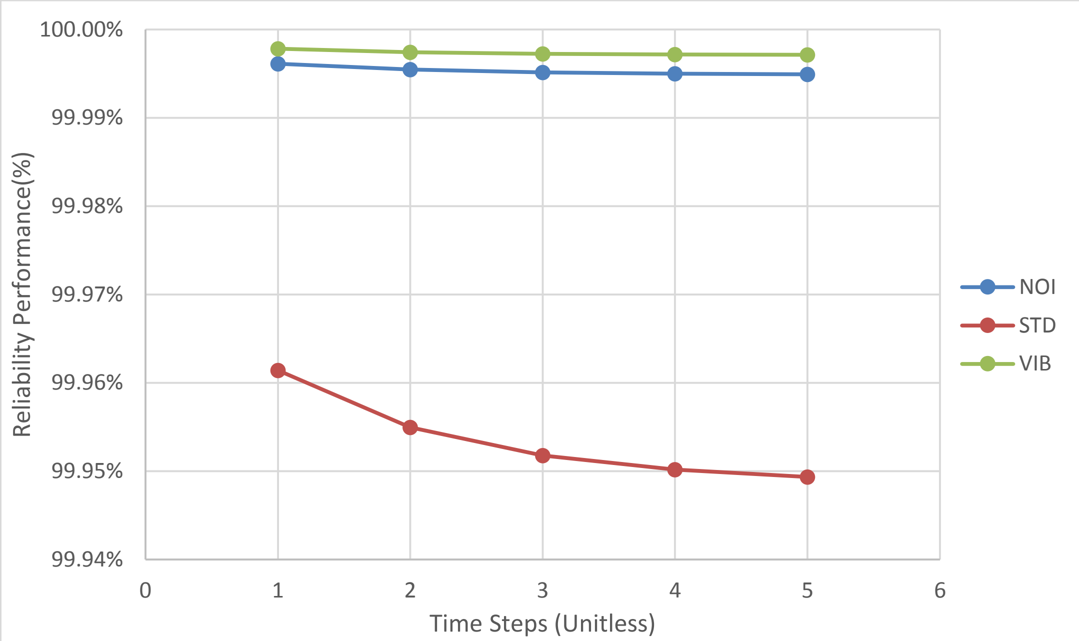

Figure 7.19 Reliability performance of oil export pump coupling driven

The reliability records provided by OREDA with regards to oil export pump mechanical power subsystem present a negligible number of failures as the predicted failure rates are expected to be higher than 97.1%. MEC subsystem consists of maintainable units such as bearings (i.e. radial and thrust), impeller and the shaft. More specifically, the radial bearing has been affected by BRD, NOI, FTS and VIB. On the other hand, the thrust bearing has been failed by BRD, ELU, OHE, STD and VIB. Additionally, the shaft is associated with failure modes such AIR, BRD, FTS, NOI, OHE and VIB, whereas, the impeller with STD and VIB.

7.2.5. Cooling water pump case study

PMRA strategy is applied on various systems aiming to identify common aspects among the involved systems of the case study, difficulties and receive valuable practical and technical input. The fifth subsystem that PMRA strategy is developed and currently tested is the cooling water pump. Compared to the previously presented pump systems (i.e. seawater lift and oil export pumps), this study is simple in network structure and failure case scenario arrangement, because a small number of components have been failed involving a smaller number of recorded failure modes.

More specifically, cooling water pump network consists of two subsystems such as the controller (CTL) and the mechanical power (MEC) and two independent components such as the valve (VLV) and the coupling driven (CDN). It is essential to clarify that these components depend on the pump's reliability performance and entire system functioning but are not considered within a particular subsystem.

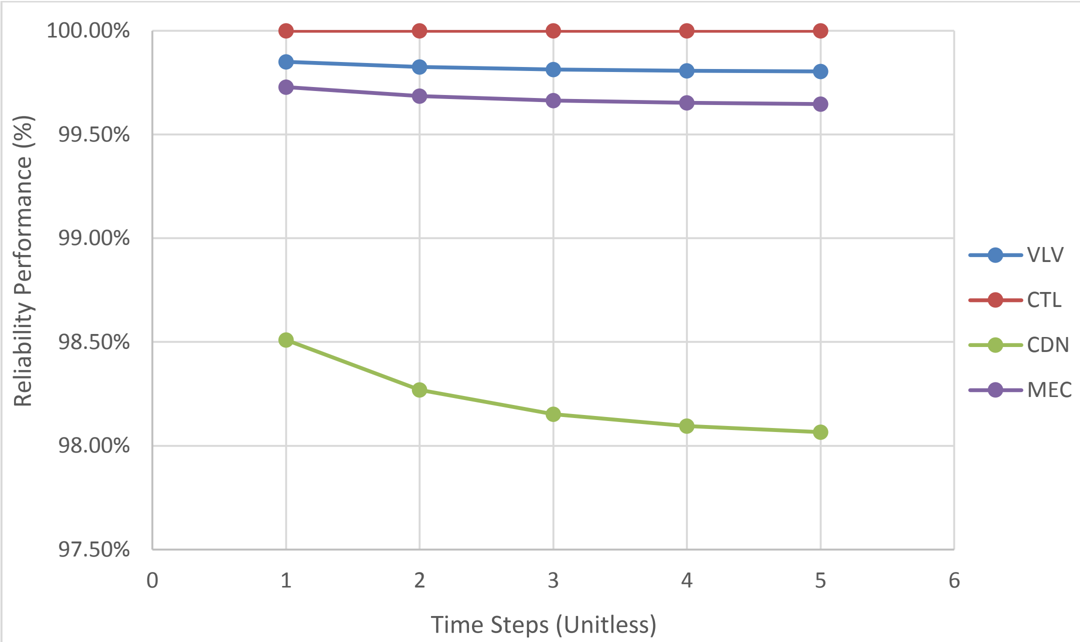

Figure 7.20 Reliability performance of Cooling Water pump (CW) subsystem level

Therefore, Figure 7.20 presents the reliability performance of the cooling water pump in regards to the developed network arrangement, the gathered processed input data and the acquired reliability performance. Coupling driven (CDN) reaches reliability at 98.5%, MEC subsystem at 99.7%, VLV at 99.85 and CTL almost 100%.

CTL is the first subsystem under reliability assessment. It consists of multiple maintainable units and components such as the actuator (ACT), cabling (CAB), control unit (CTL) and monitoring (MON). Control unit achieves high reliability performance at 99.99%, while it is associated by two failure modes such as AIR and FTS. The first failure mode at almost 99.99% lowest predicted reliability performance is linked to damaged instrument, whereas FTS (99.99%) can be due to power loss, damaged or destroyed cable among others.

Furthermore, the valve and coupling driven are two more maintainable units of cooling water pump. Valve has been diagnosed with noise (NOI) failure mode and forecasted reliability performance at 99.85%. On the other hand, coupling driven maintainable unit has been recorded with NOI failure mode as well, while its reliability performance is expected to be at the first predicted time step at 98.5%. NOI detected in the case of the coupling driven can be caused due to excessive vibration. A valuable CM practice for detecting NOI and VIB failure modes is the vibration analysis as well as measuring the pressure different (inlet/outlet) for detecting pressure drop.

Lastly, cooling water pump includes mechanical power (MEC) subsystem, which consists of bearing (BER), radial bearing (RBR) and shaft (SFT) maintainable units. BER and RBR components achieve reliability at approximately 99% the first time step of the predicted timeline. Additional information on failure mode level, both components (i.e. BER and RBR) are linked with FTS and NOI. The most common causes that can lead to these modes are associated with material wear, tear, overall collapse and inefficient lubrication of the moving parts. Direct functional relation with the bearings has the shaft component. In this case, AIR, FTS and NOI are recorded with regards to SFT for failure reasons related with these of BER and RBR.

7.2.6. Firefighting pump case study

A system onboard the ships and the offshore oil and gas platforms, which ensures safety is the firefighting pump. This system is inspected and maintained periodically, because it is not often operated. However, various components have been failed due to different failure modes. As long as the scope of this system is to ensure safety, its reliable functioning has to be confirmed. OREDA database provides failure records and involved failure modes for firefighting pumps as well. This section presents the reliability performance (current and predicted) results acquired by the PMRA strategy. Therefore, reliability assessment is taken place on subsystem and component levels by considering all the recorded failure modes.

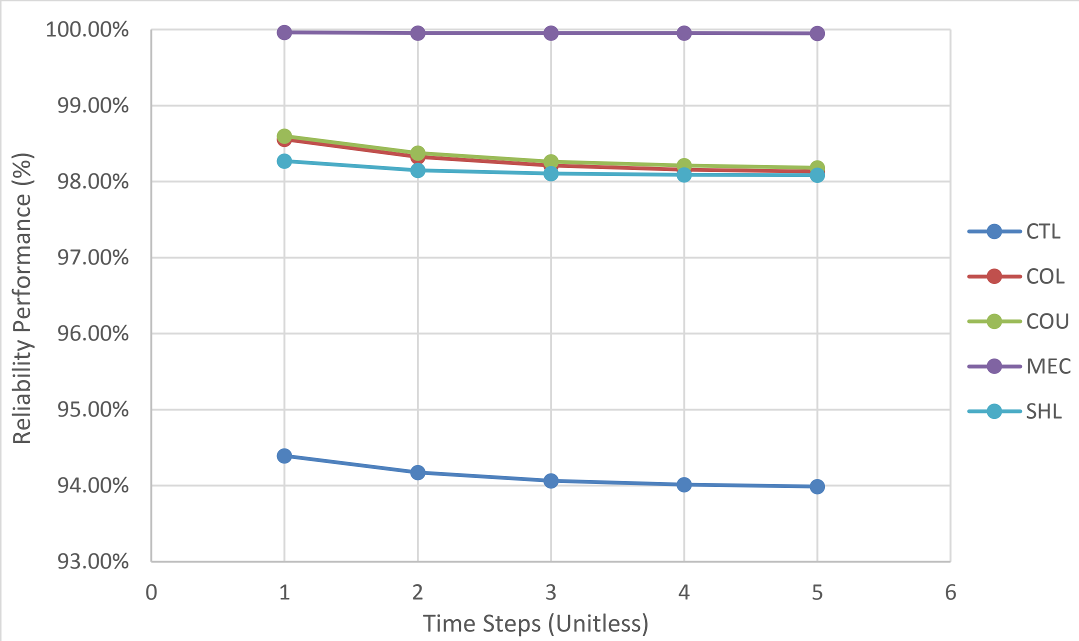

Figure 7.21 Reliability performance of Firefighting Pump (FP) subsystem level

Firstly, Figure 7.21 presents the reliability performance on subsystem level of the involved controller (CTL), cooling (COL), mechanical power (MEC), shell (SHL) subsystems and coupling driven (COU) maintainable component. The first point in timeline represents the current reliability performance, whereas points 2-5 the forecasted one. According to the PMRA strategy forecasted results, the least reliable subsystem is CTL reaching 94.39% reliability performance followed by SHL at 98.2%, COU and COL at approximately similar 98.6% and MEC at almost 100%. Figure 7.21 confirms that CTL subsystem and its maintainable units and components gained the highest proportion of the recorded failure records.

The first subsystem of firefighting pump under reliability assessment is CTL, which consists of multiple maintainable units and component such as the actuator (ACT), cabling (CAB), control unit (CTL) and monitoring (MON). The forecasted reliability assessment of the actuator is presented in connection with three failure modes such as AIR, ERO and SER. The lowest reliability performance is obtained by SER at 98.9% followed by AIR at 99.3 and ERO at 99.99%. Another essential maintainable unit of firefighting pump involved in various failure modes is the control unit. As seen in Figure 7.22 below, the predicted reliability performance is retained almost higher than 98%. However, multiple failure modes have been recorded causing failures or malfunction such as AIR, ERO, FTS, SER, STP and UST. The most likely failure mode to cause failures and malfunctions have been predicted to be AIR because it has the highest mean failure rate index and the highest proportion in control unit.

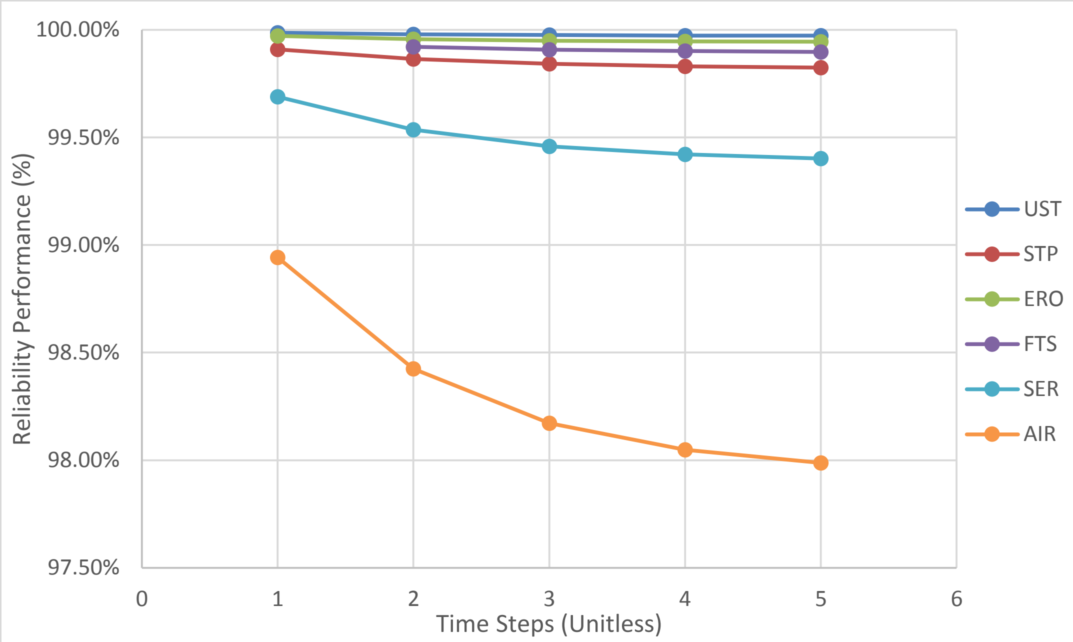

Figure 7.22 Reliability performance of Firefighting Pump (FP) control unit

SHL is the second subsystem considered in the firefighting pump network structure incorporating maintainable units such as casing (CAS), seals (SLS), lubrication (LUB) and filter (FLT). CAS has been recorded to be connected with failure modes such as ELU, OHE and STD, whereas, SLS with STD, INL, SER, ELU and OHE. On the other hand, LUB is associated with ELU and FLT with STD, INL, SER and ELU. The obtained reliability of these components retains performance greater than 98%. Furthermore, these components have been discussed in the previous pump systems (seawater lift, oil export, and cooling water).

Lastly, MEC consists of moving/rotating maintainable components such as bearing (BER), radial (RBR) and thrust bearing (THB), shaft (SFT) and impeller (IMP). Firstly, bearing acquires reliability performance higher than 99.97% by taking into account FTS and UST failure modes. On the other hand, radial bearing reaches 99.98% due to FTS, whereas thrust bearing higher than 99% due to ELU, OHE and STD. Shaft and impeller achieve reliability predictions greater than 99.97% due to AIR and FTS and SRD and UST respectively.

7.2.7. Crude oil handling pump case study

The last main system involved in the processed input data type case study is the crude oil handling pump. Its reliable operation is essential as this system retains the supply of crude oil pumps. This pump's failure rate records involve various subsystems, maintainable components and units and multiple failure modes. On the subsystem level, similarly as in the previous pump systems of the processed input case study presented, the controller (CTL), shell (SHL), cooling (COO), couplers (COU) and mechanical power (MEC) subsystems are considered. The lowest reliability performance predictions are presented by CTL at 97.73%. This reliability performance is followed by SHL at 98.21%, COO at 98.55%, MEC at 99.71% and the most reliable is COU at almost 100%.

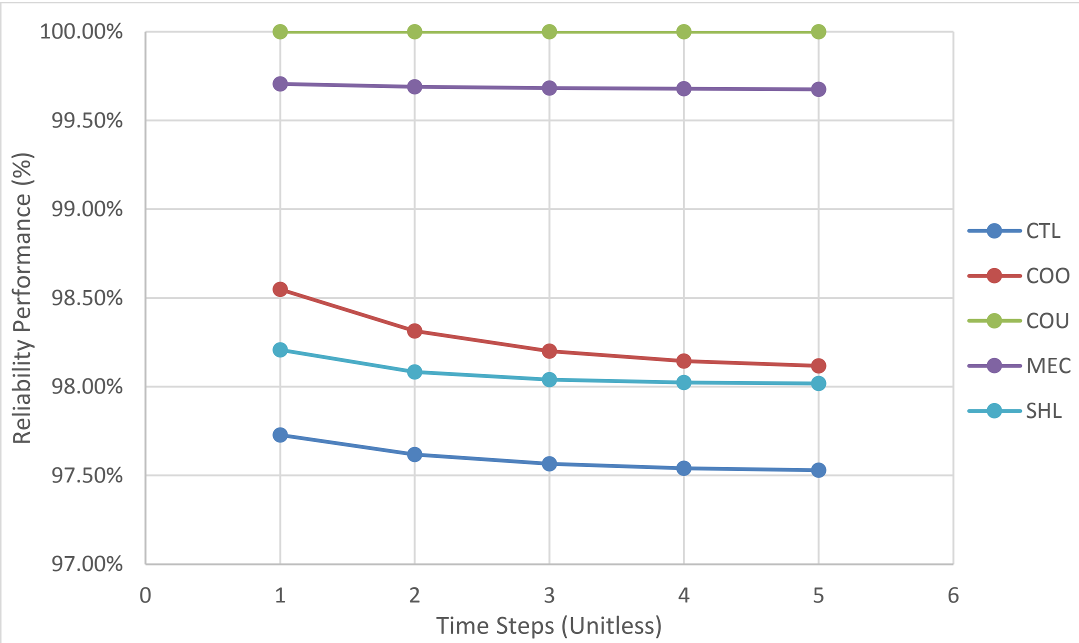

Figure 7.23 Reliability performance of crude oil handling pump subsystem level

On subsystem level, controller incorporates components and maintainable units such as actuator (ACT), cabling (CAB), control unit (CTL) and monitoring (MON). Firstly, control unit has been connected with failure modes such as AIR, ERO, SER and UST.

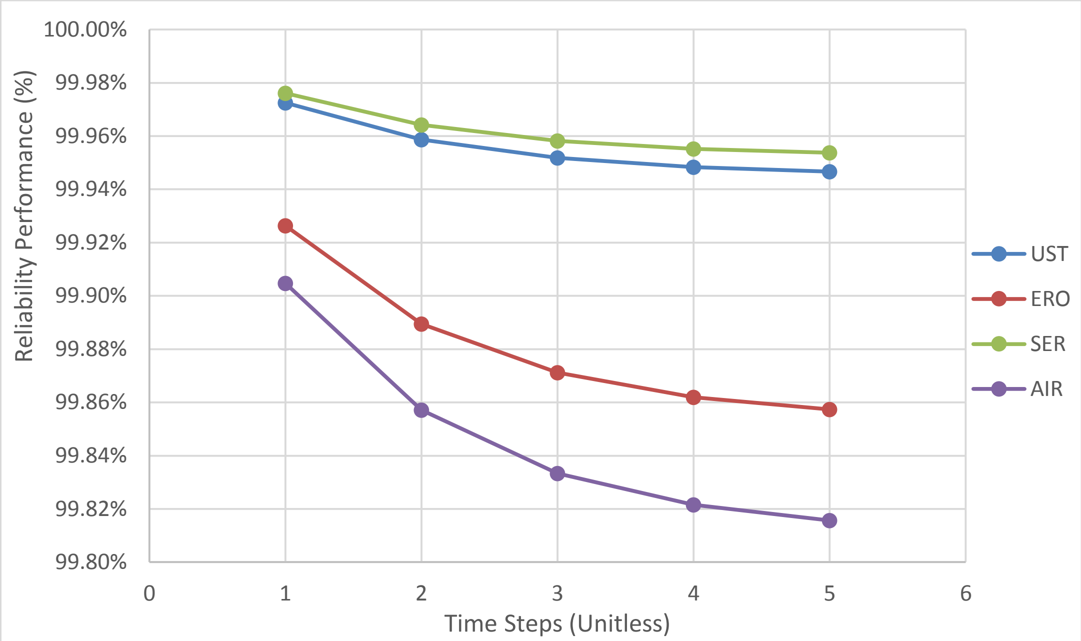

Figure 7.24 Reliability performance of crude oil handling pump control unit

All involved failure modes reach reliability performance predictions higher than 99.8%. The lowest forecasted prediction is presented by AIR followed by ERO, UST and SER. The high levels of reliability performance and the negligible reliability drop set the grounds for further functioning without any inspection or maintenance actions considerations. The remaining components and maintainable units of CTL subsystem retain reliability performance higher than 99%. The predicted reliability has been acquired within high performance levels (above 99%), so additional results are attached in Appendix G.

Similarly as in controller subsystem, SHL maintainable units and components acquire acceptable reliability performance predictions. More specifically, SHL consists of casing (CAS), filter (FLT), lubrication (LUB) and seals (SLS). CAS has been associated with BRD, ELU and OHE failure modes, whereas FLT with ELU, INL and SER modes, LUB unit with ELU and SLS components with SER, ELU, OHE, BRD and INL. These components and maintainable units have been discussed above as well as the reasons leading to this reliability drop, hence supplementary results are included in Appendix G.

The current and forecasted reliability performance of coupling driven and coupling driver components are taken into account as well. The first one has been recorded to be affected by failure modes such as UST and VIB, whereas the latter by VIB. The predictions indicate reliability higher than 99.9%, however operational issues due to vibration have been detected. Therefore, further investigation on the components lubrication should be taken place in order to prevent or avoid material degradation and potential damage or even catastrophic collapse. The most suitable condition monitoring practices involve pressure measurement at inlet/outlet of the pump in order to detect pressure drop as well as vibration monitoring for misalignment and material tear and wear.

Lastly, radial and thrust bearing (RBR and THB respectively) are rotational/moving components of MEC subsystem. Their efficient and reliable operation ensure the functioning of the pump. RBR has been detected to be caused by BRD and VIB, whereas THB by ELU, OHE and VIB. Both component reach forecasted reliability performance higher than 99.8%. However, the occurrence of failure modes such as external leakage of utility medium (ELU), overheating (OHE) and vibration (VIB) lead to failure or malfunction causes due to improper lubrication of the moving parts, misalignment of shaft through the bearings and material tear and wear.

7.3. Raw data reliability case study

In this section, the forecasted reliability performance results of the raw input data case study are demonstrated and examined. This application is developed as part of the PMRA strategy implementation by utilising raw input data gathered onboard a container ship, while sailing in actual/real operational conditions. The raw input case study of the Probabilistic Machinery Reliability Assessment (PMRA) strategy involves mainly six systems such as the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and the cylinders. The reliability performance assessment takes place on system, subsystem (if applicable), component and maintainable unit assessment as well as raw input data probabilistic processing and forecasting.

It is essential to clarify in advance that the involved input data is raw recorded within a continuous timeline of almost a month. Therefore, reliability performance predictions are demonstrated by taking into account specific time intervals. The time recorded interval is set as one measurement per operational hour. Furthermore, the results that will be demonstrated next in this section provide the recorded and predicted reliability figures. More specifically, the acquired results are plotted in monthly intervals. The first two points within the arranged timeline of the x-axis denote the reliability performance in regards to the recorded period of time. The first point (at 0.5 position) signifies the recorded reliability performance of cluster 1 as acquired by the data mining method, whereas the second point at 1.0 the second cluster. Overall, both points represent the reliability performance (tendency of deviation) of the first month (recording time). On the other hand, the following points in the timeline (i.e. 1.5 to 3.5 months) signify the acquired predicted reliability performance of the upcoming period of time. Moreover, points 1.5 and 2.0 represent the reliability performance prediction of the following month, 2.5 and 3.0 of the second predicted month and point 3.5 the reliability performance of the first cluster of the third predicted month.

7.3.1. Fuel system

The first onboard system under reliability assessment of the PMRA strategy raw input case study is the fuel system. It is structured among the fuel supply and the fuel return subsystems. Mainly two measurement sources are considered for this subsystem the fuel oil inlet temperature and pressure (respectively). The major benefit of Bayesian Belief Network (BBN) probabilistic assessment tool is the implementation of interconnections among node members, which belong to different system or subsystem. Hence, the first introduced interdependence involves the connection of cylinder exhaust gas outlet temperature with the performance of fuel supply system.

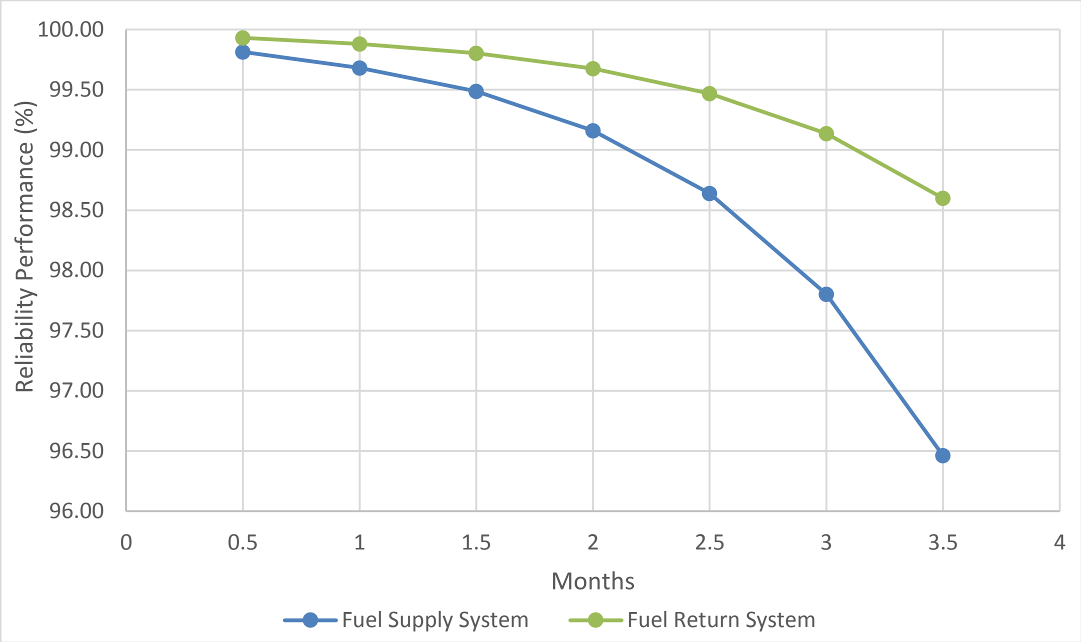

Figure 7.25 Reliability performance of fuel system – raw data

According to the acquired results, the weakest reliability performance is demonstrated by the fuel supply system followed by the fuel return system as shown in Figure 7.25. The reliability of the first is initiated at 99.88% the first two weeks of recording (0.5 month), whereas it is dropped as recorded at 99.68% the second two weeks of the first month. This reliability drop is confirmed by two observations, the temperature increase and pressure drop in the second half of the data gathering period.

It is essential to highlight that the recorded datasets for both measurement indices (i.e. fuel inlet temperature and pressure) align within the predefined acceptable operational limits. In other words, the alarm points are not reached or exceeded within this period. Therefore, they demonstrate a fully reliable condition according to the reliability and warning criteria. In the case of fuel return system, the reliability performance initiated at 99.93% and dropped to 99.88%. The predefined warning levels are not reached or exceeded, therefore non-destructed operation can be ensured.

7.3.2. Jacket cooling fresh water system

The second system under reliability assessment utilising the PMRA strategy is the jacket cooling fresh water (JCFW), which consists of the JCFW pump and the JCFW rotor. Various raw input data sources are considered in the case of this subsystem such as the JCFW outlet temperature for cylinders 1 to 8 and the cylinder JCFW inlet pressure. JCFW pump comprises of maintainable units and components such as the seals, impeller, wear-rings, housing, inlet/outlet valve, shaft and the strainer. On the other hand, JCFW pump rotor is directly connected with the cylinder JCFW inlet pressure measurement node.

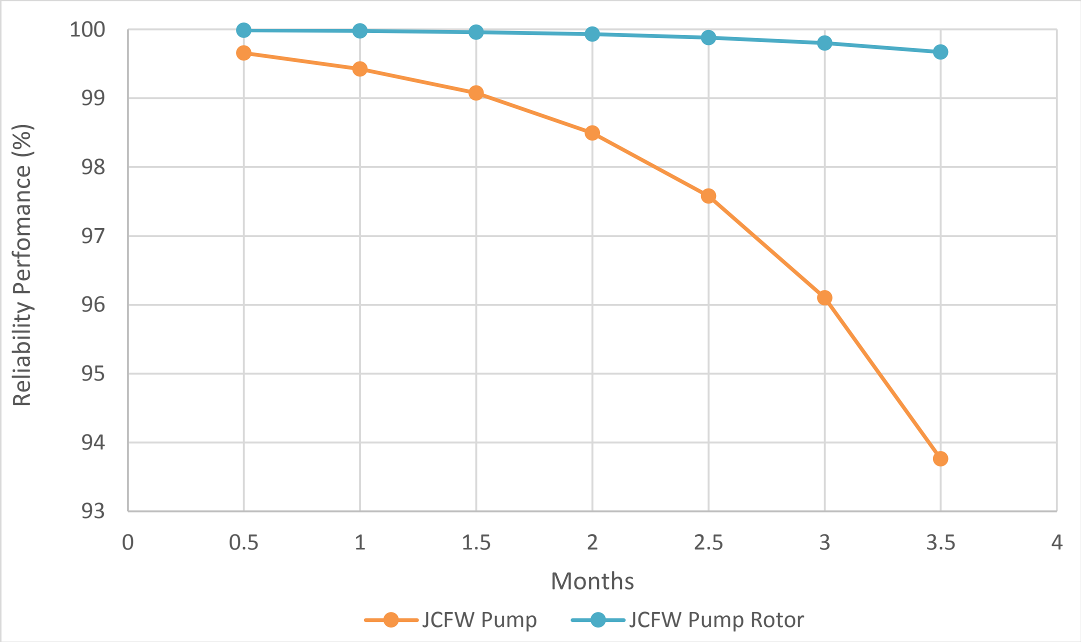

Figure 7.26 Reliability performance of jacket cooling fresh water system – raw data

On system level, Figure 7.26 presents the reliability performance of both involved main subsystems. The demonstrated results incorporate the reliability figures of the recorded input data (i.e. 0.5 and 1 month) and the forecasted period (i.e. 1.5 to 3.5 months). Overall, the JCFW pump indicates the weakest and quickest reliability drop due to the various associated input data sources and multiple maintainable units and components linked. The fast reliability drop is approved by the characteristics of the recorded input datasets. Firstly, the second half of the data gathering period confirms temperature increase and pressure drop. Therefore, all recorded input sources incline towards the predefined safety thresholds. At this point, it is essential to clarify that all recorded figures range within the appropriate safety limits. Hence, the demonstrated reliability performance inclination indicates tendency of trend change but not unsafe/unhealthy functioning. On the other hand, JCFW pump rotor show almost stable reliability performance among the collected and the forecasted period. The demonstrated prediction is confirmed by the almost steady (unchanged) cylinder JCFW inlet pressure input data collected. Further JCFW system reliability prediction results are placed in Appendix G enabling the investigation on subsystem level.

7.3.3. Lube oil system

In this section, the third considered system of PMRA strategy application is demonstrated. This is the lube oil system, which consists of the lube oil pump, rotor, filter and cooler. More specifically, the lube oil pump incorporates input from various maintainable units and components such as the seals, impeller, bearing, shaft, inlet/outlet valve, inlet strainer and the pump housing. The lube oil pump rotor is associated with the rotor bearing and electric conductor. Furthermore, the lube oil pump filter has operational connection with the lube oil pump inlet/outlet valve, filtering elements, lube oil by-pass valve and the self-cleaning control. The fourth maintainable unit is the cooler, which is associated with components such as the lube oil inlet/outlet valve, cooler plates and the regulating flow valve. Two raw input data sources are involved in the lube oil system the main lube oil inlet pressure and temperature.

The reliability performance of the lube oil subsystems is presented in Figure 7.27. More specifically, the lube oil pump achieved reliability at 99.86% and dropped at 99.76%. The weakest reliability performance, among the involved subsystems, is forecasted for the following period of time ranging from 99.61% to 97.26%.

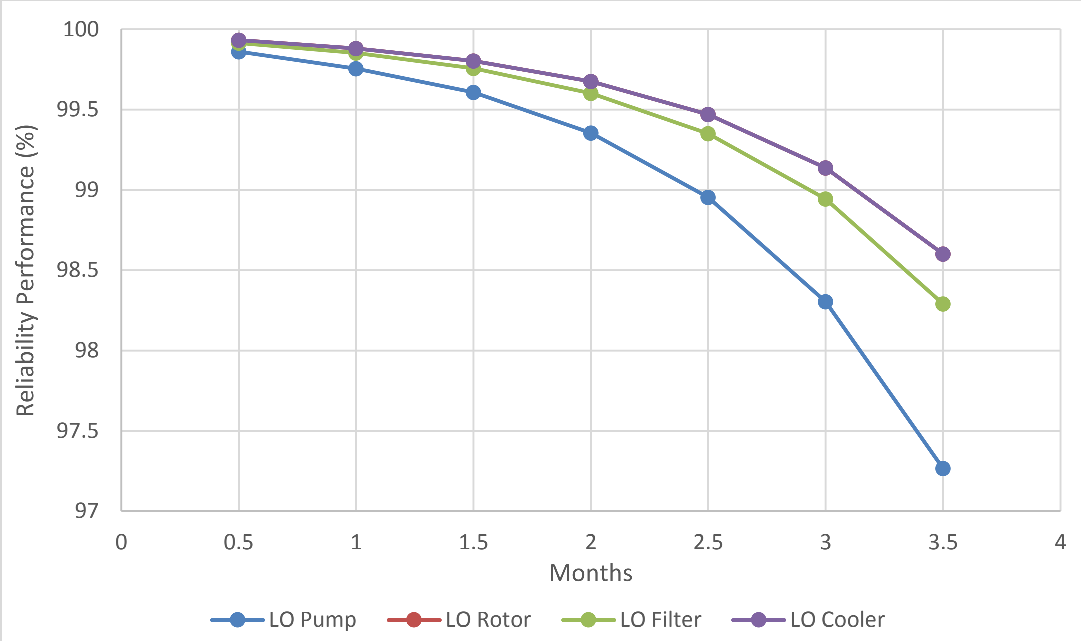

Figure 7.27 Reliability performance of lube oil system – raw data

The lube oil pump subsystem is followed by the filter, which ranges from 99.92% to 99.85% the recorded period of time and from 99.76% to 98.29% the predicted. The lube oil rotor and the cooler present the same reliability performance. Initially, they reached 99.93%, which decreased at 99.88%. This collected information is utilised for predicting the following two and a half months, which presented reliability ranged from 99.88% to 98.6%.

7.3.4. Air supply system

The following system is responsible for the appropriate transfer procedure of clean/fresh air supply within the engine cylinder units by removing and cleaning the exhaust gases. This procedure is known as scavenging. It is essential to clarify that scavenging and exhaust gas control are examined in cooperation of two engine systems, as defined in the PMRA strategy application, the air supply and the cylinders.

This section is oriented towards the reliability assessment of the air supply system, its subsystems and maintainable units and components. Firstly, air supply system consists of piston rings, injectors and manifold relief valves per cylinder and the air piping. Different sources of raw input data are involved in the air supply system such as the scavenging air receiver temperature per cylinder, scavenging air manifold pressure and main engine control air inlet pressure. Another node interconnection is required for the reliability performance assessment of piston rings and injectors by taking into account the cylinder exhaust gas outlet temperature per cylinder in parallel with the scavenging air receiver temperature per cylinder. This measurement input is mainly utilised in the cylinder subsystem, which will be presented next.

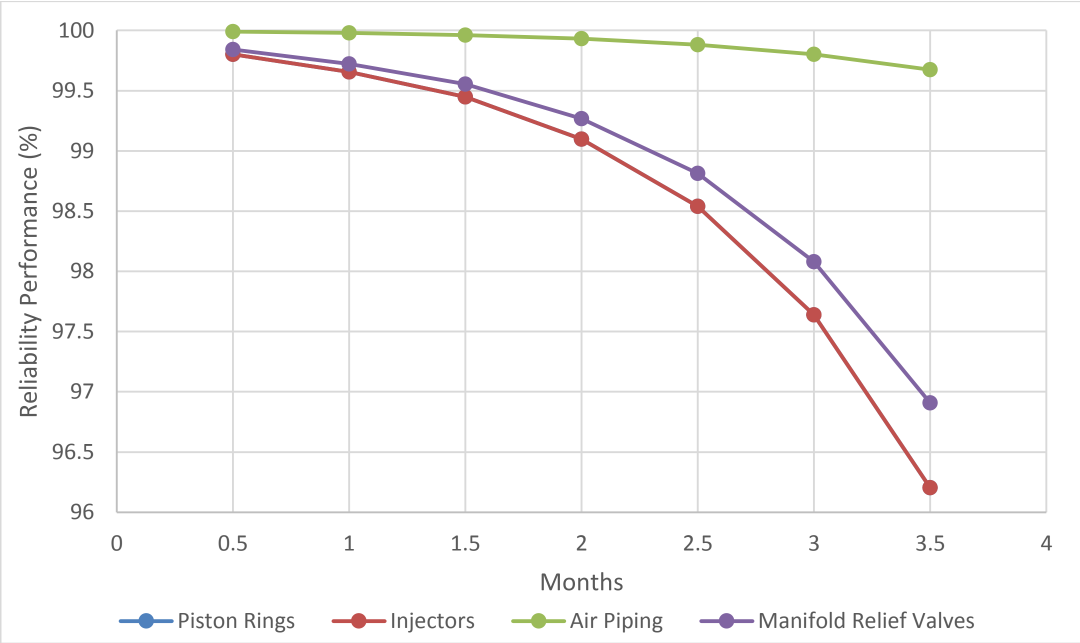

Figure 7.28 Reliability performance of air supply system – raw data

More specifically, Figure 7.28 presents the reliability performance of piston rings, injectors, air piping and manifold relief valves, while data has been recorded as well as the predicted values of the following two and a half months. Injectors and piston rings obtain the weakest reliability performance, which is initiated at 99.8% and dropped to 96.2%. These maintainable components are associated with the scavenging air receiver temperature and cylinder exhaust gas outlet temperature. Manifold relief valves present reliable operation from 99.84% to 96.91% while they are linked with the scavenging air manifold pressure. Lastly, air piping is the most reliable maintainable unit reaching figures from 99.99% to 99.67%.

It is necessary to clarify that all collected raw input datasets fulfil the safety requirements demonstrating reliable functioning without reaching or exceeding the manufacturer's warning levels. However, the datasets of the collected temperature indices increase the second half of the first (recorded) month, whereas the pressure measurements negligibly dropped. The recorded input data for the entire data gathering timeline as well as the predicted indicate reliable operation without the requirement of introducing inspection or maintenance actions. However, it is essential to continue monitoring the piston rings and injectors by ensuring that the presented reliability drop lies within the acceptable limits.

7.3.5. Bearing drive system

The following system incorporates the moving/rotating bearings, which are responsible for the motion transfer to the propeller. Bearing drive system consists of the thrust bearing, intermediate shaft bearings 1-3 and camshaft bearings (i.e. aft and fore). Due to their function of maintaining rotational motion, the control of suitable operational temperature ensures the appropriate reliable role by preventing malfunctions, overheating, material tear and wear and entire component collapse.

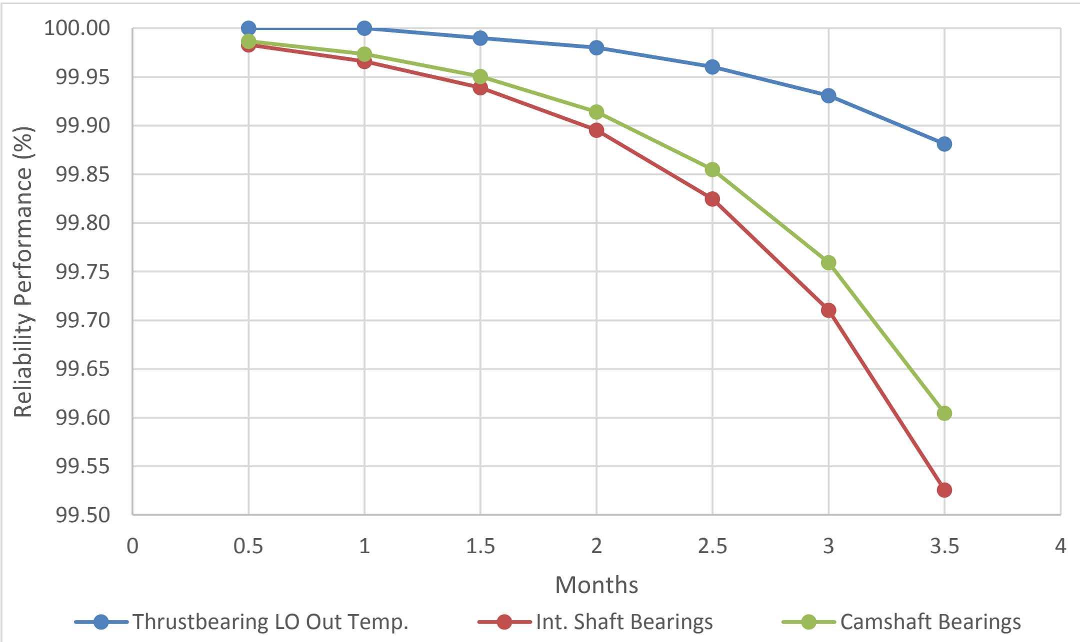

Figure 7.29 Reliability performance of bearing drive system – raw data

Therefore, the introduced raw input data requirements involve the thrust bearing lube oil outlet temperature, intermediate shaft bearing temperature (per bearing from 1 to

3) and the camshaft bearings' temperature monitoring. According to the PMRA strategy acquired results, as presented in Figure 7.29, the intermediate shaft bearings obtain the lowest reliability performance from 99.98% to 99.53%. These figures denote the performed reliability, while data was collected as well as the forecasted for the following two and a half months. The camshaft bearings range performance from 99.99% to 99.6%, whereas the thrust bearing from almost 100% to 99.88%.

All of the considered bearings indicate reliable operation by retaining almost stable temperature. Slight increase is presented causing negligible reliability drop, however the recorded and predicted figures ensure functioning lower than the predefined safety thresholds. It is essential to denote that among the weakest intermediate shaft bearings, the second bearing acquired the highest predicted temperature (lowest reliability), followed by the first and third bearing respectively. Clearly stating that all three bearings perform below the alarm points allowing undistracted operation for the predicted period of time.

7.3.6. Cylinders

The final arrangement of maintainable units and components can be assumed as system and it is known as cylinders. PMRA strategy application involves an eight cylinder, 2-stroke marine diesel engine. Therefore, raw input data measurements are collected per involved cylinder. More specifically, cylinders system consists of units such as cylinder 1 to 8. Each of these units integrates input from the particular cylinder exhaust valve, injector and piston rings.

Functional and crucial interconnection among different nodes is utilised in the case of cylinders by incorporating input from maintainable units (i.e. piston rings and injectors) of air supply subsystem. This option of flexibly arranging the network and combining input among every required node is gained by the implementation of the Bayesian Belief Networks (BBNs). In particular, injector and piston rings nodes are associated with scavenging air receiver temperature and cylinder exhaust gas outlet temperature. On the other hand, exhaust valves are connected with the involved cylinder exhaust gas outlet temperature.

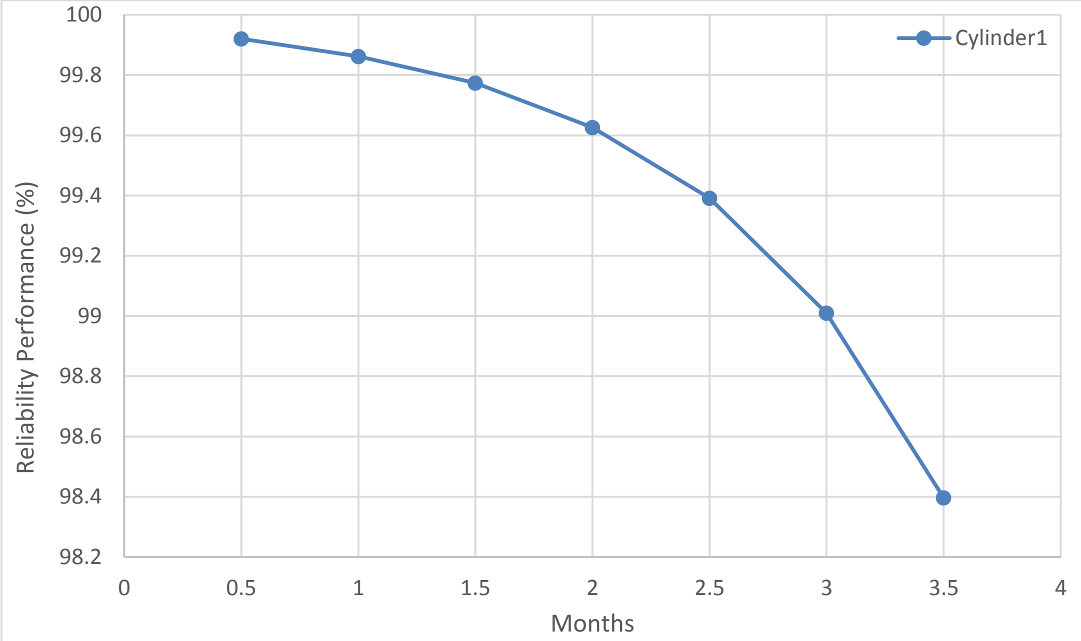

Figure 7.30 Reliability performance of cylinder 1 – raw data

As shown in Figure 7.30, the reliability performance of cylinder 1 is demonstrated for the involved marine diesel main engine. It is essential to highlight that the acquired results present almost the same reliability performance in the entire timeline, while gathering the raw data as well as in the predicted time segment for all involved cylinders. The acquired results show initial reliability performance at 99.92%, which is dropped at 99.86% during the data gathering period of time. In the following predicted timeline, the reliability varies from 99.77% to 98.4%.

The uniformity of the cylinders' results has to be explored further, in order to identify common aspects of the collected datasets. In Figure 7.31, the exhaust gas outlet temperature per cylinder is provided. More specifically, the average, maximum and deviation figures of temperature datasets per cylinder are presented. The plotted curves declare uniformity in pattern of the dataset characteristics. Therefore, each dataset per cylinder seems to perform similarly to the remaining as the maximum, average and deviation values denote.

It is worth mentioning that according to the main engine manufacturer manual the maximum acceptable cylinder exhaust gas outlet temperature is at 500°C, whereas the alarm is set at 520°C. According to Figure 7.31, the maximum reached temperature is found on cylinder 8 at 361°C, which is much lower than the maximum acceptable and the predefined alarm. Therefore, the collected data as well as the acquired predictions lead to slow steaming operation in order to reduce fuel consumption and the sailing speed (approximately service speed is at 18 knots).

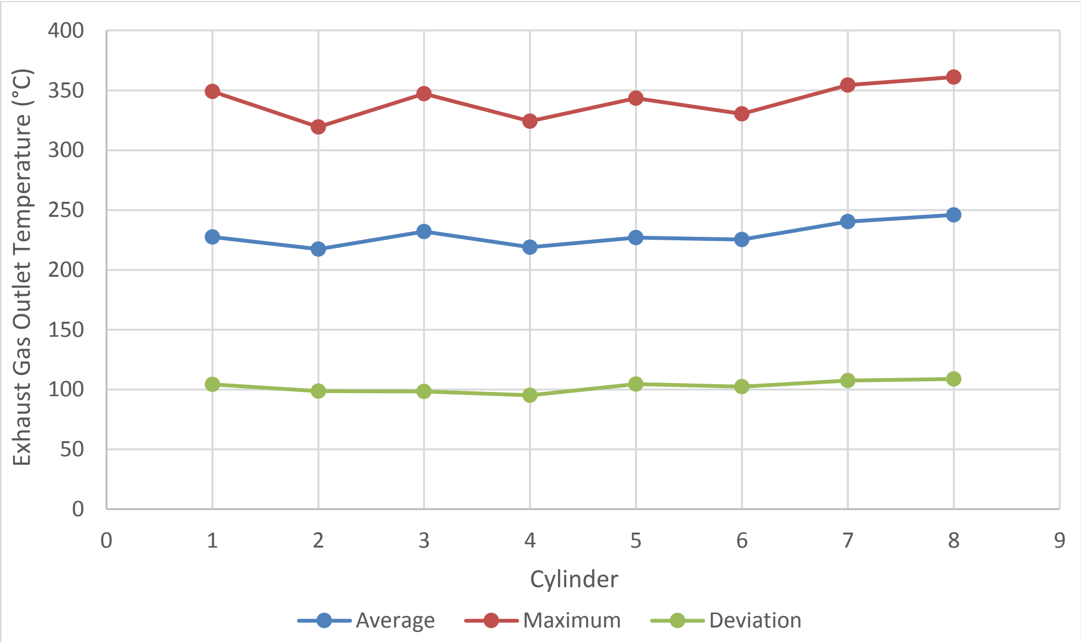

Figure 7.31 Cylinder exhaust gas outlet temperature – raw data records

7.4. Chapter summary

In this Chapter, the results of the case studies are presented. Two groups of case studies are performed involving different input data types, data gathering sources and various offshore application and ship machinery. The demonstrated and analysed results of the performed case studies are grouped among the processed input and the raw input reliability assessment respectively. In the first case study and the involved group of systems, processed input data is utilised exported by the OREDA database. This source of data is selected because it incorporates failure records as gathered by leading industrial stakeholders of the oil and gas field combining expertise and records since the first published OREDA handbook in 1984.

On the other hand, the selected systems share common structural and functional aspects as some of the installed systems onboard the merchant ships. The OREDA-based systems selected for the scope of this case study involve the 4-stroke engines, turbocharger and various pumps. The reliability assessment achieves performance predictions on system, subsystem and component levels by taking into account various recorded failure modes. More specifically, this case study implements the initial technical aspects of reliability prediction tool of PMRA such as the time dependent state modelling by employing the Markov Chains (MC) and the reliability network arrangement of Bayesian Belief Networks (BBNs). The second case study introduces raw input data collected onboard a Panamax container ship, while operating in actual sailing conditions. The scope of this case study is to assess the overall suggested Probabilistic Machinery Reliability Assessment (PMRA) methodology. The reliability performance predictions in this case study utilise systems such as the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and the cylinders.

The reliable and accurate performance of the suggested PMRA strategy has been validated utilising various commercial software. Firstly, the BBN's predictive feature has been assessed with GeNIe 2.0 and Hugin software. The results demonstrate exactly the same reliability performance as these obtained by the PMRA strategy. On the other hand, the time dependencies modelled by the Markov Chains combined with the DBBN have been tested by employing Reliability Workbench software. The tests undertaken obtained the same results; therefore, the reliability assessment tool has performed accurately according to leading software and applications in the field.

8. SENSITIVITY ANALYSIS

8.1. Chapter outline

The robust PMRA methodology has been presented in the previous chapters providing a flexible solution in predicting the reliability performance of ship machinery. The acquired reliability performance predictions indicate acceptable reliability performance in all involved systems, subsystems and maintainable units and components. The collected raw input data and predicted reliability performance prove reliable function as the obtained results vary within the acceptable operational levels as predefined by OEMs. However, it is essential to explore and prove that the suggested PMRA strategy performs efficiently under different operating conditions, which are also important for the testing process of the developed methodology. In this context, a detailed sensitivity analysis is performed presenting the level of change in the predicted reliability performance, when there is change in the provided input data. The results of this study examine the flexibility in input data deviation, ensuring accuracy in prediction and safety in operation.

8.2. Description of sensitivity analysis process

The sensitivity analysis and methodology testing are challenging tasks, because they involve modelling of complex ship machinery which consist of various subsystems, components and maintainable units. Therefore, testing the compound suggested inspection and maintenance strategy requires the implementation of specific sensitivity case scenarios which are applied on particular ship machinery. Even when a model or methodology is tested and validated uncertainty in the acquired predicted reliability performance results still exists (Baio and Dawid, 2015). Hence, in this section Sensitivity Analysis (SA) scenarios are introduced in order to quantify and qualify the uncertainty underlying the forecasted results acquired in the previous chapter.

According to Saltelli et al. (2004), in risk assessment research, SA is defined as the study which examines “how uncertainty in some model output can be apportioned, qualitatively or quantitatively, to different sources of uncertainty in the model input”.

Literature offers various techniques and scenarios in order to examine the sensitivity of risk assessment tools. Particularly in the case of Bayesian Belief Networks (BBNs), Parmigiani (2002) recommends three forms of SA such as marginalisation, scenario analysis or Deterministic Sensitivity Analysis (DSA), and Probabilistic Sensitivity Analysis (PSA). Marginalisation is the process whereby a selected part of the recorded dataset is shifted towards particular limits by reaching or exceeding these. Therefore, this SA process examines the flexibility of the developed methodology in introducing partial deviation of the utilised input data. In other words, marginalisation enhances predominantly a phenomenon by which a subset of the overall dataset is increased, decreased or excluded (deviation of subset). This SA approach examines specific performance states in order to determine particular reliability forecasted results.

The following SA approach is the scenario analysis, which is also known as Deterministic Sensitivity Analysis (DSA). In this assessment concept, the developer selects values and scenarios, where the methodology is evaluated by acquiring expected results. According to Parmigiani (2002), this procedure is simple to be implemented when the number of parameters involved is relatively small as well. The third SA approach considers all involved parameters as random quantities, which tests the methodology while enabling different repetitive simulations. This is a useful testing method, however randomisation of the involved parameters eliminates the probability of controlling uncertainty as long as factors are selected in an arbitrary order. In this Chapter, the SA scheme performed for testing the PMRA strategy is presented employing assessment aspects and features from the DSA and the marginalisation approaches. The major benefit of marginalisation and DSA approaches is that they enable the strategy testing for specific operational profiles (cases and scenarios) by simulating conditions that can be observed in actual sailing states. These SA approaches are oriented towards specific assessment scenarios, which simulate probable operational cases of the utilised ship equipment.

8.2.1. *Selecting the base ship machinery case*

The implementation of an analytical and effective SA examining all involved complex ship machinery is impractical and almost impossible as these include the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and the cylinders. This ship machinery takes into account a complex structure incorporating various nodes which denote many subsystems, maintainable units and components and associations among them. This complex structure makes SA a challenging task. Therefore, the implemented SA has to be performed on a particular component or maintainable unit, which will allow efficient and effective testing enabling the input data adjustments as required and will be demonstrated next.

An essential component for achieving the ship sailing functioning is the thrust bearing, which permits rotation between parts, while they are designed to support predominately axial load. The thrust bearing (also thrust block) is placed right after the ship Main Engine (M/E) as shown in Figure 8.1 and transfers the thrust from the propeller to the hull of the ship. Therefore, it has to be solidly manufactured, assembled and mounted on a solid frame to perform its task by withstanding normal and shock loads. According to Hyundai-MAN (2010b), due to the friction in the thrust bearing, the shaft power is approximately 1% less than the effective engine power. As stated by McCarthy (2006), thrust bearings are difficult to dismantle for inspection and maintenance activities, while their improper functioning will lead to wasted power due to friction. Hence, the friction will result in overheating the moving thrust bearing elements.

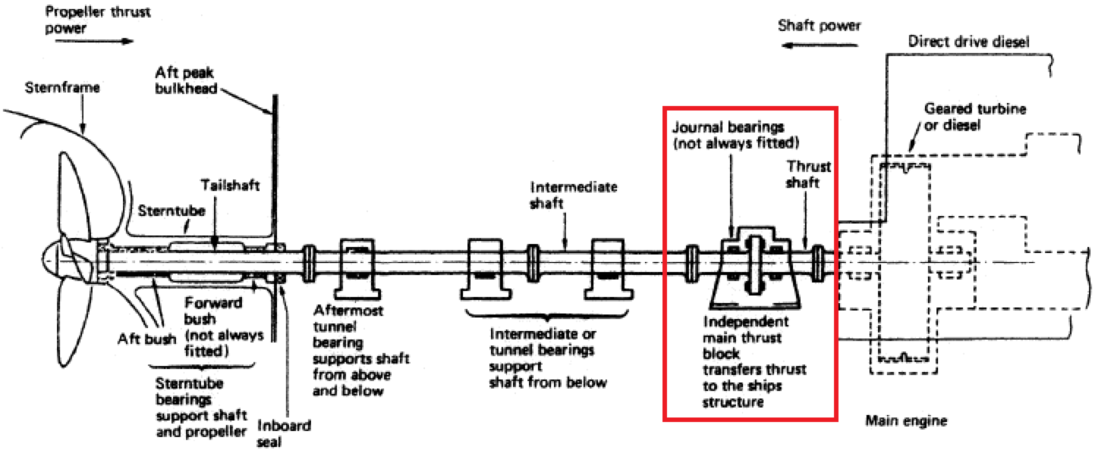

Figure 8.1 Ship shaft transmission layout engine to propeller (Taylor, 1996)

Additionally, as shown in Figure 8.1, various bearings are installed between the Main Engine (M/E) and the propeller such as the thrust bearing, intermediate or tunnel bearings to support the shaft from below, aftermost tunnel bearing to support the shaft from above and below and the sterntube bearings to support the shaft and the propeller. In regards to access for overhauling or partial dismantling, the casing consists of two halves (i.e. upper and lower/fixed) which are joined by fitted bolds. An oil scraper/skimmer removes the oil from thrust collar and directs it to the pad stops, whereas the oil level indicator displays the lube oil state and quantity by preventing unexpected lube oil leakage (Figure 8.2).

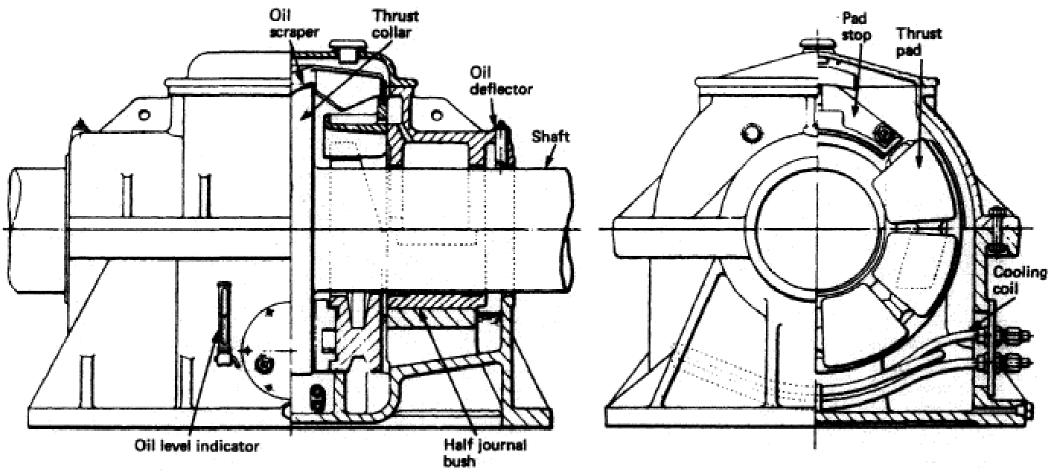

Figure 8.2 Thrust block (Taylor, 1996)

In this respect, PMRA network arrangement incorporates the bearing drive system, which consists of three intermediate shaft bearings, two camshaft bearings (i.e. aft and fore) and the thrust bearing as shown in Figure 8.3. For each of these maintainable units an hourly interval raw data is gathered. More specifically, the thrust bearings' suitable condition can be ensured by monitoring the lube oil outlet temperature. In other words, the lubrication of the component confirms the adequate cooling of the moving parts that this consists of. Therefore, proper bearing lubrication prevents overheating, which will consequently lead to material wear and tear of the inner and outer races and the rotating elements. Accordingly, the condition monitoring of the thrust bearing, taking into account lube oil outlet temperature measurements, ensures efficient functioning. Therefore, efficient functioning of the thrust bearing will eliminate or delay the necessity for inspection through overhauling by decreasing the probability of human error during dismantling. As a result, the entire detailed SA will be carried out by taking into account the thrust bearing component. Raw lube oil outlet temperature measurements were collected, while a Panamax container ship was sailing in actual operational conditions. This dataset and its acquired reliability predicted results are utilised as reference points for further SA.

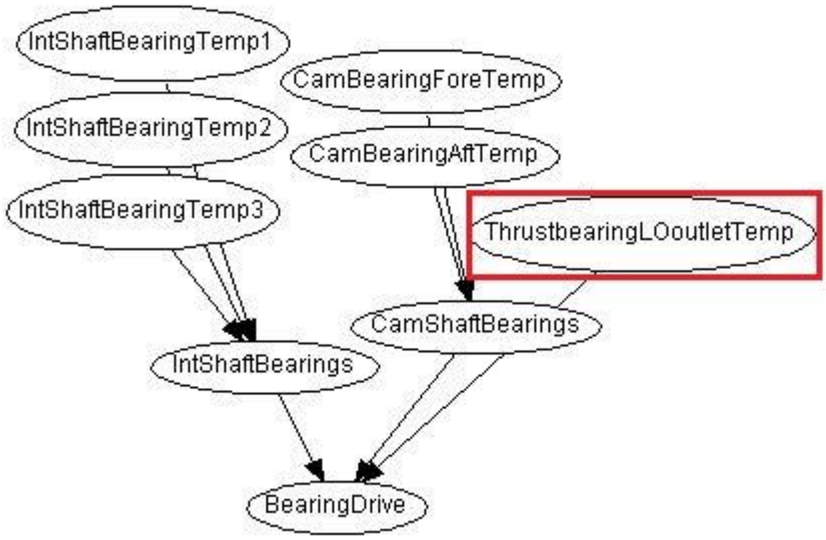

Figure 8.3 Selection of maintainable unit for sensitivity analysis (sample of network demonstrated in Chapter 6)

8.3. Deterministic Sensitivity Analysis (DSA)

Overall, PMRA strategy has been applied in two groups of case studies such as the processed and raw data respectively. Especially in the case of the raw data case study, all ship systems, subsystems and maintainable units and components achieve acceptable reliability performance in the data gathering and predictive period of time as well. It is essential to highlight that none of the systems or components reached or exceeded the predefined OEM's safety thresholds.

In this section, an analytical deterministic sensitivity analysis scheme is demonstrated taking into account different operational scenarios. The entire approach considers the raw data as baseline of further assessment. Moreover, the developed scenario analysis is applied by adjusting the raw dataset simulating actual operational conditions that may lead to failure or malfunctioning of the thrust bearing. The objectives of this sensitivity analysis are listed below:

- Examine the suggested PMRA strategy and its ability to process data and perform predictions that differ from the existing raw data
- Assess the forecasted reliability performance and provide indicative measurement conditions that will lead to unreliable predictions
- Investigate unreliable data states by utilising unhealthy input data while performing simulations through PMRA strategy

8.3.1. Assessment of gradual temperature increase

In order to examine various operational scenarios while controlling uncertainty and adjusting appropriately the raw dataset, a specific data modification plan has to be introduced. This SA scheme employs the actual raw dataset of the thrust bearing, which is named real-data (i.e. refers to initial ship measurements). The real-data is incremented by 10% in each iteration until the forecasted results illustrate a fully unreliable state (reaching almost 0% predicted reliability performance). The scenario cases are denoted as real-data increased by the particular percentage (i.e. real +10%, real +20% etc.).

First of all, it is essential to highlight that various testing and verification iterations have been carried out of increasing increments at 1% and 5%. Hence, it has been noticed that in these cases, the reliability performance predictions have not been affected, therefore no failures or malfunctions have been identified. More specifically, in cases of increment 1% and 5%, there is no deviation in the acquired predicted results. This stable predicted state confirms reliable operating condition of the thrust bearing, because real-data are a lot lower than the defined alarm/warning point. According to the testing cases undertaken, the following decided plan involves scenarios of real-data increase by +10%. This attempt intends to examine the input data deviation associated with the acquired predictions. The implemented DSA cases are listed in Table 8.1 below and performed for reasons that will be explained analytically in this section.

Table 8.1 Cases of implemented Deterministic Sensitivity Analysis (DSA)

No	**DSA Case**	**Result Description/Remarks**
1	real-data (reference point)	collected onboard, reliable state
2	real +10%	stable performance, reliable state
3	real +20%	stable performance, reliable state
4	real +30%	stable performance, reliable state
5	real +40%	stable performance, reliable state
6	real +50%	minor deviation, reliable state
7	real +51%	partially unreliable state
8	real +52%	partially unreliable state
9	real +53%	partially unreliable state
10	real +54%	excessive unreliable state
11	real +55%	excessive unreliable state
12	real +56%	fully unreliable state
13	real +57%	fully unreliable state
14	real +58%	fully unreliable state
15	real +59%	fully unreliable state
16	real +60%	fully unreliable state
17	real +61%	fully unreliable state

As shown in Table 8.1, seventeen DSA cases have been introduced for testing the predictive reliability performance of PMRA strategy and the methodology itself. Initially, it is important to clarify that the timeline has been divided into three state sections (segments). The first one involves the first month of data gathering, the second segment the first predicted month and the third section the second predicted month. These segments of time will be used to define the remarks of Table 8.1.

- **Stable performance**

This description refers to the performance (current and predicted), which has been obtained identically the same for all involved DSA cases. Minor reliability drop is assumed as stable performance (i.e. from 100% to 99.88%). It has been identified only in fully reliable state cases (reliable states in current and predicted timeline).

- **Reliable state**

It denotes the reliability performance, which has been acceptable (below threshold) for the entire timeline. In other words, no failures or malfunctions are obtained or predicted.

- **Minor deviation**

A negligible reliability drop has been identified, compared to previous cases (below threshold, small deviation).

- **Partially unreliable state**

This state denotes to both existing and forecasted states. Partially unreliable means that degradation and unreliable figures have been acquired in the predicted timeline only. The higher the temperature increase the faster the reliability drop.

- **Excessive unreliable state**

The entire predicted timeline (both forecasted months) have been within the unreliable range, below the alarm/warning threshold.

- **Fully unreliable state**

This state describes entirely unreliable performance for both existing and forecasted timeline sections. In other words, failure measurements have been recorded in the data collection period of time. More specifically in Figure 8.4, the reliability performance of the thrust bearing is demonstrated in increasing intervals of 10% up to 61%. The real-data refers to the initial dataset as collected onboard, while the ship was sailing. This dataset consists of indices *i*, which in total are 696 (measurement/data points). This process involves the escalation by the particular percentage of each recorded data point (i: index) within the overall dataset (origin of real-data).

As shown in Table 8.2 below, the thrust bearing presents identical reliability performance utilising the real-data as well as in the cases of 10% up to 40%. This similarity in the acquired results occurs due to low operational thrust bearing lube oil outlet temperature, which leads to reliable predictions. On the other hand, negligible deviation of the obtained results is presented in the case of 50%, where 10% reliability drop is forecasted at the end of the second predicted month of functioning. At this state, it is essential to highlight that 10% reliability drop in actual operational conditions is not minor decrease. The DSA plan involves 10% increment of the real-data, it has been noticed 87% reliability drop from real-data +50% to real-data +60%. Therefore, the 10% reliability drop for the cases real-data +40% to real-data +50% is denoted regarding the SA scheme as minor or negligible.

The timeline involves monthly intervals. The first month (points 0.5 and 1) refers to the data collection time, whereas points 1.5 to 3 denote the following two predicted months.

Table 8.2 DSA reliability results (%) for cases real-data +10% to +40%

Months	**real-data**	**real +10%**	**real +20%**	**real +30%**	**real +40%**
0.5	100	100	100	100	100
1	99.99	99.99	99.99	99.99	99.99
1.5	99.98	99.98	99.98	99.98	99.98
2	99.96	99.96	99.96	99.96	99.96
2.5	99.93	99.93	99.93	99.93	99.93
3	99.88	99.88	99.88	99.88	99.88

On the other hand, negligible deviation of the obtained results is presented in the case of 50% as shown in Table 8.3, where 10% reliability drop is forecasted at the end of the second predicted month of functioning. The following level of sensitivity investigation involves increase at 60% of the existing real data. In this case, the reliability drop is immediate, which starts at 80.9% and decreases down to 2.19%

(analytical values will be presented next). Due to this excessive reliability drop, further SA investigation has been carried out in intervals of 1%, between the cases of 50% and 60%. This detailed assessment explores the reliability drop and PMRA strategy performance in gradual sensitive (as it is narrowed at 1%) real-data increase.

The scenario analysis of the demonstrated outcomes indicates gradual/continuing reliability degradation, while the lube oil outlet temperature has been increased. Therefore, the first intermediate scenario above 50% examined involves 51% increase of the initial real-data temperature. Therefore, additional cases have been obtained such as real +51% to +53% as presented in Table 8.3, in order to identify the gradual reliability decrease in smaller increasing intervals of temperature (1% interval).

Table 8.3 DSA reliability results (%) for cases real-data +50% to +53%

Months	**real +50%**	**real +51%**	**real +52%**	**real +53%**
0.5	99.3	98.1	96.8	95.5
1	98.59	96.19	93.59	90.99
1.5	97.20	92.53	87.59	82.79
2	95.82	88.99	81.97	75.33
2.5	93.13	82.33	71.79	62.36
3	89.23	73.26	58.84	46.96

The examined DSA cases of real +51% to +53% demonstrate a gradual reliability drop, where unreliable input data have not been utilised yet. However, experimentally it has been confirmed that reliability performance below 80% incorporates unreliable data. This statement of the reliability threshold will be clarified in case the analytical discussion of real +56% next. Therefore, case real +51% is the first scenario, which associates unreliable prediction in the third month (73.26%). Gradually, this reliability drop to unhealthy states has been transferred to earlier predicted points in the timeline. More specifically, real +52% presents the second forecasted month to be unreliable as in real +53% case as well.

Table 8.4 DSA reliability results (%) for cases real-data +54% to +55%

Months	real +54%	real +55%
0.5	94.6	93.4
1	89.21	86.82
1.5	79.75	75.52
2	71.14	65.56
2.5	56.72	49.51
3	40.34	32.45

In cases such as real +54% and real +55% (Table 8.4), excessive unreliable state has been identified. As defined above, the entire predicted period of time has been in unreliable state. However, the data collection time (months 0.5 and 1) consists of reliable measurement below the warning threshold.

Table 8.5 DSA reliability results (%) for cases real-data +56% to +61%

Months	real +56%	real +57%	real +58%	real +59%	real +60%	real +61%
0.5	90.9	88.7	85.9	82	80.9	76.1
1	81.86	77.48	72.17	64.28	61.95	53.37
1.5	67.28	60.27	52.82	41.64	38.52	29.24
2	55.07	46.69	38.11	26.76	23.86	15.60
2.5	37.05	28.14	20.13	11.14	9.19	4.56
3	20.40	13.14	7.67	2.98	2.19	0.71

In Table 8.5, the cases of real-data +56% up to 61% have been shown. It is essential to clarify that real +56% is the first examined scenario, which involves in the recorded input data unreliable measurements. More specifically, 22 out of 696 (total size of dataset) unreliable measurements have been incorporated by increasing the real-data. The first two reliability processed points at plotted positions 0.5 and 1 reach 90.9% and 81.86% respectively. These two points denote the reliability performance of real-data, while it is increased by 56% for the first month of the data gathering period. As long as real-data +56% is the first dataset, which includes unhealthy points, performance at 90.9% and 81.86% (which is not predicted yet) defines the percentage threshold at almost 80%. In other words, reliability performance lower than 80% ensures recorded data points at 90 °C or higher.

Table 8.6 DSA cases number of unreliable data points

Case	**No of data points ≥ warning level @90 °C**
real +56%	22 out of 696
real +57%	69 out of 696
real +58%	70 out of 696
real +59%	70 out of 696
real +60%	71 out of 696
real +61%	114 out of 696

More analytically, the major reliability drop, in cases where the current data are unreliable as well, has been identified in cases real-data +56% to +61%. In Table 8.6, the number of data points (in the data collection time) above the warning level at 90 °C have been presented for the cases real-data +56% to +61%. Summarising the presented results of the developed DSA scheme, Figure 8.4 presents all involved scenarios assessed above. All previous examined scenarios from real-data up to real-data +55% of temperature (inclusive) are processed, while consisting of healthy recorded data points. However, the reliability drop of these scenarios indicates unhealthy predicted conditions in states of lower than 80% performance. Moreover, scenario analysis from real-data up to real-data +55% demonstrates the steady and progressive drop from healthy to unhealthy and unreliable predicted states. It is essential to clarify that the first two points in timeline (points 0.5 and 1) denote the recorded input data, whereas points 1.5 to 3 the predicted ones.

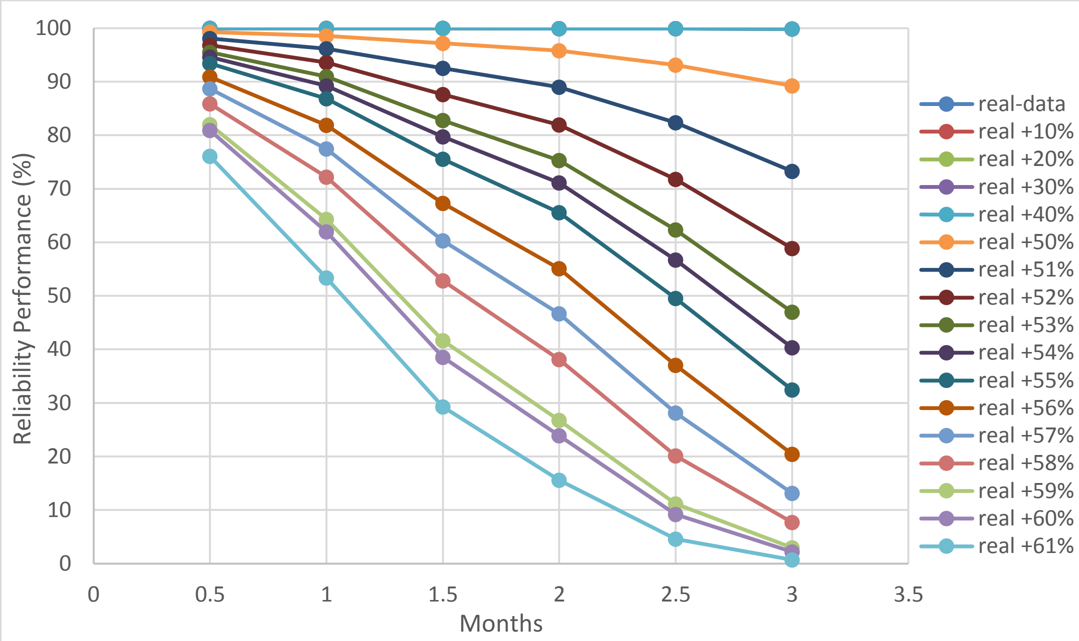

Figure 8.4 Incremental scenario analysis of thrust bearing

Summarising, the key finding of this sensitivity analysis scenario scheme includes the following:

- PMRA strategy is capable of processing reliability performance predictions by considering raw data
- Deterministic sensitivity analysis proves the capability of PMRA strategy to process successfully various datasets incorporating healthy and unhealthy data points
- The suggested DSA approach verifies the PMRA strategy in processing datasets, while confirming degradation of the reliability performance in increasing intervals of 1% and 10% of the involved temperature measurements
- According to existing real-data and the DSA scheme performed, temperature increase up to +50% indicates reliable operation for the entire predicted period of time
- For sensitivity scenarios of 51% to 53% (temperature increase) signs of unreliable predictions have gradually appeared, particularly in forecasted figures lower than 80% of reliability
- Implementation of unhealthy input data points has been taken place, where PMRA strategy has successfully detected these

Except of the PMRA strategy testing, the sensitivity analysis practically determines the flexibility level in deviating of the initial raw data. Therefore, it demonstrates the reliable, partially reliable and fully unreliable cases by providing a DSA for an early warning assessment.

8.3.2. Comparative assessment of gradual temperature increase

The idea of increasing the recorded real data, in order to examine reliable and partially reliable and gradually reliable states is demonstrated in Figure 8.5 and examined in this section. More specifically, this section employs a colour-coded approach. Three dataset states/scenarios are illustrated below including:

- Real-data (blue curve)
- Real-data +50% (green curve)
- Real-data +51% (red curve)

These case scenarios have been selected to be compared and discussed, because they present the most sensitive predicted states. They demonstrate the transition from the reliable state modelling to the gradually unreliable as real +51% case obtained the first unreliable performance in the second predicted month. The intermediate scenarios (i.e. 10% to 50%) are demonstrated and discussed analytically in the previous section. However, there is not particular interest in these cases as they present almost stable reliability performance. The idea deliberates the continuous input data increase by retaining similar data features, while ensuring the overall uniformity with the actual recorded dataset. Continuing increase of the real-data will lead to illustration of the implemented 52% to 61% (as discussed previously). Therefore, Figure 8.5 illustrates the thrust bearing lube oil outlet temperature scenarios analysis.

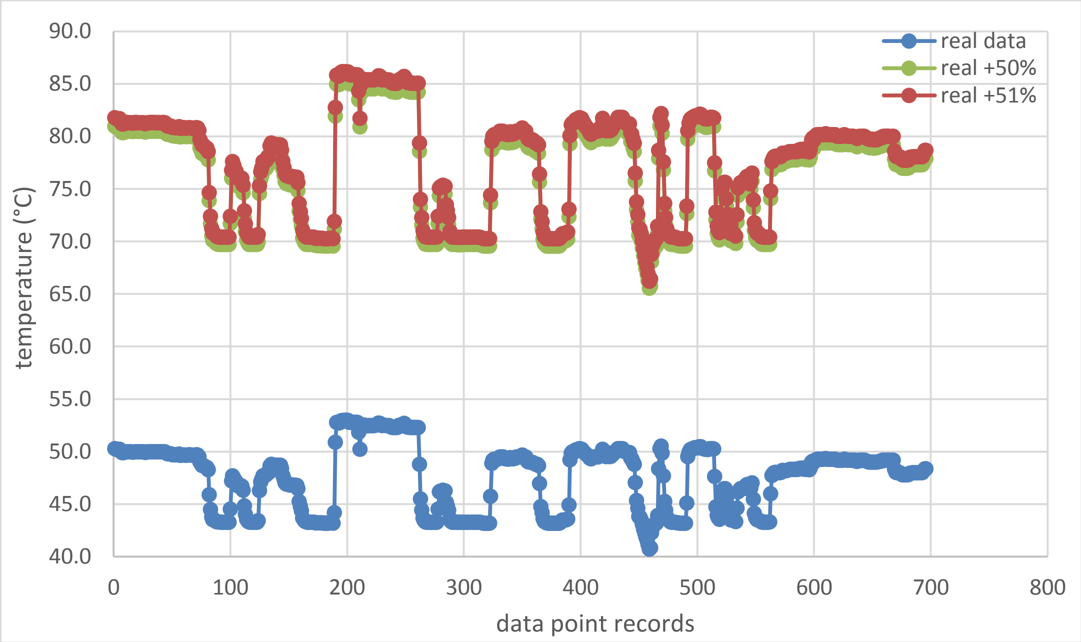

Figure 8.5 Thrust bearing lube oil outlet temperature scenarios analysis

In the plotting arrangement below as well as in Figure 8.5, the green curve demonstrates the scenario analysis of the real +50%, whereas the red curve the real +51%. These dataset present the most sensitive performance due to transition from the reliable state to the partially reliable. Comparatively, Figure 8.6 presents the reliability performance of all involved bearings incorporated into the bearing drive system. Therefore, aggregated reliability performance of the camshaft bearings (aft and fore) and the three intermediate shaft bearings have been introduced. These components (camshaft and intermediate shaft bearings) have been demonstrated in an aggregated format, because the PMRA SA examines the reliability performance of a single component as defined above (i.e. simplicity and flexibility in testing and modelling).

The components involved in the bearing drive system include the camshaft bearings (aft and fore), intermediate shaft bearings (1 to 3) and the tested thrust bearing for the scenarios of real-data +50% and 51% respectively. In Figure 8.6 below, the reliability performance of the camshaft bearings and the intermediate shaft bearings demonstrate almost identical predictions at 100% because they employ the real-datasets per component. These rea-datasets include temperature measurements a lot lower than the warning thresholds, hence predictions are almost perfect.

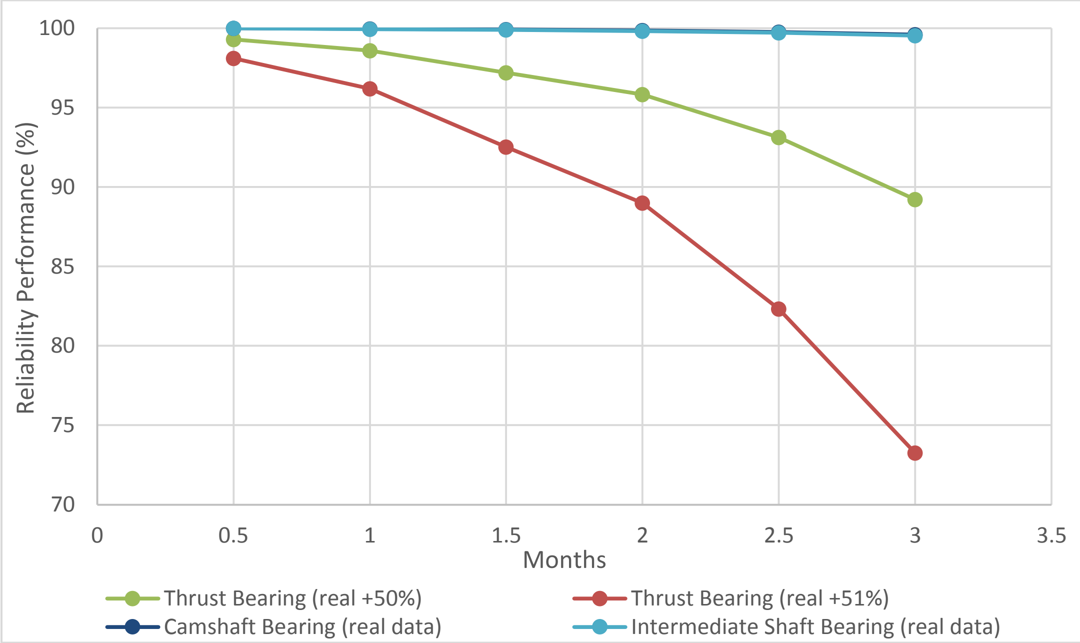

Figure 8.6 Reliability performance of various bearings and scenarios

The results of the unreliable thrust bearing presented in Figure 8.6 illustrate the gradual reliability performance drop, while the temperature is increased. Therefore, it summarises and confirms the fundamental notion that the lower the temperature the more reliable condition of the component is.

As presented in Chapter 6, the PMRA bearing drive system includes components such as the camshaft bearings (aft and fore), three intermediate shaft bearings and the thrust bearing. The following figure below examines the overall system reliability performance, while one of the involved components has declined performance due temperature increase. In this particular case, all of the bearings utilise the actual real-data, whereas the thrust bearing employs the sensitive defined cases of real-data +50% and +51% respectively. In other words, this study examines the reliability performance on system level, while one component presents degraded performance.

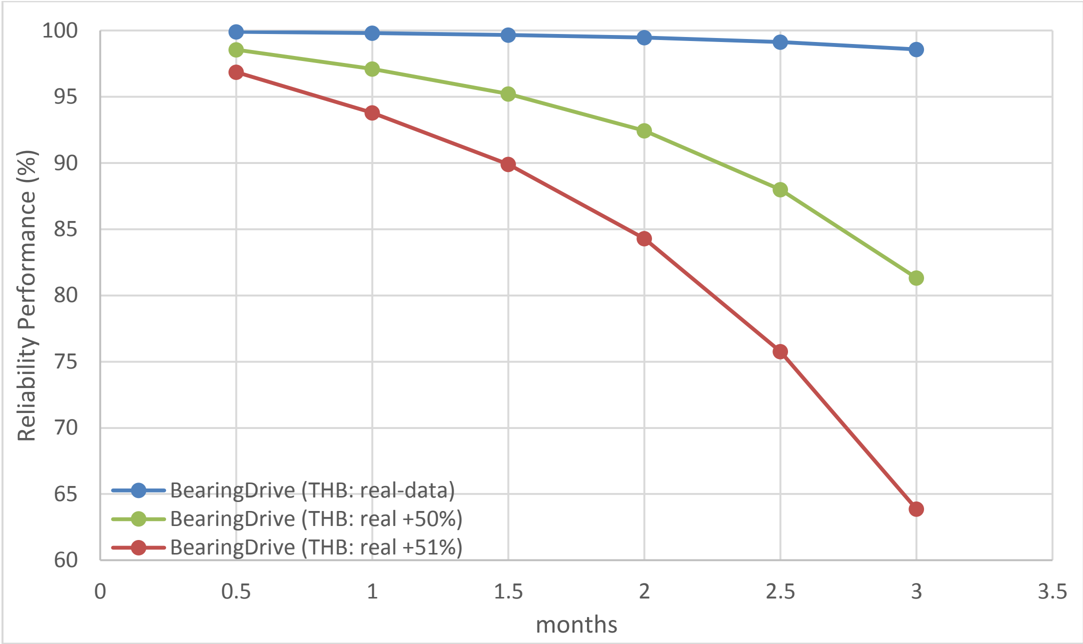

Figure 8.7 Reliability performance of bearing drive for different thrust bearing scenarios

Additionally, Figure 8.7 encompasses the reliability performance on system level, while introducing different scenarios of the Thrust Bearing (THB). Three reliability conditions of the bearing drive system are shown by taking into account the actual collected data of the camshaft bearings (aft and fore) and threw intermediate bearings. On system level, the fundamental notion stated above is confirmed as well, the lower the temperature, the higher the reliability performance is.

8.4. Marginalisation Sensitivity Analysis (MSA)

As stated above, marginalisation is the sensitivity analysis process, which examines the flexibility of the developed methodology by implementing partial deviation of the utilised input data. This deviation can be achieved by increasing or decreasing particular subsets/groups of data within the dataset in order to move data points towards predefined limits (such as the safety thresholds) by reaching or exceeding these. On the other hand, marginalisation can be implemented by excluding a particular subset of the dataset.

This SA approach examines specific performance states in order to determine particular reliability forecasted cases. In this section, two cases of Marginalisation Sensitivity Analysis (MSA) are presented by taking into account both options. The involved MSA cases that will be demonstrated next in Table 8.7.

Table 8.7 MSA introduced approaches

MSA approach	**Description**
1. MSA of increasing selected input subset	Examine the reliability performance of the thrust bearing by deviating (increasing) a particular subset of the real-data
2. MSA of excluding selected input subset	Investigate the prediction accuracy of the suggested PMRA strategy by utilising two subsets of the overall dataset

8.4.1. MSA of increasing selected input subset

More specifically, the first case investigates the reliability performance of the thrust bearing in three different operational levels. As dataset base line, the real +50% is employed, because it is sensitive enough to demonstrate unreliable states (reliability performance lower than 80%). In Figure 8.8, the input data of the three involved cases is demonstrated. Firstly, the real data increased by 50% is shown (real +50% in blue) and the real +51% (green). It is important to prompt that each dataset consists of data points *i* (*i*: stands for index or data point) having length of 696 recorded points. The newly introduced case incorporates aspects of both real +50% and real +51% cases and is denoted as real +50% (@ i:191-262 real +51%).

More analytically, the real-data has been increased by 50%, where a particular subset (index i: 191-262) has been increased by 51%. This subset is selected as it obtains the highest recorded figures within the data gathering timeline. Therefore, marginalisation of this group of points aims to investigate the importance of data population in different operational cases.

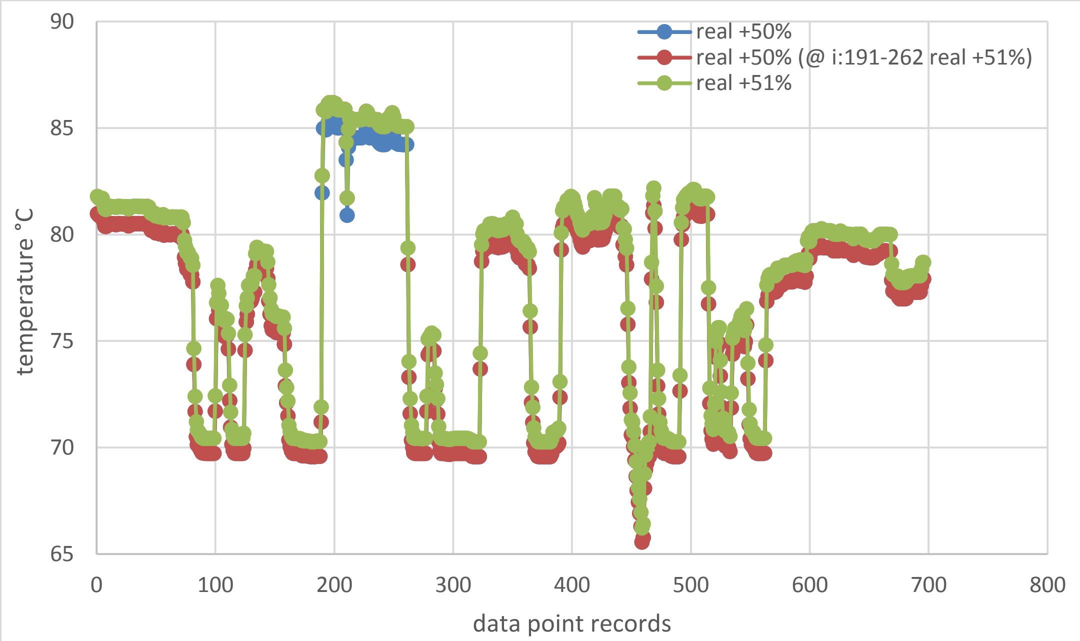

Figure 8.8 Thrust bearing lube oil outlet temperature MSA

In Figure 8.9, the acquired reliability performance results are presented for the three involved operational cases. The highest reliability for the recorded and predicted period of time is presented by the real-data +50% case (blue curve). The outcomes illustrate expected performance as the utilised dataset (real-data +50%) consists of the lowest temperature measurements among the involved plotted scenarios.

On the other hand, the lowest reliability performance among the plotted scenarios in Figure 8.9 is shown by the real +51% case (green curve). This case utilises the highest temperature records within the overall employed dataset. Hence, reliable functioning is shown up to the second month, whereas initiation of unreliable performance (82.3% and 73.3% respectively) in the third month.

An intermediate case is presented with the red curve, where the entire dataset has been increased by 50% and a subset (@ i: 191-262 real +51%) of the overall dataset includes increased values by 51%. Therefore, these MSA cases prove the capability of PMRA strategy to process reliably various datasets, while there have been partial or overall input modifications and changes. This is important point in the implementation of PMRA strategy, because the current methodology enables flexibility in assessing various scenarios without consideration of introducing code or method changes.

On the other hand, this study proves that the reliability has been affected by the population of the unreliable data points. In the case of real +51%, more data points have been increased reaching the safety/warning threshold than in the case of the real +50% (@ i: 191-262 real +51%) as the predicted results confirm. In conclusion, it has proven that the more the recorded data is, the more reliable the predictive performance will be. In other words, the population of the gathered input data has significant impact to the obtained results.

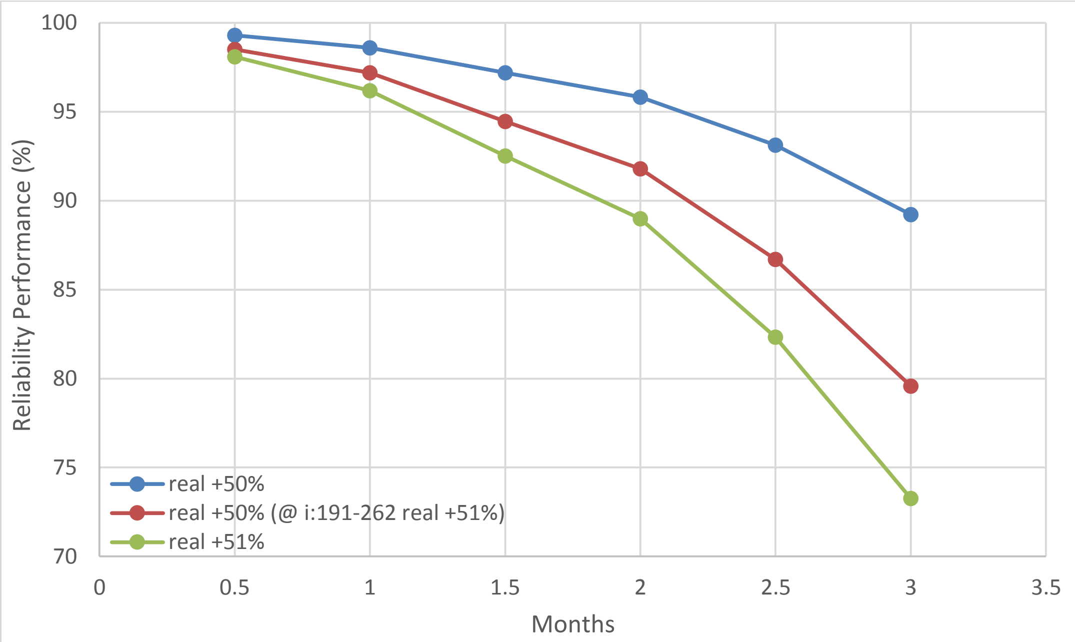

Figure 8.9 Thrust bearing MSA reliability performance

Before proceeding to the following MSA case study, it is necessary to clarify that the involved datasets such as the real-data +50%, +51% and +50 (@ i: 191-262 real +51%) have been processed into monthly intervals. Therefore, the entire dataset of the 696 data points has been considered as one set of records and has been utilised for acquiring the particular predictions. As shown in Figure 8.10 below, the data gathering process has been initiated at record point 0 and ended at point 696. All these data records illustrate almost a month of processing. This dataset processing arrangement has been utilised for real-data +50%, +51% and +50 (@ i: 191-262 real +51%) case scenarios.

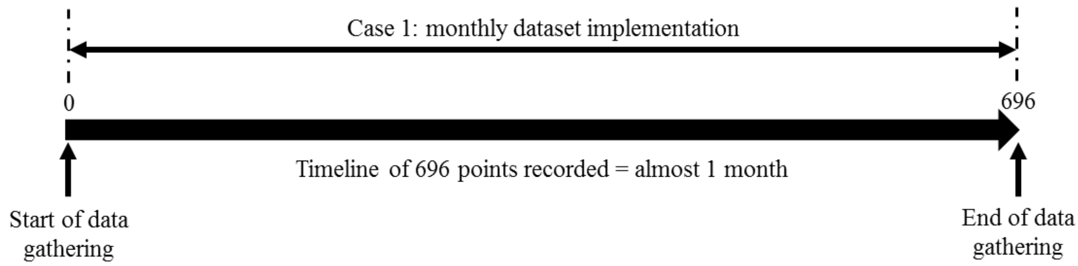

Figure 8.10 MSA increasing subset scenario processing of monthly intervals

8.4.2. *MSA of excluding selected input subset*

The following study implements the Marginalisation Sensitivity Analysis (MSA) in order to verify the predictive accuracy of the suggested PMRA strategy. More specifically, the real-data has been amended by +50% for this study. In the previously presented sensitivity assessment studies, the input data has been processed in monthly intervals by utilising the overall hourly recorded 696 data points (almost a month). However, in this study the dataset is split in two parts as shown in Figure 8.11 as input data subset (a) and (b) respectively. Part (a) involves the first half of the hourly recorded dataset (i.e. 348 data points or two weeks), whereas part (b) the second half of the real-data +50% case. This decision has been made attempting to prove the reliability performance prediction accuracy. Therefore, the idea of this case scenario is to acquire predictions of input data subset (a) and compare them with the results obtained of subset (b). According to the results obtained in the previous SA, the higher the dataset population the more accurate the predictions are. Hence, splitting the collected dataset in two subsets, it can be assumed that the data will achieve higher prediction accuracy than in splitting in three or more subsets.

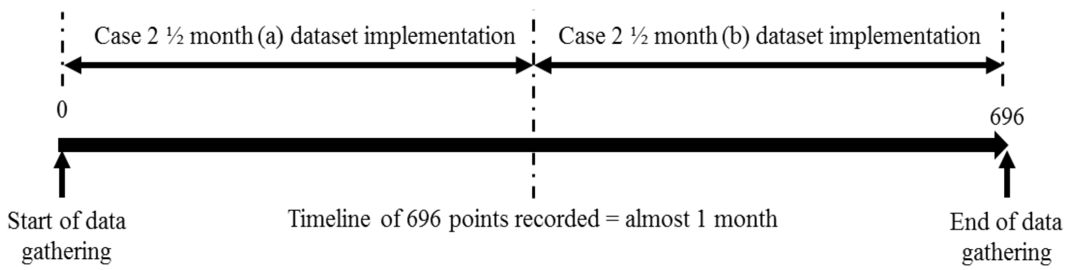

Figure 8.11 MSA excluding subset scenario processing of half monthly intervals

This study aims to examine the accuracy of PMRA strategy forecasting the reliability performance. More specifically, the predicted results acquired by the PMRA strategy of real +50% (a) are compared to the results obtained by the real +50% (b) subset of input data. Therefore, the first stage of this comparative case scenario is to separate the real-data +50% in two equal subsets. Each of these subsets has been processed by PMRA strategy independently and their results have been compared.

Figure 8.12 demonstrates the reliability performance results for real-data +50% (a), whereas, Figure 8.13 for the real-data +50% (b). It is essential to mention that the case scenario demonstrated in Figure 8.12 employs the subset (a) and excludes from processing the subset (b), and vice versa for Figure 8.13. In regards to the reliability performance curves (blue and red), it is essential to highlight that real-data +50% (a) initiated earlier in the timeline as it refers to the first half of the recorded data. Hence, real +50% (a) initiates at point 0.25 (1/4 of a month), whereas part (b) at point 0.75 (3/4 of a month).

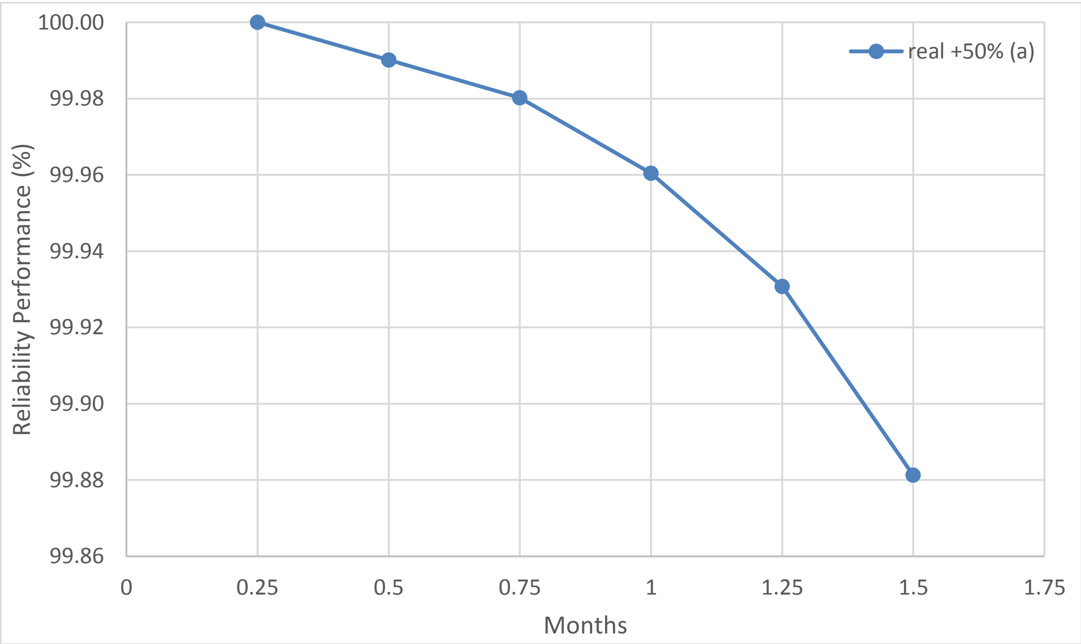

Figure 8.12 Thrust bearing MSA excluding case scenario involving subset (a)

The first two points of the reliability curves in the timeline (0.25, 0.5 and 0.75, 1 respectively) demonstrate the reliability performance of the recorded period, whereas the following points show the predicted values (description provided in Table 8.8).

The comparative study takes into account the points in timeline/x-axis 0.75, 1, 1.25 and 1.5 among the real-data +50% (a) and (b) subsets. In the case of real-data +50% (a) subset (blue curve), these reliability figures represent predicted reliability performance, which utilised input from the 0.25 and 0.5 points.

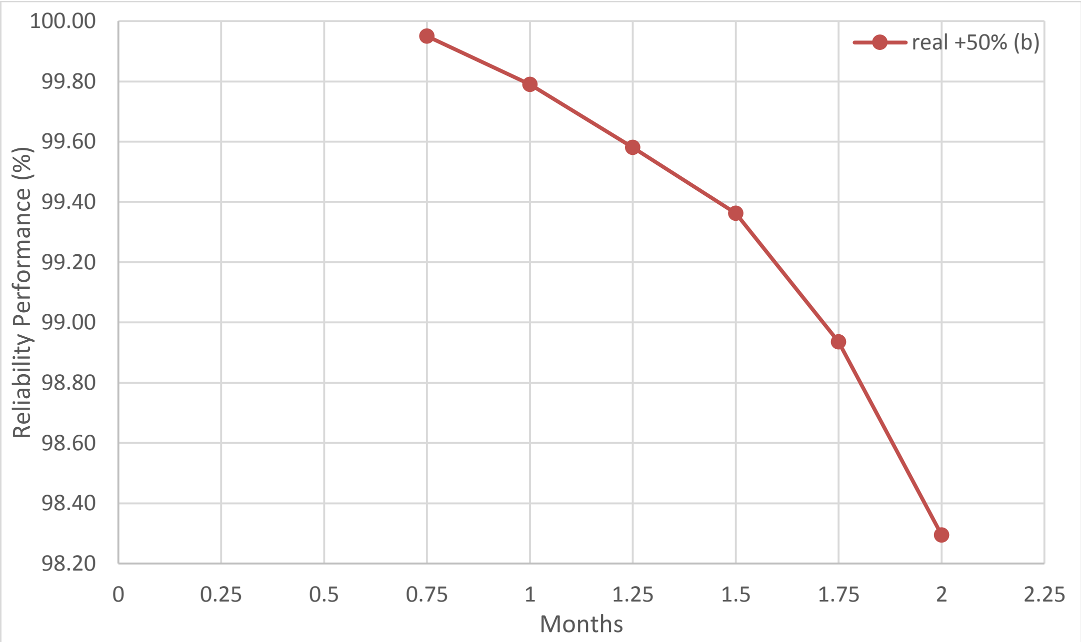

Figure 8.13 Thrust bearing MSA excluding case scenario involving subset (b)

On the other hand in regards to subset (b), points 0.75 and 1 in timeline illustrate the reliability in data gathering period of second half of the recording month. Additionally, points from 1.25 to 2 (months) in the timeline illustrate the upcoming predictions arising from the processing states of 0.75 and 1. The prediction error among the involved datasets is represented in the table below. The predictive error is reasonably low for the entire forecasted timeline, which indicates error of maximum 0.52% at the end of the second predicted month. The plotted values in Figure 8.12 are analytically clarified in Table 8.8. In conclusion, the presented predictions comparing subset (a) and (b) identify non-sensitive results for the entire forecasted period of time as the maximum error has been calculated at 0.52%.

Table 8.8 Thrust bearing verification through MSA reliability performance

Month	real +50% (a)	real +50% (a) State	real +50% (b)	real +50% (b) State	Error
0.25	100.00%	current	-	-	-
0.5	99.99%	current	-	-	-
0.75	99.98%	predicted	99.95%	current	0.03%
1	99.96%	predicted	99.79%	current	0.17%
1.25	99.93%	predicted	99.58%	predicted	0.35%
1.5	99.88%	predicted	99.36%	predicted	0.52%
1.75	-		98.94%	predicted	-
2	-		98.29%	predicted	-

8.5. Chapter summary

In this Chapter, a detailed sensitivity analysis is performed in order to present the performance of the developed PMRA strategy under different input configurations. A description of the SA process is provided by investigating and selecting the base ship machinery for introducing the SA scheme. The assessment implemented deterministic (scenario) and marginalisation sensitivity analysis practices in order to investigate the performance of the suggested strategy under various ship operational states. A verification modelling approach confirmed the accurate predictive capabilities of the suggested inspection strategy. In conclusion, it is essential to clarify that sensitivity analysis of compound condition monitoring strategies, while utilising complex ship machinery is a challenging task. Therefore, it is believed that similar testing modelling approaches have to be introduced in larger extend certifying the forecasting capabilities in different operational states.

9. DISCUSSION AND RESEARCH CONCLUSIONS

9.1. Chapter outline

In this Chapter, the overall discussion and review regarding the innovative PMRA strategy is presented in the following sections. Furthermore, the novelty of the performed research work and the suggested PMRA strategy is demonstrated. The contribution of this research to theory and practice is highlighted and the accomplishment of research aim and objectives is summarised. Lastly, the research assumptions undertaken into this study are listed contributing towards the implementation of the suggested PMRA strategy.

9.2. Review of the overall thesis

The present research has elaborated on the subject of reliability assessment of inspection and maintenance in offshore oil and gas and more specifically in the maritime transportation mode. The thesis has been initiated by presenting in Chapter 1, the background of maritime industry and increasing seaborne trade demand for transportation of various types of commodities. Through recorded historical accidents in the oil and gas and maritime sector, some lessons have been learnt, which prioritise the importance for further research and development towards safer seaborne transportation. The establishment of the research aim and objectives have been addressed in Chapter 2 by identifying the study goals for the upcoming research thesis.

Once the industrial requirements have been investigated and the research objectives defined, the following step is to scrutinise existing studies performed. This assessment is achieved undertaking a thorough and critical literature review, presented in Chapter 3, on inspection and maintenance in both academic research and industrial practices. The examined and presented critical literature review is divided in six major sections.

The first one (§3.2) overviews the maintenance strategies into major categories such as corrective, preventive, predictive and proactive approaches. The second section presents the significance of precise and well-planned inspection and maintenance practices through maintenance guidelines and regulations (§3.3). Extensive investigation in regulatory bodies such as British Standards (BS) and International Organization for Standardization (ISO), International Maritime Organization (IMO) and International Association of Classification Societies (IACS) is taken place in regards to machinery maintenance.

The outline of maintenance implementation in various industrial sectors is demonstrated in the third section of the critical literature review (§3.4) through methods such as Reliability Centred Maintenance (RCM), Total Productive Maintenance (TPM), Total Quality Management (TQM), Risk Based Inspection and Maintenance (RBI and RBM respectively), Condition Based Maintenance (CBM), Computerised Maintenance Management System (CMMS) and the holistic approach of Asset Management (AM). The advantages of the lately introduced methods such as CBM, CMMS and AM set the ground for further research and development towards the establishment of a novel and flexible inspection and maintenance strategy in maritime industry.

Therefore, the fourth section of the presented literature review (§3.5) evaluates the most-known and broadly applicable Condition Monitoring (CM) technologies such as vibration monitoring, thermography, lubrication oil analysis, visual inspection and acoustic/ultrasonic monitoring. Furthermore, monitoring diagnostic and prognostic applications are demonstrated by taking into account research and commercially available condition monitoring systems. Additionally, the fifth section of the literature review (§3.6) identifies and examines the major Condition Monitoring (CM) functionalities and the available commercial applications. The CM functionalities are classified among diagnostics and prognostics, whereas, leading software applications and industrial solutions are reviewed.

Having examined the above, the sixth section (§3.7) assesses the state-of-the-art of the maintenance optimization tools, signal processing, failure and risk analysis as well as decision-making methods from various researchers highlighting strengths and weaknesses to develop accurate CM strategy tools. In this section, different qualitative and quantitative approaches have been presented such as Artificial Neural Networks (ANNs), Expert Systems (ES), fuzzy logic and Evolutionary Algorithms (EAs). Additional, signal processing and optimisation methods assessed include different applications of Fourier Transforms (FT).

On the other hand, risk of failure identification and analysis methods has essential impact into this research by considering tools such as Failure Mode and Effect Analysis (FMEA), Fault Tree Analysis (FTA), Dynamic FTA (DFTA), implementation of Markov Analysis (MA) and the lately introduced Bayesian Belief Networks (BBNs). Decision-making is the final stage of the CM framework. This phase aims to suggest inspection and maintenance actions by prioritising critical systems, subsystems, components. In this subsection, a variety of methods have been assessed consisting of Analytical Hierarchy Process (AHP) and Rough Set (RS) among others.

The critical literature review concludes by identifying the latest research and development direction. Hence, this review identifies the research and development tendency for ship machinery inspection and maintenance. Brief critical outcomes of this review include aspects such as holistic view of ship machinery, data fusion (i.e. various sources), flexibly developed predictive reliability assessment and implementation of decision making features. These technical characteristics are utilised for structuring the proposed maintenance strategy, targeting to accomplish the predefined aim and objectives.

As long as the identification of research gaps and development direction with respect to inspection and maintenance of ship machinery is demonstrated the foundations for Chapter 4 are allocated. The proposed Probabilistic Machinery Reliability Assessment (PMRA) strategy is established by introducing the employed data analysis algorithm and reliability assessment tool. At first, an introduction into data mining field takes place outlining methods, which allow to extract information from a data set and transform it into an understandable structure for further use. The development of PMRA strategy takes place on different levels initiated by introducing the principle aspects of the suggested strategy. The model development continues by selecting the appropriate methods and tools leading to the overall establishment and proposal of PMRA strategy.

The implementation of the proposed PMRA takes place at two levels of application. These applications are separated in case studies and presented in Chapters 5 & 6 respectively. First of all, Chapter 5 includes the demonstration of case study of the primary developed dynamic reliability assessment tool as part of PMRA strategy. This case study employs processed data and introduce the Markov Chain (MC) for elaboration of the time dependences (i.e. dynamic state modelling) and establish the Dynamic Bayesian Belief Networks (DBBNs). Multiple independent main systems are considered such as the Engine, Turboexpander and various pumps. This case study contribute towards the research and development of the network arrangement by investigating various features and techniques of programming flexibly and efficiently in Java Object Oriented Programming (OOP) language. Additionally, the case study introduced in Chapter 5 sets the grounds for the overall PMRA strategy that will be presented next.

In Chapter 6, the second stage of PMRA strategy implementation takes place involving a holistic study of the entire suggested methodology. This case study considers all data processes, methods and techniques of PMRA strategy such as the data acquisition, data clustering and safety threshold implementation, reliability assessment and initial qualitative aspects of decision making. The current study utilises raw data such as temperature and pressure gathered from actual ship machinery operational conditions. Henceforth, this study intends to evaluate the entire PMRA strategy in regards to working state reliability performance predictions by employing real functioning figures. The structure of the developed PMRA strategy network consists of various raw data measurements, maintainable units and systems that the input data affects. Moreover, subsystems and maintainable units incorporate ship systems such as the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and cylinders.

The above case studies are analytically presented and assessed related to the obtained results in two major subsections of Chapter 7. The first subsection involves the processed data case study, whereas the second the raw data. Each subsection is concluded by critically presenting the outcomes and the benefits gained out of the study. In Chapter 8, a detailed Sensitivity Analysis (SA) is performed resenting the level of change in the predicted acquired results, when there is alteration in the provided input data. This SA has been introduced due to multiple reasons. First of all, the raw data gathered as well as the forecasted figures declare almost stable reliability performance, because the ship was functioning in slow steaming condition. Therefore, an analytical assessment has been introduced to confirm the accurate and efficient predictive capabilities of PMRA strategy. The performed SA applies marginalisation and Deterministic Sensitivity Analysis (DSA) scenario assessment. The results of these studies examine the flexibility in input data deviation, while ensuring accuracy in prediction.

9.3. Novelty of presented research

The novelty of the presented research comes from the developed PMRA strategy, and the ability of assessment that is accomplished in its implementation. First of all, the critical literature review is performed through a detailed analysis approach where various inspection and maintenance aspects of different industries are examined. The presented research review is oriented towards three sectors such as the evaluation and critical assessment of academic/research achievements, industrial and commercial applications and practices as well as the latest standardisation reports from leading international regulatory bodies. Therefore, the presented critical literature review has vital impact on theory and practice too. It examines strategies, methods, practices and tools by involving technological aspects such as hardware and software as well.

On the other hand, the developed PMRA strategy introduces a variety of novelties in regards to processing techniques, practical and modelling features and flexibility in implementation. Firstly, PMRA strategy achieves reliability performance assessment of ship machinery beyond diagnostics by establishing prognostic reliability state modelling. The suggested strategy recommends an individual methodology for inspection and maintenance of ship machinery. PMRA strategy integrates the assessment of the reliability performance of various onboard installed machinery provided by different manufacturers and suppliers. Therefore, this is a novel solution to combine and process information from various systems targeting a holistic view of the reliability and safety on board the ship.

Another novel feature of the suggested maintenance strategy is the utilisation of raw data for performing reliability predictions. Furthermore, an innovative data analysis and processing algorithm have been introduced for pattern recognition, which creates the ground for time-dependent (dynamic) state modelling. PMRA strategy embeds an accurate and flexible reliability assessment network arrangement for predicting the reliability performance of selected ship machinery. Additionally, this assessment takes place in an adaptable manner on system, subsystem and component level, while allowing the investigation of root cause assessment and failure interaction through the establishment of system/subsystem/component functional interdependencies.

In conclusion, various data sources such as historical, expert and raw data have been combined in the different levels of PMRA implementation. Moreover, the benefits of qualitative and quantitative assessment have been integrated in PMRA strategy gaining from the features of both. Lastly, it is essential to highlight that overall PMRA strategy consists of processing stages such as data selection, data clustering, safety index implementation, time-dependent modelling, predictive reliability assessment and lately fundamental aspects of decision making. All of these stages are adaptable and flexibly modelled allowing further investigation, testing, research and development.

9.4. Research contribution

Condition Based Maintenance (CBM) also known on-condition assessment has direct impact to industrial applications as plethora of commercial practices confirm. However, this on-condition assessment requires implementation of sophisticated processes, methods and tools. Therefore, CBM practices as the suggested PMRA strategy have direct contribution to theory and practice.

The thesis has presented a dynamic probabilistic assessment strategy for predicting the reliability performance of ship machinery. In particular, a novel strategy has been developed integrating benefits and aspects of data selection and collection, data mining methods such as k-means (Lloyd algorithm), dynamic state modelling by Markov Chains (MC), reliability assessment by Dynamic Bayesian Belief Networks (DBBNs) and decision making through Failure Modes and Effects Analysis (FMEA). Overall, qualitative and quantitaive input data types have been utilised same as assessment practices (i.e. FMEA and DBBN respectively). Lastly, sensitivity analysis has been obtained applying Marginalisation Sensitivity Analysis (MSA) and Deterministic Sensitivity Analysis (DSA), techniques suitable for testing Bayesian Belief Networks (BBNs).

The application of PMRA strategy is tackled in two cases studies, which consist of different systems. The first case study incorporates systems such as 4-stroke engine, turbocharger and various pumps, which sourced from the offshore oil and gas industry. More specifically, OREDA database provided reliability and failure records on system and component level by taking into account various failure modes. This case study introduced principal technical aspects of PMRA such as the time-dependent modelling and the reliability assessment through network arrangement. The second case study utilised raw data gathered onboard a Panamax container ship, while sailing in actual operational conditions. This study has been applied on the fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and cylinders systems. Overall, PMRA strategy aims to assist onboard crew members and operators in regards to past, current and future reliability performance. The establishment of this robust strategy directs decision makers and ship machinery operators towards safer ship functioning by deciding on necessary inspection and maintenance actions.

9.5. Accomplishment of research aim and objectives

The scope of this research is to contribute towards theory and presents actual/practical applications in regards to offshore platform oil and gas and ship machinery reliability performance predictions. The theoretical contribution is confirmed by implementing sophisticated algorithms, methods and tools, while improving the knowledge in the industrial and practical field. In this section, it is essential to summarise the objectives that were defined in Chapter 2 and discuss the progress that led to their accomplishment.

Objective 1: Investigate and critically review the existing maintenance strategies, methodologies and applied approaches in literature by assessing the state-of-the-art of Research and Development (R&D) and industrial/commercial applications and define similarities, advantages, limitations and research gaps

This objective has been achieved by investigating existing and latest maintenance strategies, methodologies, technologies and tools. The overall critical assessment led to identification of research gaps and directions. Thorough and meticulous critical review of the state-of-the-art clarified theoretical and practical requirements. Through this study as shown in Chapter 3, benefits and drawbacks of practices have been investigated, which contributed towards the establishment of the suggested PMRA strategy. In parallel with the theoretical and practical (commercial/industrial) critical review, various international standardisation and regulatory bodies have assisted this study guiding towards the latest CM practices. Through detailed analysis, the necessity for an adaptable predictive CM strategy has been identified suitable for various ship machinery. As maritime industry is undeveloped in the implementation of automated diagnostic and prognostic tools, various major gaps are identified in this industry.

Objective 2: Propose an innovative maintenance strategy for ship machinery by establishing novel data analysis methods as well as reliability assessment modelling

This is achieved by proposing and developing the Probabilistic Machinery Reliability Assessment (PMRA) strategy (Chapter 4). It integrates the advantages of pattern recognition through the employed novel and efficient data mining method. Therefore, raw data are utilised for the reliability assessment. This method is combined with the benefits arise by the implemented reliability tool. The overall PMRA strategy considers the reliability variation through the operational timeline, hence, an innovative and adaptable process has been established dealing with the time-dependencies.

Objective 3: Develop an innovative and adaptable predictive reliability assessment tool for processed data

Extensive research in regards to existing reliability assessment of machinery involves well-known qualitative and quantitative tools such as FMEA, FTA and ETA. These tools are capable in modelling machinery, however they are deficient to model complex systems and inflexible to be adapted if necessary. Therefore, PMRA strategy introduces the innovative and flexible network arrangement offered by Bayesian Belief Networks (BBNs) (Chapter 4). These networks allow the consideration of more systems or any possible adaptation in the assessment if needed. The overall reliability investigation takes place on system, subsystem and component level, while utilising reliability figures such as percentages. BBNs are integrated with the innovative and adaptable Markov Chains (MC). This tool is based on the Markov process and enables transition in time. MC modelling approach is also known dynamic or time-dependent state modelling. The integration of MC and DBBNs is novel in engineering field and particularly in maritime applications. Additionally, it is essential to highlight that the flexibility that both tools offer, enable further research and development by adapting the existing the existing effort.

Objective 4: Propose a methodology for raw data analysis to transform data into probabilistic measures that can be utilised by the developed reliability tool proposed above

So far the majority of the presented research and suggested methodologies utilise reliability assessment methods that employ reliability figures and failure records in the form of percentage. Hence, processed input data incorporates major assumptions. First of all, the input data source's processing methodology is unknown, leading to trust to the data provider. Secondly, the developed methodology relies on the input data source, which leads to dependence to external data processing developers. Therefore, the suggested PMRA strategy leads the CM and reliability assessment beyond the known techniques. It offers and integrates a data mining method for information extraction through the achieved pattern recognition as presented in Chapter 4. Moreover, the implementation of safety thresholds allows the determination of acceptable operational levels as defined by leading stakeholders in the maritime industry. PMRA strategy is oriented towards various systems provided by different suppliers (i.e. main engine, turbocharger and pumps). Therefore, OEMs are suitable as the predefined warning/alarm levels fulfil the requirements of the manufacturers.

Objective 5: Demonstrate the applicability of the developed tools on selected ship machinery by utilising processed as well as raw onboard recorded input data

PMRA strategy has been implemented in two application levels. In the first case as shown in Chapter 5, processed data has been involved extracted by the external data source of OREDA database. The case study carried out on processed data, which refer to reliability figures per system and maintainable unit and components involved. Additionally, failure modes have been recorded and associated with each component (at least one per unit). These studies were applied on offshore oil and gas platform systems such as 4-stroke engine, turbocharger and various pumps, where they share common aspects as these of ship machinery. The major benefits of these studies are incorporated in the development of the time-dependent state modelling approach in parallel to the reliability assessment tool of DBBNs. On the other hand, valuable input technical input has been provided by OREDA, which set the ground for further development.

The second application involves the predictive reliability assessment of various ship systems such as fuel, jacket cooling fresh water, lube oil, air supply, bearing drive and cylinders (Chapter 6). In this case, raw data has been gathered onboard a Panamax container ship, while operating in actual conditions. These studies examined PMRA strategy holistically and forecasted the reliability performance on system, subsystem and component levels. It is essential to highlight that both case study arrangements have been entirely developed in Java Object Oriented Programming (OOP) language. This language selection enables further flexibility in development, while allowing testing of PMRA on any operating system. The result representation and analytical discussion has taken place as well in Chapter 7. According to the acquired results, inspection and maintenance suggestions have been provided exploiting the developed FMEA.

Objective 6: Verify and test the suggested strategy through a Sensitivity Analysis (SA) scheme

This objective has been tackled extensively in Chapter 8. PMRA strategy has been tested, while introducing various input data scenarios. Mainly three sensitivity analysis approaches are explored known as Marginalisation Sensitivity Analysis (MSA) (2 concepts incorporated) and Deterministic Sensitivity Analysis (DSA). These SA methods explored and proved that PMRA strategy performs efficiently under different operating conditions. In this context, a detailed sensitivity analysis is performed presenting the level of change in the predicted reliability performance, when there is change in the provided input data. The results of this study examine the flexibility in input data deviation, ensuring accuracy in prediction and safety in operation.

9.6. Assumptions of the present thesis

In research and development, it is usual that specific assumptions are considered in order to eliminate development errors and problematic modelling as improvement is established gradually. This is the case with the thesis in hand, where some assumptions have been applied. Particularly in the processed data case study (Chapter 5), the applied assumption is related to the reliability performance of the predicted time steps. More specifically, each forecasted time step is associated with the previous one (Markov process). The first plotted point in time (in all figures of Chapter 5) refers to known input data sourced by OREDA and considered as historical record. All the following points denote predicted reliability performance. Therefore, a static historical input point has been utilised for dynamic state modelling (only in Chapter 5 case study). It is essential to highlight that this assumption has been accepted, because the PMRA strategy development was at a preliminary stage of implementing the time-dependent modelling arrangement and the reliability assessment tool.

Additionally, the time-dependent state modelling has been managed by first and second-order Markov Chain (MC) processes. According to Markov process, each time step is associated only to the previous state (i.e. single state MC modelling), whereas in second-order to the previous two time steps. These two modelling approaches assume that older recorded input data is independent to current and future states.

In the raw data case study (Chapter 6), the range of different engine loads, while the ship operates, has been considered within the acceptable operational limits. However, input data has been assumed to refer to sailing and not port conditions. Lastly, as long as a child node in the BBN arrangement has been associated to multiple parent nodes each input has equal contribution to the child node. For instance, in case a child node has two parent nodes affecting it, the contribution is 50% per input. This decision has been made as neutral (equal) weighting factors demonstrate the actual reliability degradation without the implementation of quantitative (subjective) factors. The idea behind PMRA strategy is to eliminate subjective judgment and this has been tried to be applied in all development aspects.

9.7. Chapter summary

In this Chapter, the overall discussion and the research conclusions of the present thesis have been presented. More specifically, a review of the overall thesis has been demonstrated summarising the key points of the performed research. The novelty of PMRA strategy has been highlighted, while the contribution to theory and practice is clarified. Additionally, the Chapter has been concluded by confirming the accomplishment of the proposed research aim and objectives and the discussion of deliberated assumptions.

10. RECOMMENDATIONS FOR FUTURE RESEARCH

10.1. Chapter outline

Notwithstanding the recent improvements achieved in maritime industry, while considering as well the contribution of PMRA strategy, there is substantial space for further research and development. The majority of these improvements can improve the scope of this thesis. However, there are also particular future research plans that further work has to be undertaken in order to improve current achievements. In this Chapter, these improvements and recommendations for future research and development are presented.

10.2. Recommendations and further research activities

The present thesis demonstrates the undertaken research as part of the Probabilistic Machinery Reliability Assessment (PMRA) strategy. This research introduced and established a novel probabilistic predictive reliability assessment tool for inspection and maintenance planning of ship machinery. Overall, PMRA strategy incorporates technical aspects such as data selection, gathering, processing and reliability assessment in time-dependent state modelling. Moreover, the following research areas and improvements can contribute further towards the research and development direction of PMRA strategy.

- In regards to data selection and gathering, the involvement of more data points and measurements have to be considered. The performed sensitivity analysis in Chapter 8 confirms that the population of the recorded data has a major role in the prediction accuracy. On the other hand, the larger the datasets are the more flexible research can be accomplished for training purposes of data classification methods, validation and verification.

- In addition, the main engine load has to be recorded in parallel to all involved performance measurements such as temperature and pressure. This measurement will generate the initiation of a detailed CM reliability assessment tool. The main engine operating profile can be created taking into account the level of the measured load collected. Therefore, correlation among the input data and the engine load can achieve dynamic assessment, where the safety thresholds will be specified according to the engine load range (known as performance profile in literature).
- So far literature related to ship applications and data mining method implementation has been limited. PMRA strategy innovatively established a data clustering method for information extraction and pattern recognition before the reliability assessment level. However, the enlargement of the datasets and the measurement points may require more complicated data mining methods. Therefore, further testing and validation should be necessarily required.
- In addition to the previous point, data fusion and source integration has become a major improvement in technological development and especially shipping industry (known as big data). The selection, collection and processing of big data possibly will require integration of various data extraction algorithms. In other words, combination of methods can potentially lead to accuracy and efficient enhancement.
- In regards to identification of safety thresholds and alarm/warning levels, PMRA strategy employs OEMs as these embed the expertise of manufacturers. However, sensitivity analysis and consideration of additional expert judgment (i.e. operators and onboard crewmembers) can lead to implementation of more flexible safety thresholds than the provided by the machinery suppliers by fulfilling the requirements of the performance profile as suggested above.
- The time-dependencies have been conducted utilising the Markov process. It should be highlighted that this adaptable tool enables the arrangement of more complex chain layouts (i.e. higher than second-order). Nonetheless, the more complex the MC process is, the more programming effort and processing time is required. Therefore, a balanced solution can integrate simpler chain

arrangements, while reliability fulfils safety requirements and adaptation to more complex, if reliability drop exceeds particular levels.

- Bayesian Belief Networks (BBNs) offer flexibility in arrangement, programming and integration to other methods and processing tools. Along these lines, adaptation of the networks can be achieved fulfilling the requirements of additional systems (i.e. modelling of 6-12 cylinder engines, 1-2 turbochargers etc.).
- Decision making tool is a major function of CM systems. The present thesis is oriented towards the technical aspects of CM accomplishing accurately and flexibly reliability performance predictions. Furthermore, an FMEA tool has been developed as part of PMRA strategy for fundamental decision making. An automated decision making tool can be integrated within PMRA utilising the predictions acquired considering the decision features of BBN or any external method such as AHP.

In conclusion as stated in Chapter 1, it is the author's opinion that innovative and automated unified reliability-based practices should be established in maritime transportation mode, aiming at safety enhancement, increasing availability and control of uncertainty, which leads to hazardous consequences. However, control of these factors is a challenging task and requires further research, development and effort.

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APPENDICES

Appendix A – Research and Development Direction

Appendix B – PMRA Strategy British Standards and Supportive Guidelines

Appendix C – PMRA Strategy Data Clustering Methodology Pseudocode

Appendix D – PMRA Strategy Source Code Structure Analysis

Appendix E – Processed Data Source

Appendix F – Raw Data Source

Appendix G – Results of Case Studies

APPENDIX A – RESEARCH AND DEVELOPMENT DIRECTION

Appendix A provides additional information related to Chapter 3 and the performed critical literature review. More specifically, literature research and its critical review are assessed with respect to commercially available software, programmed online platforms and applications and the latest presented research.

Commercially available condition monitoring applications

The considered information demonstrates the commercially available condition monitoring systems and applications. This section outlines benefits, features, characteristics and functions of available industrial software as shown in Table A.1. These features are mostly oriented towards data acquisition, data management, condition monitoring diagnostics, prognostics, decision making, Graphical User Interface (GUI), output extraction to customer/user.

The supplementary provided information in Appendix A.1 summaries contribution in ship machinery condition monitoring by leading stakeholders such as engine manufacturers (MAN B&W, Wartsila), ship owners/ operators (DANAOS) and Information Technology (IT) service providers (Kyma, Laros) as well as software and technology developers and providers (ABB, Kongsberg), Classification Societies (ABS) among others. For the reason that ship machinery condition monitoring is under continuous development in science and industry, the demonstrated investigation sets the grounds for further research and development with respect to technologies, methodologies and functionalities.

Table A.1 Commercially available condition monitoring systems and applications

Manufacturer/ Developer	Name	Description and features	Remarks
ABB	Asset Health Centre (AHC)	• Achieve reliability, performance and compliance goals • Prioritize equipment and/or facilities for repair/replacement • Optimize work force productivity, efficiency and effectiveness • Minimize maintenance and repair costs • Maximize network performance • Reduce risk of asset failure	• An enterprise-wide, end-to-end asset health management solution enables utilities to align business strategy and tactics
AD TEK Pte Ltd. Singapore Jotron Consultas AS Consultas Maritime Software Solutions	CONSULTAS	• Assist and support the crew with typical ship management tasks onboard • Sending selected reports to shore offices for further processing on a fleet level • Built-on an SQL platform the database contains a rewrite of previous solutions	• Connecting ships and shore offices • Bridge the gap between the maritime and IT industries • Fleet management software • Applicability on 3D hull arrangement • C-Maintenance function: graphical timeline view of previous, current and future maintenance plan • Calendar and running hour intervals considerations • Fixed monthly maintenance plan • C-budget function: support for periods of month, quarter and year
American Bureau of Shipping (ABS)	ABS-NS (NS5 Enterprise)	• Modules in software: Maintenance Manager, Drydock, Hull Inspection & Maintenance • Fleet management software available for class and operational functionality • Handles functions of operational management and maintenance, supply chain, workforce, environmental and safety • Tracking and purchasing inventory, evaluating costs and overdue jobs, conducting audits and managing additional assets without increasing staff • Maintenance manager involves preventive maintenance plan, asset hierarchy, incorporate manufacturers' specifications, generate technical and cost reports, open counter use of calendar, running hours, fuel consumption, data collected by users, readings from specialists from 3rd party software can be imported manually • Drydock module provides a standardized method for drydock planning, budgeting and document preparation across an entire fleet	• Achieve enhanced efficiency and promote cost effectiveness • Introduce KPIs, diagnostics and real-time operating information • Minimize downtime by monitoring maintenance trends, streamline purchasing, budgeting and inventory processes • Increase administrative efficiency, reduce risks through simplified safety management, and streamline data collection and reporting for environmental regulatory requirements • Generates reports in PDFs • Cooperation with third party software and tools is available • Can lead to more predictive maintenance if needed

Manufacturer/ Developer	Name	Description and features	Remarks
			• Traffic light system and use of FR, MTBF, MTTF by identify failure causes and MTTR
BASS Streamlining Maritime Operations	BASSnet Maintenance	• Standardise job practices, procure materials and report equipment conditions • Improve management of maintenance and repairs, work practices and condition monitoring of equipment as well as defects on parts and components of the vessel under warranty • Certified by BV, DNV/GL, NKK, LR, Microsoft	• Manage their global stock of spare parts • Handles assigned cargos and trade, and significantly reduces the lifecycle costs of equipment and machinery
DANAOS	DANAOS 1 Planned Maintenance System (PMS)	• Flexible specification of required maintenance integrated with spares usage features • Integrates maintenance with class surveys • Semi-annual concise maintenance and survey planning and full maintenance plan for any required period • Spare parts usage monitoring and future requirements prediction • Creation of the entire PMS • Features: planning reports, rescheduling, CM maintenance, alert notification, spare parts future prediction, critical equipment monitoring, weather routing, crew selection, risk control	Future steps and goals: • Incorporation of business goals in a unique and measurable way is the next step • Continuous monitoring of goal achievement, the identification of deviation, the monitoring of corrective actions and their results is the following step • Final step is to evaluate the risk of not achieving the goal at every operation and take the necessary cost effective controls to minimise the risk • The above steps are the key elements of the continuous improvement process (i.e. Improve-Plan-Measure-Act)
Kongsberg	Bearing Wear Condition Monitoring (BWCM)	• Crank and crosshead temperature: Measures continuously the temperature of the bearings. The BWCM system uses two sensors mounted in each cylinder compartment, measuring every time the crosshead passes Bottom Dead Centre. The KONGSBERG BWCM sensors are compensated for engine speed, engine load and engine crank case temperature • Water in oil: Sensor gives continuous measurement of moisture in oil and oil temperature. Water activity indicates directly whether there is a risk of free water formation which causes corrosion of the bearings. The measurement is also independent of oil type and age • Cylinder liner temperature: Monitors piston running performance by measuring the temperature of cylinder liners • Bearing wear: Measures the combined wear of crosshead, crank and main bearing and provides early warning of bearing seizure • Main bearing temperature: On 2-stroke engines the sensors are mounted on the main bearing girder with the tip of the sensor in direct contact with the bearing shell. The sensor measures the combined temperatures of the bearing shell and of the lubrication	Main benefits: • Approved to avoid open-up inspections • Unique long-term measuring accuracy • Compact and simple cabling and installation on the engine • Full integration and compatibility with KONGSBERG K-Chief and Autochief system • Dual sensor for continuous measurement of moisture in oil and oil temperature

Manufacturer/ Developer	Name	Description and features	Remarks
		oil that flows from the bearing. On 4-stroke engines the sensors are inserted in the main bearing cap • Shaft power: Calculates torque and power	
LAROS	Prisma Electronics SA	• LAROS can be installed easily, fast and with much lower cost than wired solutions due to fact that it uses wireless network technology Due to its innovative hardware design and intelligent communication protocol LAROS is the only monitoring solution comparing to competition that at the same time is: • -compatible with all types of sensors/devices • -redundant to all existing monitoring systems • -deployed in all parts of the vessel • -one solution for all types of vessels • -one platform for all types of measurements Fully customized remote monitoring data analysis • Unique intelligent algorithms, LAROS provides real-time analytics and reports directly to the administration headquarters which can be fully customized depending on the user needs. • Once installed LAROS solution can be easily expanded on a cost much lower than a wired solution.	So far, LAROS system has been installed and operates in various types of vessels worldwide. Ship owners report that they experience reduced fuel consumption, everyday operational cost, data entry on board, repair time and maintenance cost, breakdowns and docking down time. Furthermore, ship owners report enhanced green shipping, increased operation awareness, savings on insurance costs, improved vessels' operational efficiency and increased operational availability. LAROS applications include main engine and electrical generators performance analysis, voyage and weather information, ballast room monitoring, bridge parameters monitoring, burner, boiler, air compressors, smart fuel consumption analysis, smart engine efficiency analysis, motors and pumps condition monitoring, tanks pressure monitoring, exhaust economizers & health analysis, turbo chargers monitoring, inner gas monitoring, smart cargo monitoring
MAN B&W	CoCoS-EDS	• Unique feature, application is supplied with comprehensive data about the particular diesel engine plant • Extensive database supplied by MAN B&W Diesel saving time and resources for required input data • Designed for diesel engine surveillance, performance evaluation and to aid fault diagnosis on single and multiple engine plants • Reduces the costs of operating today's diesel engines by improved planning and optimised maintenance procedures • Objectives: effectively plan preventive and corrective maintenance work, perform CBM, create comprehensive work orders, report resource allocation and use, handle stock control and ordering, process documentation as required by Classification Societies • Features: easy to use system for multiple users, web scrollable application areas that facilitate on-site, mouse-click activation of utilities, comprehensive graphics interface	• The program forecasts the consumption of spare parts and work hours • Orders can be made and monitored at any time • Spare part catalogue contains multilevel part lists to help with overall planning. The identification of parts is helped by the inclusion of detailed graphics. Each part has accompanying in-depth information

Manufacturer/ Developer	Name	Description and features	Remarks
		for the easy interpretation of engine and maintenance data, off-line and on-line support from MAN B&W Diesel concerning maintenance instructions, spare parts catalogues, spare parts ordering, engine hardware, program software and technical support	
MAN B&W	PrimeServ (Premium Services and includes generic services delivered by MAN) SaCosone	• Qualified failure analysis on the basis of quasi real-time data • Determination of specific fault rectification measures • Machinery and equipment performance evaluation • Short/long term residual life evaluation • More precise preparation of maintenance measures • Improvement of start-up reliability and availability and cost efficiency and repair intervals	• MAN PrimeServ provides the latest monitoring, diagnostic and maintenance tools available • There is no standard duration for an Engine Management Concept (EMC) agreement – the length is as agreed between the partners – but payments are generally made monthly for an agreement's length • EMC supplies predictable capacity, meaning that MAN Diesel & Turbo equipment performs with optimal effectiveness and reliability • Since 2000, all MAN Diesel & Turbo engines have been delivered with integrated data interfaces, which can be upgraded to complete local systems for engine monitoring (CoCoS EDS) • PrimeServ Online Service transmits key engine data from any place in the world via secure data connections • PrimeServ experts analyse the data and provide valuable recommendations for maintenance/repairs of the engine or turbocharger • They can also provide the operator with remote support by accessing real-time engine data
SpecTec	Asset Management Operating System (AMOS)/ AMOS Maintenance & Procurement (M&P)	Allows maintenance, spare parts and stock control, purchasing and procurement, quality and safety documentation management, voyage management (for shipping) and personnel management	• AMOS Quality & Safety implements risk management with the ISO 31000 standards • Track equipment performance, availability and reliability to optimise maintenance strategy • Manage failures and collect reliability data as per ISO 14224

Manufacturer/ Developer	Name	Description and features	Remarks
Teledata Marine Solutions Maritime Leadership	ShipManager 7.0 SaaS	• Alerts, notifications and dashboards • Web-based application giving large flexibility to traveling managers • Access to third party users and ship's crew on leave on a selective basis • Even with limited shipboard internet, web access is achieved from the ship and shore and data transfer from the ships to the hosted server • Rent software/month than purchasing it, adjust it according to company's needs	• Exclusive offline and online access to course library by fleet personnel • Online, anytime-anywhere access available to ships and fleet personnel on leave or ashore • Huge cost-savings in the logistics of current training arrangements • Main features: rich analytics using easy-to-use interactive dashboards, pro-active detection and alerts, advanced reporting and publishing
TERO MARINE	TM Maintenance	• Involvement of inventory module, tool for managing spare parts, consumables and inventories • Extensive tools for trend analysis, enabling you to benchmark the performance of an individual vessel against another ship or entire fleet • Compare trends based on data from various equipment on board, such as NOx and CO2 emissions, compare component running hours with other component measurements, and trend consumption and condition for a number of different components • The outcome of trend analysis is graphically displayed and reported • Dry docking module allows to plan and execute complete dry docking projects • The database solution employs ADO.NET, and data is exchanged using the XML structure • For integration purposes, TM Master uses ADO to communicate with Microsoft SQL-server	• Innovative maintenance tips: built-in tools to standardise the database from ashore in combination with good co-operation from Tero-Marine • Grid and filtering features are integrated in the system for the components' specifications • Complete overview of all the information related to each individual component, including jobs, spare parts history and certificates • The module comes with flexible tools for maintenance and repairs, budgeting, tender comparison, procurement and reporting • Pre-warning of jobs due, disabling/enabling, postponing jobs to project • Inventory control: spare parts control, function hierarchy of components, stock control with consumption overview
ULYSSES SYSTEMS	Task Assistant	• Personal username and password accessing system, with the ability to view/control/access other roles depending on customizable authorization levels • Particular system (ship/office)/ role/ task/ context and voyage specific information • Automated ship to shore communications managing the full documentation (manuals, forms, check lists etc.) requirements of ISM, TMSA, and ISO • Advanced word search facilities for manuals • Support of information path data forms for cheaper transmission and statistical analysis of data	• Set-up of components, activities and spares • Critical spares management • Scheduling activities by calendar or running hours (including long-term view) • Reporting, analysing and scheduling defects

Manufacturer/ Developer	Name	Description and features	Remarks
VECTOR MARINE	Vector Maritime Suite (VMS) Vector Maintenance Manager	• Unified message manager feature: corporate mailbox forwards and stores all messages in a central database, optional web interface allows remote access to messages • Work-flow based, maritime asset management and resource planning software platform • Basic features: planned maintenance, defect management, classification and optional modules	• Manages planned maintenance, defect monitoring, repairs, work specification, dry-docking and follow up • Work is planned at equipment, system or vessel level by calendar periods and/or running hours • Job definition includes a task breakdown with instructions (i.e. skills, spares etc.) • Automated job schedule preparation, based on the running hours data, taking into account shifts in machinery utilisation • Extensive reporting tools (both static and dynamic) • Registration of defects, with detailed classification on the coding of the defect, its origin • The detailed task breakdown with the associated particulars and component history presents the manager a solid evaluation and DSS • Optional modules: photo, video logs, ultrasonic logs, parameters monitoring and chemical analysis monitoring
Wartsila	Dynamic Maintenance Plan (DMP)	• The quantifiable advantages of DMP are direct to operating cost reduction. Average savings are in the 3% range through reduced fuel/lube oil consumption, and from 5% to 15% through reduced maintenance costs • Because components are monitored constantly, dynamic maintenance localises trends in decreasing performance. Service at the appropriate time increases component life	• Example: Wartsila 46 engine’s overhaul target was recently increased from 16,000 to 20,000 hours, running on HFO, and with continuous monitoring the expectation is to reach a target of 24,000 hours
Wartsila	Propulsion Condition Monitoring Service (PCMS)	PCMS system comprises the following installations on board the vessel: • the advisory monitor (monitor the condition of mechanical parts, such as gears and bearings, but can also detect, thruster blade damage) • one or more cabinet(s) each containing: 6 accelerometers (50 kHz), 4 pressure transmitters, 1 oil monitoring unit, 1 torque measurement system (100 Hz) • PCMS tracks down incipient failures early so that customers can arrange for component replacements in a timely fashion • The data is sent by satellite to Wartsila's Propulsion Services offices, where it is continuously processed by the PCMS central core and analysed on a daily basis • The required data comes from sensors measuring vibration, hydraulic pressures and lubricant condition and the findings are compared with operational parameters, including set point and signal feedback	• Lubrication and hydraulic oils are monitored by measuring temperature, the oil-water saturation and any oil contamination • It can take months for a small bearing crack to develop into a big crack, which may lead to an expensive breakdown • Concept of input data integration: vibration almost always increases as power is raised, but abnormal levels of vibration can really only be seen properly when the relevant monitoring parameters are linked together

Manufacturer/ Developer	Name	Description and features	Remarks
		• System output report and findings: The report outlines important findings and recommendations, and describes the condition of the propulsion equipment, as well as the equipment and vessel operational profiles. The data analysts are backed by Wartsila's mechanical system, hydraulic system, control system and metallurgical experts	• LR is one of three major Classification Societies have given PCMS the seal of approval with service-level recognition. The other two are the ABS and DNV-GL. • Savings: Wartsila estimates savings as USD $3.9m + $16.3m = $20.1m - as the investment for PCMS is $680,000, the manufacturer clams net savings over the 10 years of operation could be as much as $19.42m
Wartsila	Propulsion Condition Monitoring Service (PCMS)	PCMS provides ship owners and/ or operators the ability to: • base operational decisions on the actual condition of the equipment • assess risks for upcoming contracts based on the projected reliability of the propulsion equipment • maximize the availability of the installation by performing overhauls only when needed, and by dramatically reducing the likelihood of unscheduled breakdowns • be informed of faults (such as cracks in bearings or gears) well before they lead to breakdowns • reduce the total cost of ownership and maximize profitability • increase the lifetime and preserve the good condition of the equipment through PCMS monitors vibrations, hydraulic pressures, lubrication oil temperatures, contamination, lubrication oil-water saturation, system performance parameters, torsion vibration, dynamic behaviour and sailing/ weather/ nautical information Benefits of using PCMS: known machinery condition, better risk assessment and evaluation, solid base for operational decisions, enables dynamic maintenance schedules, faults detected at an early stage, reduced risk of consecutive damage, optimized maintenance logistics and planning, periodic internal inspection of thrusters no longer required, total cost of ownership reduced, analysis by propulsion experts certified in vibration analysis	Vibrations: Three low-speed accelerometers mounted in x-, y- and z-direction on top of the propulsion machinery. Angular and parallel misalignments will create peaks at 1x, 2x and 3x the shaft frequency. The difference, however, is that in the case of parallel misalignment, the peak at 2x shaft frequency is the highest, whilst for angular misalignment the peak at 1x shaft frequency is the highest. Pattern recognition algorithms scan the frequency spectra for predefined faults such as: • Types of misalignment • Types of looseness • Gear tooth wear and gear misalignment • Different stages of bearing failure • Electric motor broken rotor bars • Electric motor eccentric rotor Shaft speed: Measures shaft rotation speed with an inductive proximity sensor. Analogue load measurement: For electric motor driven applications the load is acquired from the variable frequency drive as 4-20 mA signal. Oil measurements: An oil monitoring unit that measures the oil contamination- and oil water saturation levels and temperature in the (propeller) gearbox.

Manufacturer/ Developer	Name	Description and features	Remarks
			Hydraulic pressures: Steering and pitching (when applicable) actuation pressures are measured with pressure transmitters. Vibrations on electric motor: Three low-speed accelerometers mounted on the electric motor. High speed torque measurement: High speed torque measurement system able to detect torsional vibrations due to for example wind milling and ventilation.
Wartsila	WiMon wireless condition monitoring system	• Due to the cost efficiency, small size and ease of mounting and installation of the WiMon 100 sensor, continuous vibration monitoring can now be realized for all types of rotating machines. The autonomous WiMon 100 unit comprises a vibration sensor, a temperature sensor, a long-life battery and a WirelessHART™ radio	WiMon Data Manager has the following main functionalities: • System browser • WiMon system commissioning and main • Automated data acquisition • Storage of waveforms and dynamic data (velocity, envelope and temperature) • Operator interface for showing vibration waveforms, trends and temperatures • Waveform export support for interfacing analysis packages such as ABB Analyst

Research and development direction

Appendix A.2 presents a sample of the assessed literature sources that contributed towards setting up the dissertation's aim and objectives as well as the outline of the proposed maintenance strategy methodology. Each of the examined sources is assessed with respect to advantages of the author's/authors' proposed methodology, disadvantages or lessons learnt, key points for further research work and identified gaps as demonstrated in Table A.2.

Table A.2 Research and development direction of literature review

Source	Advantages	Shortcomings	Key points / Identified gaps
Al-Badour et al. (2011)	• Wavelet transform allows superior efficiency to fast and slow-time Fourier transform for non-stationary signals (accurate detection and localization of faults) • Fourier Transform time-based & frequency-based domain are suitable for stationary signal analysis • Wigner-Ville Distribution (WVD) good efficiency in time-frequency • Wavelet performs well at local analysis and zoom on intervals of time without losing information contained, revealing hidden aspects of data, Morlet and Gaussian wavelet good for discontinuity representation • Wavelet Transforms assessed are listed as Continuous (CWT), Discrete (DWT) and Wavelet Packet Transform (WPT). CWT best for singularity detection, WPT decomposes approximate and detailed components of signals for low and high frequency for non-stationary and stationary characteristics, best analysis for vibration signals and fault detection • Wavelet more accurate than FFT for short time signals	• Wavelet may have poor frequency resolution in the higher regions of analysis • Fast Fourier (FFT) lack of analysing extreme frequency changes yielding errors, leading to time-frequency processing through Short Time Fourier (STFT) and Wigner-Ville Distribution (WVD)	• Wavelet Packet Transform (WPT) powerful tool for detailed feature extraction • Integration of WPT and CWT can be effective method for impulsive faults • No optimal way for best mother wavelet selection, one approach is to compare the shape of fault under consideration with the wavelet function to be used • Detection of cracked gear teeth or blade vibration problems could be gained by windowing the signal into numbers of shaft revolutions and analysing them separately • Signal splitting approach for shorter computational time and smaller memory requirements, potential for parallel computational comparison
Brotherton et al. (2002)	• Two prediction considerations: (i) short term time prediction (ii) Remaining Useful Life (RUL) before a particular fault occurs and how much time is available before replacement	• Typically data is saved when a fault is detected and this stage is late for useful prognostics development	• Data fusion saves cost and weight and reduces false alarms • Data integration allows prognostics and low signal-level information enables fault detection at earlier stages
Catherall and Williams (2006)	• Short-time Fourier transform (STFT) traditional signal processing method is suitable for stationary properties • Fractional Fourier Transform (FrFT) better time-frequency resolution, non-suitable for multiple non-stationary components	• Wavelet transforms and Wigner-Ville distribution produce false signals due to cross-term interference	
Chen and Vachtsevanos (2012)	• Interval Type-2 Fuzzy Neural Network (IT2FNN) proposed for multi-step-ahead condition prediction of faulty bearings integrating fuzzy logic with multi-layer neural network • Adaptive Neuro-Fuzzy Inference System (ANFIS) most widely used neuro-fuzzy system in prediction		• Comparison between IT2FNN with ANFIS shows the first one performing with higher prediction accuracy

Source	Advantages	Shortcomings	Key points / Identified gaps
Chen et al. (2012)	• Proposed the Integration of RUL using ANFIS and high-order particle filtering for time forecasting of fault estimating the Probability Density Function (pdf) of RUL, p-stet-ahead prediction via particle sets • Multiple p-step-before states consideration compared with Markov model (only 1 previous step), high-order hidden Markov model is employed	• ANFIS reliable and robust condition predictor only for short-term conditions by missing RUL studies	• Lack of integration between multiple p-step-before filtering method with multiple p-step-ahead prediction for prediction accuracy enhancement
Demetgul et al. (2009)	• Adaptive Resonance Theory 2 (ART2) and Back propagation (Bp) ANNs excellent performance for perfect and faulty conditions • ART2 unsupervised NN monitoring process without any training, being easiest to use • Bp supervised ANN requiring training to allow algorithm selecting proper parameters	• Bp requires extensive and careful training with artificial generated data covering large number of possibilities lasting for long as it makes millions of iterations	• Bp most commonly used ANN
Dunn (2002)	• Outline of key business opportunities and trends of condition monitoring		• Holistic view of integrating CM with equipment performance monitoring needing accurate and reliable assessment and prediction methods • Integration of CM techniques with cost-effective applications of performance • Combination of CM with CMMS and process control
Estocq et al. (2006)	• De-noising signals methods assessed for bearing diagnostics: (i) Self-Adaptive Noise Cancellation (SANC) (ii) synchronous averaging (iii) wavelet method • Kurtosis and crest factor sensitive indicators to signal shape, kurtosis better indicator than crest considering that results coming from weaker measures	• STFT limitations/requirements: (i) useful signal must be slightly present within the measured signal (ii) noise must be stable (iii) noise and signal spectrum must be different • Neither kurtosis nor crest factor can detect defects in a wide frequency band (i.e. 0-20 kHz) or in narrow bands (0-5, 5-10 etc. kHz) before the spectral subtraction of signal	• Spectral subtraction method based on STFT allowing to remove stationary noise of signals • Kurtosis performs more accurately than crest indicator for detection of impulsive defects
Farrar et al. (2003)	• The proposed model is divided between: (i) active and local sensing, (ii) passive global sensing assessing system-level response and loading conditions (iii) development of sensing methodology for failure mode and degradation mechanism		• For robustness of monitoring time-varying non-stationary processes are used: (i) Auto-Regressive (AR) and Auto-Regressive with Exogenous Input (ARX) models, (ii) Time-dependent Auto-Regressive Moving-Average (TARMA) and (iii) evolutionary spectral analysis
Jang (1993)	• Fuzzy inference system implemented in framework of adaptive networks (ANFIS) • Purpose of hybrid ANFIS, the human knowledge mapping input-output using IF-THEN rules		

APPENDIX B – PMRA STRATEGY BRITISH STANDARDS AND SUPPORTIVE GUIDELINES

The author's intention with respect to PMRA strategy is to suggest a stand-alone Condition Monitoring methodology for ship machinery integrating data analysis, reliability assessment incorporating aspects of decision making. PMRA strategy provides a flexible methodology which is programmed in a structural attempt to allow further development on the existing performed work. Therefore, guidelines for standardising this methodology according to unified rules have to be introduced. PMRA strategy is developed by following suggestions provided in BS/ISO 17359 (2011) and (BS/ISO 13381, 2015). The first report provides general guidelines with respect to Condition Monitoring and diagnostics of machines, whereas, the second related to diagnostics and prognostics of machinery. Appendix B provides useful supportive information which inspired and guided the PMRA strategy development.

B.1. Guidelines of BS/ISO 17359 (2011)

This report provides guidelines for condition monitoring and diagnostics of machines utilising input and evaluation parameters such as vibration, temperature, flow rates, contamination, power, and speed typically associated with performance, condition, and quality criteria. Therefore, PMRA strategy is oriented towards temperature and pressure. Furthermore, this report highlights that the evaluation of machine function and condition may be based on performance, condition or product quality. The overview of condition monitoring procedure as provided in the report is demonstrated in Figure B.1.

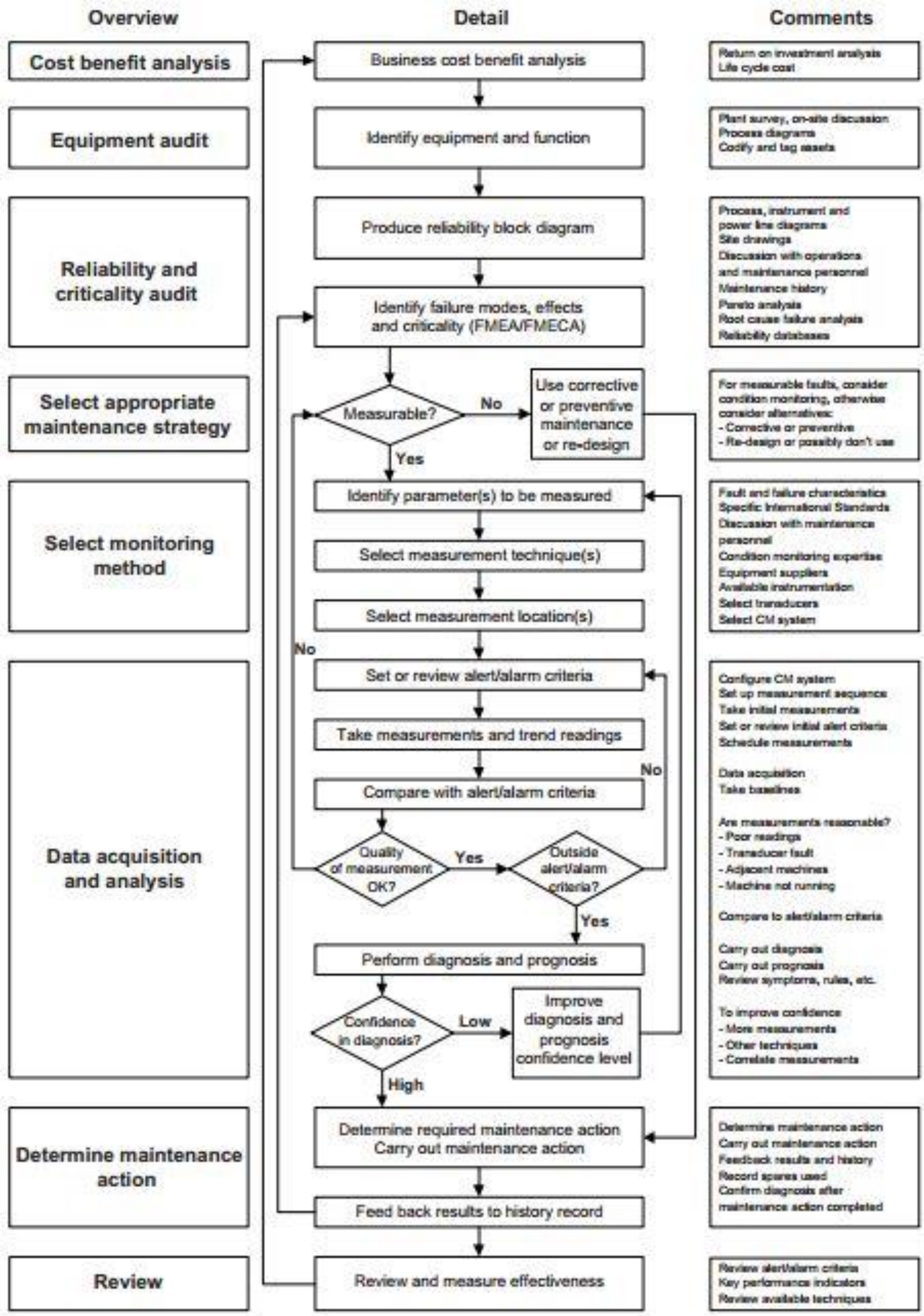

Figure B.1 BS/ISO 17359 (2011) Condition Monitoring (CM) procedure suggestion

As Figure B.1 demonstrates, machinery CM procedure is suggested to be divided in research and application sectors including Cost Benefit Analysis (CBA), equipment selection, reliability audit, selection of appropriate maintenance strategy and monitoring method, data acquisition and analysis techniques selection, determination of maintenance action suggestion and review of effectiveness.

PMRA strategy is focused towards almost all the above mentioned relevant investigation areas. First of all, Cost Benefit Analysis (CBA) is considered to identify effectiveness of CM applications and maintenance suggestion comparing existing maintenance strategies with the newly introduces CM practices. On the other hand, critical machinery, subsystems, components and measures are taken into account as literature and experts identify and suggest. It is crucial to highlight that experts and professionals contributed with their experience having expertise from onboard and onshore applications as well.

FMEA table is created utilising multiple sources such as engine manuals, reports, expert judgment, guidelines and regulations from Classification Societies. This FMEA table is demonstrated in the appropriate performed case study and the related provided supportive material. Additionally, the selection of the appropriate monitoring methods is identified through the variety of input data types such as performance measurements of pressure and temperature in critical machinery locations. These measurements are collected utilising Engine Room's control systems, DANAOS 1 Planned Maintenance System (PMS) and the integrated Laros software developed by Prisma Electronics SA. Further information related to these two platforms (i.e. DANAOS and Laros) can be found in Appendix A 'Condition Monitoring Systems', where commercially available tools and practices are demonstrated.

Lastly, maintenance actions are suggested according to the current and forecasted working state reliability performance of the selected ship machinery. Therefore, BS/ISO 17359 (2011) is considered in various levels of PMRA strategy taking into account suggestions of provided procedures and method functionalities by optimising the overall proposed PMRA research methodology.

B.2. Guidelines of BS/ISO 13381 (2015)

This report provides guidelines with respect to five distinct identified phases such as detection of problems (deviations from normal conditions), diagnosis of the faults and their causes, prognosis of future fault progression, recommendation of maintenance actions and evaluation of applied methodology. According to BS/ISO 13381 (2015), machine health prognosis demands prediction of future machine integrity and deterioration. Prognostic processes require statistical approaches to be adopted by integrating foreknowledge of the probable failure modes and understanding of the relationships between failure modes and operating conditions.

The report considers areas of analysis such as data requirements, prognostic concepts, failure and deterioration analysis as well as generic prognostic processes. Therefore, data requirements incorporate input related to:

- monitoring parameters
- current and future operating and maintenance environments
- expert knowledge of baseline
- identification of all existing failure modes
- alarm limits
- environmental data
- manufacturer's configuration and ideal operational/functioning data

Prognostic concepts and processes included refer to:

- determination or estimation of parameters or descriptor behaviours and the expected rate of deterioration
- estimation of current state
- estimation of Remaining Useful Life (RUL)
- establishment of the desired prognostic event horizon

The latest available BS/ISO 13381 (2015) considers and suggests various failure and deterioration models to be utilised for prognostics such as:

- Failure Mode Effects Criticality Analysis (FMECA)

- Event/Fault Tree Analysis (ETA and FTA respectively)
- Risk and hazardous assessment methods (multiple are defined and examined in Chapter 3 ‘Literature Review’
- physics-based damage initiation and progression models (first principle analysis)
- RUL defined as a function of acceptable confidence level and risk

Henceforth through the development of PMRA strategy, various prognostic and deterioration models are examined. PMRA strategy tackles the prognostic aspects utilising probabilistic approaches and especially the latest and most innovative Bayesian Belief Networks (BBNs). Competitors of BBNs are ETA and FTA and analytical reasons of selection of BBNs can be found in Chapter 4 ‘Proposed Maintenance Strategy for Ship Machinery’.

APPENDIX C – PMRA STRATEGY DATA CLUSTERING METHODOLOGY PSEUDOCODE

Appendix C provides supplementary information and mathematical formulation related to PMRA strategy. Specifically, this additional material aims to support the suggested methodology as demonstrated in Chapter 4 'Proposed Maintenance Strategy for Ship Machinery'. The data processing phase of PMRA strategy requires iterative procedures (i.e. convergence criteria etc.). Therefore, the representation of the iterative part of PMRA strategy through the developed and performed pseudocode is presented below. The provided part of code considers as prerequisite and already known the formulation provided in Chapter 4 such as the equations from (4.1) to (4.17).

- **PMRA strategy data processing stage prerequisites**

ds: data set

ds_j: data set clusters (j: 1, 2) for cluster 1 or cluster 2, total number of clusters k=2

μ_{ds}: mean (or centroid) of data set ds

σ_{ds}: standard deviation of data set ds

μ_{ds1L}: data set ds, cluster 1, lower L mean value

μ_{ds1H}: data set ds, cluster 1, higher H mean value

μ_{ds2L}: data set ds, cluster 2, lower L mean value

μ_{ds2H}: data set ds, cluster 2, higher H mean value

d^2_{dsj}: distance calculated utilising squared Euclidean formula for both involved clusters

- **PMRA strategy data processing stage pseudocode**

Perform PMRA strategy up to equation 4.12.

Generate three arrays:

r_1[500], r_2[500], and r_3[500] having size of 500 random indices from 0 to 1.

These arrays create uniformity in size among clusters. The size of arrays is predefined at 500 indices per array. Various investigations were undertaken while PMRA strategy was developed (i.e. i=50, 100, 1000). Through this investigation, the precision of $P_{ds}(w_t)$ and $P_{ds}(f_t)$ results was achieved at 10 decimal places. On the other hand, low array index was performing weak results at maximum 1 decimal place. It is crucial to highlight that the predefined array size utilised for clustering the gathered data is related to the size of the recorded input data.

Generate the inverse Cumulative Distribution Function (CDF) of normal cumulative distribution of the equation:

$$c_i^{(j)} = \frac{1}{2}\left[1 + \mathrm{erf}(\frac{x-\mu}{\sigma\sqrt{2}})\right] \tag{B.1}$$

Calculate $c_i^{(1)}$ which corresponds to clustered value belonging in cluster 1:

if $r_1[i{+}{+}] \geq \alpha$

then

inverse of (B.1) $c_i^{(1)}$ for values [$r_2[i{+}{+}]$, μ_{ds1L}, σ_{ds}]

else if $r_1[i{+}{+}] < \alpha$

then

inverse of (B.1) $c_i^{(1)}$ for values [$r_2[i{+}{+}]$, μ_{ds2L}, σ_{ds}]

Calculate $c_i^{(2)}$ which corresponds to clustered value belonging in cluster 2:

if $r_1[i{+}{+}] \geq \alpha$

then

inverse of (B.1) $c_i^{(2)}$ for values [r_3[i++], μ_{ds1H}, σ_{ds}]

else if r_1[i++] < α

then

inverse of (B.1) $c_i^{(2)}$ for values [r_3[i++], μ_{ds2H}, σ_{ds}]

Alpha value α denotes the proportion of clustered observations (data points):

$$\alpha = \frac{\sum_{i=1}^{m_j}(d_{ds1}^1 < d_{ds2}^2)}{m_j} \tag{B.2}$$

The selected data clustering method performs multiple iterations in order to reassign the data points within the selected clusters. At the first iteration, alpha proportion α value is assumed to be 0.5. Therefore, half of the observations are assumed to belong in the first cluster and half in the second. Each time an iteration takes place until convergence, the alpha value updates according to the actual current proportion as formed within the clusters. It is crucial to state that in case a new data set *ds* is provided to be analysed utilising PMRA strategy sourced from the same vessel and measurement point (e.g. temperature of intermediate bearing 1) the initial alpha for the new set of iterations is the last alpha gathered at the last achieved convergence. Therefore, the assessment uniformity among past and new data sets is remained, by transferring the alpha proportional value, allowing elimination of assumptions (no need to initiate PMRA strategy considering α=0.5).

PMRA strategy utilises k-means data clustering algorithm for recognising the patterns of the recorded observations (data points) such as real time sensor data. This data clustering method (k-means) iterates between two states by reassigning the observations in the considered clusters until a criterion is satisfied. Specifically, the iteration initiates by guessing (randomly) the mean values of clusters 1 and 2, for lower and higher, than the overall data set *ds*, groups (i.e. μ_{ds1L}, μ_{ds2L}, μ_{ds1H}, and μ_{ds2H}).

Ones the k-means process begins the expected (randomly guessed) mean values are substituted by the next calculated mean values (according to current cluster arrangement). The iteration progresses until guessed and next mean values are converged. Additionally, k-means convergence can be reached by considering and setting criteria with respect to the Euclidean distance demonstrated in Chapter 4 'Proposed Maintenance Strategy for Ship Machinery'. Therefore, the calculated following mean values can be calculated by following iteratively the provided pseudocode below.

Calculate next mean value for data set *ds*, cluster 1, group having lower *L* mean than the centroid of the overall *ds*:

if $d^2_{ds1} < d^2_{ds2}$

then

$$M_{ds1L} = \frac{\sum_{i=1}^{m^j} c_i^{(1)}}{n_{mds1}} \tag{B.3}$$

Calculate next mean value for data set *ds*, cluster 1, group having higher *H* mean than the centroid of the overall *ds*:

if $d^2_{ds1} < d^2_{ds2}$

then

$$M_{ds1H} = \frac{\sum_{i=1}^{m^j} c_i^{(2)}}{n_{mds2}} \tag{B.4}$$

Calculate next mean value for data set *ds*, cluster 2, group having lower *L* mean than the centroid of the overall *ds*:

if $d^2_{ds1} > d^2_{ds2}$

then

$$M_{ds2L} = \frac{\sum_{i=1}^{m^j} c_i^{(1)}}{n_{mds1}} \tag{B.5}$$

Calculate next mean value for data set *ds*, cluster 2, group having higher *H* mean than the centroid of the overall *ds*:

if $d^2_{ds1} > d^2_{ds2}$

then

$$M_{ds2H} = \frac{\sum_{i=1}^{m^j} c_i^{(2)}}{n_{mds2}} \tag{B.6}$$

APPENDIX D – PMRA STRATEGY SOURCE CODE STRUCTURE ANALYSIS

Appendix D demonstrates briefly the structure of the developed Java source code. The main scope of this analysis is to set the grounds for further research and development as well as to indicate an approach of efficient source code structure. The entire development of PMRA strategy is taken place in Java utilising the NetBeans IDE 8.0 Java code compiler. As **Error! Reference source not found.** shows, the source code s developed in thirteen major java classes (.java). These consist of CaseStudy, Configuration, DataMining, Main, NodeOrder1, NodeOrder2, NodeOrder3, NodeOrder4, NodeOrder6, NodeOrder7, NodeOrder8, Table and TableRow.

Firstly, PMRA strategy and case study are developed separately. In CaseStudy Java class the calculation node orders are included, where specific classes and methods are called and executed sequentially fulfilling the mathematical requirements of the case study model. On the other hand, Configuration class includes variables and predefined values such as safety thresholds. This class controls entirely values that may need to be adjusted for sensitivity analysis. Configuration class simplifies the structure of the code by gathering all variables together. Moreover, DataMining class consists of the iterative processes of k-means data clustering method. Main class triggers the calculations by passing the values from class to class and the final results demonstrated to user.

The Java classes NodeOrder1, NodeOrder2, NodeOrder3, NodeOrder4, NodeOrder6, NodeOrder7 and NodeOrder8 incorporate the Markov Chain calculations as well as the Dynamic Bayesian Belief Network (DBBN) equations. Each node order class refers to the number of parents each node has. Hence, if a component, subsystem or system has 4 parent nodes, the calculations will be executed through NodeOrder4 class. Lastly, Table and TableRow classes read and write input and output (results) respectively from and to Excel and text.

Therefore, the structure of the Java source code separates the case study model and the PMRA strategy. On the other hand, the suggested PMRA strategy is developed in processing segments such as configuration, data clustering, dynamic reliability assessment and Input/Output (I/O) procedures. Adjustments and further development can be considered on the existing source code.

APPENDIX E – PROCESSED DATA SOURCE

Appendix E includes supplementary information related to processed input data gathered by OREDA (2002). Firstly, the available information taxonomy of machinery derived mostly from the offshore installations is demonstrated in Figure E.1. The equipment classification consists of rotating machinery, static equipment, additional topside systems, miscellaneous and subsea equipment.

System	Equipment class	Phase I (-84 edition) (1983 – 85)	Phase II (-92 edition)[2] (1987 – 90)	Phase III (-97 edition) (1990 – 92)	Phase IV (2002 edition) (1993 – 96)	Phase V (1997 – 00)	SUM
		No. of units	No. of units	No. of units	No. of units	No. of units	No. of units
Rotating machinery	- Gas Turbines		109	54	56	28	247
	- Compressors	17	50	45	75	56	243
	- Combustion engines				39	64	103
	- Pumps	478	271	103	294	152	1298
	- Turboexpanders				7	8	15
	- Electric generators	76		49	87	8	220
	- Electric motors				56	122	178
Static equipment	- Vessels	359	329	54	148	51	941
	- Heaters and boilers				8	1	9
	- Heat exchangers	519	170	75	51	17	832
Other topside	- Valves	658	645	899	821	349	3372
	- F&G detection equipment	3683		5828	79	779	10369
	- Process sensors/control	3740		487	140	69	4436
Misc. equipment phase I only	- Misc. el. systems	1321					1321
	- Misc. safety systems	1703					1703
	- Misc. utility systems	1035					1035
	- Drilling systems	880					880
Subsea equipment	- Control systems			14		17	31
	- Wellhead & X-mas tree			21		83	104
	- Pipelines					144	144
	-Template					4	4
	- Manifold					29	29
	- Risers					42	42
	- Running tools					6	6
	- Misc. equipment (phase II)		15				15
Total		**14469**	**1589**	**7629**	**1841**	**2037**	**27565**

Figure E.1 Equipment classes list in OREDA Handbooks

As the topic of this research study is oriented towards applications in maritime industry, the initial technical implementation of PMRA strategy involves only rotating machinery similar in structure and function as these of maritime industry. Therefore, reliability records, system information and related failure modes are extracted from the rotating machinery class such as gas turbines, compressors, combustion engines, pumps, turboexpanders, electric generators and motors.

Taxonomy no		Item		
1.4.1		Machinery Combustion Enigens Diesel engine		
Population	**Installations**	**Aggregated time in service (106 hours)**		**No of demands**
		Calendar time *	**Operational time †**	
69	56	3.0067	0.0872	18474

Failure mode	**No of failures**	**Failure rate (per 106 hours).**					**Active rep.hrs**	**Repair (manhours)**		
		Lower	**Mean**	**Upper**	**SD**	**n/τ**		**Min**	**Mean**	**Max**
Critical	**52***	**0.00**	**19.10**	**90.16**	**36.84**	**17.29**	**53.8**	**1.0**	**95.3**	**2730.0**
	52†	**756.39**	**5359.16**	**13454.01**	**4149.86**	**596.01**				
Breakdown	3*	0.00	1.11	6.05	2.83	1.00	38.7	4.0	39.3	108.0
	3†	0.00	183.24	922.91	396.07	34.39				
External leakage - Utility medium	1*	0.00	1.31	6.90	5.72	0.33	-	-	-	-
	1†	3.02	646.59	2383.85	880.47	11.46				
Fail to start on demand	29*	0.00	12.22	63.54	28.24	9.65	9.5	1.0	16.9	52.0
	29†	283.72	4049.45	11650.76	3840.96	332.39				
Low output	1*	0.00	0.58	2.14	2.76	0.33	50.0	100.0	100.0	100.0
	1†	0.01	42.18	189.31	75.00	11.46				
Overheating	3*	0.00	0.81	4.18	1.81	1.00	28.7	1.0	57.0	120.0
	3†	0.00	78.13	405.69	179.68	34.39				
Parameter deviation	1*	0.00	0.58	2.14	2.76	0.33	6.0	12.0	12.0	12.0
	1†	0.01	42.18	189.31	75.00	11.46				
Spurious stop	11*	0.55	3.35	8.12	2.46	3.66	7.2	2.0	13.3	40.0
	11†	17.47	694.47	2127.98	743.18	126.08				
Vibration	3*	0.00	0.74	3.91	1.79	1.00	516.7	140.0	1116.7	2730.0
	3†	5.53	28.86	67.24	19.85	34.39				
Degraded	**123***	**0.00**	**33.40**	**183.95**	**91.72**	**40.91**	**12.3**	**1.0**	**21.6**	**207.0**
	123†	**247.06**	**5683.27**	**17075.33**	**5757.31**	**1409.80**				
Abnormal instrument reading	1*	0.00	0.29	1.43	0.60	0.33	1.5	3.0	3.0	3.0
	1†	0.10	9.62	31.45	11.46	11.46				
Erratic output	6*	0.00	1.78	9.49	7.97	2.00	11.3	1.0	21.5	60.0
	6†	6.35	564.26	1830.47	665.32	68.77				
External leakage - Fuel	5*	0.00	1.33	7.31	3.58	1.66	9.1	3.0	11.8	32.0
	5†	0.00	72.89	415.45	222.87	57.31				
External leakage - Utility medium	45*	0.00	12.10	67.00	34.19	14.97	10.2	1.0	17.3	60.0
	45†	3.62	1543.60	6123.04	2285.30	515.78				
Fail to start on demand	1*	0.00	1.31	6.90	5.72	0.33	-	12.0	12.0	12.0
	1†	3.02	646.59	2383.85	880.47	11.46				
High output	1*	0.00	0.37	0.69	2.08	0.33	4.0	4.0	4.0	4.0
	1†	0.00	88.49	445.73	191.30	11.46				
Internal leakage	9*	0.00	2.85	14.99	6.78	2.99	21.8	2.0	33.1	80.0
	9†	3.41	760.77	2829.38	1044.60	103.16				
Low output	9*	0.00	2.63	11.34	4.40	2.99	7.9	6.0	15.9	30.0
	9†	0.68	300.00	1192.33	445.28	103.16				
Noise	3*	0.00	1.28	6.67	4.78	1.00	14.0	10.0	16.7	28.0
	3†	1.15	512.08	2037.89	761.36	34.39				
Other	25*	0.00	6.22	34.99	18.45	8.31	16.1	2.0	27.7	82.0
	25†	1.96	701.82	2751.26	1022.64	286.55				
Comments										
(cont.)										

Figure E.2 Sample of combustion diesel engines reliability data table

More specifically, Figure E.2 presents a sample of reliability data table, extracted form machinery system class involving combustion diesel engines. The various demonstrated entries of the data table are listed below:

- Taxonomy number and item: Identification number
- Population: Total number of items forming the published estimation
- Installations: Total number of installations
- Number of demands: Total number of times an item is required to perform its function during the calendar year
- Aggregated time in service: Calendar time or operational time
- Failure mode: Brief description of failure occurred
- Number of failures: Total number of failure events
- Failure rate (mean, lower & upper, standard deviation σ, total number of failures)
- Active repair time (hours): Average time (hours) to repair and return the item to a state where it functions. Actual time of repair not including time to shut down the unit, issue work order, wait/delay for spare parts
- Repair (manhours): Min, mean and max hours required for repairing and restoring the function

Additional, failure rate records are provided as demonstrated in Figure E.3. The sample provided figures the maintainable item versus failure mode for combustion diesel engines, therefore the relative contribution from each maintainable item to the total failure rate is extracted. The indices/records in Figure E.3 refer to the percentages of occurrence for each combination of failure mode and maintainable item. Henceforth, the row sum demonstrate the total percentage of failures that are recorded in relation to the specific maintainable item. On the other hand, the column sum refers to the contribution of each failure in percentages in relation to the entire system, in the case of Figure E.3 the combustion diesel engines.

	AIR	BRD	ELF	ELU	ERO	FTS	HIO	INL	LOO	NOI
Actuating device	0.69	0.00	0.00	0.23	0.46	0.23	0.00	0.00	0.23	0.00
Air inlet	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00
Cabling & junction boxes	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Control unit	2.89	0.00	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.00
Cooler(s)	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.00	0.00	0.00
Cylinders	0.00	0.00	0.00	0.23	0.00	0.23	0.00	0.46	0.00	0.00
Exhaust	0.00	0.00	0.23	0.46	0.00	0.00	0.00	0.00	0.00	1.39
Fan w/motor	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.23
Filter(s)	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00
Fuel filter	0.00	0.00	0.23	0.00	0.46	0.46	0.00	0.12	0.00	0.00
Fuel pump	0.00	0.00	0.00	0.69	0.00	0.00	0.00	0.46	0.23	0.00
Heat exchanger	0.00	0.00	0.00	0.93	0.00	0.23	0.00	0.23	0.00	0.00
Heater	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hood	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00
Injections	0.00	0.00	0.00	1.85	0.12	0.00	0.00	0.12	0.69	0.00
Instrument, flow	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Instrument, general	0.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Instrument, level	2.55	0.00	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.00
Instrument, pressure	3.24	0.00	0.00	0.23	0.00	0.23	0.00	0.00	0.00	0.00
Instrument, speed	0.69	0.00	0.00	0.00	0.46	0.69	0.00	0.00	0.00	0.00
Instrument, temperature	9.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Internal power supply	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Monitoring	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oil	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other	0.00	0.00	0.00	0.23	0.23	0.23	0.00	0.00	0.23	0.00
Piping	0.00	0.00	0.69	6.48	0.00	0.00	0.00	0.00	0.00	0.00
Piston(s)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pump	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00
Pump w/motor	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.00	0.00	0.23
Radial bearing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23
Seals	0.00	0.00	0.46	1.16	0.00	0.00	0.00	1.04	0.23	0.00
Shaft	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Start control	0.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Start energy (battery, air)	0.23	0.00	0.00	1.16	0.00	1.16	0.00	0.23	0.00	0.00
Starting unit	0.46	0.00	0.00	0.46	0.00	0.46	0.00	0.00	0.00	0.00
Subunit	0.23	0.00	0.00	0.46	0.00	0.00	0.00	0.00	0.00	0.00
Super charger	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.00	0.23	0.00
Timing chain/V-belt	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Unknown	0.58	0.46	0.23	0.46	0.23	1.62	0.23	0.23	0.23	0.00
Valves	0.69	0.23	0.00	0.23	0.12	0.46	0.00	0.35	0.00	0.00
Total	25.00	0.69	2.08	17.13	2.08	7.41	0.23	3.24	2.31	2.08

Figure E.3 Sample of maintainable item versus failure mode table for combustion diesel engines

Setting equations (5.2) to (5.6) to be known and their results prerequisites for the processed input data preparation, the following mathematical expressions provide the initial failure rate figures per subsystem and system.

λ_j: failure rate per component j, considering all involved failure modes

for each $\lambda_{j\rightarrow z} \in u_{k\rightarrow l}$, k=1 to l maximum number of subsystems in system and z maximum number of components in subsystem k. Hence, the calculation of the initial recorded failure rate of subsystem u_k denoted as λ_{uk} is given by equation (E.1):

$$\lambda_{uk} = \sum_{j=1}^{z} \lambda_j \tag{E.1}$$

On the other hand, the proportion of component's *j* failure, where j ∈ u_k is given by equation (E.2):

$$\lambda_{j \in u_k} = \frac{\lambda_j}{\lambda_{uk}} \tag{E.2}$$

The initial overall system's failure figure is given by equation (E.3):

$$\lambda_s = \sum_{j=1}^{m} \lambda_j \tag{E.3}$$

Lastly, the subsystem's percentage of failure out of the overall system's reliability performance is given by equation (E.4):

$$\lambda_{ukp} = \frac{\lambda_{uk}}{\lambda_s} * 100 \tag{E.4}$$

On the other hand, equations (E.5) to (E.7) present the generic expressions of the probability of working state at component, subsystem and main system levels respectively. The equations include all possible failure scenarios (*m*: total amount of failure scenarios) and the summation of all considered failure types ($ft_{f(i)}$) (*k*: total amount of failure types), all considered components ($c_{f(x)}$) (*l:* total amount of components) and all considered sub-systems ($s_{f(y)}$) (*n:* total amount of sub-systems). In addition, the relations of *m* and *k*, *l* and *n* are presented in equations (E.8) to (E.10).

$$P(component) = \sum_{j=1}^{m} (\sum_{i=1}^{k} P(ft_{f(i)}, ft_{f(j)})) \tag{E.5}$$

$$P(subsystem) = \sum_{j=1}^{m} (\sum_{x=1}^{l} P(c_{f(x)}, c_{f(j)})) \tag{E.6}$$

$$P(main\ system) = \sum_{j=1}^{m} (\sum_{y=1}^{n} P(s_{f(y)}, s_{f(j)})) \tag{E.7}$$

$$m = 2^k \tag{E.8}$$

$$m = 2^l \tag{E.9}$$

$$m = 2^n \tag{E.10}$$

APPENDIX F – RAW DATA SOURCE

Appendix F provides additional information related to Chapter 6 and the performed case study utilising raw data. This case study employs data which recorded onboard the ship in actual operational conditions.

F.1. Alarm and warning levels

Probabilistic Machinery Reliability Assessment (PMRA) strategy makes use of reference/optimal operational levels as well as alarm/warning points identified by manufacturer's manuals and sea trials. More specifically, these implemented safety thresholds are listed below in Table F.*1* as identified by the sources and utilised in the in-house Java language developed PMRA strategy.

Table F.1 Raw data warning and operational levels

Measurement Limits	**Value**
Camshaft Bearings Temperature Alarm	75.0
Camshaft Bearings Temperature Min	50.0
Camshaft Bearings Temperature Max	70.0
Cylinder Exhaust Gas Outlet Temperature 1-8 Alarm	520.0
Cylinder Exhaust Gas Outlet Temperature 1-8 Min	380.0
Cylinder Exhaust Gas Outlet Temperature 1-8 Max	500.0
Cylinder JCFW Inlet Pressure Alarm	2.0
Cylinder JCFW Inlet Pressure Min	3.5
Cylinder JCFW Inlet Pressure Max	4.5
Fuel Oil Inlet Pressure Alarm	6.5
Fuel Oil Inlet Pressure Min	7.0
Fuel Oil Inlet Pressure Max	8.0
Fuel Oil Inlet Temperature Min	105.0
Fuel Oil Inlet Temperature Max	150.0
Intermediate Shaft Bearing Temperature 1-3 Alarm	70.0
Intermediate Shaft Bearing Temperature 1-3 Min	45.0
Intermediate Shaft Bearing Temperature 1-3 Max	65.0

Measurement Limits	Value
JCFW Outlet Temperature 1-8 Alarm	90.0
JCFW Outlet Temperature 1-8 Min	80.0
JCFW Outlet Temperature 1-8 Max	85.0
Main Lube Oil Inlet Pressure Alarm	1.9
Main Lube Oil Inlet Pressure Min	2.3
Main Lube Oil Inlet Pressure Max	2.6
Main Lube Oil Inlet Temperature Alarm	55.0
Main Lube Oil Inlet Temperature Min	40.0
Main Lube Oil Inlet Temperature Max	47.0
Main Engine Air Cooler CW Inlet Pressure Min	1.0
Main Engine Air Cooler CW Inlet Pressure Max	5.5
Main Engine Control Air Inlet Pressure Alarm	5.5
Main Engine Control Air Inlet Pressure Min	6.5
Main Engine Control Air Inlet Pressure Max	7.5
Main Engine Exhaust Valve Spring Air Pressure Alarm	5.5
Main Engine Exhaust Valve Spring Air Pressure Min	6.5
Main Engine Exhaust Valve Spring Air Pressure Max	7.5
Main Engine Start Air Pressure Min	15.0
Main Engine Start Air Pressure Max	30.0
Scavenging Air Manifold Pressure Min	0.1
Scavenging Air Receiver Temperature 1-8 Alarm	65.0
Scavenging Air Receiver Temperature 1-8 Min	25.0
Scavenging Air Receiver Temperature 1-8 Max	51.0
Thrust bearing LO Outlet Temperature Alarm	90.0
Thrust bearing LO Outlet Temperature Min	55.0
Thrust bearing LO Outlet Temperature Max	70.0

F.2. Raw data and effects assessment

Table F.2 presents an attempt of a Failure Modes and Effects Analysis (FMEA) research study performed in order to provide additional qualitative information on the developed PMRA strategy and the case study as shown in Chapter 6. This FMEA table aims to guide the decision making process and root cause analysis of the gained PMRA prediction results. On the other hand, Table F.3 provides diagnostic information and inspection and maintenance suggestions with respect to possible causes of failures or malfunctions.

The provided information in Table F.2 and Table F.3 is extracted from various sources such as Pulkrabek (1997), McGeorge (1998), Taylor (1996), Anish (2016), INCASS (2014a), INCASS (2014b), INCASS (2014c), INCASS (2015a) and INCASS (2015b). Moreover, engine manufacturers' reports and manuals are utilised for information exploration and extraction including Kawasaki (2000), (Hyundai-MAN, 2010a) and (Hyundai-MAN, 2010b) among others such as results of sea trial testing. Vital importance in the creation of these tables gains the expert judgment and discussions that taken place as part of this PhD research study with onshore professionals, chief engineers and crew members. Professionals from different maritime stakeholders such as ship owners, operators, service providers, Classification Societies, onboard crew members and condition monitoring experts contributed with their valuable knowledge and expertise in the field of marine engineering and inspection and maintenance practices.

Table F.2 Failure modes and effects analysis of PMRA strategy case study

Subsystem	Measurement	Parameter	Failure Mode	Effect of Failure	Damaged Equipment	Damaged Component	Malfunction/Failure Cause
Fuel Oil	FO Inlet	Pressure	Insufficient pumping	Engine stop	Fuel Supply	Suction pipe Fuel Supply Pump Fuel Booster Pump	Heavy leak Obstruction (particles)
			Damage of filter	Loss of redundancy	Fuel Supply	Filter	Blocking
			Lower output flow	Loss of performance, Low temperature exhaust gases	Fuel Supply	Suction pipe	Leak Obstruction (particles)
			Fuel leakage	Loss of performance		Inlet valve	Leak No Flow
			Higher fuel pressure	Lower performance to prevent failure	Fuel Return	Fuel self-pressure limiting valve	No Flow
						Isolating valves	No Flow
			Lower fuel pressure	Loss of performance	Fuel Return	Fuel pressure limiting valve	Leak
						Fuel return pipe	Leak
						Return isolating valve	Leak
		Temperature	Lower fuel temperature	Unexpected engine stop/ Loss of performance	Heating Tracers	Inlet valve	No Flow
Jacket Water Cooler	Cylinder JCFW Outlet	Temperature	Higher fresh water temperature	Engine damage	JCFW pump	Shaft Housing	Bent Shaft Misalignment
	Cylinder JCFW Inlet	Pressure	No flow	Loss of redundancy	JCFW pump Output/Supply line	Inlet/Outlet valve	No flow
			Lower fresh water supply due to pump	Loss of redundancy	Motor of JCFW pump JCFW pump	Electric conductor Rotor Bearing Rotor Inlet/Outlet valve Pump seal Wear rings Impeller Housing	Degradation Wire break Failure Loss of efficiency Leak Wear Fouling

Subsystem	Measurement	Parameter	Failure Mode	Effect of Failure	Damaged Equipment	Damaged Component	Malfunction/Failure Cause
Lube Oil	M/E LO Inlet	Pressure	No supply due to pump	Loss of redundancy	Motor of LO pump LO Pump	Electric conductor Rotor Bearing Rotor Impeller Seal Inlet/Outlet valve Bearing Shaft	Degradation Wire break Failure Loss of efficiency Wear Shaft wear Seized bearing
			No flow of oil due to filter blockage	Loss of redundancy	LO filter	Filter	Blocking
			Low supply due to pump	Loss of redundancy	LO Pump	Impeller Seal Inlet/Outlet valve Bearing Shaft	Wear Leak Shaft wear Damaged bearing
			Low supply due to filter blockage	Loss of redundancy Unexpected stop of engine Engine damage	LO Filter	Inlet/Outlet valve Self-cleaning controller Filtering elements By-pass valve	Leak Blocking
		Temperature	Lower LO temperature	Loss of efficiency (slowdown)	LO Cooler	Regulating flow valve	Control
			Higher LO temperature	Loss of efficiency (slowdown)	LO Pump LO Cooler	Shaft Housing Regulating flow valve	Bent shaft Misalignment No flow Leak Loss of control
Air Cooler	Scavenging air receiver	Temperature	Improper scavenging	Loss of engine power & High exhaust temperature at affected cylinders	Turbocharger	Piston rings injectors	faulty timing unburned fuel
	Scavenging air manifold	Pressure	Lower pressure of inlet air	Loss of performance/ Engine damage	Manifold	Air flap Relief valve	Leak Flow back Leak Improper Flow

Subsystem	**Measurement**	**Parameter**	**Failure Mode**	**Effect of Failure**	**Damaged Equipment**	**Damaged Component**	**Malfunction/Failure Cause**
			Higher pressure of inlet air	Engine damage/ Turboblower damage	Manifold	Relief valve	Improper Flow
	M/E control spring air	Pressure	Air Leakage	Derating Engine		Piping and Joints	Leak
Engine	Camshaft Bearing (aft)	Temperature	Overheating of bearing	Engine damage	Camshaft	Bearings Camshaft	Wear & Tear
	Camshaft Bearing (fore)	Temperature	Overheating of bearing	Engine damage	Camshaft	Bearings Camshaft	Wear & Tear
	Thrust bearing LO outlet	Temperature	Improper lubrication	Engine damage	Thrust bearing	LO Piping	Leak
			Shaft malfunctioning	Engine slow down	Crankshaft	Thrust bearing	Wear & Tear
	Intermediate shaft bearing	Temperature	Overheating of bearing	Engine damage	Shaft	Bearing	Wear & Tear

Subsystem	Measurement	Parameter	Failure Mode	Effect of Failure	Damaged Equipment	Damaged Component	Malfunction/Failure Cause
Cylinders	Exhaust gas outlet	Temperature	Increased Exhaust Gas Temperature		Fuel Injectors Cylinder Air coolers Turbocharger Fuel oil	Piston rings Exhaust valves	leaking or incorrectly working fuel worn fuel pumps blow-by, piston rings leaking exhaust valves fouled air side fouled water side fouling of turbine side fouling of compressor side type and quality of fuel oil Recommendations: For each cylinder check and compare fuel indices and fuel valves visually and pressure testing. For cylinder condition, compare the compression pressures from the indicator and draw diagrams. During engine standstill carry out scavenging port inspection and check exhaust valve. Check cooling capability and check cooling water and ER temperature. For fuel oil quality, if poor combustion properties exist, a reduction of Pmax can occur.

Table F.3 Diagnostic qualitative input of PMRA strategy

Indication	Possible Cause	Diagnosing
Increased exhaust gas temperature	Fuel injection equipment: -leaking or incorrectly working fuel -worn fuel pumps	As these faults occur in individual cylinders, compare: -fuel indices Check the fuel valves: -visually -by pressure testing
	Cylinder condition: -blow-by, piston rings -leaking exhaust valves	These faults occur in individual cylinders. -Compare the compression pressures from the indicator and draw diagrams -During engine standstill: Carry out scavenge port inspection Check the exhaust valves
	Air coolers: -fouled air side -fouled water side	Check cooling capability
	Climatic conditions: -extreme conditions	Check cooling water and ER temperatures
	Turbocharger -fouling of turbine side -fouling of compressor side	Use T/C synopsis methods for diagnosis*
	Fuel Oil: -type and quality	Using heavy fuel oil will normally increase temperature by approx. 15 °C, compared to the use of gas oil. Further increase of Temperature will occur when using fuel oils with particularly poor combustion properties. In this case, a reduction of Pmax can also occur.
Compression pressure	Piston rings: -leaking	Diagnosis: See Table Increased Exhaust Temperature Level – Fault Diagnosing
	Piston crown: -burnt	Check the piston crown
	Cylinder liner: -worn	Check the liner by means of the measuring tool
	Exhaust valve: -leaking -exhaust temperature rises	Check: – Cam lead

Indication	Possible Cause	Diagnosing
	-hissing sound can possibly be heard at reduced load -timing	– Hydraulic oil leakages, e.g. misalignment of high pressure pipe between exhaust valve actuator and hydraulic cylinder. – Damper arrangement for exhaust valve closing.
	Piston rod stuffing box: -leaking air is emitted from the check funnel from the stuffing box	Small leakages may occur due to erosion of the bronze segments of the stuffing box, but this is normally considered a cosmetic phenomenon. Remedy: Overhaul the stuffing box
Improper scavenging/result of high exhaust temperature	Defected: -piston rings -faulty timing -injectors	1. Affected T/C may surge and sparks will be seen at the scavenge drains 2. Result loss of engine power and high exhaust temperature at affected cylinders 3. Unburned fuel and carbon may blow into scavenge space **ACTIONS** 1. Once fire is detected the engine should be slowed down, fuel shut off from the affected cylinders and cylinder lubrication increased 2. All scavenge drains should be closed 3. A small fire will quickly burn out, but where the fire persists the engine must be stopped 4. A fire extinguishing medium should then be injected through the fittings provided in the scavenge trunking 5. Scavenge trunking should be regularly inspected and cleaned if necessary 6. Where carbon or oil build up is found in the scavenge, its source should be detected and the fault remedied 7. Scavenge drains should be regularly blown and any oil discharges investigated at the first opportunity
Fluctuation in the engine RPM or not start from standstill	Stuck fuel rack	Solution: All the mechanical links of the fuel rack must be well lubricated and greased before starting the main engine. If after starting the main engine, the engine rpm is constantly fluctuating even at lower speed in calm weather, check all the fuel rack as one or more of them must be stuck.
Leakage of starting air valve	Leakage from the starting air valve will lead to hot gasses going back to the engine air-line, which may contain thin oil film (not common though nowadays)	Solution: Normally, there is no remote monitoring of temperature for the air-line supplying air to starting air valve. The best way to determine such fault is to check the temperature of the air-line manually during manoeuvring. This problem is more likely to occur when the engine is

Indication	Possible Cause	Diagnosing
		started frequently and not when engine is running continuously.
Fuel leakage/fuel valve malfunction	1. Problem in the fuel system 2. Deviation in temperature of one unit, the fuel system, especially the fuel valve needs to be checked 3. Overhauling and pressure testing of fuel valve. If the engine is maneuvered in diesel oil, there are chances of leakage from the pump seals. Also if the fuel treatment is improper and the fuel temperature is not maintained, it can lead to cracks and leakages in high pressure fuel pipe.	Solution: Any leakage in the main engine fuel oil system can be determined from the “high pressure leak off tank” level and alarm.
Sparks in the main engine exhaust at funnel	1. Sparks coming out from the funnel, which is the main engine exhaust 2. Sparks from funnel occur due to slow steaming and frequent manoeuvrings, which build unburnt soot deposits on the Exhaust Gas Boiler (EGB)	Solution: Frequent cleaning (monthly) of the exhaust gas boiler to be preferred by the ship staff to avoid this problem.
Starting air leakage	1. The control air supplies air to different parts and systems of the main engine. It is always in open condition when the engine is in use. Small leakages are normal and can be rectified only by tightening or replacing the pipes or joints	Solution: When the E/R machinery is in working condition it is difficult to hear any air leakage sound. The best way is to trace all the air-lines and feeling all the connections/joints by hand for air leakage. The easiest way to find air leakages is when there is an intentional black out done for any job. At this moment all the machinery will be in “stop” position and leakage sound (a hissing noise) will be loud and clear. Note the leakage area to perform the repairs later.
Stuck air distributor	Air distributor is responsible for maintaining the air supply which opens the starting air valve in the engine cylinders. Since it’s a mechanical part, it is prone to malfunctioning, especially getting stuck. The main engine will not start if air distributor does not supply air to open the starting air valves as no air will be present in the cylinder to commence fuel combustion	Solution: Many engines such as MAN B&W have their air distributor located at the end, with inspection cover, which can be opened when the engine is not running for inspection and lubrication to avoid this problem.

*Turboexpander is not considered in the case study demonstrated in Chapter 6. Hence, T/C information diagnostic information is not extracted and analysed for PMRA strategy.

APPENDIX G – RESULTS OF CASE STUDIES

Appendix G provides additional results related to Chapter 7 and the performed case studies. The designed and coded Dynamic Bayesian Belief Networks (DBBNs) provide analytical reliability performance results. Therefore, supplementary results of both case study groups are placed in Appendix G below. Furthermore, DBBNs enable the calculation of any probably failure case scenario by combining input from all involved parent nodes in all probable arrangement and will be presented next.

G.1. Results of processed data reliability case study

- **Diesel Generator (D/G) case study**

In this section, supplementary working state reliability performance prediction results for the Diesel Generator (D/G) acquired by the PMRA strategy are illustrated. The acronyms utilised in this case study are listed below.

Table G.1 Acronym list of diesel generator (D/G) maintainable units and components

Acronym	**Meaning**
AIE	Air Inlet
CLI	Cylinders
COL	Cooler
CUM	Control Unit
EXI	Exhaust
FFE	Fuel Filter
FPE	Fuel Pump
IJI	Injections
LIS	Level Instrument
OIL	Oil
PIN	Pressure Instrument
PPC	Piping
PSI	Pistons
RBI	Radial Bearings
SCS	Starting Control

Acronym	Meaning
SES	Starting Energy
SFE	Shaft
SIN	Speed Instrument
SUS	Starting Unit
TIN	Temperature Instrument
VVC	Valve

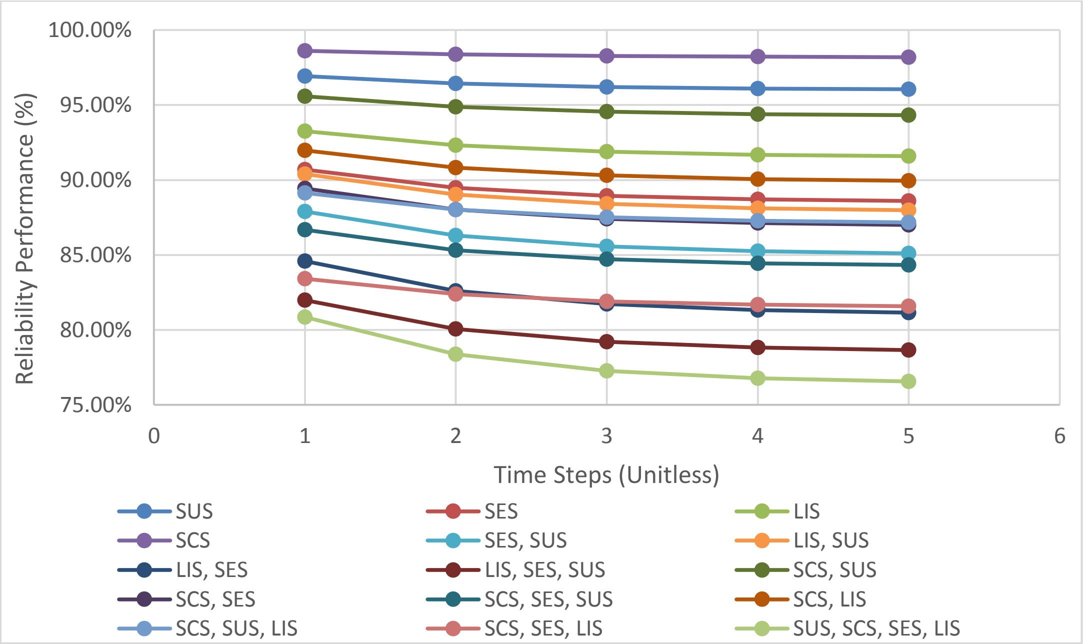

Figure G.1 Reliability performance of Diesel Generator (D/G) starting subsystem

Starting system (Figure G.1) incorporates four maintainable units and components such as the starting unit (SUS), starting control system (SCS), starting energy system (SES) and the level instrument (LIS).

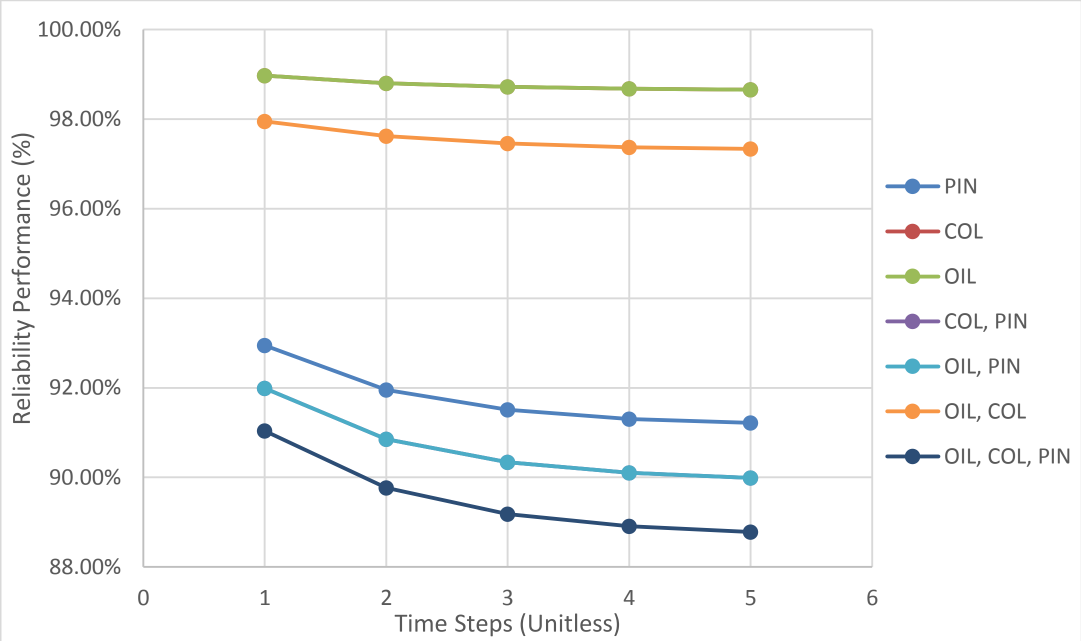

Figure G.2 Reliability performance of Diesel Generator (D/G) lubrication subsystem

In Figure G.2 the reliability performance predictions of the lubrication subsystem are presented. More specifically, lubrication (lube oil) system consists of maintainable units and components such as the oil (OIL), cooler (COL) and the pressure instrument (PIN).

On the other hand, Figure G.3 demonstrates the achieved reliability performance predictions on subsystem level of the Diesel Generator (D/G) for the control and monitoring. In particular, the overall reliability performance forecasted values for the incorporated speed instrument (SIN), temperature instrument (TIN) and the control unit for monitoring (CUM) are demonstrated.

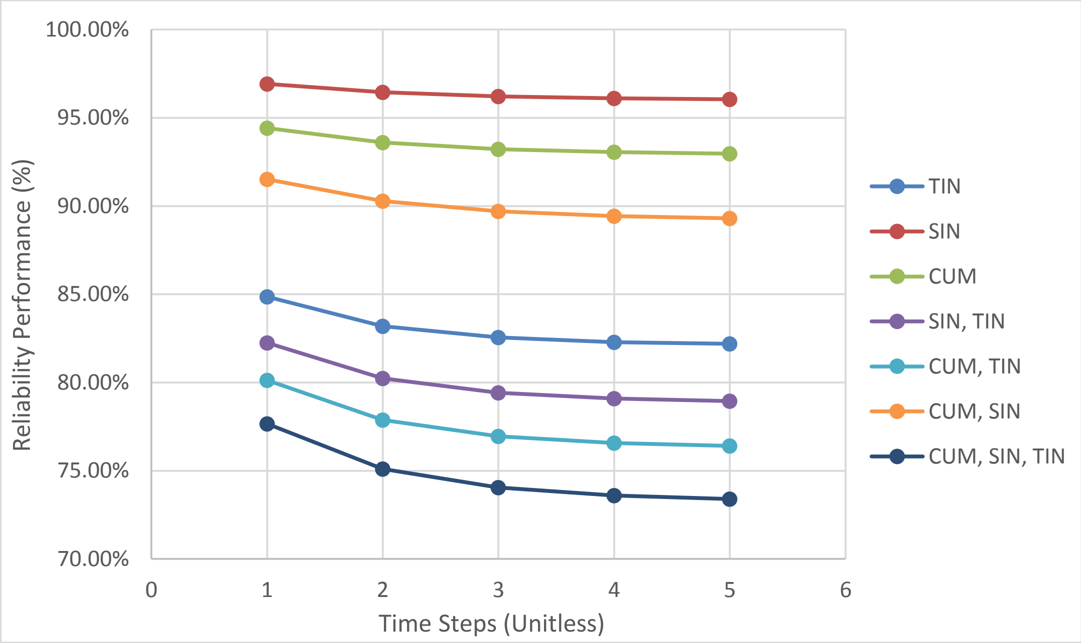

Figure G.3 Reliability performance of Diesel Generator (D/G) control monitoring subsystem

On the other hand, Figure G.4 illustrates the reliability prediction of the engine external components.

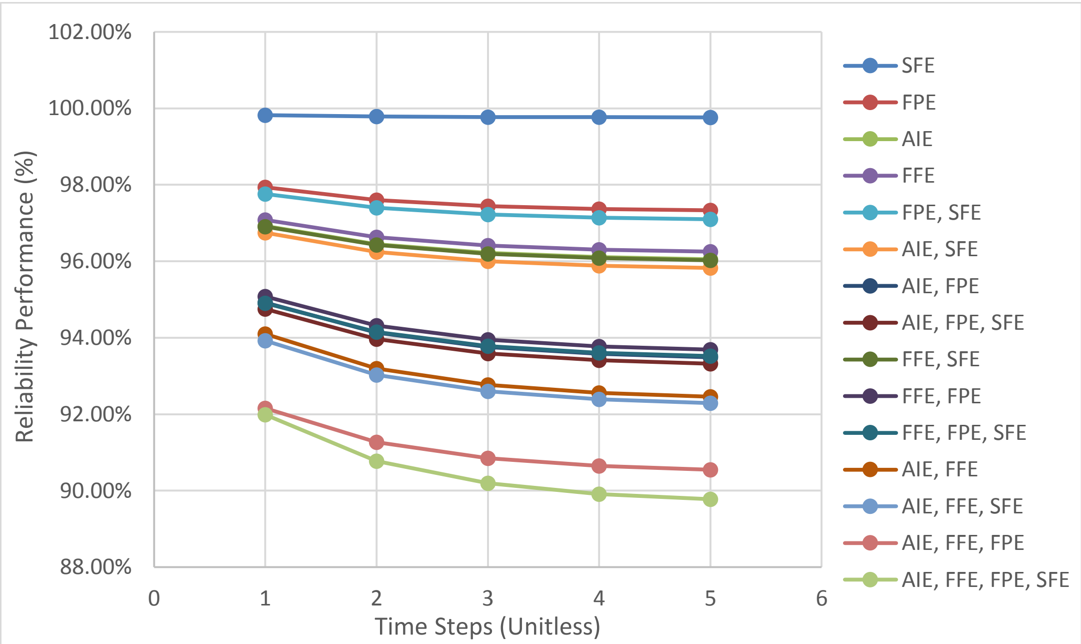

Figure G.4 Reliability performance of Diesel Generator (D/G) engine external components subsystem

This node in the developed Dynamic Bayesian Belief Network (DBBN) represents a group of components and maintainable units such as the air inlet (AIE), fuel pump (FPE), fuel filter (FFE) and the shaft (SFE). Additionally, the working state reliability performance predictions of the engine internal components subsystem are provided in Figure G.5, Figure G.6 and Figure G.7. The involved components and maintainable units include the injections (IJI), cylinders (CLI), exhaust (EXI), pistons (PSI) and radial bearings (RBI).

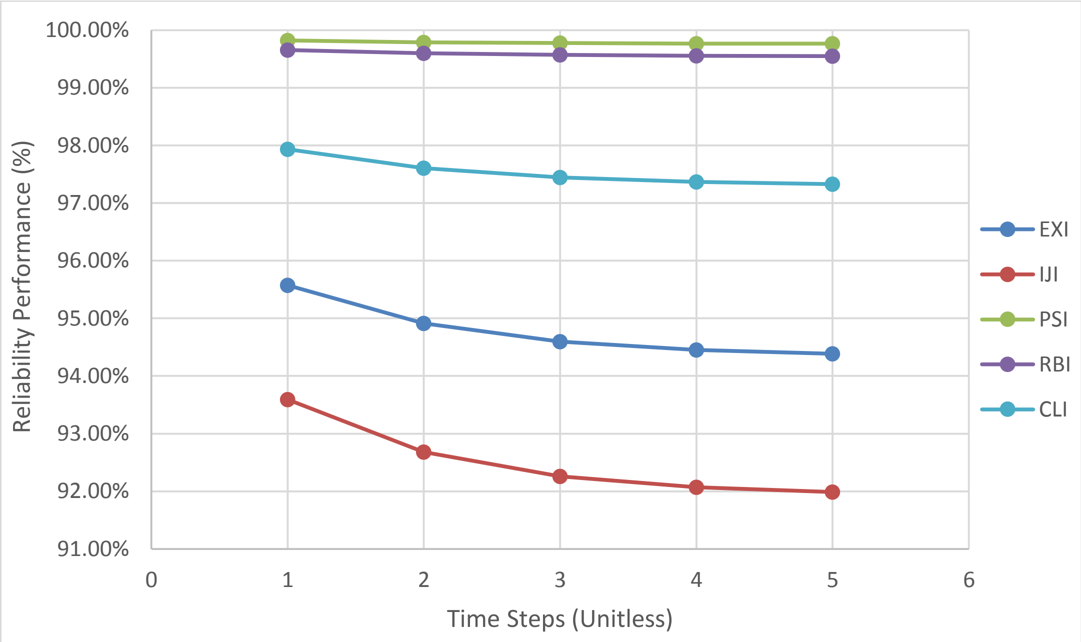

Figure G.5 Reliability performance of Diesel Generator (D/G) engine internal components subsystem (involving one component)

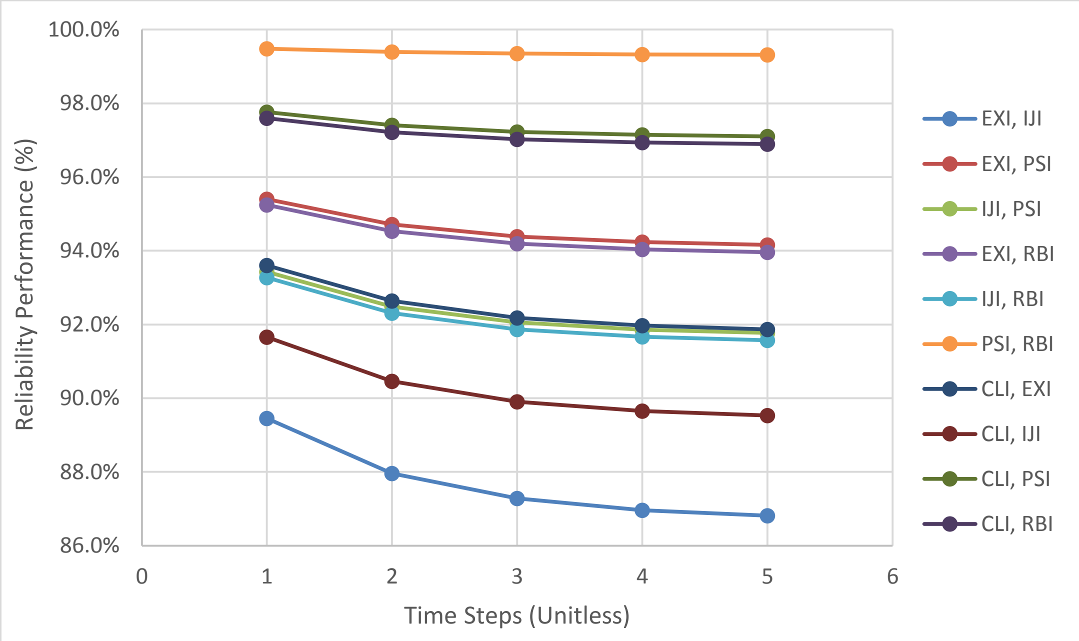

Figure G.6 Reliability performance of Diesel Generator (D/G) engine internal components subsystem (involving two components)

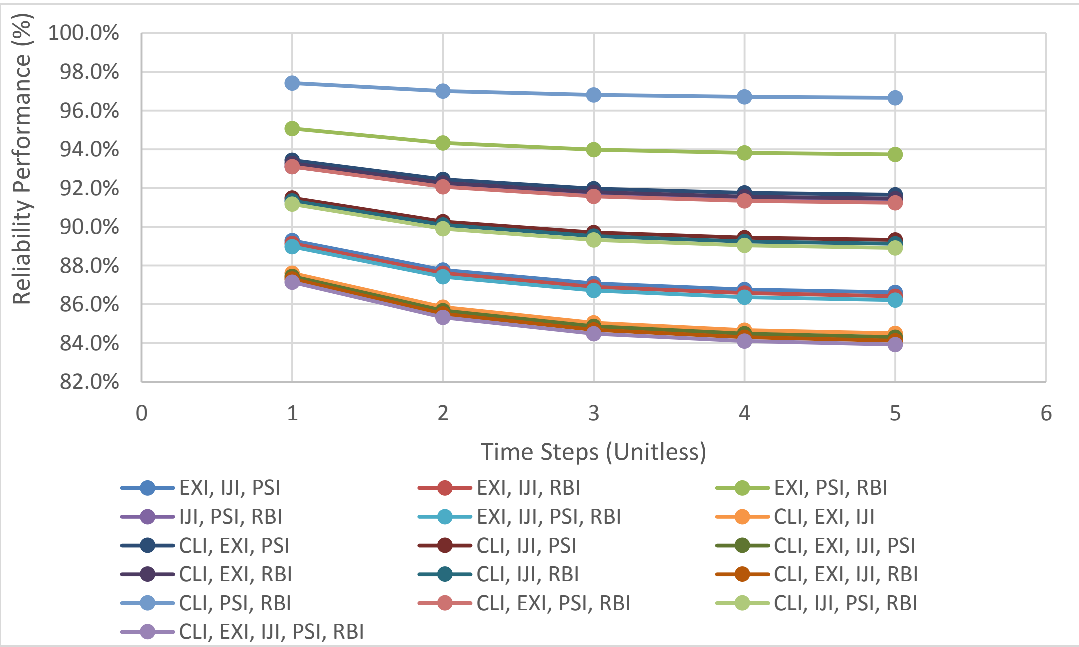

Figure G.7 Reliability performance of Diesel Generator (D/G) engine internal components subsystem (involving three, four and five components)

Lastly, the cooling subsystem is demonstrated in Figure G.8 Two maintainable units are considered in this arrangement such as the valve (VVC) and the piping (PPC).

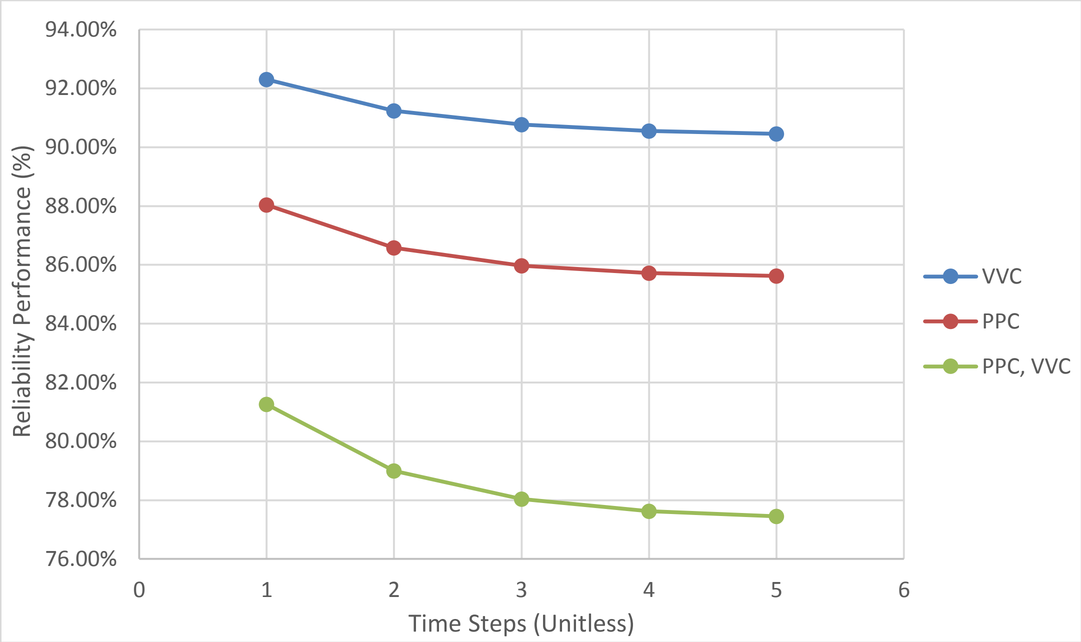

Figure G.8 Reliability performance of Diesel Generator (D/G) cooling subsystem

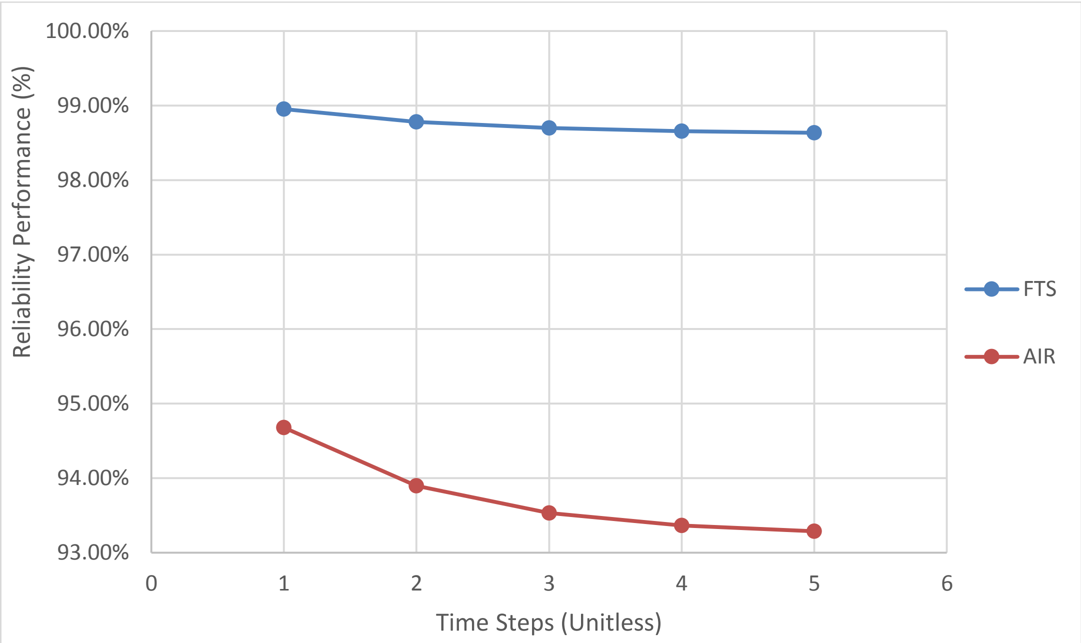

Figure G.9 Reliability performance of Diesel Generator (D/G) control unit

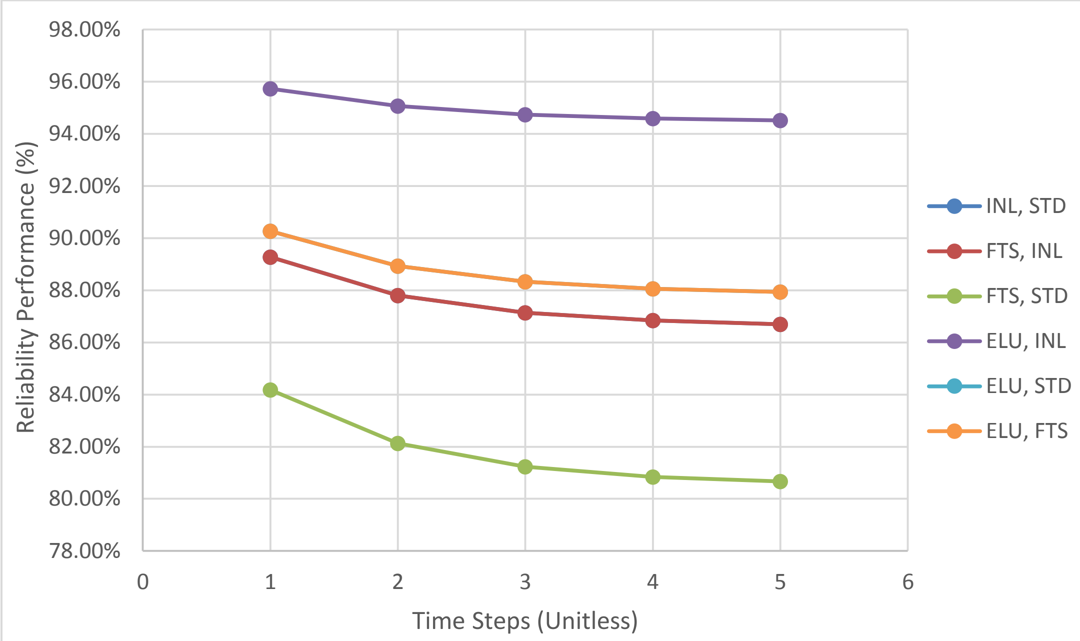

Figure G.10 Reliability performance of Diesel Generator (D/G) cylinders (involving two components)

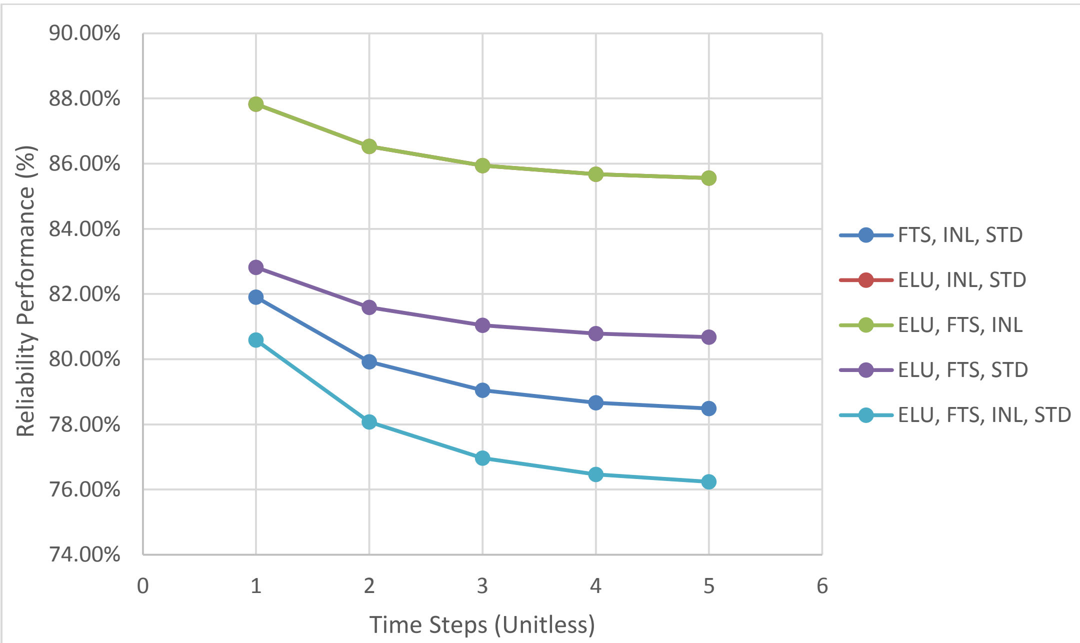

Figure G.11 Reliability performance of Diesel Generator (D/G) cylinders (involving three and four components)

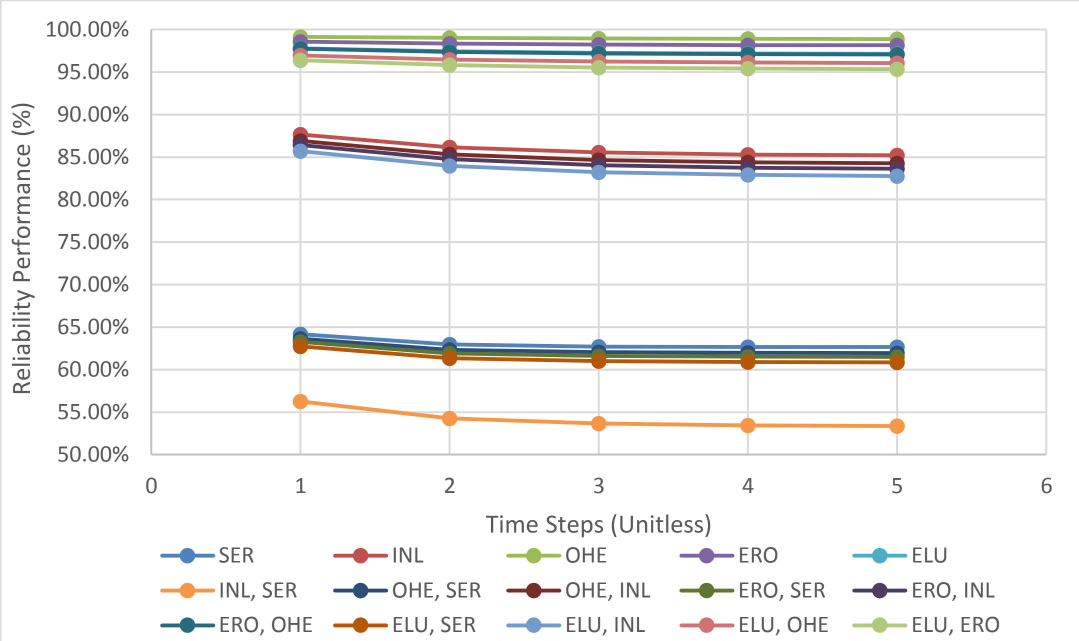

Figure G.12 Reliability performance of Diesel Generator (D/G) injections (involving one and two components)

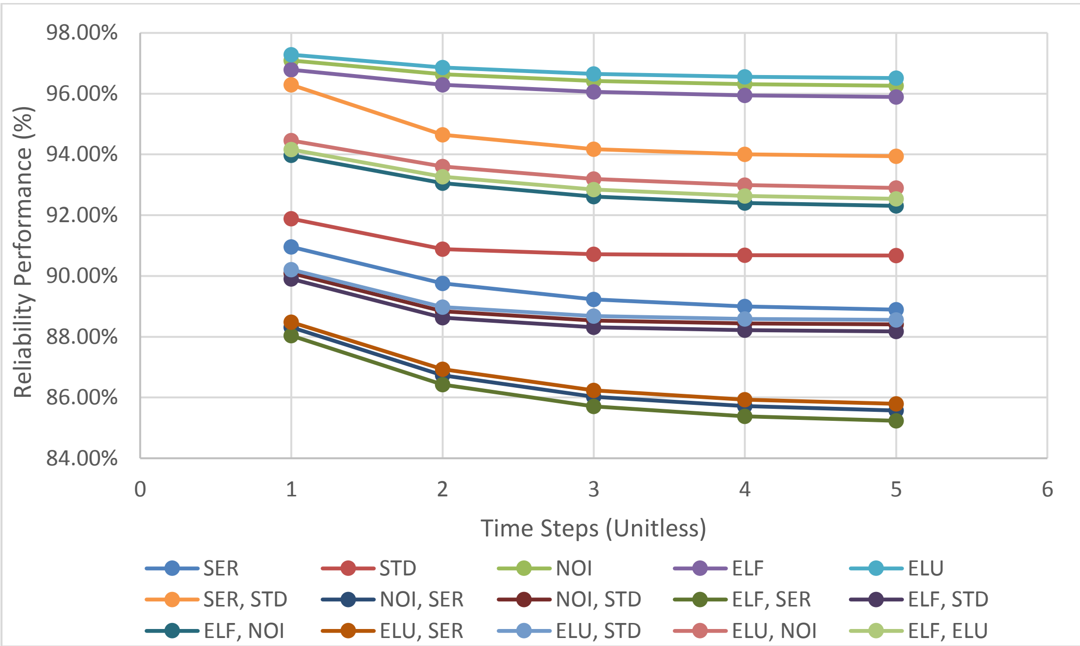

Figure G.13 Reliability performance of Diesel Generator (D/G) exhaust (involving one and two components)

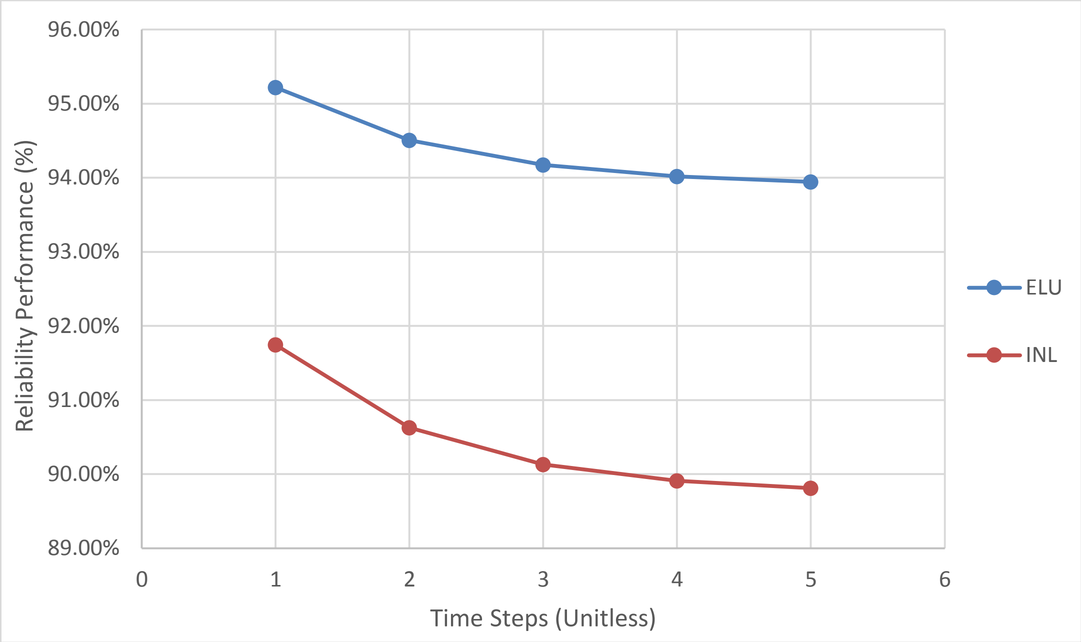

Figure G.14 Reliability performance of Diesel Generator (D/G) fuel pump

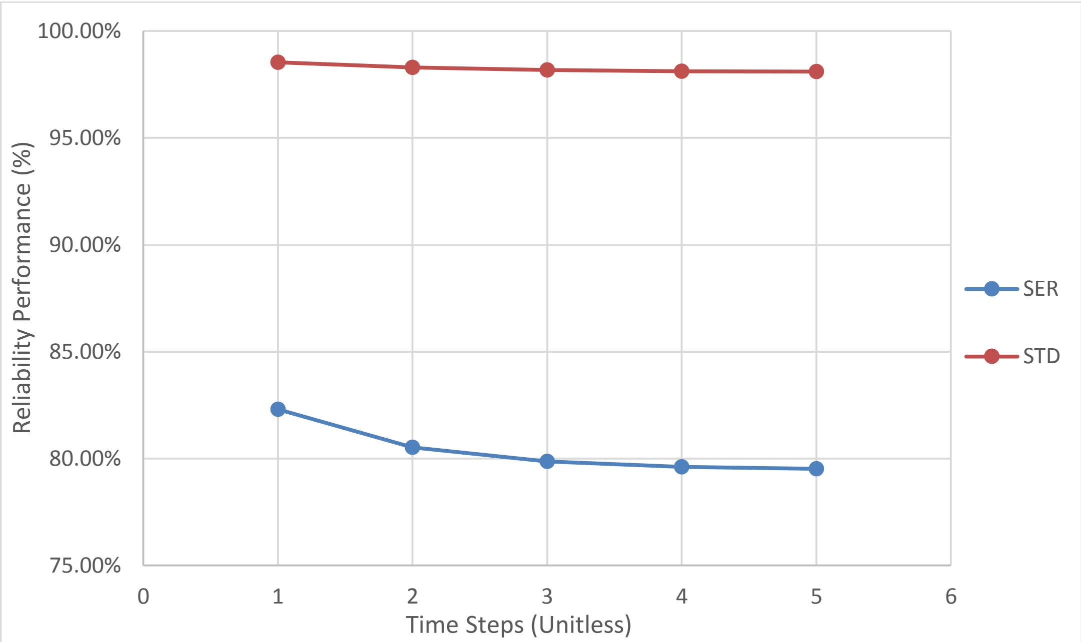

Figure G.15 Reliability performance of Diesel Generator (D/G) air inlet

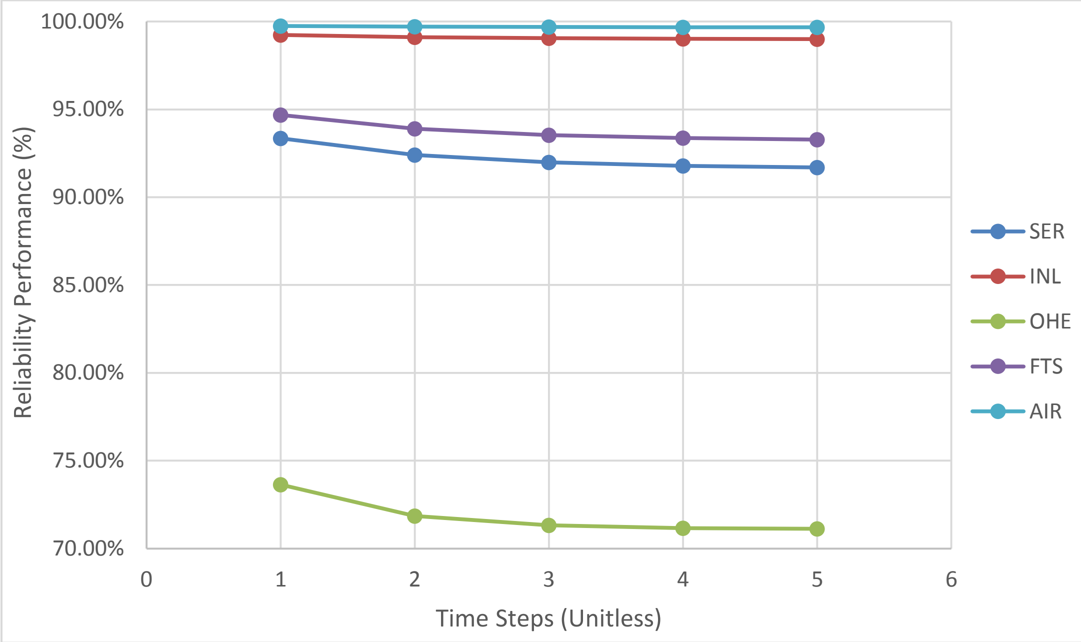

Figure G.16 Reliability performance of Diesel Generator (D/G) valve

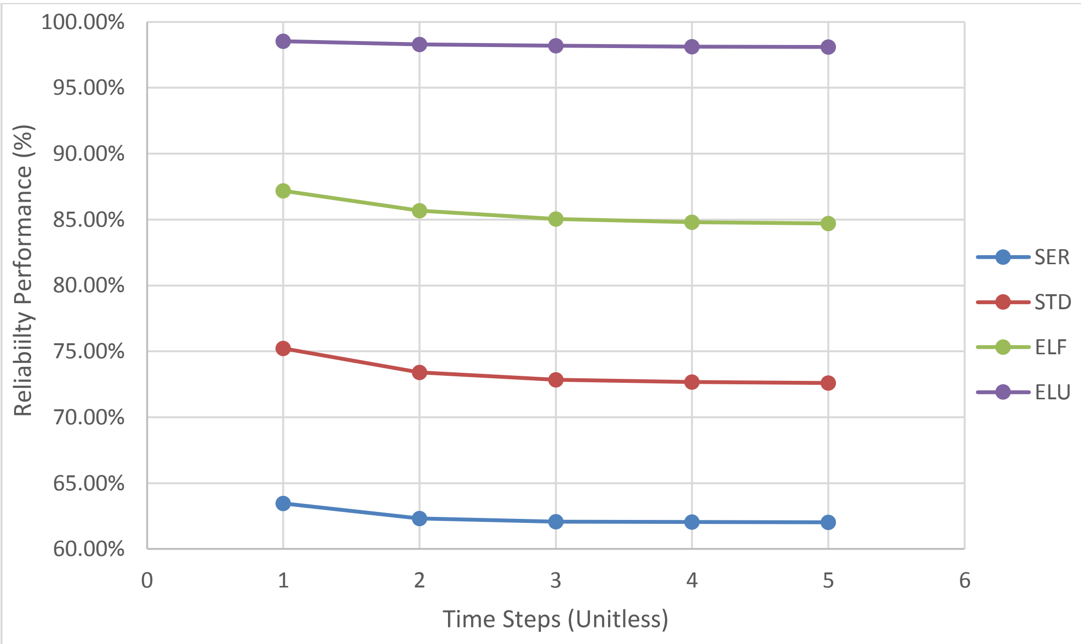

Figure G.17 Reliability performance of Diesel Generator (D/G) piping

- **Turboexpander case study**

Table G.2 Acronym list of Turboexpander maintainable units and components

Acronym	Meaning
ACT	Actuator
CNT	Control Unit
FIN	Flow Instrument
FLT	Filters
GIN	General Instrument
MON	Monitoring
OIL	Oil
PIN	Pressure Instrument
PIP	Piping
SIN	Speed Instrument
TBR	Thrust Bearing
TIN	Temperature Instrument

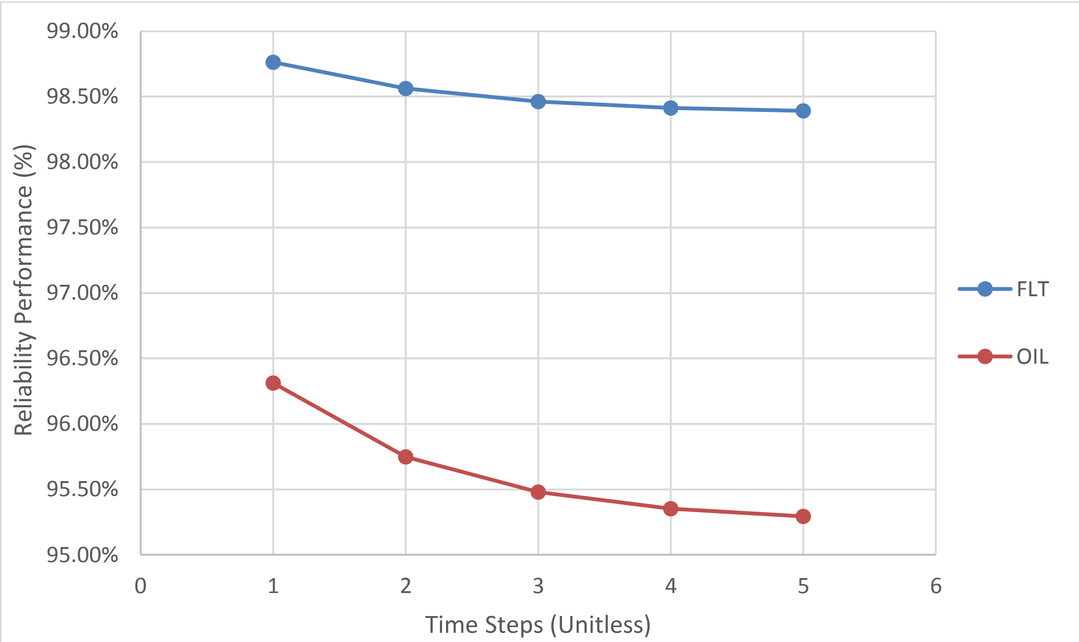

Figure G.18 Reliability performance of Turboexpander lubrication subsystem

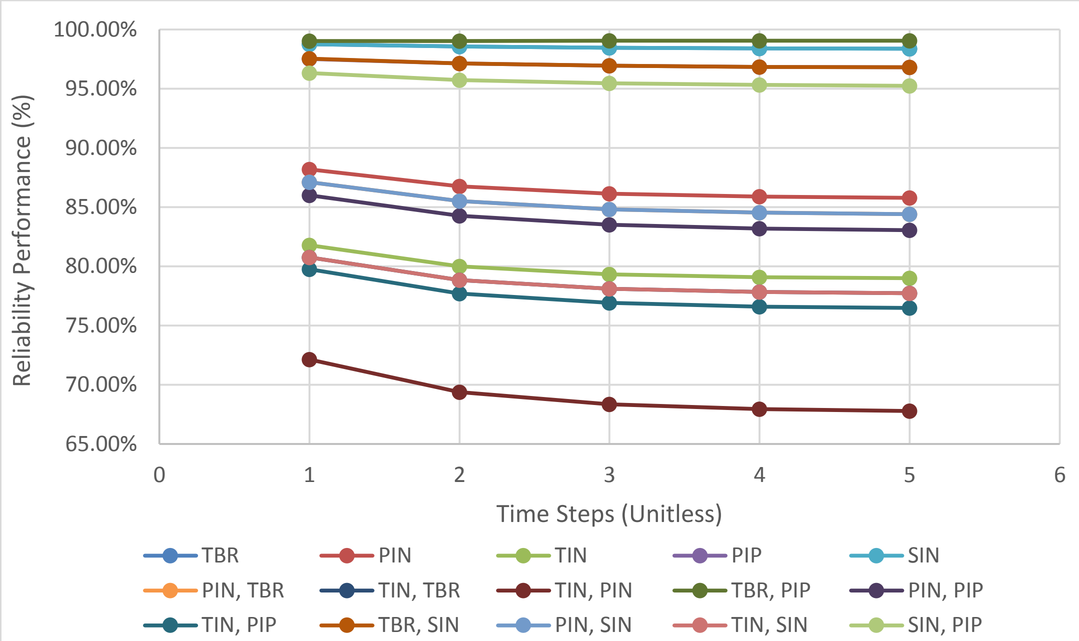

Figure G.19 Reliability performance of Turboexpander expander/recompressor turbine subsystem

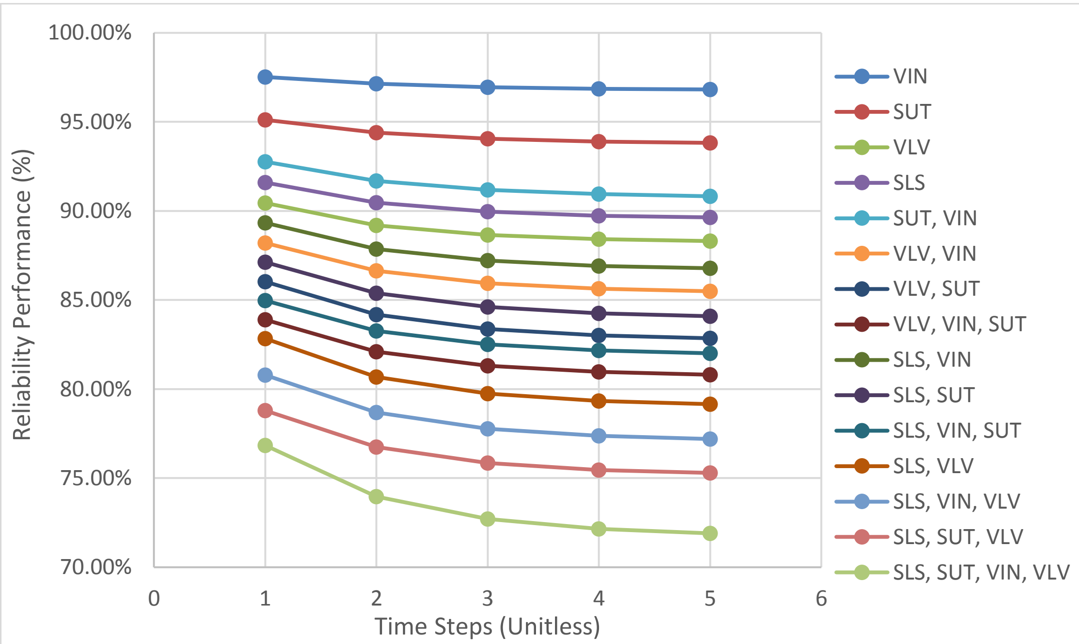

Figure G.20 Reliability performance of Turboexpander shaft and seal subsystem

- **Seawater lift pump case study**

Table G.3 Acronym list of seawater lift pump maintainable units and components

Acronym	Meaning
ACT	Actuator
BR	Bearing
CAB	Cabling
CAS	Casing
Cdriven	Coupling Driven
Cdriver	Coupling Driver
CHC	Check Valve
CON	Control Unit
FLT	Filter
IMP	Impeller
LUB	Lubrication
MON	Monitoring
RBR	Radial Bearing
SHF	Shaft
SLS	Seals
THR	Thrust Bearing

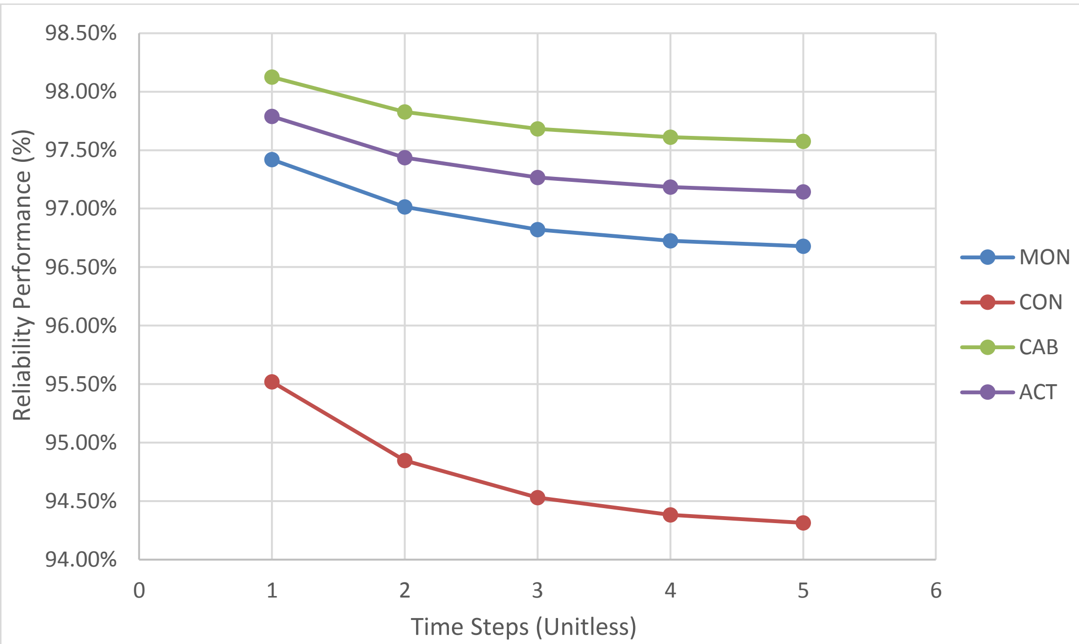

Figure G.21 Reliability performance of seawater lift pump controller subsystem

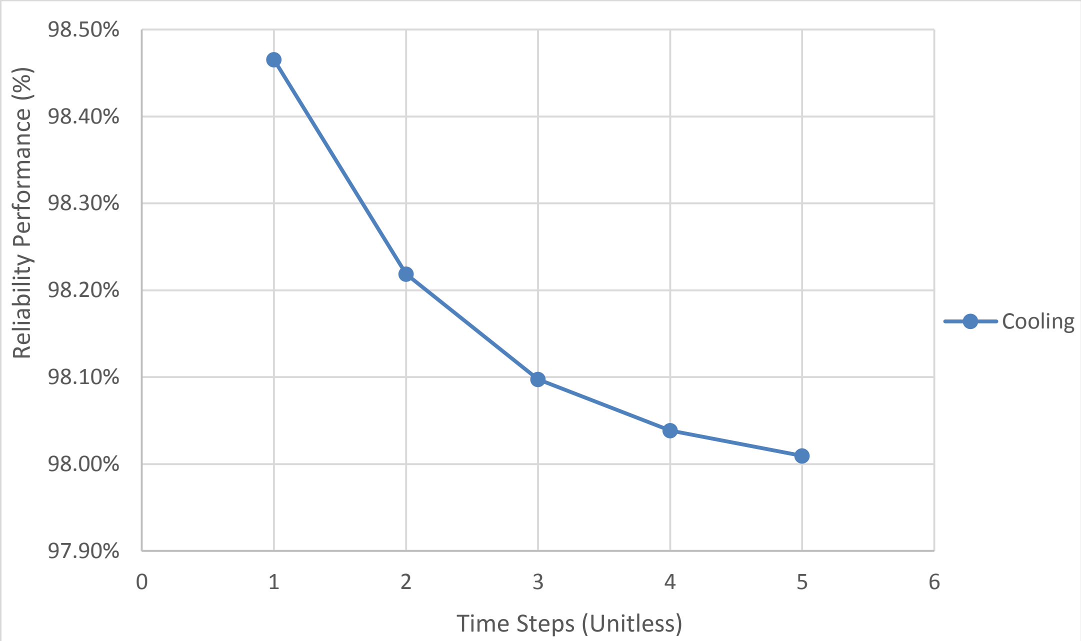

Figure G.22 Reliability performance of seawater lift pump cooling subsystem

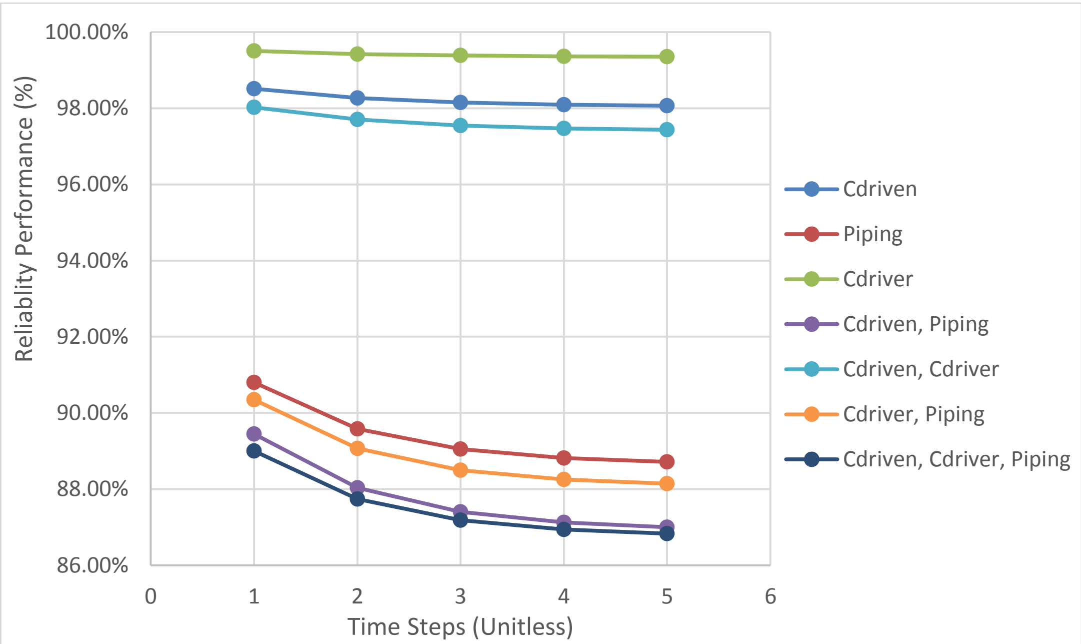

Figure G.23 Reliability performance of seawater lift pump couplers subsystem

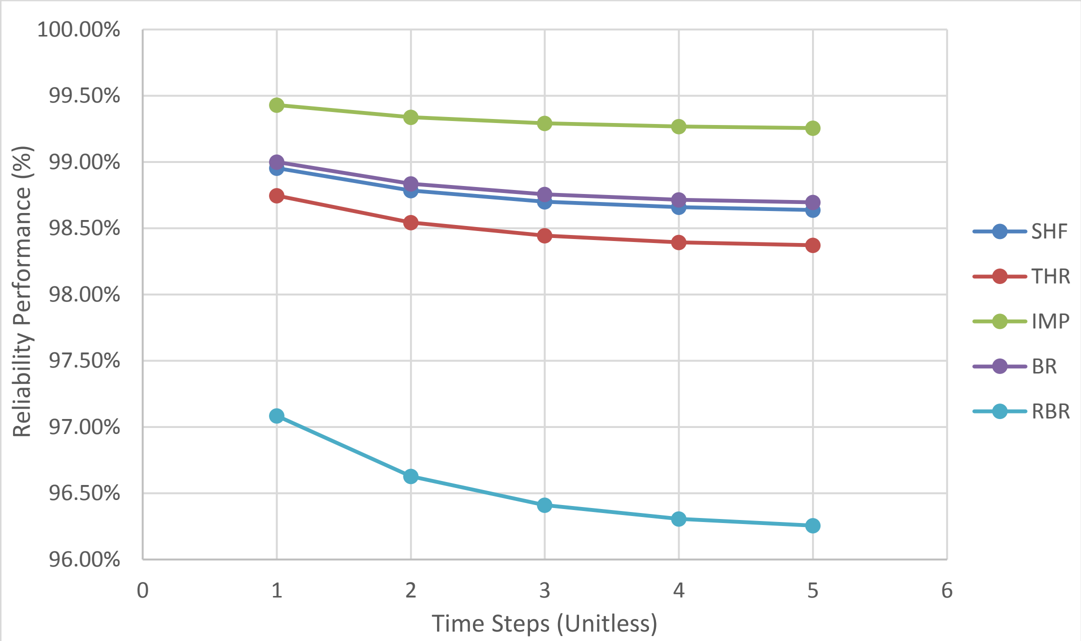

Figure G.24 Reliability performance of seawater lift pump mechanical power subsystem

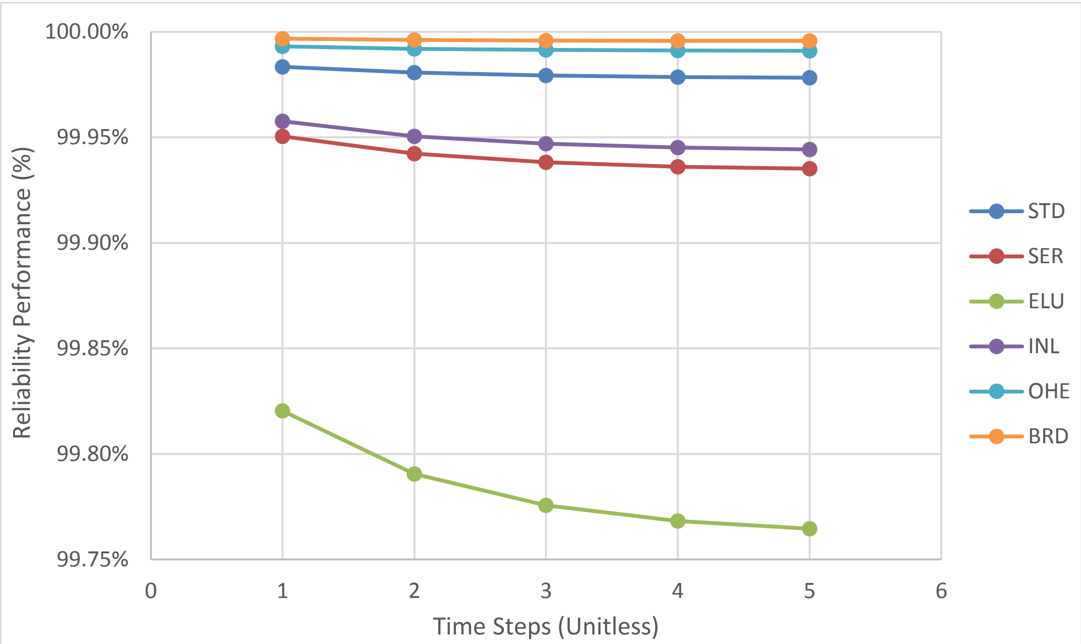

Figure G. 25 Reliability performance of seawater lift pump seals

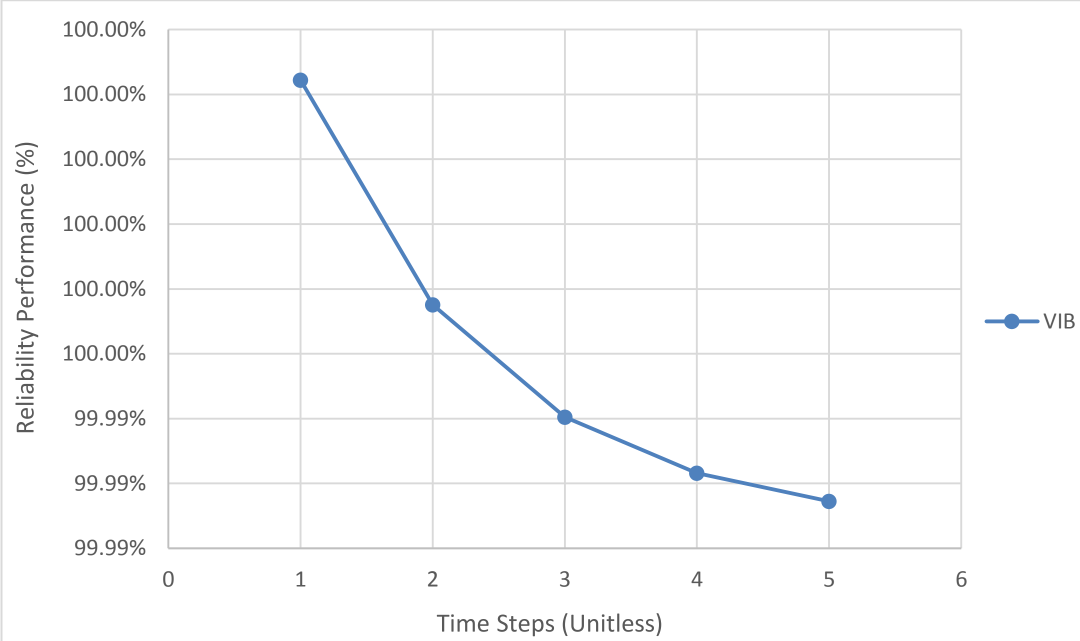

Figure G.26 Reliability performance of seawater lift pump coupling driver

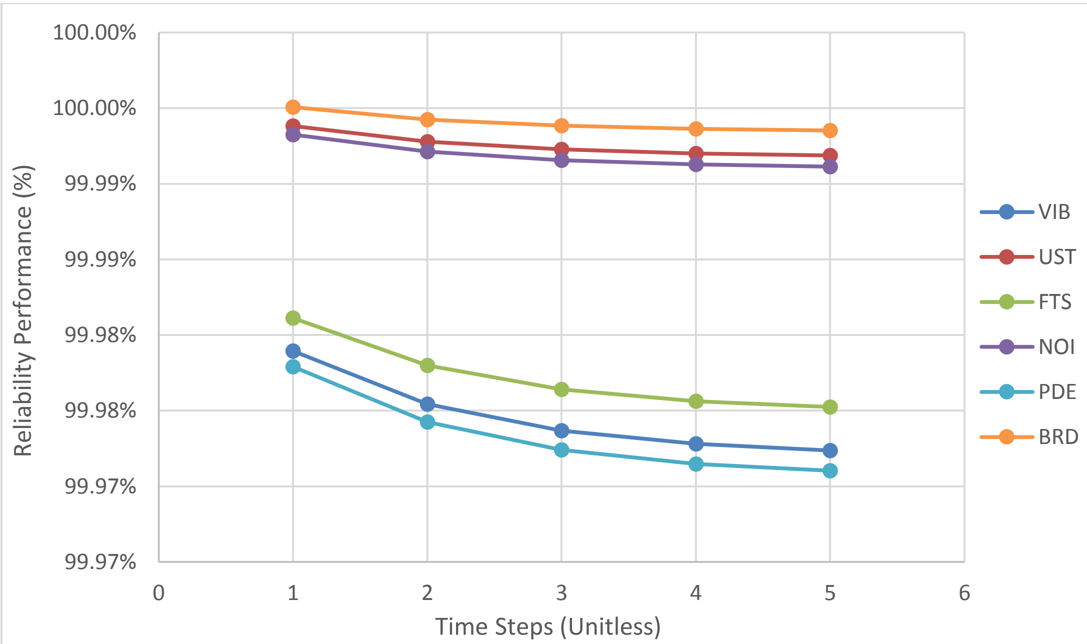

Figure G.27 Reliability performance of seawater lift pump radial bearing

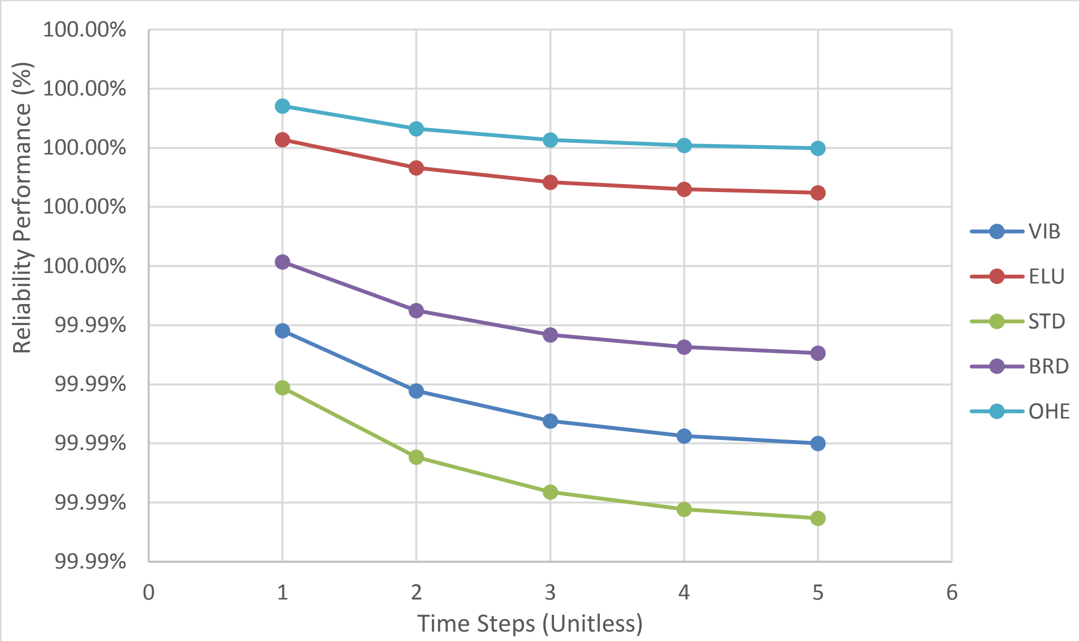

Figure G.28 Reliability performance of seawater lift pump thrust bearing

- **Oil export pump case study**

Table G.4 Acronym list of oil export pump maintainable units and components

Acronym	Meaning
ACT	Actuator
BER	Bearing
CAB	Cabling
CAS	Casing
CDN	Coupling Driven
CDR	Coupling Driver
COL	Cooling
CTL	Control Unit
FLT	Filter
IMP	Impeller
LUB	Lubrication
MON	Monitoring
RDB	Radial Bearing
SFT	Shaft
SLS	Seals
THB	Thrust Bearing
VLV	Valve

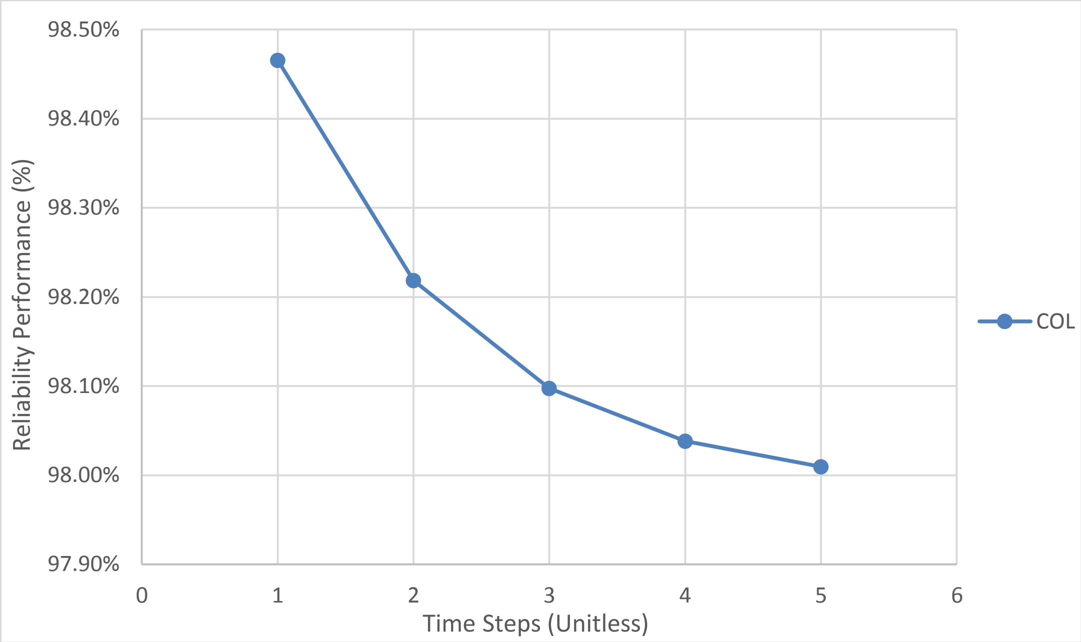

Figure G.29 Reliability performance of oil export pump cooling subsystem

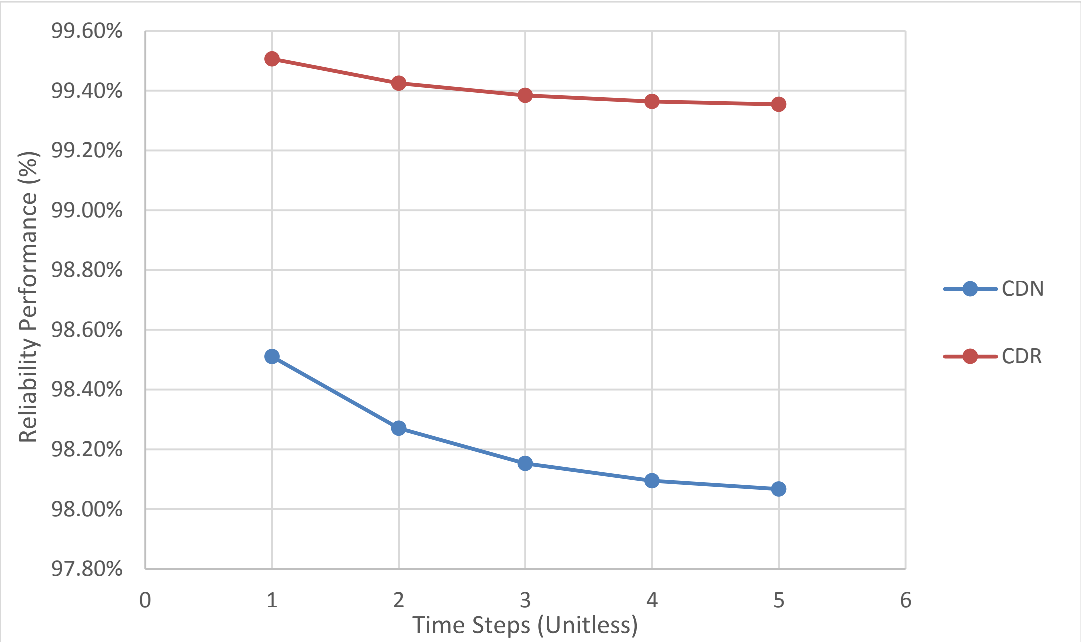

Figure G.30 Reliability performance of oil export pump couplers subsystem

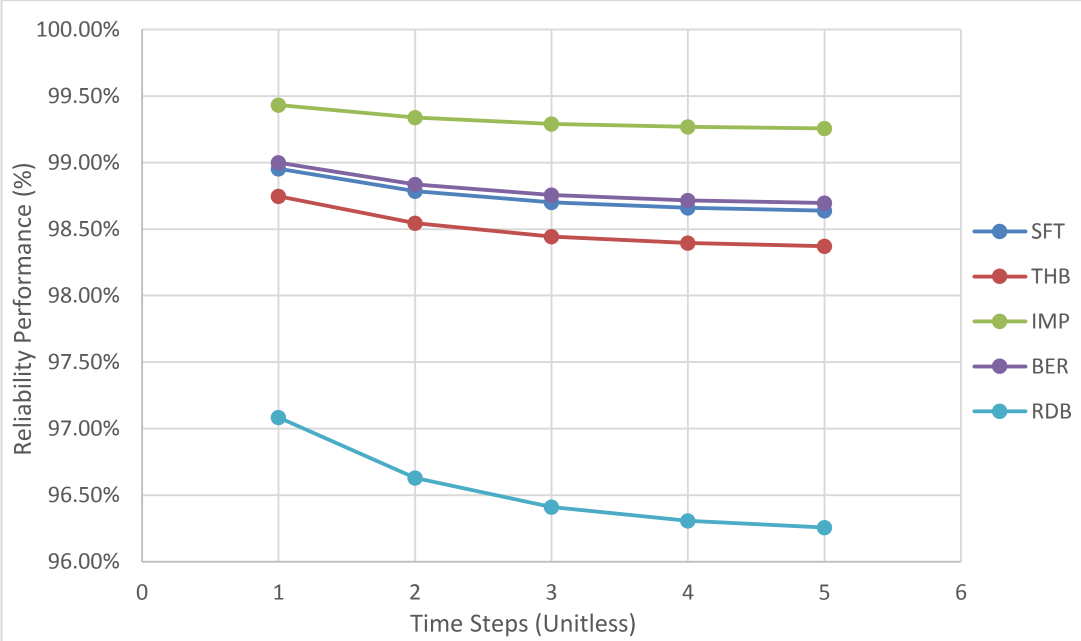

Figure G.31 Reliability performance of oil export pump mechanical power subsystem

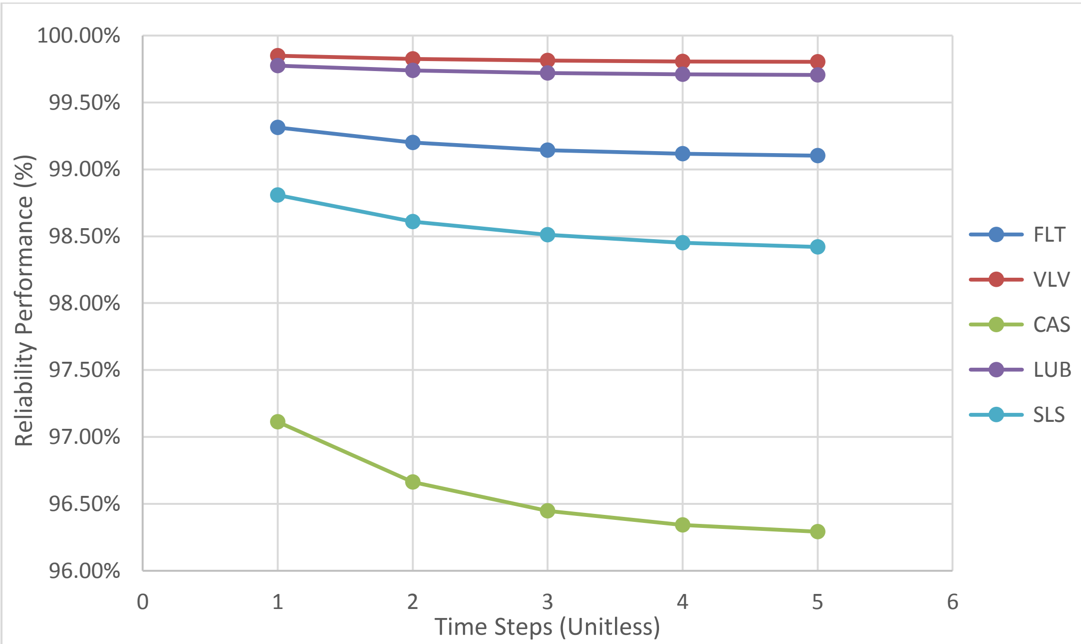

Figure G.32 Reliability performance of oil export pump shell subsystem

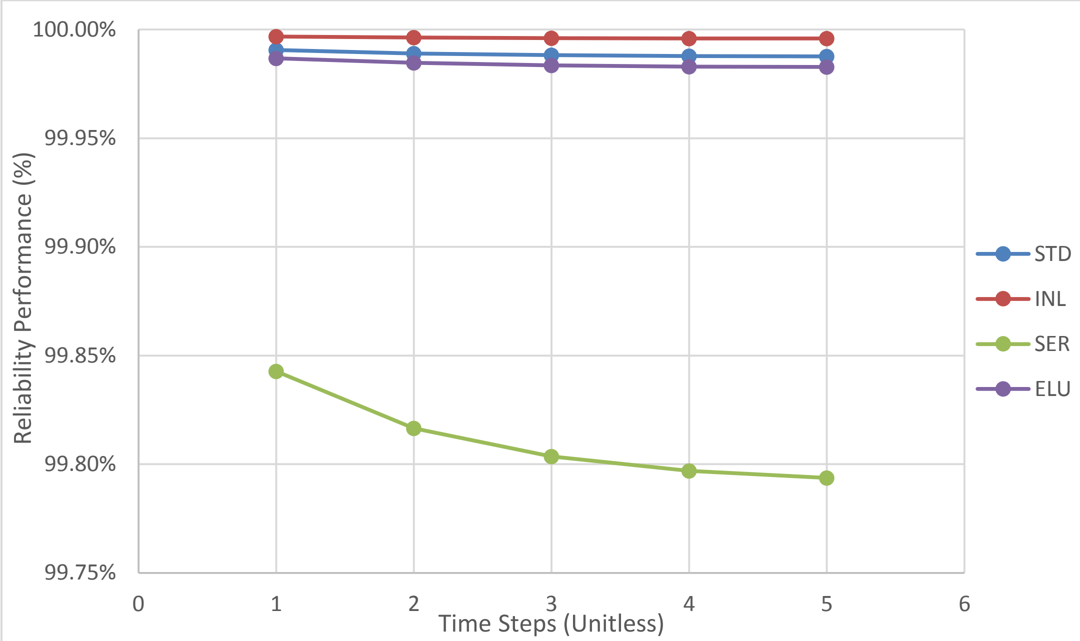

Figure G.33 Reliability performance of oil export pump filter

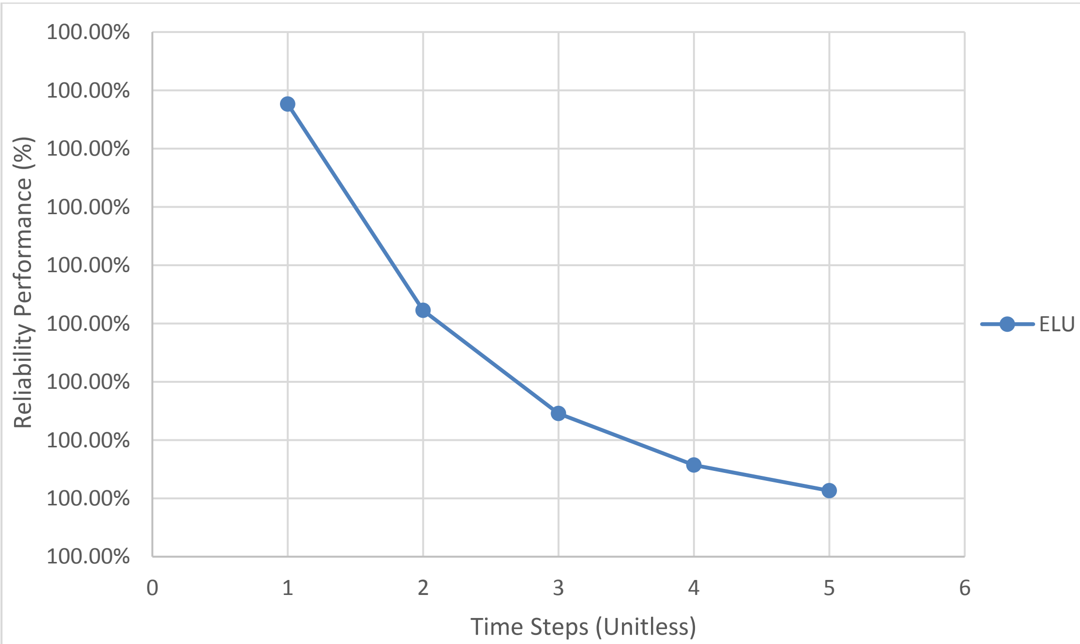

Figure G.34 Reliability performance of oil export pump lubrication

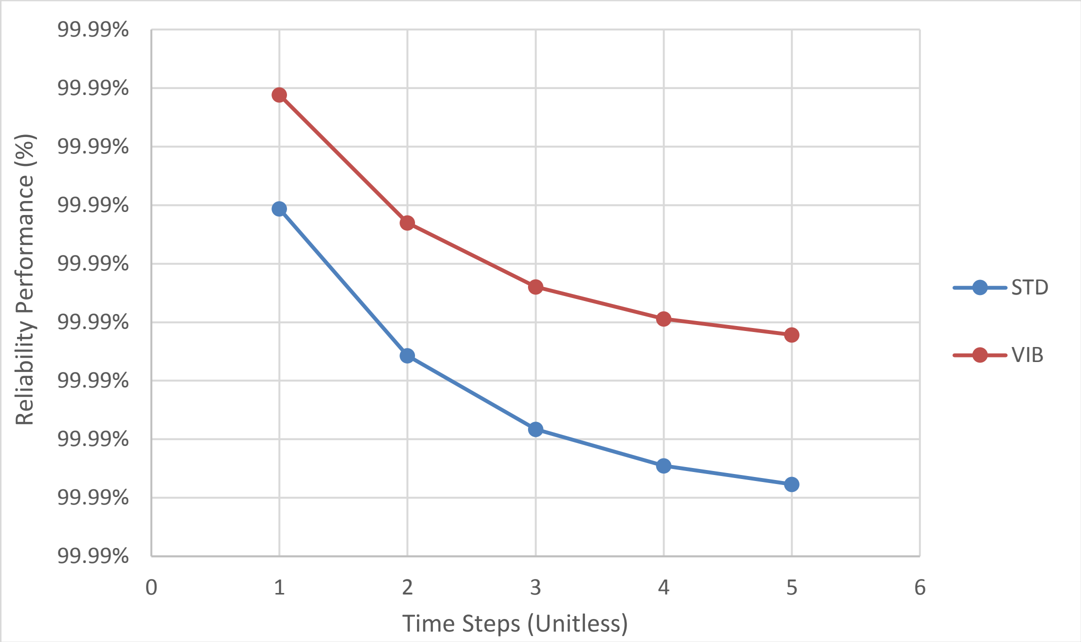

Figure G.35 Reliability performance of oil export pump impeller

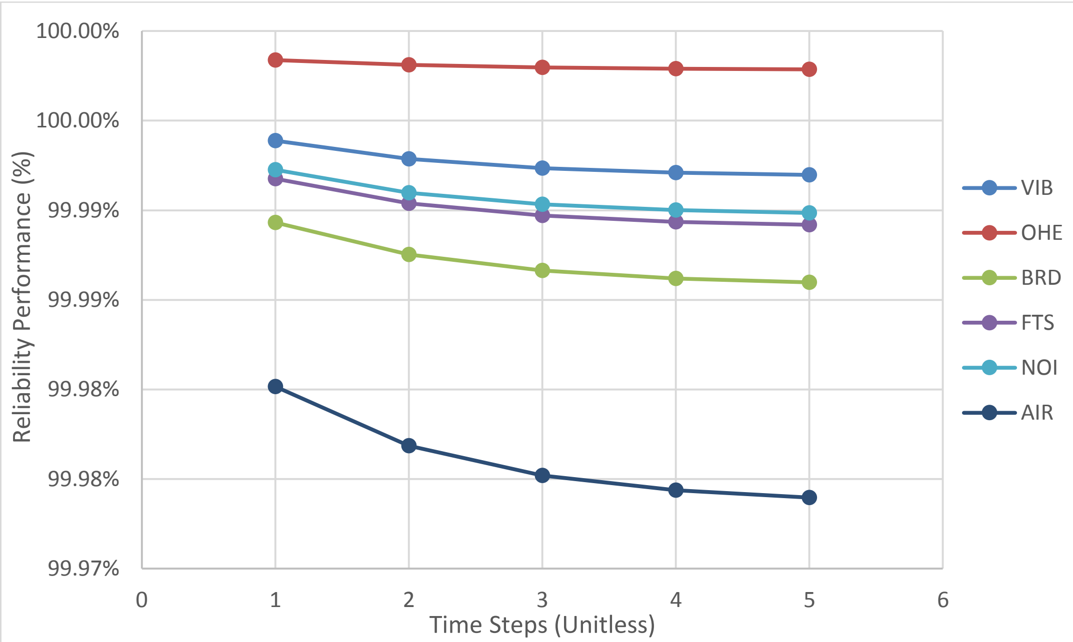

Figure G.36 Reliability performance of oil export pump shaft

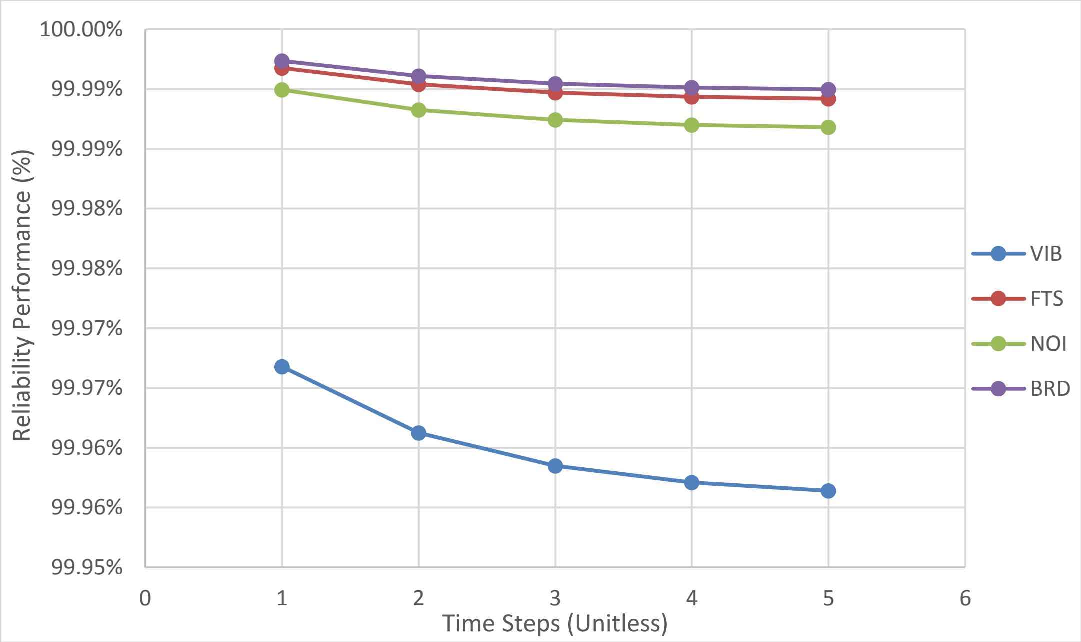

Figure G.37 Reliability performance of oil export pump radial bearing

- **Cooling Water Pump (CW) case study**

Table G.5 Acronym list of cooling water pump maintainable units and components

Acronym	Meaning
ACT	Actuator
BER	Bearing
CAB	Cabling
CDN	Coupling Driven
CTL	Control Unit
MON	Monitoring
RBR	Radial Bearing
SFT	Shaft
VLV	Valve

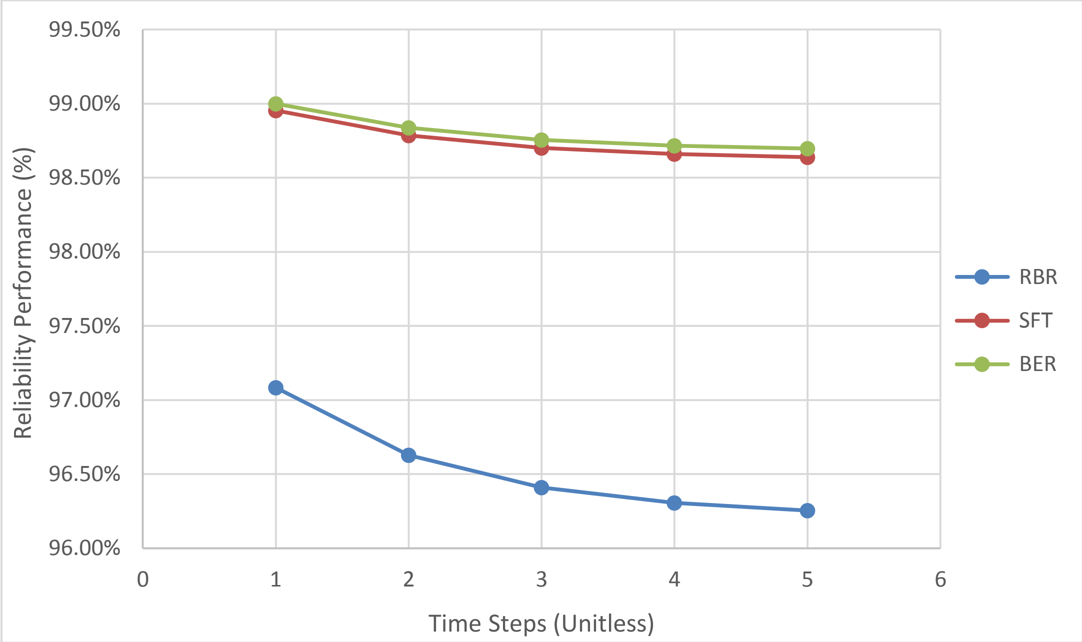

Figure G.38 Reliability performance of Cooling Water Pump (CW) mechanical power subsystem

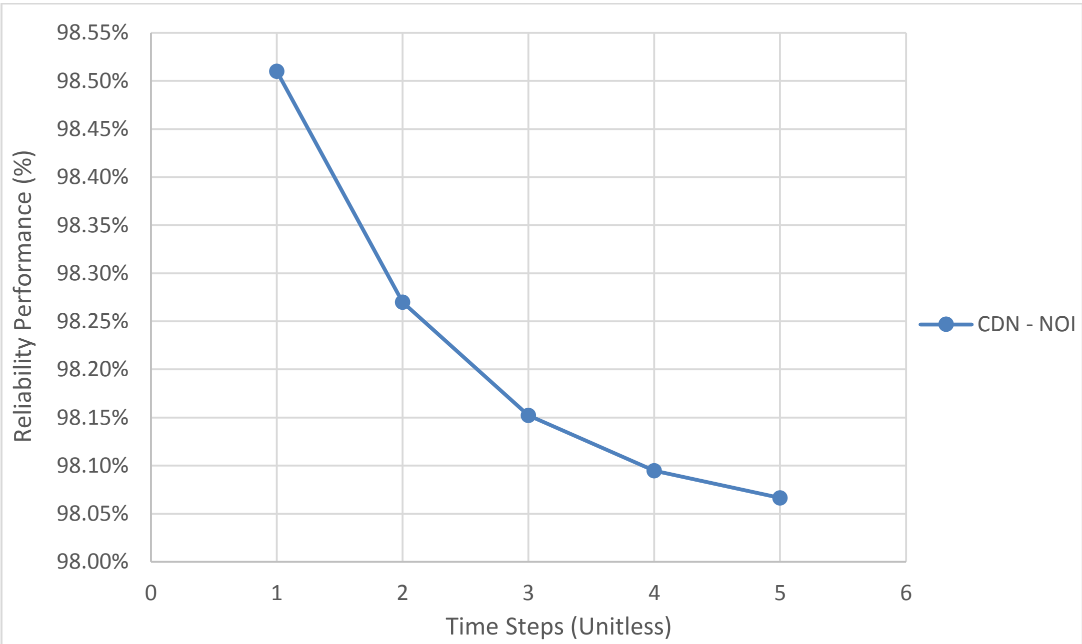

Figure G.39 Reliability performance of Cooling Water Pump (CW) coupling driven

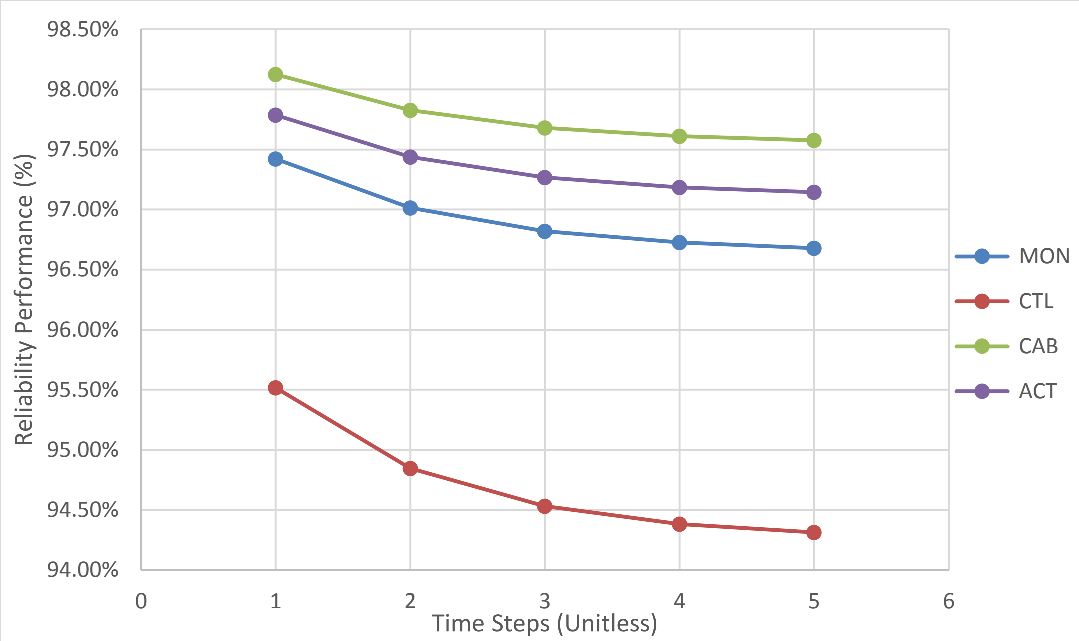

Figure G.40 Reliability performance of Cooling Water Pump (CW) controller subsystem

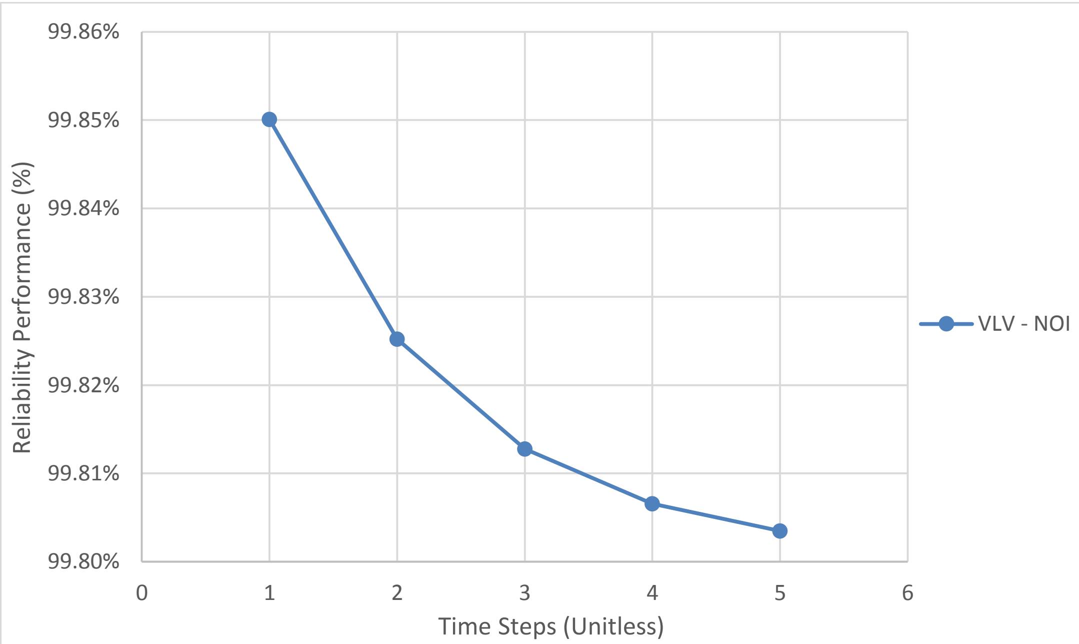

Figure G.41 Reliability performance of Cooling Water Pump (CW) valve

- **Firefighting Pump (FP) case study**

Table G.6 Acronym list of firefighting pump maintainable units and components

Acronym	Meaning
ACT	Actuator
BER	Bearing
CAB	Cabling
CAS	Casing
CTL	Control Unit
FLT	Filter
IMP	Impeller
LUB	Lubrication
MON	Monitoring
RBR	Radial Bearing
SFT	Shaft
SLS	Seals
TBR	Thrust Bearing

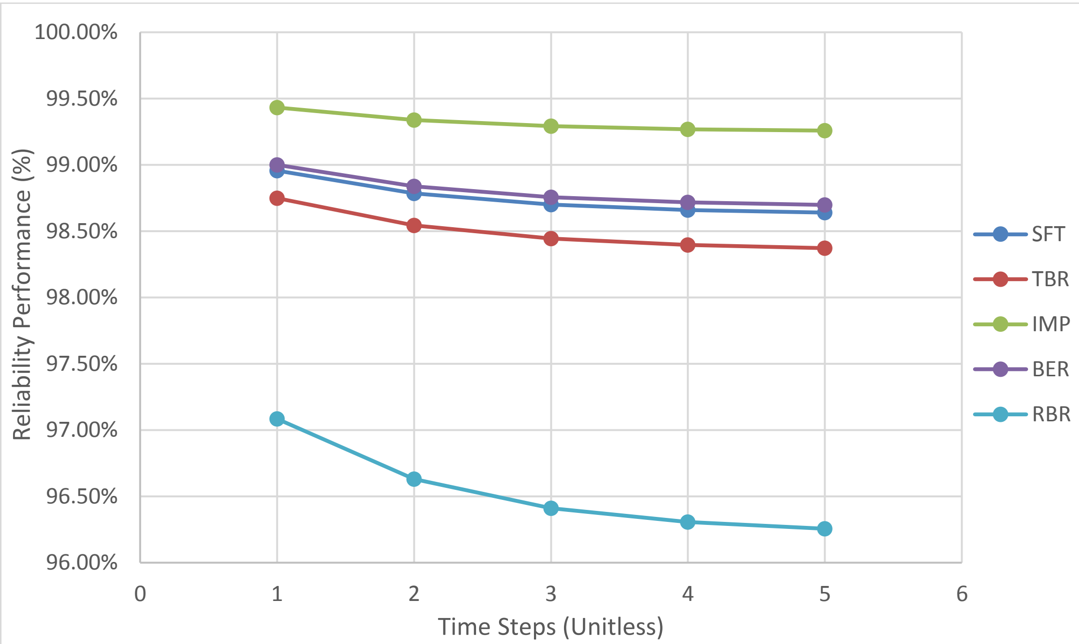

Figure G.42 Reliability performance of Firefighting Pump (FP) mechanical power subsystem

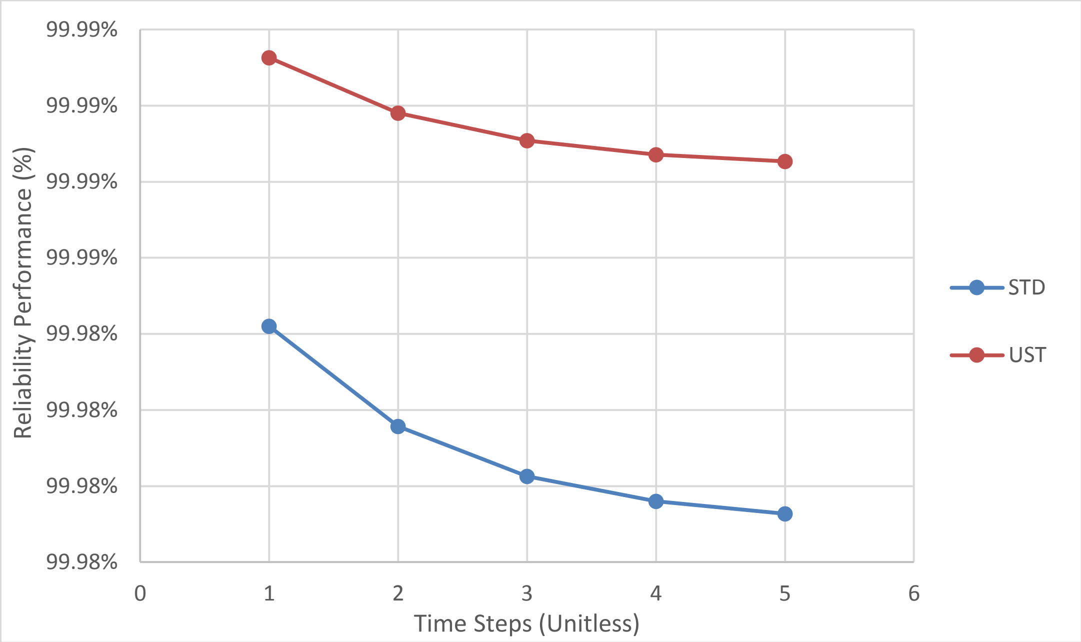

Figure G.43 Reliability performance of Firefighting Pump (FP) coupling driven

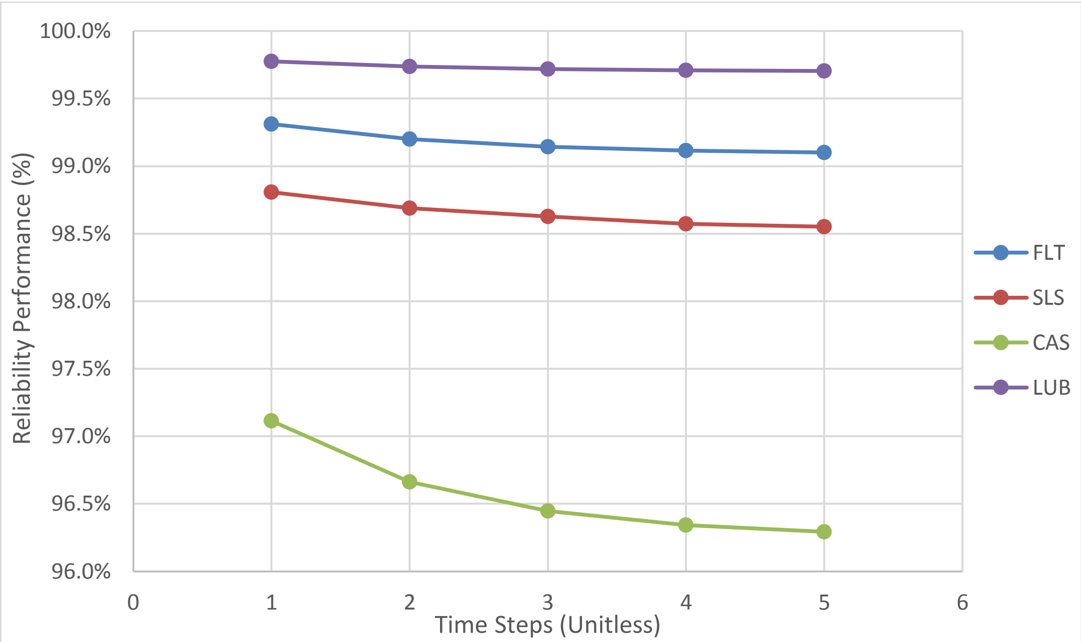

Figure G.44 Reliability performance of Firefighting Pump (FP) shell subsystem

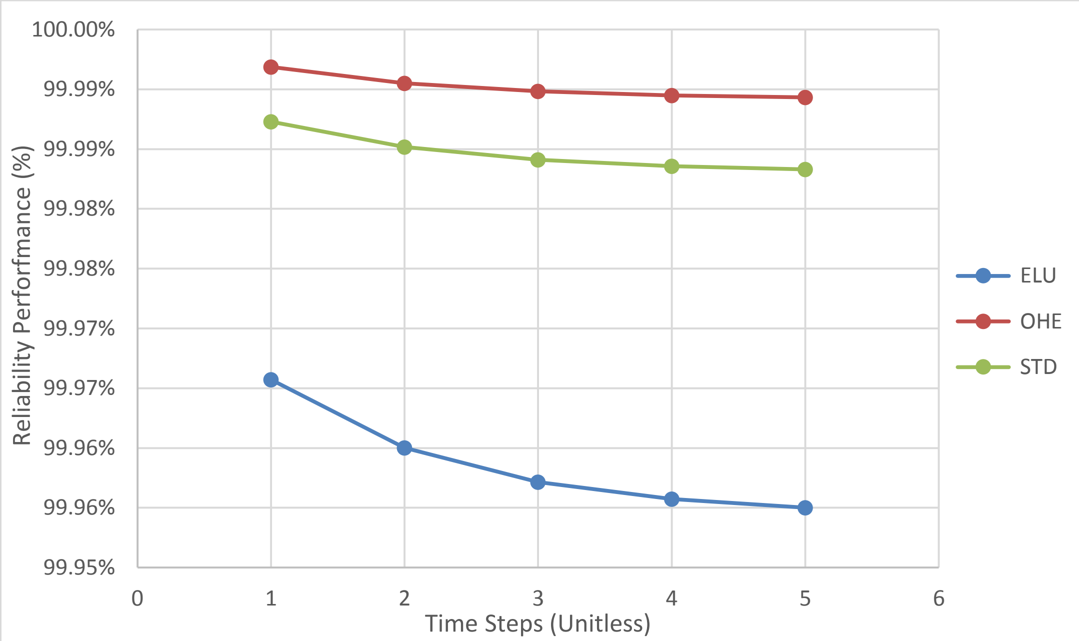

Figure G.45 Reliability performance of Firefighting Pump (FP) casing

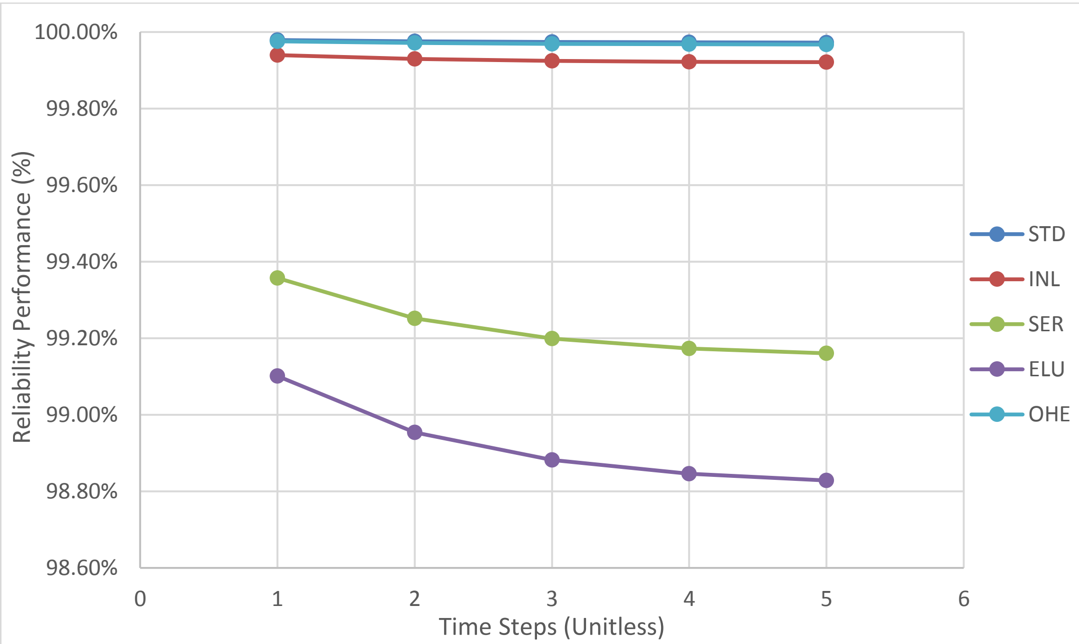

Figure G.46 Reliability performance of Firefighting Pump (FP) seals

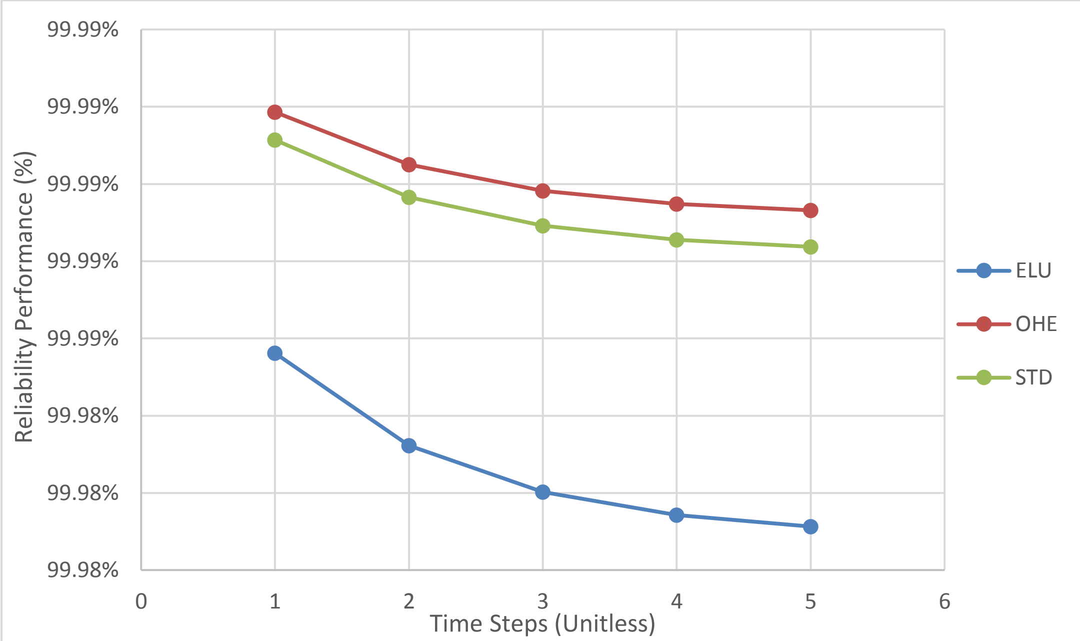

Figure G.47 Reliability performance of Firefighting Pump (FP) thrust bearing

- **Crude oil handling pump case study**

Table G.7 Acronym list of crude oil handling pump maintainable units and components

Acronym	Meaning
ACT	Actuator
BER	Bearing
CAB	Cabling
CAS	Casing
CDriven	Coupling Driven
CDriver	Coupling Driver
COL	Cooler
CTL	Control Unit
FLT	Filter
IMP	Impeller
LUB	Lubrication
MON	Monitoring
RBR	Radial Bearing
SFT	Shaft
SLS	Seals
TBR	Thrust Bearing

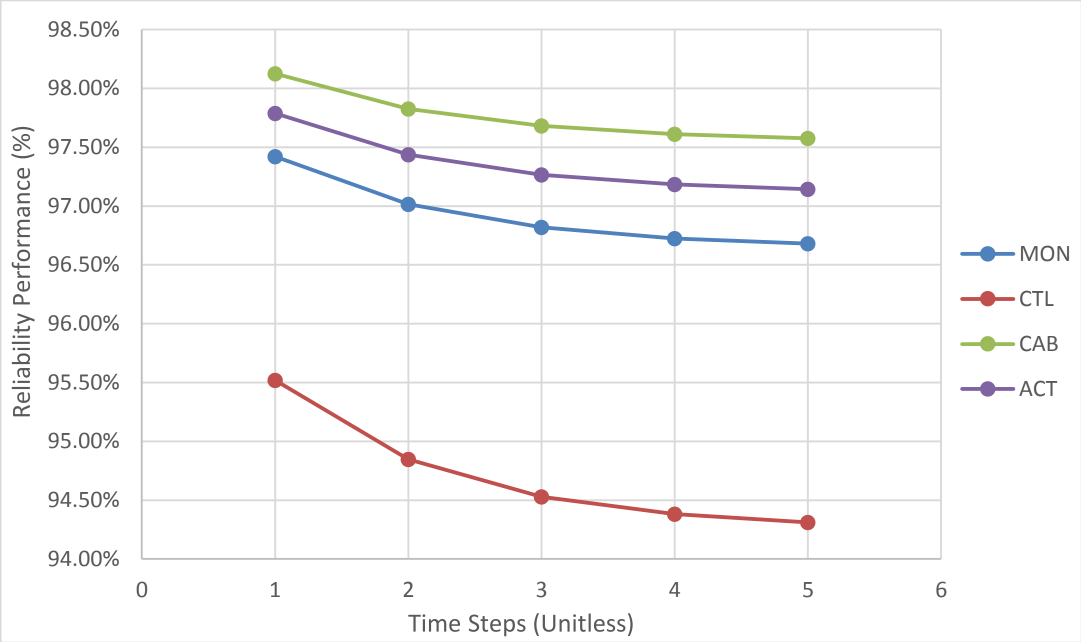

Figure G.48 Reliability performance of crude oil handling pump controller subsystem

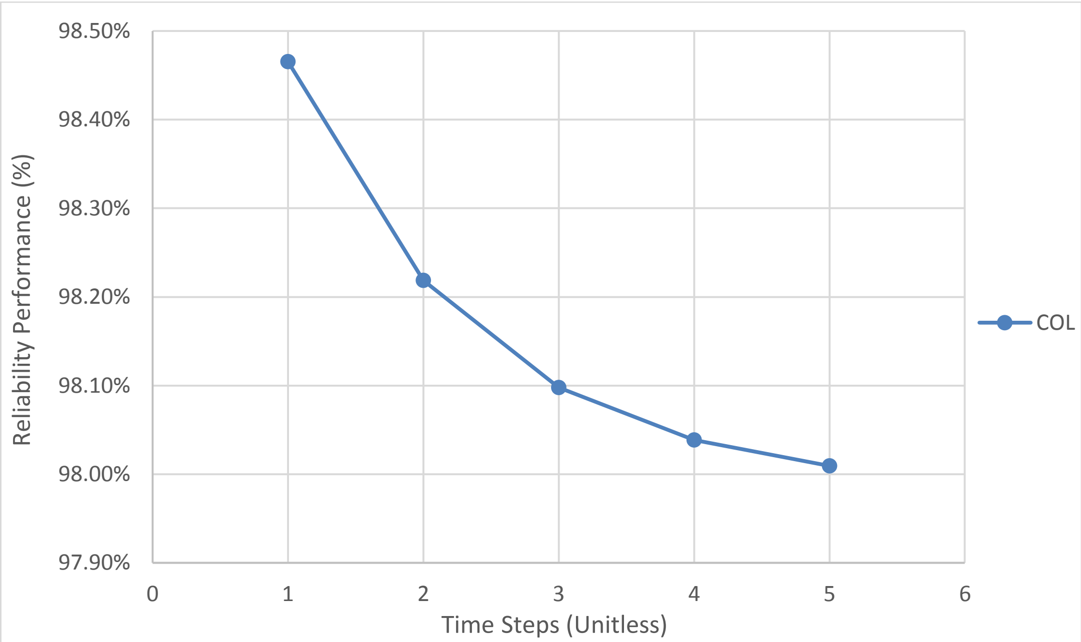

Figure G.49 Reliability performance of crude oil handling pump cooling subsystem

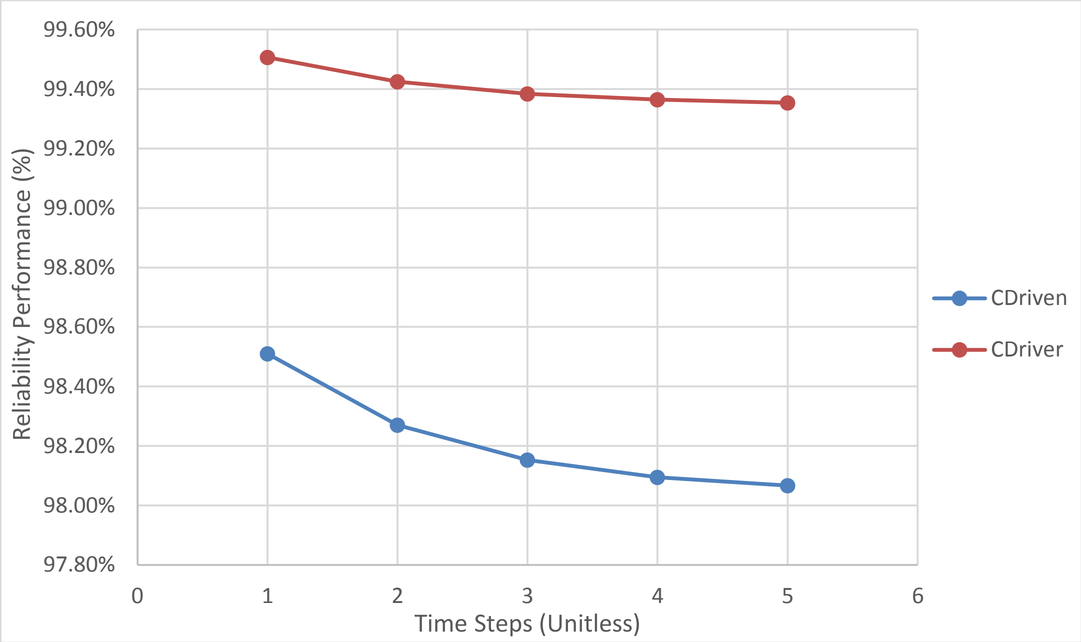

Figure G.50 Reliability performance of crude oil handling pump couplers subsystem

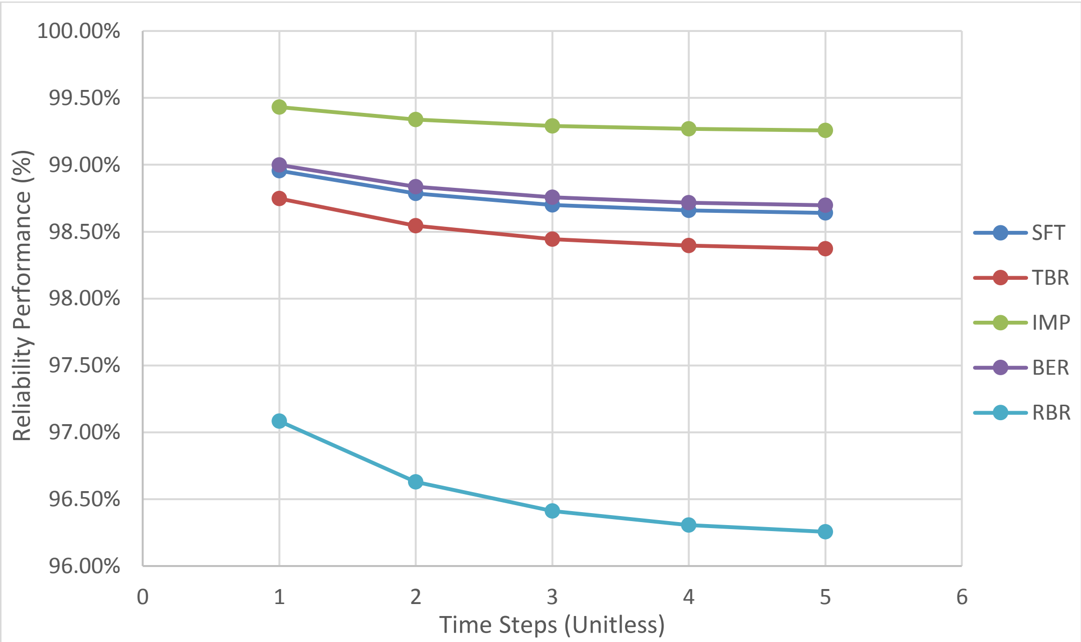

Figure G.51 Reliability performance of crude oil handling pump mechanical power subsystem

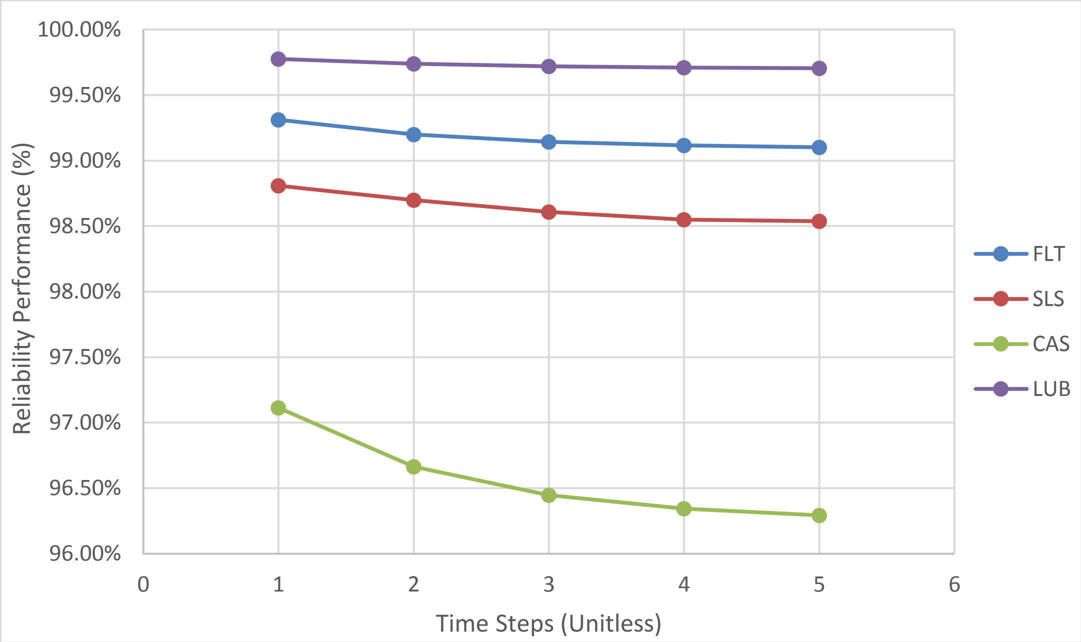

Figure G.52 Reliability performance of crude oil handling pump shell subsystem

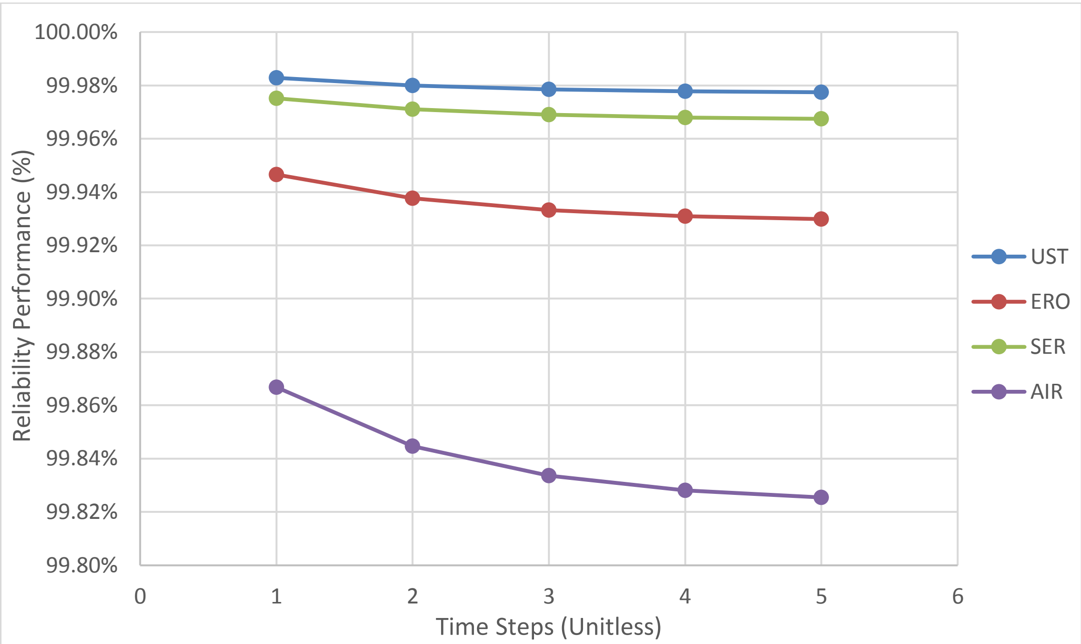

Figure G.53 Reliability performance of crude oil handling pump monitoring

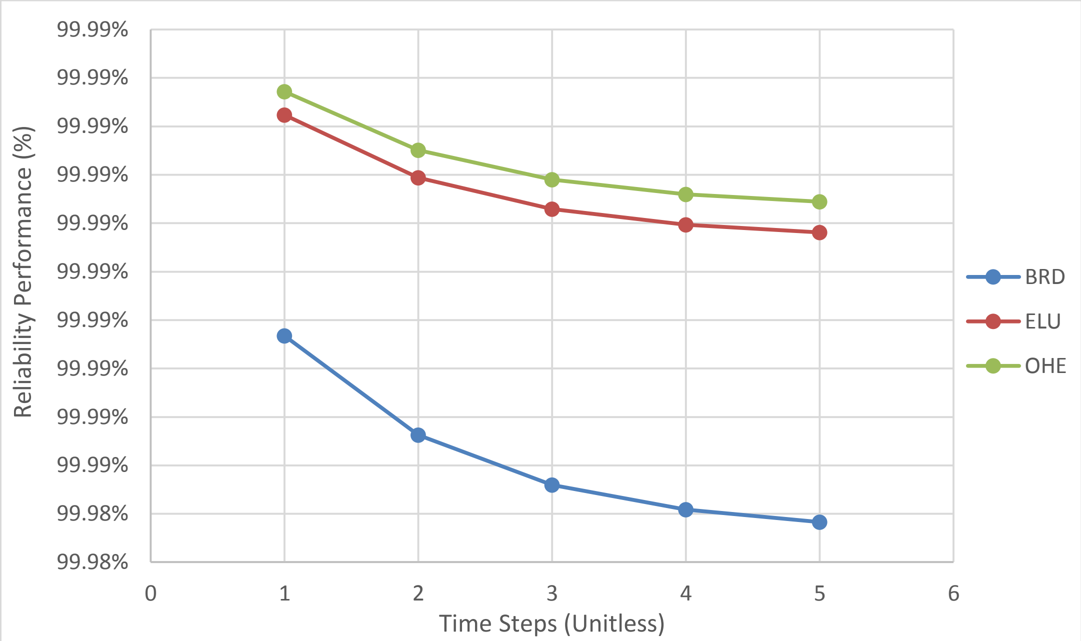

Figure G.54 Reliability performance of crude oil handling pump casing

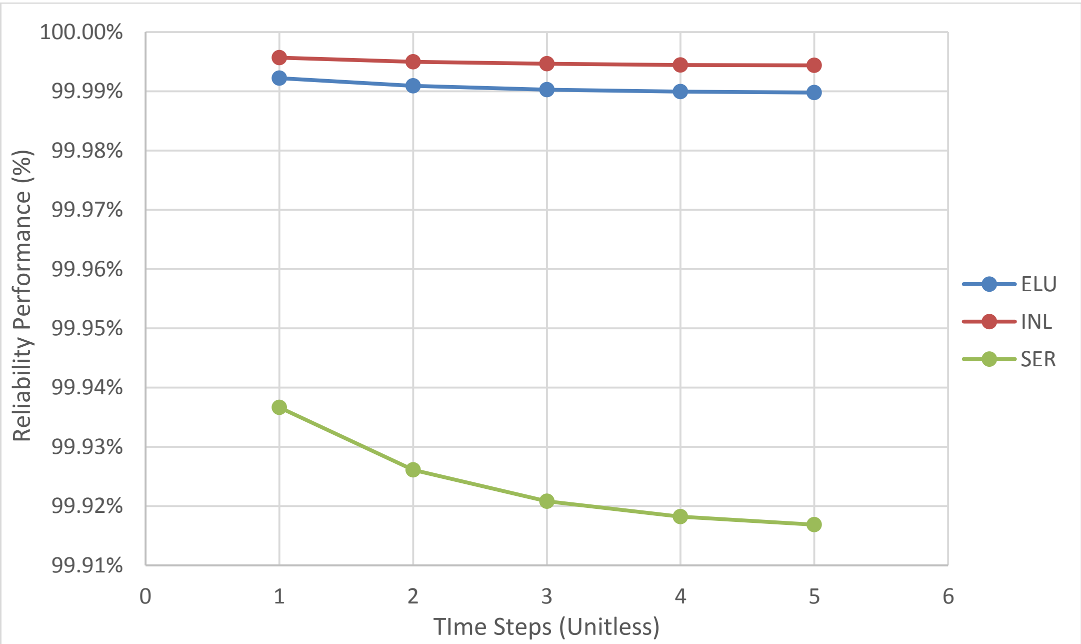

Figure G.55 Reliability performance of crude oil handling pump filter

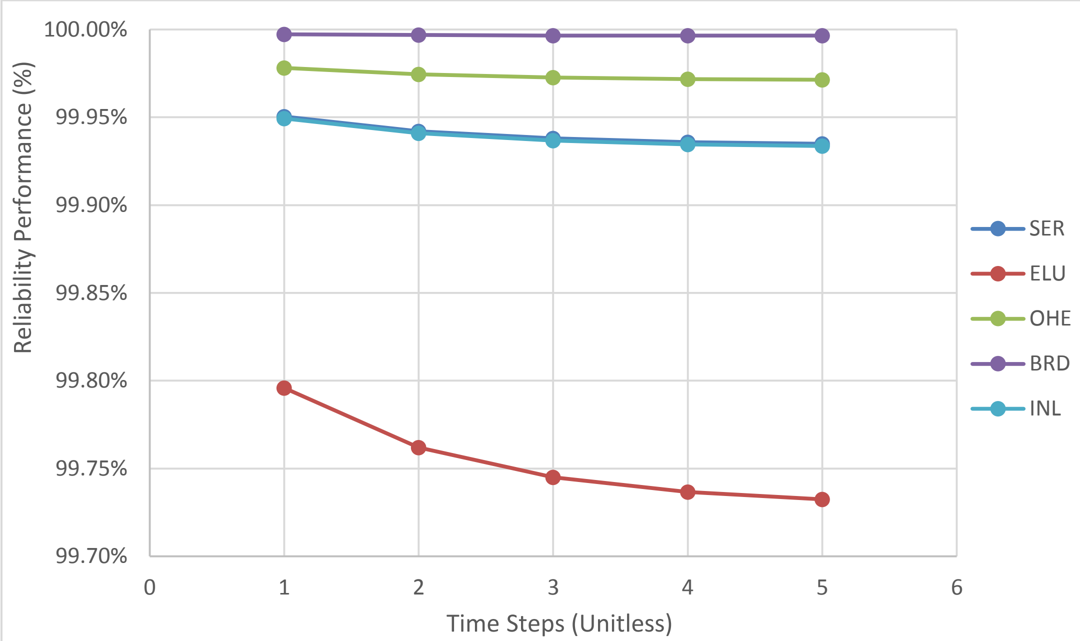

Figure G.56 Reliability performance of crude oil handling pump seals

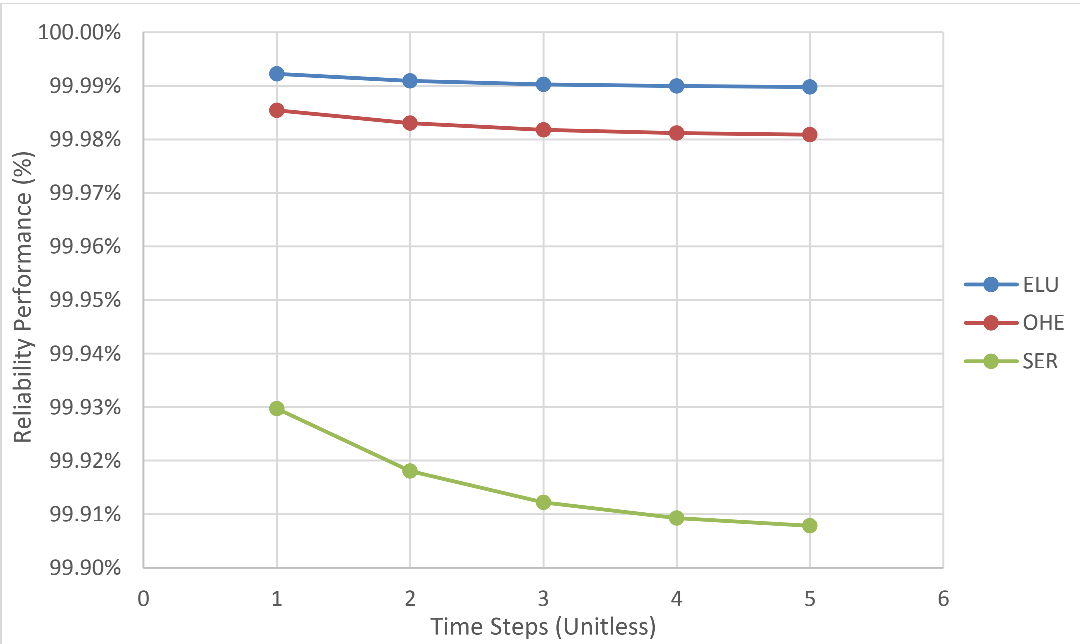

Figure G.57 Reliability performance of crude oil handling pump cooling system (failure mode level)

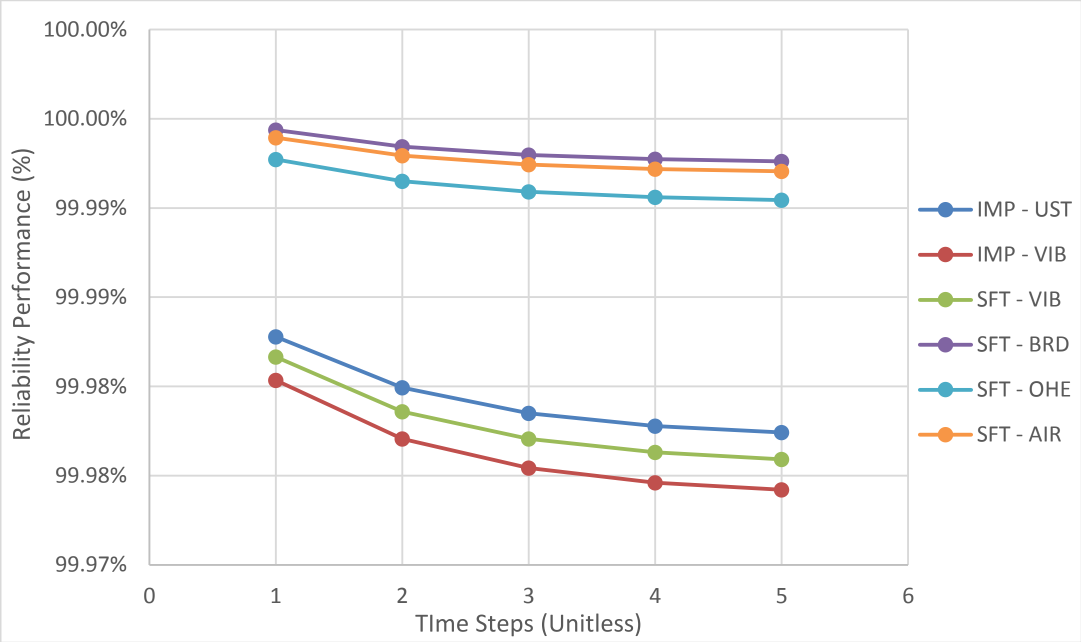

Figure G.58 Reliability performance of crude oil handling pump impeller and shaft (IMP and SFT)

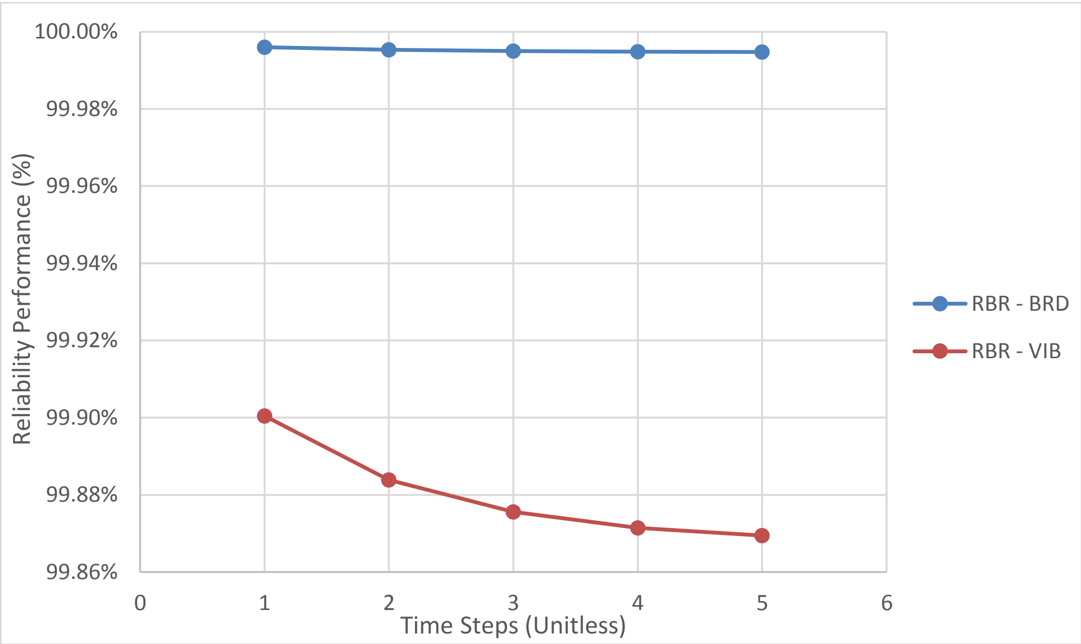

Figure G.59 Reliability performance of crude oil handling pump radial and thrust bearing (RBR and THB)

G.2. Results of raw data reliability case study

- **Fuel system**

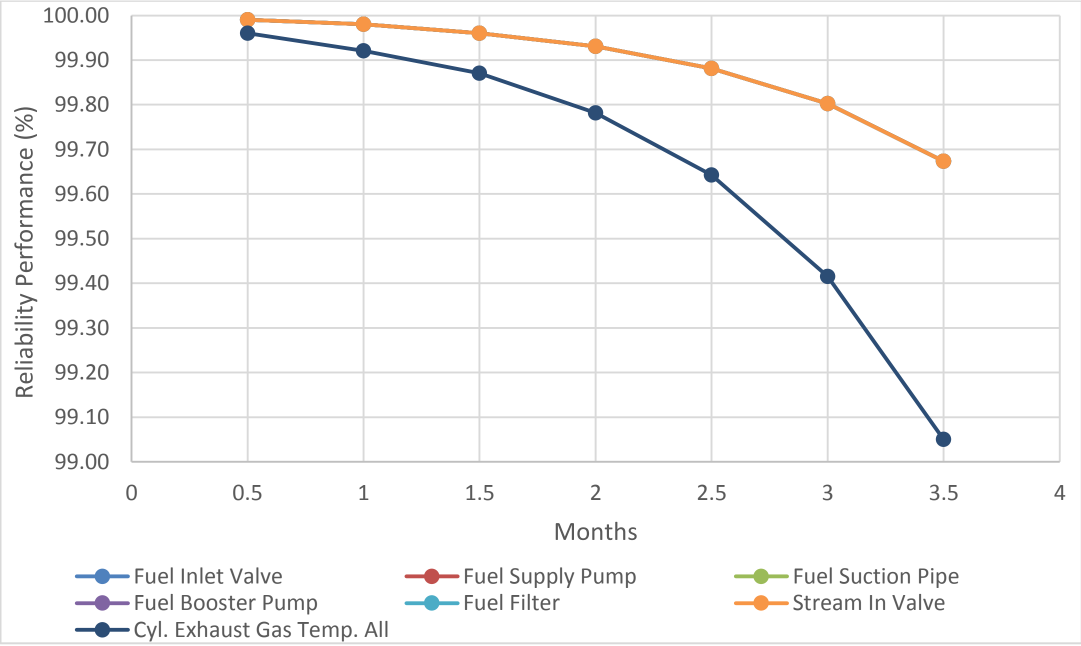

Figure G.60 Reliability performance of fuel supply – raw data

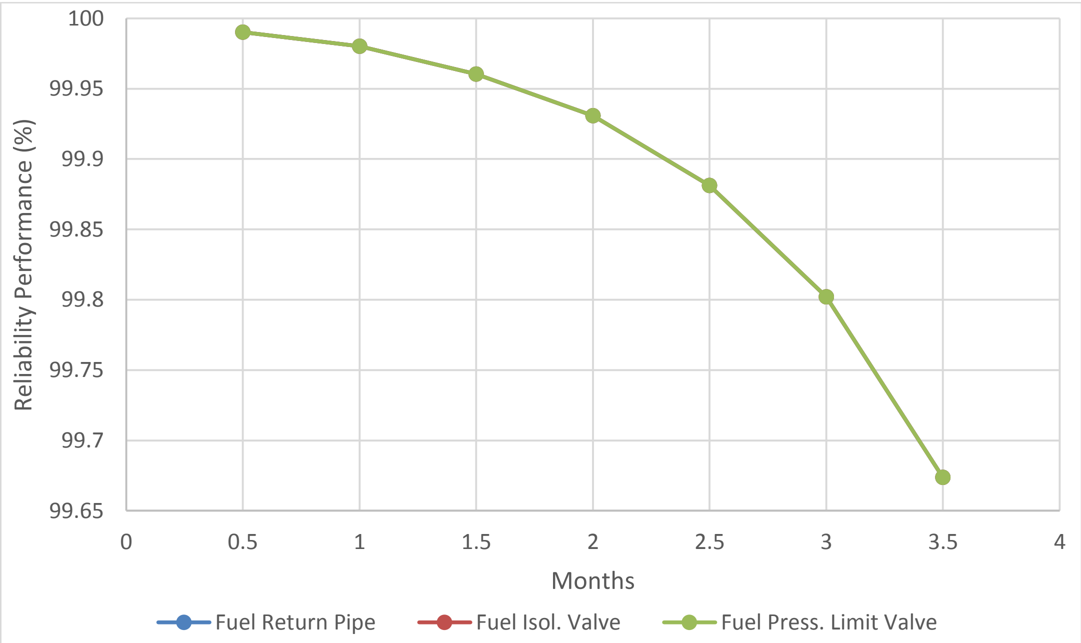

Figure G.61 Reliability performance of fuel return – raw data

- **Jacket cooling fresh water system**

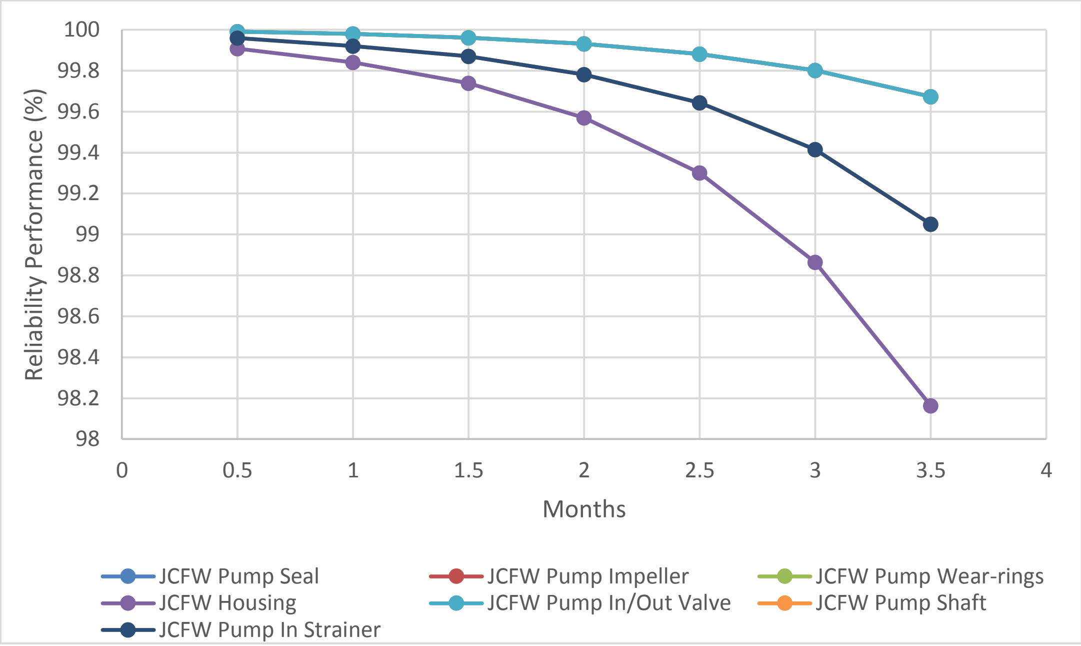

Figure G.62 Reliability performance of JCFW pump – raw data

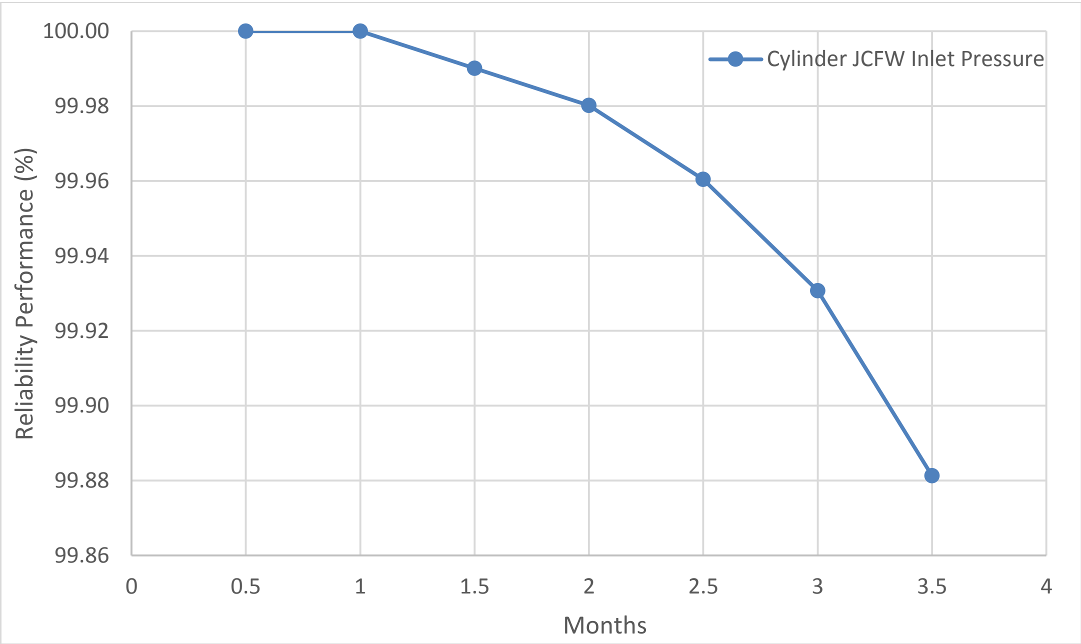

Figure G.63 Reliability performance of JCFW rotor – raw data

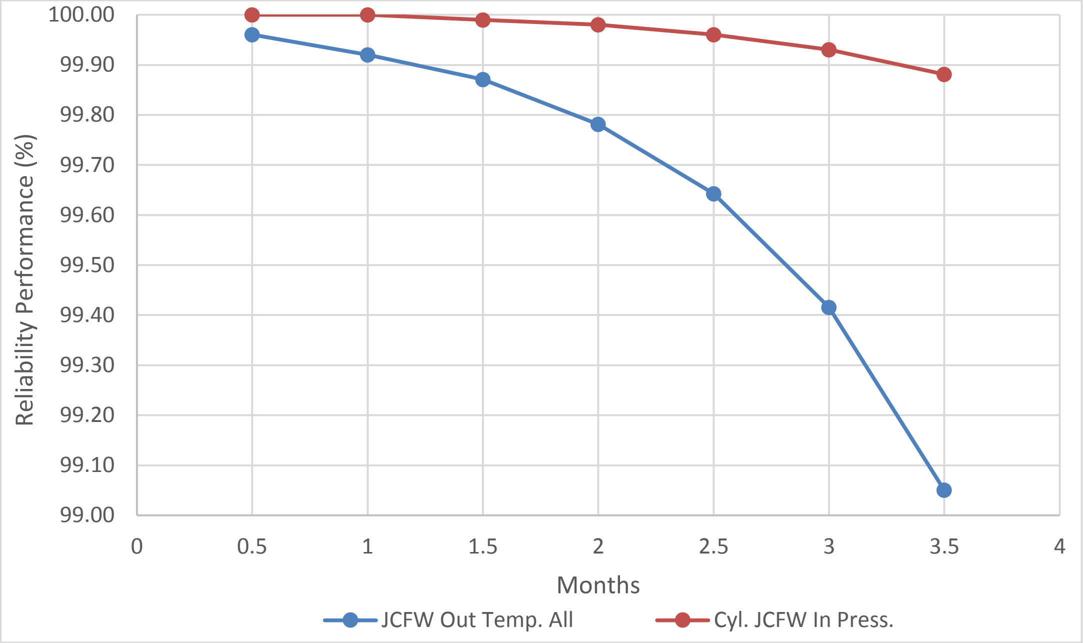

Figure G.64 Reliability performance of JCFW pump housing – raw data

- **Lube oil system**

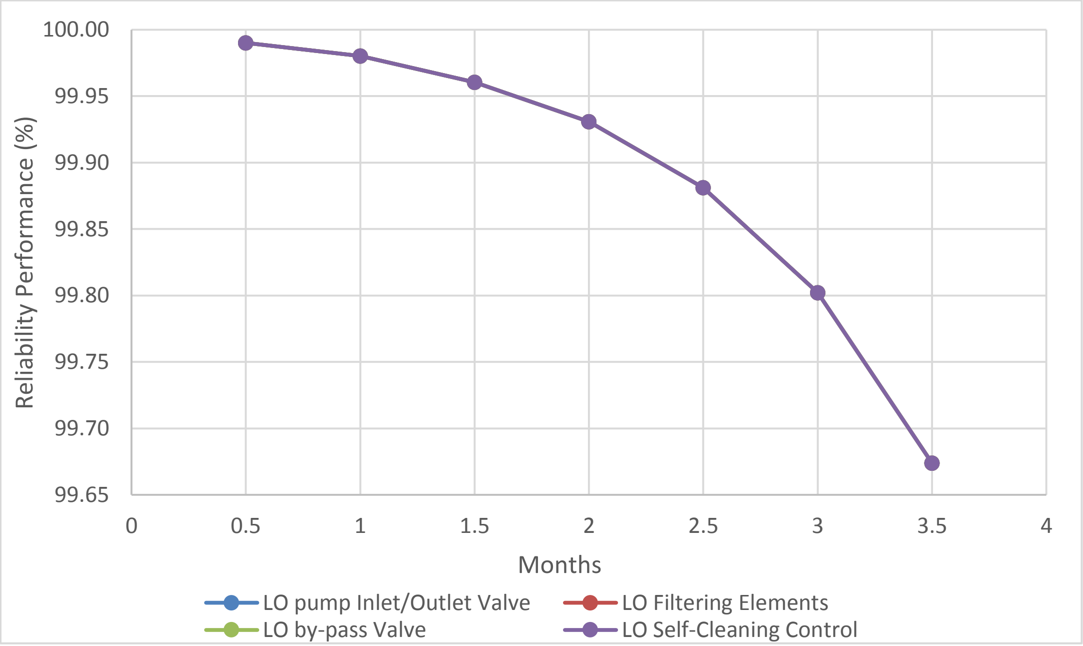

Figure G.65 Reliability performance of lube oil pump filter – raw data

- **Air supply system**

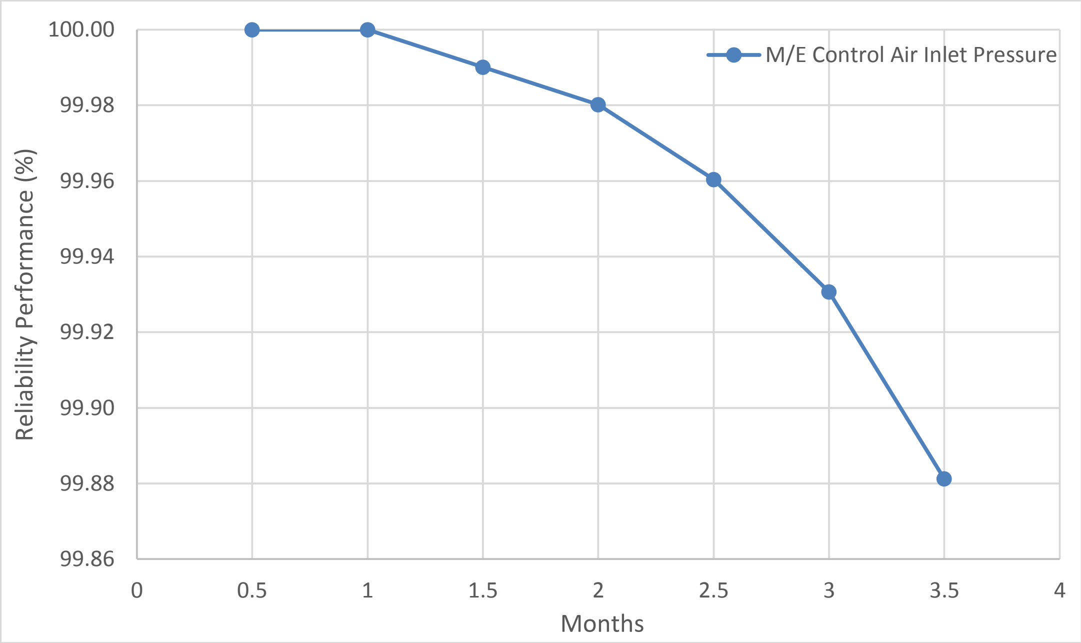

Figure G.66 Reliability performance of air piping – raw data

- **Bearing drive system**

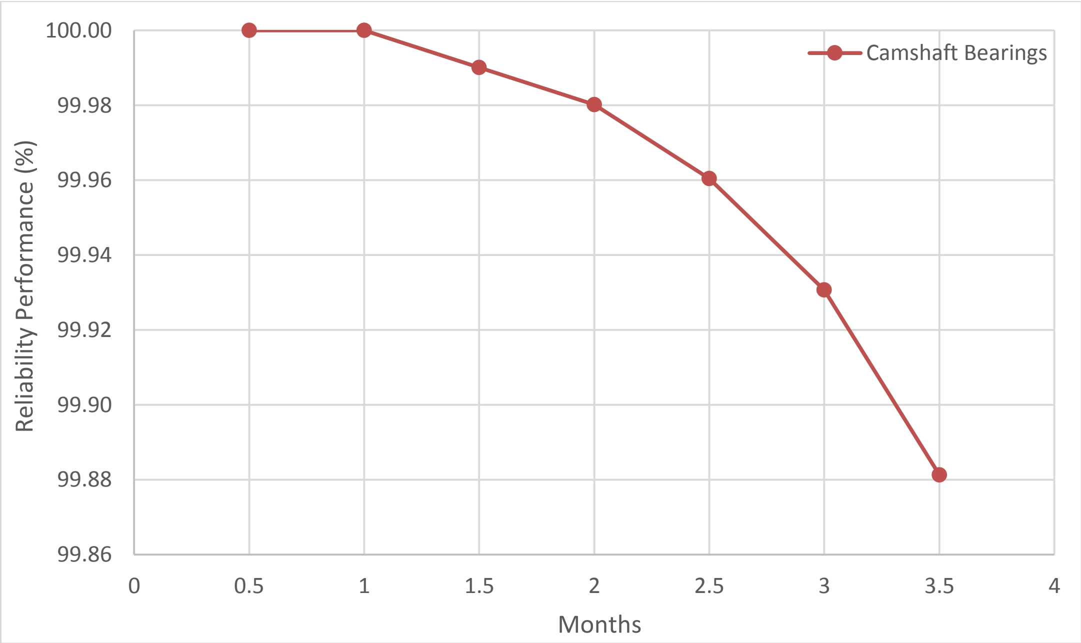

Figure G.67 Reliability performance of camshaft bearings– raw data

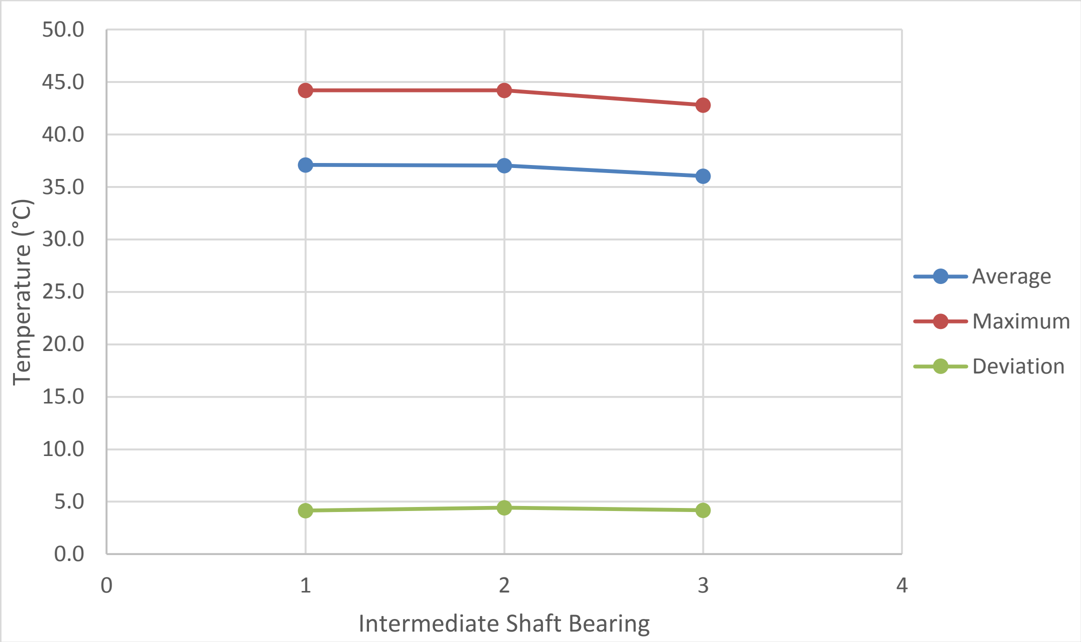

Figure G.68 Intermediate shaft bearing temperature records

- **Cylinders**

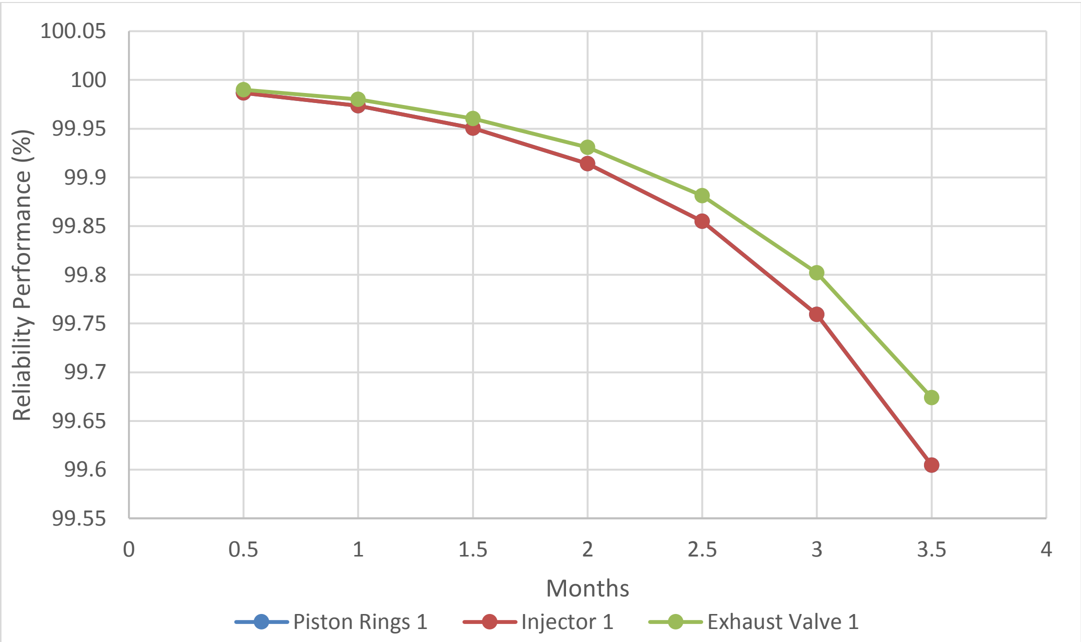

Figure G.69 Reliability performance of Cylinder 1 – raw data