A COMPREHENSIVE APPROACH TO SHIP SYSTEM MAINTENANCE MODELLING AND DECISION SUPPORT USING MACHINE LEARNING AND RELIABILITY ANALYSIS

By

Abdullahi Abdulkarim Daya

Ship Design Operations and Maintenance Modelling Centre

Department of Naval Architecture, Ocean, and Marine Engineering

University of Strathclyde, Glasgow

United Kingdom

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Author statement

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.

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Dedication

This work is dedicated to the memory of my father Abdulkarim Abdullahi Daya and Aunty Hajia Zilai Abdullahi Daya, both of blessed memories. May the Rahma of Allah be upon them.

Research Outputs

Journal Publications

Daya, A.A., & Lazakis, I. (2023). Component Criticality Analysis for Improved Ship Machinery Reliability. *Machines*, *11*(7). https://doi.org/10.3390/machines11070737

Daya, A. A., & Lazakis, I. (2023). Developing an advanced reliability analysis framework for marine systems operations and maintenance. *Ocean Engineering*, *272*. https://doi.org/10.1016/j.oceaneng.2023.113766

Conference Papers

Daya, A. A., & Lazakis, I. (2021, 16-17/09/2023). *Application of Artificial Neural Network and Dynamic Fault Tree Analysis to Enhance Reliability in Predictive Ship Machinery Health Condition Monitoring* GMO-SHIPMAR, Istanbul.

Daya A.A, Lazakis, I. (2022). *A Semi Automated Model for Improving Vessel System Reliability and Maintenance Management* RINA Autonomous ships, London.

Daya, A. A., & Lazakis, I. (2022). Investigating ship system performance degradation and failure criticality using FMECA and Artificial Neural Networks. In *Trends in Maritime Technology and Engineering Volume 2* (pp. 185-195). https://doi.org/10.1201/9781003320289-20

Conference Presentations

Marine Diesel Generator Maintenance Modelling Approach Based on Maintenance and Repair Data Analysis Using Unsupervised Learning and Dynamic Fault Tree Analysis. DSMS Conference 1-2 June 2020 University of Strathclyde, Glasgow.

Development of a Maintenance Framework Using Artificial Neural Network and Expert System for Optimal Maintenance Planning. PGR Conference June 2020. University of Strathclyde, Glasgow.

Application of Artificial Neural Network and Dynamic Fault Tree Analysis to Enhance Reliability in Predictive Ship Machinery Health Condition Monitoring GMO-SHIPMAR Conference 16-17 September 2021, Istanbul.

Investigating ship system performance degradation and failure criticality using FMECA and Artificial Neural Networks MARTECH Conference Lisbon 24-26 May 2022

A Semi Automated Model for Improving Vessel System Reliability and Maintenance Management. RINA Autonomous ships Conference 31 March-1April 2022, London

Ship System Maintenance Modelling and Decision Support System Using Dynamic Fault Tree Analysis and Bayesian Belief Networks OEMT Conference, 15-16 June 2022. University Of Strathclyde, Glasgow

Assessing Ship System Reliability and Decision Support for Maintenance Planning SNAME seminar 24/02/2023

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Trends In Shipping Decarbonisation: System Reliability Perspective, SNAME seminar 23 November 2022. University of Strathclyde, Glasgow

Book Chapter

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Unpublished Work

Daya, A. A. (2022). Improving Maintenance Data Utilisation Through Maintenance Data Management and Reliability Analysis [Research]. Nigerian Navy.

EL-Ladan, S., Daya, A.A. (2022). Sustainability of NNS THUNDER NNS OKPABANA and the CAT Class Ships - Bathtub Curve Analysis [Internal Communication].(Pigeon, 2021) Nigerian Navy.

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Nomenclature

ABS(NS)	American Bureau of Shipping (Nautical System)
ADLM	Automated Data Logging & Monitoring
AMSA	Australian Maritime Safety Agency
ANOVA	Analysis of variance
As & As	Additions and Alterations
BBN	Bayesian Belief Network
BE	Basic Event
Bir IM	Birnbaum Importance Measures
BSI	British Standards Institution
Capt	Captain
CBM	Condition Based Maintenance
CCF	Common Cause Failure
Cdr	Commander
Cdre	Commodore
CFMO	Command Fleet Maintenance Officer
CII	Carbon Intensity Index
CMDR	Commander (head of a unit)
CMMS	Computerised Maintenance Management System
CPT	Conditional Probability Table
Cri- IM	Criticality Importance Measures
DFTA	Dynamic Fault Tree
DNV	Det Norske Veritas
DSS	Decision Support System
EEDI	Energy Efficiency Design Index
EEZ	Exclusive Economic Zone
EGT	Exhaust Gas Temperature
EMS	Enterprise Management System
EMSA	European Maritime Safety Agency
ETA	Evant Tree Analysis
FDEP	Functional Dependency
FFNN	Feedforward Neural Net
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode Effect and Criticality Analysis
FMO	Fleet Maintenance Officer
FMR	Fleet Maintenance Regulations
FNR	False Negative Rate
FSG	Fleet Support Group
FSMO	Fleet Support Maintenance Officer
FSMEO	Fleet Support Marine Engineer Officer
FSWEO	Fleet Support Weapon Engineer Officer
FTA	Fault Tree Analysis

F-V IM	Fussel Vesely Importance Measures
FWT	Fresh Water Temperature
GHG	Greenhouse Gas Emissions
GoG	Gulf of Guinea
HFO	Heavy Fuel Oil
HTM	High Temperature
IACS	International Association of Classification Societies
IM	Importance Measure
IMB	International Maritime Bureau
IMO	International Maritime Organisation
INTERTANKO	International Association of Independent Tanker Owners
IoT	Internet of Things
ISM code	International Safety Management
ISO	International Standards Organisation
KW	Kilo Watt
LED	Light-emitting diode
LoP	Lubricating Oil Pressure
LoT	Lubricating Oil Temperature
Lt	Lieutenant
Lt Cdr	Lieutenant Commander
Lub	Lubricating
MAPOL	International Convention for Prevention of Pollution from Ships
MCS	Minimal Cut Set
MDG	Marine Diesel Generator
MDT	Mean Down Time
MEPC	Marine Environment Protection Committee
MP	Maintenance Period
MRO	Maintenance Repair and Overhaul
MTBF	Mean Time Between Failure
MTTF	Mean Time to Failure
NASA	National Aeronautics and Space Administration
NIMASA	Nigerian Maritime Administration and Safety Agency
NML	Normal
NN	Nigerian Navy
NOx	Nitrogen Oxide
NPRD	Non-Electronic Reliability Data
NSWC	Naval Surface Warfare Centre
NTM	Normal Temperature
NUREG	Nuclear Regulatory Report
OCIMF	Oil Companies International Marine Forum
OECD	Organisation for Economic Cooperation and Development
OEM	Original Equipment Manufacturer
OOW	Officer of the Watch
OP	Operating Period

OPV	Offshore Patrol Vessel
OREDA	Offshore and Onshore Reliability Data
OVH	Overheating
PAND	Priority- AND
PMS	Planned Maintenance System
R/Adm	Rear Admiral
RCM	Reliability Centred Maintenance
RH	Running Hours
RN	Royal Navy
RPN	Risk Priority Number
RPM	Revolution Per Minute
RW	Raw Water (sea water)
SCADA	Supervisory Control and Data Acquisition
SDG	Sustainable Development Goals
SEEMP	Ship Energy Efficiency Management Plan
SEQ	Sequence Enforcing
SMOC	Ship Maintenance and Operating Circle
SOM	Self-Organising Maps
SOP	Standard Operating Procedure
SOx	Sulphur Oxide
SLt	Sub-Lieutenant
SQEP	Suitably Qualified and Experienced Personnel
TPR	True Positive Rate
UNCTAD	United Nations Conference on Trade and Development
VLFO	Very Light Fuel Oil
WEO	Weapon Engineer Officer
WKO	Watch Keeping Officer
WKD	Watch Keeping Duties

Abstract

Maintaining machinery health and repair data is essential for efficient maintenance planning and implementation. Identifying critical components and failure causes requires detailed system reliability and diagnostics analysis. Multi-equipment holdings and long voyages across multiple climates make this challenge especially difficult for ship operators. For naval ships, the challenging environment and mission profile forced machinery to operate outside its operational envelope. Thus, this research seeks to develop a critical component analysis maintenance framework for system reliability and fault identification analysis to aid maintenance decision-making. Using reliability analysis and machine learning, critical components and faults were identified. A unique contribution of this study is the integration of fault detection analysis and reliability tools. DFT and FMECA are used to identify mission-critical components, while BBN is used for availability assessment and maintenance decision support system. This includes classification and fault detection using ANN-based machine learning models. An offshore patrol vessel power generation system with four marine diesel generators was studied. The reliability analysis shows system reliability below 70% in the first 24 of 78 operational months. Over 40% of subsystem failure and related events were isolated using reliability importance measures and minimal cuts sets. Identifying mission-critical components using Risk Priority Number in FMECA analysis enabled robust reliability and critical component analysis. Among the 4 MDGs, the lubricating system had the highest average availability of 67% and the cooling system the lowest at 38% using the DFTA minimal cut set. DSS-based 4 maintenance strategies used BBN availability and FMECA mission critical components. Because some critical parts fail frequently, Corrective Action and ConMon were recommended maintenance strategies. ANN found overheating when MDG output was above 180kva, linking component failure to generator performance. The findings improve ship system reliability and availability by reducing failures and improving maintenance strategies.

Keywords: Ship systems, maintenance, reliability analysis, fault detection, Dynamic Fault Tree, Failure Mode Effect and Criticality Analysis, Bayesian Belief Network, Artificial Neural Network.

1. Introduction

1.1 Chapter Outline

The chapter provides an overview of the thesis looking at the different types of maintenance concepts in the maritime industry and challenges within the merchant and defence Navies. Thereafter the research motivation, aims and objectives are presented to lay the foundation on which the thesis stands.

1.2 Maritime Trade and Security

Ships are crucial to the sustainment of global economy in several ways such as oil and gas servicing offshore wind support, transportation of cargo and security. The role of ships in global trade is huge and very vital to sustainment of the global economy as it allows the movement of raw materials, finished goods and intermediate goods from one country/location to the other, hence promoting economic integration and diversification. The United Nations Conference on Trade and Development (UNCTAD) estimates ships contribute about 80 % of global carriage while the Organisation for Economic Cooperation and Development puts at 90 %. This underscores the role of ships in global economy, despite the impact of COVID19 on the global economy the shipping industry has tremendous recovery across all the regions of the posting a growth of about 3.2 % in 2021(UNCTAD, 2022) with shipment reaching about 11 billion tons in 2021 up about 4 % based on 2020 values , Figure 1. Much of the cargo comes from dry and bulk carries including container ships, with some slight reduction in oil and gas cargo.

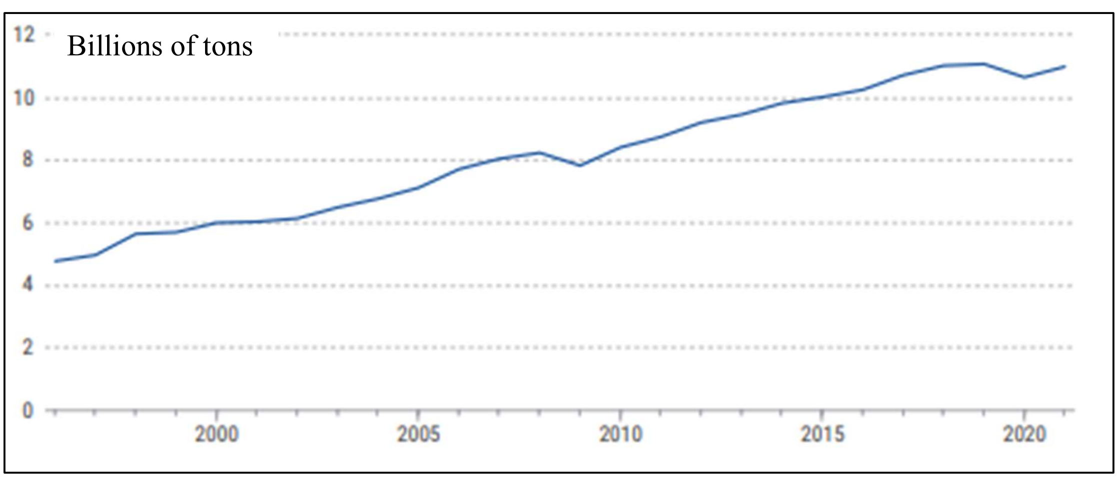

Figure 1: Trends in global maritime carriage by ships.

Security plays a vital in ensuring that global trade flourish with little or no hindrance, the responsibility for secure and safe seas largely depend on national coast guards and navies. These organisations utilise different types and mixture of platforms to ensure environmental safety and security of goods and service that ply the global maritime sea routes. Moreover, these efforts is demonstrated in the Gulf of Guinea and Horn of Africa and in recent times the Guld Aden were Global navies had to come together to ensure safe passage of merchant ships(Okafor-Yarwood et al., 2024, Vogel, 2009). The common platform used for such patrols are the frigates or OPVs,

The Naval and Coast guard vessels play vital role in the growth and developments of global maritime trade through the provision of key services to ensure safety of lives and goods at sea. Some of the services provide by these vessels includes sea security patrols, maintaining presence at sea, maintenance of traffic separation schemes, search and rescue operations including oil spill cleaning(Okafor-Yarwood et al., 2024). Moreover, challenges of insecurity along commercial shipping lanes for the conveyance of goods and service are so often targets of criminal elements such as piracy, smuggling, drugs, and human trafficking(Vogel, 2009). The security patrols and presence at sea provided by Naval, or Coast Guard vessels plays a vital role in providing confidence to chatterers, ship crew and operators on the routes which in turn improves maritime trade and economic outlook of regions or countries. According to the CRIMSON III report 2021 the additional cost incurred by shipping companies due to pirate activities in the Gulf of Guinea (GoG) within the exclusive economic zone (EEZ) of Nigeria amounts to about $880 million dollars in 2019 alone, Table 1 (Pigeon, 2021).

In this regard, Naval and Coast guard vessel play a vital role in the growth and developments of global maritime trade through the provision of key services to ensure safety of lives and goods at sea. Moreover, challenges of insecurity along commercial shipping lanes for the conveyance of goods and service are so often targets of criminal elements such as piracy, smuggling, drugs, and human trafficking. For instance, the CRIMSON III report Pigeon (2021) indicates that the additional cost incurred by shipping companies due to pirate activities in the Gulf of Guinea (GoG) within the exclusive economic zone (EEZ) of Nigeria amounts to about $880 million dollars in 2019 alone, Table 1.

Table 1: Estimated Incurred Cost due to Piracy and Robbery in GoG, 2019.

EXPENSE	AVERAGE	LOWER BOUND	UPPER BOUND
Insurance	USD 52 million	USD 52 million	USD 52 million
Labour costs	USD 471 million	USD 319 million	USD 623 million
Ship protection measures	USD 5.5 million	USD 4 million	USD 7 million
Security escort vessels	USD 176 million	USD 154 million	USD 198 million
TOTAL	**USD 704.5 million**	**USD 529 million**	**USD 880 million**

(Source: CRIMSON III)

GoG is an important maritime economic routes and account for up to 25 % of Africa's maritime traffic; the countries of the GoG together account for about 35 % of the global oil and gas reserve and other important minerals (uranium, gold, copper, diamonds, nickel, lithium etc) (Karemperidis, 2022). However, this area was under heavy pirate activities but for the intervention of security patrols coordinated by the Nigerian Maritime Administration and Safety Agency (NIMASA) in partnership with the Nigerian Navy under the Deep Blue security arrangement. Also supported by coalition of European Union and United Staes navies, saw an increased number of platforms deployed to patrol the entire GoG area (Karemperidis, 2022, Pigeon, 2021).

Therefore, coupled with extended mission time, the piracy situation and other criminal activities was reduced to bearable minimum, shown in Figure 2. These improvements have been supported by the IMO and International Maritime Bureau (IMB)(IMB, 2022).

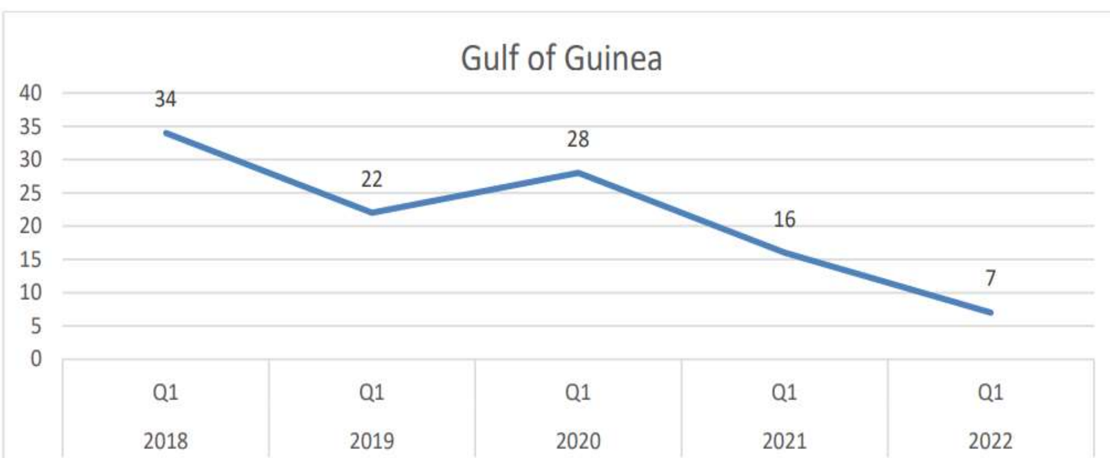

Figure 2: Total number of reported Piracy attacks within the GoG area. *(Source: IMB)*

The above achievement in maritime security were made possible due to deployment security patrols and maintenance of presence at sea provided by Naval, or Coast Guard vessels plays a vital role in providing confidence to chatterers, ship crew and operators on the routes which in turn improves maritime trade and economic outlook of regions or countries. The principal vessel deployed for these operations are mainly frigates and OPVs. These classes of vessels provide the right flexibility, endurance, speed, and equipment type needed for extended patrols to enable deterrence and benign operations.

Frigates and Corvettes have been the dominant vessels used by Navies to carry out mainly deterrence and patrol task such antisubmarine, screens and escort duties. However, these ships are generally more expensive, and the design emphasis were more military capabilities. Hence the platform equipment mix makes them unattractive for coastal patrols such as anti-piracy, anti-fishery, Oil spill detection, search and operations(Birkler, 2005). Therefore, these due challenge of cost and design priority create a better makes for OPVs which usually in the range 60-130 metres and weighing slightly above 1000 tons. Most OPVs are lightly armed, fewer crew members but design to have high endurance and with speed up to 32 knots, hence better replacement for frigates and corvettes(Hellyer, 2020). OPVs are generally deployed for counter terrorism, antipiracy, ant drug trafficking, offshore asset protection, border patrol and so on. Additional for search rescuer, oil spill detection and cleaning, helicopter operations can equally be provided as required by the operator. As is traditional with most ships OPVs use Marine diesel engines for propulsion and electricity generation.

Diesel engines are the primary source of propulsion and power generation onboard ships majority of which are design to burn single fuel with some new design having dual fuel capability. OPVs in general are design to use high speed 4 stroke marine diesel engines for both propulsion and power generation. In this regard, these engine use high speed low sulphur diesel due to IMO regulations on emissions control on marine diesel engines (IMO, 2021). To further improve the emission reduction of engines; some are dual fuel enabled, while this is a good attribute, the engines are generally sensitive to impurities or contamination in the fuels.

Overall, the introduction of the new low carbon fuels as well as low sulphur fuel present additional maintenance challenges to ship owners especially ships built in the 80s and those operating in regions with difficulty getting the right quality of fuel (Specialty, 2022). As a result, operators are faced with increasing maintenance costs due to increased repair, replacement or monitoring of fuel system component. Moreover, according to Stopford (2009) maintenance accounts for between 20-30 % of ships operating cost. On the heel of these comes the existing risks associated with loss of power due to prime mover failure either propulsion or electricity. The impact of unscheduled maintenance or failures that could lead to extended down time leading to decreased ship availability and operational disruptions that could negatively affect revenue as regards the commercial shipping or national security as in the case of Naval or Coast Guard ships. The aging situation is similar in the maritime security and defence sector such as naval and coast guard fleets (Larter, 2018, EL-Ladan, 2022). Overall the average life of ships is about 20-30 year for commercial while naval ships built differ a bit, between 15-25 or 25-35 depending on size (Tomlinson, 2015, Stopford, 2009).

In view of the above, machinery failures are among the major contributing factors to maritime accidents/incidents, some of which may be due to maintenance or human factors(Safety4Sea, 2022). Machinery failure data for naval is generally a restricted information hence not available online. Nonetheless, accident data provided by the European Maritime Safety Agency (EMSA) which covers all accident involving ships within the European waters, ships carrying European flags or in an area of importance such as the Suez or Panama Canal. The report indicates navigation related accidents account for 43 % of all accidents between 2014-2020 out of which 22 % were due to loss of propulsion power. In a report covering 2019-2021 the Australian Maritime Safety Agency (AMSA) also revealed the impacts of power, propulsion and steering as a major contributor to shipping accidents, Figure 3.

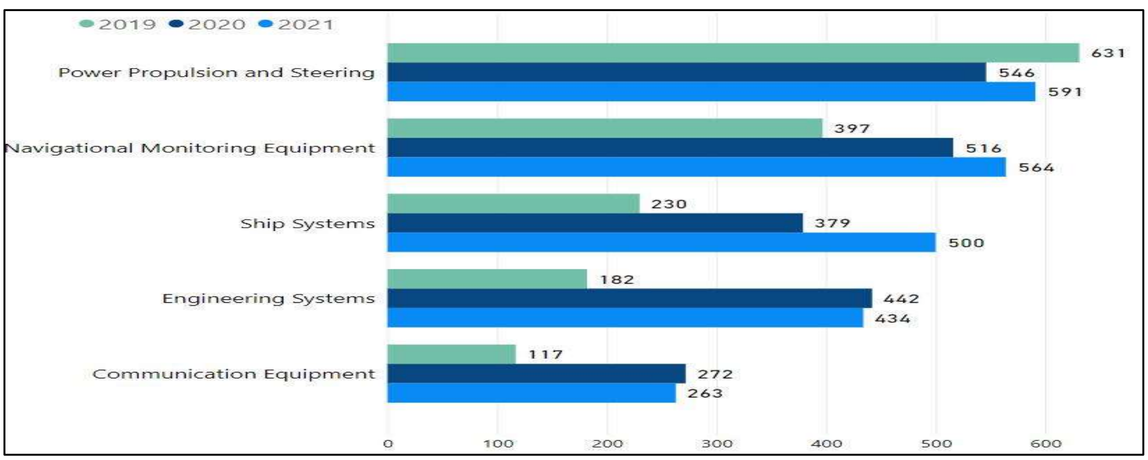

Figure 3: Contributors to shipping accident 2019-2021. *(Source: AMSA)*

Shipping failure related to main propulsion though frequent, are often not seen as safety issues while on the other hand, maintenance related oversights could potent increased emissions and safety risks. Moreover, the ISM code (IACS, 2018b) clearly linked maintenance to safety and pollution reduction and mandate operators and owners of vessels to take all responsibility to ensure compliance.

On board maintenance challenges could be in part due to operational circumstance of ships and the conservative nature of the industry which makes it hard to obtain relevant machinery health data (Raptodimos et al., 2016). Data paucity and sometimes quality is a measure issue in ship system reliability analysis owing to apprehension by ship crew or operators on possible negative consequences (Raptodimos et al., 2016). These attitudes toward implementing a better maintenance strategy can be attributed to some of the aforementioned factors. Another likely issue is maintenance planning onboard ships largely depends on OEM recommendations which are usually developed to form the bases of the Planned Maintenance System (PMS)(Lazakis et al., 2018b). The complexity of ship systems and manning levels often makes it impossible to implement PMS on board due to tight schedules as regards inspections, time based/ run replacements, operator familiarity, or lack of specialised personnel (Daya and Lazakis, 2022, Lazakis et al., 2016). This situation is common on both commercial and naval vessels, to this end classification societies, ship operators and private maintenance vendors are providing alternative solutions to overcome some of these challenges to reflect contemporary issues in ship maintenance helped by technology advances.

Advancement in technology particularly the ability of computers through artificial intelligence in almost every aspect of human endeavour has made it possible to automate or fast-track calculations, improve process and service delivery. These advances have similarly improved maintenance delivery in different industries from the industrial revolution to present industry 4.0 also referred to as Internet of Things (IoT). The maritime industry has long held time based preventive maintenance as a magic wand to ensure ship availability due to mix of timely inspection and prompt replacement of component based on age in service. However, the advent of sensors and efficient methods of data management has shown that time based preventive maintenance is costly, intrusive, and labour intensive. This realisation coupled with technology gave rise to Condition Based Maintenance and Predictive Maintenance. On the other hand, Preventive or planned maintenance system are the most widely accepted maintenance practice in the maritime industry mainly due to ease of implementation and initial cost. It is widely believed that a shift or improvements in these traditional maintenance approaches is required in the shipping industry in order to improve machinery and system reliability. Some research output has shown that Condition Based Maintenance has emerged as the most prepared maintenance strategy due mainly to the improvement in availability and capabilities in sensor technology enabling multiple and efficient data collection(Xiang et al., 2017).

Therefore, in order to ensure availability of equipment and systems, operators require an efficient maintenance approach that can minimise failures and reduce downtime through the life cycle of the asset or machinery (IACS, 2018b). In this regard there are different maintenance approaches that can provide various features depending on what the operator considers as important while ensuring that regulations are respected. In general ships are supplied with maintenance plans that are based on schedules drawn from original equipment manufacturers (OEM) operating manual. These manuals are used as the initial documents to help with routine checks and maintenance especially when most systems are new. However, operating conditions such as climate, operating profile, technical capacity and availability of genuine spare parts and the quality of other consumables such as fuel and lubricants could invalidate the initial as supplied maintenance plan or approach. On the other hand, the multiplicity of equipment which are largely independent makes the maintenance planning a huge task that cannot easily be manually achieved without some level of data automation. In this regard operators need to develop a condition monitoring maintenance strategy that is fit for purpose. Taking into considering factors such, maintenance personnel capacity, access to spare parts, environmental conditions, mission requirements, future task projections on platform or fleet as well as data management and processing(ISO, 2018a).

Therefore, this research is focused on the use of maintenance, repair, and overhaul (MRO) data backed-up with machinery condition monitoring to enable a predictive Condition Based Maintenance with emphasis on equipment criticality and reliability. Accordingly, to develop an advance maintenance framework and decision support system this research presents a novel approach in tools combination for the analysis of maintenance, repair and overhaul data using dynamic fault tree analysis (DFTA), Failure Mode Effect and Criticality Analysis (FMECA) Bayesian Belief Networks (BBN) and artificial Neural Network (ANN). These tools are combined in order to harness their unique individual and collective capabilities to present an in-depth analysis towards identifying mission critical components through both qualitative and quantitative analysis and effectively utilising available data sources. Accordingly, the impact of component reliability on system availability were analysed with significant findings on most critical components that contribute to failure and system unreliability.

1.3 Research question

How to identify and analyse component criticality to ship system availability through the development and establishment of a novel hybrid framework for system reliability analysis using a combination of reliability analysis tools and artificial intelligence for maintenance decision support system.

1.4 Main Aim

The main aim of this study is to develop an innovative hybrid maintenance framework for ship system reliability analysis by integrating artificial intelligence with reliability analysis techniques. The emphasis is placed on utilising raw data obtained from ships to derive failure rates and metrics related to the condition of machinery. The integration of these two technologies will be employed to create maintenance decision assistance for Marien Diesel Electric Power Generators, as demonstrated in a case study.

1.5 Objectives

1. Identify research gaps in system reliability analysis, component criticality, fault identification and maintenance decision support system by conducting a rigorous literature review.
2. Identify relevant reliability analysis tools for the development of a ship system component criticality analysis framework.
3. Using the data outputs (results) from the reliability analysis to develop a maintenance decision support system.
4. Development of Methodology to integrate multiple reliability analysis tools applicable to marine system reliability analysis.
5. Identify case study platform and expert group for onboard data collection and user survey analysis.
6. Engage with operators to identity areas of concern in ship maintenance and data collection process.
7. Establish ship equipment reliability and component mission criticality towards ship operational availability.
8. Identify important features for machinery health diagnosis using maintenance repair and overhaul data together with machinery health monitoring data for system reliability and diagnostic analysis.
9. Develop maintenance data collection and management approach to prioritise maintenance of critical components.
10. Utilising MRO and Condition Monitoring data to enable a decision support system for ship system maintenance.

1.6 Thesis Layout

The layout of the thesis is structured to guide the reader through the methodology sequentially based on how the tools were used in the research but not signifying any hierarchy. In this regard, the introduction provided an overview on the relevance of maintenance in the shipping industry and relevant avenues where it draws management and administrative guidance. The rest of the thesis is presented in the sketch as presented in Figure 5.

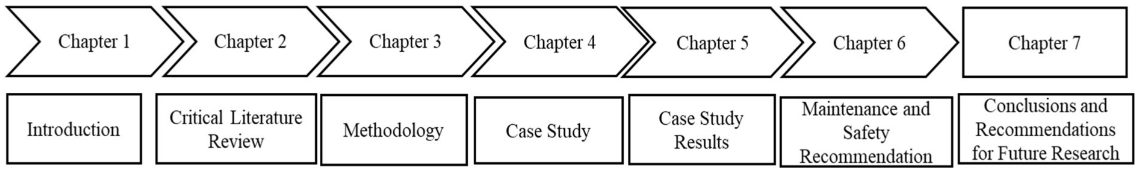

Figure 4:Thesis layout.

Chapter 1 is the introduction which provides a generic but focused background to the multiple factors influencing machinery failure and maintenance in the shipping industry. New regulations on the emission control are some of the factors that would exact some pressure on existing maintenance process onboard ships, especially that diesel engines are the primary means of propulsion and power generation on board.

Chapter 2 provides a critical literature review that takes a look firstly on maintenance in some key sectors such as power generation, nuclear, aviation, rail, automotive and the broader maritime industry. A deep dive into systems reliability analysis within the stated industries was taken with a focused on the various tools and process applied by both industry and researchers in maritime sector. The chapter also appraised component criticality as it relates to system reliability and availability in a manner that information obtained therein can be used to build a maintenance decision support system. Overall, the chapter provides a critical overview of the ongoing efforts by research institutions and industries to evolve maintenance strategy to conform with technology, environment, and society.

Chapter 3 presents a novel methodology centred around a hybrid approach to reliability and diagnosis analysis through the combination of tools to develop an advanced framework for ship machinery system reliability analysis. The tools considered in the research include Dynamic Fault Tree Analysis, Failure Mode Effect and Criticality Analysis Bayesian belief Network and Artificial Neural Networks. These tools were used to carryout machinery reliability and availability analysis, critical component analysis and failure development analysis, the application of which was demonstrated in a case study.

Chapter 4 talks about the case study in the research which gives a step-by-step analysis of how the methodology was implemented to using the raw machinery log and repair data collected onboard ships. The process of the data analysis involving data cleaning, future engineering and survey data collection were discussed. Similarly, ship and machinery as well as the characteristics of the machinery, ship operating profile including organisation maintenance guidelines were presented.

Chapter 5 in this chapter, the case study results, and analysis were presented based on the operational profile of the ship and available maintenance and repair data collected onboard. The results are presented in a manner that reflects how the various tools are used in the research in this regard the DFTA results were first presented followed by FMECA thereafter the BBN. It is important to note that the BBN used inputs from DFTA and FMECA outputs while the ANN is standalone tool used for fault detection and health deterioration analysis. A sensitivity analysis was equally carried out and presented to some parts of the recommendation provided to the operators.

Chapter 6 provides recommendation addressing maintenance and safety issues raised within the research findings. Therefore, solutions for maintenance management onboard ships focusing on the identified Mission Critical Components, and critical component reliability were discussed alongside the safety implications. In this regard, the section provides structured maintenance data management system, based on a unified structure for data collection on board ships and a standard data management collection system for shore-based maintenance deports. The suggested recommendation would help enhance machinery reliability and availability leading an improved fleet wide maintenance decision-making process.

Chapter 7, the chapter discusses the successful achievement of the research aims and objectives as outlined in the research objectives. Furthermore, the research novelty will be presented in this chapter. Thereafter, the conclusions of the research would equally be presented followed by recommendation for future research.

2 Critical Literature Review

2.1 Chapter Outline

The chapter takes a look into the progressive development of system reliability and maintenance strategy selection within the academia and industry. An overview of the various tools used for reliability analysis was conducted which highlighted the strength and weakness of some of them and how these tools have been used by the researchers for maintenance analysis. The selection of maintenance strategy is equally a huge challenge due to multiple factors that are usually peculiar to operator, hence difficult to address by generic analysis. Therefore, the review appraised relevant literature covering several industries, reliability analysis tools and the use of artificial intelligence for fault detection and degradation analysis. In this way, the research has identified important gaps in the literature which will support the methodology for the development of an advanced hybrid framework for ship system machinery reliability and maintenance selection analysis.

2.2 Appraisal on Maintenance Strategies

The maintenance as a human endeavour has been around for ages, simple tasks as the need by early humans to sharpen their hunting tools during the stone age period is an example of maintenance. Moreover, the human nature always seeks to do things differently through improving procedures and process lead to the building of complex machines and hence the need to ensure that the machines/equipment are able to work as expected when needed. In this regard, BSI (2010)defines maintenance as a combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to a state in which it can perform the required function. Following this definition, maintenance is an integral part of operations that provide the impetus for success or otherwise (Ahuja and Khamba, 2008).

Therefore, in order to ensure availability of equipment and systems, operators require an efficient maintenance approach that can minimise failures and reduce downtime through the life cycle of the asset or machinery (IACS, 2018b). In this regard there are different maintenance approaches that can provide various features depending on what the operator considers as important while ensuring that regulations are respected. In general, machinery systems are supplied with maintenance plans that are based on schedules drawn from OEM operating manuals (Dragos, 2021). These manuals are used as the initial documents to help with routine checks and maintenance especially when most systems are new. However, operating conditions such as climate, operating profile, technical capacity and availability of genuine spare parts and the quality of other consumables such as fuel and lubricants could invalidate the initial as supplied maintenance plan or approach (Marvin, 2021, Daya and Lazakis, 2023, Ford et al., 2015).

The overall goal of this research is to provide alternative approach to marine machinery maintenance through system reliability and diagnostic analysis. In this regard, the research studied various maintenance approaches practiced in different industries covering over 400 articles including academic journals, conference papers, books, and web based resources. Table 2 provides an overview of maintenance concepts and industry trends covered in the research.

Table 2 Maintenance Concepts and Industry

Maintenance concepts	Aviation	Oil & Gas	Power Generation	Nuclear Power	Offshore wind	Shipping	Manufacture
Condition based/Monitoring maintenance	*	*	*	*	*	*	*
Risk Based		*	*	*		*	
Reliability Centred Maintenance	*	*		*		*	
Predictive Maintenance	*	*	*	*	*	*	*
Life extension/ Lifecycle management		*	*	*		*	
Planned Maintenance Management	*	*	*	*	*	*	*
Risk and Reliability centred Maintenance		*				*	
Risk Based Maintenance			*			*	
Total Productive Maintenance		*	*				*

Thus, to streamline literature sources and search themes, industry and maintenance concepts were considered based on relevance to the shipping and maritime industry. It is pertinent to state that the adoption of maintenance varies from one industry to the other, usually reflecting the peculiarities of the industry especially regarding maintenance cost, associated risk and loss of production(Lazakis et al., 2016, de Jonge et al., 2016). In this regard, Figure 6 highlights maintenance preferences by industry within the reviewed literature in academic journal and conference publications.

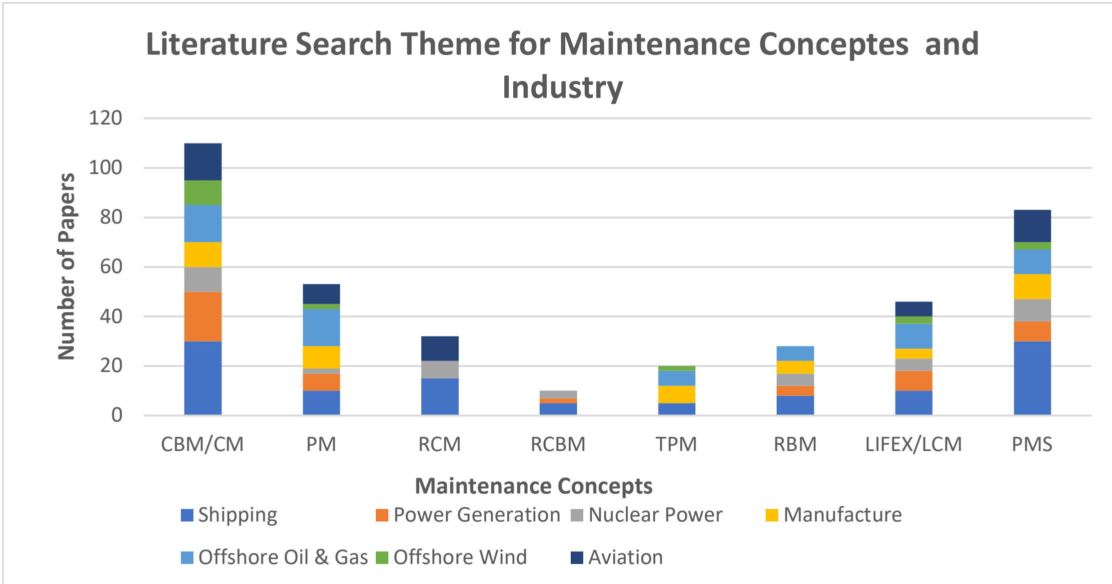

Figure 5: Maintenance Strategy Preference by Industry

On the other hand, the multiplicity of equipment which are largely independent makes the maintenance planning a huge task that cannot easily be manually achieved without some level of data automation (Schneider and Richard Cassady, 2015). Consequently, operators need to develop a maintenance strategy that best match platform operational profile and machinery condition; taking into consideration factors such as, maintenance personnel capacity, access to spare parts, environmental conditions, mission requirements, future task projections on platform or fleet as well as data management and processing (ISO, 2018a). Accordingly, a survey on the major traditional maintenance concepts is presented in the coming paragraphs.

2.2.1 Corrective Maintenance

Corrective maintenance (CM) also known as break down maintenance is the first stage of maintenance or basic aspect of any maintenance strategy. Therefore, corrective maintenance refers to all tasks that are carried out as a result of a detected failure or fault aimed at restoring the equipment functionality (Marvin, 2021). CM related activities can equally arise during a certain maintenance actions or inspection; therefore, CM tasks forms an integral part of all maintenance strategy mainly to address unplanned failures, replacement of unrepairable parts, replacement of less expensive parts or parts that are best allowed to fail or deteriorate before repairs (Khazraei and Deuse, 2011, Turan et al., 2012). It also applies to parts that have some level of redundancy of whose failure may not results to serious safety concerns, items such as electric bulbs, filters, seals, belts/chain drives, impellers etc falls into this category(Gits, 1992).

While CM activities are suited for quick fixes and low cost in the short term it is often more expensive and unreliable within the mid and long term(Deighton, 2016c).

In this regard, CM as a maintenance strategy cannot meet the demand of complex engineering systems in the contemporary industrial environment due to the increasing demands for high efficiency and emission reduced operations (Bouman et al., 2017). Regulations in places such as the Sustainable Development Goals (SDGs) are shaping the way maintenance is conducted globally as well as the maritime industry(UK-DoT, 2022). Hence, for ships to comply with MAPOL VI protocols and MEPC guidelines by the IMO they have to adopt an environmentally conscious maintenance approach which ensures equipment are operated and maintained based on improved emissions levels(IMO, 2021). Therefore, in addition to emission controls other demands such as the impact of failure on shipping availability which not only impacts on operators revenue but may also reduce chatter confidence due to unpredictability or operational inefficiencies due to equipment failures (Raptodimos et al., 2016, Stopford, 2009), it will be necessary that ship operators adopt more efficient maintenance approach that ensure system availability and safety of operations.

2.2.2 Preventive Maintenance

Preventive maintenance (PM) is a planned maintenance approach which is aimed at averting failures due to wear, age, cyclic stress or other induce stress due to operational, environmental, and associated demands. In this regard PM tasks require rigorous planning and careful implementation to be successful. Some aspect of PM tasks includes, inspection, cleaning, lubrication, calibration of parts/sensors, replacement, servicing as well as repair of worn-out parts or defective components (NAVSEA, 2021, Marvin, 2021). Improvement in data collection and computerised maintenance systems (CMMS) have greatly improve the management and process of component failure data such that spare parts and holdings can be efficiently managed based usage frequency. In this regard planning and scheduling of PM tasks can be delivered in multiple ways to enable efficient implementation (Soral, 2016, Oke and Charles-Owaba, 2006). The implementation of PM task and scheduling can be implemented through the following:

a. Age-based PM: - In the Aged based PM approach, maintenance tasks are conducted based on age of the equipment or component of interest. The age may be quantified as time in operation or by other time concepts such as the number of kilometres travelled for vehicles, the number of take-offs/landings for aeroplanes, or the number of start and stop for combustion engines. Hence using information, an inspection, servicing, or replacement may be planned.

b. Calendar/Time based: - Time based PM activities are planned based on specified calendar period such months, weeks, days, or hours. This type of maintenance is generally easy to schedule due to their routine nature, though may be difficult to implement. Moreover, Marvin (2021) emphasises that time based maintenance policy is generally easier to manage than age based maintenance policy because the maintenance can be scheduled to predefined times.

c. Condition based: - Condition based maintenance is an aspect of PM where maintenance tasks are carried out when there is clear sign of deterioration or degradation in equipment health, performance and/ or physical features. Important indicators commonly used as machinery health parameters includes variables such as vibration, temperature, pressure, amount of particle in a lubricating oil, viscosity index etc (Lazakis et al., 2016, Martin-del-Campo and Sandin, 2017)

d. Opportunity based: - This type Condition based PM relies on window of opportunities that could arise due to other planned or unplanned activities not caused by the particular equipment (Truong-Ba et al., 2019). Opportunistic PM task could be useful in managing maintenance issues of equipment or machinery parts that could require total shutdown, or removal of certain part of a machinery to be performed.

e. Overhaul:- Plant overhaul is a major PM task in many industries which is aimed at improving system performance, reliability and availability (Marvin, 2021). Overhaul maintenance is usually planned conducted when the equipment is less required or there as an alternative means of conducting the similar service provided by the machinery or plant. Nonetheless, overhaul PM can be influenced by industry requirements, environmental and economic challenges, which could result in delays and possible failure of equipment.

Overall PM strategy is seen to be widely practiced in industries such as automotive, railway, construction, power generation and shipping due to its multiple adaptations which can assist provide some assurance and economic benefits to operators. Additionally, the ability of experienced operating and maintenance staff to understand the behaviour of machinery and easily implement repairs could be a reason for its wide adaptation (Raptodimos and Lazakis, 2018). Moreover, most equipment are supplied with OEM recommended maintenance tasks which can be performed by the operator with minimal need of sensor measurement and inspections, this often enables the operator to become familiar with equipment and its behaviour. This possibility could improve the overall ability of the maintenance staff to deliver certain routine maintenance task, though could be reduced with new and less experience members of staff (Raptodimos, 2018).

PM is widely practiced onboard ships as it forms the base of Planned Maintenance System (PMS) which is the primary maintenance approach onboard ships(Lazakis, 2015, Jimenez et al., 2020). This popularity may not be unconnected with the OEM preference of providing after service support to operators which assures of genuine spare parts supply and timely delivery as opined in (Raptodimos, 2018, Heinz P. Bloch, 2006). Furthermore aspects of PM enabled through big data management and internet of things (IoT) has increased the rise to third party assert managers to provide additional service support on PM and its implementation(ABS, 2016, DNV, 2020, Galar and Kumar, 2017a). These service are especially beneficial for new ships less than 10 years old as they require less maintenance(Stopford, 2009). However as ships ages the maintenance demands increase and often done with the ships underway, hence requiring more spare parts and increased manning(Stopford, 2009, Ford et al., 2015).

Overtime the ship owners practicing PM must contend with two issues, first when the ship is new, PM strategy can lead to unnecessary spare parts onboard which may not be needed hence tying down capital, space and the likelihood of some spares getting damage due the humid condition on board. The second challenge is age related; as the ship ages, so the do the auxiliary system age and wear, hence failure becomes prevalent which impacts on the overall reliability of the main machinery. This situation makes it difficult to keep phase with PM activities thereby affecting the overall ship availability with ripple effect on revenue and operational efficiency. In retrospect despite intrusive maintenance challenges caused by inspections or checks; PM can provide a good level of equipment availability. It can easily fit to schedule by the maintenance departments and can possibly be adapted for CMMS. Hence when compared with corrective maintenance PM is more efficient and economical to implement. The downside as earlier highlighted are the increased manning levels, dependence on experience personnel and possible high spare parts demand. Moreover, further challenge as regards the OEM support came to limelight due global travel ban as result of the COVID19 pandemic.

In this regard, a desirable maintenance strategy for ship operators and maintenance department is one that can anticipate failure, repairs or replacement based on equipment history or performance. Such a maintenance strategy could help the ship operator to understand the right level of manning needed and when failure becomes to frequent such that maintaining the equipment is no longer economical. Realising this means the ability to predict failures and how they occur which can be achieved through the implementing predictive maintenance strategy.

2.2.3 Predictive Maintenance

Predictive maintenance (PdM) as described by the BSI (2010) is a condition based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item. Marvin (2021) further adds that PdM extends CBM by adding theory and methods used to predict the time item will fail, therefore allowing a PdM task to be planned for a suitable time prior to the failure of a maintainable item. Based on the forgoing predictive maintenance rides on organisational ability to efficiently collect and manage data. Though even the previous maintenance concept depends on machinery data collection, however when compared to predictive maintenance the level of scrutiny, amount of data and variables or data features will be much higher(Galar and Kumar, 2017d, Bousdekis et al., 2018). In this regard emplacing predictive maintenance regime require adequate provision of sensors to monitor and store machinery health data as well as maintenance and repair records.

According to Heinz P. Bloch (2006), predictive maintenance if applied properly is the most cost effective strategy especially in the process industry, as it leverages on the improved sensor technology and operator experience too. Safety critical industries such as oil and gas and nuclear power generation also utilise the PdM technologies on systems that presents high safety and security risks. For instance within Nuclear Power Plant (NPP) industry PdM has proved to increase system operability, reliability and reduced possibility of unwanted reactor trips(IAEA, 2007), same possibility can be said for other industrial sectors within the power generation and oil and gas sectors (Melani et al., 2018, OREDA, 2002, Ayo-Imoru and Cilliers, 2018). The appeal for the adoption of PdM technologies is enabled by a variety of sensors that could provide recording and storing of machinery health data such as thermography, vibration and oil analysis both onsite and remotely(Zhao et al., 2017, Fuller et al., 2020, Galar and Kumar, 2017d). This also promotes the penetration of CSMS, CMMS, Machinery diagnostic system or expert systems.

PdM has also been implemented within industry and academia through reliability and maintainability procedures using historical data such as MTTF, MTBF, Monte Carlo simulation and Weibull analysis (Lazakis et al., 2016, Gkerekos et al., 2019, OREDA, 2002). These techniques as well as data driven approaches using machine learning algorithms for fault identification and diagnosis have shown promising results for PdM that eliminates intrusion approach in PM(Soliman, 2020, Rivas et al., 2020, Velasco-Gallego and Lazakis, 2022a, Lazakis et al., 2018b). Moreover, predictive analysis of machinery health monitoring as presented by (Gkerekos et al., 2019, Daya and Lazakis, 2021, Soliman, 2020, Rivas et al., 2020, Velasco-Gallego and Lazakis, 2022a, Lazakis et al., 2018b) could help in manging GHG emissions as it enables understanding of machinery health degradation that could results to increased consumption or incomplete combustion. It also enabled the operators with an idea of when to make parts replacement to reduce the possibility of high emission rates on ships with older systems(Karatuğ and Arslanoğlu, 2022).

In general, PdM provides greater system availability and reliability, in relatively cost-effective manner when compared to the rest of the primary maintenance strategy. It also does not rely on the ability of the maintenance crew to identify fault hence given some flexibility as regards staffing challenges. However other authors as Lazakis et al. (2016),Jardine et al. (2006),Marvin (2021) opined that PdM reliance on sensors, which could be costly and data management requirement could provide additional challenges too. Moreover, sensor error, noisy data, feature overlap presents additional challenges as regards the implementation of PdM. Accordingly, notwithstanding the advantages in the traditional maintenance concepts some the inherent shortcomings in them can best be addressed through hybridisation of two or more concepts.

2.3 Maintenance Evolution

Overall all maintenance actions come under two major types, namely Corrective and Preventive(Marvin, 2021, Khazraei and Deuse, 2011). Corrective maintenance is generally targeted at items that can be allowed to fail, unrepairable or can be deferred, while preventive maintenance provides much wider coverage. This being that all PM tasks are aimed at avoiding or minimising the impact of failure to the system availability, hence the primary classifications are time based, clock/calendar based, and condition based. In the case of PdM, there is no general agreement among authors if it is one of the primary maintenance or an advanced preventive maintenance. Nonetheless, it comes with some distinctive features that makes it predictive. PdM relies more on statistical and probabilistic failure analysis to provide insight into machinery failures and the possibility of occurrence within a time frame or certain load and environmental condition. Therefore, unlike PM which depends more on inspections, survey reports, condition monitoring sensors to help planning and scheduling of maintenance task; PdM thrives through data collection, management and analysis capabilities for repair and maintenance planning. In this regard several adaptations of Corrective maintenance, Preventive Maintenance and Predictive Maintenance have been developed aimed at addressing or adopting maintenance to existing machinery, policy demands as well as techno economic and environmental considerations(Ben-Daya, 2009). Besides, technology advancements, system complexity, safety concerns as well risk associated to some failures regarding revenue lose or environmental pollution, has made necessary for maintenance to evolve over the last century, Figure 7.

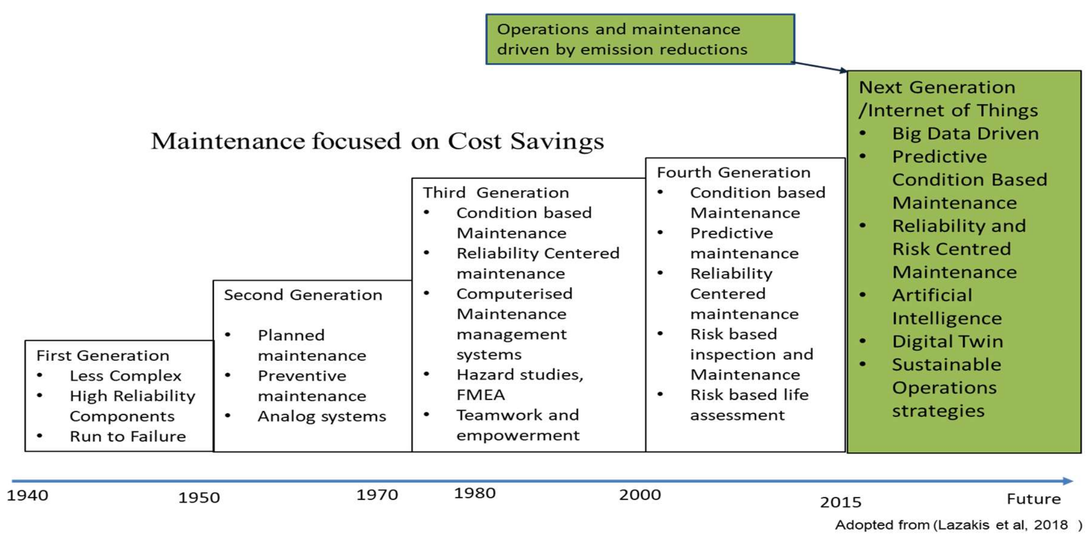

Figure 6: Evolution of Maintenance

2.3.1 Planned Maintenance System (PMS)

Planned Maintenance system (PMS) is type of maintenance strategy that combines primarily the features of corrective and preventive condition monitoring strategy. It involves the repair, replacement, inspection and survey of machinery and equipment in order to avoid unexpected failure during use or when required(Ben-Daya, 2009). Primarily it aims to reduce cost and improve operational reliability which are usually measured in loss of production or operational availability (Ben-Daya, 2009, Daya and Lazakis, 2022). PMS is an efficient maintenance approach as regard timely prevention or identification of failure and fault respectively. Moreover, unlike most organised maintenance concept, PMS is flexible enough to be uniquely adopted by units within a large organisation improving control and asset management(NAVSEA, 2021). In this regard it is common to see PMS activities as part of other maintenance strategy implementation. In particular TPM and RCM adopt PMS procedures to address equipment that are categorise as time dependent, low maintenance cost and low criticality in order to eliminate non-essential asset to assist with management(Heinz P. Bloch, 2006).

Ashayeri (2012) highlights that PMS in the process industry is less costly and can ensure machinery availability within the medium and long term. Similarly in a review on TPM Ahuja and Khamba (2008) emphasised the role of planned maintenance in the implementation of TPM precisely on the overall maintenance logistics and employee engagement. Lazakis et al. (2010) and Dikis (2017) reiterated the importance of PMS in enabling maintenance data collection and management in PdM implementation. Moreover, PMS offers additional value towards maintenance data in that it utilises reliability measures such as failure rates, MTBF, MTTF as well as MTR (Lazakis et al., 2016). A detailed PMS documentation further provides the number of personnel, qualification, materiel needed and estimated duration to carry out certain details. In this regard, PMS provides a good maintenance platform for the industry provided that equipment and spare parts list have been standardised (DoD, 2005a, OPNAVINST, 2019). Overall, PMS is applied in the industry within various maintenance strategy owing to its usage of historical data for maintenance planning and scheduling (Okoh et al., 2014, Rusin and Bieniek, 2017). This feature in PMS allows for deferring of maintenance action to suitable time which as described in (Gits, 1992) enables continuity in production in other words improves availability.

Unarguably PMS is the most widely practiced maintenance strategy onboard ships of any type or class as it afford both the ship owner and operator the level of assurance both in machinery availability and revenue forecast (Stopford, 2009, Raptodimos, 2018, Lazakis et al., 2018b, Soral, 2016). Overall, PMS provides the flexibility, confidence, and facility for adaptation irrespective of the size of organisation; though in bigger organisations some level of computerisation will be required due to the size of data required. The successful implementation of PMS depends on some key factors which include suitably qualified and experience personnel (SQEP), efficient data record and data management, sufficient number of personnel and most importantly a good spare parts and consumables holding onboard (Tomlinson, 2015, Gits, 1992).

The need for the above requirements is mainly because PMS follows a predetermined scheduling process, therefore logistics planning for maintenance activity can be time and resource consuming due to difference in technical specifications of the individual equipment (Ben-Daya, 2009).Though the PMS scheduling document provides detailed explanation and all requirements as regards spare parts and other consumables; issues could arise due to obsolescence, equipment replacement during upgrade, and budgetary constraints (Catt, 2021, Deighton, 2016c). In developing a reliability and criticality-based maintenance framework (RCBM) Lazakis and Ölçer (2015), Lazakis et al. (2016) identifies large spares parts holding and intrusive maintenance actions as some of the drawbacks in PMS as well as other PM base maintenance. Furthermore, (New, 2014) on the application PMS in the RN highlights similar issues in addition to space constraints and reduction in ship staff workload. Moreover, shifting from PMS to other maintenance strategy which adopts less inspection and invasive techniques has proved to increased platform availability and freed funds to other aspects (New, 2014, Lazakis et al., 2016, Cort, 2017).

2.3.2 Condition Based Maintenance (CBM)

Condition Based Maintenance (CBM) strategy adopts multiple maintenance approaches to ensure system reliability and availability while taking into consideration the dynamics in usage and age with respect failure and repairability of subsystem (Vamsi et al., 2019, IAEA, 2007, Wu et al., 2007). In this regard CBM provides a wide range of maintenance possibilities through a systematic approach of grouping or clustering maintenance actions (ISO, 2018a, Jardine et al., 2006). Therefore CBM relies much on condition monitoring strategy through data collection and management by onboard ship crew, this is more so as advance diagnostics analysis depend on actual sensor data for analysis and data collection approach (Raptodimos and Lazakis, 2018). The collection of data for ship maintenance purpose can be categorised into structural and machinery data. Structural data covers information on corrosion, hull, stiffeners, girders, decks, paint scheme and all other fixtures and machinery foundation, while machineries include all equipment used for propulsion, power generation and auxiliaries used onboard. The process of collecting CBM data is described in a paper by (Lazakis et al., 2016, Lazakis et al., 2018a) which presented on the outcome of a measurement campaign part of Inspection Capabilities for Enhanced Ship Safety (INCASS) case study conducted on board container ships and provides a customised methodology for monitoring important machinery systems. The use of sensors and data management in CBM enables the adaptation and ranking of maintenance activities such as inspections or part replacement which allows for a better management of personnel and materiel (Daya and Lazakis, 2022, de Jonge et al., 2017).

Moreover, with the advent of data analytics and machine learning models CBM is increasingly being adopted in areas that require remote monitoring due to wireless sensor technology which enables a continues transmission and automatic data recording and transmission obtained in offshore oil and gas and offshore wind (Niculita et al., 2017, ABS, 2016, Dao et al., 2018, Bangalore and Patriksson, 2018). In this regard, CBM has become accessible and implemented by researchers and industry with the ability to use real time machinery condition in predicting the future condition of a remote assets, offshore asset or a vessel this also enables the operators to monitor and record data in real-time (Lazakis et al., 2018b, Lazakis et al., 2018a, Velasco-Gallego and Lazakis, 2022b). In this regard CBM benefits the operators with a better understanding on the reliability of equipment, while the OEM also understand additional weakness in design.

Therefore, similar to other industry, the shipping industry is making gradual shift to adopt or implement CBM strategy onboard due to low cost sensors, increased penetration in wireless technology and regulatory frameworks (Raptodimos et al., 2016, IACS, 2018a). Moreover, the ISM code as contained in IMO (2018a) and IACS (2018b) together with individual classification societies have indicated interest towards the implementation of CBM on onboard ships. This is more due to the increased scrutiny on ships to align with the IMO's ambition of reducing carbon emissions from diesel engines (UK-DoT, 2022, IMO, 2021). Thus, enabling efficient machinery condition monitoring data could go a long way in reducing performance deterioration particularly in diesel engines which could potentially increase fuel consumption and emission (Gkerekos et al., 2019). Lazakis et al. (2018b) stressed the relevance of CBM in reducing spare parts holding while and Xiang et al. (2017) highlights' CBM in contractual maintenance agreements and proposed a performance based rather than material based contracts. The authors here argued that CBM is key in supporting the implementation of performance based contractual agreements as it provides more flexibility since the actual machinery condition is as provided either by direct monitoring or sensors which both the operator and contractor have direct access to.

Nonetheless, the challenges of integrating CBM to an existing system arises from cost of implementation, technology acquisition such as sensors and retrofitting requirements. Additional investment would also be required in data collection and management, upgrade of personnel knowledge and training to adopt the new technology and use efficiently knowledge (Doherty, 2016). Moreover, the challenge of handling huge amount of sensor data increases the risk of noisy data which require statistical and domain knowledge to ensure a clean data. On the other hand, there is also the challenge of using handheld sensors for periodic recording of machinery health indicators such as thermography, acoustics, and vibration which presents additional challenge with experience of the reader and quality of the equipment (Ford et al., 2015, Raptodimos, 2018).

Furthermore real time data collection presents additional challenges with regards to quality and security of information which as highlighted by Cipollini et al. (2018b) in the case of naval ships due to intrusion on maintenance data and location privacy. Some of these are of serious concerns for Naval ships, hence the recommendation for periodic monitoring/data transmission or provision of bespoke maintenance system. Currently some of these technologies are being tested on board some Naval ships on equipment such as gas turbines, diesel generators and reduction gears (Berghout et al., 2021, NAVSEA, 2021, Tomlinson, 2017). Therefore, to overcome of some the draw backs associated with CBM alternative maintenance that prioritise the risk of machinery failure to maintenance planning by considering the risk of failure to plant availability and overall safety would be required (Rusin and Bieniek, 2017, Tan et al., 2011, Kiran et al., 2016, Arunraj and Maiti, 2007). An alternative view by (Lazakis et al., 2018b, Turan et al., 2012, Leimeister and Kolios, 2018, Eriksen et al., 2021) focused more the reliability and criticality of component or equipment to overall availability of the platform. These group contends that the reliability of an equipment is a better representation of its availability which also helps to narrow overall monitoring and maintenance efforts (NASA, 2008).

2.3.3 Reliability Centred Maintenance (RCM)

The origins of RCM was the aviation industry developed by a team of engineers of United Airlines; RCM is described as a maintenance strategy that logically optimises the different types of maintenance practices while minimising overall cost of maintenance (NASA, 2008). System reliability is key in aircraft maintenance, which the traditional time schedule maintenance in the air industry could not keep phase with as regards safety of passengers and assets (Ben-Daya, 2009). In this regard RCM develop steps to carry out through failure analysis to identify critical components to equipment reliability and provide maintenance solution (NAVSEA, 2007, New, 2014, NASA, 2008). Thus, the RCM strategy depends on all available maintenance approach to ensure system reliability. Consequently, realising the success of RCM in the aviation industry, other industry also adopted its strategy particularly the oil and gas, nuclear and power generation as well as manufacturing (Khazraei and Deuse, 2011, Deighton, 2016c, Heinz P. Bloch, 2006).

The implementation of RCM requires assembling a team of experts with technical background and understanding of the facility or platform. These will be guided by some important points as highlighted in (Dhillon, 2006, NAVSEA, 2007). The team will make a methodical review based on seven fundamentals questions as follows:

1. The intended functions and performance characteristics of the considered asset.
2. The failures that may occur.
3. The failure causes.
4. The consequences of the failure
5. The impact of the failure
6. The potential preventive measures
7. The measures to be taken in the absence of implementable preventive action.

The RCM philosophy recognised the fact that failures and components have different significance and impact on system reliability, therefore highlighting this difference could go a long way in improving the maintenance delivery. In this regard it uses the seven questions to focused on the basic cause of equipment failure (NASA, 2008, Deighton, 2016b). Overall RCM tends to be adoptable to both equipment conditions and environmental changes. Especially that it uses CBM approach to enable the use of machinery health data for failure and diagnostic analysis hence allowing for a more critical maintenance analysis (Smith, 2017b). Therefore, the process enables the onboarding of new equipment or system or the optimisation of maintenance strategy on existing equipment (Raptodimos, 2018, NAVSEA, 2021).

The benefit of RCM is as seen in other industry leads to its adaptation in the military particularly the US Navy, Army, NASA, the Royal Navy as well as merchant fleets (New, 2014, NAVSEA, 2007). In its RCM manual NASA also believes that RCM can be used to address environmental challenges related to its operations and other government departments (NASA, 2008). RCM implementation onboard ship can significantly increase system reliability as well as the increase flexibility in maintenance planning (Raptodimos, 2018). According to (Kalghatgi, 2022) the availability of big data presents a good opportunity for the implementation RCM onboard. In recognising some of the benefits with the implementation of RCM by the RN New (2014) highlighted that up to 40% saving was achieved in maintenance, material and reduction of downtime in addition to improve safety in maintenance and platform operations.

Eriksen et al. (2021) in examining the applicability of RCM for unmanned cargo ship also signifies the capabilities of RCM as regards analysis and identifying system reliability, however, is shot of clearly allocating preventive and corrective maintenance tasks, which is a challenging issue for unmanned vessels. Similarly, the implementation of RCM onboard ship presents it challenges, chief among which is personnel training and acceptance of the required RCM actions which is need based, not a scheduled routine. A further issue is to do with OEMs who in most cases want to retain the control of maintenance delivery for their equipment as it forms part of their revenue, hence making difficult to fit equipment in RCM strategy. Overall, significant time and resource commitment is needed for RCM analysis. Due to this, implementation of RCM could be burdensome to onboard maintenance staff who are engaged in the routine of watch keeping and running other machineries. In this regard narrowing the scope of equipment to be covered RCM onboard would ensure the staff pay more attention on a particular set of tools or systems (New, 2014).

2.3.4 Maintenance and Big data (Industry 4.0)

The emergence of advance sensor technology gave rise to big data management as operators are able collect large amount of machinery health data at short intervals and enabled by high speed internet and wireless connectivity (Bousdekis et al., 2018, Galar and Kumar, 2017b). The combination of these technologies enables companies to monitor machinery real time online and some case provide control and diagnosis (Galar and Kumar, 2017d). Therefore big data or industry 4.0 enables real-time insights into equipment performance, scheduling optimization, and downtime reduction, hence revolutionising how maintenance operations are carried out across a variety of industries (Fuller et al., 2020). Companies can foresee equipment failure and carry out proactive maintenance by evaluating data from sensors and other sources, which lowers the possibility of unscheduled downtime and boosts overall equipment efficiency (Mihanovic, 2016).

Overall, the essence of maintenance data management is to make sense of the information available in a set of data collected from single or multiple machinery. Therefore (DNV, 2020) defines data as any reinterpretable representation of information in a formalised manner suitable for communication. While ship data as described in (ISO, 2018b) is a measurement value from shipboard machine and equipment to which a time stamp is added. Maintenance engineers have for long depended on machinery data as main source of information for understanding the present and future health condition of the machinery. Moreover, the evolution of maintenance towards predictive condition-based maintenance and condition monitoring is largely made possible through the application of big data management technologies such as sensors capable of individual component condition monitoring, online real time monitoring, and cloud computing etc. These developments enabled the implementation of supervisory control and data acquisition (SCADA) particularly in the offshore wind power generation where physical human monitoring is impractical, hence expanding the possibility of remote control and monitoring of systems (Zaher et al., 2009, Dao et al., 2018, Bangalore and Patriksson, 2018). Similarly, a broad methodology utilising various sensor data and technologies has been presented in the INCASS project which provides research data base and methodology for both ship machinery and structural risk analysis enabled by the combination of sensor data, failure and repair data for machinery health and reliability analysis (Lazakis, 2015, Eriksen et al., 2021). Nonetheless, these technologies present some challenges which companies need to be aware of as follows (DNV, 2020):

1. Data quality: Successful implementation depends on the quality of data; therefore, it is important to ensure data accuracy, completeness, reflectiveness, and relevance to the requirement of the ship.

2. Data Security: Appropriate security measures are needed to guard against cyberattacks and unauthorised access when storing and transmitting huge amounts of data from sensors and other sources.

3. Data Integration: In order to analyse and interpret big data from diverse sources, the right tools and technologies must be used.

4. Competence: Companies must ensure they have the right competence and tools in obtaining, analysing, and interpreting data so that they may make wise judgements, hence ships must have the requisite expertise or hire one.

2.3.5 Summary on Maintenance Strategy and Maintenance Evolution

Improvement in maintenance practice and strategy were necessary to keep phase with technology advancements in machinery design, construction, and functions. The idea of maintenance has been with humanity since the time humans knows how to use tool for hunting (Dhillon, 2006). In this regard modern maintenance practice showed tremendous improvement around the period of World War 2 through to the 1960s with many developments coming from national defence forces particularly the US and European countries. Consequently, the early development of maintenance actions were generally categorised into 2 major types, namely Corrective and Preventive (Marvin, 2021, Khazraei and Deuse, 2011). Corrective maintenance is generally targeted at items that can be allowed to fail, unrepairable or can be deferred, while preventive maintenance provides much wider coverage. This being that all PM tasks are aimed at avoiding or minimising the impact of failure to the system availability, hence the primary classifications are time based, clock/calendar based, and condition based. In the case of PdM, there is no general agreement among authors if it is one of the primary maintenance or an advanced preventive maintenance. Overall advance in sensor technology and data collection lead to the adaptation of other derivatives of maintenance such as PM, CBM and RCM which are generally a combination of one or more of the traditional maintenance practices with aid of computers as obtained in CMMS.

On the other hand, the emergence of advance sensor technologies gave rise to big data management as operators are able collect large amount of machinery health data at short intervals, these aided by wireless technology enabled by high speed internet and wireless connectivity (Bousdekis et al., 2018, Galar and Kumar, 2017b). The combination of these technologies enables companies to monitor machinery in real time online and in some cases provide control and diagnosis (Galar and Kumar, 2017d). Therefore big data or industry 4.0 enables real-time insights into equipment performance, scheduling optimization, and downtime reduction, hence revolutionising how maintenance operations are carried out across a variety of industries (Fuller et al., 2020). Companies can foresee equipment failure and carry out proactive maintenance by evaluating data from sensors and other sources, which lowers the possibility of unscheduled downtime and boosts overall equipment efficiency (Mihanovic, 2016). Therefore, going forward, especially with desire to decarbonise the shipping industry the driving idea behind maintenance will be centred towards emission reduction related priorities and optimisation of shipping operations towards low energy consumption operations and behaviour.

2.4. Maintenance in the Maritime Industry

Ships of any type are structures that are operated through a network of systems majority of which are interdependent for their correct functioning. These interconnectivities between systems onboard ships enable economic and efficient operations and maintenance of all equipment/system. While this interdependencies comes with a lot of advantages a challenge lies in failure of equipment that provide utility to other ship system. Therefore maintenance efforts are directed to ensure these failures do not occur and when they do, the impact can be managed efficiently (Lazakis & Ölçer, 2016). This is more so, as the cost of routine maintenance accounts for about 14 % of ships operating cost which increases as the ships ages (Stopford, 2010). Therefore, when this cost is considered against the impact of unscheduled maintenance and the likely operational delays which is a major concern for naval and coast guard ships (Goossens & Basten, 2015). It then becomes necessary that ships maintenance adopts a flexible maintenance approach that ensures an efficient and cost-effective operational availability (Lazakis et al., 2016). In this regard, other maintenance styles were introduced to overcome some of the challenges when using tradition maintenance (Gits, 1992), (Lazakis & Ölçer, 2016). Similarly (Shafiee, 2015) provides a review on maintenance selection strategy which highlighted the dynamics involve in maintenance selection especially in a complex environment as such ships. Planned Maintenance System (PMS) has remained the mainstay of ships maintenance for both civil and defence sectors (Lazakis et al., 2018), (New, 2012). Increasing number of research conducted on ship maintenance has shown that the preferred maintenance onboard ships is preventive maintenance system followed by predictive maintenance system (Lazakis et al., 2018,Lazakis et al., 2016).

Overall, there are interest to adopt more efficient maintenance systems but reluctance by organisations (ship owners) to adopt or update technology could be a hinderance due to cost of technology, installation of new sensors, system upgrade and training to match new technologies (Tomlinson, 2016). Notwithstanding, the need to improve the flexibility for on board maintenance and the current regulations towards reducing emissions and the strategy by some OEM to adopt remanufacturing which offers some discount for operators participating in the scheme would help change the dynamics of maintenance to be more efficient (International Resource Panel, 2017,IACS Rec, 2018). Moreover, it has been established that cost of maintenance increases with the age of equipment, but can be controlled with more optimised maintenance strategy (Lazakis et al., 2019). Moreover, the availability of maintenance management software has helped in automating maintenance scheduling as well as onboard diagnostic equipment. Nonetheless, there remains the need for in house capability to analyse and provide personalised maintenance solution peculiar to the operational environment.

2.5. Sources of Ship Maintenance Guidance and Regulations

The shipping industry plays very vital role in global trade, oil and gas and maritime security sector control. In this regard ships are subject to generic and particular regulations depending on company, country of origin (flag state), location (port state) and regional and the class it belongs to (Stopford, 2009). Overall shipping maintenance guidelines and regulations are drawn from the IMO protocols (MARPOL VI), classification society recommendations and additional demands that could come from other relevant organisation as such insurance companies and recently other climate concerns. Moreover, individual companies will have their specific guidelines as contained in the Standard Operating Procedure (SOP) of the company and OEMs of the equipment onboard. In the case of naval ship these requirements could slightly be different as regards higher reliability and availability demands on equipment as provided by respective service maintenance handbooks (NAVSEA, 2021, NAVSEA, 2007, MoD, 2007, DoD, 1980). The class societies equally provide additional guidance for the construction of naval ships, which could equally form part of additional maintenance guidelines (ClassNK, 2022, ABS, 2023, Register, 2022).

In this regard, maintenance guidance and regulations are drawn from multiple sources and often updated to reflect changes as may be passed by respective authorities. Overall, these regulations have wider implications as regard equipment reliability and safety of operations and personnel onboard. Additional regulations are also established onboard either by the captain of the ship or chief engineer in the case of the Naval ships these rules are set out in captain standing order book or the engineer officers standing order book. An overview of the key sectors influencing maritime maintenance guidelines, regulation and practices is given is at Appendix 1:

2.6. Naval Maintenance Concepts

Maintenance concepts adopted onboard navy ships is not largely different from what is obtained on board merchant ships except that the level of availability expected for naval ships demands high level of equipment reliability. Additional level of redundancy that could add to complexities in machinery arrangements is often provided due to the nature of their operations and crew size in order to improve utility, habitability onboard and able to with stand frequent heavy loading (EL-Ladan, 2022, NAVSEA, 2021). In this regard naval maintenance concept are design to ensure that equipment are available when needed and are maintainable (Nguyen, 2017). Accordingly, maintenance concept in navies involves various aspects such as PM, CM, PdM, and CBM. Therefore hybrid maintenance approach such as PMS and RCM are the most practiced onboard (Tomlinson, 2015, New, 2014),

The adoption of PMS within the navy allows for a more streamlined documentation of activities such inspection, cleaning, testing and calibrations of equipment most of which are routine activities. PMS also enables the implementation of both corrective and preventive maintenance in a single document hence making material estimation such lubricants, spares, and other consumables. However, PMS activities are largely driven on preventive maintenance task leading to large store and spare parts holding majority are not fast moving hence occupying much needed space onboard. Personnel engagement in routine maintenance activities such inspections, cleaning and test related activities tend to overwhelmed the technical departments, hence affecting their ability to carry out more relevant task (Tomlinson, 2015, Office).Moreover, inspection or calibration activities in PMS could lead to unintended faults, hence the desire of navies to shift to a maintenance strategy with more precise tasking and less stores requirements (Goossens and Basten, 2015). Consequently, this lead to gradual shift towards RCM in most navies (NAVSEA, 2007, DoD, 2005b).

RCM as a maintenance method prioritises maintenance tasks based on the importance of the assets being maintained. RCM is utilised extensively by the Navy to guarantee the readiness and reliability of mission-critical equipment and systems. In this regard it is generally applied to complex systems such as aircraft, ships, and submarines. The RCM method requires a comprehensive examination of each system to determine potential failure modes, their causes, and their impacts. In addition, the analysis considers the mission-criticality of the system, the possibility, and repercussions of failure, as well as the effectiveness and cost of maintenance measures. RCM is a key component of the Navy's maintenance programme since it ensures the availability and reliability of critical machinery and systems when required. RCM serves to maximise the Navy's operational readiness and efficiency by prioritising maintenance actions based on the importance of the equipment and mission requirements.

The amount of equipment and individual components that need to be planned and accounted for in any maintenance strategy is huge and cannot be easily managed by traditional filling system. In this regard naval maintenance concept also includes the use of various computer management systems to plan, perform, and track maintenance tasks, including the use of CMMS and EMS. Similar advance services are provided in the form of product lifecycle management by asset management companies or classification societies (ABS, 2016, DNV, 2017). The prevalence of intelligent sensors and the internet has led to further advances in the naval maintenance towards the use of advance expert diagnostics system, big data, and remote monitoring. Moreover, naval maintenance concepts may involve the use of predictive maintenance, sophisticated analytics, and other developing technologies to optimise maintenance processes and increase asset availability. In essence, the naval maintenance concept is a holistic approach to ensuring the operational readiness of the fleet through the use of a variety of maintenance tactics and technologies. It is a key component of naval operations and contributes to the safety and effectiveness of naval platforms.

2.4.3 Factors affecting Maintenance in the Maritime Industry

The marine sector plays a vital role in international trade and transportation, as such ships cover great distance spanning various geographical and climate zones. Gits (1992) observed that introduction of advanced system and equipment, growing concern about the environment and increasing labours cost have made the improvement of maintenance control imperative, Figure 9 presents some factors that influence maintenance onboard ships. Moreover, ships require great investment from conception through to the building stage. The lifecycle spanning about 25-40 years and cost about 75 % of the ship’s production cost (Liu and Frangopol, 2019, Stopford, 2009).

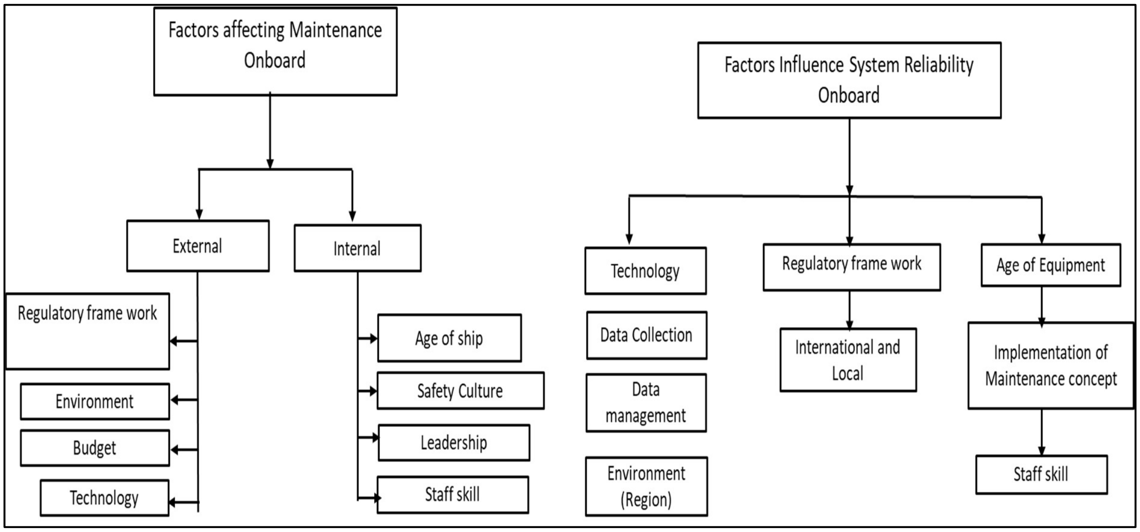

Figure 7: Factors affecting maintenance onboard ships.

Therefore, maintaining the effectiveness and safety of ships is crucial, to ensure good condition, reliable operations, and clean machinery operations with the acceptable global emissions levels. Overall, some factors affecting maintenance onboard ships can be summarised as follows:

1. Age of the vessel: Aging is a significant factor in ship maintenance, as ship ages and the equipment get older the maintenance demands become more intensive. The aging process increase the rates at which components and systems start to deteriorate, hence regular maintenance becomes necessary to keep it operating safely and efficiently(Specialty, 2022).

2. Operating conditions: The harsh conditions of the maritime environment can take a toll on a vessel's systems and components, increasing the need for maintenance. In this regard, vessels operating in rough seas or extreme temperatures may experience more wear and tear than those operating in calm waters. Similarly, the impact of marine growth and high humidity presents a serious maintenance issue for vessels in the operating in the tropics.

3. Type of vessel: Different types of vessels have different maintenance requirements. For example, a cargo ship may have different maintenance needs than a cruise ship or a fishing boat. Furthermore, the type of cargo a ship carries plays important role in determining maintenance intensity onboard regarding either hull or machinery

(ClassNK, 2017). Corrosion and cargo tank cleaning are issues for crude carriers, whereas chemical tankers require specialist coatings and materials to guard against toxic and corrosive cargo. Bulk carriers must deal with cargo hold cleaning and structural difficulties, whereas cargo carriers must use specialised equipment and procedures to protect cargo and avoid damage during transportation(Soliman et al., 2016). These among other critical conditions present peculiar challenges to respective ship types.

4. Regulatory requirements: Maritime regulations require vessels to undergo regular inspections and maintenance to ensure they follow safety standards, failure to comply can result in fines or even the revocation of a vessel's operating license (Bourneuf, 1991). Moreover, the current derive to decarbonisation is a good example of regulations and maintenance regime. For instance under Annex VI of the IMO MAPOL protocol there are technical and operational measures to improve energy efficiency onboard which includes the EEDI and SEEMP, both of which maintenance can play a vital role in achieving the desired target (Agency, 2020, Dragos, 2021).

5. Maintenance scheduling: Proper maintenance scheduling is critical to ensuring a vessel remains in good condition. Regular inspections and preventative maintenance can help to identify and address potential issues before they become serious problems (IACS, 2018b). Moreover poor and inefficient maintenance could unplanned breakdown which are more costly to fix and could lead to accidents (Nguyen, 2017). Similarly, low System reliability impacts negatively on ships operational availability and National security especially in the case of maritime law enforcement agencies (Daya and Lazakis, 2022). Hence shipping companies adopt to maintenance strategies that best fits their operational profile.

6. Training and expertise: The knowledge and expertise of the crew and maintenance personnel can also have a significant impact on a vessel's maintenance. Crew members who are properly trained in maintenance procedures and safety protocols are more likely to identify potential issues and address them before they become serious problems. According to Doherty (2016) maritime accidents reports frequently cite poor procedures as contributing factors towards maritime accidents. The lack of trained and

experience crew increase dependency on OEM or vendors for maintenance and repair(Ford et al., 2015). This potent a potential danger to the ship and the fleet at larger in that ship crew may not be able carry out critical repairs while ship is at sea. Moreover, dependence on OEMs crew knowledge for onboard systems and reduces ship capability regarding deployment especially fir Navies (Ford et al., 2015).

2.7 Maintenance Data Collection and Analysis

The challenges with information management on board and shore maintenance bases require great attention as errors, delays or miss representation of data could lead to unintended consequences regarding data representation. Therefore, data collection process is one aspect of the issues; harmonising the relevant raw data for maintenance plaining among the relevant stake holders could present another challenge. It is therefore important that key machinery health parameters and reliability measurement are identified and agreed upon by respective departments and each department receives what is relevant to it regarding maintenance planning, budgeting, and implementation.

Accordingly, streamlining of multiple information sources from onboard to shore maintenance bases in order to provide adequate but quality data has been identified as key to implementing a good maintenance management (Ford et al., 2013). Moreover, a classical work for onboard data collection was presented in INCASS MRA tool (Raptodimos et al., 2016) and provides data source for ships maintenance as well as tools relevant to system reliability analysis (Gkerekos et al., 2019). In this regard the process involved in on board data collection was presented (Cheliotis et al., 2019) which describes a data driven multiple regression algorithms for predicting fuel consumption of a ship main propulsion engine based on two different shipboard data acquisition strategies. The strategies were noon-reports and Automated Data Logging & Monitoring (ADLM) systems in which the paper highlighted the relevance of the ADLM over the noon-reports due to its increased frequency of data logging and reduced error. Overall sensors located at important point around machinery and other critical components provide the primary data needed for maintenance data and machinery health management (Velasco-Gallego and Lazakis, 2020).

On the other hand, shipboard operators provide additional details as regards failures and unscheduled maintenance, though this repots can as well be provide via ADLM systems that can identify certain failures. However, automated monitoring system are limited to the kind programmed fault s in failure data reporting and monitoring because they are mostly programmed to. This is more relevant when the role of auxiliary systems is being considered especially those not integral to the main machineries.

In this regard, (Lazakis et al., 2018a) discussed a system of predicting machinery health monitoring using ANN and FTA for reliability analysis, the methodology has successfully identified and defined measurement for machinery data through step-by-step demonstration of the process and identification of critical component using FTA. Moreover, ISO 19847 and ISO19845 provides standard guidelines and definition for onboard ship data collection, storage, management, and transmission via the internet. Nonetheless there already exist commonly understood formats for managing and collecting data onboard ships that are generated via various sources on board, as shown in Figure 10. Although, there may be nomenclature difference for instance between merchant and naval ships, but the records may still be referring to the same objective. It is a standard requirement for merchant ships to hold historical records of ship repair and maintenance being managed by Classification society who also provide additional standards and guidelines for data collection and management (Raptodimos, 2016, Cipollini et al., 2018b).

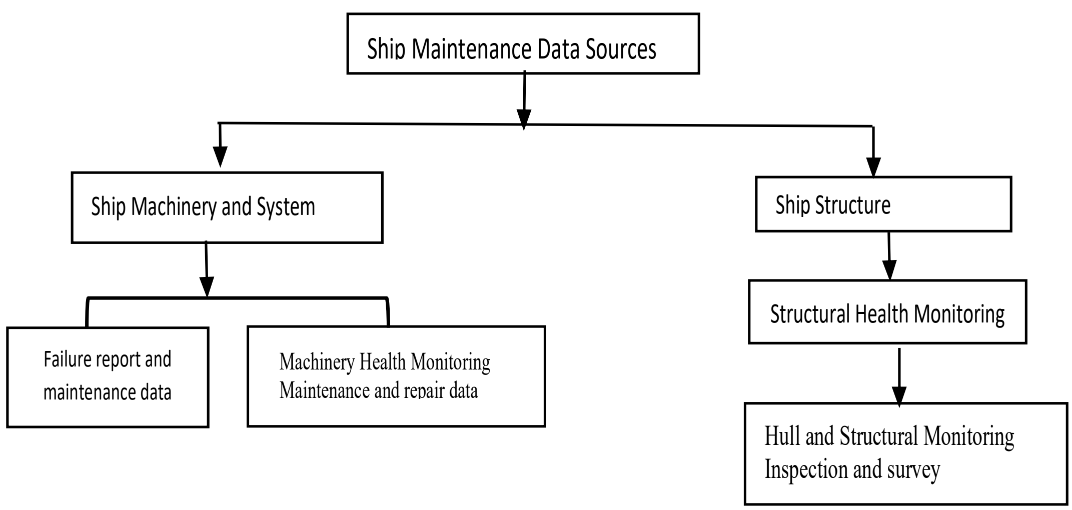

Figure 8: Ship Maintenance data Sources.

The aforementioned is not the same for naval ships nonetheless similar procedures and guidelines are followed for collecting data as provided in (DNV-GL, 2020, Iraklis Lazakis, 2015). Therefore, in addition to maintaining hard copy records of machinery failure and repair reports within the ship technical department. A navy ship also maintains the ship bridge log, officer of the watch (OOW) incident report book and ship operational state among other records report. These documents provide vital information on the location, speed, time, engine speed, generator(s) online, as well as other system operational within a given time. The records provide hourly updates of operational state and consumption rates of important machinery. Typically, a machinery health consists of time series data points of some important parameters, such as temperature, pressure, vibration, consumption rates, outputs, speed, load, deflections, and clearances.

2.8 Background on System Reliability tools

System reliability analysis is central to the successful implementation of any maintenance strategy as it provides clear insight on machinery behaviour and the impacts of failure on availability of machineries up to system levels. Accordingly, reliability analysis tools are widely used to support maintenance strategy selection or implementation in line with organisational objectives. Therefore, various maintenance strategy such as Reliability Centred Maintenance, Risk based Maintenance, Total Productive Maintenance, Risk and Reliability Based Maintenance etc draw from existing maintenance approach using system reliability analysis to provide a tailored maintenance system(Cheliotis et al., 2020). RCM developed in aviation industry and United States Navy in the 1970s (NAVSEA, 2007) provides clear intersection on the combination of various maintenance strategy and used of reliability tools. Moreover, maintainability analysis carried out at the design stage of products or platforms such ships or aircraft and other complex machinery are carried with use of reliability analysis tools such FMEA, ETA, DFTA, BBN etc(Li et al., 2023, Hirzinger and Nackenhorst, 2023).

On the other hand, maintenance planning and implementation within industries follows a combine approach whereby systems or components are maintenance based on failure behaviour either through condition monitoring or predictive maintenance process(Deighton, 2016a). This process was made possible overtime due to reliability and machinery health data analysis (Chemweno et al., 2018, Kalghatgi, 2022). The essence of these tools can be seen in the planning and implementation of maintenance strategies such as PMS which is stipulates time-based approach and CBM that relies on sensor deployments both of which are commonly adopted onboard ships(Cicek and Celik, 2013, Cipollini et al., 2018a, Lazakis et al., 2016, Jakkula et al., 2020) . In general reliability analysis tools examine the effects and risk of failure by considering quantitative and qualitative aspects of machinery maintenance and operations data(Karatuğ and Arslanoğlu, 2022).

To this end, various researchers have implemented the use of some tools such as FTA, ETA and RBD mostly combined to provide maintenance analysis approach in order overcome issues such as discretisation, linguistic restriction, and expert judgment (Kampitsis and Panagiotidou, 2022, Jun and Kim, 2017, Khakzad et al., 2011, Duan and Zhou, 2012). Research efforts by (Lazakis et al., 2010, Lazakis et al., 2016, Lazakis and Ölçer, 2015, Konstantinos, 2010) implemented a risk and reliability assessment methods of FMECA and FTA as well as using Fuzzy Multi Criteria Decision Making Approach (FCDMA) in order to identify critical components and provide maintenance decision support for ships with focus on equipment risk and criticality to maintenance. Other tools such as Bayesian belief networks, Monte Carlo simulation, Markov chains, Petri Nets and Weibull analysis among others have been applied to model maintenance planning (Leimeister and Kolios, 2018, Kabir and Papadopoulos, 2019, Melani et al., 2018).

On the other hand, complex system reliability analysis requiring inputs that are largely non-binary and continuous with stochastic failure behaviour would require different approach to address temporal system state or a repairable mechanical system that can operate satisfactorily at degraded condition. Recent research efforts have also focused on ship machinery real-time anomaly detection for fault diagnosis (Velasco-Gallego and Lazakis, 2022a); application of Bayesian and machine learning-based fault detection and diagnostics (Cheliotis et all, 2022); real-time data-driven missing data imputation evaluation for short-term sensor data of marine systems (Velasco-Gallego and Lazakis, 2020); and the development of a time series imaging approach for fault classification (Velasco-Gallego and Lazakis, 2022b). Therefore, additional flexibility to produce a representative model taking all possible consideration will be required.

Consequently, researchers have resorted to the use of multiple tools to accommodate system dependencies and complexities of multi system (Lazakis et al., 2016, Marvin, 2021, Piadeh et al., 2018). This strategy enables the use of multiple data types for reliability analysis and the use of tools in a more flexible manner(Leimeister and Kolios, 2018). In general reliability analysis tools examine the effects and risk of failure by considering quantitative and qualitative aspects of the operations and repair data. It is therefore critical that researchers adopt hybrid approaches that combine a number of reliability tools in order to overcome some of the inherent deficiencies of individual tools or take advantage of other tools flexibility and depth of application, as shown in (Lazakis and Ölçer, 2015, Raptodimos et al., 2016, Emovon et al., 2015).

Moreover, establishing component criticality to aid maintenance planning is a key aspect of maintenance strategy implementation. For instance, (Lazakis et al., 2010) presented a combination of FMEA and FTA tools for critical component identification in order to increase ship machinery availability. A combination of reliability tools and ANN was used to develop predictive condition monitoring (Cheliotis et al., 2020, Raptodimos and Lazakis, 2018), which shows the competitive flexibility that can be driven due to the use of reliability tools and numerical methods in system reliability analysis. The criticality of a system, component, or event in FMEA is derived by the use of RPN (Cicek and Celik, 2013, Marvin, 2021).

Additionally. reliability analysis tools examine the risks of failures by considering quantitative and qualitative aspects. In this case, the selection of tools for reliability analysis depends on factors such as the depth of analysis intended, the system to be analysed, the type of data (qualitative or quantitative), the objective of the analysis, tool availability, the availability of computing resources, and the interaction between systems and/or components. Other factors include tool characteristics, i.e., inductive or deductive-based analysis (Marvin, 2021, Hirzinger and Nackenhorst, 2023). Additionally, research gaps in the literature provide another important factor in the selection of tools for reliability analysis; therefore, additional research work is needed to identify a better or more efficient way of conducting similar analysis. In doing so, tools are assessed based on their strength or compatibility with the research at hand. Some of the notable reliability analysis considered in the research adi tools include ETA, FTA, Dynamic FTA (DFTA), FMEA, FMECA, and Bayes' Theorem presenting the Bayesian Belief Networks (BBNs), Weibull Analysis, Markov Chains as well as other decision support systems such as AHP, ANP and MCDM.

2.8.1 Failure Mode Effect and Criticality Analysis

Failure Mode Effect and Criticality Analysis is an evaluation technique to determine the impact of failure or malfunction of system, equipment or components failures by evaluating and prioritising the effect of individual failures (Daya and Lazakis, 2022, NASA, 2008). FMECA is composed of 2 analyses, FMEA and Criticality Analysis (CA)(Fu et al., 2022). The FMEA is focused on how equipment and system have failed or may fail to perform their function and the effects of these failures, to identify any required corrective actions for implementation to eliminate or minimize the likelihood of severity of failure. While criticality analysis is done to enable prioritization of the failure modes for potential corrective action(Astrom, 2002, Ceylan et al., 2022). FMECA is a widely used tool for reliability, criticality and risk analysis across industry and academia, as it does not require much technical knowledge but provides good insight into system failures or malfunction (Marvin, 2021, DoD, 1989). Cicek et al (Cicek and Celik, 2013) presented an approach for identifying and controlling potential failure or operational errors that trigger crankcase explosion using FMECA. In (Lazakis et al., 2018b) FMEA was used for defect analysis on ship main propulsion engine by identifying critical engine failures for maintenance decision making. FMEA can equally be modified for specific application as presented in (Shafiee et al., 2016, Niculita et al., 2017) where a modified Ageing Failure Mode and Effects Analysis (AFMEA) and Functional Failure Mode Effects and Criticality Analysis (FFMECA) was done for the techno-economic life extension analysis of offshore structure and for ship systems respectively.

FMECA is a major component used for system analysis of important maintenance concepts such as RCM and PMS as it presents a clear view of equipment, component, and personnel interaction and how risk and reliability issues can be mitigated. Mechanical system component failure analysis with FMECA is generally robust particularly in establishing modes of failure and efforts to mitigate or prevent them, however is not practically possible to determine the probability of occurrence for each identified failure rate (NSWC, 2011). In this regard is most common to see FMECA being used alongside other tools for system reliability study (DoD, 2005b, Melani et al., 2018). This is more so, as the analysis depends on qualitative inputs that can be influenced by the experience or sentiments of respondents, hence subjective(Lazakis, 2015). Overall, the limitation due to the subjectivity and interpretation of results can be addressed ranking using weights, fuzzy methods or hierarchical approach such AHP (Saaty, 2016, Ahn and Kurt, 2020).

Accordingly, this paper has adopted the use of FMECA for system reliability analysis in order to account for expert knowledge in failure and mission critical component analysis. FMECA also help capture some subjective operator sentiments which could agree or disagree with reliability results obtained from objective methodologies such as FTA (NASA, 2002, Marvin, 2021). Therefore, to address the challenge of interpretation and subjectivity in FMECA analysis a weighting method was introduced to account for experience and years in service of all respondents (Ceylan et al., 2022). In doing these, issues of under scoring or over scoring certain failures due to inexperience or narrow judgement can be addressed, hence providing a fairly represented analysis of failure analysis. Nonetheless, the approach has its own constraints and prospects which need to be carefully considered when adopting FMECA for any analysis. Below, are some important factors to consider.

Prospects:

1. 1.Efficient in Failure Mode identification: FMECA is good in identifying of potential failure modes, at an early stage of the system development or operation, thus helping to mitigate the adverse consequence of such failures.
2. Comprehensive Analysis: The process of FMECA development provides a structured approach to systematically identify all potential failure modes, causes, effects, and criticalities. Thereby helping, to provide a better understanding of the component and system fault interaction leading to failure development.
3. Prioritisation of Risks: Through the risk priority number (RPN) based on criticality analysis, FMECA ranks failure modes using their criticality, considering factors like severity, frequency of occurrence, and detectability. This prioritization aids in focusing resources on addressing the most critical risks first.
4. Improved Reliability: By addressing potential failure modes and their effects, FMECA contributes to improving the reliability of the system. It helps in designing robust systems and implementing preventive and corrective measures to enhance reliability.
5. Enhanced Safety: Identifying critical failure modes and their effects allows for implementing safety measures to minimize risks to personnel, equipment, and the environment, thus enhancing overall safety

Constraints:

1. Subjectivity in Assessment: Despite its structured approach, there can be subjectivity involved in assessing factors such as the severity of failure effects or the likelihood of occurrence. Different analysts may assign different ratings, leading to variations in results.
2. Resource-Intensive: FMECA can be resource-intensive, requiring significant time, expertise, and data inputs for conducting a thorough analysis. This can be a challenge, especially for complex systems with numerous components and interactions.
3. Limited Predictive Capability: Although FMECA may offer preventive measures to help prevent unforeseen failure modes, it is generally not suited for predictive analysis.
4. Static Analysis: FMECA depends on historical data and the expert opinion of a system at a specific point in time. Therefore, it does not account for systems's behaviour over

time, such as degradation of components or evolving failure modes, without regular updates.

5. Difficult to Automate: Typically, the FMECA process is specific to a particular system or domain, making it difficult for another system to adopt using computer algorithms.
6. Depends on Data Quality: The quality and accuracy of data inputs pertaining to system components, failure rates, and maintenance records determine the accuracy of FMECA.

2.8.2. Dynamic Fault Tree Analysis

Fault tree analysis (FTA) is a static method for analysing component faults in systems or equipment by identifying all possible causes of likely failures and impacts on the system through the logical analysis of dependencies of basic events that lead to the undesired event, the top event of the fault tree(NASA, 2002, Lazakis et al., 2018b). FTA is an important tool for reliability and risk analysis as it provides critical information used to prioritize the importance of the contributors to the undesired events (Relex, 2003). Fault Tree Analysis (FTA) procedure is based on Boolean law by applying gates and events to describe faulty components and possible event(s) that could develop a fault. FTA is an important tool for reliability and risk analysis as it provides critical information used to prioritize the importance of the contributors to the undesired event i.e., fault or failure. However, FTA has some shortcomings to do with sequence dependencies, temporal order of occurrence and redundancies due to standby systems, consequently DFTA was developed to address these constraints in the static FTA.

The dynamic gates which include Priority and gate (PAND), Sequence Enforcing gate (SEQ), Functional Dependency gate (FDEP), Spare gate (SPARE) and the spare event when added to the FTA structure becomes Dynamic FTA (NASA, 2002). In the PAND gate events are prioritized from left to right such that the left most event (fault) is considered first before the next; similarly, SEQ considers events in left to right fashion however rather than prioritizing it enforces hence ensuring that events follow the expected failure mechanism (Kabir, 2017). On the other hand, the FDEP though evaluate events from left to right it does that considering the occurrence of primary, or causal event which is independent of other faults to the right (Kabir, 2017). The SPARE gate and event have unique attributes and functions; though events are evaluated from left to right as obtained in other gates, the dormancy factor feature of the spare event makes lot of difference. The dormancy factor is a measure of the ratio between failure and operational rate of the spare event in the standby mode (NASA, 2002). A cold spare has dormancy factor 0, a hot spare has dormancy factor 1 and a warm spare has a dormancy factor between 0 and 1 (Relex, 2003). The application of dynamic gates and use of spare gates to analysis improvements in maintenance approach was presented in both authors demonstrated how these dynamic gates can be applied to model time and sequence dependent failures.

In this regard, the dynamic gates in combination with other static gates provide a much more robust yet simple structure compared to tools like Markov Chains and RBD. Therefore, DFTA is suitable for modelling complex systems failure behaviour with respect to sequence and dependencies, particularly where the temporal order of the occurrence of events is important to analysis. This is particularly important in order to account for the failure dynamics mechanical systems, while not disregarding the impact of environmental elements, temperature, and other factors (Kabir, 2017). The reliability of mechanical systems does not follow constant failure rate as obtained in electrical systems such as semiconductor, LED, and software (NSWC, 2011, Relex, 2003, Lazakis et al., 2016). Reliability data bases for mechanical components such as OREDA, NUREG, NSWC, NPRD provide high quality failure rate information on various components and procedures for conducting reliability predictions (Marvin, 2021). However, component failure rates for repairable mechanical systems are influenced by multiple factors and may not follow constant failure rates of generic distribution such as Weibull, Normal, Lognormal the likes (Anantharaman et al., 2018, Scheu et al., 2017).

Overall, DFTA provides a platform that is capable for analysing repairable system while considering other factors such as dependencies and temporal behaviour or partially operating state analysis (Zhou et al., 2022, Lazakis et al., 2016, Marko Cerpin, 2002). Therefore, this makes it very relevant in analysing system improvements as presented in (Turan et al., 2012, Daya and Lazakis, 2021, Zhou et al., 2022, Lazakis et al., 2016, Marko Cerpin, 2002). Overall, these additional gates provided more scope in DFT analysis (Ruijters and Stoelinga, 2015, Kabir, 2017) which can be used to factor repair or improvements due to routine maintenance. Moreover, additional outputs such as the reliability importance measures and minimal cuts sets in the DFTA are equally influenced by the logic structure of the model, meaning that the output of static and a dynamic FT would be significantly different and reflective of the whatever dependencies exist in the model.

2.8.2.1 Reliability Importance Measures

Reliability Importance measurers assist in identifying the event that, if improved, is most likely to produce significant improvement in equipment or system performance (Raptodimos, 2018, Lazakis et al., 2018b). In essence the IM helps the operators, maintenance crew, administrators including regulatory agency in prioritisation of actions that could bring improvement in equipment/system reliability. Among the commonly used IM are Birnbaum (Bir), Fussell-Vesely(F-V) and Criticality (Cri). The Bir IM evaluates the occurrence of the top events based the probability of basic event occurring or not occurring, hence the higher the probability basic events the higher the chances of the top event occurring (Konstantinos, 2010). Criticality (Cri) IM is calculated in a similar way to Bir IM except that it considers the probability in the occurrence of the basic event to the occurrences of the top event. On the other hand, the F-V calculation adopts an entirely different approach in that; it uses the minimal cut set summation i.e., the minimum number of basic events that contribute to the top event. Therefore, the F-V consider the contribution of the basic event to occurrence of the top event irrespective of how it contributes to the failure. The Bir IM and Cri IM were considered in this research however comparing the two measures; Bir IM is more reflective of the component's criticality as modelled.

Lazakis et al. (2010) presented a DFTA analysis on MDG where the reliability IM were used to identified critical components on MDG. Reliability importance measures are equally used for analysis especially on safety critical system where component critically is key to the safe operation of such system (Ayo-Imoru and Cilliers, 2018, Fu et al., 2022). Using the risk achievement worth (RAW) and risk reduction worth (RRW) (Volkanovski et al., 2009) introduced a methodology that can be applied to measure power distribution network criticality. Similarly, the importance measure can be used towards improving the overall understanding of either weakest component or the most reliable component in system such that maintenance planners are able to balance their effort. Moreover, when components have been identified as critical or related failure can be a high risk maintenance planners are able to provide remedial plans against sudden failure or ensure sufficient quantities of a parts are held in stock(Liang et al., 2010). The Bir IM as highlighted earlier, measures the contribution of the most critical component to the occurrence of the top event, hence helping to clearly identify what component need improvement. In this regard, researchers have adopted Bir IM to enable identification critical system failures to avoid catastrophic failures like crank case explosion in diesel engines (Zhang et al., 2022, Chen et al., 2023).

2.8.2.2 Minimal Cut Set

The outcome of reliability analysis provides several additional important insights on failure or fault development one of such is the cut set. Cut set is a set of events, which if they all occur, will result in the top event of the fault occurring (NASA, 2002). Cut set is a product of the fault tree which forms the failure path of an evaluated fault tree. In this regard, minimal cut set, is the smallest set of basic events, which if they all occur will result in the top event occurring (NASA, 2002). However, it is important to note that a single basic event can equally form a cut set depending on the arrangement of the fault tree, Figure 9 is an example of cut set in which BE1 or BE2 with either BE2 or BE4 or both must occur for the top event to occur. However, Figure 10 with similar structure with an OR top gate is slightly different, in that all the nodes connecting to the top event can be potential cut sets; this highlights potential area where improvements can be achieved either through redesign or simply altering the system to improve its reliability. Some prospects and constraints of the DFTA are given below.

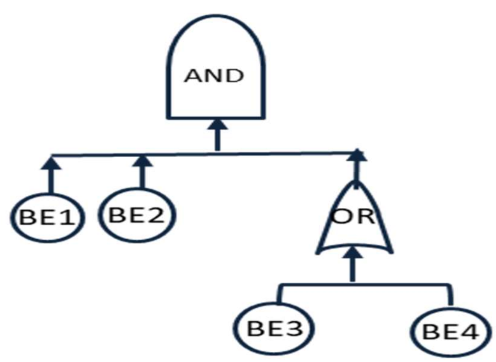

Figure 9: Minimal Cut set formation with AND gate

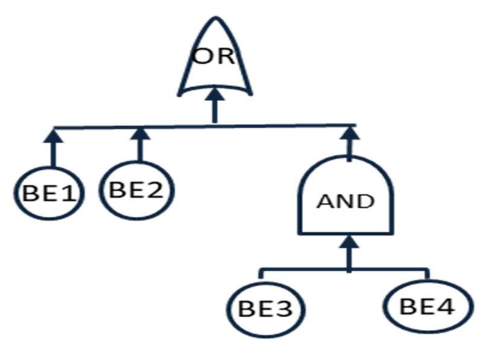

Figure 10: Minimal Cut set formation with OR gate.

Prospects:

1. Ability to track system events and component dependencies and interactions.
2. Enables dynamic behaviour modelling by considering events and components time-dependent interactions.
3. Real-time analysis can monitor system dependability and failure probabilities in real time.
4. Quantitative analysis quantifies system reliability by assigning probabilities to events and estimating system state and failure mode probabilities.

5. DFTA visualises the fault tree, making it easier to comprehend and discuss system reliability and failure modes.
6. By comparing system performance and component dependability, DFTA can help inform judgements.

Constrains

1. Model creation and verification are time-consuming and require expert knowledge.
2. Complexity and data requirements involve detailed knowledge of the system's components, failure modes, and interdependencies.
3. Sensitivity to assumptions, such as probabilities, repair techniques, and maintenance policies.
4. Dynamic behaviour assumptions for event probabilities and repair or maintenance schedules could lead to inaccurate results.
5. Model size could become difficult to manage and interpret for complex systems.

2.8.3 Bayesian Belief Network

Bayesian Belief Networks (BBN) provides a good platform for dependability analysis, cause, effect, and inferential analysis in wide range of sectors covering health care, human reliability, machinery system reliability and decision support system. BBN are represented as direct acyclic graph (DAG) which consist of chance nodes (variables) representing possible outcomes of system states and a given set of arrows (connections) indicating dependability/relationships. The nodes can take variable inputs in BBN analysis which can be continues or discreet and are not restricted to single top event, hence providing great flexibility unlike fault tress or RBD (Kabir and Papadopoulos, 2019). BBN can be used to represent cause and effect between parts of system or equipment by identifying potential causes of failure. Authors have used BBN for fault and diagnostic analysis as well decision support system (DSS), for instance Jun *et.al* (Jun and Kim, 2017) presented a Bayesian based fault identification system for CBM by discretising continues parameters based on maximum likelihood estimation (MLE) to identify failure conditions; the research used the discretised feature as binary inputs for the BBN conditional probability table (CPT). Similarly, to address port energy efficiency towards the reduction ships emission during port calls a strategy using BBNs was presented (Canbulat et al., 2019). This research also provides how BBN conditional probability can efficiently in-cooperate to expert knowledge to provide vital inputs in decision making variables in areas where there is in adequate data or literature.

Bayesian updating or inference provides bases for the use of influence diagrams in decisions analysis by computing the impact of new evidence to the probability of events and the influence on all related nodes (BayesFusion, 2020). As such BN provide a good platform for DSS especially in maintenance strategy when considering several dependent and independent factors. Conducting system reliability and maintenance analysis demands in puts from multiple sources which the BN platform can accommodate as compared to other tools. Papers by Jun et la, (Jun and Kim, 2017) and Li et al (Li et al., 2020) provides methodologies for the use of BBN in reliability analysis, however while (Jun and Kim, 2017) focused on fault diagnose (Li et al., 2020) emphases on component reliability with limited analysis on factors affecting the reliability. Furthermore, BBN have been used to provide inferential analysis in conjunction with other tools such as Markov chain and Petri-nets especially in risk and reliability analysis (Galagedarage Don and Khan, 2019, Kabir and Papadopoulos, 2019, Khakzad et al., 2011, Kampitsis and Panagiotidou, 2022). BBN based DSS are widely applied in maritime industry to handle operational issues such as human factors and procedural issues such as maintenance (Ahn and Kurt, 2020, Kampitsis and Panagiotidou, 2022). Similarly in the field of ship system reliability analysis Lazakis et al (Lazakis et al., 2016) has presented on the use of BBN and FTA for ship machinery cooling system reliability analysis and DSS. Likewise, BahooToroody et al (Bahoo et al., 2022) applied a combination BBN and Markov chain Monte Carlo simulation to analyses machinery reliability estimation onboard autonomous ships to help maintenance planning and decision.

Prospects:

1. Ability to produce an acceptable model with limited information using probabilistic inference.
2. Good at modelling complex systems using both quantitative and qualitative data.
3. As a directed acyclic graph, BBN enables comprehensive visualisation of interactions between systems/components/events.
4. Ability to conduct analysis through the integration of multiple data types such as expert knowledge, empirical data, and historical records.
5. Efficient for building decision support models.

Constraints:

1. The accuracy of the model depends on probabilistic data estimates.
2. BBN structure can be complex and requires expert knowledge.
3. Increased complexity with an increase in the size of the model may require expert knowledge for interpretation.
4. Computationally complex with an increase in data size and types, hence making probabilistic inference difficult.
5. Susceptibility to model assumptions/expert judgement, which may interfere with output quality.

2.8.4 Markov Chains

Markov chains are a reliability analysis tool commonly used to analyse both reparable and non-reparable systems. Markov analysis differs from other reliability prediction tools by considering the current system's operational or failed state to determine the future system state. It offers real-time information on the operational status of systems or machinery, which is especially beneficial for repairable mechanical systems(Galagedarage Don and Khan, 2019). Markov chains, like other reliability analysis tools, utilise the probability of events in systems or machinery to represent state transitions. Transition probabilities between states are established using factors like historical data, expert knowledge, or mathematical models. By examining transition probabilities, Markov chains offer insights into system reliability and availability(Konstantinos, 2010). This allows for the identification of crucial components, assessment of maintenance approaches, and enhancement of system performance.

Markov Chains are commonly used to analyse the reliability of systems in various industries. Compared to other tools, they can handle the complex dynamic time state transitions of component reliability by identifying and defining the various states the system can be in. Therefore, calculating the probabilities of moving from one state to another during a specific time period. Various factors influence the potential probabilities, including component reliability, maintenance procedures, and environmental factors(Smith, 2017a). System reliability analysis using Markov chains has been discussed (Galagedarage Don and Khan, 2019) . The challenge of implementing Markov chains lies in the time state explosion limitation Furthermore,(Yevkin, 2016)had embraced the momentary calm regarding this issue. This necessitates Arranging the transition probabilities into a matrix, with each element denoting the probability of moving from one state to another. This aids in pinpointing crucial elements that impact system performance and can steer decision-making for maintenance strategies or design enhancements.

Prospects

1. Markov chains are versatile for reliability analysis as they can model complex systems with multiple states and transitions.

2. Markov chains offer a quantitative method for analysing system reliability by calculating probabilities and studying steady-state behaviour.

3. Markov chains provide a straightforward and intuitive way to represent system behaviour, facilitating the comprehension and communication of reliability insights to stakeholders.

4. Sensitivity analysis using Markov chains allows analysts to evaluate how alterations in transition probabilities or system configurations affect reliability and availability.

5. Optimisation: Markov chains are utilised for optimisation, like identifying the best maintenance schedules or redundancy setups to enhance system reliability and reduce costs.

Constraints:

1. Markov chains are based on assumptions like the Markov property and constant transition probabilities, which may not always be applicable in real-world systems.

2. Elaborateness: Developing and evaluating Markov chain models for extensive or intricate systems can be computationally demanding and necessitate specialised knowledge.

3. Data requirements: When dealing with rare events or intricate systems with numerous components, it can be challenging to gather data on transition probabilities, which is what Markov chains need to work.

4. Narrow scope: Not all facets of system behaviour, such as interdependencies among parts or outside variables that affect dependability, may be captured by Markov chains.

5. The accuracy of results derived from Markov chain analysis depends on the quality of the input data and assumptions in the model, necessitating careful attention to ensure their validity and precision.

2.8.5 Weibull Distribution

Weibull distribution analysis is the most commonly utilised statistical method for analysing system life data reliability, exceeding exponential, lognormal, and normal distributions. The Weibull distribution is valuable for assessing the reliability of products and systems, as well as for forecasting failure rates and determining the remaining useful life(Abernethy, 2004). Weibull analysis involves graphically examining probability plots to determine the most suitable distribution for a specific set of life data related to certain failure modes. The Weibull distribution is known for its versatility in representing various failure behaviours, which is valuable in engineering and reliability contexts. The analysis is performed using life data, including failure rates, cycles, start-stops, MTBF, and other reliability metrics utilised for failure distribution. Many organisations, especially the armed forces, have found the utilisation of the Weibull distribution to be highly beneficial for maintenance and equipment lifecycle management. This tool is used in reliability analysis to create a versatile and strong structure for modelling lifetime distributions, estimating parameters from failure data, analysing reliability metrics, and predicting future performance.

Weibull analysis uses statistical distribution to predict the lifespan of products in a population. The parameterized distribution of the representative sample is utilised to estimate crucial life characteristics of the product, such as reliability, probability of failure at a specific time, mean life, and failure rate. The Weibull distribution does not necessitate a large amount of failure data or distributions for an informed analysis. By analysing Weibull plots and estimating parameters like the shape parameter (β) and scale parameter (η), maintenance engineers or operators can schedule maintenance activities and create effective maintenance solutions tailored to the specific requirements of machinery and components. Its extensive use across industries such as manufacturing, aerospace, automotive, and healthcare highlights its crucial role in guaranteeing the dependability and safety of products and systems.

Prospects

1. Flexibility: Failure patterns ranging from early-life failures to wear-out failures and constant failure rates can all be accommodated by the Weibull distribution, which is

incredibly flexible. This adaptability allows for modelling a variety of failure data seen in actual systems.

2. Parameter Interpretation: The shape parameter (β) and scale parameter (η) of the Weibull distribution have clear meanings. β signifies the shape of the failure distribution (e.g., exponential, bathtub), while η denotes the scale or characteristic life of the system. This facilitates engineers in comprehending and conveying the findings of Weibull analysis.
3. Goodness-of-fit: Weibull analysis often provides good fits to empirical failure data, especially when the failure pattern follows a Weibull distribution. Engineers can use this to create precise models and forecasts of system reliability using failure data, which helps in making well-informed decisions.
4. Parameter Estimation: Established methods like maximum likelihood estimation (MLE) and least squares estimation (LSE) are commonly used to estimate the parameters of the Weibull distribution from failure data. These techniques are commonly found in statistical software programmes and are relatively easy to implement.
5. Reliability Prediction: The Weibull distribution predicts reliability metrics like failure probability, mean time to failure (MTTF), and reliability at specific time intervals. This information is crucial for evaluating system reliability, scheduling maintenance tasks, and enhancing design choices.

Constraints

1. Assumption of Distribution: The main drawback of using the Weibull distribution is that it presumes that the failure data follows a Weibull distribution. Deviation from a Weibull distribution can lead to inaccurate or misleading reliability estimates when using Weibull analysis.
2. Limited Sample Size: Weibull analysis may necessitate a relatively substantial sample size to achieve dependable parameter estimates, particularly for accurately estimating the shape parameter (β). Reliability estimates obtained from Weibull analysis may be less reliable when sample sizes are small, or failure data are sparse.
3. Interpretation Complexity: Although the parameters of the Weibull distribution are intuitively understandable, interpreting Weibull plots and analysing failure data can be

intricate, particularly for individuals who are not experts in the field. Incorrect interpretation of Weibull analysis results can result in inaccurate conclusions or decisions about system reliability.

4. Impact of Outliers: Abnormalities or outliers in the failure data can have a big impact on the Weibull analysis's findings, especially when it comes to parameter estimation. Thorough data preprocessing and outlier detection techniques are essential to reduce the influence of outliers on Weibull analysis results.
5. Limited Applicability to Certain Cases: Although the Weibull distribution is frequently used in reliability analysis, there may be situations in which other models or distributions are better suited to represent particular data features or failure trends. Engineers should assess the suitability of the Weibull distribution based on the failure data characteristics and underlying failure mechanisms.

2.8.6 Reliability Block Diagrams

Reliability Block Diagrams (RBDs) are graphical representations used in system reliability analyses to model the reliability of complex systems composed of interconnected components. It displays the logical connections between components required to accomplish a specific system function(Relex, 2003). For systems with multiple functions, each function must be evaluated separately, and a distinct reliability block diagram must be created for each function(Ruijters and Stoelinga, 2015). RBDs are commonly utilised to depict active components of a system in a way that enables a thorough search to identify all pathways, explicitly dealing with system dependencies. This method is useful in troubleshooting electrical circuits, piping, and other mechanical systems. RBDs were noted in a review to share a comparable function with FTAs, as both can offer qualitative and quantitative analysis from systems to component level. Reliability analysis with Reliability Block Diagrams (RBDs) primarily involves the use of Boolean OR and AND gates(Li et al., 2020, Jakkula et al., 2020). It is typically used for systems arranged in series, parallel, and standby/redundant configurations. RBDs are commonly utilised alongside other reliability tools like FTA, FMEA, and BBN. Kim (Kim, 2011)introduced reliability block diagram with general gates (RBDGG) to overcome the limitations of traditional RBDs by incorporating a general purpose node that facilitates precise matching between components.

A Reliability Block Diagram (RBD) is a visual representation that illustrates the functional reliability connections between a system and its components. It can also be seen as a model defining system failure or success. It does not always pertain to the physical linking of components or sub-units. The RBD needs to demonstrate the input and output flow necessary for a specific function of the system under review. RBDs must model events that are completely independent of each other. When analysing the reliability of complex repairable systems, it is crucial to consider the sequence, dependencies, and operational state of different equipment in a way that captures the dynamic or transient nature of fault development. RBDs are not suitable for handling sequence-dependent failures, and analysing the reliability of large systems with multiple dependent failures can be challenging and complex. As a result, the development of dynamic fault tree analysis (DFTA) tools that offer a suitable platform for examining system state and dependencies is pertinent, as this is the case with the majority of static reliability analysis tools(Relex, 2003, Zhou et al., 2022).

Prospects:

1. Visualisation: RBDs make the system's architecture and component relationships easy to see and understand. As a result, the structure and dependencies of the system are easier to grasp for engineers and other stakeholders.

2. Modularity: RBDs enable the modular modelling of system components, which facilitates the management and analysis of sizable and intricate systems. Each block symbolises a component or subsystem, and the links between blocks indicate the dependability flow.

3. Quantitative analysis: RBDs are capable of integrating quantitative reliability information, such as failure and repair rates and reliability distributions, for every component. This enables the quantitative assessment of system reliability parameters, including system availability, mean time to failure, and reliability allocation.

4. Flexibility: RBDs can be readily adjusted to take into account modifications to the setup, design, or operational environment of the system. This adaptability allows them to be beneficial for examining systems at various developmental phases or for assessing different design choices.

5. Risk assessment: RBDs evaluate the impact of component failures on system performance and identify important components or failure modes that pose the highest risk to dependability. This information can assist in prioritising maintenance, testing, or design enhancements to reduce hazards.

Constraints

1. Simplifying assumptions: RBDs frequently rely on assumptions that may not always hold true in practice, such as the assumption of constant failure rates or the independence of components. These presumptions may result in mistakes in forecasts and risk evaluations in the conduct of system reliability analysis.

2. Complexity: RBDs are useful for modelling basic systems but can become too complicated to maintain for big or linked systems. Managing the numerous components and connections in a complex RBD can be difficult and may necessitate the use of specialised tools or software.
3. Limited dynamic analysis: RBDs are static models that only include steady-state reliability measures and do not account for system dynamics over time. This constraint reduces their suitability for evaluating temporary or time-dependent occurrences, including system startup/shutdown or transient errors.
4. Availability of data: Obtaining accurate data on component reliability metrics, such as failure rates and repair durations, may be challenging, particularly for new or specialised components. This might create ambiguity in dependability forecasts and necessitate dependence on expert judgement or estimating methods.
5. Expert Knowledge requirements: Reliability Block Diagrams are a helpful tool for analysing and visualising the reliability of complex systems. They offer a modular and adaptable approach for quantitative reliability research. It is crucial to acknowledge the limitations of these tools and use them in combination with other methodologies and tools to guarantee precise and thorough reliability evaluations.

2.8.7 Evant Tree Analysis

Event tree analysis (ETA) uses inductive reasoning to present graphical possible outcomes of an occurrence that results from a selected initiating event (Crawley, 2020). Event Tree Analysis (ETA) is commonly used for investigating risks and accidents due to its graphical representation of events that typically begin with an initiating event in a binary format, such as true or false, yes or no(Marvin, 2021). This methodology enhanced ETA's effectiveness in risk analysis by enabling the identification of cause-and-effect relationships and establishing the probability of occurrence. Risk is typically linked to safety systems, however in system maintenance, risk can be related with the repercussions of failures on personnel safety, accidents, and product quality. Risk issues in maintenance include environmental conditions, spare parts supply delays, and skills and knowledge gaps, which can lead to prolonged unavailability. An assessment of the risk of spare parts shortage caused by unforeseen operating environment circumstances was conducted using ETA and discussed in reference (Ghodrati et al., 2007). The authors recognised production and economic losses as significant operational risks. Piadeh et al. (Piadeh et al., 2018) employed ETA for reliability analysis of an industrial wastewater treatment facility to determine individual system reliability and its impact on system failure. The study utilised Fault Tree Analysis (FTA) along with Event Tree Analysis (ETA) for analysing failure likelihood due to system complexities (Piadeh et al., 2018).

ETA is widely used in risk analysis for safety systems and equipment availability. It involves a binary process that necessitates probability inputs at the basic or end events level(Crawley, 2020). However, using ETA to analyse complex systems will necessitate additional inputs that are predominantly non-binary and continuous. Furthermore, when analysing interactions in complex systems, creating a model that accurately represents the temporal system state or a repairable mechanical system functioning under degraded conditions will necessitate added flexibility. Researchers have utilised many strategies to address system dependencies and difficulties in numerous systems (Lazakis et al., 2016, Marvin, 2021, Piadeh et al., 2018)This technique allows for the use of various data types for dependability analysis and the utilisation of tools in a more adaptable way(Leimeister and Kolios, 2018). Overall, ETA is a useful technique for system reliability analysis that provides a structured, probabilistic approach to identifying and evaluating potential failure scenarios. Its adaptability is enhanced by its graphical representation, probabilistic assessment capabilities, and integration with other methods.

Prospects:

1. Structured analysis: Event tree analysis offers a systematic framework for discovering and assessing probable events and their implications inside a system. This methodical approach ensures that all pertinent circumstances are taken into account and assessed.
2. Graphical representation: Event trees' graphical format facilitates the visualisation and comprehension of the order of events and their connections within a system. This visual

representation improves communication and promotes collaboration among stakeholders.

3. Quantitative evaluation: To determine the possibility and effect of various occurrences on system reliability, event tree analysis might include quantitative data, such as probabilities and consequences. This enables a more thorough and quantitative study in contrast to qualitative methods.
4. Risk assessment: Event tree analysis uses many scenarios and their probability to identify high-risk occurrences and possible outcomes. This process makes risk assessment possible. This information can assist in prioritising risk mitigation activities and efficiently allocating resources.
5. Decision support: Event tree analysis helps assess different approaches or actions to enhance system reliability. Decision-makers can optimise system performance by evaluating the consequences of various situations.

Constraints

1. Elaborating and examining event trees for intricate systems can be time-consuming and necessitate specialised knowledge. Handling the numerous events and branches in a comprehensive event tree can be intricate and demanding.

2. Data prerequisites: Event tree analysis depends on precise and dependable data regarding event probabilities, consequences, and interconnections within the system. Acquiring and confirming this data may pose challenges, particularly for uncommon occurrences or situations with restricted historical data.
3. Subjectivity: The construction of event trees involves making assumptions and judgments about the events, their probabilities, and their consequences. Subjective decisions can create ambiguity and unpredictability in the analysis, impacting the trustworthiness of the results.
4. Sensitivity to assumptions: The results of event tree analysis might be influenced by the assumptions made, such as event probability or repercussions. Performing sensitivity analysis is essential for assessing the impact of modifications on the results.

5. Expert Knowledge: The accuracy of analysis is to great extent dependent on the on the knowledge and specialisation of the experts that carry out the analysis.

2.9 Ship maintenance Decision Support System

Maintenance planning and decision marking for ship systems can be complex due to the operational nature, space constraint and onboard environment. Hence maintenance as well as spare parts holding must be carefully considered so that failures and repairs are adequately prioritised to avoid problems with onboard spare parts holding and technical skills mix. Decision support system can be employed to help reduce the challenge of managing alternative situations due competing priorities. A Decision support system (DSS) can be developed through several alterative tools based on preference and problem at hand. DSS are widely applied in maritime industry to handle operational issues such as human factors and procedural issues such as maintenance (Ahn and Kurt, 2020, Shafiee, 2015, Bousdekis et al., 2018). Therefore the approach taken to conduct the analysis and provide different types of maintenance decision making employs' multiple tools to overcome some inherent complexities (Lazakis et al., 2016, Galar and Kumar, 2017c). In general maintenance decision can be prescriptive, descriptive or both (Galar and Kumar, 2017c). The approach to any DSS is determined by factors such as machinery or system, relevant issues impacting on system availability and reliability as well as extent of analysis to be conducted. In this regard most often different type of tools have been employed to enable detailed and conclusive analysis such that DSS analysis is able to provide relevant suggestions reflective of the presented constraints (Saaty, 2016, de Boer et al., 1997).

2.9.1 Analytical Hierarchy Process

Saaty (2016) describes the Analytic Hierarchy Process (AHP) as a method for measuring relative values on absolute scales for both tangible and intangible criteria. It relies on the judgement of experts and existing data to make decisions. One of the most significant challenges that AHP is concerned with addressing is the fact that decision makers are confronted with a multitude of options and the measurement of intangibles(Karatuğ et al., 2022). AHP is one of the most used decision-making approaches in a variety of fields, and it is often used in conjunction with other multi-objective, multi-criteria, and multiparty decision-making processes. Overall, AHP offers a hierarchical decision-making process that is based on a set of pairwise evaluations of possibilities and characteristics, which results in a solution that is relatively easier to implement for a complex problem(Galar and Kumar, 2017c). In this regard, AHP was described as a structured technique for dealing with complex decisions. Therefore, rather than prescribing a ‘‘correct’’ decision, the AHP helps the decision makers find the one that best suits their needs and their understanding of the problem.

The AHP method involves creating a hierarchical structure of goals, criteria, sub-criteria, and alternatives, followed by analysis using expert opinions in the field(Chemweno et al., 2018). Equipment maintenance strategy selection is an issue that has been in the centre of many research efforts ranging from corporate to industrial fields. In the maritime sector AHP has been numerously applied to aid decision making areas such as vessel operating system, maintenance strategy and alternative machinery system to be used onboard. The use of AHP for the maintenance policy selection the process involved 3 levels, first level is goal i.e identifying maintenance policy for each mentioned risk rating scale, second level is consisted of criteria and third level is alternative (maintenance). Other factors considered in the AHP were, safety, cost and accessibility (Tan et al., 2011). Nonetheless, hierarchical nature of AHP makes more cumbersome as regards ordering the criteria of attributes among within the available options in a decision that may not have any vertical relationship. Hence increasing complexity of regarding

Prospects

1. Hierarchical Decision-Making: AHP offers a structured framework for making decisions, allowing complicated situations to be simplified down to manageable components. By adhering to this methodical framework, decision-makers can systematically evaluate all pertinent criteria and alternatives.

2. Multiple Criteria Analysis: Using AHP, decision-makers can assess options concurrently according to several criteria. This allows for a thorough evaluation of many alternatives, considering issues like cost, time, quality, and risk.

3. Subjective Preference Incorporation: Using pairwise comparisons, AHP takes decision-makers subjective assessments and preferences into account. This makes it easier to reach consensus and involve stakeholders in the decision-making process by enabling decision-makers to articulate their preferences quantitatively.

4. Quantitative analysis: AHP uses mathematical algorithms to aggregate preferences and assign numerical values to paired comparisons to produce quantitative results. This

quantitative analysis aids in objectively prioritising alternatives and making decisions based on evidence.

5. Transparency: AHP fosters transparency in the decision-making process through the provision of a comprehensive justification for the final decisions, encompassing the prioritisation of criteria and alternatives as well as the factors that impacted the ultimate determination.

Constraints

1. Bias and Subjectivity: When making pairwise comparisons, AHP depends significantly on decision-makers' subjective judgements. Subjectivity can create biases and inconsistencies in decision-making, resulting in sometimes incorrect conclusions.

2. Intricacy: AHP may prove to be intricate and time-intensive, especially when applied to sizable and complex decision hierarchies that encompass numerous criteria and alternatives. It may be difficult for decision-makers to effectively manage the large number of pairwise comparisons and aggregate preferences, which require meticulous attention to detail.

3. Ability to scale: AHP may struggle to efficiently handle intricate decision problems involving numerous criteria and choices. As the decision hierarchy expands, the number of pairwise comparisons grows exponentially, posing challenges for decision-makers in managing and interpreting the data.

4. Complexity in Interpretation: Understanding the outcomes of AHP may be difficult, especially for individuals lacking expertise in decision analysis or mathematics. Comprehending the consequences of the combined preferences and how they might be turned into practical judgements may necessitate further training or experience.

5. Sensitivity to Input: Varying final decision outcomes might arise from AHP results that are sensitive to even little modifications in the pairwise comparison judgements. Decision-makers may need to perform sensitivity analysis to evaluate the resilience of their decisions to variations in input parameters, potentially complicating the decision-making process.

2.9.2 Analytical Network Process

Developed from the Analytic Hierarchy Process (AHP), the Analytical Network Process (ANP) is a decision-making methodology capable of managing complex situations involving feedback loops and interdependencies (Saaty, 2016). The ANP enhances the AHP by removing the need to order components in a hierarchical chain and instead organising them in a network based on direct relationships. Thus, enabling more accurate decision-making based on direct interconnections that meet specific criteria inside a directed network. Although AHP offers a structured method based on understanding the relationships between elements, ANP gives a more comprehensive approach by including causal influences, making it a more effective tool for describing decision-making processes(Karatuğ et al., 2023, Shafiee et al., 2016). AHP relies on a hierarchical procedure for decision-making, which introduces subjectivity and dependence on expert knowledge and predefined factors. The Analytic Network Process (ANP) is also more objective and better able to represent real-world situations when interdependence, feedback, and cycling their effects are added to the supermatrix.

The Analytic Network Process (ANP) could be a significantly more successful decision-making tool in practice compared to the Analytic Hierarchy Process (AHP). It can be used to assess and rank options in decision-making processes connected to reliability analysis or maintenance decision making (Arjomandi et al., 2021). Constructing an ANP platform requires making intricate judgements in four phases: The decision-making process involves analysing hierarchies, networks of influences, and objective facts to determine the most desirable alternative based on control criteria. Pairwise comparisons are made between elements to establish priorities and create super matrices of priority vectors(Saaty, 2016). A subjective value system is used to evaluate decisions and combine priorities to rank alternatives. Sensitivity analysis is conducted to assess the stability of the best outcome under varying judgements. Each phase has primary problems that are then categorised into secondary concerns, which are then broken down into even smaller ones. Hence enabling more granular considerations especially in maintenance DSS and technology selection where lower event could have a greater impact on the final outcome or decision (Gupta and Mishra, 2018, Tan et al., 2011). Some key benefits and challenges with ANP in DSS as given follows:

Prospects:

1. Flexibility: Decision-makers can model complex decision problems involving interdependencies, feedback loops, and interactions between criteria and alternatives

using ANP, which provides more flexibility than AHP in this regard. ANP's flexibility allows it to better handle the inherent complexity of real-world decision-making scenarios.

2. Interdependencies Handling: By explicitly taking into account the relationships and dependencies that exist between criteria and alternatives, ANP enables decision-makers to represent intricate relationships and dependencies within the decision hierarchy. This allows for a more thorough evaluation of the decision problem and aids in understanding the relationships between various factors that impact the decision result.
3. Feedback Loops: Decision-makers can more accurately model dynamic decision-making processes and iterative decision cycles by using ANP to handle feedback loops, in which the result of one decision influences subsequent decisions.
4. Holistic Analysis: By taking into account the direct and indirect relationships between criteria and alternatives, ANP encourages a holistic analysis of decision problems, offering a completer and more integrated viewpoint on the decision-making process.
5. Quantitative and Qualitative Factors: ANP enables decision-makers to accommodate a wider range of decision criteria and capture diverse aspects of the decision problem by incorporating both quantitative and qualitative factors into the decision analysis.

Constraints

1. Complexity: ANP can be difficult and computationally demanding, especially for large and elaborate decision networks with numerous elements and connections. Handling the intricacy of ANP models and effectively understanding the results can be difficult, necessitating specialised knowledge and resources.
2. Subjectivity: To establish pairwise comparisons and represent relationships between decision network pieces, ANP, like AHP, depends on decision-makers' subjective judgements.
3. Data Requirements: ANP may necessitate a substantial amount of data inputs, such as pairwise comparison judgements, interaction intensities, and feedback loop parameters, to construct and evaluate decision networks efficiently.
4. Model Interpretation: It can be difficult to interpret ANP models and comprehend the implications of the decision results, especially for decision-makers who are not well-versed in network theory or decision analysis.

2.9.3 Multi Criteria Decision Making

The design of maintenance DSS involves several constraints all of which must be given due consideration, hence the adoption of multiple tools such as Fuzzy multi attribute group decision Making (FMAGDM), Technique for Order Performance by Similarity to Ideal Situation (TOPSIS), Group Decision Making (GDM) Analytical Hierarchy Process(AHP) Bayesian Network (BN), (Jia and Jia, 2022, F.V. Jensen, 2007). In applying such approach Lazakis and Ölçer (2015) presented FMAGDM to address selection of maintenance strategy onboard a diving support vessel where multiple criteria such as equipment criticality, skills, cost of maintenance, and expert knowledge on some issues were considered. Jia and Jia (2022) also proposed a methodology for the optimisation of PMS intervals considering safety and environmental constraints using a combination of GDM and TOPSIS. An overarching challenge in maintenance DSS is incorporating multiple decision makers while making sure biases regarding experience, expertise and professional background are accounted for. The use of MAGDM, TOPSIS and FMAGM has been demonstrated to account for such biases including that of techno economic choices by (Asuquo et al., 2019, Lazakis et al., 2016, Shafiee et al., 2016).

Subjectivity in decision making could arise due to the professional background and experience of the analyst(s) or an organisation which may distort the accuracy of the decision-making process. To address these approaches as the fuzzy theory, Bayesian decision theoretic and weighting methods have adopted to enable balance representation of all criteria (Daya and Lazakis, 2023, Karatuğ et al., 2022). Overcoming subjectivity in machinery maintenance DSS OEM and other asset management companies are providing onboard expert system that can give accurate decision and suggest maintenance action for the operators based on actual equipment condition (Galar and Kumar, 2017c, Jia and Jia, 2022). Moreover, big data and AI have also help increase the deployment of remote motoring system such as supervisory control and data acquisition (SCADA) and digital twins hence enhancing accurate machinery health monitoring irrespective of location (Fuller et al., 2020). In this regard the use of Machine learning approach for diagnostics, prognosis and degradation analysis to provide vital inputs on machinery health helps reduce ambiguity and subjectivity in DSS analysis as the outputs are based on objective qualitative analysis (Daya and Lazakis, 2023, Wu et al., 2007).

Prospects:

1. Comprehensive Evaluation: MCDM lets decision-makers evaluate alternatives using numerous criteria at once. This captures the many complexities of system reliability and maintenance decision-making.
2. Clarity in Decision Process: MCDM's structured and transparent decision-making process lets stakeholders comprehend decisions and their rationale. Transparency builds confidence and accountability in decision-making.
3. Reduced Conflicting Objectives: System reliability and maintenance decision-making generally involves lowering costs and increasing reliability. MCDM helps openly considers criterion trade-offs and finds compromise solutions to balance these opposing goals.
4. Stakeholder Preferences Consideration: MCDM incorporates stakeholder preferences and priorities into decision-making. MCDM ensures decisions meet stakeholders' goals by including them in setting criteria and weighting them according to certain preferences.
5. Systematic Approach to Decision Making: MCDM guides decision-makers through discovering options, setting criteria, assessing alternatives, and choosing the optimal option. This organised strategy lowers prejudice and ensures decision consistency.

Constraints:

1. Complexity: MCDM approaches can be complicated when dealing with many criteria, options, and interactions. Decision-makers, especially in resource-constrained situations or highly conflicting interest, may struggle to manage this complexity due to time, resources, and expertise.
2. Subjectivity: Decision-makers and stakeholders apply weights to criteria and score options in MCDM. These subjective inputs might contribute biases and uncertainties into decision-making, compromising decision robustness and trustworthiness.
3. Data Availability and Quality: MCDM evaluates criteria including performance measurements, cost estimates, and expert opinions using accurate data. Data availability and quality can vary, causing judgement uncertainty and mistakes. Complex systems and evolving technology make it difficult to get accurate and current data.

4. Trade-off challenges: MCDM requires decision-makers to trade-off conflicting objectives, which can be difficult when stakeholders have different interests or preferences. Negotiating and compromising to resolve these trade-offs and establish stakeholder consensus may delay or dispute decision-making.
5. Model Complexity and Interpretation: Some MCDM methods use complicated mathematical models and algorithms to evaluate and choose the optimal solution. Decision-makers without a quantitative background may struggle to understand and comprehend these models, restricting their adoption of MCDM.

2.10 Artificial Neural Networks (ANN)

ANNs are a form of machine learning algorithm that is inspired by the structure and function of the human brain. ANNs are made up of interconnected nodes or neurons that process and transfer data. ANN are widely used for statistical analysis and data modelling commonly applied as alternatives to standard nonlinear regression or cluster analysis. Hence, their extensive use in classification, forecasting such as diagnosis, signal processing, speech and image recognition (Gurney, 1997, Mandic & Chambers, 2001). ANN are defined as interconnected assembly of simple processing elements (units or nodes) whose functionality is loosely based on the animal brain neural. The networks have a processing ability stored in the interunit connection strengths, weights, obtained by a process of adaptation to , or learning from, a set of training patterns (Gurney, 1997). The computational models or nodes are connected through weights that are adapted during use or training to improve performance (Mandic and Chambers, 2001). Therefore the ability of the ANNs to learn, identify patterns and predict them has made their application in the field maintenance very widely, (Raptodimos & Lazakis, 2018, Vanem & Brandsæter, 2019, Stetco et al., 2019, Lugosch et al., 2020). The process involves the basic node which provides a linear combination of N weights $w_1 \ldots\ldots, w_N$ and N inputs $x_{1,\ldots\ldots} x_N$ and passes the results through a nonlinearity Φ as shown Figure 11.

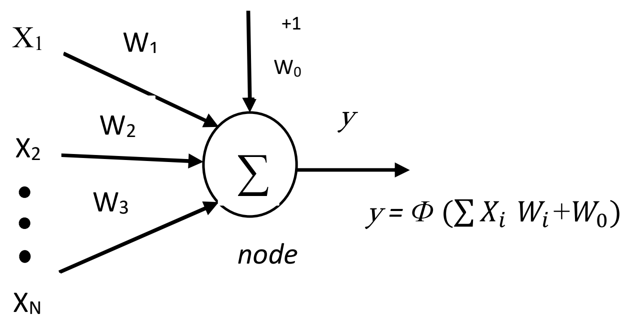

Figure 11: A neural network architecture.

In general, there two types of machine learning approaches; namely supervised and unsupervised learning. The supervised machine learning is used to train a model with labelled data, that is the features to be looked out are already known, therefore the algorithm is trained to look out for those features in the input data. On the other hand, unsupervised learning deals with unlabelled data which means the algorithm will identify the unique features in the data and partition it accordingly. Unsupervised learning is useful for exploring data in order to understand the natural patten of the data especially when there is no specific information about significant incidents in the data that can easily point to some fault indicators. Artificial Neural Network (ANN) is a machine learning algorithm that can be used to enable diagnostics or pattern recognition in a data set. ANNs are described as networks composed of nonlinear computational elements that work in parallel and arranged in a manner similar to biological neural interaction (Danilo P. Mandic, 2001). The main parameter that determines an ANN model is the number of layer hidden layers between the input and the output neurons and the hidden layer sizes (Gkerekos et al., 2019). ANN are attractive for diagnostics or classification models as they can learn from past examples of the provided data and can easily identify subtle features with no prior knowledge.

Accordingly, ANN are widely employed for multiple tasks such as clustering, forecasting, prediction, pattern recognition, classification, and feature engineering (Gurney, 1997). The use of ANN and Regression technics was employed to estimated vessel power and fuel consumption where the model was able predict to predict actual vessel fuel consumption in real time (Farag and Ölçer, 2020). The use of ANN for fault classification has been employed by (Raptodimos and Lazakis, 2018)using self-organising map an ANN clustering algorithm analyses the health parameter of a marine diesel engine looking at exhaust gas temperature, piston cooling outlet temperature and piston cooling inlet pressure. Therefore, the performance of ANN in prediction and classification as reviewed in (Stetco et al., 2019, Velasco-Gallego and Lazakis, 2020) was presented to be good in handling nonlinear high dimensional data having fewer data set. In this regard building the success of ANN this work will apply the use of ANN on a labelled data for diagnostic analysis on MDG.

2.9.1 Types of ANN

1. Feedforward neural net: One of the first types of neural networks is the feedforward network (FF), which consists of successive layers of artificial neurons that process data in a unidirectional fashion. Most feedforward neural networks nowadays are "deep feedforward" and have many layers (including multiple "hidden" levels). Backpropagation is an error-correction technique commonly used with feedforward neural networks. It goes backwards from the output of the neural network to the input, looking for mistakes along the way. It's common to see deep feedforward neural networks in basic yet potent models(Stetco et al., 2019, Wang et al., 2023).

2. Recurrent Neural Networks: In contrast to feedforward neural networks, recurrent neural networks (RNNs) can make sense of data that is time-related or sequential. In contrast to feedforward neural networks, which utilise weights at each node, recurrent neural networks can use the events of the preceding layer to influence the results of the current layer. For use in tasks such as natural language processing, RNNs can "remember" contextual terms. Common applications of RNNs include speech recognition, translation, and picture captioning (Karatuğ et al., 2023, Kang et al., 2023, Gupta et al., 2022).

3. Long/Short term memory (LSTM): Advanced RNNs known as long/short term memory (LSTM) may "remember" what happened in earlier levels by referencing stored information. Speech recognition and prediction are two common applications of LTSM, which differs from RNNs in that it uses "memory cells" to retain information from several layers' past (Xiao et al., 2019)'

4. Convolutional Neural Networks (CNN): CNNs are multi-layer networks that filter individual pixels or regions of an image before reassembling the whole. They are most employed for image recognition (in the fully connected layer). Simple picture features,

such colours and edges, may be searched for by the first few convolutional layers, whereas more complicated characteristics may be searched for by later layers (Li et al., 2018, Wang et al., 2023, Velasco-Gallego and Lazakis, 2022b).

2.9.2. Self-Organising Maps

Artificial Neural Network (ANN) have been applied in the field of maintenance for machinery health analysis and prediction of machinery condition by various authors. As an unsupervised learning method SOM are effective for data analysis and clustering as presented in (Yu et al., 2015) used identifying nonlinear latent features from high dimensional data. Therefore, riding on the existing success and procedures in the use of ANN for machinery data analysis, this research will employ ANN for fault classification and detection, fault/condition prediction and machinery remaining useful life analysis(Wu et al., 2007). ANN approach for fault detection was applied with FTA to identify critical component of a diesel generators in a research presented by (Y. Raptodimos & Lazakis, 2017). In some cases, machinery fault data are recorded without identifying the fault signals, therefore this requires the data clustering. Clustering is form of unclassified machine learning which is applied of machinery diagnostics (Christos Gkerekos et al., 2019). The advantages of using clustering models help identify possible clusters as well as the most influential clusters in the data. In research ANN Self Organising Map (SOM) were used for clustering of machinery log data of DG. SOM consists of competitive layer which can classify a dataset of vectors with any number of dimensions as the number neurons in the layer and are good for dimensionality reduction as presented in (Raptodimos & Lazakis, 2018) (Ponmalai & Kamath, 2019).

2.9.3. Application of ANN Machinery Health Diagnostics

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Prospects:

1. ANNs are good for pattern recognition and can recognise complex machinery defect patterns.
2. ANNs can model nonlinear input-output relationships.
3. ANNs can efficiently adapt, and generalised data can learn fault patterns from fault data and detect errors in real time or on new equipment instances.
4. Feature extraction: ANNs can learn and extract useful characteristics from raw sensor data without manual feature engineering.
5. ANNs enable real-time monitoring and therefore, can continuously monitor machinery and detect faults, i.e., online.

Constraints:

1. ANNs require relatively large, labelled training data to accurately learn fault patterns.
2. Difficulty in understand the model's predictions, as such, can make fault detection results hard to explain or defend.
3. ANNs can be overfitted to training data and fail to generalise to unseen data.
4. ANNs are sensitive to training data quality and representativeness. Hence, data pre-processing is very necessary for quality analysis.
5. Training large, deep, or high-dimensional ANNs can be computationally intensive.

2.10 Summary of Related Works

A rigorous critical literature review on the different types of maintenance approaches adopted in various industries such as, power generation, nuclear, aviation and aerospace as well as oil and gas were done to establish the factors influencing maintenance strategy selection in them. Some of the key drivers in maintenance strategy selection includes ensuring system availability to maintain revenue or service delivery. However, to achieve that safety of operators and reliability of equipment remains paramount, while factors such as cost of maintenance, efficiency in repair and maintenance are equally key. In this regard due to multiple and often conflict factors in maintenance choice researchers both in academia and the industry have adopted to the use of multiple tools to enable more efficient and diversified consideration. These tools are further complemented with machine learning solutions to provide further capabilities on fault and degradation analysis for machinery systems. A summary of research related to this work highlighting the current tread of maintenance and DSS in the marine industry is at Appendix 2.

2.11 Identified Gaps

Research efforts by authors in the field of ship system reliability has produced a huge knowledge base and techniques for the conduct of ship system reliability, machinery health and maintenance analysis. The outcome of many research efforts often provides solutions accompanied with additional grey areas needing more clarification. Consequently, some of the gaps identified in literature that aligns to the research motivations includes the following:

1. Identifying component criticality to system availability.
2. Maintenance action prioritisation to reflect failure severity with regard to vessel operational demands.
3. The lack of a machinery health and failure data base that can be accessed by researchers as obtained in other disciplines.
4. Challenges with incoherent approaches in the data collection and analysis process in the maritime industry.
5. Selecting maintenance decisions to reflect the operator's sentiment.
6. Selection of tools to enable results validation within the research lifecycle.
7. Identification of mission-critical components and faults using a combination of DFTA IM, FMECA RPN, and ANN
8. Using outputs from the DFTA and FMECA as inputs for the BBN model for system availability and utility for maintenance decision support systems.
9. The use of ANN for fault identification and diagnostics to identify dominant failure causes based on reliability analysis outcomes.

2.12 Chapter Summary

This chapter provides a critical review on the literature consulted for the research. An appraisal on maintenance strategy was given with a look at traditional maintenance concepts highlighting some of the challenges that lead to gradual transition to other maintenance concepts. An overview on the evolution on maintenance and adoption through the industries was given including factors influencing the acceptance or implantation of the evolve concepts. Likewise, a detail discussion on some reliability analysis tools was provided given their strength and weakness leading to the selection of the tools used in this research. Like most other industries the shipping industry is highly regulated to enable structured operational administration of all activities in the sector, hence an overview on the role of IMO, classification societies and other related agency was given including the respective roles each play in developing maintenance and environmental regulations for the shipping industry. The chapter was concluded by given a summary related works and identified research gaps.

3. Methodology

3.1 Chapter Outline

The chapter discusses the process and steps taken to develop a methodology that addresses the identified research gaps, in particular that of component failure criticality to mission availability. Moreover, the critical literature review identified the research duration as a limitation in the ability of researchers to validate some of results and finding especially in the field of system reliability analysis study. In this regard the chapter highlights the key tools used in the methodology and how the inputs interact with one another to provide a systematic analysis of component criticality leading to a maintenance DSS. Accordingly, section 3.2 gives an overview of the methodology framework, the step-by-step development of the framework is presented in section 3.3. Data collection and utilisation, for the respective tools used in the research is presented in sections 3.4 to 3.8; while section 3.9 presents the chapter summary.

3.2 Overview of Methodology Framework

The methodology provides a detailed and comprehensive analysis that identifies critical components in relation to ship availability and maintenance effort in an inclusive manner that can account for operator concerns, OEMs' recommendations, and environmental influence. Therefore, unlike data driven approaches that depends on machinery health parameters that could be impacted by sensor noise or errors in recording. Furthermore, failure probability analysis such as Weibull distribution, bathtub curve, Mean Time to Failure (MTTF) are generic in nature and lack the analytical prowess to identify failures responsible for machinery unreliability. Other graphical approaches such as the bathtub curve, Weibull distribution also relies on failure rate data and probability distribution, which are insufficient to identify issues such as single point failure, common cause failures or critical components within a system and its components. Moreover, machinery failures can occur due to material or design defects, age/wear out and poor maintenance or intrusively due to maintenance action. Therefore, a hybrid approach considering the multiple dynamics in system reliability and failure mechanics needs to be developed. Accordingly, to develop a ship reliability analysis alongside a maintenance decision support system these selected tools provide a good match and can accommodate all the relevant variables as compared to using one or a couple of these tools.

In this regard, this work presents a novel approach to system reliability and fault detection methodology related to hybrid marine system component reliability analysis and fault detection framework through the combination of reliability analysis tools and ANN. The tools used includes dynamic fault tree (DFTA) for system reliability and criticality analysis, failure mode effect and criticality analysis (FMECA) for identification of mission critical component accounting for operator sentiment and Bayesian Belief network (BBN) for dependability analysis and maintenance decision support system (DSS). To complement the reliability analysis models a machine learning model base on artificial neural network was also developed for classification and fault detection. Furthermore, data collection was achieved through on-board data collection campaign and questionnaire. On board data collection campaign was done through the collection of raw machinery log data and maintenance, repair, and overhaul (MRO) data were obtained. The overall methodology framework is presented in Figure 13.

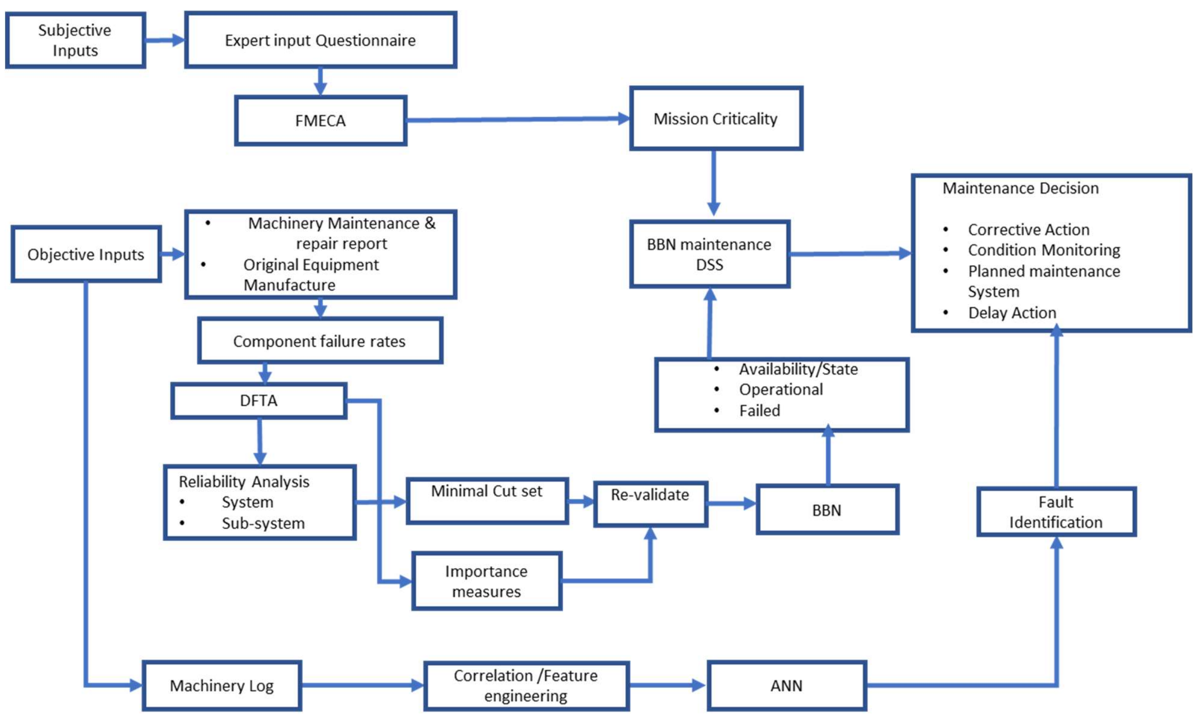

Figure 12: Methodology framework.

3.3 Methodology Framework Development

The methodology is hinged on three broad areas, which are the System reliability analysis using DFTA, FMECA was used for generating RPN to obtain mission critical component, while fault detection and prediction using ANNs. BBN was used for developing a system availability model and a maintenance decision support system. This process would assist both onboard technical staff as well as shore support units, including high level organisational maintenance budgeting and logistics planning. The process of the research involves collection of machinery data from an Offshore Patrol Vessel (OPV) which was then analysed to generate outputs relevant to machinery health performance indicators. Therefore, the coming section will highlight a novel methodology through the combination of reliability analysis and artificial intelligence using artificial neural networks machining learning capabilities. The combination of this unique tools enables the harnessing of individual capabilities of the tools towards achieving the research objectives with regards to component criticality and maintenance decision support system.

3.4 Data Collection and Preparation

The data for this research was obtained through data collection campaign onboard a Nigerian Navy OPV. Machinery health and historical data such as maintenance and overhaul records repair data as well adopted deviations on machinery health records were collected. Overall machinery log for up to 12 calendar months and historical records up to 18 months were accessed. However, the machinery log data and some part of the maintenance and overhaul data were in manuscript form hence the need to convert to electronic format. This situation brough some challenges regarding the quality of data especially noise in numerical data and consistency in maintenance and repair reports. Therefore, in some cases the raw data must be re-accessed multiple times to ensure correctness and completeness of entries new data has to be collected from the operator. Therefore, to address some of the problems, short demonstration on data collection training was given to the technical staff. Additionally, staff were assured that the data is only meant for research and will not use for any investigative purpose that could lead to any disciplinary action against anyone. This helped restore the confidence of the respective personnel and data quality was improved.

Nonetheless, the approach in data pre-processing helped to address some challenges to do with missing values, outliers or ‘not a number’ (NAN) entries. Otherwise, available statistical process of filling missing values such as linear interpolation, median and median value where used. Unfortunately, some of the fill missing value methods do not handle outliers properly. Hence outlier detection methods were adopted depending on the parameter being analysed. Moreover, considering the dimensionality of the data it becomes very difficult to adopt single approach of outlier cleaning. The main approaches used for this analysis were the interquartile range (IQR) for natural number values, while other numbers especially floating and values <1 present most problems, in this regards an iterative approach was adopted ensuring cleansed data is consistent with original data. Methods used includes Grubbs, generalised extreme Studentised deviate test for outliers (gesd), median and median approaches.

Furthermore, the tools used for developing the framework require multiple data types due to the type of inputs variables required. Overall, 3 type variables were adopted, namely, continues, discrete and ordinal based on Likert scale. The continues and discrete variable were used as objective inputs while Likert variables were used for the subjective inputs. Moreover, some of the restriction in modelling certain failures such as common cause failure (CCF) in DFTA and ranking of criticality in FMECA can only be achieved through making some discrete and Likert variables. Consequently, the input data was categorised into Subjective and Objective inputs as describe below.

3.3.1 Subjective Data Inputs

A key difficulty in maintenance planning is handling equipment defects that are not fully addressed in OEM maintenance and troubleshooting manuals, such as environment-related faults, design restrictions, incorrect application, or unsuitable operation. These sorts of defects typically result in frequent equipment failures and performance deterioration, reducing system reliability and overall platform availability. Therefore, considering that some of these local faults are not well documented in the OEM's maintenance and troubleshooting manual and the possibility that the operators may not have experience similar faults or are new to the equipment. In this regard maintenance staff would need to come with a separate approach to address the problem. Accordingly, the procedures and process for maintenance planning would largely depends on the understanding of the operator. Therefore, capturing the operators' thoughts based on usage and experience would provide additional evidence to enable an depth and accurate analysis. Hence the need to adopt a qualitative approach that the operator can relate with to help provide clear unambiguous feedback.

In this context, information from operators regarding operations, maintenance as well in service as adaptations which may deviate from OEM recommended settings need to be captured. Additionally, interpreting, and inputting information extracted from maintenance and repair records cannot be done using numerical values because of ambiguity and influence factors such as knowledge, competence, workplace restrictions and logistics challenges. Therefore, adopting tools like FMECA and BBN help address the aforementioned difficulties in reliability and maintenance decision support analysis. Nonetheless, the accuracy in subjective analysis could be impacted by biases and translational mismatch, while deterministic outputs obtained using high quality data can provide a very good objective analysis with good confidence levels for maintenance planning.

3.3.2 Objective Data Inputs

The methodology adopted in this research draws from multiple data sources some of which are raw machinery log data, maintenance and repair data including technical reports, others are output from tools used in the research. This process enables a more robust analysis especially considering the duration of the research will not allow verification or implement the methodology onboard. Accordingly, the objective inputs are independent numerical variables and not controlled by the modeler. These include failure rates obtained from machinery failure data used as inputs for the DFTA, RPN values from FMECA, and MCS probabilities from the DFTA results used as inputs in the BBN. Furthermore, availability percentages from the BBN were used to build the DSS model which was complemented by MCS from the DFTA.

Numerical discrete or continues variables were the main data types for the objective inputs, used with DFTA, BBN and ANN. The numerical variables provide accurate measurement as regards system reliability in the case of DFTA, while for the BBN the conditional probability table was populated using IM probability of occurrence in put. Moreover, aggregating and weighting of the FMECA respondent was equally developed using numerical values which were translated to ordinal variables. This aspect of the methodology lacks flexibility, and outputs are generally deterministic in nature. However, several factors can be responsible for certain failure or system reliability difficulties that cannot be expressed or measured using numerical analysis. For instance, deviations from initial design operating conditions due to unavailability of certain items such as quality of lubricant or fuels or environment conditions could result to increased rate of failure hence leading to unrealistic reliability estimations. Accordingly, the adopted tools used in developing the methodology would be discussed in the coming section beginning with subjective inputs using FMECA.

3.4 FMECA

FMECA is widely applied in maintenance and risk analysis to provide clear understanding and procedure on what can go wrong, how it could go wrong , why it goes wrong, and how it can be corrected or addressed (Marvin, 2021). The Criticality Analysis (CA) provides a means of identifying the events, occurrence or components that need more attention to avoid more serious or catastrophic situations(Melani et al., 2018). FMECA is a bottom-up approach which provides a systematic methodology to gain deep insight on failures and their course on an equipment or system. Therefore, measuring criticality in FMECA helps to explicitly bring out the most critical component failure which can assist in maintenance actions and planning.

Therefore, the criticality ranking based on risk use a combination of the consequence (severity) of the failure and the anticipated likelihood of the consequence occurring (ABS, 2015). Criticality analysis will highlight failure modes with probability of occurrence and severity of consequence, allowing corrective actions to be implemented where they produce greatest impact. Given the overall lack of reliability data for many marine systems and components, performing an assessment on qualitative level based on experience and knowledge of the system is sometimes the only means by which to achieve a meaningful criticality assessment. For the FMECA a survey was conducted based on the DFTA criticality output of components that contributes to 40 per cent and above in DGs unreliability.

In this regard subjective operator inputs were obtained using FMECA, the relevance which of can be described in 2 folds. The first is to evaluate operator sentiments and priorities specially to do with failures and maintenance challenges such as expertise and causes of extended down times. This was also used to establish maintenance critical failures and machinery parts. The second aspect was to validate critical components obtained using DFTA quantitative analysis reliability importance measures. Therefore, to establish these 2 goals using FMECA analysis, a questionnaire was produced and distributed using the Qualtrics survey software, Table 2 is a template of the FMECA table used.

Table 3: FMECA sample table

Subsystem	Component	Function	Description of Failure			Effects of Failure				Safeguards		Criticality	Severity	Likelihood	RPN
			Mode	Causes	Detection	Local	Global	Influence	TTR	Prevention	Mitigation	1-10	1-10	1-10	CxSxL

The FMECA survey questions were aimed at identifying components that presents the greatest challenge to the conduct of maintenance onboard using risk priority number. The RPN use 3 categorical variables namely identification, severity and likelihood usually measured in a linear scale based on increasing importance i.e 1 – 10. The scale used for the analysis is presented in Tables 2,3 and 4 which shows the linear and Likert scale including colour codes representing respective scale values (Tan et al., 2011, Jeong et al., 2018). However, is worth noting that in this research detectability was replaced with criticality. This is because, the level of sensors and monitoring deployed on the MDGs as well as watch keeping is significantly high and adequate to establish the onset of faults. Moreover, the sensors signals are transmitted and displayed in the different location within the engine rooms, personnel leaving spaces and chief engineers' cabin, in addition to hourly log taking of the MDG health parameter in visual inspection. Therefore, it is expected that faults are more easily identified hence reducing the risk of faults escalation due to identification challenges.

In this regard, criticality, determines the immediate impact of failure event to the equipment availability and functions. Meaning that, a failure mode due to which the ship will not achieve one or more of its the mission's targets is will be considered as critical (NASA, 2008). Severity, on the other hand, assesses how the failure affects the operational availability of the equipment or system regarding normal operation and the duration it takes to be repaired or restored to normal operational levels. Severity is described as the worst potential consequence of the failure determined by the degree of injury, property damage or system damage that could occur. Lastly, likelihood and refers to the failure rate of the component including possibility and frequency of the fault occurring over a certain time frame(ASEMS, 2017, Daya and Lazakis, 2022).

The above explanation provides a guide to help respondents assess all the criteria against the candidate failures and components. Thereafter the responses were aggregated through weight system to obtain single outcome to quantify the 3 criteria needed for the calculating the RPN which are Criticality (C), Severity (S) and Likelihood (L). The RPN was used to get the mission criticality of the components or faults which is given by RPN= CxSxL scored on a scale 0 - 100; 0 being minor or low and 100 very high score as regards impact. The FMECA was conducted through a survey completed by the engineering personnel of the organisation most of whom are either electrical or marine engineers with varied level of technical knowledge and experience. In this regard, a 2-weight system was introduced to account for experience and expertise.

Accordingly, all individual inputs were evaluated to reflect years of experience and specialization of the respondents. For instance, response on piston failure by a marine engineer with 12 years' experience will have more weight compared to that of electrical engineer with same experience and vice versa if the response were to be on alternator parts. Therefore, respondents were asked to rank faults/failures based on 3 criteria on a linear scale from one (1) to ten (10). These criteria were Criticality, Severity and Likelihood as defined below.

Criticality: Criticality determines the immediate impact of failure event to the equipment availability and loss of function. In this context, critical failures refer to failure events that negatively impacts on the ability of the ship to achieve one or more of the mission's targets and associated vulnerabilities to the vessel pending failure rectification (NASA, 2008a). The criticality definition is presented in Table 3.

Table 4: Criticality Table and definitions

Criticality			
Linear scale (1-10)	Criticality Level	Descriptions	Remarks
1	Minor	A component failure or event that has no immediate impact on platform or personnel safety and will not lead to any reduction in operations or mission readiness of the platform	No impact
2-3	Low	Failure or event that could cause slight delay/deterioration system capability but will not affect its availability. System may require minor repair action that can be undertaken while the ship is underway.	A failure that can be rectified by ship staff such as sea chest blockage
4-6	Marginal (Moderate)	A Failure that could result to deterioration in system capability and availability which may require unscheduled repair that can be conducted by ship staff.	Repair that can be done by ship staff with or without FSG assistance but may require spares not held onboard.
7-8	Critical (High)	Failure that results to loss of system capability and can influence the efficient operation of other systems. Component or equipment will require repair causing operational or mission postponement	Failure that will lead to ship returning to harbour.
9-10	Major (Very High)	A potential failure could cause complete system loss that will require FGS or OEM assistance	Failure may lead to mission cancellation or return to harbour

Severity: Severity assesses how the failure impacts on the operational availability of the equipment or system regarding normal operation and the duration it takes to be repaired or restored to normal operational levels. Severity in this regard, provides a measurement of how an equipment is resilient to failure and what if any are the impact of the failure on personnel safety due to the equipment failure. Table provides the definitions for severity. The severity was described by (*System Reliability Theory*, 2021) as the worst potential consequence of the failure determined by the degree of injury, property damage or system damage that could occur.

Table 5: Severity Table and definitions

SEVERITY			
Linear scale (1-10)	**Severity Level**	**Descriptions**	**Remarks**
1	Minor	Failure or event that has little or no significant impact system capability and availability	A failure that will not hinder or delay any operational/mission activity
2-3	Low	Failure or event that could cause slight deterioration of system capability but will not affect it availability. System may require minor repair action.	Component/system failure that are easily affected by ship staff
4-6	Marginal (Moderate)	Failure could result to deterioration in system capability which may require unscheduled repair or may cause minor health hazard or injury to the user. A failure event that may cause delay to operational activity but may not affect overall mission objective.	Ship may require external technical or spare part assistant
7-8	Critical (High)	Failure causes loss of system capability and availability or may cause a serious health hazard or serious injury to the user. A failure will cause delay of about a week and will require FSG or other specialist assistant requiring spare parts that are readily available onboard.	Failure that will require ship to send and OPDEF, work order and spare parts requisition, but may not warrant, OEM or contractor assistance
9-10	Major (Very High)	A potential failure could cause complete system loss and /or death of user(s). A failure event which may lead to extended downtime due to spare parts or OEM assistance or due to extend of damage affecting other systems.	Failure that will require ship to send and OPDEF, abort mission and may need NHQ intervention.

Likelihood: This refers to the failure rate of the component including possibility and frequency of the fault occurring over a certain time frame(MIL-STD 1629A, 1980).The likelihood of failure is an important determinant of system operational resilience. Table 4 presents the likelihood definitions used in the research.

Table 6: Likelihood Table and definitions

LIKELIHOOD			
Linear scale (1-10)	Likelihood Level	Descriptions	Failure Rate
1	Remote	Failure is unlikely. No failure associated with almost identical items	10^{-6}
2-3	Low	Isolated failure associated with component or equipment.	10^{-5}
4-6	Moderate	Occasional failure but not in major proportions	10^{-3}
7-8	High	Generally associated with components or system which often fail	10^{-2}
9-10	Very High	A component or equipment with very high failure rate	10^{-1}

3.4.1 Estimated RPN

The RPN was calculated from the obtained population mean by multiplying each criterion based on the assigned weights according to the seniority of the respondents as a percentage of the original value as in equation 1 and 2. The linear values used for the criteria was between | 1 – 10 | therefore was 0 ≤RPN ≥ 1000. In this regard to obtain the Mission Criticality was normalised to ≤100 using the min-max normaliser equation 3.

$$Weighted\ average\ w = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}\ \ Equation\ 1$$

$$RPN = \sum_{i=\leq 1} Cw_i \times Sw_i \times Lw_i\ Equation\ 2$$

$$RPN_{norm} = \frac{X - min\ (X)}{max(X) - min(X)} = Mission\ Criticality\ \ Equation\ 3$$

3.5 DFTA

Static Fault Tree Analysis (FTA) procedure is based on Boolean law by applying gates and events to describe faulty components and possible event(s) that could develop a fault(Kabir, 2017). FTA is an important tool for reliability and risk analysis as it provides critical information used to prioritize the importance of the contributors to the undesired event i.e., fault or failure. However, static FTA has some shortcomings to do with sequence dependencies, temporal order of occurrence and redundancies due to standby systems. Therefore, DFTA with addition of four gates and one basic event has provided a much flexible way of modelling faults/failures in complex systems with respect to sequence and dependencies, which means the temporal order of the occurrence of events is important to analysis.

The dynamic fault tree analysis (DFTA) is an extension of standard fault tree analysis (FTA) that provides for time or sequence dependent analysis and can also prioritise events for analysis. DFTA is selected for this study in order to utilise its system dependent relationship on the effect of component failures. The DFTA tool used for machinery/system reliability and availability analysis used input data generated from the operational records of 4 diesel generators for a ship power generation system. Therefore, a DFTA structure representing the functional ship power generation system as well as the individual diesel generators was built. System reliability in DFTA involves generating a qualitative model of the fault tree usually from the minimal cut sets on the logic gate of the fault tree. Thereafter, quantitative analysis using reliability and maintainability data such as failure rates/frequency, failure probability, mean time to failure or repair rate can be used (Windchill, 2015), by calculating the unavailability and the unreliability of the system to be done .

Accordingly, failure and maintenance data over a period of 6 calendar years obtained from the maintenance records was processed to generate components failure rates ($\curlywedge$) based on equation 4. The model structure was built suing both static and dynamic FT gates and events to reflect the mode of failures and in other cases dependency and sequence. Therefore, top events and sub-events were modelled using dynamic gates while gates connecting to the main system were modelled using static FTs this procedure is necessary to reduce memory usage and improve calculation time. The probabilities for the static gates used were generally AND gate equation 5, OR gate equation 6 and voting gate equitation 7. Voting gates (equation 8) account for multiple connected components (*k out of n*) such as injection nozzles, cylinder blocks, fuel day tanks or supply lines. Correct functioning of system requires all component but is not necessarily impaired due to a few faulty ones.

$$\curlywedge = \frac{n}{\tau} \quad \textit{Equation 4}$$

Where n is number of failures (10^6) and τ is aggregated time in service of individual DG. The inputs for the gates are obtained with the below equations.

Probability of occurrence of an AND gate is given as:

$$Pr\{A\} = Pr\{A_1\} \bullet Pr\{A_2|A_1\} \bullet \dots \bullet Pr\{A_n|A_{1,}A_{2,} \dots, A_{n-1}\} \quad \textit{Equation 5}$$

If all events are independent, then.

$$\Pr\{A\} = Pr\{A_1\} \bullet Pr\{A_2\} \bullet \dots \bullet Pr\{A_n\}$$

For an OR gate given $A_1, A_2 \dots.., A_n$ as inputs and A is the output of the OR gate, the probability of its occurrence (top event) =

$$Pr\{A\} = Pr\{A_1\} + Pr\{A_2| \sim A_1\} + \dots + Pr\{A_n| \sim A_1, \sim A_2, \dots \sim A_{n-1}\} \quad \textit{Equation 6}$$

If all events are independent

$$Pr\{A\} = Pr\{A_1\} + Pr\{A_2\} \bullet Pr\{\sim A_1\} + \dots + Pr\{A_n\} \bullet Pr\{\sim A_1\} \bullet Pr\{\sim A_2\} \bullet \dots \bullet Pr\{\sim A_{n-1}\}$$

$$= PrP\{A_1\} + Pr\{A_2\} \bullet (1 - Pr\{A_1\}) + \dots + Pr\{A_n\} \bullet (1 - Pr\{A_1\}) \bullet (1 - Pr\{A_2\}) \bullet \dots \bullet (1 - Pr\{A_{n-1}\})$$

$$= 1 - (1 - Pr\{A_1\}) \bullet (1 - Pr\{A_2\}) \bullet \dots \bullet (1 - Pr\{A_{n-1}\})$$

In the above formular A is the top event, A_1, A_2 …., A_n are lower events.

Voting gate:

$$PrA = C_k^n (r)^k (1-r)^{n-k} + \cdots + C_n^n \, (r)^n (1-r)^{n-n} \quad \textit{Equation 7}$$

The minimal cut set for top event is obtain via equation 8.

$$T = \; M_1 + M_2 \; + \cdots + M_K \quad \textit{Equation 8}$$

Where T is the top event and M_i are the minimal cut set.

On the minimal cut set for a specific component can be given by equation 9

$$M_i = \; X_1 \bullet X_2 \; \bullet \ldots \bullet X_n \quad \textit{Equation 9}$$

The establishing the unreliability in the system as well as the machinery, while identifying the most critical component in the system or machinery. In addition, the cut set function of the DFTA is relevant in analysing the failure path and possible way of mitigating them. The output from the DFTA tool namely machinery reliability, component criticality and cut set were used as inputs for the BBN condition probability analysis.

3.5.1 Reliability Importance Measures

Reliability importance measures (IM) are a means to identify the most critical component or situation that contributes to the occurrence of the basic event leading up to equipment failure or top event occurrence(Daya and Lazakis, 2021). In essence the IM helps the operators, maintenance crew, administrators including regulatory agency in prioritisation of actions that could improve equipment or system reliability. These IM includes Birnbaum (Bir), Fussell-Vesely(F-V) and Criticality (Cri). The Bir IM evaluates the occurrence of the top events based the probability of basic event occurring or not occurring, hence the higher the probability of the basic events the high chances of top event occurring. Criticality (Cri) IM is calculated in a similar way to Bir IM except that it considers the probability in the occurrence of the basic event to the occurrences of the top event. On the other hand, the F-V calculation adopts an entirely different approach in that; it uses the minimal cut set summation i.e., the minimum number of basic events that contribute to the top event. Therefore, the F-V consider the contribution of the basic event to occurrence of the top event irrespective of how it contributes to the failure.

In this regard, in order to enable a robust criticality analysis for more than 290 basic events modelled at component level failures per individual DG, the Bir IM was adopted. The Bir calculation method provides more accurate results as compared to the other 2 IM, this is because it considers all possible failures based on their individual contributions and occurrence. Moreover, the use of dynamic gates also provides additional complexity to the calculation in that the location of event, the type and position of gates must be considered for calculating the reliability of the component. For instance, some of the draw backs with the Cri and F-V is the possibility of overlooking or over emphasising faults which might give rise to high reliability or low reliability. The cut set approach used to determine criticality in F-V method could give rise to false high reliability depending on the connection of the events to the top gate, especially when using non dynamic gates as it tends to consider only the probability of occurrence against sequences and dependencies. Bir IM as the measure in the increase in probability of the top event due to the occurrence of event A, equation 11. Equation 10 is relevant for in analysing a system or global criticality while equation 12 solves for local or sub-system level component criticality.

$$I^B(i|t) = \frac{\partial y(p(t))}{\partial p_i(t)} = h\left(1_{i,}p(t)\right) - h\left(0_{i,}p(t)\right) \text{Equation 10}$$

Where:

$I^B(i|t)$ = *Birnbaum criticality at time t*

h $(1_{i,}\, p(t))$ = *system reliability when system is functioning*

h $(0_{i,}\, p(t))$ = *system reliability when system has failed*

$$l_i^B(A) = (P\{X|A\} - P\{|X|{\sim}A\}) \text{Equation 11}$$

Where:

$l_i^B(A)$ = Birnbaum importance measures of for event *A*

A = the event whose importance is being measured

~A= the event did occur

X = top event

3.5.2 Minimal Cut Set

A minimal cut set (MCS) is the smallest set of events, which, if they all occur, cause the top event to occur(Windchill, 2015). The qualitative analysis is performed using the structure of the DFTA dependent on logic properties of the gates, while the quantitative analysis uses MRO data such as failure rate, MTBF, and frequency. The quantitative analysis outputs are objective results that includes system unreliability, unavailability and reliability importance measures which provide critical components failures. However, the MCS evaluation is based on the output evaluated using the logic combination of the top event occurrence usually from left to right. Therefore, to obtain the MCS the DFTA structure representing each DG was built based on the functional relationship and system boundary of the sub-systems on the respective marine DGs.

Accordingly, the product of the MCS derived from evaluated fault tree was used to identify or isolate important failures in a system or sub-system. Moreover, considering that a single basic event can equally form a cut set depending on the arrangement of the fault tree; goes to show how important the qualitative evaluation of fault trees can be. Figure 13 provides some instance of MCS; such that sub-system 1 having an AND gate fails only when all the events have occurred however the intermediate OR gate fail when any of its BEs occur; while in the case of Sub-system 2, the occurrence of BE 7 or BE8 is an MCS. On the other hand, sub-system 3 has all the BEs as MCS due to the AND top gate. This highlights potential area where improvements can be achieved either through redesign or simply altering the system to improve its reliability.

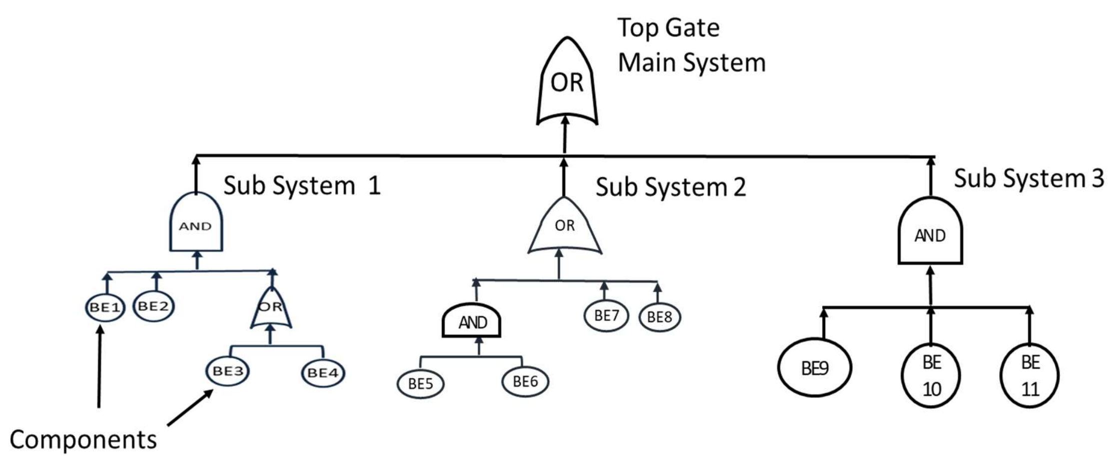

Figure 13 :Example of MCS formation.

3.6 Machinery Data Collection and Labelling

The machinery log data collected was an unlabelled time series hourly log data for fresh and raw cooling water temperatures and pressure, exhaust gas temperature, lubricating oil temperature and pressure, power output and running hours. The timeseries data was in manuscript form while the text data for them MRO data was in word format. The MRO provides details on time of failure and cause of failure, while the timeseries data only gives the values of parameter at the respective time. Therefore, there was no indication of failure or the operational condition of respective machinery at any giving time except for start and stop periods. The first step is the data collection campaign onboard an Offshore Patrol Vessel (OPV). Data obtained included maintenance and repairs data as well as raw machinery log data. Thereafter the data was transformed to the appropriate format using excel, Figure 14 is a representation of the methodology.

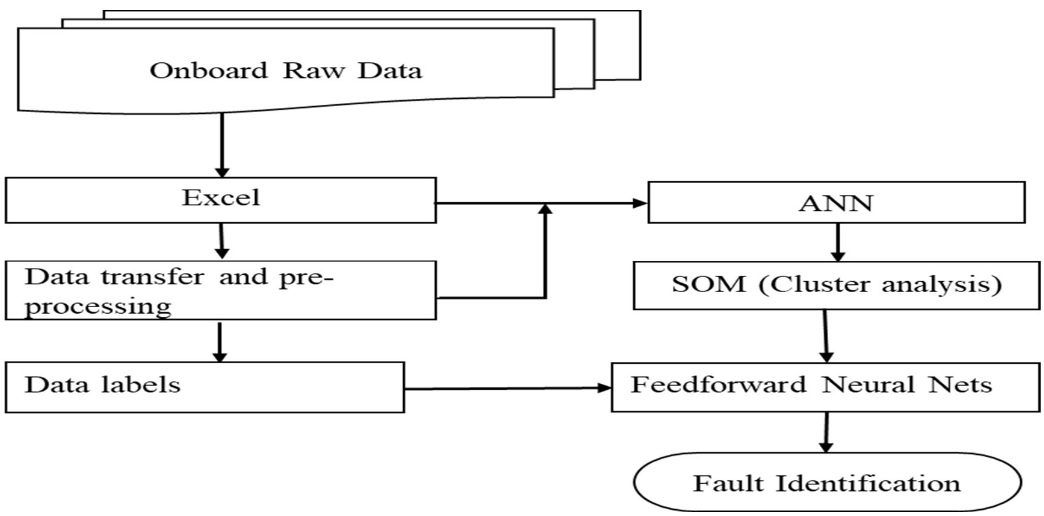

Figure 14: Data Cleaning and ANN approach.

Consequently, first task after transcription to excel format data was to carry out pre-processing data by removing nonnumeric (NAN) values, and initial outlier removal by using interquartile range based on the operational data ranges as provided by the Original Equipment Manufacturer (OEM) and the Operator. The process was used to set the lowest values, normal values, and highest values. Therefore, mean value of each variable was derived using arithmetic mean in equation 12, which can also be given as the average value using Q3 – Q1= Q2 of the data values. Next was getting the, Q2 which is taken as the interquartile range, while Q3 represent 75% of the sample and Q1 represent 25 percent of the data, the quantiles can be computed by using equation 13-15. Therefore, after obtaining the quartiles a value of 15% was added to the upper limits to account for the disparity between the OEM and operator's limits. Therefore, this helped improved the validity of the data by eliminating the relatively very low operating parameter values to become more acceptable. The 15% was the upper limit accepted by the operator as an indication of fault while any value 25% more than limit is a sign of failure.

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}$$ *Equation 12*

$$Q_1 = \frac{N}{4}$$ *Equation 13*

$$Q_2 = \frac{N}{2}$$ *Equation 14*

$$Q_3 = 3\left(\frac{N}{4}\right)$$ *Equation 15*

3.6.1 Data Labelling

Following the above analysis, the data was labelled to identify the faults and operating condition for machine learning purpose. Therefore, considering that there was no actual indication of faulty data from the operators' log, the research relied on expert knowledge and operators' recommendation on data alarm limits to form the bases of fault identification, also provides the lower and upper acceptable operating limits for the diesel generator. The fault class label for the diagnostic analysis was derived based on the labels as well as additional information from the failure data. The failure data was used to compare start- stops times and corresponding incident reports, which sometimes gives some valuable information regarding log readings. In this regard, a nested IF – ELSE analysis was conducted to get the fault class and operating temperature condition, the process is illustrated in Figure 15.

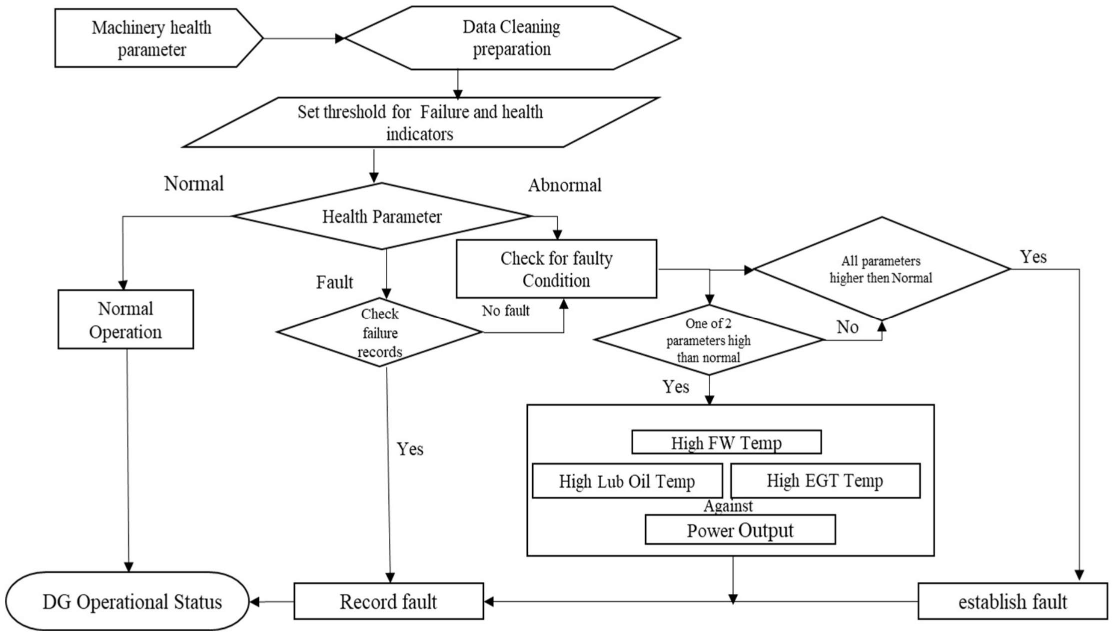

Figure 15: Fault labelling.

3.7 Artificial Neural Network

Artificial Neural Network were used for both unsupervised and supervised learning analysis. The unsupervised learning was done using ANN SOM clustering for feature engineering and dimensionality reduction, while Feedforward Neural Nets (FFNN) was applied supervised classification analysis. ANN are widely used for statistical analysis and data modelling commonly applied as alternatives to standard nonlinear regression or cluster analysis. The process involves the basic node which provides a linear combination of N weights $w_1 \ldots\ldots, w_N$ and N inputs $x_{1,\ldots\ldots} x_N$ and

$$y = \sum_{i=1}^{N} w_i * x_i + w_0 \quad \textit{Equation 16}$$

3.7.1 Artificial Neural Network Self Organising Maps

Self-Organising Maps are ANN an unsupervised learning method that are effective for data analysis and clustering. ANN SOM are especially effective for the identification of nonlinear latent features in high dimensional data. Consequently, building on the success and procedures in the use of ANN for machinery data analysis, ANN SOM were adopted for data clustering. The advantages of using clustering models help identify possible clusters as well as the most influential clusters in the data. In research ANN Self Organising Map (SOM) were used for clustering of machinery log data of DG. SOM consists of competitive layer which can classify a dataset of vectors with any number of dimensions as the number neurons in the layer and are good for dimensionality reduction.

Implementing SOM requires the initial training which composes of three phases namely, competition cooperation and adaption(Kohonen, 2013). The neurons are trained during the competition by competing with each other, whereby the neuron having weight vector closest to the input signal vector is declared as the winner neuron or the Best Matching Unit (BMU). The process can be demonstrated; thus, taken the input signal vector to be represented by I = [$I_1, I_2, I_3 \ldots I_n$]^T and the weight vector is represented by W = [$W_1, W_2, W_3 \ldots W_n$]^T. The difference between the weight vector and input signal vector is computed as the Euclidean Distance between them given by equation 17.

$$E = \| I - W \| \sqrt{\sum_{i=1}^{n} (I_i - W_i)^2} \quad \textit{Equation 17}$$

The above equation determines the neuron with the smallest E obtained, which is also the BMU. This is followed by the cooperation phase where the direct neighbourhood neurons of the BMU are identified. The third phase is the adaptation process which neurons are selectively tuned to adopt a specific pattern on the lattice that corresponds to a specific feature of the input vector. The tuning function is written as:

$$W(t+1) = W(t) + \alpha(t)\theta(t)[I(t) - W(t)] \quad \textit{Equation 18}$$

Where $\alpha(t)$ is the tuning rate and $\theta(t)$ is the exponential neighbour function; $\alpha(t)$ decrease exponentially with further iteration hence refining the training the process, this can be represented in the following equation.

$$\alpha(t) = \alpha_0 e^{(-\frac{t}{\lambda})} \quad \textit{Equation 19}$$

where α_0 is the initial learning rate and λ is the time constant given by.

$$\lambda \frac{N}{\sigma_0} \quad \textit{Equation 20}$$

In the above equation N is the total number of training samples and σ_0 is the radius of the map. The radius is calculated as the Euclidean distance between the coordinates of the outmost neuron and the centre neuron.

$$\sigma_0 = \| T_{outmost} - T_{centre} \| \quad \textit{Equation 21}$$

In equation 21, $T_{outmost}$ and T_{centre} stands for the coordinate of the outmost and central neurons respectively. The overall process is an iterative one to identify the closest neuron to the BMU, thereby fitting the data to required cluster using $\theta(t)$ equation 22.

$$\theta(t) = \left(\frac{\|T_j - T_{BMU}\|^2}{2\sigma(t)^2}\right) \text{ Equation 22}$$

$$\sigma(t) = \sigma_0 exp\left(\frac{-t}{\lambda}\right) \text{ Equation 23}$$

In equation 22 $T_j = [t_j^1 \; t_j^2]$ which denotes the coordinates of each neuron in a 2D map, T_{BMU} is the coordinate of the best matching unit and σ(t) is the radius of the neighbourhood as shown in equation 23. Therefore, the neurons will keep on updating getting BMU, this process can be summarised as follows:

1. Weight initialisation
2. Selection of the network input vector from the dataset
3. Calculating the BMU
4. Calculating and updating the radius neurons in the neighbourhood.
5. Adjusting the weights of neighbourhood neurons closer to the input neuron
6. The network is updated iteratively by repeating steps 2 through 5.

The process of obtaining the BMU eliminates those neurons that are far from the input neuron. In this regard weight vectors of the BMU and those of the neighbours are adjusted closer to the input data samples. Therefore, this process competitively arranges the neurons thus mapping the data to the required or available clusters based on similarity to the input data weight vector. The iteration ends when the maximum number of training epochs are completed after which a 2D topology map showing weight of the interconnected neurons. The pattern on map corresponds to the number and most influential features in the data. In this respect, SOM uses unsupervised learning to produce a map of the input thus providing a good solution for interpreting highly dimensional data making a good candidate in machinery fault diagnosis.

3.7.2 Feedforward Neural Net

Diagnostics analysis involves recognising patterns in the data that indicates the presence of variations pointing to a change in the normal health parameters of the system or machinery of interest. A supervised ANN feedforward neural network was implemented for the classification analysis. Feedforward ANN is a time series algorithm that can be used for both function fitting and pattern recognition(Sazli, 2006). The Feedforward networks usually have single or multilayer hidden sigmoid neurons followed by a series of output neurons. Multiple layers of neurons with nonlinear transfer functions enable the network to learn nonlinear relationships between input and output vectors(Umair Sarwar, 2014).

A two-layer feedforward network with sigmoid activation and SoftMax output neurons were adopted for the study based on equation 24. The sigmoid activation function, equation 25, helps to improve the prediction capability of the neurons by adding bias and non-linearity while the SoftMax activation function, equation 25, is a probability function with values between 0 and 1. The most likely probability being 1 and vice-versa. Both sigmoid and SoftMax are used for classification problems, and they help improve the model's capability(Gurney, 1997)

$$y_k\ (x, w) = \ \sigma\ \left(\sum_{j=i}^{M} w\ _{kj}^{(2)}\ h\left(\sum_{i=1}^{D} w\ _{ji}^{(1)} + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right) \quad \textit{Equation 24}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad \textit{Equation 25}$$

$$\frac{exp\ (a_k)}{\sum_j exp\ (a_j)} \quad \textit{Equation 26}$$

3.8 Bayesian Belief Networks

Bayesian belief networks (BBN) provide efficient and flexible platform for the conduct of numerical analysis to aid decision making impacted by conflicting priorities. BBNs can be up dated with new data at any point during the analysis thereby providing a very efficient tool for decision support system especially for complex system maintenance analysis(Sakar et al., 2021). BBN analysis is conducted based on DAG structure consisting of nodes of various shapes representing events and their probabilities, connected to arrows indicating dependencies or influence. Conditional probability tables (CPT) of discrete or continues variables provide inputs for the nodes in the influence diagrams. The CPT can be updated according to data availability which provide the evidence (E) and event occurring. The evidence is used by the BN's inference engine to update the prior occurrence of event equation 27 (F.V. Jensen, 2007).

$$P(U|E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \quad \textit{Equation 27}$$

The above equation represents the overall structure of the influence diagram for a BN structure analysis. In this case the conditional probabilities of failure are presented as parent event and faults are presented as children P (Failure | Fault event). In this regard the influence diagrams for the building the maintenance DSS was generated using the CPT output Bayesian network. Overall, the parent/child relationship of the BN structure is derived from the Bayesian theorem and chain rule that enables the quantification of relationships among the variables. Hence the joint probability distribution *of P(U)* represented by child(ren) A_i for each node on the network can be evaluated based on equation 28.

$$P(U) = \prod_{i=1}^{n} P(A_i|Pa(A_i)) \quad \text{Equation 28}$$

Where $Pa(A_i)$ are the parents of Ai *in* $P(U)$ reflects the overall relation of the nodes in the network.

In this regard the Bayesian network and influence diagram for the DSS were build using the Genie software (BayesFusion, 2020). Building the DSS require different approach as it requires utility inputs as value for decision choices. Therefore, first step in BBN analysis was to get sub-system availability using the MCS probability of occurrence obtained from the DFT analysis used as probabilities for the CPT of all the chance nodes. The BN chance nodes have 3 level first level identifies the probability of occurrence of the fault as a child of a component failure indicating either failed or not failed. The failure node represent components are linked as child nodes to subsystem node which provides the output is either available or not available depending on probability of occurrence of MCS in CPT, Figure 16 a simple sketch of the BBN structure.

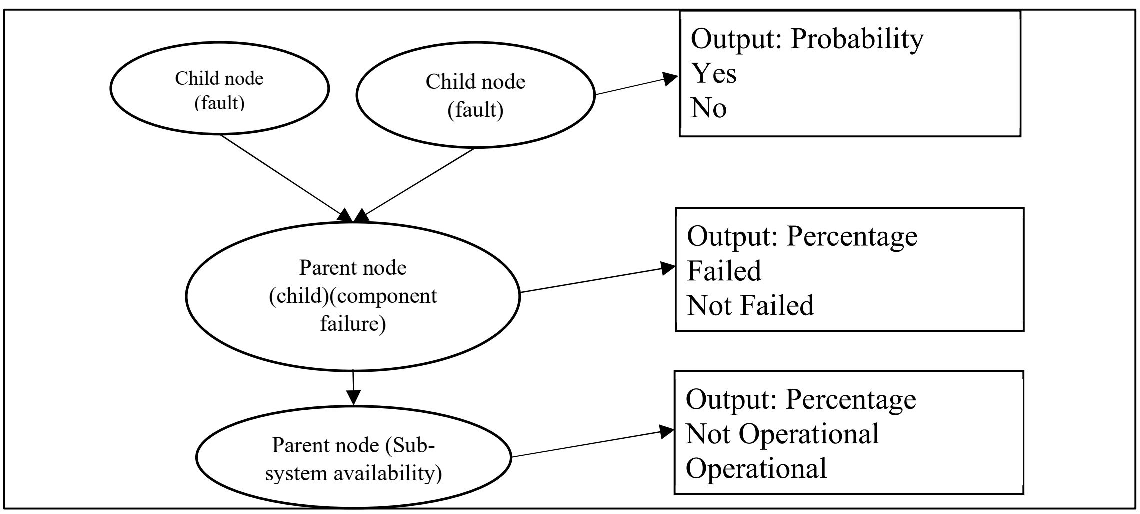

Figure 16: BBN structure

3.8.1 Maintenance Strategy Decision Support System Framework

The Maintenance Strategy Decision Support System (DSS) extends from the BBN with additional input from the other tools in particular the DFTA and FMECA as well as BBN influence diagrams. The BN availability output together with the FMECA RPN provides vital inputs for the DSS in addition to maintenance strategy choices. The influence diagram for the maintenance decision support uses additional nodes namely, decision and utility (value) nodes, each of which provides a complementary evaluation of the input variables. The decision nodes take in variable assigned by the decision maker in order to model available decision variables. The value node, also known as the utility node, is the second node in the decision process. It assigns a numerical score to each possible outcome of the parent node, reflecting how desirable that outcome is. The last node is the chance nodes which contain random variables representing uncertainties or probabilities that are relevant to the occurrence of the events (BayesFusion, 2020, Daya and Lazakis, 2023).

Accordingly, the inputs in making up decision nodes were probabilities of MCS of the components of each sub-system as inputs in CPT. Therefore, these 3 nodes formed the methodology of the DSS which interpret the desired outcomes based on the available choices while; the value node takes in continues variables as a measure of the parent nodes (subcomponent) criticality. In this way the utility value nodes provide the expected utility of a parent node or top event feeding it to decision node to get its availability percentage the decision variables are the maintenance strategy options in Table 6. The BN availability output together with the FMECA RPN provides vital inputs for the DSS in addition to maintenance strategy choices. Therefore, the maintenance DSS incorporate The model for the maintenance DSS has two additional types of nodes namely, decision nodes and value node. Decision nodes represents the choices that the decision maker can make i.e., maintenance strategy choices. On the other hand, value or utility nodes evaluate how desirable the outcomes of the decision process are, based on a numerical utility function for each possible outcome of the parent node. These nodes complement the inputs variables in the diagram. The last node is the chance nodes which contains MCS probability variables obtained through DFTA components analysis. This values are used as entries to CPT representing uncertainties or probabilities that are relevant to the occurrence of the events(BayesFusion, 2020).

Therefore, these 3 nodes formed the methodology of the DSS which interpret the desired outcomes based on the available choices while; the value node takes in continues variables as a measure of the parent nodes (subcomponent) criticality. In this way the utility value nodes provide the expected utility of a parent node or top event feeding it to decision node to get its availability percentage. Therefore, the decision node in the influence diagram contains maintenance decision choices which are dependent on the RPN variables inputs in value nodes as shown Table 6.

Table 6: Maintenance Strategy Options

Maintenance Strategy	Definition	RPN Range (0-100)
Corrective Action	This is recommended for very high to high mission critical component or faults for example sea water supply pump impeller, fuel supply pump, automatic voltage regulator faults etc.	75-100
Condition Monitoring	This strategy serves as intervention to ensure system availability targeted at component or failures whose early identification could avert major operational delays.	55-75
Planned Maintenance System	The PMS maintenance choices prioritise time dependent component failures with no immediate impacts to availability repair requirements.	35-55
Delay Action	Delay action maintenance choice is directed at those components with good resilience or sufficient redundancy such that there is little or no danger personnel and system safety.	0-35

The definition in Table 6 provides a general guidance in the maintenance selection process in the DSS and used in the decision nodes. Making the selection depend on 2 variables which include the RPN and availability. In this regard the normalised RPN factors down time, maintenance cost and lost utility due to failure have been accounted for while the availability factors in component availability within operational period. Hence all the DGs are evaluated based on 2 main factors which are availability and system/component mission criticality based on RPN values as presented in Table 7.

Table 7: DSS ranking scale.

Linear Scale (1-10)	Severity Level	Criticality Level	Likelihood Level	Maintenance Decision	Normalised RPN (Utility Value)
0	Minor	Minor	Remote	Delay Action	0-35
1-4	Low	Low	Low	Delay Action/PMS	
4-6	Moderate	Moderate	Moderate	PMS	35-55
6-8	High	High	High	ConMon/Corrective Action	55-75
8-10	Very High	Very High	Very High	Corrective Action	75-100

3.9 Chapter Summary

The chapter presents a methodology that provides a comprehensive analysis towards improving ship availability and maintenance decision support, considering various factors such as operator concerns, original equipment manufacturer (OEM) recommendations, and environmental impact. Accordingly, it proposes a hybrid approach to system reliability and failure mechanics that integrates multiple tools such as Dynamic fault tree (DFTA) for system reliability and criticality analysis, failure mode effect and criticality analysis (FMECA) for identifying mission-critical components while considering operator sentiment, and Bayesian Belief Network (BBN) for dependability analysis and maintenance decision support system (DSS) are the selected analysis tools. In addition, an artificial neural network-based machine learning model is devised for classification and fault detection.

In this regard, data used for the research was obtained through on-board data collection campaign and survey through questionnaire. The data collected includes machinery health log data and maintenance, repair, and overhaul (MRO) reports. Therefore, through a systematic combination of data acquisition methods, system reliability analysis and data analytics the chapter provides insight on the methods adopted to develop a hybrid framework for reliability analysis and fault detection of marine system components. Overall, this chapter presents a methodology that integrates multiple tools, including DFTA, FMECA, BBN, and machine learning, to develop a hybrid marine system component reliability analysis and fault detection framework. The inclusion of on-board data collection and operator input through questionnaires enhances the comprehensiveness and inclusivity of the analysis.

4. Case Study

4.1 Chapter Outline

As a follow-up chapter to the presented methodology, this chapter shall present the process and adoption necessary for the successful implementation of the approach. The data used for the research was obtained from an Offshore Patrol Vessel (OPV) serving with Nigerian Navy. In this regard the analysis and tools used for the research were selected to address both generic and specific component criticality and maintenance decision support system for ships of any type. Accordingly, this chapter is presented in 4 sections: Section 4.2 describes case study data acquisition process and overview of the case study vessel operational profile. Thereafter, Section 4.3 presents the case study models and data categorisation process. This is followed by Section 4.4 showing the development of the FMECA tool including the survey process using a questionnaire. The DFT analysis is presented in Section 4.5 which includes the criticality analysis using Birnbaum importance measures, the minimal cut sets result critical faults as well as the use of dynamic SPARE gates to indicate effect on maintenance improvements to system availability. The correlation analysis of machinery data and future engineering as well as fault identification using ANN comes in Section 4.6. Section 4.7 describes the BBN model and the overall maintenance DSS.

4.2 Case Study Overview

The case study is conducted on the power generation system (PGS) of an offshore patrol vessel (OPV) consisting of 4 main MDGs with no emergency. The PGS of a ship provide one of the most critical services onboard, therefore failure or degradation in performance would result to serious interference on the vessel availability and in some case risk to lives and property. Moreover, the fact that the MDGs remain the primary source of power supply to the ship makes the PGS a very critical system onboard which the ship cannot afford to lose. Accordingly, operators desire to avoid extended downtime on key ship systems, such as power generation plants, as this can lead to undesirable consequences beyond economic and operational losses.

In this regard, the selection of the MDGs onboard the OPV is premised on the critical role the MDGs provide onboard which is vital to safety, habitability, and services. Additionally, the MDGs onboard are a new introduction to the Nigerian Navy, therefore there are some differences as regarding maintenance and servicing routine with the common models of MDGs used onboard other Nigerian Navy ships. Accordingly, these differences are further complicated by the lack of maintenance documentation and adequate training to the ship staff, due to which majority of time the OEM has to send representatives to conduct ship level maintenance tasks. This coupled with the inability of the MDGs to take up to 50% of rated capacity is a cause for concern. Hence the need to research on some of these issues with a view to identifying the cause of failure, mission critical components and critical faults.

Therefore, a methodology to analyse the factors affecting the reliability of individual diesel generators as well as the most critical components to failure is presented using FMECA and DFT analysis, while BBN was used to suggest a maintenance approach based on cut set analyses. In this way, all the major reliability issues were investigated, and related components prone to failure were identified. Moreover, the SPARE Gate analysis provides a means to simulate or measure improvements that can be achieved through implanting additional maintenance practices such as inspection, testing, and monitoring.

However, to enable a comprehensive analysis of failures and their causes, there is a need to further investigate machinery performance data. In this regard, machinery health parameters obtained through machinery hourly log data were utilised for diagnostic analysis using machine learning. Therefore, ANN SOM was implemented for unsupervised learning, while feedforward neural nets were adopted for supervised learning pattern recognition analysis. It was important to implement both supervised and unsupervised learning methods to improve the quality of results. Moreover, the raw data collected from the case study vessel was unlabelled; hence, unsupervised learning was adopted to improve feature engineering through pattern recognition.

4.2.1 Case Study Vessel Operational Profile

The vessel selected for this research belong to the Centenary Class OPVs of the Nigerian Navy. The vessel is mainly engaged in patrol duties typically lasting 3-4 weeks at sea and 2 weeks at harbour. In additional to normal patrol the vessel can conduct search and rescue operation, oil spill clean-up and helicopter recovery and launching. Hence, the PGS is unarguably the most critical system onboard. Accordingly, it is equipped with 4xMDGs rated at 440Volts, 60Htz 3phase, 400kW, with no emergency MDG. All MDGs can operate individually and in parallel during high load demands or as required. Furthermore, is a standard practice in navies to run on parallel MDGs while transiting through a channel or any area of restricted traffic. In this regard MDGs usually have high running hours compared to most machineries onboard. Moreover, the MDGs are used for power generation only and are the primary source of power to the ship both at harbour and at sea except occasionally when the ship is at her home port where she receives shore power supply.

Overall, the MDGs have an average monthly running hours of about 160 hrs per generator. It therefore becomes important to ensure their availability while efficiently putting in place a maintenance strategy that considers the environment. In this regard, failure rate data over a period of 6 calendar years obtained from the maintenance records and used as input for the DFTA analysis. Therefore, Table 9 provides a summary of the failure rates obtained for the individual MDGs, and a complete failure rate data is presented in Appendix 3.

Table 8: Component failure rate per 10000 hours samples

Components			**Frequency**			
	Failure type	**Action taken**	**MDG1**	**MDG2**	**MDG3**	**MDG4**
Turbo charger	Black smoke	Replaced, Repaired	8	10	12	12
Lub oil cooler	oil leakage	1. Replaced 2. Cleaned and zinc anode replaced*	16	18	15	16
	external leakage		10	8	8	12
Oil cooler valve	failed	remove/repaired	1	1	2	1
Cylinder head	1. oil leakage 2.Fresh water leakage from A2 exhaust 3. Unable to start	1.Liner, O-ring replaced (G1&G3) 2. Cylinder replaced (G3&G2) replaced gasket (G3)	20	19	1 x (A1&A2) 3x (A2, liner) 2x (A2 head) 1x (A3& B2 gskt)	21
		Guide bushing	20	14	20	20
		O-ring	28	32	23	23
		Holding bolts	18	17	17	16
Cylinder jacket/sleeve	1.Scuffed x 4 2. Cracked x 2	replaced	11	12	11	12
Piston	Rings	Replaced	12	13	13	14
	cooling/crown		8	13	15	14
ConRod	bent		7	9	8	9
	Gudgeon pin		8	6	8	6
Drive belt	failed	replaced	8	8	9	11
	Torn(wear)	replace	11	5	9	3
Mech Injector pump	1. Cracked bolts 2. Broken bolts 3. Broken shims	1. Replace bolt and drive (G1&G3) 2. Replace bolt, pulley, and set injector timing (G1&G2)	16	12	12	13
	Drive	defects	22	20	21	24

4.3. Case Study Model Development

The case study implements a novel methodology through the combination of reliability analysis tools to address maintenance challenges on the power generation plant onboard an offshore patrol vessel (OPV). Moreover, failure of the power generation system for naval platforms has several implications especially considering the number of personnel onboard, and vulnerability due to loss of weapons, surveillance, and habitation platforms usage. The location and type of failure are important factors to be considered in maintenance planning due to logistics and OEM related concerns. Furthermore, conducting analysis of this nature is tasking and equally wide due to multiple factors and components involved. External influences from other service providers such as engine room air supply fan, location of fuel supply tanks, seawater supply connections were among some key influencers to engine room machinery reliability. Human factors such as skills level, knowledge of equipment, ease of access to equipment for maintenance and repair purposes could affect the quality of work and reliability of operation.

In view of the above, it becomes necessary to delineate boundaries establishing local and global limits to factors that can cause failures or influence them. Therefore, considering that not all these factors are within the control of the operators due to natural and human influences which can be difficult to model. A system boundary was designed to limit the extent of the model to only the systems directly connected to the MDG or systems that are externally rigidly connected to MDG such as the sea chest for sea water supply and the fuel supply system, as represented in Figure 17.

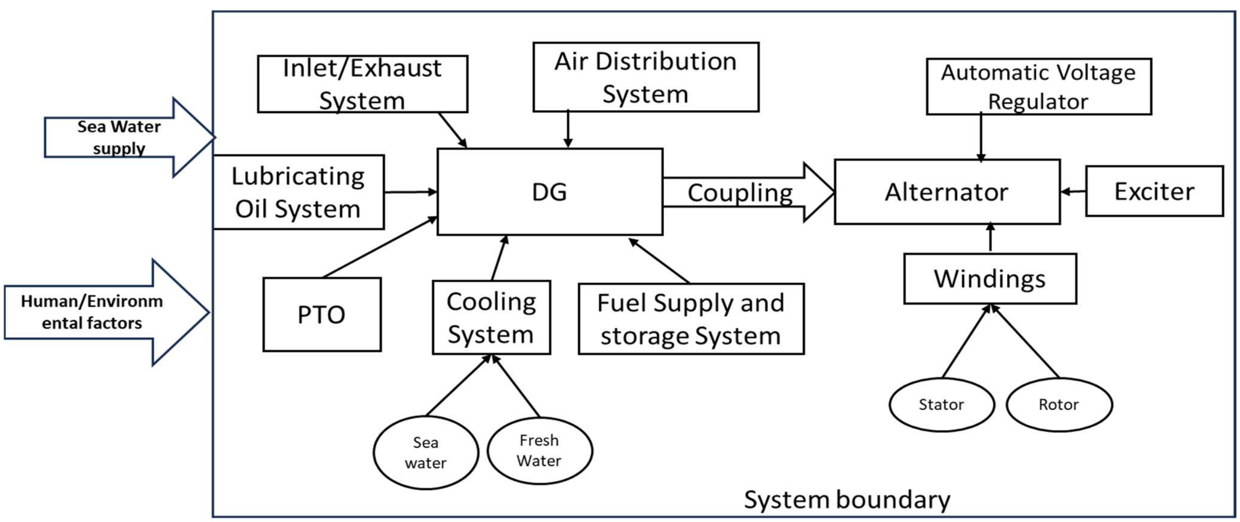

Figure 17: Case Study System boundary.

Accordingly, having established the system boundaries; data categorisation used for the analysis in the research will be discussed. As earlier highlighted the research utilises a combination of reliability and data driven analysis tools which required different data types. In this regard, to help clarify this requirement a data categorisation was adopted to cover subjective and objective inputs of the analysis. The subjective aspect of the case study provides intuitive guidance on model quality, while the objective part of the methodology provides numerical analysis using failure rates obtained from MRO data and machinery log data as inputs to DFTA and ANN respectively. Subjective analysis using FMECA presents experts judgement about failure and component criticality that formed the bases of the RPN. In this regard derived objective and subjective outputs namely IM and MSC from the DFTA and RPN from the FMECA were used as inputs for BBN therefore forming the bases for maintenance strategy selection of individual generators. A list of inputs and outputs and respective tools employed in the thesis is presented in Table 10.

Table 9: Employed Tools Inputs and Outputs

Tool	Inputs	Outputs
FMECA	1. Failure Modes 2. Numerical values for Criticality Severity and Likelihood	1. RPN 2. Categorical values for Criticality Severity and Likelihood
DFTA	Component Failure Rates	1.Reliability 2. Availability 3. Reliability importance measures 4.Minimal Cut Sets
BBN Availability	1.Minimal Cuts Set 2. Failure rate percentages	1. Availability
BBN DSS	1. Availability 2. Risk Priority Number 3. Utility (FMECA survey comments)	Maintenance Decision
ANN	1. Machinery Health Data 2. Fault label data	Fault identification Anomaly Identification

4.3.1 Overview of Input Data

Data plays important role in vessel lifecycle management especially with the advances and access to sensor technology. Machinery health monitoring has become even more affordable and customised enabling real time data monitoring, recording, transmission, and analysis. Hence improving data driven analysis while enhancing the use of historical and quantitative data utilisation in maintenance planning and management. The data utilisation in this research epitomised the importance and benefits of utilising multiple data types for machinery system reliability and fault identification. Accordingly, as has been discussed earlier, data has been categorised into subjective and objective data to ensure adequate information extraction from both historical data, parametric machinery health data, and equipment operators. The approach enables in-depth and realistic analysis through combined evaluation of deterministic and non-deterministic data outputs.

Accordingly, categorising data into 2 broad types namely Subjective and Objective is design to improve data extraction and utilisation especially in real time dynamic operational circumstance. Often, equipment does not work within the designed operational envelope, therefore, operators are challenged to adopt alternative means operate machinery more efficiently, through load evaluation, adjustment of operational parameter limits and physical additions or alteration to ensure that equipment work within safe limits. However, this adaptation and alteration could distort the normal way an equipment work hence adding more complexity in maintenance data collection and analysis. In this regard, subjective data analysis provides a measured approach on data collection an information extraction from equipment operators. The objective data type includes information extracted from machinery historical data and machinery health data obtained from machinery logs.

4.3.2 Input data description

In general information from equipment operators is important in providing clarity during data analysis and it serves the time or need to always fall back to the operator for clarification. For instance, at the time of data collection there was noticeable difference between the maximum operating temperatures recorded in the log and what is provided in the operating manual of the MDGs. Furthermore, the difference between the rated output and attained maximum power output the MDGs in service was up to 45%. It was therefore necessary to establish those difference and reflect it the data cleaning process because that could impact on the outlier analysis. Hence, a modified data range was adopted as shown in Table 11.

Table 10: MDG Health Parameter Ranges

DG health parameter	**Normal range**	**Operating Range Variation**		**Alarm**
		Operator	OEM	
Freshwater Temperature A /B-Bank	76-82	85 C	90 C	90-92 C
Exhaust gas Temperatures A/B-Bank	250-520	480 C	500 C	520 C
Lub Oil Temperature	40-95	90	110	113
Lub oil Pressure	0.45-0.6	0.8	0.1	0.12
Engine power output (kilowatt)	100-350KW	240KW	400KW	440KW

The case study was focused on analysing machinery health and maintenance history in order to gain insight into operational and reliability issue of MDGs. In this regard this section provides a detailed description of the input data used for this case study aimed at analysing historical data related to machinery health and maintenance activities to identify patterns, predict failures, and optimize maintenance DSS. The dataset includes information on the 4

MDGs and their corresponding maintenance records. The data is organised into several tables and includes the following categories of information.

4.3.2.1 Sensor Data

Generator log data covering approximately 4800 operating hours over a duration of about 18 calendar months was collected. The available data obtained from the 4 diesel generators comprised of 9 headings obtained from 11 distinct sensors. (1) Generator Speed, (2) Lubricating Oil Pressure, (3) Fresh water temperature bank A (4) Fresh water temperature bank B, (5) Fresh Water Pressure (6) Lubricating oil temperature, (7) Exhaust gas temperature bank A, (8) Exhaust gas temperature bank B, (9) Generator running hours (10) Generator Power Output and (11) Datetime, as presented in Table 12. A sample MDG1 used as training data is at Appendix 4.

Table 11: Sensor data parameters

No	Parameter	Abbreviation
1	Lubricating Oil Pressure	LoP
2	Cooling Fresh Water Temperature	FWT(A/B)
3	Lubricating Oil Temperature	LoT
4	Fresh water pressure	FWP
5	Exhaust Gas temperature	EGT(A/B)
6	Engine Speed	RPM
7	Power Out Put	KW
8	Generator running hours	HRS
9	Datetime	H:M

4.3.2.2 Machinery history

Machinery history information covering up to about 78 operational months was collected. The information includes data on maintenance activities such as repairs, overhauls as well as schedule maintenance activities forming part of PMS. This information provides insight on failures, their frequency, and dates while in some cases the causes or triggers of the failures is also available. The MRO also provide what maintenance action was taken regarding replacement or repair of components or in some case remedial actions taken to alleviate the situation. Overall, machinery historical data despite some errors in recordings and some ambiguous inputs, provides important details that can be used with machinery log data for fault identification or investigating unclear records in logs. This information that was used to calculate the failure rate data used as inputs for the DFTA analysis.

Therefore, the data was reformatted to enable its usage for both the reliability analysis and fault identification. Consequently, FMECA approach was taken to update the raw data from the ship and the columns names were given as Machinery identification, Component, failure type, failure cause, action taken. A sample of the original report collected from the operators is shown in Table 13.

Table 12: Raw Maintenance Repair and Overhaul Data Collected from Case Study Ship

Serial	**Date of occurrence**	**Generator**	**Defects of Generator**	**Action Taken**	**Action Performed by Manufacturer/Ship Staff**
(a)	(b)	(c)	(d)	(e)	(f)
1.	March 2014	Generator 1	Partially black smoke	Replaced Turbo Charger	
2.		Generator 2	Partially black smoke	Replaced Turbo Charger	
3.		Generator 3	Partially black smoke	Replaced Turbo Charger	
4.		Generator 4	Partially black smoke	Replaced Turbo Charger	
5.		Generator 2	Defective AVR	Replaced AVR	
6.	16 Jun 14	Generator 4	Oil leakage from Oil cooler	Replaced oil cooler	
7.	October 2014	Generator 3	Oil leakages from A1 and A2 Cylinder head	Replace Cylinder head O rings	
8.	19 Dec 14	Generator 3	Cracked A2 cylinder Liner	Liner replaced with new one and some o rings	
9.	1 Jan 14	Generator 3	Broken gear Train	Replaced gear train for injector pump drive	
10.	16 Apr 15	Generator 3	Torn Pulley belt	Replace pulley belts.	Ship staff
11.	17 Apr 15	Generator 1	Cracked bolts on injector pump drive	Replace cracked bolts and pump drive.	
12.		-	Injection Pump drive bolts broken	Replaced bolts, pulley and set Injection timing	
13.	6 May 15	Generator 1	Cut pulley belt	Belt Replaced	Ship staff
14.		Generator 3	Worn out pulley belt	Belt replaced	Ship staff

Moreover, the tools adopted for the research would require multiple input types in order to factor some additional variables which are largely subjective but could help with maintenance DSS outcome. This is more so, as there are multiple issues affecting maintenance delivery onboard ships some of which includes, training, quality of fuels and lubricants, operation requirements and environment/ climate conditions which may not be adequately captured by the OEM. In view of the forgoing the data was broadly classified into subjective and objective data as explained below.

4.3.2.3 Subjective Input

Subjective input obtained through FMECA analysis was done for the MDGs. The FMECA was targeted at getting expert opinion on the how failures mechanism and how the DGs are impacted by these failures. It also provides experts judgement on how this failure affect platform availability due to issue such as, spare parts availability, technical expertise, delays due to OEM and impact of the operational environment including practices. The outcomes from the FMECA were used to generate the RPN number and normalised to obtain the mission critical component. Details of the subject inputs analysis are discussed under FMECA process presented in section 4.4.

4.3.2.4 Objective Inputs

The objective phase of the case study provides a system reliability analysis using quantitative failure rates values of the 4 MDGs, therefore providing a numerically objective input. The DFTA results include component reliability, importance measures (criticality) and cut sets, which provide a significant understanding on the MDGs reliability. However, it was difficult to identify specific repair, maintenance or component failure that present the highest challenge to the operators. Therefore, considering that the MCS is a combination of minimum number of events which must occur for the top event to occur (component failure); it therefore provides a good source of variables for building the BBN while taking additional inputs from the FMECA as RPN.

4.4 FMECA Process

The FMECA survey was design to cover failure impacts on the major sub-systems of the MDGs as perceived by the operator. In this regard respondents were asked to provide numerical response in a scale of 0-10 on Criticality, Severity and Likelihood of 81 faults on different components of the MDG. Overall, all respondents are engineers with varying experience and specialisation. In this regard, consideration for experience includes years in service which ranges between 5 and 28 years, types of ships and unit served as well as positions held. On the other hand, specialisation categories were mainly 2 which are Marine and Weapon Electrical engineers. The 2 variables, experience and specialisation were used as weights in percentages and applied to individual inputs of all respondents. Table 14 shows respondents experience and assigned weights. The assign weights are a product experience in years and positions held.

Table 13: FMECA survey weights applied to Respondents.

Positions	Respondents	Experience	Ag Weight	Applied weight (%)
WKO/WKD	2	3-5years	50+0	50
WKDWEO/MEO	2	5-11 years	60+0	60
WEO/MEO	4	11-15 years	65+5	70
FSWEO/FSMEO	5	15-20 years	70+10	80
FSMO/FSG CMDR	3	20-24 years	75+15	90
FSMO/FSG CMDR	2	24-28 years	80+20	1
FSG CMDR	2	28-30 years	100+0	1

Accordingly, all individual inputs were evaluated to reflect years of experience and specialisation of the respondents based on equation 29. Thereafter, provides the required groupings to get the population mean were collected to arrive at single output per criteria equation 30. Adopting the above weights, individual responses were evaluated according to experience and specialisation to obtain the population mean equation. Thereafter a weighted average is taken for each grouped experience, equation 31, which provides single category for criticality analysis to obtain RPN.

$$W_1 = \sum_{i>0}^{n} C_1 \left(\frac{e+s}{100}\right) + C_2 \left(\frac{e+s}{100}\right) \ldots\ldots C_i \left(\frac{e+s}{100}\right) \quad \textit{Equation 29}$$

Where W_1 is the weighted component score for rank 1, n is the number of respondents in that rank, C is evaluated criterion.

$$\mu = \frac{\sum x}{N} \quad \textit{Equation 30}$$

$$population\ mean\ \mu = \frac{\sum x}{N} \quad \textit{Equation 31}$$

Where μ is the population mean, x = data values, N = number of samples

Using the population mean for each group the weighted RPN for each subsystem and component was evaluated and normalised to ≤100.

4.4.1 FMECA Survey Questionnaire Design

Information obtained from operators can help provide further insight regarding operations and maintenance of equipment especially with a tool that provides some flexibility in both input data and output data. In this regard, the survey questionnaire was design to highlight the significance of the key components in all the seven subsystems of the MDG and that of the alternator. In this regard, a total of eight subsystems were presented in the survey questionnaire.

The FMECA table was developed in collaboration with the engineering personnel representative from the case study ship, the 3 representatives from the fleet support groups and 2 representatives from the naval Engineering branch at the headquarters. Additionally, the commanding officers of the case study ship and her sister ship were equally consulted. This process helped to build the FMECA inputs collaboratively prior to sending the questionnaire. The Survey questionnaire is at Appendix 5.

The experience level of the respondents was between 5 to 28 years of service and drawn from the 2 specializations which are Marine and Weapon Electrical Engineer. Both specialisations are expected to have good understanding of how DGs work and the interaction between the subsystems of the MDG. Therefore, appropriate statistical models were used to gain insight of the data. The survey was conducted mainly to quantify the 3 criteria needed for the calculating the RPN which are Criticality (C), Severity (S) and Likelihood (L). Thereafter, the sample and population of mean of the seven groups were taken, however the difference of the was marginal hence the population mean was used to compute the overall result for the analysis. Table 15 - Rank and Weights method shows the applied weights per group using equation 32.

$$Samplme\ mean, \bar{x} = \frac{\sum \bar{x}}{n} \quad Equation\ 32$$

Where, W = weighted average, n= number of samples, w_i = Weights applied to X values and X_i = data values to be averaged

Where μ is the population mean, x = data values, n = number of samples

Table 14:Rank and number of respondents in each category

Ranks	Number	Weights	Positions	Weights	Total A	Total B	Applied weight (%)
Slt	2	50	WKO/WKD	Non	50	Non	50
Lt	2	60	WKDWEO/MEO	10	60	70	60
Lt Cdr	4	60	WEO/MEO	10	60	70	70
Cdr	5	65	FSWEO/FSMEO	15	65	80	80
Capt	3	70	FSMO/FSG CMDR	20	70	90	90
Cdre	2	80	FSMO/FSG CMDR	20	80	100	100
R/Adm	2	100	FSG CMDR	Non	100	100	100

Therefore, due to limited reliability data for marine systems, qualitative assessment based on experience and system knowledge is often the only way to conduct a meaningful criticality assessment. Accordingly, the following criteria were shared with respondents to support their judgement in the assessment.

a. Failure Consequence (Influence/Factors): The way(s) in which the effects of a failure or a multiple matter (evidence of failure, impact on safety, the environment, operational capability, direct and indirect costs)

b. Critical failure: A failure mode characterised by an immediate impact on the ship's ability to proceed or fulfil a mission, potentially resulting in the necessity to abandon the mission.

c. Severity assessment: A means of establishing the risk to platform and personnel arising from the occurrence of a failure mode. It is based on a combination of the worst-case consequences of the event coupled with the probability of its occurrence.

d. Environmental Consequences: A failure mode or multiple has environmental consequences if it could breach any corporate, municipal, regional., national or international environmental standard or regulation that applies to the physical asset or system under consideration.

e. Detectability: Detectability is a variable used for measuring the RPN, however in the analysis detectability is replaced with Criticality based the definition given in "b" above. The Mission Criticality is evaluated based on adopted RPN approach which replaces detectability with critical failure. In the context of the research criticality is looking at the immediate impact of the failure event on the equipment or platform availability and readiness; consequently, Mission Criticality is given by Critical failure x Severity x Likelihood.

4.4.2 Component Mission Criticality Assessment Process

FMECA helps to explicitly bring out the most critical component failure which can assist in maintenance actions and planning. Therefore, the criticality ranking based on risk use a combination of the consequence (severity) of the failure and the anticipated likelihood of the consequence occurring (Marvin, 2021). Mission Criticality analysis will highlight failure modes based on their impact to availability, probability of occurrence and severity of consequence. Evaluating these three factors would enable a more streamed line process to implement most effective maintenance action. In this regard, the Component Mission

Criticality was obtained as normalised RPN as stated. Overall, the Mission Criticality goes beyond just the RPN but it also take into account the additional factors such as repair time, ability of ship crew to rectify fault at sea as well as the immediate impact of the failure to ship operations. These insights were obtained from the FMECA Effect of failure section based on the three descriptive variables: Local, Global and Influence/Factors. In this regard, the components were.

4.5 DYNAMIC FAULT TREE ANALYSIS

The DFTA analysis provides both qualitative and quantitative calculations. The qualitative analysis is performed using the structure of the DFTA dependent on logic properties of the gates. Windchill risk and reliability software was used for conducting this research, and it takes failure rate, MTBF, and frequency as inputs for reliability analysis. In this regard, component failure rates generated from the collected MRO data of the case study MDGs were used as inputs for the DFTA models. The generated output from the DFTA analysis includes system unreliability, unavailability, and reliability importance measures (IM) as well as minimal cut sets (MCS). Two of these outputs, were used foe building the BBN availability model details of which are contained in section 4.6.

4.5.1. Developing DFTA Structure and Input

The DFTA tool used for machinery/system reliability and availability analysis used input data generated from the operational records of 4 diesel generators for a ship power generation system. Therefore, a DFTA structure representing a functional ship power generation system as well as the individual diesel generators were developed. Figure 18 present a general view of the MDGs within the PGS while Figure 19 presents a explode subsystem view of MDG1. Developed DFTA structures for individual MDGs are presented in Appendix 6. System reliability in DFTA involves generating a qualitative model of the fault tree usually from the minimal cut sets on the logic gate of the fault tree. Thereafter, quantitative analysis using reliability and maintainability data such as failure rates/frequency, failure probability, mean time to failure or repair rate can be used.

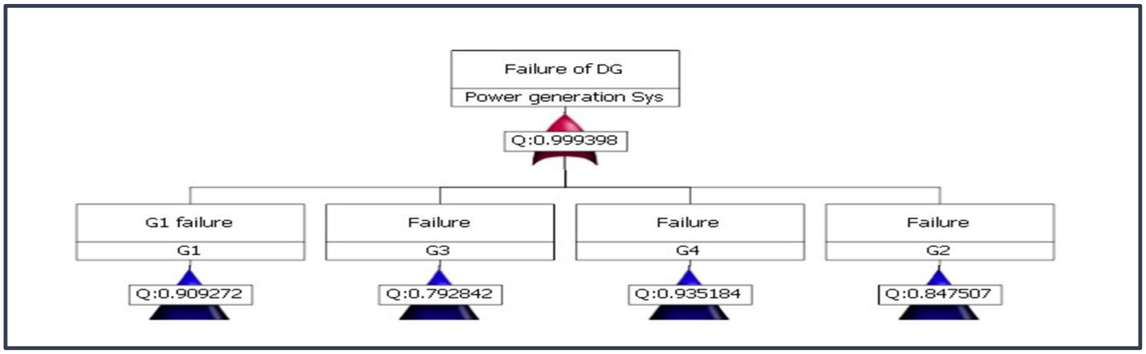

Figure 18: Power Generation System DFTA structure

Accordingly, failure and maintenance data over a period of 6 calendar years obtained from the maintenance records was processed to generate components failure rates (⅄). The model structure was built using both static and dynamic FT gates and events to reflect the mode of failures and in other cases dependency and sequence. Therefore, top events and sub-events were modelled using dynamic gates while gates connecting to the main system were modelled using static FTs this procedure is necessary to reduce memory usage and improve calculation time. The probabilities for the static gates used were generally AND gate, OR gate and VOTING gate. Voting gates are particularly important in accounting for multiple connected components (*k out of n*) such as injection nozzles, cylinder blocks, fuel day tanks or supply line, this is because correct functioning of system requires all component but is not necessarily impaired due to a few faulty ones.

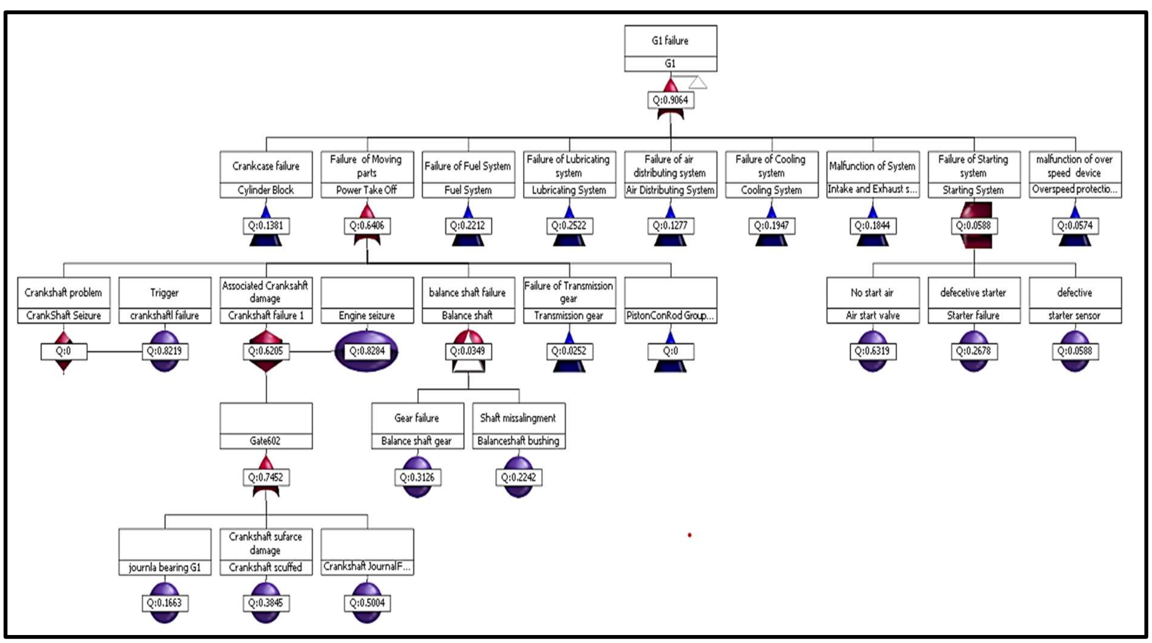

Figure 19: MDG1 DFTA Structure

4.5.2 Reliability Importance Measures

The reliability importance measures (IM) obtained through the DFTA provides information on most critical components in the various sub-systems including other auxiliary connections, like the sea chest. The Bir IM adopted to present the critical components shows better representation of the component failures based on the modelled structure as well as the number of components to analysed Table 16. Accordingly, in order to reflect some standard operating procedure as regards ship availability of the Navy's maintenance planning the study puts component criticality threshold at 40 %.

Table 15: List of components analysed.

Equipment	Subsystem	Component
Diesel Engine	Cylinder Block	Crankcase
		Cylinder liner failure
		Cylinder head bolts
		Top Cylinder gasket
		Cylinder head O-ring
		Defective engine seats
		Engine vibration
	Power Take Off (moving parts)	Crank Shaft failure
		Journal Bearings
		Piston assembly (Gudgeon Pin, rings, crown)
		Connect Rod
		Transmission gear
		Pulleys
		Balance shaft
	Cooling System	Heat Exchanger Tubes
		Sea water no return valve
		Sea water strainer
		Fresh Water Thermostat
		Fresh Water circulation pump
		Charge air Cooler
		Lub Oil Cooler
		Lub Oil Cooler thermostat
		Sea Water pump impeller
	Fuel Supply System	Fuel supply pump pulley bolts
		Fuel pump pulley bolts
		High pressure Fuel supply pipe
		Fuel return line
		High pressure Fuel supply pump (common rail)
		High pressure Fuel supply pump (gang injection system)
		Manual pre-supply fuel pump
		Injection Pump
		Injector nozzle
		Primary Fuel Filter
		Secondary Fuel Filter
	Air Distribution System	Cam shaft
		Tappet
		Valve assembly
		Charge air cooler
	Lubricating System	Oil Filter
		Oil pump
		Cooling Nozzle
		Turbocharger
		Injection pump
		Tappets
		Rocker
		Bypass valve
		Crankshaft

		Lub oil pump
	Inlet/Exhaust System	Valve Seat
		Air filter
		Tappet
		Air cooler
Alternator	Stator/rotor	Rotor Bearing
		Rotor coil/winding
		Exciter
		Automatic Voltage Regulator
		Stator windings
		Air gap

Furthermore, one of the novel ideas in this research is the component criticality mapping to faults using the BBN analysis tool which uses the DFTA IM and MCS as inputs. This approach is relevant to the realisation of the overall maintenance platform being developed which is geared towards a more flexible maintenance approach updated based on actual machinery operating condition. Component criticality for individual components was obtained from the DFTA analysis. The Bir IM was used to present the most critical components this is mainly because of its ability to identify the most critical component once the top event is said to have occurred. Moreover, readings for Cri and FV IM were obtained, but all appear to have the same values and were low, such that the system may not require any significant improvements, hence not a good representation of the case study maintenance and failure reports.

4.5.3 Minimal Cut Set

Minimal Cut sets are a combinations of component failures that can lead to the occurrence of a top-level undesired event or system failure. It helps in understanding the critical paths or failure modes that can cause the system to fail. Accordingly, MCS were adopted for qualitative analysis of the DFT and as input for BBN. MCS were adopted from BNN to conducted dependability analysis which accounts for CCF. Overall, there are several identified MCS in the study, however, to improve data management the study has identified 10 MCS as most critical components.

Overall, 8 subsystems and dependent components were modelled and analysed as shown in the BN structure. Using a bottom-up approach, discrete chance nodes were used to model faults which are then connected to parent chance nodes representing component having probability values as inputs to the CPT. The component chance nodes are linked to all possible faults including faults in other subsystems that could elicit multiple component failure as such resulting to greater maintenance or availability problems. The flexibility in BN that enables modelling CCF is very helpful in modelling complex failure interactions between components that serve many systems or subsystems.

4.5.4 Spare Gates

Spare gates are used to represent spares or redundancy in systems, sub-systems, and component duplication for enhance services or increase output. In this regard, can be modelled to represent how active a component or equipment is connected i.e., active standby, passive stand-by or dormant stand-by. Consequently, spares gates are categorised into hot, warm, or cold spares depending on their connection to the system which can be represented with 1 as active spare, 0-1 as warm spare(passive) and 0 as cold spare(dormant). A cold spare doesn't fail if the main spare failed while active and warm spares can fail with failure the main spare. This feature allows spare gates to be used to mimic spare parts availability, standby or redundant or alternate system. Additional they can be to simulate or model improvement in system configuration or maintenance action that could improve reliability Figure 20.

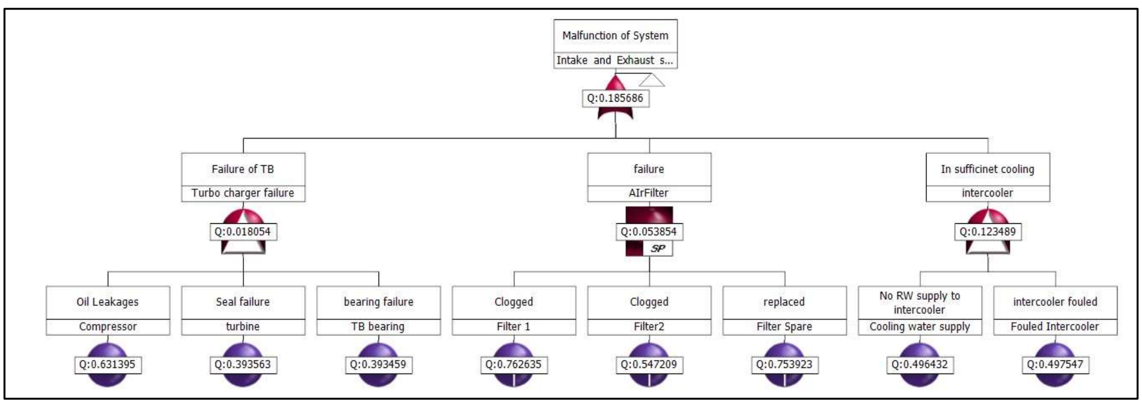

Figure 20: Spare gate instance in alternative repair

It is common to have parts in MDGs that are either redundant or active, for instance the cylinders, pistons and injector nozzles in multiple cylinder engines are a good example of active redundancies that can be modelled with spare gates. Components such as duplex filters, sea chest valve and emergency cooling systems have been modelled to consider impact on MDG availability. Figure 21 is an instance on the use of spare gate considering repairs remedial effect of crankcase repairs and replacement on the DG operational reliability. Overall, the spare gates provide a lot of flexibility that can be very useful for maintenance planning and in some cases procurement design analysis. In this case study spare gates were used on model some fault that appear prevalent on some MDGs, Table 17 is a list of system and faults modelled using spare gates. This approach was adopted since all MDGs appear to present common patten of failure and in most cases the same approach can be used to rectify the problem. Therefore, addressing a certain common fault one MDG can be applied to all.

Table 16: System and faults modelled with spare gates.

System	Fault	MDGs Applied
Cooling System		MDG2, MDG3
Sea chest	Blockages clearance	
Sea water strainer	swaps	
Fuel System		
Injector Nozzles	Nozzle failure	All MDGs
Fuel Filters	Filter swaps	
Crankcase	Crankcase /explosion	MDG1
Inlet and exhaust system		All MDGs
Air filer	Replacement	
Lubricating oil System		MDG3, MDG4
Oil Cooler	leakages	
thermostat	blacked	

4.6. Machinery Log Data analysis

As part of the overall case study, a data collection campaign was conducted onboard the case study ship. Machinery log data for 4 MDGs was access through the ship technical staff, with permission of the ship operators. The machinery data were collected in manuscript using large note books usually covering 3 months. Each MDG had a dedicated book, and all books are centrally managed by the Technical Department secretariat, which can be accessed in case of any disparity in the collected data. Overall, there were 8 parameters collected from 11 unique sensors. These sensors include datetime, Revolution Per Minute (RPM), Lubricating Oil Pressure (LoP), Fresh Water Temperature (FWT) bank A, Fresh Water Temperature (FWT) bank B, Lubricating Oil Temperature (LoT) and Fresh Water Pressure (FWP). Others are Exhaust Gas Temperature (EGT) bank A, Exhaust Gas Temperature (EGT) bank B, Running Hours, and Power Output in kilowatt (KW), Table 19 show the 8 parameters their limits.

Table 17: MDG health parameters and ranges

No	Parameter	Abbreviation	Operating Ranges		Alarm
			Min	Max	
1	Lubricating Oil Pressure	LoP	0.4 Mpa	0.55 Mpa	>0.6
2	Cooling Fresh Water Temperature	FWT(A/B)	75 ^{o}C	80 ^{o}C	>85 ^{o}C
3	Lubricating Oil Temperature	LoT	30 ^{o}C	110 ^{o}C	> 120 ^{o}C
4	Fresh water pressure	FWP	0.02 Mpa	0.25Mpa	>0.3
5	Exhaust Gas temperature	EGT(A/B)	220 ^{o}C	400 ^{o}C	>520
6	Engine Speed	RPM	1789 RPM	1850 RPM	2052 RPM
7	Power Out Put	KW	0	440KVA	440Kva
8	Generator running hours	HRS	≥ 2000hours		

4.6.1 Exploratory Data Analysis

The machinery health data collected for the analysis was in manuscript, therefore needs to be cleaned to remove entry and typo graphical errors during data transfer to electronic copy. Microsoft Excel was used for data entry and initial cleaning of some error entries was done using the built filter functions. However, due to data size and dimensionality of variables in the data it became difficult to carry out missing data imputation, outlier detection filling and trend analysis with the excel. In this regard both Excel and MATLAB were used in the initial data cleaning process afterwards MATLAB was used for detailed exploratory data analysis.

It is pertinent to state that the collected machinery health data was not labelled hence there the need to conduct further analysis to gain insight on fault indicators based on data threshold. In this regard, fault data was established based on data limits set by the operator and OEM alarm levels and extracted from the collected data. Therefore, using the Quartile method an acceptable minimum and maximum threshold on each of the variables was generated. In this regard, the data was arranged in ascending order to enable the division into the 4 parts such that Q2 represents all the nearest values to mean which are represent the safe working range and forms largest part of the data. While Q1 and Q3 represent lowest and median values representing about 5 and 75 percent of the data respectively. Q4 represent the highest data levels close to the maximum threshold values. Table 19. Using these values, the threshold for the outlier detection was set which was then used with MATLAB.

Table 18: Derived data limits

Future	RPM	LoP	FWT - A	FWT - B	LoT	FWP	EGT- A	EGT - B	Power (KW)
Minimum	1791	0.32	56	58	59	0.04	160	154	10
Q1	1798	0.39	64	71	86	0.08	303	309	100
MEDIAN	1800	0.433	65.2	73.9	87.45	0.078	329.5	321.9	120
Q3	1800	0.456	66.2	75.6	89.3	0.083	350.4	342.65	140
Maximum	1901	382	81.4	91.4	97.7	0.884	3340.3	3114	240
Q2(Mean)	1799	1.00	65.26	73	87	0.09	335	331	123
IQR	2	0.065	2	4.8	3.6	0.008	47.05	33.25	40
IQRx1.5	3	0.10	3	7.2	5.4	0.012	71	50	60
Lower limit	1795	0.30	61	64	80.3	0.063	233	260	40
Upper limit	1803	0.553	69.2	82.8	94.7	0.095	421	393	200

Conversely, addressing the discrepancy between the operator and OEM alarm levels requires careful consideration. In this regard, following the determination of quartiles, a 15% increment was applied to the upper limits. Accordingly, maximum threshold for outlier detection were based on Alarm levels presented in Table 21.

Table 19: Alarm levels for fault classification

DG health parameter	Normal range	Alarm
Freshwater Temperature A/ B-Bank	76-82	90 C
Exhaust gas Temperatures A/B-Bank	250-520	520 C
Lub Oil Temperature	40-95	113
Lub oil Pressure	0.45-0.6	0.12
Engine power output (kilowatt)	100-350KW	440KW

Using the obtained data values filling missing values and outlier detection was conducted on the data. Missing values were filled using linear interpolation and, in some case, forward fill/backword fill was used especially on variables representing temperature as they can change in no particular patten. Therefore, using this method would help retain the randomness in the time series as regard fault development. Similarly, considering the dimensionality of the data it becomes very difficult to adopt single approach of outlier cleaning.

Therefore, 3 outlier detection methods namely: Grubbs, generalised extreme Studentised deviate test for outliers (GESD) and linear interpolation were considered. Out of the three methods, the GESD and linear interpolation were used, while the Grubbs method was dropped due to the fact it assumes a normally distributed data with a single outlier hence unsuitable for machinery health data applications. Moreover, machinery sensor data would contain multiple outliers due to multiple factors, such as sensor noise, logging error, test data or transient records. On the other hand, is equally important to provide values indicating acceptable low and high data threshold that represents the ideal machinery operating limits. Otherwise, it is possible to miss categorised low and high values that represent actual machinery health anomalies.

Accordingly, the GESD was adopted to for outlier detection as it perform well on time series data having multiple missing values. Therefore, to ensure efficient analysis each column was treated independently especially that GESD is not as efficient when handling multivariate data sets. Similarly, missing values imputation was done using linear interpolation against some of the available methods such as mean, median, Last Observation Carried Forward (LOCF) etc. Moreover, linear interpolation also helps to preserve seasonality in time series data, hence improving the overall quality of information that can be extracted from the data. Accordingly, the outlier detection was conducted before the data missing data analysis to help maintain the centrality of data while conducting further data cleaning activities. This approach further helps to maintain the linear relationship between numbers which makes better for the linear interpolation approach to missing value imputation.

4.6.2 Feature Engineering

Feature engineering is needed to improve the accuracy of machine learning models in both prediction and diagnosis. Moreso, for MDGs or machinery that undergo frequent servicing or some maintenance procedure to ensure reliable operations, is usually difficult to identify failure and degradation by just analysing the trends in the data. In this regard, feature engineering helps fine-tune the data and brings out the most responsive predictor variables. Moreover, it also helps reduce the volume of data required which enables a more focused analysis. Consequently, Correlation analysis and Analysis of Variance (ANOVA) were used to get the relation between the variables in order identify the right response and predictor variables. Correlation analysis provides the linear relationship within the multiple variables in the data based on R-value between -1 and +1. The closer a value is to 1 the stronger the relation and vice-versa.

Similarly, ANOVA provides a statistical relationship within variable against target independent variable or variables. By comparing the difference among means of the independent variables and how each affects the dependent variable ANOVA establish the statistical relationship as the F-score of individual variables. Accordingly, ANOVA was used to determine feature importance of 7 variables that were found to be important for the analysis as implemented in the correlation analysis. Overall, the R-values of the correlation Matrix and ANOVA feature provided the foundation of the variables adopted in the machine learning analysis. Moreover, the two approaches were adopted based on acceptance in the research community for understanding the strength of relationship among variables statistical features, hence improving mutual validation. In this regard, Table 21 presents 7 variables used for both Correlation and ANOVA analysis, while the other variables collected were not used in the analysis are equally presented in Table 21. These, variables were not used because they do not impact the MDGs health and are not good indicators as regards performance and diagnostic analysis.

Table 20: Variables used for Correlation Analysis

Parameter (Variable) used	Abbreviations
Power Output	kw
Exhaust Gas Temperature A -Banks	ETA (EGTA)
Exhaust Gas Temperature B-Bank	ETB(EGTB)
Fresh Water Temperature A-Bank	FWTA
Fresh Water Temperature B-Bank	FWTB
Lubricating Oil Temperature	LoT
Parameters not used	
Fresh Water Pressure	FWP
Lubricating oil Pressure	LoP
Running Hours	H
Date Time	DT
MDG speed	RPM

4.6.3 ANN diagnostic Models

Artificial Neural Network (ANN) have been applied in the field of maintenance for machinery health analysis and prediction of machinery condition by various authors. Consequently, ANN has been adopted for machinery data analysis in this research for fault classification and detection. The analysis involves recognising patterns in the data that indicates the presence of variations pointing to a change in the normal health parameters of the system or machinery of interest. A supervised ANN feedforward neural network was implemented for the classification analysis. Feedforward ANN is a time series algorithm that can be used for both function fitting and pattern recognition. The Feedforward networks (FFNNs) usually have single or multilayer hidden sigmoid neurons followed by a series of output neurons. Multiple layers of neurons with nonlinear transfer functions enable the network to learn nonlinear relationships between input and output vectors.

4.6.3.1 ANN Self Organising Map Model

Feature selection is very vital to the success of the diagnostic analysis, in this regard careful attention was made to ensure that the feature selected among the variables is a good representation of the machinery health predictor. Moreover, the fact that the data was unlabelled an unsupervised learning was used to investigate the patterns in the data in order to identify the unique features in the data and partition it accordingly. In this regard cluster analysis was done using ANN Self-Organising. The adoption of ANN was to enable the identification of clusters in the data based on how the cluster are portioned. Machinery health time series dataset are in general multivariate made up of multiple variables representing the dynamic relationship of individual health parameters against its performance. Hence, this informed in the selection of ANN self-organising map SOM) due to their ability in handling high dimensional multivariate data in for feature engineering and dimensionality reduction. It provides good visualisation of the relevant data classes passed. Number of neurons, maximum of epochs, learning rate.

Accordingly, for the cluster analysis ANN SOM were used to improve the features selection for the faut detection model. The 6 variables were used as inputs for the clustering using a SOM topology consisting of 100 neurons arranged in 8x10 hexagonal grid. The during initial training 6x6 hexagonal grid was used which provides more than 6 clusters that were poorly defined. Consequently, more training was done using additional layers in order to improve the performance of the model output. Therefore, with increase in the number of layers the model ability to partitioned the clusters increases albeit with blurry. Accordingly, having released 3 distinct clusters the training was stopped and the fault detection model defined along the 3 faults.

4.6.3.2 Fault Detection

In general machinery failures give warning signs prior to occurrence by showing abnormal readings or slow deterioration in performance which may not very noticeable. Therefore, understanding the signs heralding failures would significantly help operators overcome most of the critical challenges in machinery failure and possibly abating it all together. In this regard, machinery log data collected from the case study ship were used to develop a diagnostic model. Input and response variables were obtained based on the outcome of featuring engineering, Table 23 presents the response and predictor variables. The predictor variables are represents the most sensitive parameters to the response variable considering the thermodynamics behaviour diesel engine.

Table 21: Diagnostic inputs variables

Variable	Abbreviations	Remarks
Fresh Water Temperature A-Bank	FWTA	Response Variable
Fresh Water Temperature B-Bank	FWTB	Response Variable
Exhaust Gas Temperature B-Bank	ETB(EGTB)	Response Variable
Exhaust Gas Temperature A -Banks	ETA (EGTA)	Response Variable
Lubricating Oil Temperature	LoT	Response Variable
Lubricating oil Pressure	LoP	Response Variable
Power Output	Kw	Predictor Variable

Fault classes were built to reflect the operational alarm levels of the MDGs rather than the the design alarm levels taking in both OEM and operator limits as earlier highlighted in section 4.6.1. Moreover, the fault detection analysis phase of the machinery health parameter can help with more valuable information on changes that occur at certain load condition which may not be capture in operations manual. In this regard data threshold values presented in Table 24 were established to enable the fault detection model.

Table 22: Limits of Data Labels used for fault identification.

Fault	Fault Number	Fault Identity	Health Parameter	MDG Operating Temperature (^{0}C)
Normal Temperature	1	NTM	Normal Exhaust Temperature	80-110
High Temperature	2	HTM	High Exhaust temperature	110-115
Overheating	3	OVH	Engine Overheating	Max 120

Fault identification values were then developed using threshold values in Table 24. In this regard, using three fault classes namely Normal, Abnormal and Fault the diagnostic analysis for faut identification taking temperature as an indicator was conducted. Table 24 presents a extracted fault class data from actual data machinery health data that was used for the diagnostics analysis.

Table 23: Fault Labels

RPM	LoP	FWTA	FWTB	LoT	FWP	EGTA	EGTB	RH	KW	Fault Code	Temp
1800	0.458	72.9	75.4	90	0.067	332.1	319.5	5234	115	100	NML
1800	0.465	72.8	75.3	89.9	0.068	335.3	323.9	5235	120	100	NML
1800	0.59	72.01	74.06	89.3	0.068	329.5	316.7	5236	115	010	HTM
1800	0.53	70.7	73.2	87.6	0.068	310.2	29.4	5262	100	100	NML
1800	0.58	78	80.68	96.2	0.066	366.1	355.9	5294	150	001	OVH
1801	0.58	75.8	78.6	94.6	0.067	360.4	351.7	5298	140	010	HTM
1800	0.504	76.2	79.1	95	0.067	361.2	353.1	5299	140	010	HTM
1800	0.58	78.6	78.7	94.5	0.067	359.1	350.1	5300	140	010	HTM
1800	0.502	76.2	79.1	94.8	0.067	358.3	351	5201	140	010	HTM
1800	0.499	75.8	78.8	95.6	0.067	360.1	353.7	5302	150	100	NML
1800	0.488	77.8	80.5	96.1	0.066	374.2	363.3	5203	140	001	OVH
1800	0.498	77.3	80	95.8	0.066	364.3	354.3	5204	150	010	HTM

4.6.3.3 ANN Feedforward model

The task of fault identification is categorised as pattern recognition and can be implemented using multiple ANN models. In this case study, FFNN are adopted due to their simple architecture, ease of implementation and ability to acquire features from raw data. Moreover, FFNN are robust in handle non-linear relationships, and ability to generalise to unseen data.

They can be scaled to accommodate a variety of problem complexities, efficiently process data in parallel, and simultaneously manage multiple faults. Therefore, machinery health data collected from the case study vessel used for the diagnostics analysis. These consist of data collected from 4 different MDGs with same parameters as explained in section 4.6. FFNNs like most data driven methods adapt to specific fault patterns without relying on predefined principles because they are data driven. A two-layer feedforward network with sigmoid activation and SoftMax output neurons was adopted for the study. The model topology showing number of input, hidden and output layers as well as the activation functions are presented in Figure 21.

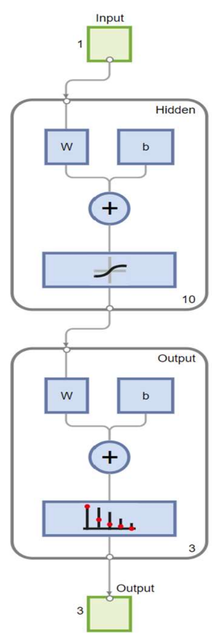

Figure 21: Adopted FFNN topography (Source: MathWorks 2023)

The sigmoid activation function helps to improve the prediction capability of the neurons by adding bias and non-linearity to the weights of the layers within a probability of 0 and 1. In this regard, each neuron representing a feature is activated on the strength of its association to the target variable, with 1 being a strong probability and 0 indicating week relationship. Overall, sigmoid is very efficient for binary classification problems on turning the input layers. The SoftMax function transforms the input vector into a probability distribution, with the output of each element ranging between 0 and 1. The aggregate of all output probabilities equals 1. The SoftMax function accentuates the differences between the input vector's elements, bringing the largest element closer to 1 (highest probability) and the others closer to 0.

Given the above context, a two-layer FFNN was developed for the fault detection analysis. The network comprised of 10 neurons in the hidden layer and 3 neurons in the output layer, utilizing the sigmoid activation function for the input layer and the SoftMax activation function for the output layer. The 10 neurons take the input predictor variables among the 7 variables presented in table 22 and compare to the 3-response fault class. The fault detection model was trained iteratively using all the predictor variables iteratively to until a good fit performance was achieved after 32 epochs. The best matching model was obtained using the Exhaust Gas Temperature as the predictor variable and Power output as the response variable.

The iterative training process using the selected features was done iteratively to help arrive at good conversion. In this regard, the performance of the training process to develop the diagnostic using FFNN presented in the below figures. Overall, the predictor variables consist of 1090 observations from 7 features out of which one was used, while the response variable includes 1090 observations from 3 classes. The data was them split 70 % training, 15 % validation and 15% test. A learning of was left at the default 0.01, as there was no need to change the it since the convergence was achieved in leas then 30 seconds at epoch 26 as shown in figure 23 after about 6 validation checks figure 24.

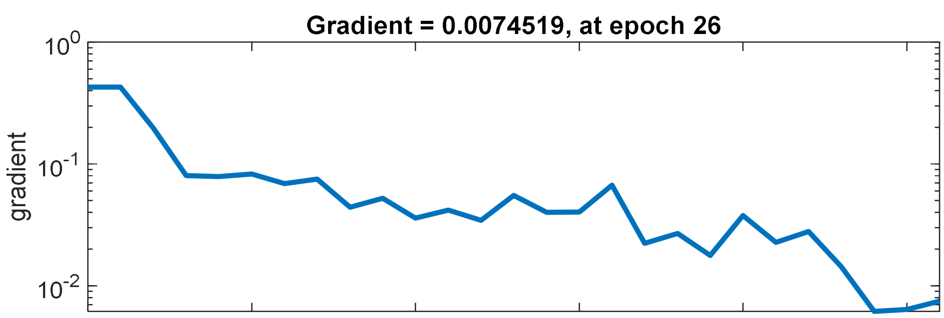

Figure 22: Training Gradient for the selected case study model

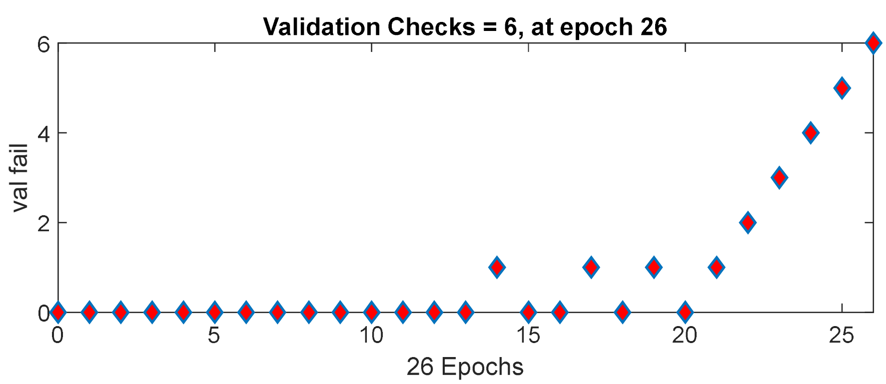

Figure 23: Validation checks for trained model

Additional information on the training model performance highlighting correctness of the training process as regards identification of classes in the data using (receiver operating characteristics) ROC. The ROC provides information on the proportion of how the model correctly or wrongly a captures a class indicated using True Positive Rate (TPR) and False Positive Rates (FPR) respectively as presented in figure 25.

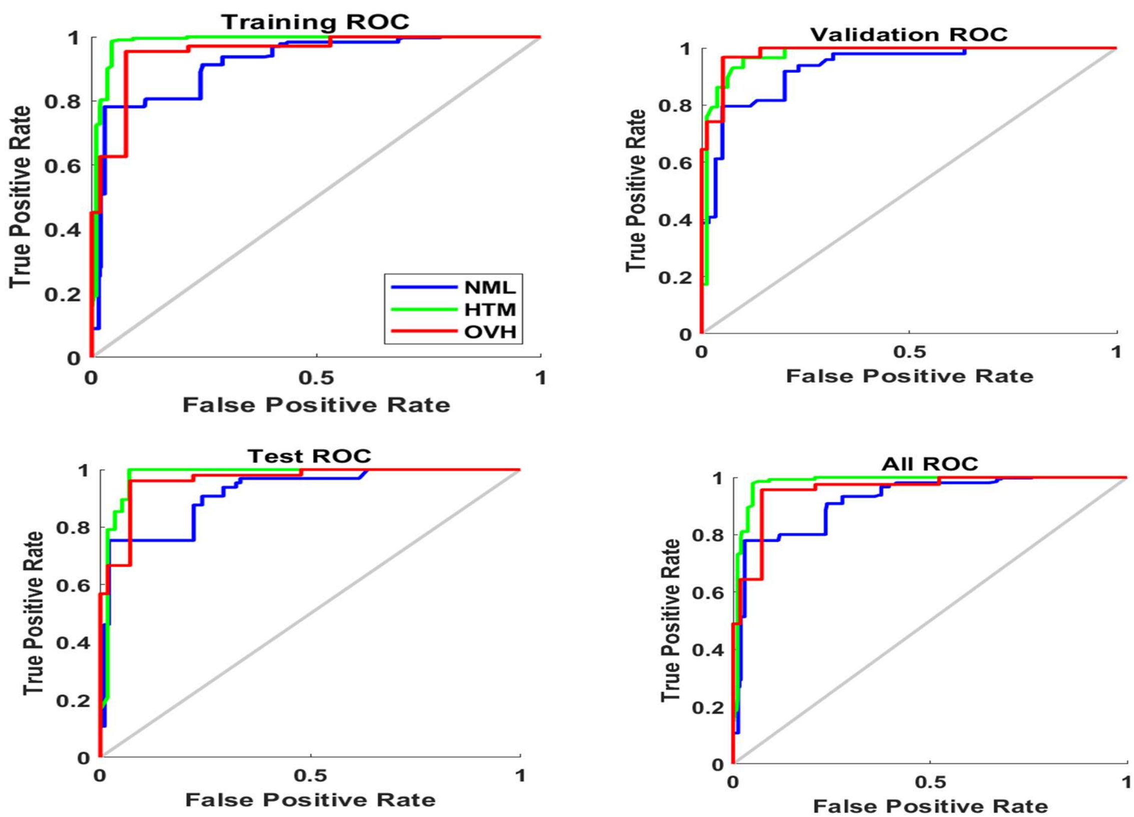

Figure 24: Model performance-based ROC scores.

Additional details on the training performance is given in the confusion matrix of the training, validation and test partitions. The matrices provide the percentage accuracy at each level of the model development as well as a combined or generic matrix for the 3 levels. Overall, the each of the classes had over 80 % score in matrices, which suggest a strong model performance. Furthermore, the combine output of the matrices as shown All Confusion matrix in figure 26, shows a collative score for the classes at 83.7 %; which proves the quality of the data and the choice of response predictor variables. The overall picture on model accuracy based on the confusion matrix for the diagnostic training model is presented figure 26. Nonetheless, the performance of the training model is further highlight in Figure 27. The best validation performance was achieved after epoch 46 on the 4th iteration which returned a cross entropy values as follows: training 0.1394, validation 0.1485 and test 0.1424.

Figure 25: Confusion Matrix for diagnostic Model.

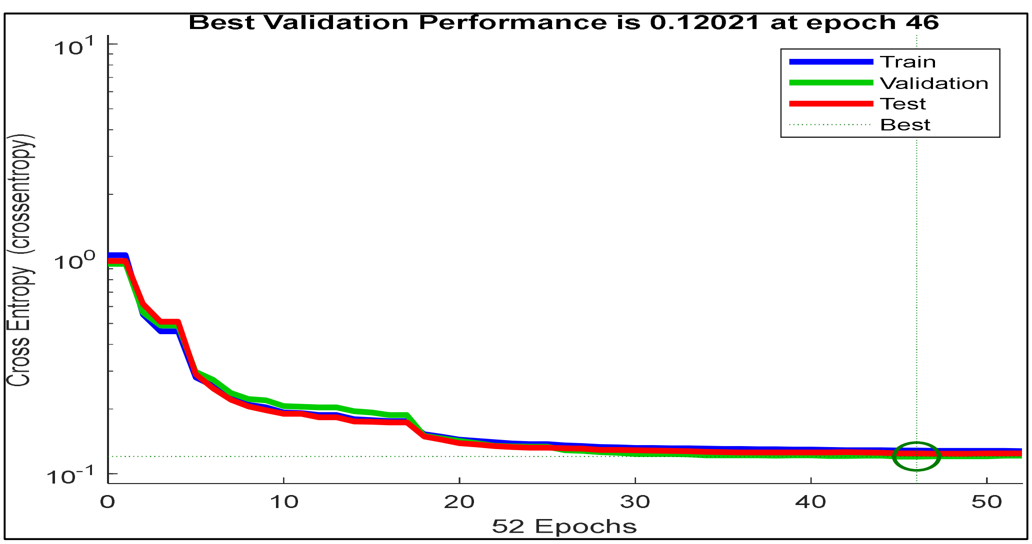

Figure 26: Model Performance graph

Overall, the application of FFNNs in this study provides additional data driven evidential layer to enhance both the reliability and decision support aspect of the research. Moreover, being data driven, FFNNs adapt to specific fault patterns without relying on predefined rules. These features positioned them as well-suited for fault identification tasks due to their simplicity, ability to learn features from raw data, handling of non-linear relationships, and capacity for generalization to unseen data. They can be scaled for various problem complexities, efficiently process data in parallel, and handle multiple faults simultaneously. FFNNs offer a powerful approach for fault identification, relying on their strengths in feature learning and non-linear processing. Overall, machine learning approach in fault identification and performance degradation analysis enhances the outcome of reliability analysis by providing further evidence through machinery health data.

In perspective, combining FFNNs and BBNs in a maintenance decision support system has various advantages, such as learning patterns from data, FFNNs improve defect identification, whereas BBNs provide probabilistic reasoning and handle uncertainty. This combination coupled with additional inputs from the DFTA and FMECA tools enhances reliability assessment and decision analysis while the feature learning aid with real time fault identification. The system becomes flexible, continuously learning from fresh data, and human bias is reduced. The flexible and adaptable decision framework leads to more accurate and informed maintenance decisions, ultimately boosting system reliability, minimising downtime, and improving operational safety.

4.7 Bayesian Belief Network Model Development

Bayesian belief networks (BBN) provide efficient and flexible platform for the conduct of numerical analysis to aid decision making impacted by conflicting priorities. BBNs can be updated with new data at any point during the analysis thereby providing a very efficient tool for decision support system especially for complex system maintenance analysis. Therefore, this phase of the case study provides a system reliability analysis using quantitative failure rates values of the 4 marine DGs used for the study, hence providing a numerically objective output. The DFTA results includes component reliability, importance measures (criticality) and cut sets, which provide a significant understanding on the DGs reliability. However, it was difficult to identify specific repair, maintenance or component failure that presents the most challenge to the operators. Therefore, considering that the MCS is combination of minimum number of events which must occur for the top event to occur (component failure) it therefore provides a good source of variables for building BBN. Accordingly, in building the BBN availability model a selection of top 10 most critical components obtained from the DFTA MCS were used to build the child nodes to the main subsystems of each MDG. Each of child nodes is connected to all possible fault event responsible for the it's occurrence as well as the probability of the event occurring, Figure 27 shows BBN availability structure used for the case study.

Having developed the BBN availability structure and model the output obtained and the structure were adopted to develop the DSS model. Accordingly, the DSS model takes inputs from 2 sources namely the BBN availability and Mission Criticality obtained from the FMECA. In addition to the FMECA Mission Criticality additional factors affecting the delivery of maintenance were obtain under the Effects of Failure within the FMECA table as were extracted from information analysis further provides insight on other challenges which are not captured within the DFTA but are required in developing the DSS model. Additional influencing factors which are not capture in the DFTA and may not be easily presented in a quantitative manner. This, for instance could include problems such logistics delays, lack of spare parts onboard, personnel shortages or lack of skilled ones which can also referred to as Suitably Qualified and Experience Personnel (SQEP).

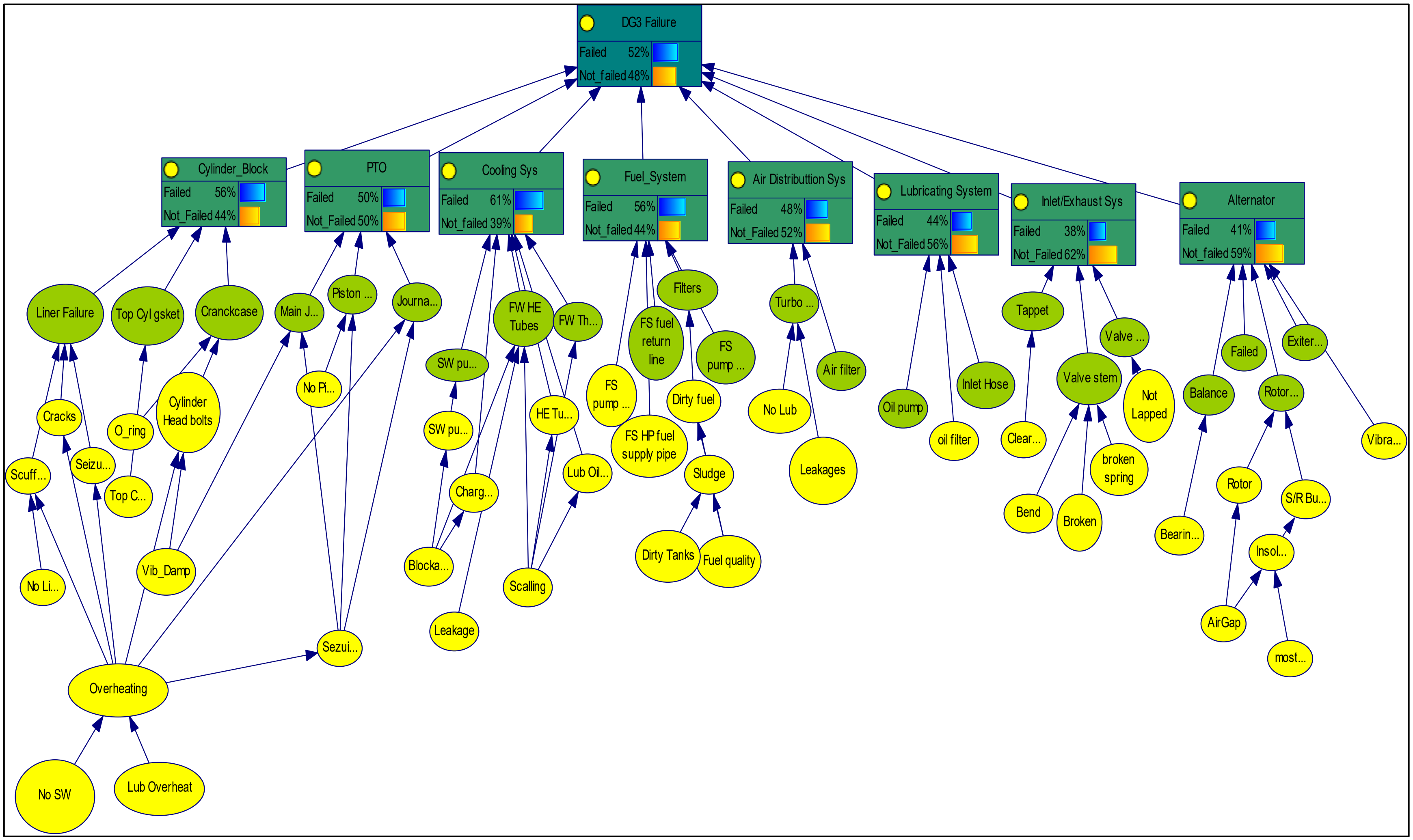

Figure 27: BBN Structure

4.7.1 BBN Availability Analysis

Availability plays vital role in platform maintenance planning, in that reliability does not always suggest good system availability. Moreover, when other influencers such as Mean Time to Repair (MTTR), spare parts availability, availability of suitably qualified personnel (SQEP) etc are considered. The aforementioned are not necessarily inherent to the machinery rather operational environment and organisational handicaps. In this regard BBN reliability analysis takes inputs from the FMECA criticality based on RPN values and the MCS from the DFTA to model MDG availability as influenced by sub-system failure. Is worth mentioning that the availability analysis model serves additional purpose in building the DSS model. Moreover, the BBN availability model was necessary to model common cause failures component failures across subsystems two important functions which cannot be modelled using DFTA.

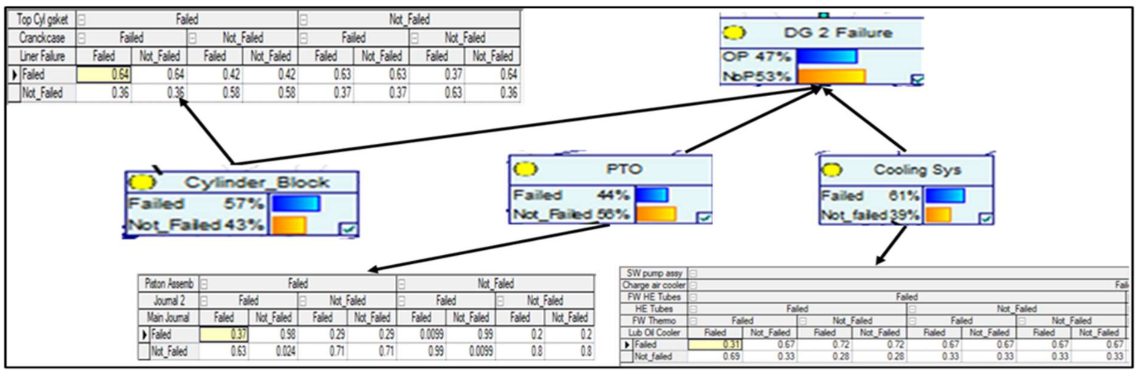

Figure 28:Sample of BBN showing CPT and linked subsystems.

The inputs for the BBN availability analysis were structured in 4 levels, the first level is the Machine/equipment, second level represent the subsystem level. The third level represent components and CCF links while fourth level is the faults inputs. The CPTs take probability values obtained from the MCS which then determines the availability of the component building up to the machinery. Figure 28 is a sample of the BBN structure, showing 3 out of the 8 subsystem and an abridge part of the CPT. The flexibility in BBN which allows modelling CCF is very helpful in presenting complex failure interactions between components that serve many systems or subsystems. The process also enables more efficiently evaluation of the MCS, and their impacts were more highlighted using BBN analysis, hence one of the many reasons of using BBN for this analysis. Moreover, the cumulative probability of the child nodes occurrence determines the operational health condition of the parent component node at the sub-system level.

4.7.2 Maintenance Decision Support System model

The DSS was built on the existing BBN structure and takes inputs from all the 8 subsystems and RPN values. Therefore, within the DSS process the non-availability of subsystem obtained in the BBN is translated to reflect the ranking table in line with RPN outputs. Additional nodes namely decision and value nodes were used in conjunction with the chance nodes. The decision nodes are used to represent variables controlled by the decision maker while the value nodes provide a measure of the desirability of the decision outcomes based on DSS process. Following the above process, the DSS had 2 decision nodes with maintenance strategy and criticality level options as input; while the value nodes had RPN values that serve as measurement of how the operators perceive the impact of failure on the MDGs and ship operation availability has RPN as its inputs. The decision nodes are used to represent variables controlled by the decision maker while the value nodes provide a measure of the desirability of the decision outcomes based on DSS process as shown in Figure 29.

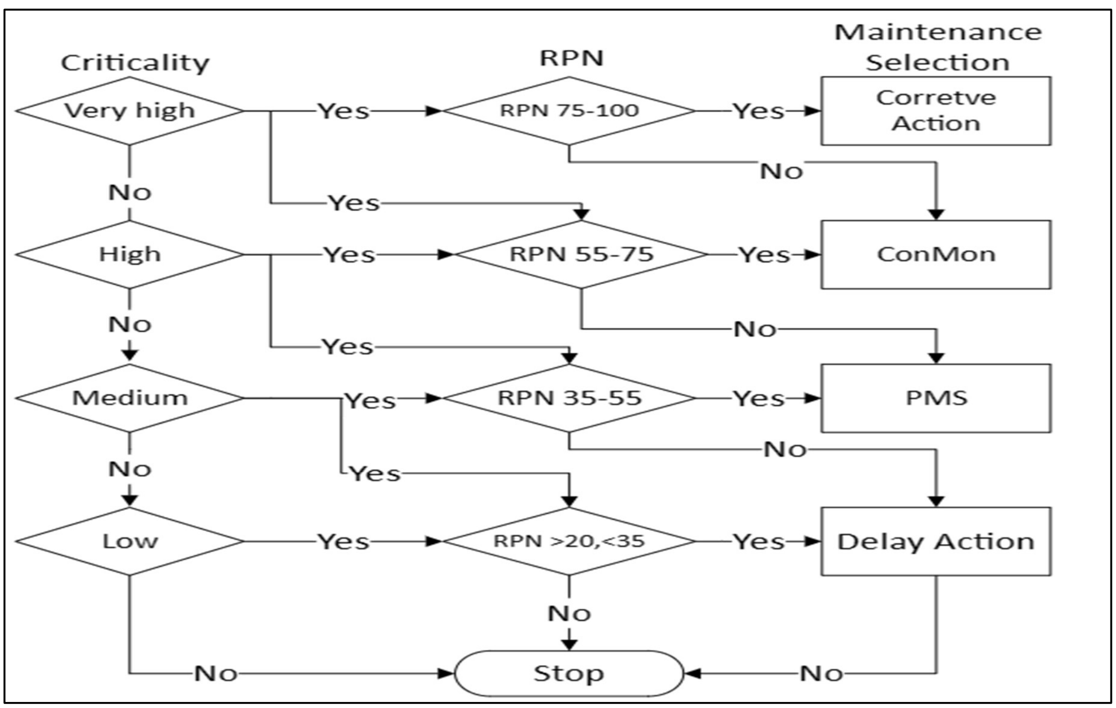

Figure 29: DSS process diagram.

Following the above process, the DSS had 2 decision nodes with maintenance strategy and criticality level options as input; while the value nodes had RPN values that serve as measurement of how the operators perceive the impact of failure on the MDGs and ship operation availability has RPN as its inputs. In this regard the 8 chance nodes connect to value node provides the MDG availability inputs in percentages while the 2 decision nodes feed in decision choices as regards the MDGs availability and sub-system criticality as shown in Figure 30.

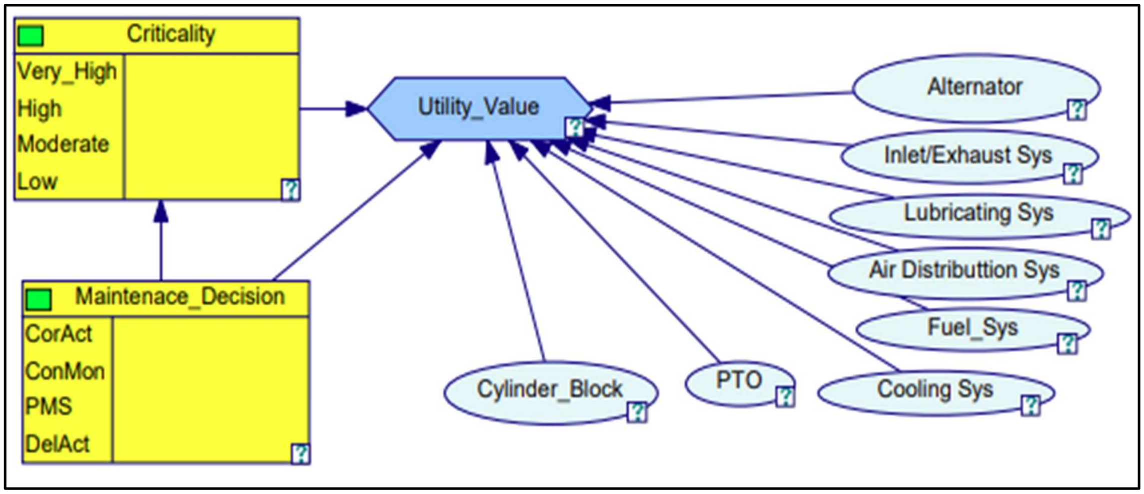

Figure 30: DSS Structure

4.8 Chapter Summary

The power generation system provides the most vital utility on board ships which suggests the level of redundancy and design resilience usually provided by ship builders. These features are common for both merchant and naval ships though with significant high operational demand for the naval platforms. Failure of the power generation system for naval platforms has several implications especially considering the number of personnel onboard, and vulnerability due to loss of weapons, surveillance, and habitation platforms usage. The location and type of failure are important factors to be considered in maintenance planning due logistics and OEM related concerns. In this regard the suggested case study implements a novel methodology through the combination of reliability analysis tools to address maintenance challenges on the power generation plant onboard an offshore patrol vessel (OPV).

Accordingly, data analysis for this research was designed to cover subjective and objective analysis. The subjective aspect of case study provides intuitive guidance on model quality, while the objective part of the methodology provides numerical analysis using failure rates as inputs. The FMECA analysis presents experts judgement about failure and critical system component while the DFTA is a quantitative analysis on system component reliability. The inputs for the BN analysis were obtained from both failure rates and cut set output of the DFT analysis, while RPN numbers from FMECA analysis was used as bases for maintenance strategy selection of individual generators. Therefore, data used for the analysis includes FMECA conducted via online survey, failure rates using maintenance and repair data collected from 4 marine diesel generator plants, each rated at 400kW and can operate parallel or individual. This was followed by discussion about operation and maintenance process onboard including wider discussion to gain expert perception of maintenance process in the fleet.

5 Case Study Results

5.1 Chapter Outline

This chapter presents the Case Study analysis results based on the methodology as applied on the subject ship. In this regard, the results obtained from individual tools would be presented in the following sections: Section 5.2 provides an overview of the research input data. Thereafter, Section 5.3 presents the FMECA results covering the survey results and Mission Critical Component results, this would be followed by DFT analysis in Section 5.3. ANN fault identification is presented in section 5.4. Section 5.5 present the BBN results including the maintenance DSS outcomes. The Chapter summary is presented in Section 5.6.

5.2 Failure Mode Effects and Criticality Analysis Result

FMECA survey was conducted to get the opinion of operators and senior administrators in the engineering branch of the case study ship operator. This would help provide some insight on how this failure affect platform availability due to issue such as, spare parts availability, technical expertise, delays due to OEM and impact of the operational environment including practices. These outcomes from the FMECA were used to generate RPN number and normalised to obtain the Component Mission Criticality.

5.2.1 Survey Data Output

A survey was conducted to get the opinion of operators and administrators in an organisation with a fleet strength of more about 40 ships of various sizes mainly used for security patrols. The survey consisted of about 20 questions on various types of faults and failure conditions covering DG system including the alternator. The approach is adopted in order to account for expert knowledge, organisational peculiarities, and challenges to do with access to original equipment manufacturers representatives. Therefore, the list of respondents is made up of personnel who had served onboard the ship, currently serving onboard and those working/worked at the shore maintenance units responsible for maintaining the ship. Further other experts come from the Naval Engineering branch due to their experience as marine engineers or electrical engineers and have put about 15 years in service.

Furthermore, due to the disparity, in experience level and local knowledge of the ship by working directly with the MDGs and board the other class of ships. Therefore, to account for gaps or difference in knowledge and experience levels weights are added to according to individual in puts. Some of the consideration in the weight was based on seniority level among respondents which varies between 4 to 28 years and experience as regards positions held and other special qualifications.

In this regard, having received the feedback a weight is added to individual inputs based on the person rank and experience, thereafter all scores for that particular component are summed up and divided with by the total number of inputs; the average is taken as the score for that particular criterion in RPN. This process is repeated all through for the all the components in the survey.

5.2.2 Ranking of Mission Critical Components

The FMECA survey outputs provides a very important input to the overall analysis as regards what may have not been carefully accounted for in the maintenance and repair data collected of the DGs. Moreover, the MRO used was for and individual ship while the FMECA data was the response from over 20 experts with varying professional experience. Though the FMECA has in no way influenced the DFTA results its only used to complement it for the second aspect of the BBN analysis which is the maintenance DSS. The fact that DFTA cannot account for issues to do with unplanned downtime, quality of replacement parts, design related unreliability and generic human factor concern. The FMECA helps in addressing these issues as well as other environmentally induced failures which were not factored during installation but were not necessarily design related. Therefore, the FMECA survey was designed to capture some of these problems, to also highlight how the operators evaluated the most critical failures to ship availability and repairs Table 25 is an abridge version of the FMECA results showing the RPN and Normalised RPN which is the Mission Critical Component. A complete FMECA table is at Appendix 7.

Table 24:RPN Values

ALL DGs	Subsystem	Component	Mode	Causes	TTR	Criticality Min 1 Max10	Severity Min1 Max 10	Likelihood Min 1 Max 10	RPN CxSxL	Mission Criticality
1	Cylinder Block	Crankcase	Cracking	1. Overheating 2. Excessive Vibration 3. Failure of Piston/Connect Rod/Valves 4. Loss Cylinder heard bolts. 5. Lose Foundation bolt	1-3months	8	7	4	224	65
		Cylinder liner failure	1. Cracks 2. Scuffing 3. Seizure	1. High Temperature operation 2. Lubrication Failure 3. Water ingress 4. Piston or rings failure	1wk-3months (dependingspare parts availability)	8	6	4	192	55
		Cylinder head bolts	1. Loose 2. Not firm	1. High Vibration 2. Wrong torque 3. High temperature stress 4. Material Failure	1-3hrs	7	6	8	336	100
		Top Cylinder gasket	1. Burnt 2. Material Failure	1. Overheating	10-24hrs	7	6	5	210	60
		Cylinder head O-ring	Deformation	1. Excessive Temperatures	2 wk-2 months	7	6	5	210	60
2	Power Take Off	Crank Shaft	1. Surface roughness 2. Mis alignment	1. High Vibration 2. Lose of Lubrication 3. High Stress due to piston or connect rod failure	1 month	8	7	3	168	47
		Journal Bearing	Friction and seizure	1. Lubrication Failure 2. Overheating 3. Crankshaft alignment 4. High Stress due to piston or connect rod failure	6hrs-2 days(with spare availability) 1-2 months (OEM to supply spares)	7	7	4	196	56
3	Cooling System	Heat Exchanger Tubes	1. Scale build up 2. Leakages	1. Material Failure 2. Corrosion 3. water impurities	30min-6hrs	5	6	7	210	60
		FW circulation pump	1. No water supply 2. Drop in pressure	1. Impaler failure 2. Mechanical Failure 3.V- Belt failure	2hrs-4weeks	7	6	4	168	47
		SW pump assembly	1. No SW supply 2. Drop in pressure	1. Shaft wear 2. Mechanical seal failure 3. Casing wear	2-4hrs	7	6	4	168	47
		Fuel Quality	1. Loss of power 2. Erratic operation 3.Filter blockage 4. Sludge accumulate in tanks	1, Low grade bunker fuel. 2. Fuel contamination in storage. 3. High moisture content	1-2weeks	6	6	6	216	62

The FMECA results in Table 25, provide the Mission Critical numbers as derived from the RPN. The Mission Criticality as earlier discussed is a product of criticality, severity, and likelihood. The overall essence of the FMECA is to obtain expert opinion on components fault development and failure. Hence these scores provide valuable indication on components whose failures of concern. Therefore, as observed the highest score in all the criteria was 8 out of a possible maximum score of 10, this signifies some consciousness and genuine effort by the respondents to provide a realistic assessment of the MDGs.

Overall, component associated to the crankcase and power take off seem to have the most serious consequences as regard failure. For instance, crack on crankcase and roughening of cylinder liners were scored 8 in criticality which indicates how immediate the impact is felt and long duration fixing of the problem. Because most times the OEM has be called in, the situation simile with that of the crankshaft bearing journal which also require calibration using precision instrument. On the other a slightly different trend was noticed with the Likelihood score of cylinder head bolts being the highest at 8 even though the criticality and severity were at 7 and 6 respectively. The possibility of this occurrence is due to the increased frequency of cylinder head bolts to get lose within every 100 hrs of operation, even though the TTR was shot usually around 1 to 3 hours, depending on the temperature of the MDG. This trend was equally noticed within the DFTA IM as presented in table 26 and tables presenting MCS. Nonetheless, it was identified that the MDG were not provided with resilient mountings hence the possibility of excessive vibration leading to loosing of the cylinder head bolts. This challenge is responsible for significant damage to the MDG.

5.3 Dynamic Fault Tree Analysis Results

Results from the Dynamic Fault Tree Analysis (DFTA) provides a component level system reliability analysis as obtained from the failure rate value of the 4 MDGs. Therefore, the low level analysis provides great depth and coverage on all the possible failures that could occur within the MDG system boundary. Moreover, few external but associated failures such as sea blockages and fuel quality had to be considered dure to the frequency and impact on overall system availability. Overall, the DFTA structure has 300 events and 162 gates representing multiple faults and affected faults. The DFTA provided very important results that can stand alone but can further be used to gain more insight especially towards maintenance planning. Accordingly, the results obtained from various output are presented in the coming sections, starting with reliability outcomes.

5.3.1 System Reliability Results

The analysis was conducted on systems, sub-systems, and components of individual engines. An overview of the reliability of the PGS and the MDGs is presented in Figures 31 and 32, respectively. Figure 31 provides an overview of individual MDG reliability against the overall PGS reliability, which is the cumulative reliability of all MDGs. Therefore, following the operational requirements, the PGS reliability develops a steady decline by the seventh month, and similarly, Figure 32 shows very low reliability, especially for MDG 1 just about the fifth month. Overall, the results indicate a high level of unreliability in all the MDGs, which explains the low reliability of the PGS in line with the operators' requirements.

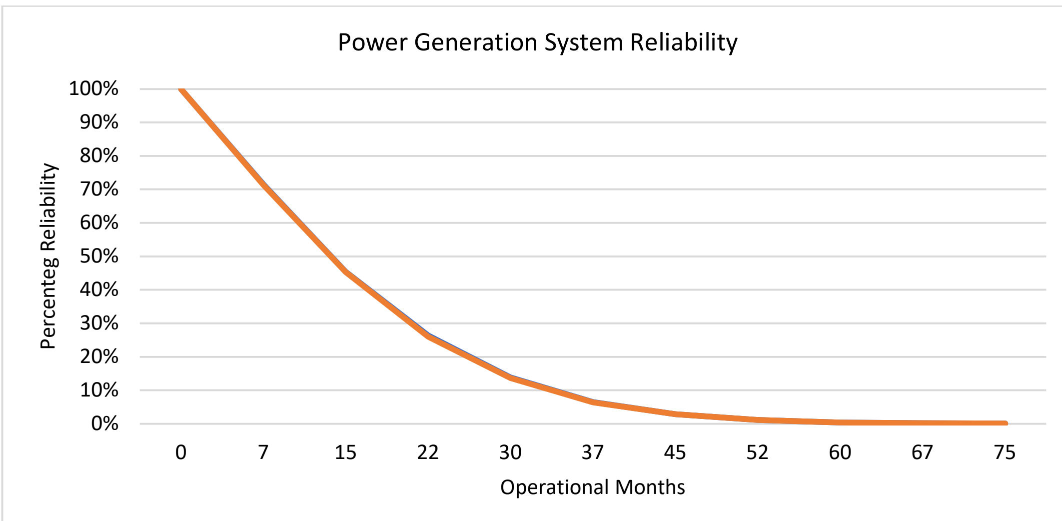

Figure 31:Overall Power Generation System Reliability

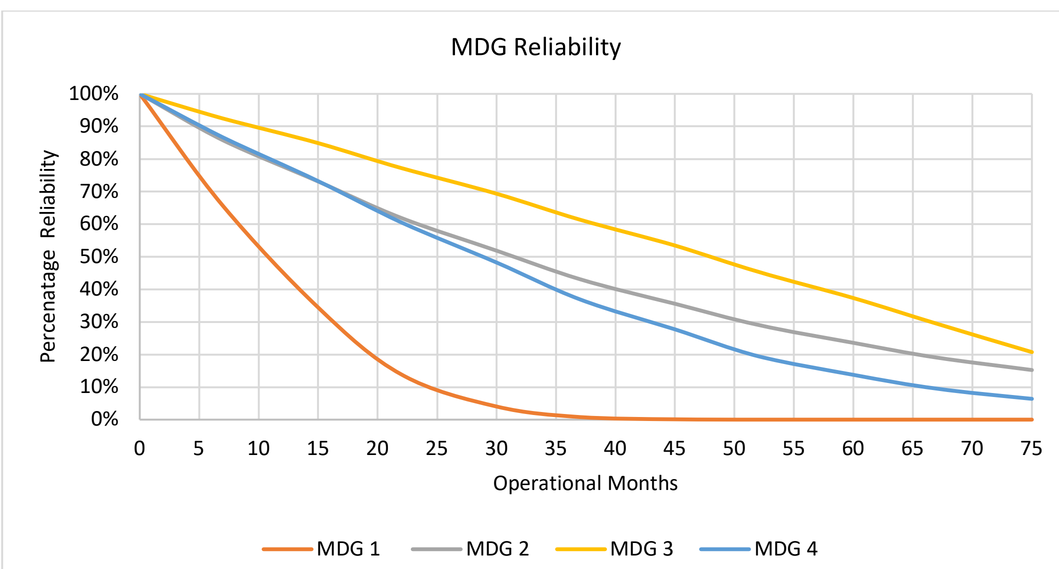

Figure 32: View of Individual MDG Reliability

The overall reliability results show a reasonably good reliability up about 7months in the case of MDG 1 while MDGs 2 and 4 was at 10 months with MDG 3 retaining about 22 months of 80 % within the early life of the MDGs. However, a steady deterioration was presented especially from the 15th month for MDG1, which going by the OEM mid-life overhaul at 60 months is an indication low reliability. Nonetheless, MDGs 2,3 and 4 were reasonably able to retain 80 % reliability within the first 20 months. However, going by the operator's minimum equipment reliability requirement of 80 % prior to deployment. Then the situation in MDGs , particularly MDG 1 is undesirable especially for a Naval vessel that can be deployed, within short notice. Moreover, the situation with MDG 1 follows an infant mortality characteristic in a bathtub curve diagram, because the steep slope is an indication of serious reliability issues within the first few months the MDG's life. Therefore, the need to conduct detail component level analysis to clearly understand the role of components unreliability on the MDGS which can help ascertain the components and fault that are leading to the sub-subsystem failures.

5.3.2.1 Sub-System Reliability Results

The analysis conducted on the other subsystem helped to provide further insight on the overall reliability of individual DGs and most importantly it identified where the major challenge is regarding all the 4 MDGs. For instance, the Crankcase has been identified to be the most critical component of the DGs. Although the cylinder blocks of most diesel generator or prime movers are the among the most reliable parts of the generator mainly because they are static and are generally provided with good protection against likely cause of failure. The protection provide for the cylinder block is in recognition of the vital role it plays in any internal combustion engine configuration. Therefore, the high level of unreliability displayed by the DGs could be attributed to the crankcase, especially that all other sub-system on the DG rely on the integrity of the crankcase. The combined reliability of the sub-systems is presented in Figures 33-39.

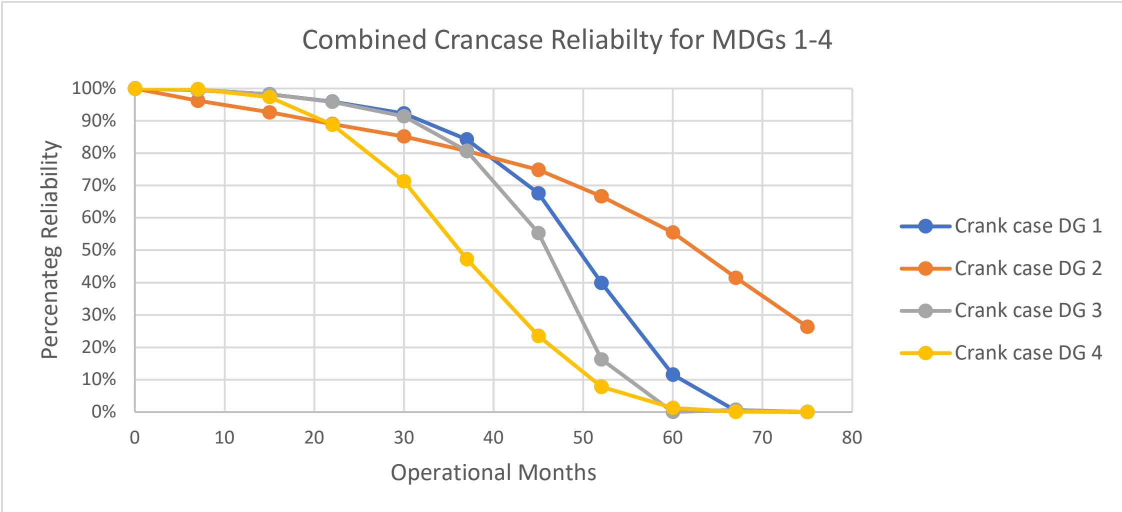

Figure 33:Combined MDG Crankcase Reliability

The combined reliability of the crankcase presented in Figure 33 shows the reliability curve for the 4 MDGs. As expected, the MDGs had varying reliability values which indicates the dynamics surrounding the failures among the 4 MDGs, nonetheless MDGs 3 and 4 seems to follow same patten in relation to the crankcase reliability. A major problem with the crankcase as discussed with the operators was that the MDGs were not initially mounted with resilient engine seats hence there were challenges with excessive vibration leading to loosening of top cylinder bolts. Obviously top cylinders bolts are very important for the correct operation of any diesel engine. Moreover, excessive vibration could lead to further damages affecting the internal moving parts such as the connect rods and likely the crank shaft. In this regard, the multiplicity of the problems could be responsible to the challenges surround the crankcase unreliability.

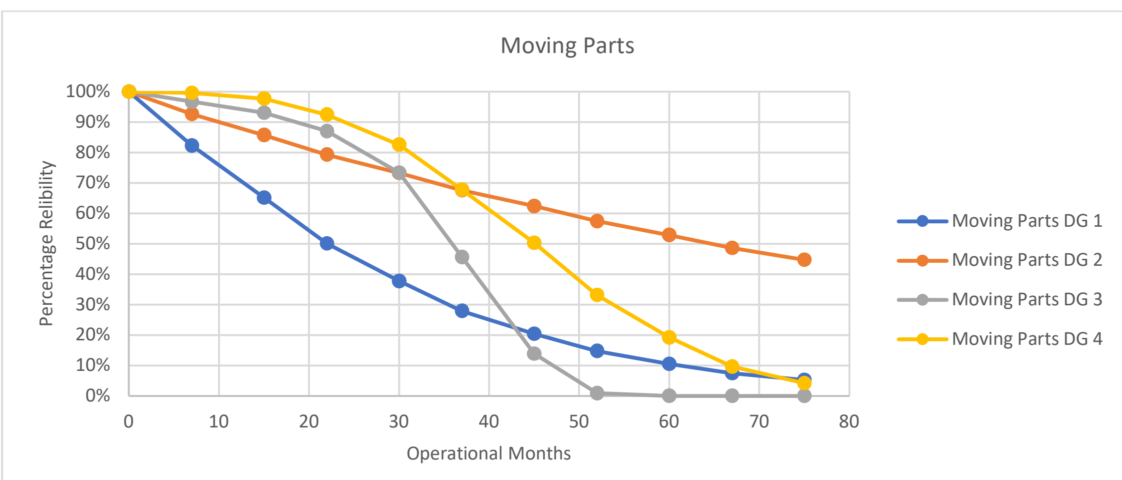

Figure 34: Combined Moving Parts Reliability

The reliability of the Moving parts is presented in Figure 34, shows a relatively low reliability. This situation was mainly due to failures related to components especially piston rings, but further analysis revealed a remote but important factor contributing to the failure in components of the moving parts. Overall, the subsystems on all the for the MDGs didn't show a very good reliability even going by the OEM recommendations. In general, the OEM's maintenance are mainly to serve as guidance to the operator. Nonetheless, the equipment is not expected to deviate much from the manufacturer's initial maintenance projections especially within the first 5 years notwithstanding the warranty agreement. In this regard reliability result are indication of inappropriate maintenance or low manufacturing is standards.

The low reliability in the moving parts shares some similarity with the reliability curve of the crankcase. Therefore, this indicates that the level of failure noticed in the crankcase could be related to failure in moving parts or vice-versa. Moreover, the failure rates of cylinder bolts and associated gasket kits are important indicators that can influence other failures in the rotating parts of the generators. Nonetheless, additional problems in particular the sea chest blockage could give rise to the MDG operating at relatively elevated temperatures even during normal operating loads. This therefore means that at peak periods the MDGs are likely to operate at much higher temperatures which in some cases may be ignored by the operators either due to workload or assumed new normal.

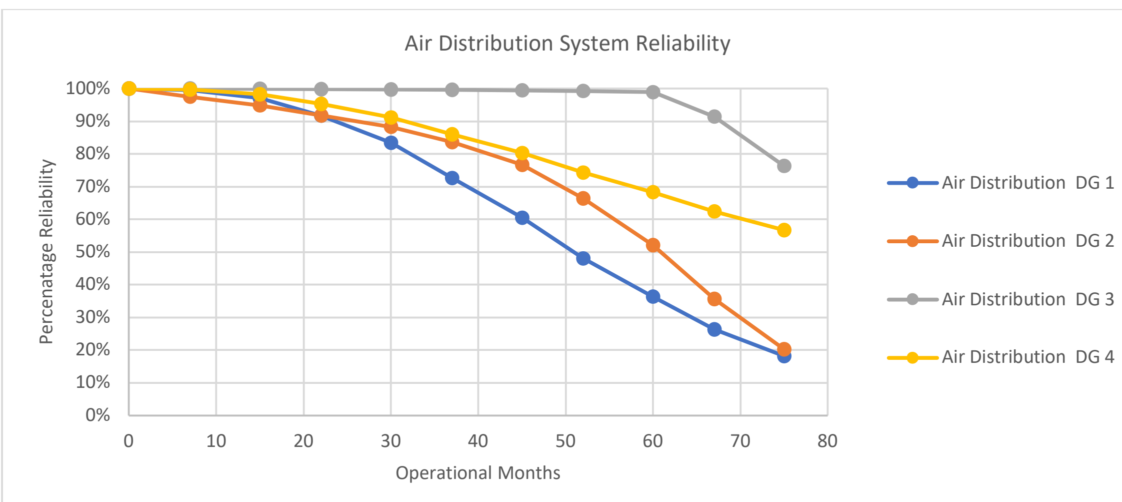

Figure 35: Combined Reliability of Air Distribution System

The Air Distribution System Figure 35 has a good overall reliability compared to rest of the subsystems. Again, the MDGs showed significant similarities in the system reliability based on location, MDG 1 and 2 had lower reliability compared to MGD 3 and 4. Though there are no clear reasons for such disparity, a likely problem could be related to ship air supply intakes and other reasons could be attributed to turbo charger faults and air cooler fouling problems. Moreover, cooling problems due sea chest blockages and tube fouling are common among the MDGs.

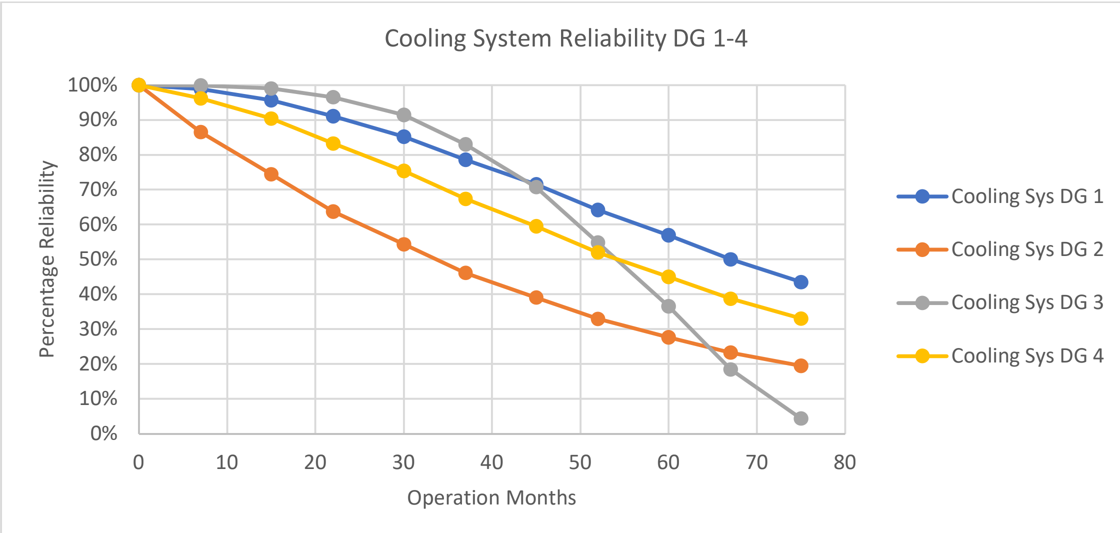

Figure 36: Combined Cooling System Reliability

The cooling system presented in Figure 36, has a very central role in the reliability of the MDGs since a lot rely on it and the sea chest remains a serious challenge. The cooling system was designed with reasonable amount of redundancy. However, due to inadequate waste disposal, the water around the harbour has lots of floating debris which always goes to block the sea chest, hence affecting normal water flow to the MDGs. Therefore, while all the MDGs have dedicated sea chest supply access, in most cases the supply can be blocked at the same time. On the other hand, challenge of fouling is always there to impurities in the sea water, lack of additives for freshwater cooling system. These problems coupled with the failure of the pulley belts for pumps have remained the major challenges influencing the reliability of the cooling system.

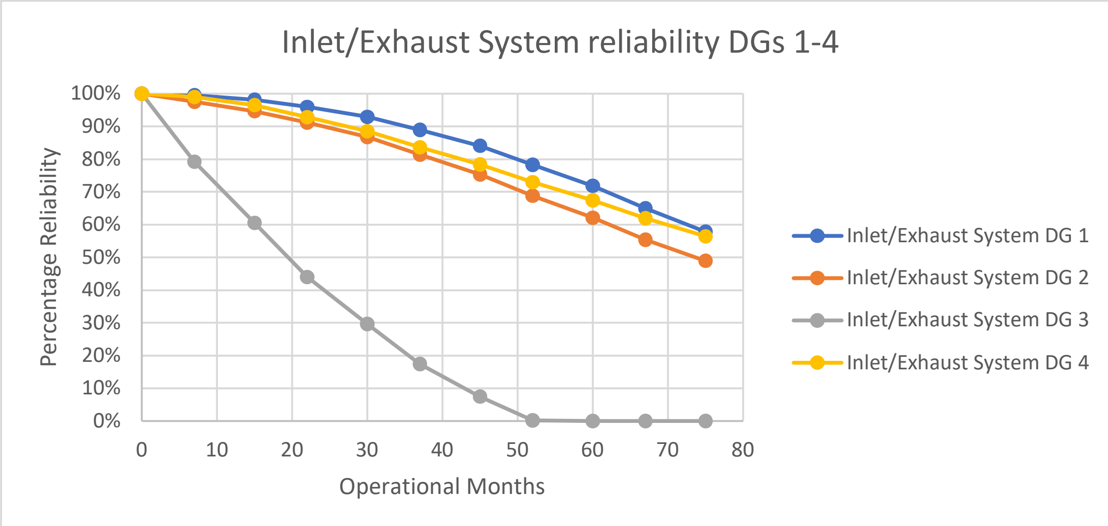

Figure 37:Combined Inlet/Exhaust System Reliability

The inlet and exhaust system reliability in as shown in Figure 37 equally revealed an important failure situation which further buttress the low reliability of the crankcase in MDG3 and relatively good reliability of MDG2. A strong reason for these problem in the inlet and outlet was to do with the tappet clearance required every 250 hrs which at a point the operator decided to increase the checks to 500hrs due to non-availability of 2 other MDGs. These failures can be attributed to both design and maintenance of the MDGs. Thus, providing additional sensors with alarm limits to measure and provide alerts on the exhaust gas temperatures variations can lead to significant reduction in failures.

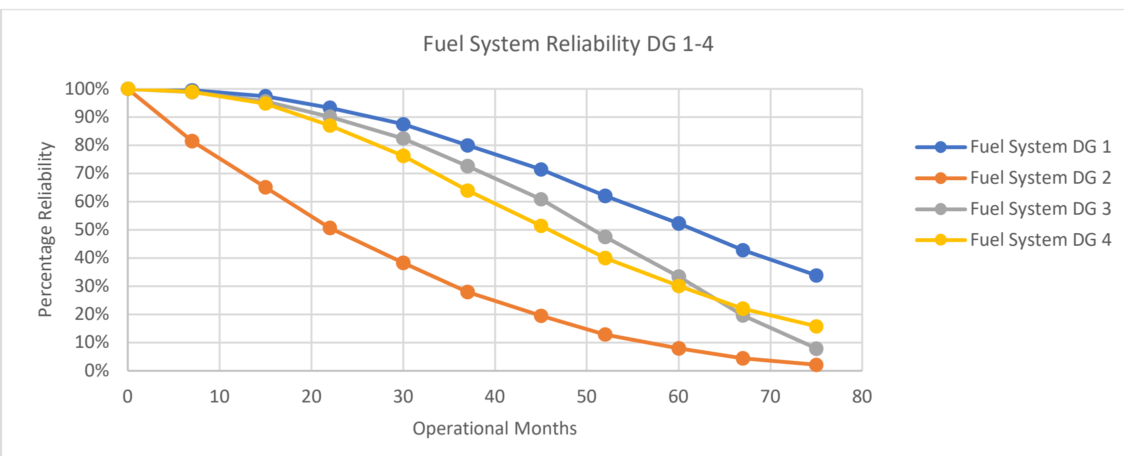

Figure 38:Combined Fuel System Reliability

The fuel reliability analysis presented one of the most challenging situations due to multiple factors to be considered a lot of which are somehow external to the MDG but to contribute many failures. Hence, the curves as shown in Figure 38 for the fuel system of all 4 MDGs shows a common trend except for MDG 2. Although, there are some local problems common to all the MDGs regarding the mechanical fuel injection pump pulley drive bolts getting loose which causes it damage belts. This impact also goes further to affecting the mechanical components of the pump, such as the plunger and the springs that usually get damaged due to unbalanced forces. A further challenge on the fuel system is that of fuel quality which is not only low but contains a lot of impurities such as sea water. The presence of moisture due to water content in the tanks and tropical nature of the environment enable some microbes to thrive and form sludge within the tanks hence blocking fuel filters there by affecting the supply pressure.

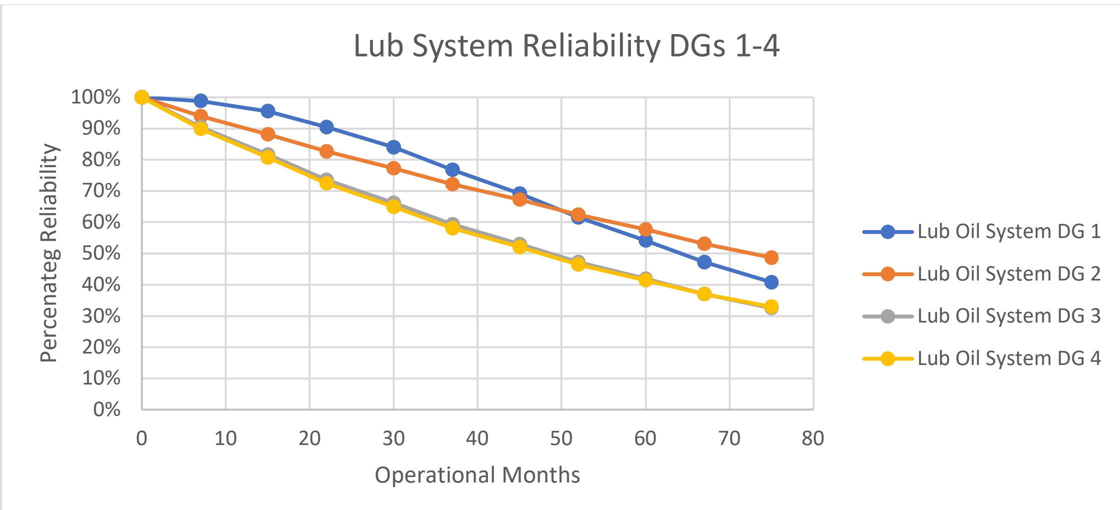

Figure 39: Combined Lub System Reliability

The lub oil system is one of the most reliable of all the systems, and this is for good reasons. Moreover, any failure or fault in the lub oil system has one of the most devasting consequences influencing other systems such as the moving parts and turbo charge. In fact, most of the turbo charge failures reported on the MDGs were due to lubrication failures. Nonetheless, the failures in the lub oil pump or filters are seldom reported. However, the persistent problem of cylinder head bolts loosening and that of overheating usually result to lub oil contamination. In few instances lub oil dilution has been reported due to excessive fuel delivery by fuel injection nozzle. In this regard, most often than not the failures withing the lub oil are generally influence by some of the stated factors. Figure 36 presents the system reliability results for all MDGs.

Overall, the subsystems on all the MDGs presented a low level of reliability even during the first 5-years warranty period by the OEM. Though, the OEM's maintenance is mainly to serve as guidance to the operator. Nonetheless, the equipment is not expected to deviate much from the manufacturer's initial maintenance projections especially within the first 5 years notwithstanding the warranty agreement. In this regard, the reliability result is indication of maintenance challenges or design issues, in which case identifying components with high failure rates as well as the failure mechanism can go along to improve the reliability of the MDGs. Hence to address some of these issues it would be relevant to identify the components responsible or most affected by the failures through the reliability importance measures of the DFTA.

5.3.2 Reliability Importance measures

The reliability importance measure provides quantitative indicators on component criticality for individual components model in the MDGS which adds to more than 300 events. Accordingly, the Bir IM was used to present the most critical components; this is mainly because of its ability to identify the most critical component once the top event is said to have occurred, hence most effective when dealing low level granular analysis. Moreover, readings for Cri and FV IM were obtained, but all appear to have the same values and were low especially when considered along the Minimal Cut Set results. Therefore, obtained values from the other IM outputs suggest a more robust and reliable system contrary what the reliability output indicates. Consequently, the other IMs are a good representation of the case study maintenance and failure reports. An overview how the other IMs compare with Bir IM is presented in Table 26.

Table 25: Comparison of the three IM values

Event	Birnbaum	Criticality	Fussell-Vesely
Sea Chest	0.497018	0.497018	0.013959
Intercooler	0.497018	0.013959	0.013959
Heat exchanger	0.527822	0.024646	0.024646
Fuel Supply pump	0.604233	0.023861	0.023861
Journal bearing	0.632121	0.022580	0.022580
Main bearing	0.632121	0.022580	0.022580
Cylinder head O-ring	0.634048	0.062717	0.062717
Tappets/Valves	0.795919	0.027337	0.027337
Heat Exchanger tubes	0.826296	0.024646	0.024646
Guide Bushing	0.887586	0.062717	0.062717
Crankshaft	1.000000	0.046463	0.046463
Governor	1.00000	0.043901	0.043901
Cylinder head Bolts	1.0000	0.062942	0.062942
Injection nozzles	1.0000	0.073272	0.073272

The Bir IM values for the 4 MDGs revealed multiple faults affecting component failure, each with varying degrees of influence. The analysis aimed to discern the disparities in the impact of faults on component failures, focusing on individual components contributing up to 40% of system unreliability. Maintaining the component criticality at 40% was aimed to ensure a manageable number of components while upholding the system's integrity. Moreover, the key considerations in the study were to identify and evaluate the influence of faults on critical system components. To achieve this, the focus was placed on individual components that contributed up to 40% of the system's overall unreliability. By concentrating on these critical components, the analysis aimed to pinpoint the areas that required immediate attention and corrective actions to enhance the system's overall performance.

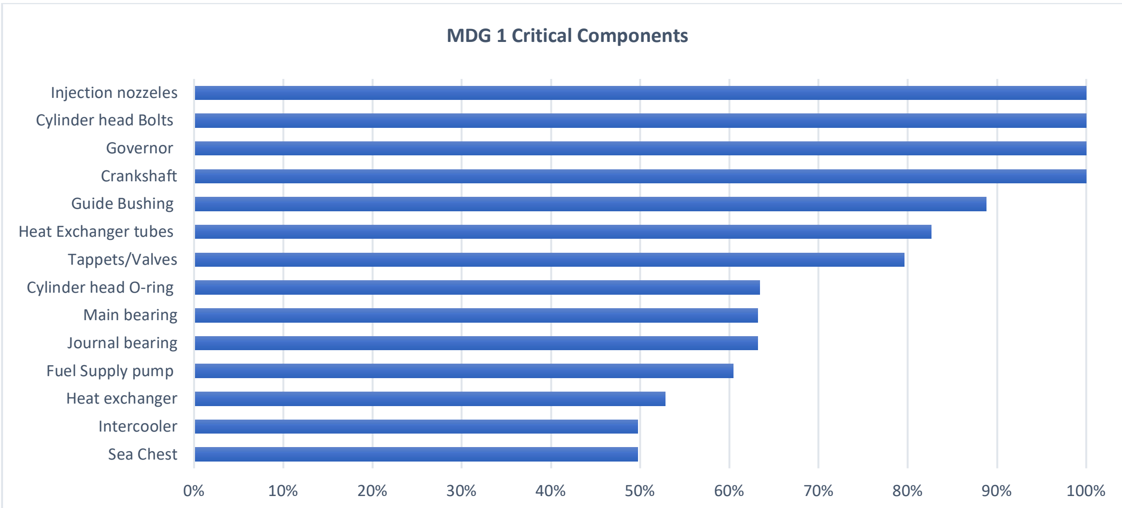

Figure 40: MDG 1 Critical Component

The IM for MDG 1 presented in Figure 40 shows most critical components to system failures. Top among the list are injector nozzles, cylinder head bolts, governor and the crankshaft, these components are critical not because of failure propensities but failure impact on machinery availability. Closely related to 4 most critical components are the heat exchanger tubes and tappets/valve, these components are in that position due to overall impact on the MDG when they fail. Moreover, as for the tappets and valves, the challenge was related to the frequency of clearance inspection needed, which imposes additional constraints on overall MDG reliability. One major issue with clearance inspection was the need for qualified personnel and the possible consequences that could be encountered if handled by unqualified personnel. Overall, most of the components that appeared in Figure 41 are related to one another either due to susceptibility to high temperature fault or vibration impact. Vibration as earlier highlighted was one of the key issues the MDGs due to wrong error of installation.

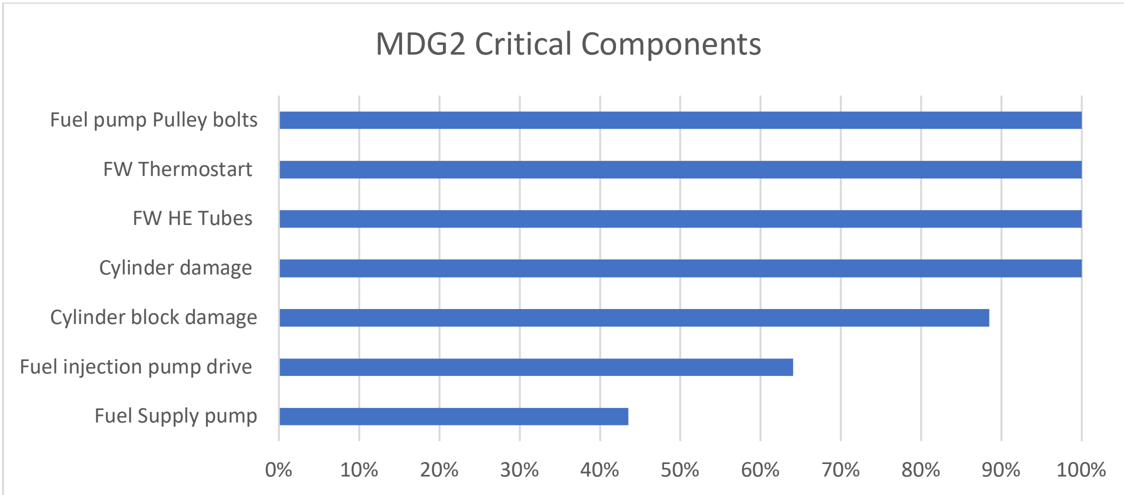

Figure 41:MDG2 Critical Component

MDG 2 critical components presented in Figure 42, are quite close to those of MDG 1 though with fewer components belonging to same sub-systems. For instance, the fuel pump pulley bolts and freshwater thermostat still belong to the fuel system and cooling system respectively, which were among top components of MDG 1. In this regard, for these 2 MDGs the approach to monitoring and maintenance could be reviewed to ascertain the issues with the similarity. As regard the cylinder damage this could as result of the cylinder head bolts loosening or the failure due to freshwater thermostat failure. As gathered from the operator thermostat failure is major can lead to some major problems especially in situation when the MDG were loaded rapidly leading sudden increase in operating temperature under with less than optimum cooling. In this regard the operator simply resorted to removing the thermostat to alleviate the situation.

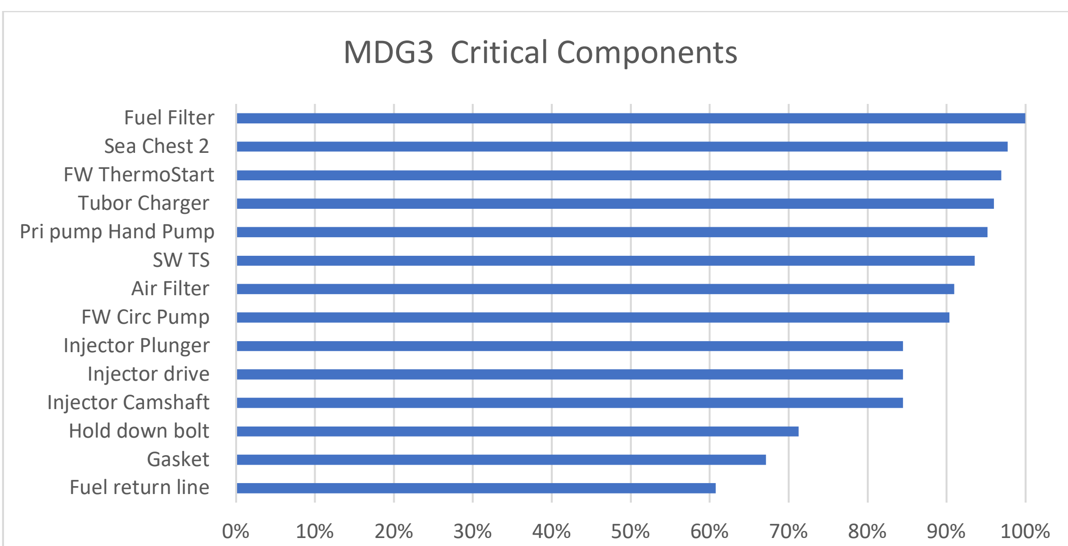

Figure 42: MDG 3 Critical Components

Figure 42 presents the most critical components of MDG 3, with little deviation from that of first 2 MDGs i.e. 1 and 2. In above result, fuel filter happens to top the chart, one of the reasons for this was that the filter casing for this particular MDG was leaking, hence the reason why the primary hand lift pump making the list due to pressure drop issues. Nonetheless, all the MDGs had issues with the fuel system due to quality of fuel and unreliability on other components in the fuel system. Moreover, it would be noticed that some of components that appeared in MDG 1 are also in MDG 2 hence the need to pay more attention to this component in order to seek of alternative means of addressing the issue. However, turbo charger and air filter being among the critical components for this MDG is a cause for concern.

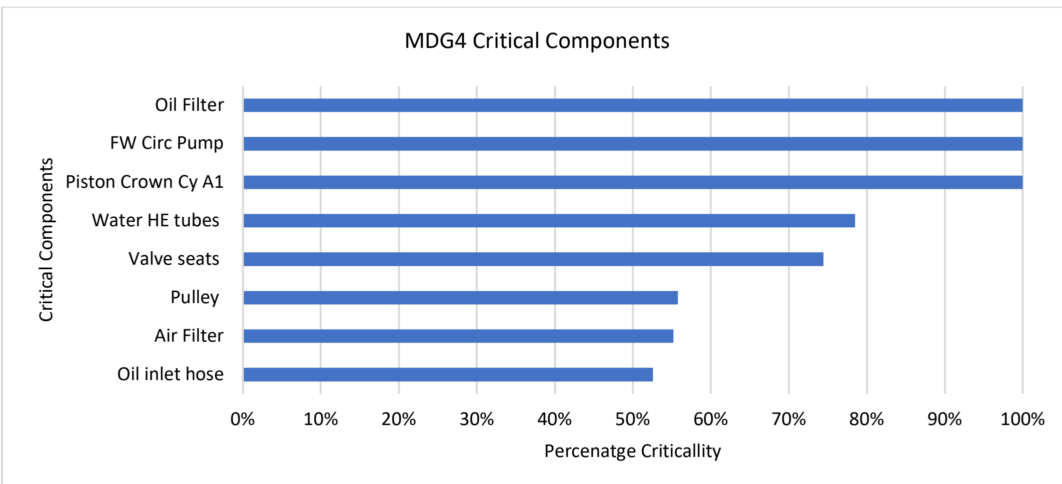

Figure 43:MDG4 Critical Components

The IM output for MDG 4 as shown in Figure 43, share some common features with that of MDG 3, and this is good as it is consistent with the reliability analysis output. However, the appearance of oil filter and oil hose is a deviation from all the other results. Moreover, failures relating to lubricating system in the MRO only appear in few instances, the occurrence of such faults is viewed very seriously. Most importantly that lub oil system faults require more careful rectification from qualified personnel. The problem with the freshwater circulation pump is generally the same with those of the other MDGs as earlier highlighted and is a common problem too. Nonetheless, piston crown for cylinder 1 appearing as critical component could be as result of repeated failures after replacement.

In general, this is the case when such fault occurs, and the components were not replaced properly. For instance, the piston discussed above, had defective rings that were changed but the cylinder liner which shows visible friction signs was not. Hence after the replacement the MDG worked for short period with relatively low output and persistent overheating, eventually leading to seizure due crankshaft journal failure. As results of these multiple failures the liner was replaced the crankshaft was resurfaced which eventually downgraded the MDGs overall output.

Accordingly, any component contributing more than 40% to system or subsystem unavailability should be termed as critical across all MDGs. Interestingly, there are components that tend to appear in all DGs, this therefore is an indication of an important area to note by both the operators and the manufacturers. For instance, the problem with cylinder head bolt getting loose could be attributed to high vibration and can cause significant damage to the generator. On the other hand, there are significant failures involving the freshwater cooling system components as well as host of other components.

The above 4 figures are mainly to do with components that require more attention in maintenance as well as logistics. The relevance of identifying the component would aid understanding of the impact of failure and components that are critical to it. Moreover, each of the component's failure has been linked to action events on the DFTA structure which are related to it. Therefore, by doing this the DFTA can serve both as means to identify the right spare holding and areas that require improvement in maintenance scheduling, technical crew training and environmental influence.

5.3.2.1 Common Critical Component to All MDGs

Reliability importance measures (IMs) for the 4 individual MDGs shows that all the MDGs maintain certain commonality as regards component criticality. Therefore, taking advantage of the 40 % criticality ranking for component criticality an opportunity arises to enable a collective maintenance and spare parts planning for all the MDGs especially at the fleet level. This also provide an important area to note by operators at ship and fleet level as well as the manufactures. For instance, the problem with cylinder head bolt getting loose could be attributed to high vibration and can cause significant damage to the generator and is common to all the MDGs. Similarly, there are significant failures involving the freshwater cooling system components, pulley belts for sea and freshwater pumps and other components like the tappets and air filter.

In view of the above, component susceptible to failures due to similar faults could be considered collectively and solution address such issues could be generated through the fleet either by adopting a working solution form a ship or a fleet wide recommendation. Therefore, instead of considering a single MDG, a collection if all critical components can be made at the fleet level while at the ship or platform MDGs can be considered individually. This brings to light the importance of component criticality to faults mapping as implemented in this research. Moreover, the overall maintenance platform being developed is geared towards a more flexible maintenance approach that can be updated based on actual machinery operating condition either through manual or automated data imputation.

The Bir IM was used to present the most critical components, being that it is the most responsive to the DFTA structure as well as the number of components to analyse. Figure 57 presents a bar chat showing 21 of the common critical components based on reliability IM for the MDGs. The figure gives an overview of the most critical components in the various sub-systems, including other auxiliary connections like the sea chest. The sea chest for instance, was designed to provide good flexibility in that each of the 4 MDGs has a direct connection seawater intake and a common link to an alternative seawater intake from another MDGs supply line. Likewise, a third connection serves as an emergency supply which is common to all MDGS. Overall, the IMs in Figure 44 represent components that have at least contributed more than 50% of all failures within the period analysed that are common to all the MDGs.

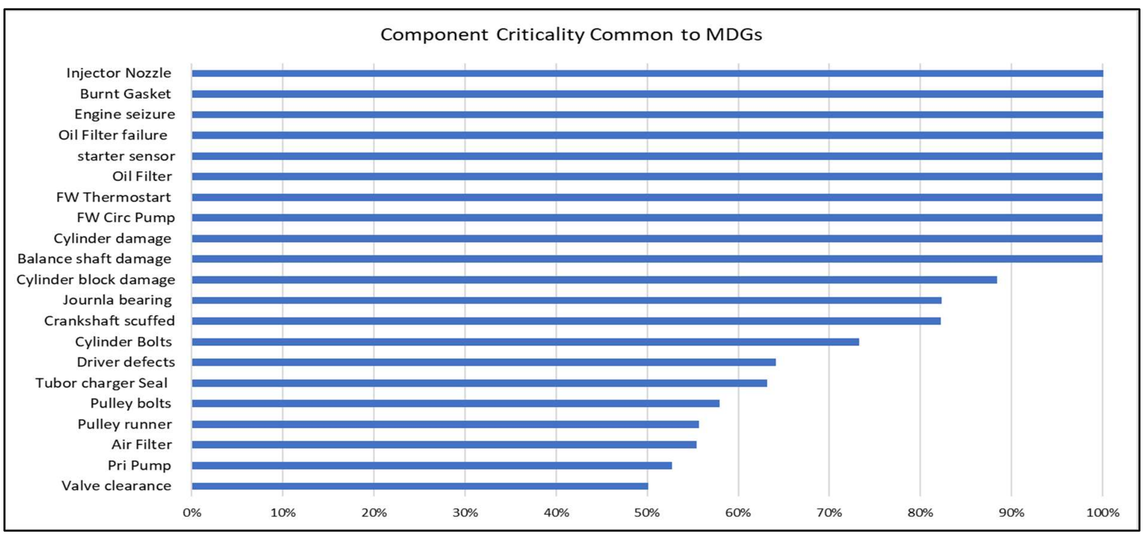

Figure 44: Common critical components to all MDGs.

Overall, the reliability IMs provided some key insight on the failures affecting the MDGs, as well as key insights on the reliability of subsystem these components belong. Most important in this consideration is the issue of repair time, spare availability and SQEP availability as some of the faults cannot be repaired by the generality of personal on board. For instances, tightening the cylinder head bolts requires the use of special toque wrench and most be done in certain patten otherwise there is the risk of stress damage or over tightening. Similarly, replacement of pulley belts can be tricky due tensioning and location of the pump, hence, faults occurring at sea could be very critical to repair.

On the other hand, some faults are not likely to be fixed at sea or even by the operator; these faults requite OEM attention which usually entails international travel as well as freight of needed parts. This adds to overall Operational cost (OPEX) and extended downtime which further adds to deterioration of other systems. In this regard, the IM outputs are extremely valuable information that can effectively improve maintenance delivery, on board spare parts stocking and deployment plans. It would also help the Commanding Officer, or the chief engineer be conscious of the competence in the technical staffing mix such that the right parts are held onboard, and all envisaged faults can be handle event at sea.

5.3.3 Minimal Cut Set

The DFTA results includes component reliability, importance measures (criticality) and the MCS. The MCS provide a significant understanding on the MDGs reliability. The cut set are very significant in maintenance management especially with common cause failures. Especially that the MCS are a combination of minimum number of events which must occur for the top event to occur (component failure), they play very important role in maintenance planning. For instance, knowing that scaling of freshwater heat exchange occurs very often and can be responsible for some failures, therefore any effort to reduce or prevent failure can contribute significantly to reducing downtime or unplanned maintenance. Most importantly, the cut set unlike the IM represents faults which if improved can significantly improve system reliability.

In this regard, the most critical MCS with significant contribution to failures on MDGS are presented in Tables 27 – 30. Each the MDG is presented in separate table, having 2 columns, the first column is for the subsystem which written in bold and the MCS (failure) are listed under. The second the column is the percentage impact the failure has on subsystem and MDG reliability. Overall, the tables provide some revealing insights on the component's failure and insights on likely maintenance issues as well as quality of repair work or spare parts.

Table 26: MDG 1 Minimal Cut Sets

Event	Percentage Occurrence	Event	Percentage Occurrence
Moving parts		**Cooling System**	
Crankshaft failure	80	FW heat exchanger Scale built up	80
Engine seizure	80	FW Heat Exchanger tubes puncture	50
Main bearing	60	Seachest blockages 1	70
Crankshaft Journal Failure	50	Lub oil cooler tube rapture	60
Journal bearing failure	60	RW impeller	80
Damage to Piston/ConRod	90	FW Pump impeller	80
Piston ring damage A2, A3, B1, B4, B5	50	FW pump V belt damage	70
Fuel System		**Inlet/Exhaust**	
Secondary Filter 1	80	Missed tappet checks	75
Primary filter 1	78	Exhaust Valve carbon deposit	80
Governor fault	78	Exhaust valve clearance	52
No fuel Supply	83	Tappet fault all valves clearance	61
Fuel Pump lift	86	**Cylinder block**	
Fuel pump erratic behaviour	69	Damaged O-ring A2, A3, B1, B5	83
HP pump mech failure	64	Burnt Gasket A2, B1, B3, B5	72
Injector nozzles all Cylinders	72	Guide Bushing B4	72
Charge Air System		Loose Bolts all Cylinders	68
Turbo charger Lubrication failed	75		
Air filter Clogged	76		

Table 27: MDG 2 Minimal Cut Sets

Event	Percentage Occurrence	Event	Percentage Occurrence
Moving parts		**Cooling System**	
Crankshaft failure	80	FW heat exchanger tube scale	94
Main bearing	60	FW Heat Exchanger tubes puncture	53
Crankshaft Journal Failure	50	Seachest blockages 1	71
Journal bearing failure	60	Lub oil cooler tube rapture	63
Piston damage	90	RW impeller	84
Piston Crown failure	90	**Inlet/Exhaust**	
Fuel System		Missed tappet checks	75
Secondary Filter 1	75	Exhaust Valve carbon deposit	80
Primary filter 1	78	Exhaust valve clearance	52
Governor fault	78	Tappet fault all valves clearance	61
No fuel Supply	83	**Cylinder block**	
Fuel Pump lift	86	Damaged O-ring A2, A3, B1, B5	83
Injector nozzles all Cylinders	72	Burnt Gasket A2, B1, B3, B5	72
Charge Air System		Guide Bushing B4	72
Turbo charger	75	Loose Bolts all Cylinders	68

Table 28: MDG 3 Minimal Cut Sets

Event	Percentage Occurrence	Event	Percentage Occurrence
Moving parts		**Cooling System**	
Crankshaft failure	80	FW heat exchange tube scale	94
Main bearing	60	FW Heat Exchanger tubes puncture	53
Crankshaft Journal Failure	50	Seachest blockages 1	71
Journal bearing failure	60	Lub oil cooler tube rapture	63
Piston damage	90	RW impeller	84
Piston Crown failure	90	**Inlet/Exhaust System**	
Fuel System		Missed tappet checks	75
Secondary Filter 1	75	Exhaust Valve carbon deposit	80
Primary filter 1	78	Exhaust valve clearance	52
Governor fault	78	Tappet fault all valves clearance	61
No fuel Supply	83	Valve Stem bent	89
Fuel Pump lift	86	**Cylinder block**	
Injector nozzles all Cylinders	72	Damaged O-ring A2, A3, B1, B5	83
Charge Air System		Burnt Gasket A2, B1, B3, B5	72
Turbo charger	75	Guide Bushing B4	72
		Loose Bolts all Cylinders	68
		Starting System	
		Starter Pinion	66

Table 29: MDG 4 Minimal Cut Sets

Event	Percentage Occurrence	Event	Percentage Occurrence
Moving parts		**Cooling sys**	
Rocker Arm	84	FW heat exchange tube scale	70
ConRod arm B1	44	Intercooler fins fouling	53
ConRod arm A6	44	Seachest blockages 1	71
Piston Crown	54	Lub oil cooler tube rapture	63
Piston ring damage	70	RW impeller	84
Fuel System		Oil Cooler fouling	60
primary filter	79	**Inlet/Exhaust**	
Secondary Filter 1	75	Missed tappet checks	75
Primary pump	64	Exhaust Valve carbon deposit	80
Governor fault	78	Exhaust valve clearance	52
HP Supply leakages	85	Tappet fault all valves clearance	86
Injector camshaft failure	54	**Cylinder block**	
Injector nozzles all Cylinders	72	Damaged O-ring A2, A3, B1, B5	77
Governor drive	77	Burnt Gasket A2, B1, B3, B5	73
Charge Air System		Guide Bushing B4	72
Turbo charger	52	Loose Bolts all Cylinders	68
Air Filter Clogged	77	**Starting System**	
		Air Starter pinion	63

The results of the MCS for all the MDGs shows some similarity in faults albeit with MDGs showing high percentages on the contribution of some faults. The most of these differences are common with the Moving parts and Cooling system. Failures on the cooling system are of particular interest considering the wider impact it can generate especially with sea water cooling components installed with thermostat. A most critical failure occurs when the thermostat fails closed, in components such as the oil cooler or the air cooler, because these components will necessarily stop MDG from working but could have a long-term performance penalty on it. In relation to the modelled moving parts, there seems to be a patten that the crankshaft and associated accessories re-occurs in 3 out of the 4 MDGs which rise a fundamental question as to cause of failure. However, based on the modelled analysis it can be seen that failures on the cooling seawater system have a far reaching impact on other subsystems.

MCS obtained through DFTA for individual sub systems had dual purposes, the first was its relevance within the DFTA framework and the second was its use as input to build the BN probability analysis. This would discuss the relevance of the MCS within the DFTA framework, which is critical failure path identification. Nonetheless, some failures can be triggered by a fault in another system, hence the relevance of investigating interrelationship in component failures. A case in view is the crank case failure of the MDGs investigated, which exhibited a concerning low level of reliability due to faults initiated in other system and the crankcase seemed not designed handle; particularly faults originating from the lubrication and freshwater cooling as well as the air distribution system.

Moreover, another important factor with MCS is that events are considered based on their contribution to failure not only occurrence. In some cases, failure occurrence may not necessarily be the reason why a component becomes critical to maintenance. In most cases factors such as down time, cost of repairs and repair capability could be major concerns for operators. For Instance, overheating related failures are dominated by sea water heat exchanger scaling which are mainly of concern because of the envisaged operational interruption. However, lubrication system failures or losing alternator exciter which seldom happens but their occurrence could lead to serious consequence. In this regard, the capturing of these types of faults by MCS formation based on the qualitative structure of the DFTA is very important for maintenance scheduling and in some cases could help to be the bases of Additions and Alterations (As&As) during docking or refit process. In general, these types of critical faults once identified can be well planned for, either by providing alternative systems, introducing additional repair or inspection to improve monitoring and quick intervention.

5.3.4 Sensitivity Analysis

In order to understand the impact of further deterioration in reliability a sensitivity analysis was conducted on specific components that were deemed highly critical based on available failure rate data, DFTA outputs, and concerns voiced by operators. This selective approach was adopted due to resource constraints and the expected benefits of such an analysis. In this regard, the sensitivity analysis evaluates how variations in input values for specific variables impact the outcomes of a mathematical model. In our case, this analysis helps us understand the extent to which changes in failure rates can influence overall reliability. Consequently, it offers valuable insights into areas that would require more resources or attention to prevent further degradation, A detailed sensitivity analysis for the MDGs is Appendix 8.

Tables 31 and 32 presents the sensitivity analysis conducted on the crankcase and moving parts (PTO) respectively as both are the most critical subsystems in the MDGs and have among the longest time to repair. This is partly because the crankcase and the crankshaft are not generally held as spares on board, and only in limited quantity at the technical store depot. Furthermore, replacing and installation process of this components requires elaborate planning, use of special tools.

Table 30:Crancase sensitivity for MDG 3

MDG 3 Crankcase sensitivity				
Months	Base	Base +10%	Base+20%	Base+30%
0	1.00	1.00	1.00	1.00
7	0.99	0.99	0.99	0.99
15	0.96	0.94	0.93	0.91
22	0.86	0.82	0.78	0.73
30	0.71	0.64	0.56	0.49
37	0.52	0.43	0.34	0.26
45	0.34	0.25	0.17	0.12
52	0.20	0.12	0.07	0.04
60	0.10	0.05	0.03	0.01
67	0.04	0.02	0.01	0.00
75	0.02	0.01	0.00	0.00

Table 31: Moving Parts sensitivity for MDG 3

MDG 3 Moving Parts Sensitivity table				
Months	Initial	+10%	+20%	+30
0	1.00	1.00	1.00	1.00
7	0.99	0.99	0.99	0.99
15	0.96	0.95	0.95	0.94
22	0.86	0.85	0.84	0.82
30	0.71	0.68	0.65	0.63
37	0.52	0.48	0.43	0.38
45	0.34	0.28	0.21	0.14
52	0.20	0.12	0.04	0.04
60	0.10	0.01	0.01	0.02
67	0.04	0.01	0.00	0.02
75	0.02	0.01	0.02	0.03

To obtain the sensitive values, the failure rates values were varied in increasing manner by 10,20 and 30 percentage points to explore how any increase in the failure rates can alter the overall reliability and perhaps the resilience of the PGS as regards reliability in the context of the operational environment. Accordingly, looking the crankcase results in Table 33, against the operators SOP of maintaining 80 per cent availability, would be difficult after the first 20 months. The first instance of 10 % narrowly crossed with just 2 months and for the subsequent 20 and 30 %s component resilience was minimal. It therefore indicates that the MDG will require all the necessary attention it deserves, and operators must ensure that the faults that could add excessive stress to the cylinder block, liners and pistons must be avoided. Alternatively, the OEM could be called on to provide additional guidelines as regards monitoring and inspection for the crankcase.

The moving parts sensitivity shows more resilience to varying failure rates as compared to crankcase, at least within the first 22 months across all the 3 variations. Nonetheless, by the 30^{th} month there is an overall reduction in reliability, meaning that the MDG will have such failures while still under warranty. In this regard, the OEM may need investigate further the problems with MDG or the operator could as well as appraise the workings of the MDGs and monitoring process. This is not to say, operators are not aware of the monitoring and maintenance on board, however there could be need for additional training or provision of additional sensors, improvements around MDGs such as cooling water supply, vibration monitoring and additional safety measures to reduce overheating. Moreover, utilisation of advanced data analysis such as machine learning can provide further insight on the causes of failure through health parameters analysis.

5.3.4.1 Critical Component Sensitivity Analysis

Sensitivity analysis was carried out on some components that were considered highly critical based on available failure rate data, DFTA out puts and perceived concerns from the operators. Though not all components were considered mainly because of required to carry out the analysis and possible derived benefit. Therefore, recognising the benefits a sensitivity analysis is used to identify how much variations in the input values for given variable impact the results of mathematic model. In this regard, conducting the sensitivity analysis on some key components gives an idea of how the variation in failure rates can affect overall reliability. It therefore provides an understanding on were to focus more resources in order to avoid further deterioration.

The crankcase of MDG 3 had a relatively good reliability as compared the other MDGs, therefore it can be used to analyse the impact of further deterioration on system reliability as compared to MDGs with low reliability. In this regard MDG 3, crankcase reliability sensitivity curves are shown Figure 45. The curves showed reduction in reliability variations of 10%, 20% and 30% against normal reliability curve. The relevance of this can be more related to product lifecycle projections on availability and repair especially on a part like the crank case which can sometimes be unrepairable. Hence, with the sensitivity analysis values the operators can major or make a good estimation the impact of certain failure due to lack of maintenance or intervention. In the case of the crank case failure, lack of resilient mountings was adjudged be among the major cause of failure due to vibration.

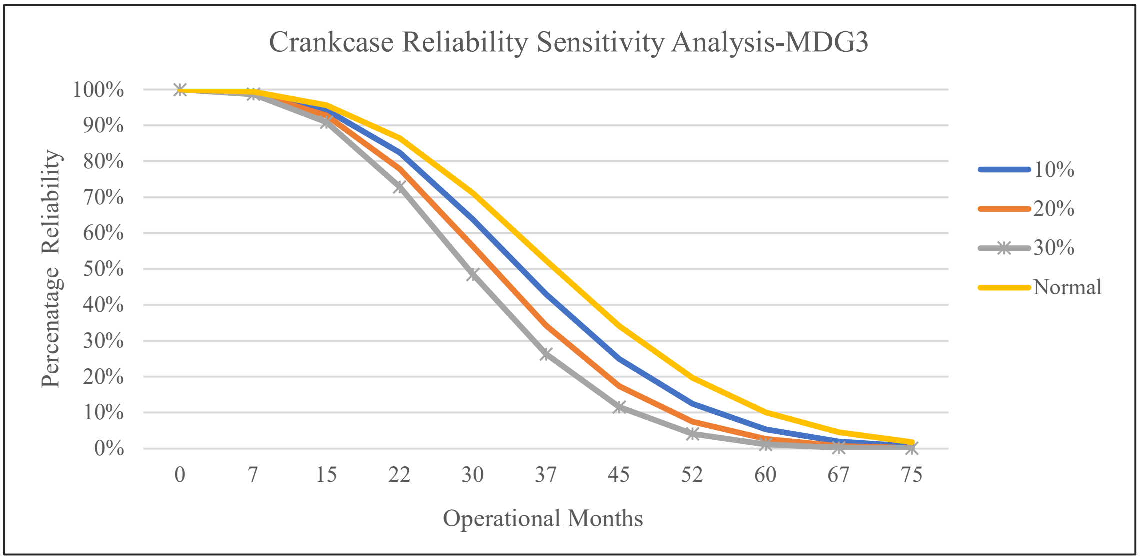

Figure 45: Sensitivity analysis for MDG 3 Crankcase

Nonetheless, other issues as such frequent overheating and over rating of the MDGs by the OEM could play a role in this unreliability conditions. Other important factors adding to the failure conditions could only be investigated through machinery health data analysis using machine learning tools such ANN algorithms.

5.3.5 Dynamic Fault Tree Analysis Spare Gate

Spare gates are used to represent spares or redundancy in systems, basically spares gates are categorised into hot, warm, or cold spares depending on their connection to the system which can be represented with 1 as active spare, 0-1 as warm spare and 0 as cold spare. A cold spare doesn't fail if the main spare failed while active and warm spares can fail with the failure of the main spare. This feature allows spare gates to be used to mimic improvement in system configuration or maintenance action that could improve reliability. This feature of the spare gates makes it one the most important gates in the DFTA dynamic gates. In additional to the possibility of modelling complementary equipment in a system it gives the flexibility of modelling repairs or intervention activity that could improve overall reliability of an equipment or related component.

Utilising these features some key sub-systems on one of the MDGs were analysed to evaluate possible gains in reliability. It was obvious from the results presented in Figures 46-49 that spare gate can clearly show improvement in reliability. Though to achieve this require a good understanding of the system and it works as well as the process of evaluation in the software environment. In particular, identifying how the components are impacted by certain faults or how the system is impacted by the failure of the component matters a lot. Therefore, as can been seen in the Figures some the system presented wide reliability improvements while others had narrow curve. Nonetheless, the idea is to see the possibility of the improving the base reliability of the MDGs using existing inspection and intervention techniques already known to the operators.

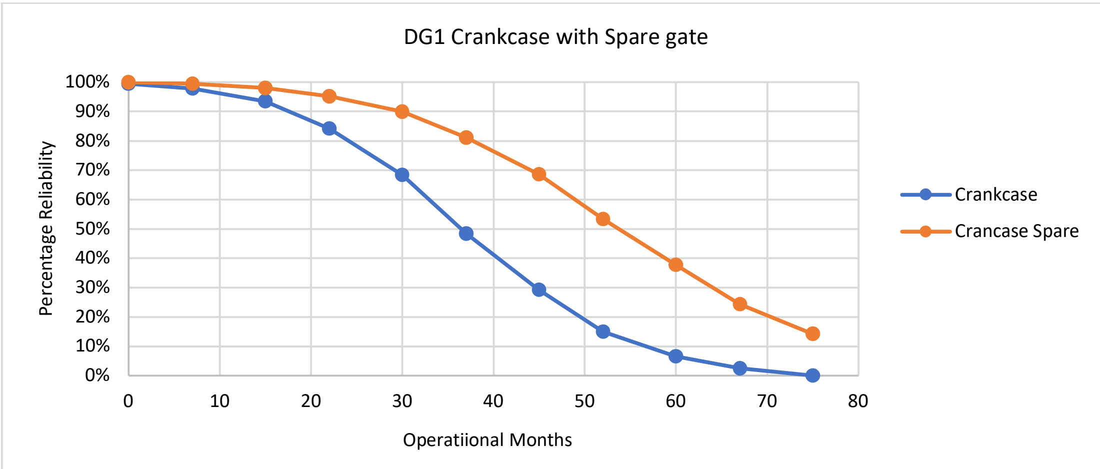

Figure 46: Improvement Using Spare Gate on MDG 3 crankcase.

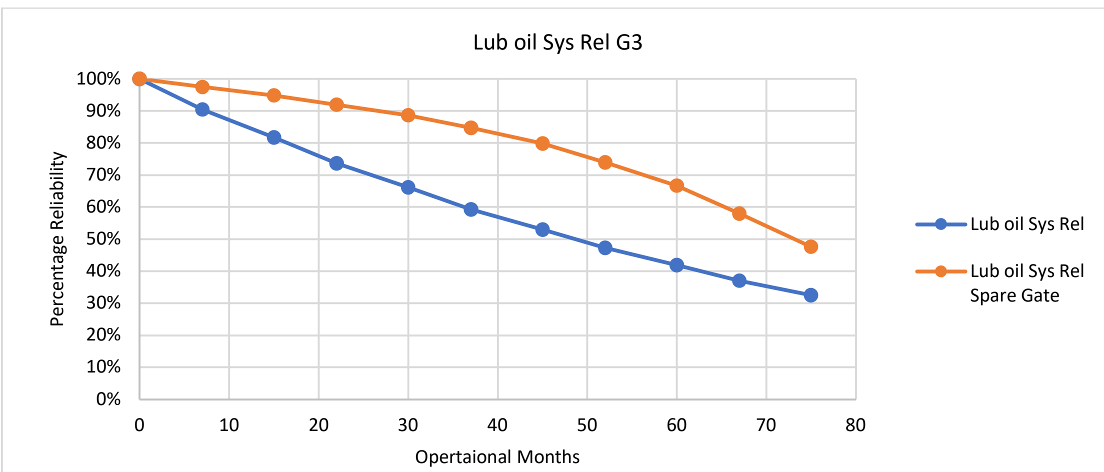

Figure 47:Improvements Using Spare Gates on G3 Lub Oil System

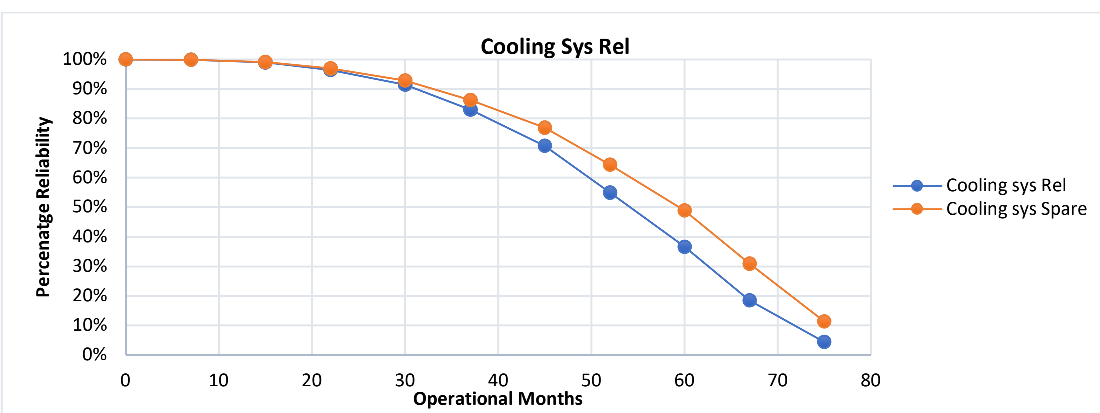

Figure 48:Improvements Using Spare Gates on MDG 3 Cooling System

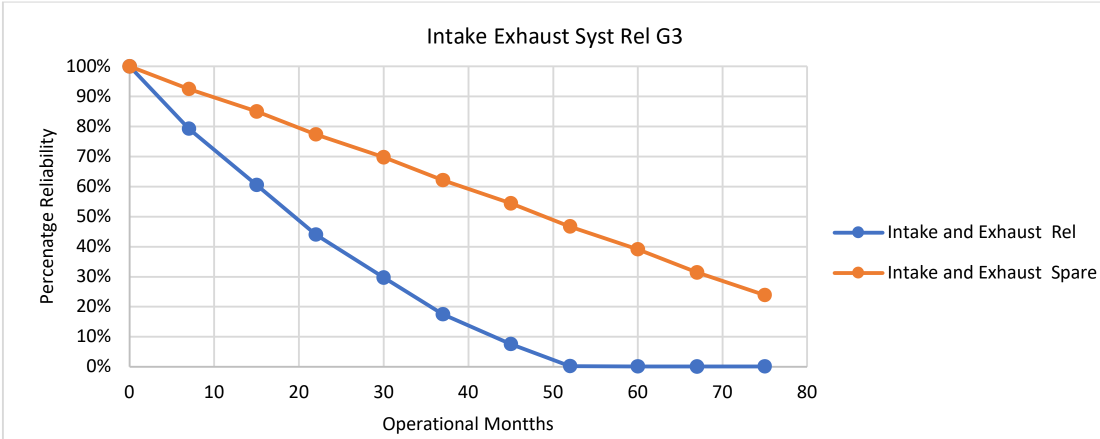

Figure 49:Improvements Using Spare Gates on MDG 3 Intake and Exhaust System

Having in mind the operational availability requirements of 80% by the operator, the target for the improvements using the spare gates was to maintain a minimum of 80% system reliability within the first 24 operational months. Although this may be seen as insignificant, but looking at all the figures it would be noticed that it was only the cooling system that maintained its reliability well to the 40th month. Here several factors could responsible most important would be the level of built in redundancy in the sea water supply line, others could be the ease with which personnel can rectify fault, possibility of switching supply lines without having shutdown the MDG. The ability to easily detect overheating especially on freshwater system is another factor.

On the other hand, Intake system presents a rather low reliability at just around the 7th months, this call for concern, particularly considering how faults in the Intake and Exhaust system influences performance and emissions. However, this may not be unconnected with the fact that fault affecting valves, tappets and/or the rocker arms require reasonably high skills levels which may not always be available. The fact that tappet clearance checks and setting were to be done every 250hrs seemed shot and may be factor in the low reliability presented, either due to delays or wrong calibration. Overall, the most improvement achieved was in the lubricating oil system; base 80 % reliability was at up to 16 months, after there was steady decline to lowest of 30 % by 75th month. However, with the spare gates additional 30 months were gained, and the lowest reliability value was about 47%, against the 30% based on the initial reliability. In essence the spare gates have provided a good insight on how maintenance action targeted the right components can transform the reliability of equipment.

The DTFA analysis essentially provides in depth top-down analysis of individual system on the 4 MDGs in the case study. The outputs from the DFTA includes the system reliability curves which provides the reliability of about 8 subsystems of the MDGs. Other output obtained from the DFTA includes the reliability IM and MSC. The reliability IM provides quantitative indicators on component criticality for individual components model in the MDGS. The Bir IM was used to present the most critical components; this is mainly because of its ability to identify the most critical component once the top event is said to have occurred, hence most effective when dealing low level granular analysis. On the other hand, the MCS are the combination of minimum number of events which must occur for the top event to occur (component failure), they play very important role in maintenance planning especially in identifying important faults and their impacts on component reliability.

5.3.5.1 Archived Maintenance Improvement Using Spare gates.

Spare gates are utilised to denote spare or redundant components in systems reliability analysis. In this regard, experts in this field are able to utilise these features in spare gates to model the expected behaviours of machinery after repairs or maintenance action. This feat is made possible due to the probability distribution of on how the gates behave when model as active shaving the probability of 1, a warm with a probability of 0-1, and a cold represented by 0. Therefore, by implication the cold spare is not impacted due to the failure of primary spare since is not connected or active, the active has the inverse effect, whereas warm spares can fail with varying degree of impact on the equipment. Therefore, these features enabled spare gates to be used to mimic improvement in system configuration or maintenance action that could improve reliability. Figure 40 shows achieved reliability improvements in MDG1 crankcase reliability, due to additional consideration and improvements as gathered from the operators.

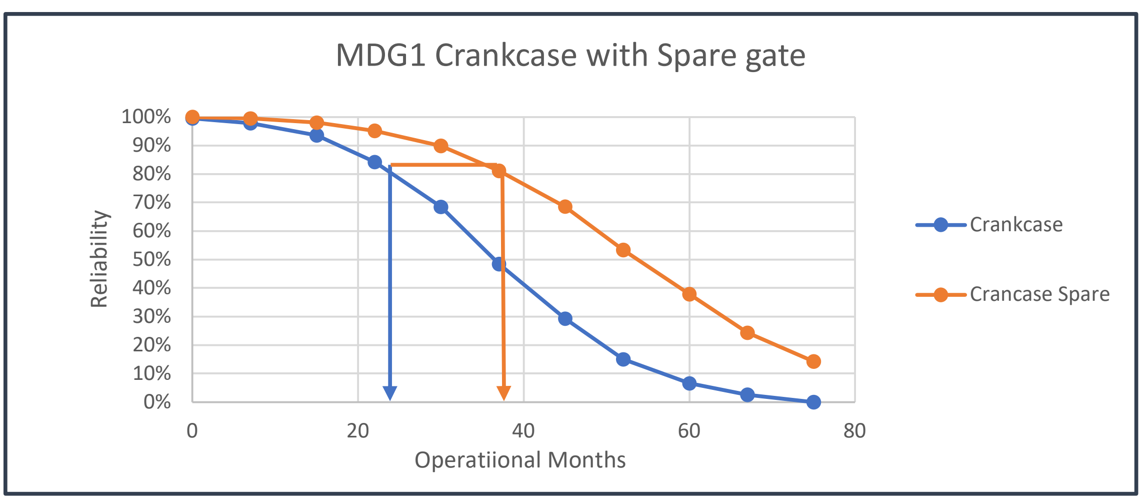

Figure 50:Improvements achieved using spare gates MDG1 Crankcase

Faults that can be influenced vibration were among the most obvious causes of failure on the cylinder due to lack of vibration damping resulting in the cylinder bolts getting loos. Consequently, causing rapid overheating and imbalance on the valves which in some case leads extended valve travel beyond the piston maximum travel at top dead centre. Therefore, it was common to have bent valve stems as leading cause of damage to piston crown, and consequent damages to the cylinder liners and eventual cracks to the cylinder block.

Figure 51 is the intake and exhaust system of MDG 3 which also presented a very low reliability levels at the stage of operations. Therefore, it was also selected to investigate the use of spare gates to highlight possible reliability improvements considering additional maintenance, inspection, or any sort of intervention by the operators. The improvement recorded were remarkable considering the nature of faults and components involved. Some of the recommended interventions includes increase in the number of hours required to for tappet clearance from 200 hours to 500 hours and the increase monitoring of exhaust gas temperatures. Similarly, a recommendation to provide a shore DG for the ships while harbour to help reduce the overall running hours.

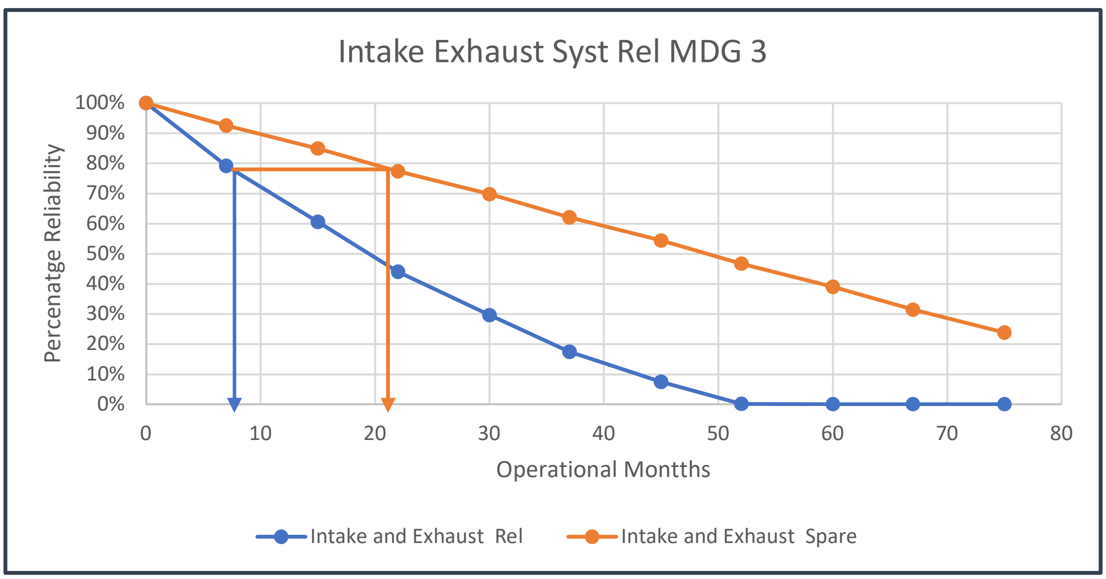

Figure 51:Achieved improvements using spare gates MDG 3 Intake/Exhaust System

Table 47 shows some achievements in reliability due to additional measures to improve maintenance or condition health monitoring approaches across the MDGs.

Table 32: Some achieved reliability improvements using spare gates.

Gen Sub-System	80 % Reliability	80 % Improved Reliability
Crankcase MDG1	22 months	37 months
Inlet and Exhaust System MDG3	7 months	21 months
Lubricating Oil System MDG3	15 months	45 months
Moving Parts MDG4	30 months	50 months

Accordingly, after the detail analysis on system reliability and having obtained the associated outputs, the spare gates was used to model possible improvements that can be achieved through maintenance, inspection, and repairs actions. This process uses the spare gates to model any intervention and how it affects the overall reliability of the system. Overall, the DFTA is very effective in structurally analysing the impact of components failure on the reliability of a system, also providing means to model alternative of improvements to unreliability. However, the DTFA's greatest challenge is diagnosing the symptoms faults. Hence, ANN analysis was adopted to help in developing a data driving method to interrogating the machinery health data as regard fault detection analysis.

5.4 Artificial Neural Networks Analysis

An ANN fault detection model using a feedforward neural net was built to provide further details as regards the major courses of failure and how they can be related to identified faults. Moreover, one of the goals of maintenance planning is to improve efficiency both in spare parts holding and the procurement process. Therefore, using the ANN would help identify faults that can be linked to the identified critical components. The available data obtained from the four diesel generators consisted of eight headings: (1) Generator Speed; (2) Lubricating Oil Pressure; (3) Fresh water temperature bank A; (4) Fresh water temperature bank B; (5) Fresh Water Pressure; (6) Lubricating oil temperature; (7) Exhaust gas temperature bank A; (8) Exhaust gas temperature bank B; (9) Generator running hours; (10) Generator Power Output; and (11) Datetime, as shown in Table 33, are a list of diesel generator parameters and their limits.

Table 33: MDG Operating Parameters

Parameter	Operating Ranges		
	Min	Max	Alarm Level
Engine Speed (RPM)	1789	1850	2052
Lubricating Oil Pressure (Mpa)	0.4	0.55	>0.6
Cooling Fresh Water Temperature banks, A (°C)	75	80	>85 °C
Cooling Fresh Water Temperature banks, B (°C)	75	80	>85 °C
Fresh water pressure (Mpa)	0.02	0.25	>0.3
Lubricating Oil Temperature (°C)	30	110	>120 °C
Exhaust Gas temperature banks A (°C)	220	400	>520
Exhaust Gas temperature banks B (°C)	220	400	>520
Generator running hours	≥2000 h	N/A	N/A
Power Output (Kw)	0	350 Kw	350 Kw
Date/time	January 2019	December 2019	N/A

Considering, that raw machinery data is not free from errors in recording and sensor noise, coupled with the fact that the data for this research had to be transcribed. Data cleaning has to be conducted prior to the exploratory analysis and feature engineering. This process involves, removing or cleaning empty cell, wrong entries, and outliers. Further, in order to ascertain which of the parameters would be relevant for the study correlation, ANOVA and ANN SOM were used to carry out feature selection after the data cleaning, 7 out of 11 parameters presented in table 33 were selected for the analysis.

5.4.1 Data Cleaning

The first task in the data cleaning was to get the summary of the collected machinery log data as shown in Table 34. Data cleaning was conducted using the MATLAB data cleaning app to replace non-numeric values and cleaned empty cell. Thereafter transcription to excel out pre-processing data by removing nonnumeric (NAN) values, and initial outlier removal by using interquartile range based on the operational data ranges as provided by the Original Equipment Manufacturer (OEM) and the Operator. Therefore, after obtaining the quartiles a value of 15% was added to the upper limits to account for the disparity between the OEM and operator's limits. The process helped improved the validity of the data by eliminating the relatively very low operating parameter values to become more acceptable. The 15% was the upper limit accepted by the operator as an indication of fault while any value 25% more than limit is a sign of failure.

Table 34: Summary of MDG hourly log data.

	RPM	LoP	FWTA	FWTB	LoT	FWP	EGTA	EGTB	HRS	KW
count	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0
mean	1800.1	0.50	66.1	68.8	84.4	0.08	334.7	317.6	2527.3	128.3
std	2.9	0.10	3.4	3.8	4.7	0.01	39.3	38.9	2703.2	34.7
min	1783.0	0.33	40.7	42.7	41.6	0.05	161.2	146.9	523.0	65.0
25%	1798.5	0.38	65.2	67.7	82.4	0.07	310.2	287.5	603.3	100.0
50%	1800.0	0.56	66.2	68.8	84.6	0.07	339.5	325.8	636.5	130.0
75%	1801.0	0.57	67.4	70.3	86.4	0.08	352.0	337.5	6340.8	140.0
max	1812.0	0.86	74.1	77.1	94.0	0.12	426.8	408.1	6379.0	240.0

Using the quantile analysis, the data limits for the diesel generators was derived to provide a good fit that reflects the operator's data limits as presented earlier, believing also that it will further improve the model quality. Table 35 shows the data limits used to extract outliers for the data. This was adopted because of the disparity between the OEM and the Operators in one hand and in the other hand the outlier detection for machinery health parameters can be tricky and require expert knowledge. In particular, the pressure and power output values can be of great concern and so the limits had to be observed carefully. Hence the process was relatively tricky and iterative to ensure that the original data features were retained in the overall data that would be used for diagnostic analysis.

Table 35: Derived data limits for the diagnostic analysis

Future	RPM	LoP	FWT - A	FWT - B	LoT	FWP	EGT- A	GET - B	Power (KW)
Minimum	1791	0.32	56	58	59	0.04	160	154	10
Q1	1798	0.39	64	71	86	0.08	303	309	100
MEDIAN	1800	0.433	65.2	73.9	87.45	0.078	329.5	321.9	120
Q3	1800	0.456	66.2	75.6	89.3	0.083	350.4	342.65	140
Maximum	1901	382	81.4	91.4	97.7	0.884	3340.3	3114	240
Q2(Mean)	1799	1.00	65.26	73	87	0.09	335	331	123
IQR	2	0.065	2	4.8	3.6	0.008	47.05	33.25	40
IQRx1.5	3	0.10	3	7.2	5.4	0.012	71	50	60
Lower limit	1795	0.30	61	64	80.3	0.063	233	260	40
Upper limit	1803	0.553	69.2	82.8	94.7	0.095	421	393	200

5.4.2 MDG Health Feature Selection

Feature engineering was carried out in order to identify key data variables within the collected data that can be used for diagnostic analysis. In this regard 3 approaches were done in order to provide strong evidence for any variable to be used. Accordingly, correlation was first to be used which was later followed by ANOVA analysis and then ANN SOM. Both Correlation and ANOVA analysis provide insight into the relationships and differences among variables. However, correlation analysis highlights the strength and direction of the linear relationship between two continuous variables, which helps determine how one variable affects another, while ANOVA test compares the means of two or more variables by testing the categorical independent variable-based group means for statistical significance. On the other hand, ANN SOM uses machine learning approach to cluster the data based on similarity to a certain feature representing a dominant variable.

5.4.2.1 Correlation Analysis Results

Correlation analysis was conducted to gain further inside on the relationship among the parameters. A regression correlation (R-Value) on comparing 7 health parameters with the target features was conducted as presented in Figure 47. The R-value is measure of how well the variation of the inputs is with the target, values close to one show good fit or relationship between the features. Overall, out of the 7 parameters LoP had least correlation value hence it was dropped from further analysis. In this regard, the correlation analysis identified 6 out the 7 selected features that have responds greatly to any shift in power output given kilowatt. The obtained R-values were then considered in chosen the feature for the next step of the analysis.

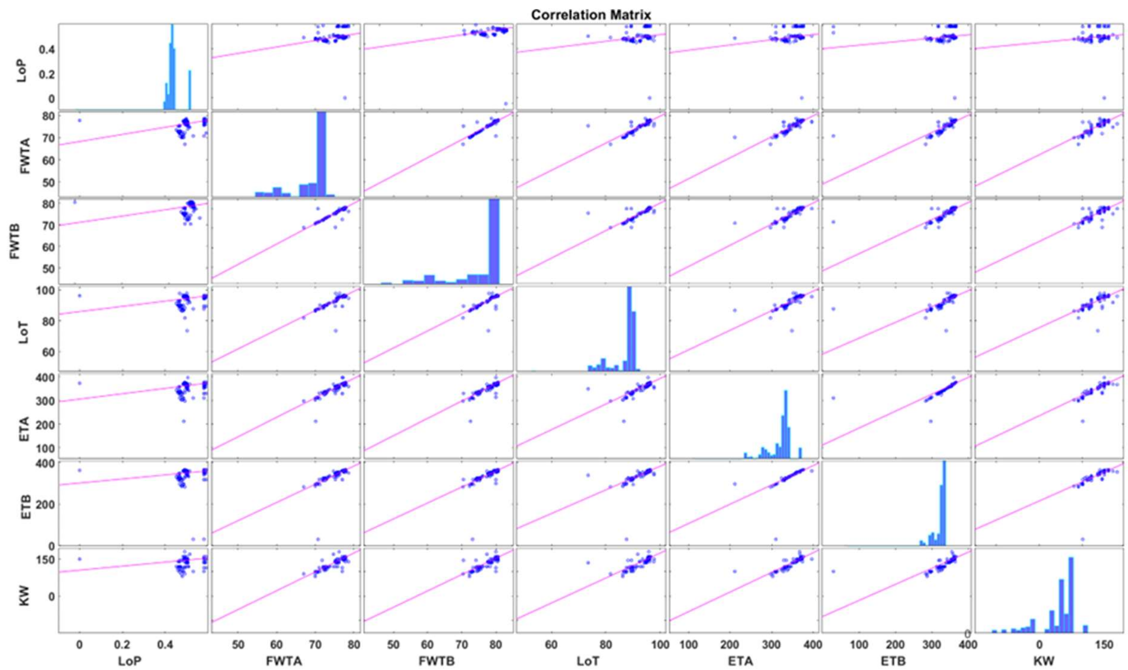

Figure 52:Combined MDG Correlation Matrix

Table 36 gives a list of the variables and the corresponding R-values for the correlation, again it shows good response on temperature health parameters, except in this Fresh water temperature provides a good response with just a point difference. However, there appear an appreciable difference in that if exhaust gas temperatures, ETA (EGTA) appears high much higher than ETB and this is the same in the 4 MDGs.

Table 36: R-values for correlation

Parameter	Abbreviation	R Values against KW
Power Output	Kilowatt (KW)	0
Exhaust Gas Temperature A-Bank	ETA	0.83
Exhaust Gas Temperature B-Bank	ETB	0.78
Lubricating Oil Temperature	LoT	0.81
Fresh Water Temperature A	FWT-A	0.85
Fresh Water Temperature A	FWT-B	0.84
Lubricating Oil Pressure	LoP	0.16

Though there is no very convincing reason for this disparity some possible reason could be due to local influences such as the MDG position in the engine room and sensor location. Moreover, this difference appear in the FWT values such that the FWTA is also slightly higher than FWTB, and this is presented in the EGT values. Efforts to check the trend in incidents did produce a clear indication that the temperature differences influence failures on the MDGs. Having had the correlation results, a look at the ANOVA analysis is presented next.

5.4.2.2 Analysis of Variance Results

Analysis of Variance (ANOVA) was used to determine feature importance, and seven data features were found to be important for the analysis. These include Power output (kw), Exhaust gas temperature (EGT) A and B, Fresh Water temperature (FWT) A and B, Lubricating Oil Temperature (LoT), and location data, as shown in Table 40. The ANOVA ranking like the SOM and correlation analysis ranks the temperature parameter indicators high except it ranks Exhaust gas temperature much high then FWT. Furthermore, the ANOVA ranking for the EGT is much higher as compared to the other variables in the previous 2 analysis. The significance of the ANOVA ranking is the confirmation of the EGT as condition indicator for increase in power output; this also conforms with other analysis such as gas path analysis (GPA). Moreover, the gap in ranking among the variables provide a good incentive to select EGT as strong condition indicator.

Table 37: ANOVA ranking output.

Features	ANOVA Ranking
EGTA	8.9
EGTB	8.5
LoT	8.5
FWTA	0.6
FWTB	1.0
Power Output	6.7

Overall, the exploratory data analysis has helped revealed additional details on the data limits which has improved the outlier detection process, it has also revealed the discrepancies between the A and B banks of the MDGs. Most important the response of temperature parameters especially that of EGT to MDG performance is not only important to the diagnostic analysis but a testament to the quality of the data.

5.4.2.3 Cluster Analysis with ANN Self Organising Maps

ANN algorithm for clustering wase used for dimensionality reduction that can give insight about high dimensional data with minimal computing. Unsupervised learning is useful for exploring data in order to understand the natural patten of the data especially when there is no specific information about significant incidents in the data that can easily point to some fault indicators. The data collected was hourly machinery log of the DGs hence with no indication failure or maintenance periods. Therefore, one of the best possible methods to get the information was to conduct cluster analysis, consequently ANN SOM was used for dimensionality reduction and clustering in the collected data from the case study ships. The analysis provides, insight on the main groups and identifying the health parameters can be used for further diagnostics analysis.

In view of the above, having conducted correlation analysis the initial training was conducted with 6 inputs based on R- values of the parameters. In this regard, the health parameters used for the SOM analysis are presented in table 37. As can be seen, there are 2 columns in the tables which that represents operating ranges i.e Normal and Abnormal. These columns were generated to highlight the difference in operating values between the operator and the OEM. Moreover, this disparity in the values had created additional barrier during the outlier detection process. This is due to the possible area where outlier analysis becomes tricky despite the fact that the operator recommends using an agreed range it may be necessary to consider the OEM ranges before concluding on some results. Nonetheless, the values presented Table 37 were implemented for outlier detection and replacement.

Table 38: MDG health Parameter used for SOM clustering.

DG health parameter	Normal range	Abnormal range		Alarm
		Operator	OEM	
Freshwater Temperature A-Bank	76-82	85 C	90 C	90-92 C
Freshwater Temperature B-Bank	76-82	85 C	90 C	90-92 C
Exhaust gas Temperatures A-Bank	250-520	480 C	500 C	520 C
Exhaust gas Temperatures B-Bank	250-520	480 C	500 C	520 C
Lub Oil Temperature	40-95	90	110	113
Engine power output (kilowatt)	100-350KW	240KW	400KW	440KW

Overall, the SOM topology presented 5 distinct clusters which are good representation of the input data. The weight input in Figure 53 shows an 8-by-10 two-dimensional map of 100 neurons during the training as described in section 4.6.3.1. The colour variation in the map topology indicates the strength of connection between the neurons; lighter colours indicate short and strong connections while darker colours indicate distant and weak connections. Similarity, the difference in pattern colours indicates how correlated the data cluster are to one another.

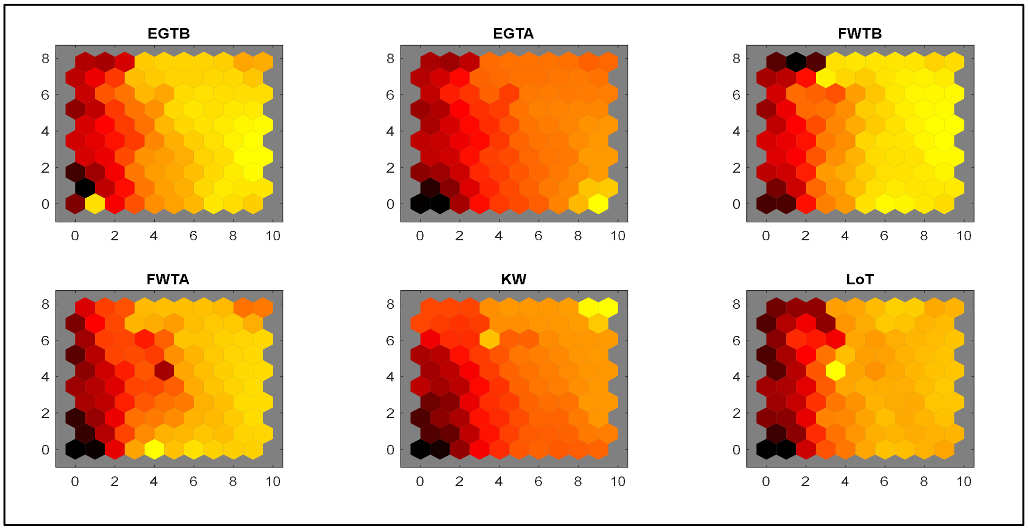

Figure 53: SOM training outputs

Accordingly, the cluster weights of Exhaust Gas Temperature B-bank (EGTB) and Fresh Water Temperature B-bank (FWTB) showed a strong correlation which is not present in Fresh Water Temperature A-bank (FWTA) and FWTB. There is also a strong correlation between Power Output in Kilo Watts (KW) and Exhaust Gas Temperature A-bank (EGTA) and to an extent Lubricating Oil Temperature (LoT), therefore the 3 parameters provide a good set of health indicators for further analysis. On the other hand, the slight disparity between both EGT- A/B and FWT - A/B could be an indication of a more serious problem that operators may need to further investigate.

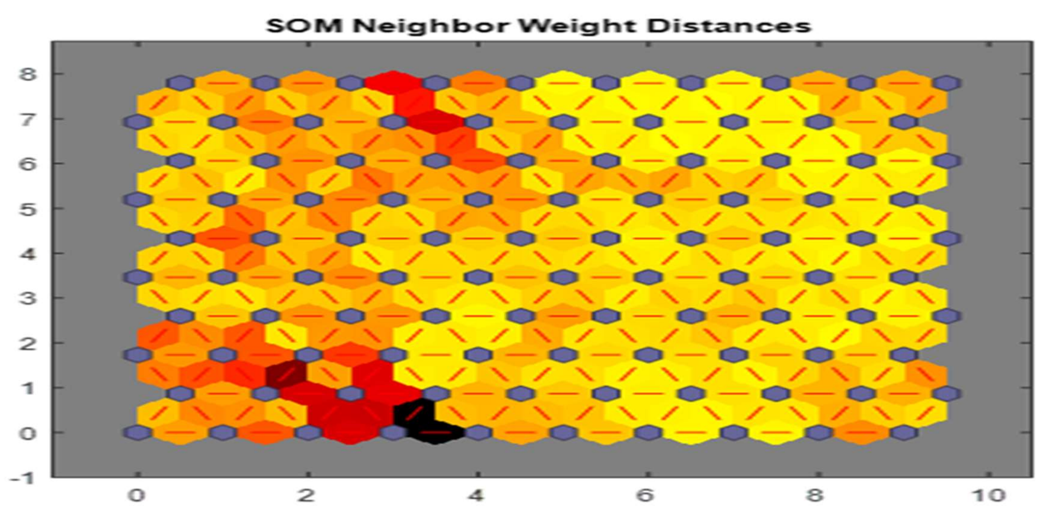

Figure 54:SOM Neighbour weight distance.

Furthermore, the SOM neighbourhood weight distances in Figure 54, shows relatively high dimensional data with about 5 clusters as can be seen within the lower left centre having distinct clusters compare to the lower right end. In contrast the upper right is equally a different concentration of clusters, hence an indication of varying health parameters in the data that points to normal and abnormal data conditions. Moreover, this points to the multi dimensionality of the data especially when considering the interrelation between the variables. Nonetheless the dark colours indicate the strong connection in the weight distances in relation be the input weights in Figure18. In this regard, using the SOM has helped reduced the number of features that can be confidently used for further analysis, it also gave credence to use of exhaust gas temperature as predictor variables.

5.4.2 Diagnostic Results

The fault identification analysis using a feed-forward ANN with two layers based on sigmoid and SoftMax activation functions was used for the classification analysis. A time series data of about 3000 data points was used; the data was divided into three categories: 70% for training, 15% for validation, and 15% for testing. The anomaly data labels presented in Table 39 were used for the initial training using MDG 1; this was executed to develop a single model for all four MDGs. Hence, the labelled fault data using Temperature fault codes (Temp) was used for fault detection, which contains three fault classes. Accordingly, overall training data utilised 20% of the data from all MDGS added to MDG1 data before splitting, as earlier highlighted.

Table 39:Sample of fault data labels

Rev/ Minute	Lub oil Pressure	Fresh Water Temp A	Fresh Water Temp B	Lub oil Temo	Fresh Water Pressure	Exhaust Gas Temp A	Exhaust Gas Temp B	Running Hours	Kilo Water	Temp Code
1800	0.458	72.9	75.4	90	0.067	332.1	319.5	5234	115	NML
1800	0.465	72.8	75.3	89.9	0.068	335.3	323.9	5235	120	NML
1800	0.59	72.01	74.06	89.3	0.068	329.5	316.7	5236	115	HTM
1800	0.53	70.7	73.2	87.6	0.068	310.2	29.4	5262	100	NML
1800	0.58	78	80.68	96.2	0.066	366.1	355.9	5294	150	OVH
1801	0.58	75.8	78.6	94.6	0.067	360.4	351.7	5298	140	HTM
1800	0.504	76.2	79.1	95	0.067	361.2	353.1	5299	140	HTM
1800	0.58	78.6	78.7	94.5	0.067	359.1	350.1	5300	140	HTM
1800	0.502	76.2	79.1	94.8	0.067	358.3	351	5201	140	HTM
1800	0.499	75.8	78.8	95.6	0.067	360.1	353.7	5302	150	NML
1800	0.488	77.8	80.5	96.1	0.066	374.2	363.3	5203	140	OVH
1800	0.498	77.3	80	95.8	0.066	364.3	354.3	5204	150	HTM

This shows that the model has performed well for the diagnostics and can be deployed or adopted for the set of generators. Although considering the datapoints, it is believed that the model might behave slightly differently with a larger data set. Nonetheless, in all the classes, the model has achieved more than 97% accuracy between the true and predicted classes. Figure 8 shows the performance of the model in identifying the three classes, namely NML, HTM and

OVH as well as Consequently, power output (KW) was used as an independent variable, MDG 1 data was used for the first training data set, using the LoT, ETA, FWTA a as the predictor variable of all of which had an ANOVA score above 8.5, hence the relevance to as fault indicators. Figure 55 shows the model performance of the first training set.

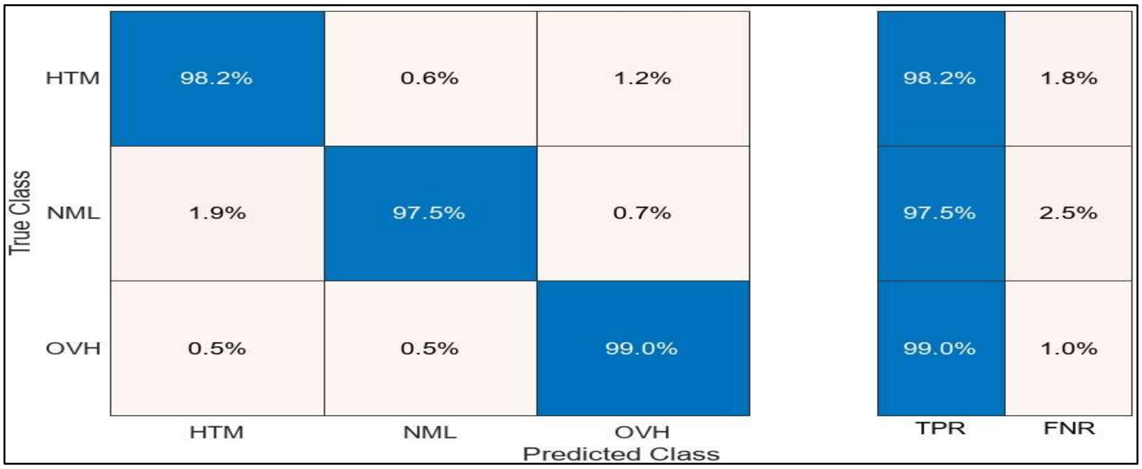

Figure 55: Training Model performance

Accordingly, the selection of the LoT as a predictor is premised on its fidelity to indicate performance degradation as well as the overall health of internal combustion engines. The results of the original model using MDG 1 are shown in Figure 56. The fault identification scatter plot in indicates that the MDG was operating at relatively elevated temperatures usually above 80 degrees. Similarly, an indication of abnormally operating condition is the region of overheating situation around 60kw to 100kw as indicated in Figure 56.

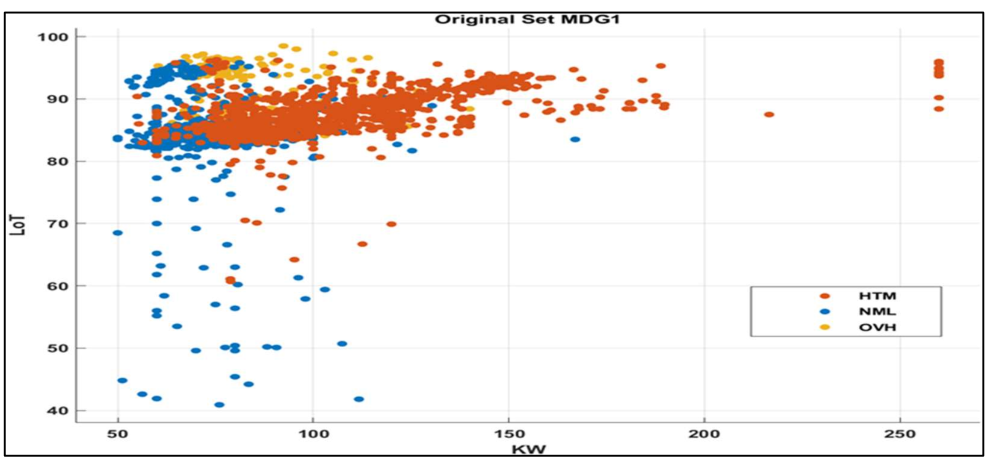

Figure 56:Original Model.

Following the original data set diagnostics outcome using the LoT. An example prediction test was performed using MDG1 data, as shown in Figure 57, and the test model accuracy is shown in Figure 58. In the original and test model scatter plots there appear a similar pattern as of fault development, which indicates that the MDG runs at relatively high temperature for most of the time. It is worthy to note that the OEM normal operating temperature rangers are different from the operator's ranges as presented in table 37. Hence the results being more on the HTM label.

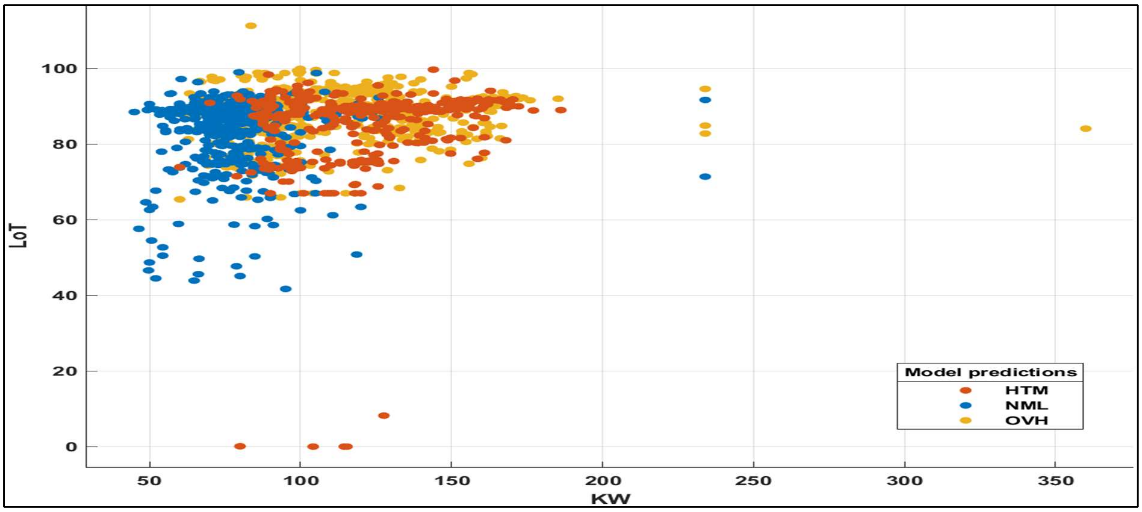

Figure 57: Prediction fault identification model with MDG1 data.

The model was deployed on the combined data of the MDGs, and good enough, the result remains consistent with both the validation and test data results earlier presented. The prediction model shows more fault detections with improved accuracy, mainly because of improved data.

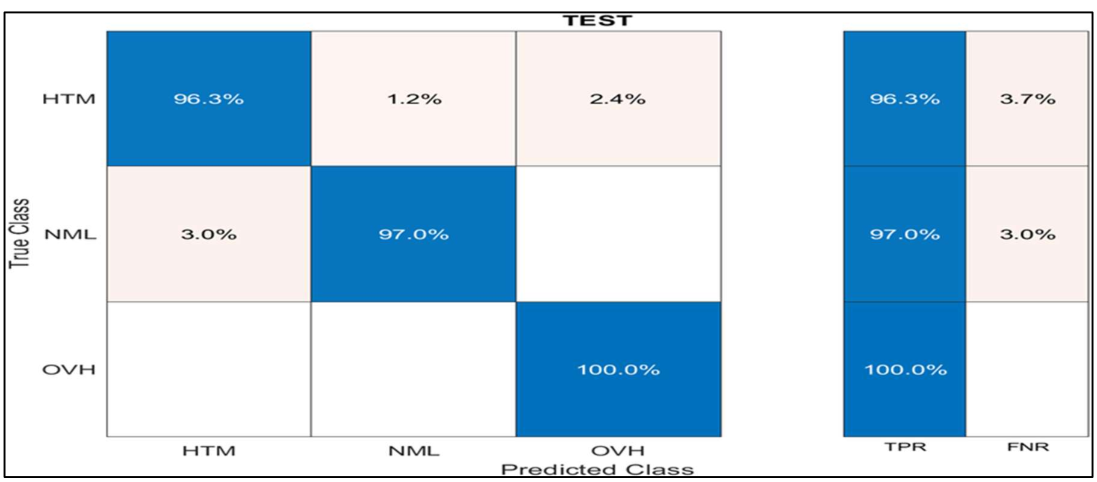

Figure 58: Test model accuracy.

The result of the analysis is presented in Figure 59, as can be seen, the fault concentration zone is still representative of the original training model. However, the prediction using data from different engine presents slightly different health diagnostics. Therefore, based on the above test result combine data from MDG 2 and 4 was used for the diagnostic analysis. The scatter plots in figure 59 are the results obtained using the data the MDG 2 and 4 on LoT. Similar to the original data from MDG1 the data presents a similar pattern of high temperature operating usually above 100kw, this presents a very important feature regarding fault development for the 4 MDGs.

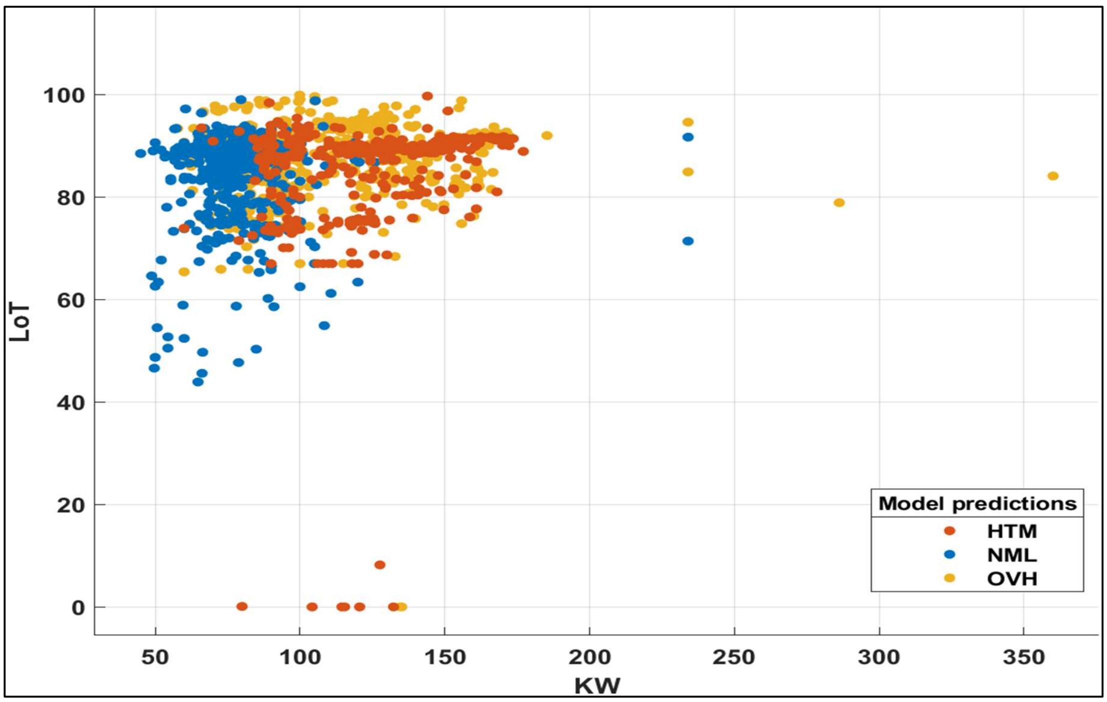

Figure 59:Prediction using a sample dataset of all MDGs comparing the LoT and ETA outputs.

Similarly further investigation based on the ETA as shown in Figure 60 shows common trend. Though, LoT scatter output the ETA data has no clear define the fault boundaries as most of the OVH and HTM pattens overlap. Overall, the result still valid but goes to indicate how the various condition parameters interact with a healthy engine. Therefore, based on the findings from predicted model clear insight can be deduced regarding the component criticality results.

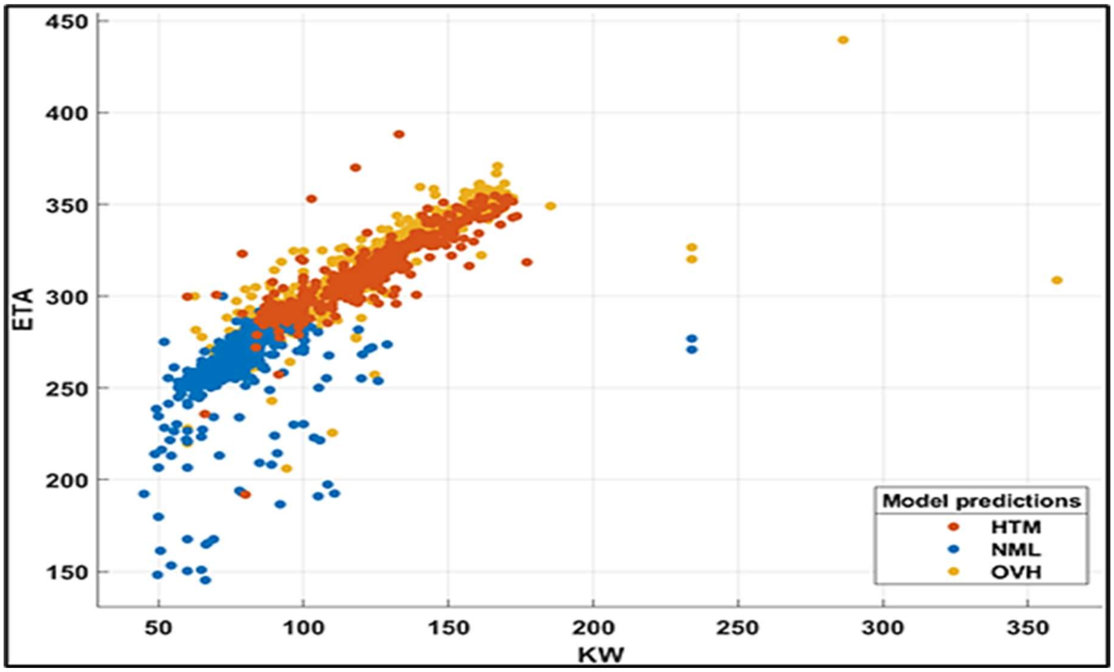

Figure 60:Prediction using a sample dataset of all MDGs comparing the ETA outputs.

An additional output from FWTA also provides a more clearly defined health parameter scatter plot. Figure 61 presents the diagnostics using FWTA which shows better separated regions, i.e. the NML points are more clearly defined and the OVH points are equally defined in certain regions of FWTA as compare to the LoT and ETA outcomes.

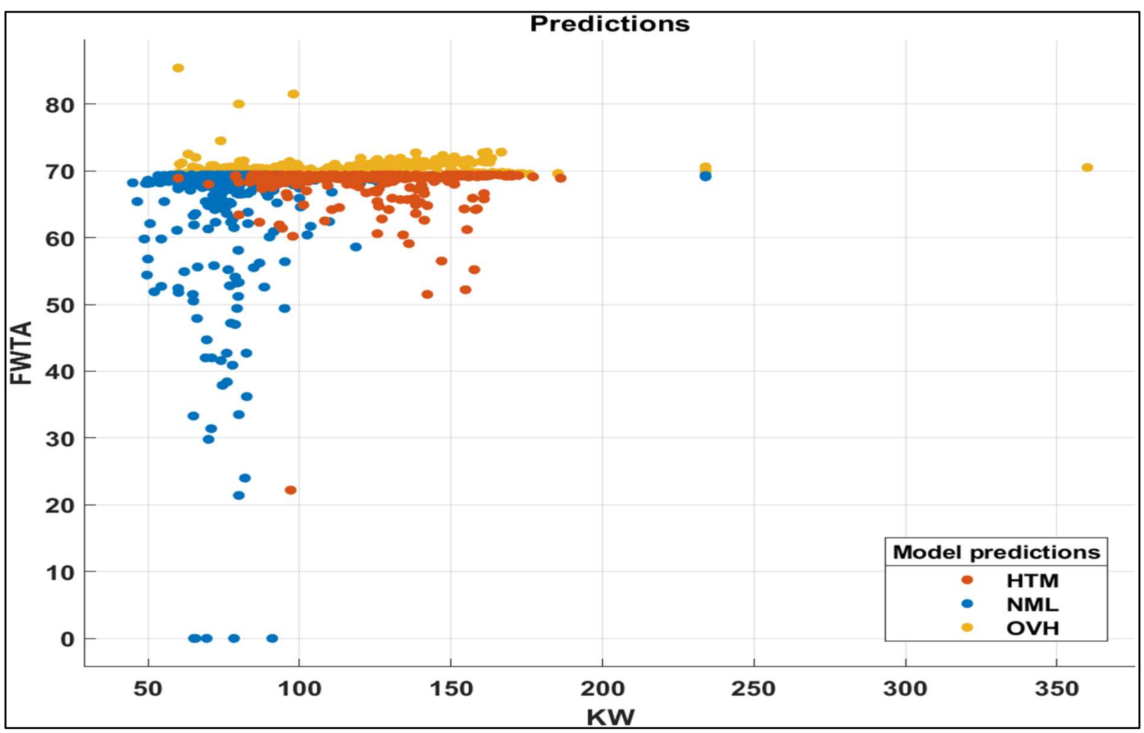

Figure 61:Prediction using a sample dataset of all MDGs comparing the FWTA outputs.

Overall, diagnostics scatter plots using the LoT, ETA and FWTA diagnostic model as presented in this research has good fitness for fault detection. Though each of the plots presented varying levels of intensity regarding the fault classes and common regions that the MDGs tend to deviated from acceptable or normal operating ranges. Accordingly, there is results established a reasonable ground for a relatively low reliability as well as concerns regarding the cooling system and cylinder head bolts reliability concerns. Therefore, the link between component reliability and fault can be established based on the bases that the MDGs operate most of the time at relatively high temperature above the normal operating range but below alarm levels.

Furthermore, the component reliability analysis has identified components such as the sea chest, FW heat exchanger, tappet clearance, and turbo charger among the most critical to MDG reliability. All the stated components can be associated with temperature increases and performance degradation in the MDG. On the other hand, location data also suggests that a significant number of faults occur when the ship is at the harbour, as presented in Table 40. Hence, in perspective, the MDGs are run most of the time when the ship is alongside at the harbour; this could explain the reliability issues with the sea chest and air filter due to objects in the water and air quality around the port.

Table 40: MDG failure count by location.

Location	Period	Count	
		Normal	Fault
Harbour	January–December 2019	1043	17
Sea		822	14

5.5 BBN Results

In this section results from 2 models would be presented, the first is the availability model and second would discuss the maintenance DSS. These two results are presented together because DSS was built using BBN decision theoretic model which also takes input from the availability BBN probabilistic model. Overall, the BBN availability model was mainly built to address issues regarding common course and single point failures (CCF and SPF). These types of failures are very critical failures in both maintenance and operation planning particularly for naval vessels due to emergency operational circumstances. Moreover, PGS reliability is of great concern for all ship operators irrespective of sector, as it provides the highest utility and ensures collective safety of operators, passengers, equipment, and cargo.

5.5.1 Availability Results

The BBN model investigated multiple failure types and their impact on components and DG availability. Modelled components were from DFTA MCS and their failure probability from the collected MRO data. MCS obtained through DFTA for individual sub systems were used as inputs to build the BN probability analysis. MCS being a combination of events or failures that leads to the system or subsystem failure can be efficiently utilised to improve system availability. Nonetheless, some failures can be triggered by a fault in another system, especially in marine diesel generators where many faults are interrelated due to system dependencies. For instance, one of the most important failures on the MDGs was crank case failure. But this failure was influenced by multiple factors from other subsystem such as the lubricating system and the cooling freshwater system as well as the air distribution system. Similar, turbo charger failure is one critical failure which is usually due to failure in lubricating oil supply to which serve booth cooling and lubrication. Overall, these failures occur not because the component in not reliable rather a supporting component is not, hence this brings to the fore the place of CCF and SPF in availability analysis.

Consequently, in view of the above, it is sometimes difficult to isolate component failure to the influencing faults and measure the influence levels. In this regard, the approach in this research is to identify the MCS which provide us with the components of interest. Thereafter the faults generated and linked to all the components that can be impacted by the fault irrespective of the originating system. Accordingly, this approach helps to address CCF in a more graphical way using connection as well the parent – child influence relationship which makes modelling both iterative and intuitive. Therefore, this brings to perspective what components are prone to certain faults and would help with prioritising maintenance and spare parts projection as necessary.

The inputs from Table 41 were used to evaluate the availability for individual MDGs as well as the main subsystem. All the subsystems were modelled based on the MDG structure presented earlier in Case Study Section. Therefore, the subsystems (grandparent node) are connected to individual components (parent nodes) which are evaluated based on fault represented by (grandchild nodes). The CPTs of the grandchildren nodes or simply put basic events take the faults and its frequency of occurrence as inputs, hence modelling the variable impacts of same fault on different components was possible.

Table 41:Modelled Components and faults/failures

Sub-System	Component	Fault/failure	Sub-System	Component	Fault/failure
Cylinder Block	Crankcase	1.Cracking	**Fuel Supply System**	Fuel supply pump pulley bolts	36. loose Bolts 37. Brake
	1. Cylinder liner failure	2. Cracks 3. Scuffing 4. Seizure		Fuel supply pump drive	38. Gear tooth alignment. 39. Gear tooth failure
	2.Cylinder head bolts	5. Lose 6. Not firm		High pressure Fuel supply pipe	40. leakage 41. loose
	Top Cylinder gasket	7. Burnt 8. Material Failure		Fuel return line	42. leakage 43. loose
	Vibration Dampers	9. Cracks 10. Compression		High pressure Fuel supply pump	44. Loose mounting bolts. 45. Driver failure
	Engine Seat	11. Braking 12. Deformation 13. Corrosion		Fuel Quality	46. Loss of power 47. Erratic operation 48.Filter blockage 49. Sludge accumulation in tanks
	Cylinder head O-ring	14.Deformation		Primary Fuel Filter	50.Reduced fuel flow 51. Blockages
Power Take Off	Crank Shaft	15. Surface roughness 16. Misalignment		Secondary Fuel Filter	52. Flow loss 53. Blockage
	Journal Bearing	17.Friction and seizure		Dirty Fuel Tanks	54. Presence of particulate matter in fuel 55. Blockages in fuel filters. 56. Low pressure in fuel system
Cooling System	Heat Exchanger Tubes	18. Scale build-up 19. Leakages	**Air Distribution System**	Turbo charger	57.Oil leakage 58. stiffness
	Sea Chest	20. Blockage 21. Corrosion		Air filter	59. Restricted air flow
	FW HE Tubes	22. Scale buildup 23. Leakages	**Lubricating System**	Oil Filter	60. Leakages 61 Blockages 62. Broken housing

	FW Thermostat	24. Failed Closed		Lub oil inlet Hose	63. Leakages 64. Broken housing
	Charge air Cooler	25. Scale buildup 26. Internal Leakages		Oil Pump	65. Not pumping oil 66. Reduced pressure 67. Over Pressure
	Lub Oil Cooler	27. Scale buildup 28. Internal Leakages	**Inlet/Exhaust System**	Valve Seat	68. Air leakages2. 69. Valve spring
	FW circulation pump	29. No water supply 30. Drop in pressure		Tappet	70. Clearance
	Oil Cooler thermostat	31. Failed Closed		Valve Stem	71. Bend 72. Break
	SW pump assembly	32. No SW supply 33 Drop in pressure	**Alternator**	Stator/rotor	73. Rotor Bearing failure 74. Insolation breakdown 75.Burnt alternator 76.Prime mover and alternator alignment
	SW pump impeller	34.Impler blades brake or corrosion 35. Pump casing wear			77.Vibration
					78.Automatic Voltage Regulator failure 79.Exciter failure 80.Air gap failure 81. Alignment

The BBN availability was also designed to investigate the dependability relationships between components in order to understand how component failures impact on one another. Therefore, with this in mind CCF were modelled to understand which MCS are more critical especially regarding rectification while at sea and MTTR. Overall, the MTTR and repair capability at sea were among the most important concerns of the operator. Moreover, one of the key issues in maintenance planning is MTTR as well as system availability is MTTR because is governed by many factors which are unfortunately not universal, hence the operator cannot rely on OEM's recommendation. The BBN availability models for individual MDGs are presented the following Figures 62-65. Each of the model shows both the availability and critical failure path which are represented by the red to pink colours, the higher the intensity of the red colour the more critical component the box or oval shape is, with reducing intensity indicated by the pink.

Accordingly, the availability model for MDG 1 presented in Figure 62 shows the most sensitive failure path as well as the associated components which includes top cylinder gasket, vibration damper and crankcase. Similar, MDGs 2 and 3 presented in Figures 63 and 64 respectively all had the crankcase as the most critical component to availability, except that in MDG 3 has further criticality with PTO being red. More interesting is the connection both the PTO and crankcase shares with vibration dampers thus highlighting the CCF influence. A Further CCF down the was overheating affecting cylinder head gasket while causing seizure in moving parts. Nonetheless, MDG 4 in Figure 65, presents a different scenario compared to the other MDGs in that PTO was the most critical to availability due to main crankshaft journal and journal bearing failures influenced by vibration issues and overheating. These results provide very valuable information and can be used either independently or combination with other outcomes to aid maintenance and personnel planning for on board maintenance organisations.

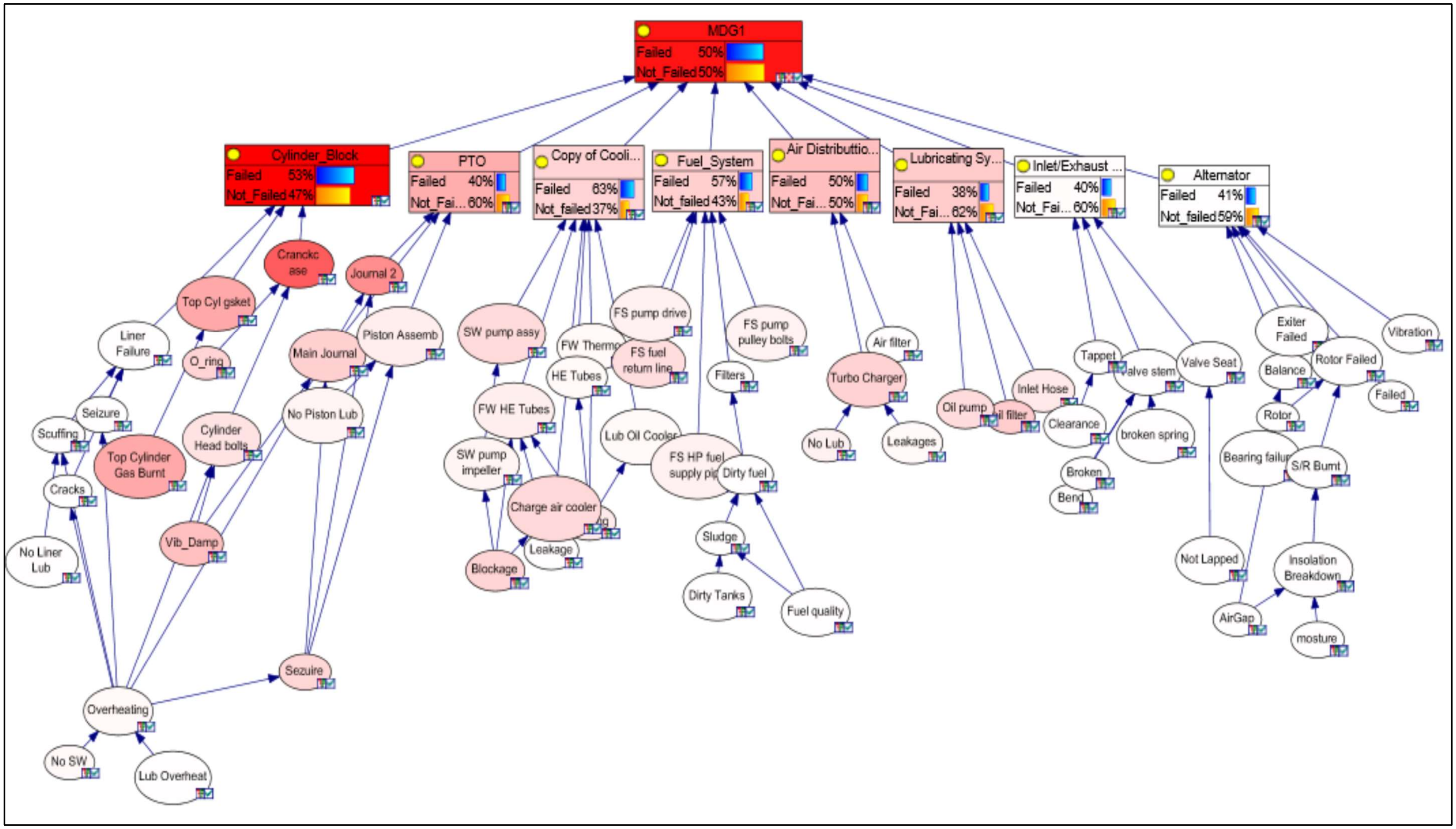

Figure 62:MDG1 BBN Availability Model

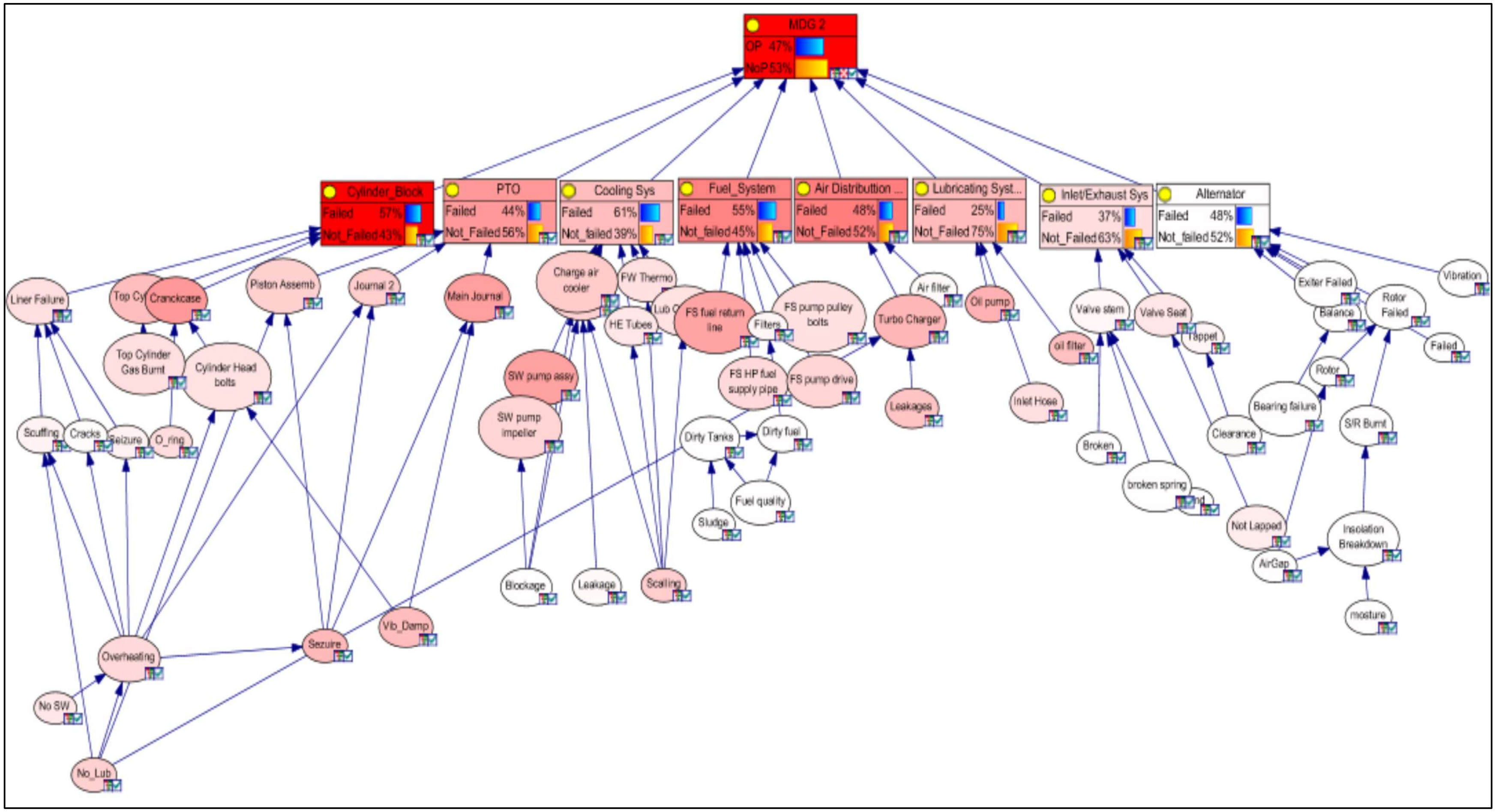

Figure 63:MDG 2 BBN Availability Model

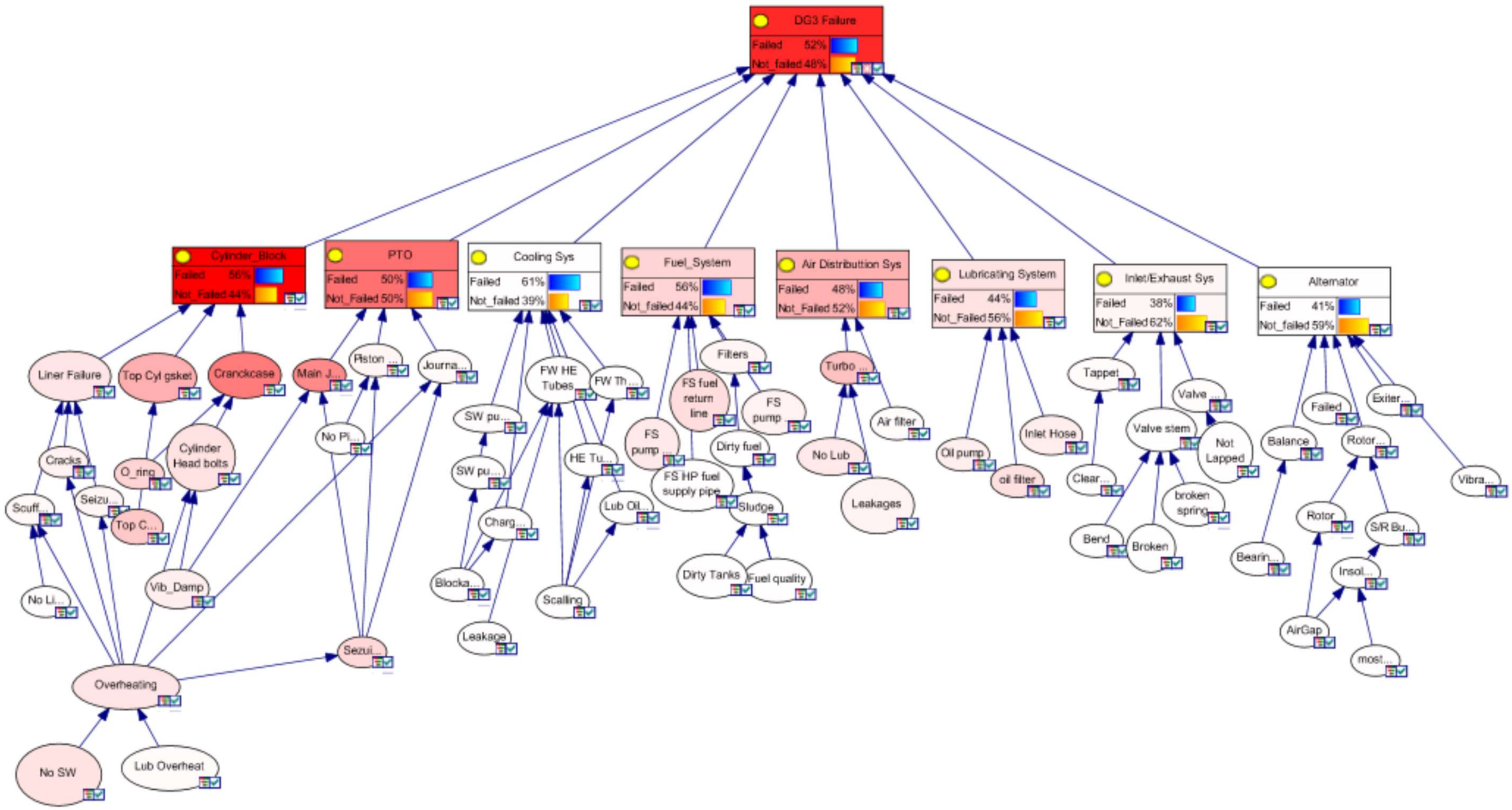

Figure 64: MDG 3 BBN Availability Model

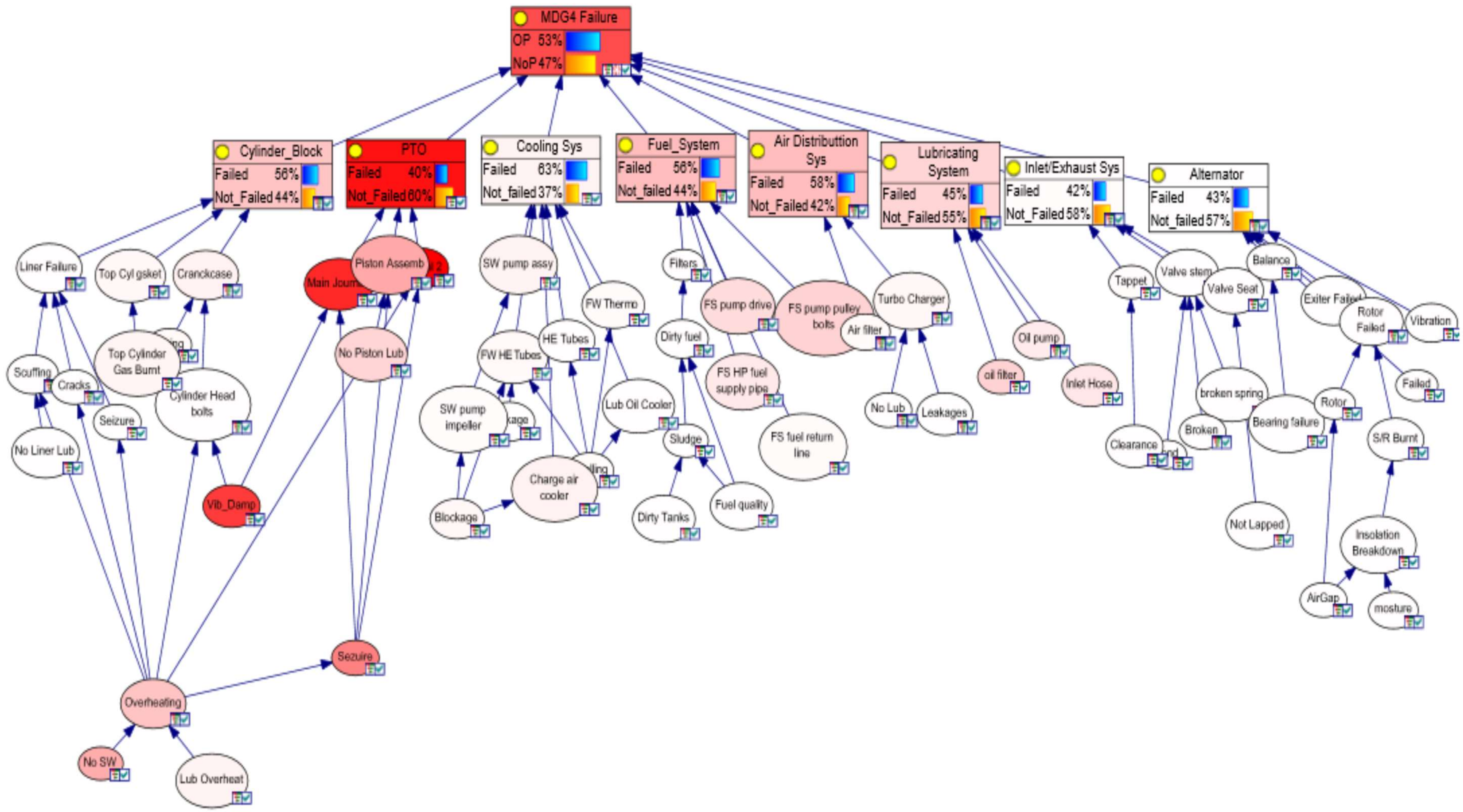

Figure 65: MDG 4 BBN Availability Mode

Overall, the availability results presented in Table 42 shows that all 4 MDGs had varying degrees of availability with MDG2 being slightly more available as compared to the rest. The subsystem availability particularly that of the lubricating system of MDG2 at 75% is an important pointer. Moreover, the lubricating subsystem is one of the most reliable subsystems in most MDGs, this can be attributed to the centrality of its function particularly to the moving parts and heat transfer. On the other hand, a very critical situation is presented in the cooling system with availability values below 40% which is far below the expected availability of the operator.

Table 42: BBN MDG and Component availability

MDG	MDG1	MDG2	MDG3	MDG4
Individual Availability	50 %	47%	52%	53%
Subsystem Availability				
Cylinder Block	47 %	43 %	44 %	44 %
PTO	60 %	56 %	50%	60 %
Cooling	37%	39%	39%	37%
Fuel System	43 %	45 %	44 %	44 %
Air Distribution	50 %	52 %	52 %	42 %
Lubrication	62 %	75 %	56 %	55 %
Inlet and Exhaust	60%	63%	62%	58%
Alternator	59%	52%	59%	57%

The low availability values could be linked to the sea chest blockages which can be very frequent and rapid scale build-up of the cooling fins. Nonetheless, the cooling system for the ships in question has at least 4 redundant sources of water supply in addition to the inline source, while this design helps reduce the risk of overheating due to delays in switching water sources. It is important that some early warning system is provided to ensure that watch keepers are adequately alerted at the onset of any pressure reduction in water supply or temperature increase for at least 10 minutes with no corresponding increase in demands or beyond normal threshold. The subsystem availability indicates where maintenance effort should be directed. However, to improve maintenance decision making additional issues that influence delivery and quality of maintenance needs to be considered.

5.5.1.1 Operational Availability in Perspective

The BBN model for each of the 4 MDG was developed in 2 phases, the first phase was the subsystem availability analysis and second was the maintenance DSS analysis. The component availability analysis was developed around the MCS that contribute to about 50 % of failures as obtained in the DFTA, the CPT tables were populated using failure rates of candidate components as well as the impacts of the associated faults on those components. The BBN also provides the capability to model and measure the impact of CCF across components and subsystems. Therefore, reducing duplicity and enhancing the fault impact assessment. Consequently, the maintenance DSS draws from the robust availability model structure using input from FMECA RPN to evaluate Component Mission Criticality against its utility and overall availability.

The BBN availability model was designed to investigate key component availability of the PGS, especially considering the role it plays regarding safety of operators, passengers, equipment, and cargo. Therefore, the model investigated multiple failure types and their impact on components and MDG availability. Modelled components were from DFTA MCS and their failure probability from the collected MRO data. This input was used to obtain the availability for individual DGs as well as the main subsystems modelled. The results shows that all 4 DGs had varying degrees of availability as presented in Table 43. Overall, MDG2 had lowest availability which conforms with the collective component availability analysis results. In general, all the MDGs maintained slightly above average availability of 50%, which translate to about 50.5 % overall PGS availability.

Table 43: MDG Availability and Reliability

	MDG Availability	80% Reliability within research data period
DG1	50 %	7 months
DG2	47 %	10 months
DG3	52 %	22 months
DG4	53 %	11 months

The individual MDG ability was generally low, considering the stipulated SOP of 80 % operational availability expected by the operator within any given vessel operation period, of 12 months. Moreover, the MDGs availability side by side their reliability obtained in the DFTA as shown in Table 8 within the approximately 78 months of operational months is a clear testament to both low reliability and availability. However, MDGs had better availability numbers as compared to the reliability figures. This could be explained by the installed redundancy in the PGS which despite the low reliability the PGS has proved relatively available. Nonetheless, it would be necessary to come with more efficient and responsive maintenance platform that could improve the both the availability and reliability of MDGs. This can be achieved through a systematic approach by harnessing information from machinery maintenance record, repair reports and machinery health monitoring records in unified platform to aid with maintenance planning decision support.

5.5.2 DSS Results

The maintenance DSS was developed using 2 major input sources namely the availability for the BBN and RPN from the FMECA. The significance of the FMECA is in providing survey inputs which add more intuition to the overall DSS as regards the operators thought on all the modelled failure types and their impacts. According, 4 maintenance strategy options were adopted for developing the maintenance DSS; these are Corrective Action, Condition Monitoring (ConMon), Planned Maintenance System (PMS) and Delay Action, details are presented in Table 44.

Table 44: Maintenance DSS ranking Scale and definitions.

Linear Scale (1-10)	Severity Level	Criticality Level	Likelihood Level	Maintenance Decision	Definition	Component Mission Criticality
0	Minor	Minor	Remote	Delay Action	Delay action maintenance choice is directed at those components with good resilience or sufficient redundancy such that there is little or no danger personnel and system safety.	0-35
1-4	Low	Low	Low	Delay Action/PMS		
4-6	Moderate	Moderate	Moderate	PMS	The PMS maintenance choices prioritise time dependent component failures with no immediate impacts to availability repair requirements.	35-55
6-8	High	High		ConMon/Corrective Action	This strategy serves as intervention to ensure system availability targeted at component or failures whose early identification could avert major operational delays.	55-75
8-10	Very High	Very High	Very High	Corrective Action	This is recommended for very high to high mission critical component or faults for example sea water supply pump impeller, fuel supply pump, automatic voltage regulator faults etc.	75-100

The first 2 options are meant for high critical failures or component with severe failure consequences while the last 2 are to address failures with time dependent pattern or equipment with high redundancy and low criticality. Hence to standardise the maintenance criticality 4 levels are also adopted namely Very High, High, Medium, and Low and to conform the with maintenance strategy in order of hierarchy. The same also applies to the RPN values against the maintenance strategy options.

The approach compares the criticality in decreasing priority from very high to low based on RPN numerical values where 100 represent the highest possible outcome and 0 lowest possible outcome. The RPN values provide an iterative procedure using the linear scale ranges to place components to certain maintenance strategy group. Therefore, this helps ease some of the restriction of the component criticality Likert scale, hence providing a flexible procedure to prioritise system maintenance. Accordingly, the inputs for the overall BBN DSS comprise of the subsystem RPN, critical components and their cut set as well as the relevant CCF as shown in Table 45.

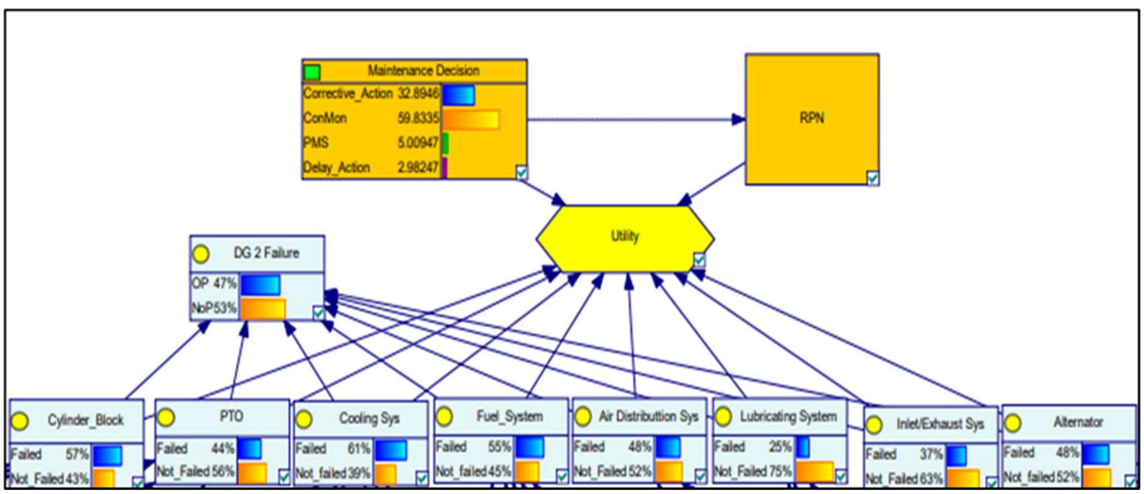

Figure 66:BBN component availability and RPN.

Consequently, using these values, the DSS was built based on the structure shown in Figure 66 representing MDG 2, showing the 3 additional nodes, 2 decision nodes in orange and 1 utility node in yellow. The decision node 'Maintenance Decision' is defined by independent variables of maintenance strategy choices and is a parent to Utility node which is a dependent variable and child to another decision node 'RPN'. The decision node 'RPN' takes information representing the maintenance decision arrangements and matched with RPN criticality hierarchy based on RPN scale. Complete maintenance DSS structures developed for the MDGs are at Appendix 9.

Table 45: DSS BBN Inputs

Sub-System	RPN	Components	MCS	CCF	Mode	Causes
Cylinder Block	65%	7	6	1	Overheating	No cooling water, lubrication oil failure, vibration, gasket damage, seizure
PTO	58%	3	2	2	Seizure, Overheating	Missed timing, Overheating,
Cooling	64 %	6	2	3	Reduced Cooling, No cooling	Sea chest blockages, scaling, thermostat fault, Pump failure
Fuel System	34%	5	4	3	Low Pressure, No supply, contamination	Air log, dirty tanks, filter blockage, fuel quality
Air Distribution	33%	2	2	0	Low supply, Hot air	Air filter blockage, air cooler fouling
Lubrication	3%	3	2	0	Low pressure, No supply, contamination	Filter blockage, Pump failure Seal failure
Inlet and Exhaust	0 %	4	4	3	Missed timing, valve clearance, poor scavenge.	Valve setting/tappet clearance, weak spring, valve seat, bent valve stem.
Alternator	14%	4	10	5	Overheating, rubbing, load shedding, no output, degraded performance (low voltage/ frequency)	Bearing failure. Miss alignment (lose of air gap), defective AVR, defective exciter, vibration.

Accordingly, the rest of the DSS allocates percentage values between 0-100 to each of the 4-maintenance strategy choice for the MDG based on the input data. The allocated percentage for each of the strategy determines how the maintenance action, planning and monitoring should be prioritised. This allows for flexibility regarding distribution of resources such as personnel, spare parts, logistic support, and operational deployment. Furthermore, high criticality ranking for ConMon indicates the need for additional monitoring approach which can be addition of sensors, increased inspection frequency or watchkeeping attention. The overall outcome for the maintenance strategy selection DSS of the MDGs is presented in Figure 67. The analysis indicates how each of the DGs fit to a certain maintenance strategy regime as a reflection of the main variables i.e., utility and RPN.

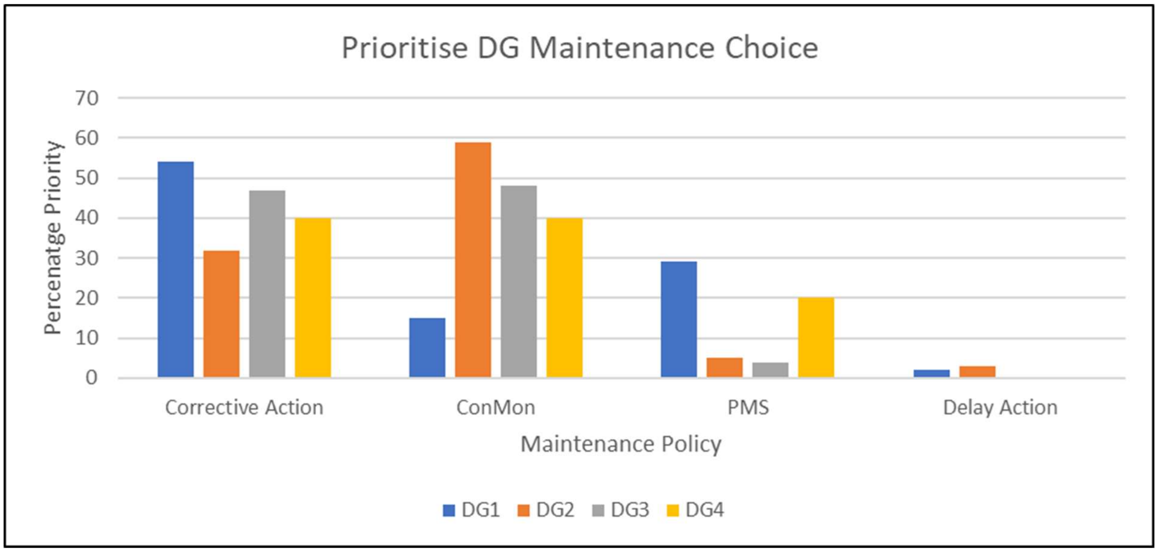

Figure 67:Maintenance DSS choice for all MDGs.

In all, Corrective Action and ConMon appear to be the most preferred choice for all the MDGs except for MDG1 with relatively low figures in ConMon but high in PMS. Only MDG1 and 2 seem to have some values for Delay Action and present high figures both Corrective Action and ConMon. This suggests that the 2 generators are highly maintenance intensive, moreover MDG1 has about 54% to corrective action and MDG2 is about 58 % in ConMon. On the other hand, MDG3 and MDG4 fall in relatively similar level of priority levels except in PMS where MDG4 numbers appear much higher than that of MDG3. A likely reason for this could be that MDG1 and 2 are located in the same engine room likewise MDG 3 and 4. As such due to shared resources such as sea chest, ventilation, fuel line and local stress such vibration, the generators tend to present similar pattern of failure. Though some of these findings were not apparent to the operators prior to this research, however, were consistent with similar research findings within the shipping industry and others with focus on Naval ship platforms. Moreover, the FMECA findings also provide additional evidence as to the acceptability of the research findings and relevance of the methodology.

5.6 Chapter Summary

This chapter presents the case study's results, focusing on the input data, operator opinion, and research modelling tools used. The FMECA results were used to generate Mission Critical Components and establish the maintenance DSS process. The DFTA results provided insights into the relevance of operator opinion in research modelling and the development of DFTA, BBN, and ANN. The DFTA outputs were also used to generate input for modelling availability analysis in the DFTA through MCS. The ANN classification using FFNN was developed to identify major causes of failure in MDGs. Data cleaning and engineering were conducted to ensure data quality and accuracy of fault identification analysis.

The BBN availability and maintenance DSS presented the availability of MDGs based on their components. A maintenance DSS was built using inputs from both DFTA and FMECA, proposing four main strategy choices: Delay Action, Corrective Action, ConMon, and PMS. The results showed that all four MDGs had varying degrees of availability, with MDG2 being slightly more available. However, a critical situation was presented in the cooling system, with availability values below 40%, below the expected operator's expected availability of 80%. Corrective Action and ConMon were the most preferred choices for all MDGs, except for MDG1 and 2 with relatively low figures in ConMon but high in PMS.

6. Recommendations on Maintenance Strategy

The proposed maintenance DSS demonstrated provides a comprehensive approach that can be implemented onboard ships and be extended to shore maintenance offices or base in case of fleet maintenance requirements. It can also be used as a bridge to cross from manual data collection and management to automated data management. Nonetheless, some level of human interface will be needed especially onboard naval ships. Therefore, implementing the methodology for the case study ship and other ships will be based on a structured maintenance data management that will require a unified structure for data collection on board ships as well as providing a standard data management collection system. Overall, the system will be able to establish priority level according to the maintenance task responsibility. The ship staff being the first level of maintenance will manage and hold data on simple failures and faults that are easily manage on board and do not involve extended repair time. The second level of maintenance is the shore establishment, which receive maintenance request that are beyond ship staff or may require longer repair time, or bigger logistics.

6.1 Chapter Outline

Analysis and discussions on the case study are presented in this chapter with more focus on possible consequences of the results and recommended solutions for maintenance management. Accordingly, starting with the Maintenance DSS results in Section 6.2 given more details on the relevance of Mission Critical Components. Section 6.3 will discuss the ANN analysis and its application to the DSS. The role of the of Onboard maintenance department is presented in Section 6.4, while section 6.5 discussed on Shore maintenance Department.

6.2 Implementing the Maintenance DSS Results

Planning and scheduling of maintenance task as well as efficient capture of machinery data are necessary for the establishment or implementation of any maintenance strategy. In this regard, the maintenance DSS model was designed to draw from multiple inputs source to improve data coverage in component failure dynamics. Accordingly, the inputs for the overall maintenance DSS includes MDG availability from BBN, Component Mission Criticality from RPN and as well as influence factors such SQEB, environment and quality of spares or consumables like lubricating oil, fuel, and additives. Accordingly, the DSS allocates percentage values between 0-100 to each of the 4-maintenance strategy choice for the MDG based on the input data and consideration for influence factors controlled by the model. The allocated percentage for each of the strategy determines how the maintenance action, planning and monitoring should be prioritised, Table 46 shows maintenance DSS points for all the MDGs.

Table 46: Maintenance decision choices

Maintenance Strategy	DG1	DG2	DG3	DG4
Corrective Action	54%	33%	47%	40%
Condition Monitoring	16%	60%	48%	40%
Planned Maintenance System	30%	5%	4%	20%
Delay Action	2%	3%	0%	0%

The strategy grouping helps increase flexibility regarding distribution of resources such as personnel, spare parts, logistic support, and operational deployment. This is achieved based on the priority associated with the strategy. For instance, the Delay Action generally covers failure or maintenance action which do not require immediate repairs and are not a safety risk. On the other hand, ConMon refers to failure or components which require more attention to prevent from failing or the consequences of their failure cause delays or safety risk. Accordingly having this in mind, the operators can adequately improve health monitoring of critical components by deploying sensors more efficiently, increased inspection frequency or modify watchkeeping approach.

On the other hand, to improve maintenance decision making additional issues that influence delivery and quality of maintenance on board in the shore maintenance organisations need to be carefully looked at. Moreover, the challenges faced by shore maintenance units are generally different from those on board. Nonetheless there are issues that can be common to all, such availability of SQEP, special tools, data management and information extraction and many other things. In this regard, effort is made to make separate recommendation to address peculiarities of each maintenance tier.

6.3. ANN Analysis for Maintenance DSS

In general machinery failures give warning signs prior to occurrence by showing abnormal readings or slow deterioration in performance which may not very noticeable. Therefore, understanding the signs heralding failures would significantly help operators overcome most of the critical challenges in machinery failure and possibly abating it all together. Machinery enables operators to achieve much of this and predict future failures, hence increasing overall equipment availability, improvement in system reliability and likely cost servings. Moreover, the insight gained during the analysis phase of the machinery health parameter can help with more valuable information on changes that occur at certain load condition which may not be capture in operations manual. Therefore, the operator can use this gained information to improve maintenance and operations practices. In this regard, ANN analysis was conducted alongside the system reliability analysis on the MDGs to help fault identification related system failures.

6.3.1 Fault Identification

An ANN fault detection model using a FFNN was built to provide further details as regard the major courses of failure. Moreover, one of the goals of maintenance planning is improve efficiency both in spare parts holding, procurement process and task. Therefore, using the ANN would help identify fault that can be linked to the identified critical components Table 51 is a list of diesel generator parameters and their limits. In all there are 9 parameters collected for analysis however based on preliminary analysis just about 5 parameters have shown strong correlation in the data. The application of ANN in the research is mainly fault (anomaly) classification.

The fault identification training using harmonised data from the 4 MDGs; this was done to develop a single model for all the 4 MDGs. Hence fault data in was used for fault detection which contain 3 fault classes namely Normal, Fault, and Abnormal. A second fault class which uses temperature thresholds as predictor with Lub oil pressure as responses was also generated. Accordingly, overall training data utilised 20 % of data from all MDGS data before splitting as earlier highlighted. Using this information, the analysis was also able to establish that most faults are related to overheating and occur when the ships is at harbour.

Based on the above fault classes the diagnostic analysis for faut identification taking temperature as an indicator was conducted. In this regard the model was presented with a harmonised data from the generator for diagnostic analysis based on the same labelled parameters using power output (KW) as independent variable while lubricating oil temperature (LoT) as predictor, Table 47 presents the limits of data labels used of the fault identification.

Table 47: Limits of Data Labels used for fault identification.

Fault	Fault Identity	Fault Parameter	Temperature Ranges(^{0}C)	Operating State
Normal Temperature	NTM	Normal Lubricating Oil Temperature	80-110	Normal
High Temperature	HTM	High Lubricating Oil temperature	110-115	Abnormal
Overheating	OVH	Engine Overheating	Max 120	Fault/Failure

The variable used for the fault identification were selected based on the feature selection analysis conducted, out of which EGT and LoT showed good response to variation in power output. The choice of LoT out of the 5 parameters was premised on the correlation R-value. Moreover, the other 4 variables have some level of disparity between the individual banks, this difference is also present in the R-value in the correlation plot with a difference of 0.04 for the exhaust temperatures while 0.01 for the cooling water temperature. In this regard, considering that LoT readings are taken from a single source it is expected that it would be more responsive for diagnostics analysis especially targeting the internal components such as the piston, crankshaft, liners, and other associated components.

Overall, the diagnostics analysis has provided a key insight on the challenge with overheating experienced on all the MDGs. However, more important is that all the incidences were preceded by high temperature situations at relatively low load conditions. A typical problem here could be poor atomisation or tappet clearance setting. Hence models like this also points to insipient failure issues in the data that might not have been reported or noticed in normal reports. This numbers may be insignificant however, the impact over time could lead to significant reliability issues. Moreover, one of the most frequent problems in the repair report was overheating related challenges to do with sea chest blockages and scaling of heat exchanger tubes which reduce the heat transfer efficiency of the heat exchangers.

Overall, the fault identification analysis has been instrumental in identifying failure conditions that can be related to reliability results. These results would significantly reinforce the reliability analysis outcome but will also raise the issue regarding the performance of the MDGs at above 50 % of rated output. In fact, the LoT diagnostics analysis and EGT fault identification analysis both have identified the maximum loads the MDGs overheat. In general, using both EGT and LoT safe working load for the MDGs was between 160 and 200kw. So therefore, with this finding, it is safe to say that the MDGs are overrated hence the operator can decide to take this up with the OEM. On the other hand, maintenance planning and other Integrated Logistics Support (ILS) services that came with the MDGs will have to be validated. Hence, the need to come with a new maintenance planning and scheduling process that would reflect the actual field performance and reliability of the MDGs. In this regard, a BBN analysis was conducted for sub-system availability and maintenance DSS development.

6.4 Onboard Maintenance Department

The suggested approach is based on a structured maintenance data management that will standardise data collection on board all Nigerian Navy (NN) ships. Presently, all ships have a format they use in collecting machinery health data such as machinery watch logbooks, defects report book, PMS daily records and machinery operational state. The challenge currently is on data standardisation to ease collection and analysis at Fleet Support Group (FSG) level and Fleet Maintenance Office (FMO) at the Logistic Command Headquarters (HQ LOC). The proposed approach is hinged on 4 areas that includes, standardised data collection across ship of the same class, provision of desktop or laptop computers to all ships, developing a data transmission and management plan from ships to FGSs, provide big data analytic centre at the HQLOC for the FMO. with additional personnel and equipment to handle maintenance feedback and analysis.

Standardised data collection approach is the most fundamental aspect of any efficient maintenance system especially data driven approaches aimed at improving condition monitoring. A template can be made for machinery log using Microsoft excel spread sheet with standardised columns for each class of ship providing details such a condition of equipment at the time of shutdown and location of ship while data was recoded. A pilot programme using some selected machinery can be used develop a template that can be adopted for other vessels. Thereafter, a data transmission and management plan will be required due to the size of data to be managed. Depending on some specifics such as information security and cost implications, a choice can be made to hire a company that can provide big data solutions to help with handling transmission and managing the server at shore maintenance units and Fleet maintenance office. Alternatively, a dedicated data centre can be provided which can run and manned by the staff of the company and configured to received data via voice or text message.

6.4.1 Mission Critical Components

Ships are designed for multiple purposes; however, the general purpose is enabling movement of goods, people and conduct of services from one location to the other with ability to stay away at sea for extended periods. In this regard, it is important that the machineries can provide the expected utility and if failure occurs it is important that the technical crew is able to manage it by fixing it or mitigating the associated risks. Moreover, in the case of Naval ships, situations can be very tensed requiring extended deployment beyond initial deployment plans. In some cases, crew may need to carry out equipment repairs at difficult conditions to enable the ship to maintain acceptable operation readiness level while at sea or outside home port due to operational demand. Table 48 provides a list of Mission Critical Component (MCC) obtained as obtained through FMECA.

Table 48: Mission Critical Component and failure modes TTR

Subsystem	Component	Failure Mode	Time to repair
Cylinder Block	Crankcase	1.Cracking	1-3months
	Cylinder liner failure	2. Cracks 3. Scuffing 4. Seizure	1wk-3months (depending spare parts availability)
	Cylinder head bolts	5. Loose 6. Not tight	1-3hrs
	Top Cylinder gasket	7. Burnt 8. Material Failure	10-24hrs
	Cylinder head O-ring	9.Deformation	2 wk-2 months
Power Take Off	Crank Shaft	10. Surface roughness 11. Misalignment	1 month
	Journal Bearing	12.Friction and seizure	6hrs-2 days (with spare availability) 1-2 months (OEM to supply spares)
Cooling System	Heat Exchanger Tubes	13. Scale build-up 14. Leakages	30min-6hrs
	FW circulation pump	16. No water supply 17. Drop in pressure	2hrs-4weeks
	SW pump assembly	18. No SW supply 19 Drop in pressure	2-4hrs
	Fuel Quality	20. Loss of power 21. Erratic operation 22.Filter blockage 23. Sludge accumulation in tanks	1-2weeks

In this regard, considering the significance of the PGS to ship availability and the possible risk associated to its failure, it is important that the perspective of the machinery operators and maintenance managers are taken into consideration. Moreover, it is common to have ships undertake repairs while under way to ensure that at least 2 MDGs are available, hence any repair that cannot be undertaken by ship's staff while underway is viewed as critical and can affect overall ship availability or deployments. Consequently, the RPN obtained through the results of the FMECA highlights these critical failures which may not be seen as important by OEMs, but the operator's environment and operational circumstance made it so.

The results in table 48 presents 11 MCC and 23 out of about 80 failure modes analysed, most of these faults had low likelihood but with high criticality and severity values. Therefore, taking from the definition of these two factors the operators are more concerned with failures that affects ship availability. This is not to say safety is not of concern, in fact the threat to safety as regards loss in power generation output could be in two-fold. First is safety and security both external and internal to the ship. The second is operational external safety due to threats on national assets and safety of navigation which is equally a safety concern to personnel onboard. In this regard, minor or major failures that can be repaired while underway or which do not expose the ship to danger i.e., loss of 2 out of the 4 MDGs is within acceptable limits. On the other hand, major faut occurring at sea or at forward operating base, where a ship can expect immediate logistics support regarding spare parts or specialist intervention is usually not seen a critical situation. Some of these faults could include AVR replacement, injection pump or governor failures, because the components can easily be transported, and installation can be managed by ship crew.

Moreover, taking look at the cylinder block bolts in Table 48, with RPN score of 100 indicates an extremely critical situation as compared to some other failures with similar importance like the top cylinder gasket. However, there appears a wide gap in the RPN ranking, likely due to possible consequence of failure impact on the other subsystem of the MDG despite the short time to repair. Similarly, looking at the time to repair on some components like the journal bearing with RPN score of 64 but could take months to repair (depending on spare parts availability); but was seen as less of a challenge by operator as compared to the cylinder block related faults. Therefore, the significance of the values in Table 48, are in the insight provided regarding the perspective of the operators on the MDGs regarding the navy's operational demands, maintenance practice and capabilities including environmental conditions.

Overall, the FMECA was not only useful in generating the RPN, but the process of the survey analysis and extraction gave added insight on failure modes and challenges arising from MTTR. The MTTR adds the critically of component failure due to possible delays in ship deployment hence these faults are viewed very seriously by the operator. Accordingly, the RPN and other outputs of the FMECA analysis provides very useful inputs for building the DSS and in some cases the DFTA results were compared with FMECA criticality levels to improve consistency in output. The process helped developed a dynamic and reflective maintenance strategy that can be applied to address the prevailing operational and health condition of the MDGs on board the case study ship.

6.4.1 Impact of Mission Critical Component Failure Safety Onboard

Power outage or blackout can happen as result of the MDG tripping off to avert a more serious failure or damage. Ships are design with excess capacity in power generation to account for tripping due to overload or serious fault. Accordingly, load shading between MDGs, emergency generators as well as battery backup are among the primary alternatives provided onboard most ships to reduce the impact of sudden power failures. Nonetheless, despite these measure blackouts occur onboard and when they occur the risk to personnel and vessel safety can be huge. Consequently, some of the critical fault identified in the case study be responsible of the major to power supply onboard. Some of these faults and likely safety concerns are discussed below to enable the operator take additional precautions.

6.4.1.1 Fuel Leaks

Fuel leakages results due to lose fuel supply pipes, broken seal or during maintenance work on the fuel system. Therefore, defects on fuel line needs be handled carefully as fuel spillage ship's engine room or machinery space pose significant safety risks that can jeopardize the vessel, crew safety, and environment. Some associated risk to fuel leaks in the engine includes fire hazard through the create as the presence of fuel vapours increases the risk of ignition sources, such as hot surfaces, electrical equipment, or sparks from machinery. Slippages could also occure due to spilled decks, additionally excessive exposure to fuel vapours can also pose serious health risks to crew members in case of inhalation which results to respiratory problems, dizziness, nausea, and headaches. Additionally, fuel leaks to the bilge could lead to environmental pollution due to leaks. Excessive leaks from the engine can contaminate the surrounding waterways that could result to environmental damage to marine ecosystems.

6.4.1.2 Engine seizure

Engine seizure refers to the sudden and complete failure of the MDG and is among the critical failure which could be due to crank shaft journal failure, piston crown and/or piston ring damage, severe damage to connect rod as well as sever engine overheating. These failures collectively or in isolation could bring about serious risk to safety of navigation and personnel onboard. The local impact of such faults in addition to severe damage to the MDG results in black out onboard a ship that could course significant safety risks that can endanger the vessel, its crew, and the environment. The course of engine seizure are generally as a result of mechanical issues.

6.4.1.3 Crank Case Explosion

The crank case explosion occurs in engines due to accumulation of oil mist in the presence high temperature air enough to ignite the mixture. Ordinarily, this could be managed by the relief valves located on the engines crank case, however, malfunction could happed due to improper maintenance, fault crankcase pressure sensor. On the other hand, faults such as fuel over delivery, defective piston rings, as well as insufficient charge air due turbo charger fault can be precursors to possible high temperature and built-up of high volatile gases. These therefore bring to the fore the importance of maintenance to safety of both personnel on board and navigation of the ship.

Overall, the above discussed failure can result in power outage which is major risk to vessel. Generality of ship PGS are design with adequate backup and or load sharing onboard able to minimise the impact of blackout. However, no matter momentary it is the impact of black-out on ship can pose significant safety implications, impacting various systems and operations critical for the vessel's safety, crew well-being, and in some case the environment as discussed below:

1. Navigation and Manoeuvrability: Ship navigation equipment such as radar, GPS and electronic charts needs uninterrupted power to function efficiently, therefore any disruption in the supply of electricity especially in busy areas such ports or harbour approaches poses a serious risk and potential navigational hazard. Similarly, power interruption to the propulsion and steering system of the ship could limit the ship's manoeuvrability and increasing the risk of collisions or grounding.

2. Communication Disruption. The power outages on board ship irrespective of location has the potential to cause serious disruptions in various communication systems, such as radio, satellite, and onboard intercoms. Although, the system could have a battery back-up arrangement, but prolong period of power outages can impact on the ability of the back-up power to hold-on. Overall, the disruption can degrade the crew's capacity to effectively communicate on board, other vessels, or shore authorities during emergency situations. Furthermore, the possibility of batteries on handheld radios to runout is equally high. Therefore, emergency blackouts can course significant disruption and pose a very serious safety threat to personnel and vessel especially in busy arears.

3. Life Support and Emergency lighting: Power outages can have an impact on life-support systems on board, such as ventilation, air conditioning, and heating systems. These systems are crucial for ensuring that crew cabins, machinery spaces, and other compartments remain habitable. The crew's health and other equipment may be compromised due to possible

discomfort such as heat stress or freezing resulting from a power outage. Similarly, a black out could possibly affect the emergency lighting systems the impact of which can affect visibility in hallways, stairwells, and other vital locations during power outages. The absence of emergency illumination might result in disorientation, impeding the process of evacuating and heightening the likelihood of accidents or injuries.

4. Risk to Auxiliary Systems: Auxiliary machineries play vital role onboard due to the peculiarity of the utility extracted from them. These systems such as the refrigeration, sewage treatment, fire mains, freshwater production and cargo handling equipment rely on continuous power supply. Therefore, any interruption could result to a trip in some equipment which may require reset or manual turning on. Disruption of these systems due to power outages can affect crew comfort, hygiene standards, and overall operational efficiency, leading to health and safety concerns. Furthermore, disruption in the functioning of cargo handling equipment such as cranes, pumps, and conveyors, could potentially result to cargo shifting, spillages and /or damage. Similarly, inadequate power supply to fire pumps, sprinkler systems, and firefighting equipment can hinder firefighting efforts, hence escalating the risk of fire-related incidents onboard.

The discussed safety risks are of high priority which though the operators had in place emergency plan for such occurrences. Furthermore, routine safety drills and inspections by shore maintenance departments are held at intervals to ensure crew preparedness during such eventualities. However, having an adequate maintenance, performance degradation and system alarm levels would help avert such eventualities or in the least reduced the impacts. In this regard, the impact of these critical faults could be addressed through efficient condition monitoring that can be established through the use of appropriate sensors on MDGs to monitor oil mist built-up, crankcase pressure, provision of sufficient air circulation system in the engine room or machinery spaces. Additional considerations includes, regular inspection and maintenance of fuel systems, installation of leak detection systems, implementation of emergency response procedures, crew training on spill response protocols, and adherence to regulatory standards for fuel handling and storage.

Overall, fostering a safety culture onboard that emphasizes awareness, vigilance, and prompt reporting of potential hazards is essential for preventing accidents and minimizing impacts. Therefore, it is important that in addition to what ever the ship crew is doing onboard to ensure safety of operations, The navy needs to ensure that personnel are adequately aware about possible dangers due to some of these failures. Similarly, the next level of maintenance providers such as shore maintenance needs to part of whate training is provided to the onboard staff.

6.5 Shore Maintenance Department

A big data analytic centre will be required to help harmonise information coming from ships to shore maintenance centres and to central maintenance control or operations office. These centres can automatically present an overview of ship system and equipment at the shore maintenance office and the main operations office. Therefore, the setup will provide a summary of the operations status of each ship, identify common problems across ship class, account for most frequent failures and most important course of failure. There may be need to provide additional training to personnel on the sue and benefit of the system. Furthermore, the system at central operations can be programmed to provide further information regarding possibility of extended down times due to spare parts and technical expertise. The information and analysis conducted at the different levels of maintenance can be used to form the bases of spare parts accusation, system redesign, platform suitability appraisal etc.

A data transmission and management plan will be required due to the size of data to be managed. Depending on some specifics such as information security and cost implications, the NN can hire a company that can provide big data solutions to help with handling transmission and managing the server at FSG and HQ LOC. There are several companies that provide end to end cloud data (Big Data) security as well as platform locally and international. The NN can decide to develop an in-house big data solution or hire a reputable provider. On the other hand, data collection and management in the FSGs will need a dedicated office and a reasonably efficient computer with a good memory size and backup arrangement. The initial analysis starts at the FSG where it aggregates to find trends in both logs and defect books which will be forwarded to HQ LOG based on some set criteria to be determined. In this regard, it is important that officers and ratings are trained in data analysis and handling to ease and facilitate their work.

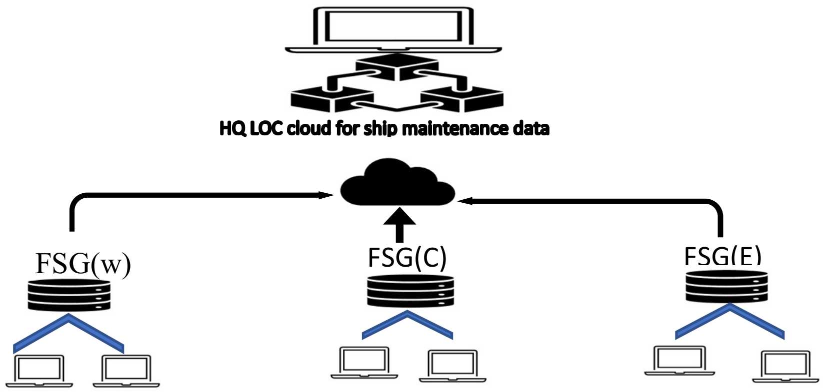

Figure 68:Proposed Maintenance Data and Information management structure.

A big data analytic centre that can automatically present an overview of ship system and equipment is to be provided HQLOC Big data analytic Centre at CFMOs' office in addition to a few officers responsible for generating and documenting mission critical equipment, components, or failures. A recommended setup is presented in Figure 68. Mission Critical equipment here means any system/equipment that is critical to sites (platform) mission or is essential for the platform performance to meet its goals. Similarly, the system at HQ LOC can be programmed to provide further information regarding possibility of extended down times due to spare parts and technical expertise it should also establish equipment with increased seasonal failures. The information and analysis conducted by the CFMO office could be used to form the bases of spare parts accusation, system redesign, platform suitability appraisal etc. Additionally, a duplicate of the data analytic centre should be provided for the Naval Engineering Branch at Naval Headquarters to facilitate information sharing and decision making.

6.5.1 Implementation Workflow for a Data Driven Machinery Condition Monitoring

Maintenance data management is crucial for ensuring assets fulfil their intended use over their expected life span. Technological advancements in machinery and system configuration have led to improvements in sensor technologies, enabling improved system reliability, risk reduction, and reduced environmental impacts. Advanced condition monitoring systems enable remote monitoring and online transmission of data, primarily enabled by the Internet of Things (IoT). However, challenges remain with data format, collection and transmission, security, and integration of the system platform. The maintenance strategy in the Nigeran Navy (NN) is developed based on FMR 002, which provides for the implementation of a planned maintenance system (PMS). PMS relies on time-based scheduling and condition monitoring techniques to identify and correct potential problems before equipment or systems become inoperable. However, failures increase with the ageing of equipment, leading to reduced system reliability and platform availability. Overall, data driven condition monitoring plays vital role in of Maintenance Data Management. Nonetheless, implementation may come with some challenges in data format, collection and transmission, security, and integration of the system platform. Hence phased approach was developed to enable implementation as follows:

a. Phase 1: Platform selection
b. Phase 2: Equipment audit
c. Phase 3: Machinery reliability and criticality assessment
d. Phase 4: Machinery health parameter identification
e. Phase 5: Data collection and acquisition infrastructure
f. Phase 6: Data storage and management infrastructure
g. Phase 7: Training and development.

Phase 1: Platform selection

Predictive condition monitoring is a rigorous and cost-intensive process, with initial implementation on ships or a couple of ships serving as pilot platforms. Factors to consider include cost-benefit analysis, expected remaining life in service, types of equipment onboard, existing sensors for condition monitoring, and potential benefits such as improved ship availability, efficient maintenance, reduced risk of unscheduled maintenance, and cost effectiveness.

Phase 2: Equipment Audit

This phase involves identifying all equipment and associated power supplies, linkages, and control systems, as well as processes to be considered in the condition monitoring. A schematic block diagram of the main machinery and associated fixtures can be generated, focusing on system requirements, operating conditions, and boundary conditions.

Phase 3: Machinery Reliability and Criticality Assessment

This phase establishes the historical reliability of the equipment based on existing MRO reports and failure data. A machinery criticality assessment is necessary to prioritize the list of machines to be included in the predictive machinery programme. Factors to consider include cost/impact of machine downtime on operations, failure rates, consequences of machinery failure on other equipment, replacement cost, cost of maintenance or repairs, availability of suitably qualified personnel, life cycle cost, and cots of the monitoring system.

Phase 4: Machinery health parameter identification

Not all machinery health indicators are suitable for data-driven predictive condition monitoring, so measurement techniques, data collection points, and sensor types should be carefully selected to ensure only relevant parameters are taken. The NN should ensure that all new procurements come with a standard unified data acquisition platform for all diesel engines on board. Similarly, other equipment and critical components may need to be provided with suitable measurement technologies.

Phase 5: data collection and acquisition infrastructure

In Phase 5 of the plan, the focus is on data collection and acquisition infrastructure. The measurement technique is important in selecting the relevant parameters for diagnostics and fault identification. The type of machine determines the sensors that provide valuable data. Existing measurement techniques in the Navy can be used initially, but a standard unified data acquisition platform is needed for all diesel engines. Other equipment and components may require suitable measurement technologies, such as oil analysis for diesel engines. The data acquisition infrastructure currently in place is basic and lacks standardization. There is a need for accurate and efficient data collection methods, including standardizing data recording formats, using digital means of recording, installing digital sensors, establishing an onboard data platform, and developing data transmission platforms and protocols.

Phase 6: Data storage and management infrastructure

In Phase 6 of the data storage and management infrastructure, the focus is on managing the large amount of data generated by equipment and machinery. This data can be difficult to handle and analyse, especially for inexperienced operators. By using computer programs that can quickly analyse thousands of data points, potential failures can be identified and predicted. This technology can lead to improvements in machinery availability and a better understanding of critical failures. The data storage system infrastructure can be implemented through on-board ship data storage, automated on-board data storage and transmission, or cloud-based storage and transmission. Various off-the-shelf enterprise maintenance management systems are available, or the NN can develop their own maintenance platform. Cloud services from reputable vendors like IBM, Microsoft, AWS, Cisco, and Dell can be used to implement different infrastructure options such as SaaS, IaaS, or PaaS.

Phase 7: Training and Development

Establishing a data-driven condition monitoring and maintenance platform requires multiple skills and knowledge levels. In this regard, all personnel responsible for ship maintenance must be trained in basic Word and Microsoft Excel, data collection and pre-processing, machine learning, and other system reliability software programmes. To enable correct interpretation of results and integrate with data-driven outputs.

6.6 Chapter Summary

The chapter discusses the novel methodology for implementing maintenance data systems (MDGs) on Nigerian Navy ships. It highlights the agreement on component and failure criticality based on operator and reliability analysis outputs. The ANN fault diagnostics analysis highlights the dominance of overheating as a key fault in MDGs and the inability of MDGs to generate above 50% of rated output. The proposed maintenance DSS provides a comprehensive approach that can be implemented onboard ships and extended to shore maintenance offices or bases for fleet maintenance requirements.

Accordingly, a guide on how to implement a data driven maintenance planning procedure was provided. To bridge the gap from manual data collection and management to automated data management the operator can implement the recommendation provided in this chapter. This can help establish priority levels according to maintenance task responsibility, with ship staff managing simple failures and faults and shore establishment handling larger maintenance requests. Overall, the proposed methodology aims to improve maintenance decision-making and enhance the reliability and availability of machinery on ships.

7. Conclusions and Recommendations for Future Research

7.1Chapter outline

The chapter discusses the successful achievement of the research aims and objectives outlined earlier in Section 7.2. The research novelty is presented in Section 7.3, thereafter, the conclusions of the research are presented in Section 7.4. Section 7.5 provides recommendation for future research and the chapter summary is presented in Section 7.6.

7.2 Accomplishment of Research Aims and Objectives

The main aim of this research is to develop a novel hybrid maintenance framework for ship system reliability analysis through the combination of reliability analysis tools and artificial intelligence. Accordingly, an extensive literature review was conducted to identify research gaps across industry, academia, and the application of tools. Thereafter a methodology that illustrated the step-by-step integration of all the tools used in the research was implemented through the presented case study. Therefore, the research objectives enumerated in chapter 1 have been addressed within the overall research framework as discussed in the following paragraphs.

Objective 1: Identify research gaps in system reliability analysis, component criticality, fault identification and maintenance decision support system by conducting a rigorous literature review.

The first objective of this research was centred on identifying research gaps in generic maintenance strategy and system reliability within the maritime industry, with a focus on Ships; owing the role they play in global trade and security. Moreover, the nature of deployment and extended voyages can lead to high levels of stress on both human and machines, that could lead operational creep that impact on the risks of failure. Therefore, this was done, through a careful and system appraisal of literature covering industry such as defence and aerospace, power generation, oil and gas, renewables with particular to interest towards offshore wind as well as the nuclear industry. Moreover, academic research papers and books dealing with system reliability and component criticality analysis including use of machine learning for fault identification were equally reviewed in detail to come with areas that needs further investigation.

Moreover, importance of operators' sentiments in system reliability and recognition in overall maintenance DSS were discovered to be critical issue requiring further investigation especially in less developed areas of the world where OEM presence could be a challenge. Therefore, the literature review has identified these gaps as well as stereotypical implementation of traditional maintenance strategies which do not guarantee equipment availability. Consequently, the methodology presented in this work was designed to improve the utilisation of machinery historical and health data for identification of Mission Critical Component and development of maintenance DSS.

Objective 2: Develop a ship system component criticality and maintenance framework to address system reliability and maintenance decision support system based on the identified research gaps using a combination of reliability analysis tools and machine learning.

Objective was addressed through the novel methodology developed in Chapter 3 which provides a systematic approach in data classification and integration to suite the tools used in in the research. The methodology provides a detailed and comprehensive analysis that identifies critical components in relation to ship availability and maintenance effort in an inclusive manner that can account for operator concerns, OEMs' recommendations, and environmental influence. In this regard, this work presents a hybrid marine system component reliability analysis and fault detection framework using a combination of tools that includes dynamic fault tree (DFTA) for system reliability and criticality analysis, failure mode effect and criticality analysis (FMECA) for identification of mission critical component accounting for operator sentiment and Bayesian Belief network (BBN) for dependability analysis and maintenance decision support system (DSS). To complement the reliability analysis models a machine learning model base on artificial neural network (ANN) was also developed for classification and fault detection. Furthermore, data collection was achieved through on-board data collection campaign and questionnaire. On board data collection campaign was done through collection machinery raw machinery log data and maintenance, repair, and overhaul (MRO) data were obtained to demonstrate the novel methodology.

Objective 3: Identify case study platform and expert group for onboard data collection and user survey analysis.

To enable proper implementation of the developed methodology a case study platform was to selected for machinery data collection. Accordingly, following acceptance of the terms and condition of data collection, protection and storage, permission was granted to the for data on non-disclosure bases. Accordingly, an onboard data collection campaign was conducted which includes machinery maintenance, repair, and overhaul data (MRO) collection, machinery health log data (MHM) collection. In this regard about 48 months' worth of historical MRO was collected, while the remaining MRO was simultaneously collected about 18 months MHM data. Thereafter, operators granted a survey to be conducted for FMECA purposes. The survey was done to obtain the operator perception regarding different type of failures, maintenance, component repair and logistical issues as it pertains to system reliability and platform availability.

Hence, using the MRO data, component failure rates were derived for the DFTA analysis, while a survey was conducted to develop the FMECA. Using outputs such as RPN component mission criticality was established; the RPN together with MCS from the DFTA were used to develop maintenance DSS using BBN decision theoretic platform. Similarly, machinery health log data was used to train ANN FFNN to develop a fault identification model to improve the maintenance DSS suggestions. The overall case study procedure was presented in chapter 4.

Objective 4: Establish ship equipment reliability and component mission criticality towards ship operational availability.

All aspects of this objective were realised in chapter 5, using FMECA and DFTA to evaluate collected data which includes survey and MRO reports. The necessity of FMECA in the research was to ensure that analysis took in too account operator expert opinion on how failures and failure modes impact maintenance planning, delivery as well as the overall perception of the technical staff on the reliability MDGs being the case study equipment. It also provides experts judgement on how this failure affect platform availability due to issue such as, spare parts availability, technical expertise, delays due to OEM and impact of the operational environment including practices. Accordingly, the Component Mission Criticality obtained from the FMECA analysis was used to drive the component mission criticality that was used as major input for the maintenance DSS.

Similarly, DFTA was conducted on individual MDGs of the case study vessel, to obtain system, and sub-system reliability, reliability importance measures that provides component criticality and minimal cut sets. The combination of these outputs gave detail view of the reliability issues associated with the MDGs. Moreover, the operators SOP was considered to enable a practical understanding of reliability situations with MDGs. Accordingly, some of the outputs from the DFTA in particular the MCS were used to develop the BBN availability model used for the maintenance DSS.

Objective 5: Identify important features for machinery health diagnosis using maintenance repair and overhaul data together with machinery health monitoring data for system reliability and diagnostic analysis.

The initial steps to achieving this objective were presented in Chapter where the case study vessel and the PGS were identified, as well as data classification regarding tools to suite tool requirements. In this regard, the FMECA, DFTA ,BBN and the ANN development process were discussed highlighting the need for individual process within the overall framework. Accordingly, the FMECA provides vital inputs understanding failures and how they impact ships operational availability and the necessary insights towards developing the DFTA, BBN and ANN.

The DFTA outputs were additionally utilised to generate input for modelling the availability analysis in the DFTA through MCS. The BBN was modelled to get MDG availability over the operation months analysed, in this regard, MCS provide the major failures affecting component availability. Consequently, ANN classification using FFNN was developed and implemented for faults identification in order to adequately identify the major causes of failure in MDGs. Overall, EGT was used as the predictor variable and KW as used response variable. In generally the ANN diagnostic analysis identified overheating as the major fault type in all 4 MDGs, which supports the DFTA IM regarding the criticality of some cooling system component especially FW heat exchangers and the sea chest.

Thereafter, in Chapter 5, a feature selection was carried out to ensure that selected variables are good representation of the machinery health predictor. Especially, that the data was unlabelled, in this regard multi approaches were adopted to ensure fitness and quality of selected data features. Consequently, feature engineering was done using 3 methods, ANN Self-Organising Maps (SOM), correlation analysis and analysis of variance (ANOVA). The reason to adopt these 3 approaches was that ANN SOM as part of ANN unsupervised learning which can identify, and partition data based on the most prominent features of the data; while correlation analysis gives R-value which provide relationship within the data variables strength of influence to each other. In the case of ANOVA, it can be utilised to evaluate the relationship between each individual feature (predictor variable) and the response variable (target variable). It helps determine which characteristics have a significant impact on predictor and are likely to be important for modelling.

Objective 6: Develop maintenance data collection and management approach to prioritise maintenance of critical components.

Objective 6 was achieved and presented in chapter 4 through to 5, this is first seen in data categorisation to cover subjective and objective data in the analysis. The subjective aspect of the case study provides intuitive guidance on model quality, while the objective part of the methodology provides numerical analysis using failure rates as inputs. The FMECA analysis presents experts judgement about failure and critical system component while the DFTA is a quantitative analysis on system component reliability. The inputs for the BN analysis were obtained from both failure rates and MCS output of the DFT analysis, while RPN numbers from FMECA analysis were used as bases for maintenance strategy selection of individual generators. Accordingly, the DSS allocates percentage values between 0-100 to each of the 4-maintenance strategy choice for the DG based on the input data. The allocated percentage for each of the strategy determines how the maintenance action, planning and monitoring should be prioritised.

Objective 7: Utilising MRO and Condition Monitoring data to enable decision support system for ship system maintenance.

Chapter 5 and 6 discussed the implementation and the utilisation of MRO and condition monitoring data to build a maintenance DSS. The maintenance DSS model was designed to draw from multiple inputs source to improve data coverage in component failure dynamics. Accordingly, the inputs for the overall maintenance DSS includes MDG availability from BBN, Component Mission Criticality from RPN and as well influence factors such SQEB, environment and quality of spares or consumables like lubricating oil, fuel, and additives. Accordingly, the DSS allocates percentage values between 0-100 to each of the 4-maintenance strategy choice for the MDG based on the input data and consideration for influence factors controlled by the model. The 4 maintenance options are, Corrective Action, Delay Action, ConMon and PMS. Furthermore, the allocated percentage for each of the strategy determines how the maintenance action, planning and monitoring could be prioritised.

Overall, the proposed maintenance DSS provides a comprehensive approach that can be implemented onboard ships and extended to shore maintenance offices or bases for fleet maintenance requirements. It can bridge the gap from manual data collection and management to automated data management. The methodology requires a structured maintenance data management system, requiring a unified structure for data collection on board ships and a standard data management collection system. The system can establish priority levels according to maintenance task responsibility, with ship staff managing simple failures and faults and shore establishment handling larger maintenance requests. Overall, the proposed methodology aims to improve maintenance decision-making and enhance the reliability and availability of machinery on ships.

7.3 Novelty of Presented Research

The research presents a novel methodology through the combination of reliability analysis and artificial intelligence using artificial neural networks machining learning capabilities. The combination of these unique tools enables the harnessing of individual capabilities of the tools towards achieving the research objectives as regards component criticality and maintenance decision support system.

- Development of a hybrid maintenance platform using a unique combination of selected reliability tools to enable system reliability analysis for component mission criticality analysis.

- Development of integrated system reliability and maintenance DSS using reliability analysis and data-driven tools for system reliability and diagnostic analysis for improved availability.

- Development of operator and OEM machinery health parameter blend threshold for diagnostic analysis based on actual collected.

- Feature extraction using a combination of ANN SOM, correlation analysis and ANOVA for identification of responsive features to MDG faults and failure identification. This was used for ANN FFNN fault identification modelling mapped to DFTA component criticality outputs.

- Implementation of combined system reliability and diagnostic using ANN FFNN for naval ship power generation system reliability and availability analysis.

- Establishing an innovative approach for Naval Ship maintenance DSS through FMECA and reliability analysis tools, that enables combination of expert knowledge and reliability tools to component criticality analysis.

- Identifying critical component failures to address equipment reliability and availability within the operators assign limits of availability.

- Utilising FMECA RPN and DFTA MCS as secondary inputs data for implementing maintenance DSS.

7.4 Conclusions

Shipping controls up to 80% of the carriage of global goods and services as well as the share of global trade. In this regard, an overview of the importance of ships in ensuring the security and safety of seafarers, goods, and services, as well as other critical support services such as search and rescue operations, oil spill cleaning, firefighting, etc., has been discussed. Notwithstanding, as ships provide these all-important services, the industry is grappling with ageing ships and new regulations on emission control such as the EEDI and CII, which put further constraints on the reliability of older ship machinery in addition to the existing challenges of the relatively high failure rate of the propulsion and power generation machines. Moreover, the issue of new fuels as regards their impact on maintenance should be of concern due to the fact that diesel engines are by far the primary sources of both propulsive and electric power generation on board. Consequently, the reliability of these systems is very much related to ship availability as well as fleet performance. Therefore, considering existing and emerging challenges in marine diesel engine reliability, this research provides an advanced platform for ship system and machinery reliability analysis and maintenance DSS.

In this regard, a critical review of related literature was conducted for the research. An appraisal of maintenance strategy was given with a look at traditional maintenance concepts, highlighting some of the challenges that led to a gradual transition to other maintenance concepts. An overview of the evolution of maintenance and adoption through the industries was given, including factors influencing the acceptance or implantation of the evolved concepts. Like most other industries, the shipping industry is highly regulated to enable structured operational administration of all activities in the sector; hence, an overview of the role of IMO, classification societies, and other related agencies was given, including the respective roles each plays in developing maintenance and environmental regulations for the shipping industry. In this regard, tools used for system reliability were discussed, including diagnosis and prognosis analysis tools that can help with maintenance planning and decision-making. Accordingly, a summary of the most notable related work to the research as well as research gaps in relation to the research area of interest were provided.

The methodology section gives a step-by-step plan for developing a ship system reliability and fault identification platform to improve ship availability and maintenance decision support systems, considering things like operator concerns, OEM recommendations, and environmental impact. In this way, it suggests a hybrid approach to system reliability and failure mechanics that uses multiple tools, such as DFTA for system reliability and criticality analysis, FMECA for identifying mission-critical components while taking operator opinion into account, and BBN for dependability analysis and maintenance DSS. In addition, an artificial neural network-based machine learning model was developed for classification and fault detection. This hybrid approach allows for a more comprehensive understanding of system reliability and failure mechanics, taking into consideration both technical aspects and the human factor. By combining tools like DFTA, FMECA, and BBN, it is possible to identify critical components and their impact on the system's overall performance. The artificial neural network-based machine learning model further enhances fault detection capabilities, enabling proactive maintenance and minimising downtime. Overall, this integrated approach improves system dependability, reduces environmental impact, and enhances overall operational efficiency.

The data used for the research was obtained through an on-board data collection campaign and a questionnaire survey. The data collected includes machinery health log data and MRO reports. So, a methodical mix of data acquisition methods, system reliability analysis, and data analytics made it possible to use the method to create a hybrid framework for analysing the reliability of marine systems and components and finding faults. Furthermore, data categorization was adopted to enable the use of multiple tool types; hence, subjective data was used to enable the imputation of other non-categorical data. On the other hand, objective data was used to handle categorical and quantitative data types. Overall, the methodology shows how multiple data types and tools were integrated to develop a hybrid marine system component reliability analysis and fault detection framework. The inclusion of on-board data collection and operator input through questionnaires enhances the comprehensiveness and inclusivity of the analysis.

A case study section was conducted to demonstrate the novel methodology on a PGS consisting of four MDGs. The selection of the PGS was premised on its utility on board ships, which is stressed by the level of redundancy and design resilience usually provided by ship builders. This redundancy and system resilience are common for both merchant and naval ships, though there is a significant operational demand for the naval platforms. Failure of the power generation system for naval platforms has several implications, especially considering the number of personnel onboard and vulnerability due to loss of weapons and surveillance systems, as well as safety and habitation on board. Additionally, location and type of failure are important factors to be considered in maintenance planning due to logistics and OEM-related concerns. In this regard, the suggested case study implements a novel methodology through the combination of reliability analysis tools to address maintenance challenges on the power generation plant onboard an OPV.

Accordingly, the research data was categorised into subjective and objective analyses to ease data interpretation and tool compatibility. The subjective aspect of the case study provides intuitive guidance on model quality, while the objective part of the methodology provides numerical analysis using failure rates as inputs. The FMECA analysis presents expert judgements about failure and critical system components, while the DFTA is a quantitative analysis of system component reliability. The inputs for the BBN analysis were obtained from both failure rates and the cut set output of the DFT analysis, while RPN numbers from the FMECA analysis were used as bases for the maintenance strategy selection of individual generators. Therefore, the data used for the analysis includes FMECA conducted via an online survey and failure rates using maintenance and repair data collected from case study MDGs. Additionally, a rigorous data cleaning and feature engineering process was carried out in order to implement the classification and fault identification model using the ANN FFNN.

The case study analysis was presented sequentially based on how the tools were integrated into the methodology. In this regard, the FMECA results reflect the input data, operator opinion, and research modelling tools used. The FMECA results were used to generate mission-critical components and establish the maintenance DSS process. The DFTA results provided insights into the relevance of operator opinion in research modelling and the development of DFTA, BBN, and ANN. The DFTA outputs were also used to generate input for modelling availability analysis in the DFTA through MCS. The ANN classification using FFNN was developed to identify major causes of failure in the MDGs. Data cleaning and engineering were conducted to ensure data quality and accuracy for the fault identification analysis.

Accordingly, the BBN availability and maintenance DSS presented the availability of MDGs based on their components. A maintenance DSS was built using inputs from both DFTA and FMECA, proposing four main strategy choices: delay action, corrective action, ConMon, and PMS. Overall, the results showed that all four MDGs had varying degrees of availability, with MDG 2 being slightly more available. However, a critical situation was presented in the cooling system, with availability values below 40%, below the operator's expected availability of 80%. Corrective Action and ConMon were the most preferred choices for all MDGs, except for MDGs 1 and 2, which had relatively low figures in ConMon but high figures in PMS. This suggests that there may be specific issues or challenges in the maintenance and monitoring of MDGs 1 and 2, which could be addressed through improvements in the ConMon system. Additionally, further investigation is needed to understand why the cooling system is experiencing such low availability and to develop a more effective corrective action plan to bring it up to the desired level of 80%.

The suggested maintenance decision support system (DSS) offers a comprehensive method that may be deployed both on ships and extended to shore maintenance offices or bases to address fleet maintenance needs. Additionally, it can serve as a means to facilitate the shift from manual data collection and management processes to automated data management systems. However, it is imperative to acknowledge that a certain degree of human interaction will remain necessary, particularly in the context of naval vessels. Consequently, the implementation of the methodology for the case study ship and other ships will rely on a systematic approach to managing maintenance data. This approach necessitates the establishment of a standardised framework for collecting, storing, and analysing data, along with the need for skilled personnel to operate and interpret automated systems. As a result, the complexity and cost of maintenance operations may potentially be heightened. The collection of data on board ships, together with the implementation of a standardised data management system,

The aforementioned statement underscores the consensus reached on the significance of component and failure criticality, as determined through an examination of operator and reliability analysis results. The fault diagnostics investigation utilising artificial neural networks (ANN) reveals that overheating is a prominent problem in the malfunctioning of MDGs (main drive generators). Additionally, it indicates that MDGs are incapable of generating more than 50% of their designated output. Additionally, the system has the capability to assign priority levels based on maintenance job responsibilities, whereby ship personnel are responsible for addressing basic failures and defects while sophisticated maintenance requests are handled by shore establishments. The primary objective of the proposed technique is to enhance maintenance decision-making processes and optimise the dependability and availability of machinery installed aboard ships.

7.5 Recommendations for Future Research

This research has a laid a foundation for hybrid multi-tool reliability and diagnostics platform for system reliability analysis; by the infusion of expert knowledge, reliability analysis process and data driven methods. The generated results from the analysis are detailed and specific to subsystems and related components. Furthermore, results can be further exploited to address areas of maintenance staff shortages for certain failure types. Moreover, the developed reliability and diagnostic analysis framework provides the ability to validate component criticality based secondary results analysis of the tools used, hence reducing or the need for onboard trial phase. Nonetheless, a lot can done in the field of ship system reliability analysis to add on the existing research. Accordingly, future research direction could investigate the following.

- Application of ANN and FMECA analysis for performance degradation, fault classification, and failure risk analysis for mapping to component failure against ship maintenance crew capability.
- Implement the use of machine learning algorithms such as Support Vector Machines, Naïve Baise, and other Generative Algorithms for fault identification and
- Improvement on existing data driven procedure by acquisition of more data points from onboard machinery health records.
- Develop a methodology to address challenges of data quality and accuracy due to operator apprehension and confidence in providing accurate machinery health records for research purposes.

- Automated platform for system reliability and diagnostics analysis to generate mission critical components and failure based on artificial intelligence and system reliability insights.
- Application of artificial neural networks for fault detection and the development of a methodology for estimating the remaining useful life of ship system components, along with a spare parts estimation process.
- In the light of shipping the decarbonisation the developed methodology could be used to investigate the impact and use of biofuels and other alternative fuels on engine system and component's reliability.
- Developing emission control measures by linking ship machinery emissions data and maintenance DSS records to reduce overall generated emissions due to both ships' operations and maintenance related activities.
- Developing a maintenance DSS using a combination of machine learning and decisions support tools such as Analytic Hierarchy Process, Analytic Network Process and Multi criteria decision making and fuzzy theory.
- Fault mapping using Clusters and Classification analysis together with component reliability analysis using tools such as Markov chains.

7.6 Chapter Summary

This chapter provides an overview on the accomplishment of the research aims and objectives by highlighting how and where in the research this were achieved. The research novelties were also outlined buttressing the relevance of the developed methodology in the area of system reliability in particular to naval ships and systems. The conclusion provides a bird's eye view on the main points from chapter of the discussed, hence giving a general view of the work. In recognition, of the dynamic nature and limitation of research due so many constraints, recommendations for future work were presented.

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APPENDIX 1: Important Stake Holders in the Development of Maritime Maintenance Regulations and Guidelines

1. IMO: The IMO protocols such as MARPOL Annex VI convention for the prevention of air pollution from ship, the IMO enacts regulations that guide the conduct of ship operations and maintenance. These rules play the most vital role in the enactment of laws and regulations which governs design and manufacture of systems that goes onboard the ship. For instance, one of the key aspects of MARPOL Annex VI was the sulphur oxide (SOx) and nitrogen oxide (NOx) cap which ship can emit to about 0.50m/m. This therefore means change to type of ship fuel from HFO to VLFO or MGO. The conventions through the MEPC 76 also require that all ships meet certain energy efficiency requirements to meet the IMO emission target.(IMO, 2018b, IMO, 2021). In this regard the protocols and regulation emanating from IMO regarding energy efficiency or pollution reduction impact directly on the system onboard as well as maintenance regime that can efficiently achieve the right system reliability and availability. However, this also comes with additional issues, some which are raised in discussion with ship operators; pointing that the new regulations on emissions create more maintenance issues and repairs than before.

2. Flag State: Flag states is the state in which the ship is registered as such they play vital role in the enactment of rules and regulations that can impact on the conduct of ship operations and by extension maintenance(Stopford, 2009). Moreover, international maritime laws are developed by the participation of the flag state. For instance, the emission control areas (ECAS) that enforces the SOx and NOx levels are an aspect of the flag state control which must be complied with. In this regard ship must use Tier 3 engines or exhaust gas scrubbers.

3. Coastal State: These are countries in whose waters ship trade, therefore play vital role in the formulation of maintenance regulations. Port state regulation are aimed at ships calling at their ports and hence ships must comply with the international maritime safety security and environmental requirements. Therefore, these regulations are enforced by port states control authorities which includes inspection of ship maintenance covering machinery, hull equipment as well as personnel

competency(IMO, 2018a). These inspections are aimed at ensuring that ships are seaworthy, safe for habitation and are also using the recommended fuels or other related materiel. Moreover, failure to comply with the port state regulations could result to arrest or denying the ship use of the port or entering the territorial waters of the country(Agency, 2020).

4. Classification Societies: Classification societies play vital role in the generation of guidance for ship maintenance in that they participate in the beginning of ship design up to delivery and through to ship lifecycle. In this regard is mandatory for ship be classed to in order to be accepted insurance companies, to maintain flag state licence on trade on in a port state. In addition, classification societies also provide information on the standards of ships construction and integrity of its machinery hence helping charterers in identifying suitable ship for their trade. Moreover, majority of flag state have delegated their statutory activities to class societies as ' Recognised Organisations' (ROs)(Ashdown, 2019).Consequently, classification societies have an overarching role in the shipping and maritime industry of developing rules and implementing them(Stopford, 2009, Bourneuf, 1991). Some roles they play includes.

    a. Developing rules.
    b. Technical plan review for new ships.
    c. Survey during construction
    d. Classification certificate
    e. Periodic survey for maintenance
    f. Consultancy for ship owners and governments
    g. Maintenance and technical services.
    h. Representing Governments

5. The International Association of Classification Societies (IACS): IACS was formed in 1968 with members drawn from the major classification of societies(Bourneuf, 1991). The purpose of the organisation is to work towards the improvement of standards of safety at sea, provide consultation and cooperation with relevant international maritime organisations. IACS has two main aims: to introduce uniformity into the rules developed by class societies and to act as the interface between class societies as well

as to function as a collaborator between its members and outside organizations and in particular the IMO. In this regard IACS serves as principal technical partner to IMO. Therefore, IACS roles as regards regulations in ship maintenance includes creating ship maintenance standards covering equipment and system inspection, repair, and testing. It also provides advises on new maintenance technology. Furthermore, IACS collaborates with regulatory agencies like the IMO to ensure that regulations are technically sound and practical for ship operators to implement. Some of its overside functions include training ship operators and maintenance staff to comply with regulations. Moreover, ship safety and environmental performance depend on IACS maintenance rule, technical competence and close cooperation with regulatory organisations and industry partners(Ashdown, 2019). This role played by IACS help design and implement appropriate shipping industry maintenance standards and regulations.

6. OCIMF: The Oil Companies International Marine Forum (OCIMF) is a non-profit organisation comprised of oil companies, ship owners, and other maritime industry players, which is dedicated to promoting safety and environmental protection in the transportation and handling of crude oil, petroleum products, and natural gas(OCIMF, 2023). This organisation also plays vital role in the development of vessel maintenance regulations and guidelines. It does this through the establishment and publication of marine operations rules and standards, such as vessel inspection and vetting, mooring, and cargo transfer. It also provides training and education to its members in order to promotes best practises in the business. Through this efforts OCIMF has created several essential rules and standards for vessel maintenance such as the Tanker Management and Self-Assessment (TMSA) and The Ship Inspection Report (SIRE) Program. The TMSA gives tanker operators a framework for assessing and improving their safety and environmental management systems, as well as maintenance processes. Similarly, the SIRE programme provides a complete checklist for vessel maintenance and inspection, which aids in the maintenance and operation of boats in a safe and sustainable manner which is used to check the condition of tankers and other vessels, is also published by OCIMF. In general, OCIMF's involvement in the formulation of vessel maintenance laws and recommendations is centred on enhancing the shipping

industry's safety and environmental performance, as well as fostering sustainable development through the adoption of best practises.

7. INTERTANKO: The international Association of Independent Tanker Owners, is a trade association constituted in 1970 with the aim of representing and promoting the interest of its members(INTERTANKO, 2021). In this regard, INTERTANKO, provides a forum where industry meet and discuss maritime policies pertaining independent tanker and chemical carrier owners. The association has 16 committees covering various aspects of interest to its members. INTERTANKO has an observer status with IMO, UNCTAD and works closely with other stake holder such as IACS, OCIMF, the EU commission, flag, and port state. Consequently, INTERTANKO offers other service to ensure that it’s adhered to required standards on maintenance for hull and machinery and those this through multiple ways some of which includes publication of annual. guidance notes s and safety operation it INTERTANKO works closely with the IMO to ensure its members have understood their obligations as regarding all IMO regulations.

APPENDIX 2: Related Works

Authors	Maintenance Concepts	Publications	Methodology
BahooToroody Ahmad	Machinery RUL estimation, RCM and CBM	Prognostic health management of repairable ship systems through different autonomy degree; From current condition to fully autonomous ship. *Reliability Engineering & System Safety*, *221*. https://doi.org/10.1016/j.ress.2022.108355 On reliability assessment of ship machinery system in different autonomy degree; A Bayesian-based approach. *Ocean Engineering*, *254*. https://doi.org/10.1016/j.oceaneng.2022.111252	Bayesian Inference analysis, Weibull prediction and Markov Chain Monte-Carlo
Cipollini, Francesca	Data driven Machinery health and Condition Monitoring	Condition-Based Maintenance of Naval Propulsion Systems with supervised Data Analysis. *Ocean Engineering.* Condition-based maintenance of naval propulsion systems: Data analysis with minimal feedback," *Reliability Engineering & System Safety,* vol. 177	Data driven Model for naval propulsion systems, developing unsupervised and supervised machine learning models for degradation and classification
Iraklis Lazakis	Total Quality Maintenance, Reliability Centred Maintenance, Predictive Maintenance	Advanced Ship Systems Condition Monitoring for Enhanced Inspection, Maintenance and Decision Making in Ship Operations. *Transportation Research Procedia,* 14**,** 1679-1688. Investigating an SVM-driven, one-class approach to estimating ship systems condition. *Ships and Offshore Structures,* 14**,** 432-441 Increasing ship operational reliability through the implementation of a holistic maintenance management strategy. *Ships and Offshore Structures,* 5**,** 337-357. Selection of the best maintenance approach in the maritime industry under fuzzy multiple attributive group decision-making environment. *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, *230*(2), 297-309. https://doi.org/10.1177/1475090215569819	Dynamic Fault Trees, Failure Mechanism Effect and Criticality Analysis and Fuzzy Set Theory

Kagla Karatug	Maintenance Selection, Condition Monitoring Reliability Centred Maintenance,	Determination of a maintenance strategy for machinery systems of autonomous ships. *Ocean Engineering,* 266. 2022 Development of condition-based maintenance strategy for fault diagnosis for ship engine systems. *Ocean Engineering,* 256. 2022 Design of a decision support system to achieve condition-based maintenance in ship machinery systems. Ocean Engineering, 281. 2023	FMEA, maintenance decision making, Artificial Neural Net Diagnostics assessment, Maintenance decision support system for the condition-based maintenance of ship machinery systems using adaptive neuro-fuzzy inference system (ANFIS) approach and artificial neural network (ANN) for machinery health estimation process was also performed.
Gkerekos, C., Lazakis, I. & Theotokatos, G.	Data driven machinery condition health monitoring and predictive analysis	Machine learning models for predicting ship main engine Fuel Oil Consumption: A comparative study. Ocean Engineering, 188. 2019	Multiple regression algorithms for predicting ship main engine Fuel Oil Consumption using machinery operational data using Support Vector Machines (SVMs), Random Forest Regressors (RFRs), Extra Trees Regressors (ETRs), Artificial Neural Networks (ANNs) etc.
Cheliotis, M. et.al.	Data clustering to address Machinery health date cleaning and imputation of missing values	A novel data condition and performance hybrid imputation method for energy efficient operations of marine systems. Ocean Engineering, 188.2019 Machine learning and data-driven fault detection for ship systems operations. Ocean Engineering, 216. 2020	Imputation method for enhancing the quality of condition data from marine machinery systems based on hybrid k-NN and MICE imputation algorithm. Data-driven fault detection for shipboard systems, combining

			Expected Behaviour (EB) models with Exponentially Weighted Moving Average (EWMA). For detection of developing faults in Main Engine cylinder Exhaust Gas (EG) temperature and ME scavenging air pressure.
Konstantinos Dikis	Condition Based Maintenance, Probabilistic Machinery Reliability Assessment	*Risk and Reliability Analysis Tool Development for Ship Machinery Establishment of a novel predictive reliability assessment strategy for ship machinery.* PhD thesis, University of Strathclyde	Markov Chain, Failure Mechanism Effect Analysis, Dynamic Bayesian Belief Networks (DBBNs) for the reliability assessment -
Yiannis Raptodimos,	Condition Based Maintenance,	Ship Sensors Data Collection & Analysis for Condition Monitoring of Ship Structures & Machinery Systems. *Smart Ships Technology 2016.* Using artificial neural network-self-organising map for data clustering of marine engine condition monitoring applications. *Ships and Offshore Structures*, *13*(6), 649–656. Fault tree analysis and artificial neural network modelling for establishing a predictive ship machinery maintenance methodology. *RINA, Royal Institution of Naval Architects - Smart Ship Technology 2017*.	Artificial Neural Network, degradation, and fault detection Reliability Block Diagrams, and Dynamic Fault Trees for system reliability analysis
Arjomandi, M. A., et.al.	CBM, RCM, PM, and CM.	A fuzzy DEMATEL-ANP-VIKOR analytical model for maintenance strategy selection of safety critical assets. Advances in Mechanical Engineering, 13. 2021	DEMATL-ANP, VIKOR for maintenance decision were fuzzy DEMATEL importance weights of decision criteria while VIKOR was to rank the available maintenance strategy options.
Eriksen, S., Utne, I. B. & Lützen, M.	CBM, RCM and PM	An RCM approach for assessing reliability challenges and maintenance needs of unmanned cargo ships. Reliability Engineering & System Safety, 210. 2021	Maintenance selection Unmanned Marien Vehicles

Kalghatgi, U. S	Reliability Centred Maintenance, Big data, and Artificial Intelligence	Creating Value for Reliability Centered Maintenance (RCM) in Ship Machinery Maintenance from BIG Data and Artificial Intelligence. *Journal of The Institution of Engineers (India): Series C.* 2022.	Developing the process of deploying IoT and AI to enhance ship machinery diagnostics for the implementation of RCM.
Velasco-Gallego, C. & Lazakis, I	Machinery Data analysis for development of for missing data imputation, outlier detection and diagnostics analysis	Real-time data-driven missing data imputation for short-term sensor data of marine systems. A comparative study. Ocean Engineering, 218. 2020. A real-time anomaly detection intelligent system for fault diagnosis of marine machinery. Expert Systems with Applications, 204. 2022a. A real-time data-driven framework for the identification of steady states of marine machinery. Applied Ocean Research, 121. 2022b.	Clustering models like k-means and GMMs with EM algorithm for anomaly detection. Missing data imputation using the MICE to improve data cleaning for anomaly detection on ship machinery. Real-time Anomaly Detection Intelligent System (RADIS) framework, constituted by a Long Short-Term Memory-based Variational aimed to address gaps in the maritime industry in relation to data-driven model to enabling smart maintenance.

APPENDIX 3: MDG FAILURE RATE TABLE

Failure Cases			Frequency of Failure					Failure Rates /10,000HRS			
Component	**Failure Type**	**Action Taken**									
			G1	G2	G3	G4		G1	G2	G3	G4
Turbo charger	Black smoke	replaced, repaired	8	10	12	12		62.5	78.1	93.8	93.8
Lub oil cooler	Oil leakage	1. replaced 2. cleaned and zinc anode replaced	16	18	15	16		125.0	140.6	117.2	125.0
	external leakage		10	8	8	12		78.1	62.5	62.5	93.8
Oil valve	failed	remove/repaired	1	1	2	1		7.8	7.8	15.6	7.8
Cylinder head	1.Oil leakage 2.Fresh water leakage from A2 exhaust 2.Unable to start	1.Liner,Oring replaced(G1&G3) 2. Cylinder replaced(G3&G2) replaced gasket (G3)	20	19	19	21		156.3	148.4	148.4	164.1
		Guide bushing	20	14	20	20		156.3	109.4	156.3	156.3
		O-ring	28	32	23	23		218.8	250.0	179.7	179.7
		Holding bolts	18	17	17	16		140.6	132.8	132.8	125.0
Cylinder jacket/sleeve	1. Scuffed 2. cracked	replaced	11	12	11	12		85.9	93.8	85.9	93.8
Piston	Rings	Replaced	12	13	13	14		93.8	101.6	101.6	109.4
	cooling/crown		8	13	15	7		62.5	101.6	117.2	54.7
ConRod	bent		7	9	8	9		54.7	70.3	62.5	70.3
	Gudgeon pin		8	6	8	6		62.5	46.9	62.5	46.9
Drive belt	failed	replaced	8	8	9	11		62.5	62.5	70.3	85.9
	Worn-out	replace	11	5	9	3		85.9	39.1	70.3	23.4
Mech Injector pump	1. Cracked bolts 2. Broken bolts 3. Broken shims	1. Replace bolt and drive(G1&,G3) 2. Replace bolt, pulley, and set injector timing(G1&2) 3. Replaced shims	16	12	12	13		125.0	93.8	93.8	101.6

	Drive	defects	22	20	21	24		171.9	156.3	164.1	187.5
Injector Pump	failure	failure	30	28	22	28		234.4	218.8	171.9	218.8
Air Starter	failed Stater starting sensor	repaired x 3 replaced x1	16	16	16	16		125.0	125.0	125.0	125.0
Governor failure	1.Failure 2. Hunting		24	20	24	24		187.5	156.3	187.5	187.5
Intercooler	1. High exhaust temp 2. leakages 3. Overheating	1.Cleaned 2. Retightened 3. Replaced gasket	11	13	16	11		85.9	101.6	125.0	85.9
HP fuel line	leakages	Retightened	28	24	30	31		218.8	187.5	234.4	242.2
freshwater impeller	wear	replaced	26	21	21	23		203.1	164.1	164.1	179.7
Freshwater thermostats	failure	removed	8	8	8	8		62.5	62.5	62.5	62.5
freshwater pump	1.leakages, worn out pulley belt 2. Pipe	replaced	10	17	15	14		78.1	132.8	117.2	109.4
	pulley		4	4	5	4		31.3	31.3	39.1	31.3
Sea water valve	failed	Replaced	3	4	3	2		23.4	31.3	23.4	15.6
Sea water impeller	failed	Replaced	30	19	27	23		234.4	148.4	210.9	179.7
Sea water pump case	failed	replaced	7	9	10	12		54.7	70.3	78.1	93.8
Sea water pump	1.failed 2.blockage	1. Replaced 2. Cleared	6	3	4	3		46.9	23.4	31.3	23.4
Sea chest	Cleared		20	17	20	20		156.3	132.8	156.3	156.3
Injector nozzles	1.failed 2.hard starting	1.Replaced 2.Replacement(all 12) 3. Serviced (3 replaced)	20	30	24	18		156.3	234.4	187.5	140.6
Gear train for injector pump drive	Broken		4	3	3	5		31.3	23.4	23.4	39.1
Starting air line	leakages	Retightened	2	1	1	2		15.6	7.8	7.8	15.6

Exhaust gas temp sensor	failed	replaced	4	3	3	5		31.3	23.4	23.4	39.1
Multiple sensor failure	failed	remodification	1	3	1	1		7.8	23.4	7.8	7.8
Crankshaft	damages	replace/repaired	6	4	3	3		46.9	31.3	23.4	23.4
Crankshaft pulley belt	Worn out	replaced	2	6	3	7		15.6	46.9	23.4	54.7
balance shaft	failure		6	5	5	4		46.9	39.1	39.1	31.3
	alignment		4	3	4	3		31.3	23.4	31.3	23.4
Crank case	failed	replaced	3	2	3	2		23.4	15.6	23.4	15.6
Crank case	Cracked	Repair	4	4	4	4		31.3	31.3	31.3	31.3
Lub Temp sensor	1. failed 2.leakage	1.Replaced 2. replaced gaskets	3	2	0	2		23.4	15.6	0.0	15.6
Heat exchanger	Overheating	1.Heat exchanger back flushed 2.fresh water supply Hose reconnected	28	30	29	20		218.8	234.4	226.6	156.3
	Tubes leaking	internal leakages	12	18	12	8		93.8	140.6	93.8	62.5
Emergency Cooling failure	No/low water supply	blockages	7	8	5	6		54.7	62.5	39.1	46.9
Lub Oil line	blocked	cleared	3	3	2	3		23.4	23.4	15.6	23.4
Zinc Anode	1. Depleted 2.Replaced(lub oil cooler)	Replaced(all)	8	8	8	8		62.5	62.5	62.5	62.5
tappet	Tappet clearance overdue	clearance adjusted(Mar)	30	30	30	32		234.4	234.4	234.4	250.0
Exhaust Manifold	Constricted due to broken studs & heat seal	Replacement studs & seal	1	1	2	1		7.8	7.8	15.6	7.8
Freshwater pipe	leakage	repaired	1	0	1	1		7.8	0.0	7.8	7.8
Transmission gear	Miss alignment	Repaired	4	4	4	4		31.3	31.3	31.3	31.3
fuel tank	dirty/sludge		12	12	12	12		93.8	93.8	93.8	93.8

bad fuel	Sludge / water	Evacuation Tank cleaning	10	10	10	10		78.1	78.1	78.1	78.1
Fuel Filter Sec	leakages		16	16	16	16		125.0	125.0	125.0	125.0
fuel filter Sec	Clogged	rectified	26	26	26	26		203.1	203.1	203.1	203.1
Fuel Filter Pir	leakages		16	14	16	17		125.0	109.4	125.0	132.8
fuel filter Pri	clogged		24	24	24	24		187.5	187.5	187.5	187.5
Fuel Supply pump	failure		26	20	18	15		203.1	156.3	140.6	117.2
fuel hand pump	failure		8	12	12	12		62.5	93.8	93.8	93.8
Lub oil pump	defective		4	4	4	4		31.3	31.3	31.3	31.3
Lub oil filter	defective base	replaced	10	10	12	13		78.1	78.1	93.8	101.6
Journal bearing cooling	Engine not starting	replaced	3	2	2	3		23.4	15.6	15.6	23.4
main bearing	No/poor cooling	repaired/replaced	4	3	3	3		31.3	23.4	23.4	23.4
Valve (inlet/exhaust)	clearance/ carbon		12	14	16	13		93.8	109.4	125.0	101.6
valve spring	weak/broken		8	8	7	9		62.5	62.5	54.7	70.3
Air filter	clogged		23	23	23	23		179.7	179.7	179.7	179.7
Oil Thermostat	failure		1	0	2	1		7.8	0.0	15.6	7.8
Intercooler Thermostat	failure		3	4	3	4		23.4	31.3	23.4	31.3
Intercooler	fouled/failure		11	12	12	12		85.9	93.8	93.8	93.8
Overspeed device			16	12	13	10		125.0	93.8	101.6	78.1
Total failure			833	814	821	805					

APPENDIX 4: MDG1 Machinery Log Data

Time	Engine Speed (rpm)	Lub Oil Press. (Mpa)	Fresh Water Temp A-Bank (°C)	Fresh Water Temp B-Bank (°C)	Lub Oil Temp (°C)	Fresh Water Press (Mpa)	Exhaust Temp A-Bank (°C)	Exhaust Temp B-Bank (°C)	Genny Running Hours (Hrs)	Power (kW)
	≥ 1000	≥ 0.4	≤ 75	≤ 75	≤ 105		≤ 500	≤ 500		
07:00:00	1800	0.458	72.9	75.4	90	0.067	332.1	319.5	5234	115
08:00:00	1800	0.465	72.8	75.3	89.9	0.068	335.3	323.9	5235	120
09:00:00	1800	0.563	7201	7406	89.3	0.068	329.5	316.7	5236	115
10:00:00	1800	0.468	72.3	74.7	89.2	0.068	323.6	324.6	5237	105
11:00:00	1798	0.471	72.4	74.9	89.6	0.069	335.9	323.9	5238	120
12:00:00	1798	0.459	72.7	75.1	89.8	0.068	337.4	325.5	5239	105
13:00:00	1796	0.461	72.4	74.9	89.9	0.068	337.3	324.5	5240	120
14:00:00	1796	0.491	72.2	74.5	88.2	0.061	332.7	325.6	5241	115
15:00:00	1796	0.482	71	73.3	87.5	0.068	330.7	317.5	5242	115
16:00:00	1796	0.479	70	72.3	86.2	0.069	302.3	286.2	5242	80
17:00:00	1796	0.475	70	72.3	86.3	0.069	302	286.1	5244	90
18:00:00	1796	0.465	72	74.4	88.9	0.068	330.5	312.8	5245	120
19:00:00	1798	0.466	72.2	74.6	89.2	0.068	331.5	319	5246	110
20:00:00	1798	0.467	73.1	75.7	90.7	0.067	340.7	329.1	5247	110
21:00:00	1796	0.504	73.7	76.2	91.4	0.067	346.5	335.3	5248	120
22:00:00	1798	0.451	73.5	76	91.2	0.067	343.4	330.7	5249	120
23:30:00	1798	0.469	73	75.4	89.9	0.067	334.1	321.5	5250	120
16:00:00	1801	0.491	67	70.4	81.7	0.072	297.3	282.3	5250	90
17:00:00	1800	0.486	70.1	72.6	86.6	0.069	211.5	296.3	5251	100
18:00:00	1800	0.485	70	72.5	86.9	0.069	310	295.1	5252	100
19:00:00	1800	0.477	70.5	73	87.4	0.069	313.1	298.3	5253	100
20:00:00	1800	0.478	70.6	7301	87.6	0.069	313.5	298.6	5254	100
21:00:00	1800	0.467	70.6	73	87.5	0.069	310.3	295.8	5255	97
22:00:00	1800	0.483	70.7	73.2	87.6	0.068	310.2	29.4	5256	100
12:00:00	1798	0.473	725	74.5	89.2	0.068	328.4	317.4	5261	100
13:00:00	1798	500	75.6	78.3	94.1	0.067	351.2	340	5262	135
14:00:00	1798	0.502	75.3	77.8	73.5	0.067	348.6	338.4	5263	135
15:00:00	1796	0.509	74.7	77.3	92.7	0.067	341.2	332.2	5264	120
16:00:00	1796	0.506	76	78.7	94.5	0.067	355.6	345.9	5265	135
17:00:00	1796	0.5	76.3	79	97.7	0.067	352.3	341	5266	150
18:00:00	1798	0.492	75.8	78.3	93.6	0.066	343.4	332.9	5267	120
19:00:00	1798	0.468	75.3	77.4	92.8	0.067	341.6	332.8	5268	120
16:00:00	1800	0.491	76.9	79.8	95.8	0.067	370.8	360.6	5269	160
17:00:00	1800	0.494	77.2	80.1	96.1	0.067	367.8	356.7	5270	150
18:00:00	1800	0.477	72.6	75.2	89.8	0.067	325.9	313.7	5271	110
19:00:00	1798	0.514	74.7	77.4	91.7	0.068	368.5	357.6	5272	170
23:00:00	1800	0.465	75.1	77.7	92.5	0.67	358.9	347.8	5274	140
00:00:00	1800	0.467	75.3	78	97.6	0.067	358.4	348.2	5275	140

01:00:00	1800	0.459	75.2	77.8	92.6	0.067	353.8	342.5	5276	140
02:00:00	1798	0.466	75.4	77.6	92.4	0.066	358.6	346.4	5277	140
03:00:00	1801	0.467	75.2	70.5	89.4	0.068	329.5	318	5278	145
04:00:00	1796	0.475	71.8	74.2	88.1	0.068	335.2	322.2	5279	145
05:00:00	1800	0.485	71.2	73.5	8702	0.0687	307.5	293	5280	100
06:00:00	1800	0.489	77.5	80.7	95.8	0.067	369.6	359.2	5281	145
07:00:00	1800	0.499	77.3	80	95.5	0.067	363	353.9	5282	145
08:00:00	1800	0.493	77.6	80.2	95.6	0.067	362.2	352.2	5283	150
09:00:00	1800	0.483	78	80.6	96.2	0.066	366.1	355.9	5284	150
23:00:00	1800	0.506	75.6	78.3	93.5	0.068	363.3	353.7	5293	150
00:00:00	1800	0.497	76.1	78.8	95	0.067	356.2	347.4	5294	135
01:00:00	1801	0.502	75.5	78.4	94.5	0.067	359.7	349.7	5295	140
02:00:00	1801	0.503	75.8	78.6	94.6	0.067	360.4	351.7	5296	140
03:00:00	1800	0.504	76.2	79.1	95	0.067	361.2	353.1	5297	140
04:00:00	1800	0.493	78.6	78.7	94.5	0.067	359.1	350.1	5298	140
05:00:00	1800	0.502	76.2	79.1	94.8	0.067	358.3	351	5299	140
06:00:00	1800	0.499	75.8	78.8	95.6	0.067	360.1	353.7	5300	150
07:00:00	1800	0.488	77.8	80.5	96.1	0.066	374.2	363.3	5201	140
08:00:00	1800	0.498	77.3	80	95.8	0.066	364.3	354.3	5302	150
09:00:00	1798	0.497	77.3	80	95.8	0.066	368.2	354	5203	150
10:00:00	1800	0.492	76.2	80	95.8	0.062	367.4	354.2	5204	150
11:00:00	1800	0.49	76.2	80	95.8	0.062	367.4	354.2	5304	180
12:00:00	1800	0.492	77.9	80.6	96.2	0.066	371.8	361.1	5306	160
13:00:00	1808	0.482	77.4	80.2	96.5	0.066	369.5	359.5	5307	160
14:00:00	1800	0.482	77.4	80.2	95.5	0.066	369.5	359.5	5307	160
15:00:00	1801	0.494	77.5	80.2	95.7	0.066	371	361.4	5309	155
16:00:00	1800	0.5	77.7	80.5	96.1	0.066	372.6	362.1	5310	150
17:00:00	1801	0.501	77.7	80.5	95.9	0.066	371.2	361	5311	160
18:00:00	1801	0.505	770.2	80	95.5	0.066	396.6	358.8	5212	150
19:00:00	1800	0.489	77.8	80.5	96.2	0.066	376.3	365.4	5313	160
20:00:00	1800	0.49	77.9	80.7	96.3	0.65	376.7	365.5	5314	160
21:00:00	1800	0.503	77.3	80.1	95.6	0.065	370.8	360.1	5315	150
22:00:00	1796	3.503	77.9	80.7	96.2	0.065	375.7	364.5	5316	160
23:00:00	1796	0.488	77.2	79.9	95.4	0.065	372.1	362	5317	155
00:00:00	1798	0.498	77.4	80.2	95.7	0.865	373.6	362.7	5318	150
01:00:00	1800	0.498	77.3	79.4	95.3	0.066	372.2	361.8	5319	150
02:00:00	1800	0.503	77.5	79.6	95.4	0.067	370.1	360.2	5320	150
03:00:00	1798	0.501	77	79.7	95.1	0.065	369.2	359.4	5321	150
04:00:00	1796	0.496	77.7	79.7	95.2	0.065	370.1	360.4	5322	150
05:00:00	1794	0.486	0.486	79.5	95.3	0.066	368.7	359.4	5318	150
06:00:00	1800	0.499	75.8	78.8	95.6	0.067	360.1	353.7	5300	150
07:00:00	1800	0.488	77.8	80.5	96.1	0.066	374.2	363.3	5201	140
08:00:00	1800	0.498	77.3	80	95.8	0.066	364.3	354.3	5302	150
09:00:00	1798	0.497	77.3	80	95.8	0.066	368.2	354	5203	150
14:00:00	1796	0.482	71	73.3	87.5	0.068	330.7	317.5	5242	115
15:00:00	1796	0.479	70	72.3	86.2	0.069	302.3	286.2	5242	80
16:00:00	1796	0.475	70	72.3	86.3	0.069	302	286.1	5244	90
17:00:00	1796	0.465	72	74.4	88.9	0.068	330.5	312.8	5245	120

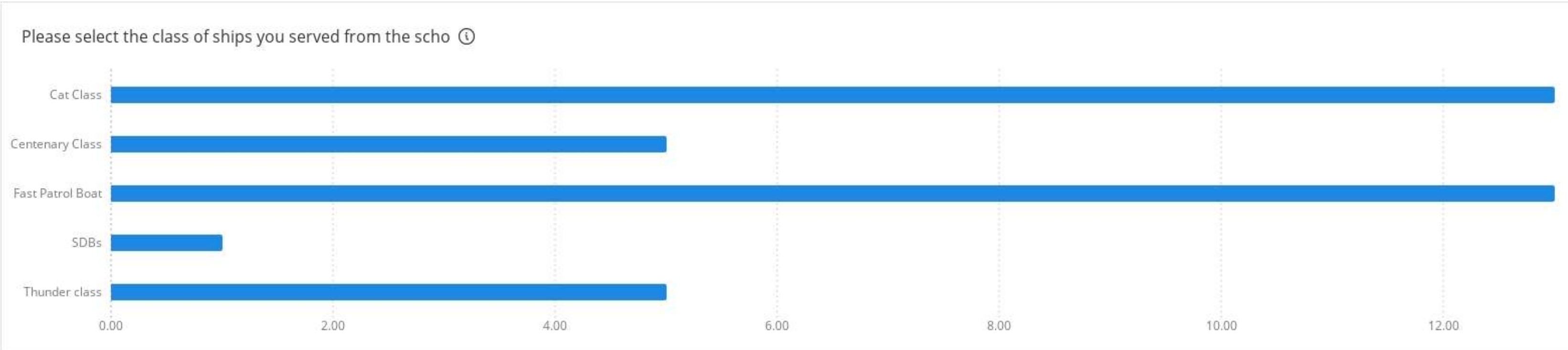
18:00:00	1798	0.466	72.2	74.6	89.2	0.068	331.5	319	5246	110
19:00:00	1798	0.467	73.1	75.7	90.7	0.067	340.7	329.1	5247	110
20:00:00	1796	0.504	73.7	76.2	91.4	0.067	346.5	335.3	5248	120
21:00:00	1798	0.451	73.5	76	91.2	0.067	343.4	330.7	5249	120
12:00:00	1798	0.473	725	74.5	89.2	0.068	328.4	317.4	5261	100
13:00:00	1798	500	75.6	78.3	94.1	0.067	351.2	340	5262	135
14:00:00	1798	0.502	75.3	77.8	73.5	0.067	348.6	338.4	5263	135

APPENDIX 5: FMECA SURVEY REPORT

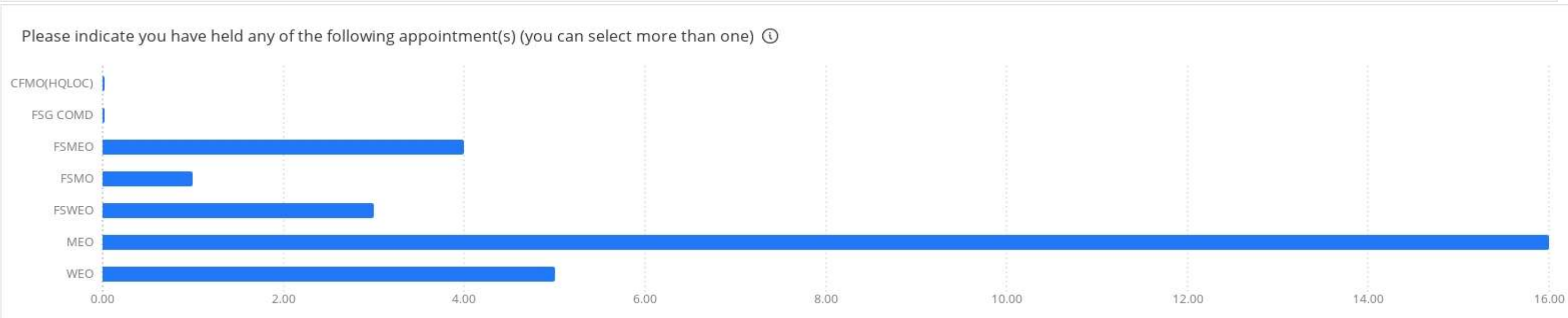
Specialisation

Rank

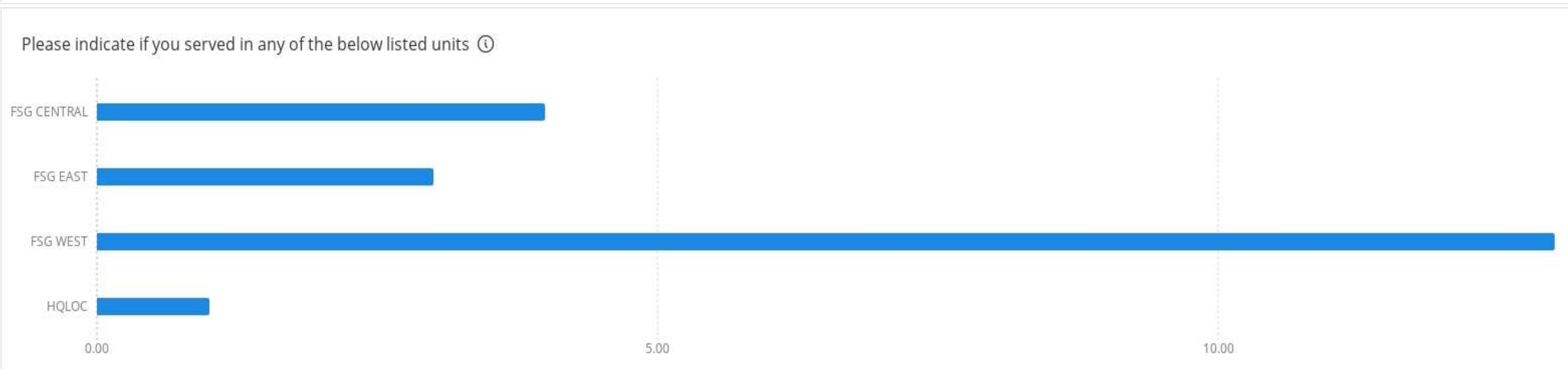
Rank
Lieutenant commander
Commander
Lieutenant Commander



Please select the class of ships you served from the scho
Cat Class
Centenary Class
Fast Patrol Boat
SDBs
Thunder class
0.00
2.00
4.00
6.00
8.00
10.00
12.00



Please indicate you have held any of the following appointment(s) (you can select more than one)
CFMO(HQLOC)
FSG COMD
FSMEO
FSMO
FSWEO
MEO
WEO
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00



Please indicate if you served in any of the below listed units
FSG CENTRAL
FSG EAST
FSG WEST
HQLOC
0.00
5.00
10.00

Cylinder Block

Cylinder Block: Crankcase failure	Average	Minimum	Maximum	Count
Criticality	5.79	0.00	10.00	19
Severity	5.42	0.00	10.00	19
Likelihood	2.68	0.00	10.00	19

Cylinder Block

Cylinder Block: Top cylinder gasket/Oring failure	Average	Minimum	Maximum	Count
Criticality	4.74	0.00	10.00	19
Severity	4.58	0.00	10.00	19
Likelihood	3.53	0.00	8.00	19

Cylinder Block

Cylinder Block: Cylinder liner failure	Average	Minimum	Maximum	Count
Criticality	5.84	0.00	10.00	19
Severity	4.63	0.00	10.00	19
Likelihood	2.68	0.00	7.00	19

Cylinder Block ⓘ

Cylinder Block: Engine Vibration	Average	Minimum	Maximum	Count
Criticality	3.74	0.00	8.00	19
Severity	3.47	0.00	8.00	19
Likelihood	3.11	0.00	9.00	19

Cylinder Block ⓘ

Cylinder Block: Defective engine seat/mounts	Average	Minimum	Maximum	Count
Criticality	3.00	0.00	10.00	19
Severity	3.21	0.00	10.00	19
Likelihood	2.37	0.00	7.00	19

Power Transmission ⓘ

Power Transmission: Crank Shaft Failure	Average	Minimum	Maximum	Count
Criticality	6.11	0.00	10.00	19
Severity	5.26	0.00	10.00	19
Likelihood	2.32	0.00	9.00	19

Power Transmission

Power Transmission: Journal bearing failure	Average	Minimum	Maximum	Count
Criticality	5.16	0.00	10.00	19
Severity	5.47	0.00	10.00	19
Likelihood	2.95	0.00	9.00	19

Cooling System

Cooling System: Sea chest blockage	Average	Minimum	Maximum	Count
Criticality	3.63	0.00	10.00	19
Severity	4.05	0.00	10.00	19
Likelihood	5.16	0.00	10.00	19

Cooling System

Cooling System: Sea chest valve failure	Average	Minimum	Maximum	Count
Criticality	4.21	0.00	10.00	19
Severity	4.32	0.00	10.00	19
Likelihood	3.05	0.00	9.00	19

Cooling System

Cooling System: Fresh water heat exchanger scaling	Average	Minimum	Maximum	Count
Criticality	3.74	0.00	9.00	19
Severity	3.84	0.00	8.00	19
Likelihood	3.68	0.00	8.00	19

Cooling System

Cooling System: Fresh water circulation pump failure	Average	Minimum	Maximum	Count
Criticality	4.68	0.00	10.00	19
Severity	4.68	0.00	10.00	19
Likelihood	2.95	0.00	9.00	19

Cooling System

Cooling System: Sea water pump assembly failure	Average	Minimum	Maximum	Count
Criticality	5.00	0.00	10.00	19
Severity	4.26	0.00	10.00	19
Likelihood	3.11	0.00	9.00	19

Cooling System

Cooling System: Freshwater thermostat failed closed	Average	Minimum	Maximum	Count
Criticality	4.16	0.00	10.00	19
Severity	4.16	0.00	10.00	19
Likelihood	2.53	0.00	9.00	19

Cooling System

Cooling System: Sea water pump impeller failure	Average	Minimum	Maximum	Count
Criticality	4.32	0.00	10.00	19
Severity	4.32	0.00	10.00	19
Likelihood	3.21	0.00	8.00	19

Cooling System

Cooling System: Charge air cooler tubes leakages	Average	Minimum	Maximum	Count
Criticality	4.16	0.00	9.00	19
Severity	3.84	0.00	8.00	19
Likelihood	2.95	0.00	7.00	19

Cooling System

Cooling System: Charge air cooler fouling	Average	Minimum	Maximum	Count
Criticality	3.74	0.00	8.00	19
Severity	3.74	0.00	10.00	19
Likelihood	2.84	0.00	8.00	19

Cooling System ⓘ

Cooling System: Lub oil cooler fouling	Average	Minimum	Maximum	Count
Criticality	3.95	0.00	10.00	19
Severity	4.32	0.00	10.00	19
Likelihood	2.89	0.00	8.00	19

Fuel Supply System ⓘ

Fuel Supply System: HP Fuel pump drive failure	Average	Minimum	Maximum	Count
Criticality	4.16	0.00	10.00	19
Severity	4.16	0.00	10.00	19
Likelihood	2.47	0.00	9.00	19

Cooling System ⓘ

Cooling System: Lub oil cooler thermostat	Average	Minimum	Maximum	Count
Criticality	4.11	0.00	10.00	18
Severity	3.84	0.00	10.00	19
Likelihood	2.79	0.00	8.00	19

Fuel Supply System ⓘ

Fuel Supply System: HP fuel pump internal failure	Average	Minimum	Maximum	Count
Criticality	4.11	0.00	10.00	19
Severity	4.16	0.00	10.00	19
Likelihood	2.47	0.00	8.00	19

Fuel Supply System

Fuel Supply System: HP fuel line leakages	Average	Minimum	Maximum	Count
Criticality	3.42	0.00	8.00	19
Severity	3.32	0.00	8.00	19
Likelihood	2.95	0.00	8.00	19

Fuel Supply System

Fuel Supply System: bad fuel quality	Average	Minimum	Maximum	Count
Criticality	4.42	0.00	10.00	19
Severity	4.11	0.00	10.00	19
Likelihood	4.16	0.00	10.00	19

Fuel Supply System

Fuel Supply System: fuel filter blockages	Average	Minimum	Maximum	Count
Criticality	3.32	0.00	8.00	19
Severity	3.63	0.00	8.00	19
Likelihood	3.74	0.00	10.00	19

Fuel Supply System

Fuel Supply System: Sludge accumulation in fuel tanks	Average	Minimum	Maximum	Count
Criticality	3.11	0.00	8.00	19
Severity	3.16	0.00	8.00	19
Likelihood	3.89	0.00	9.00	19

Fuel Supply System

Fuel Supply System: Charge air cooler tubes leakages	Average	Minimum	Maximum	Count
Criticality	3.32	0.00	8.00	19
Severity	3.05	0.00	7.00	19
Likelihood	2.53	0.00	9.00	19

Fuel Supply System

Fuel Supply System: Lub oil cooler thermostat	Average	Minimum	Maximum	Count
Criticality	3.74	0.00	10.00	19
Severity	4.00	0.00	10.00	19
Likelihood	2.26	0.00	8.00	19

Fuel Supply System

Fuel Supply System: Lub oil cooler fouling	Average	Minimum	Maximum	Count
Criticality	3.74	0.00	10.00	19
Severity	4.11	0.00	10.00	19
Likelihood	2.63	0.00	8.00	19

Fuel Supply System

Fuel Supply System: HP Fuel pump drive failure	Average	Minimum	Maximum	Count
Criticality	2.89	0.00	10.00	19
Severity	2.74	0.00	10.00	19
Likelihood	1.84	0.00	9.00	19

Fuel Supply System

Fuel Supply System: HP fuel pump internal failure	Average	Minimum	Maximum	Count
Criticality	3.00	0.00	10.00	19
Severity	2.84	0.00	10.00	19
Likelihood	1.63	0.00	7.00	19

Fuel Supply System

Fuel Supply System: HP fuel line leakages	Average	Minimum	Maximum	Count
Criticality	2.32	0.00	8.00	19
Severity	2.79	0.00	8.00	19
Likelihood	1.95	0.00	9.00	19

Fuel Supply System

Fuel Supply System: bad fuel quality	Average	Minimum	Maximum	Count
Criticality	3.11	0.00	10.00	19
Severity	3.26	0.00	10.00	19
Likelihood	2.95	0.00	10.00	19

Fuel Supply System

Fuel Supply System: fuel filter blockages	Average	Minimum	Maximum	Count
Criticality	2.32	0.00	8.00	19
Severity	2.89	0.00	9.00	19
Likelihood	2.89	0.00	10.00	19

Fuel Supply System

Fuel Supply System: Sludge accumulation in fuel tanks	Average	Minimum	Maximum	Count
Criticality	2.21	0.00	8.00	19
Severity	2.16	0.00	8.00	19
Likelihood	3.05	0.00	9.00	19

Air Distribution System

Air Distribution System: Turbo Charger fault	Average	Minimum	Maximum	Count
Criticality	3.95	0.00	9.00	19
Severity	4.05	0.00	10.00	19
Likelihood	2.63	0.00	8.00	19

Air Distribution System

Air Distribution System: blocked air filter	Average	Minimum	Maximum	Count
Criticality	3.05	0.00	10.00	19
Severity	2.95	0.00	10.00	19
Likelihood	2.89	0.00	10.00	19

Lubricating oil System

Lubricating oil System: Lub oil pump failure	Average	Minimum	Maximum	Count
Criticality	4.05	0.00	10.00	19
Severity	3.63	0.00	10.00	19
Likelihood	1.63	0.00	9.00	19

Lubricating oil System

Lubricating oil System: Blocked oil filter	Average	Minimum	Maximum	Count
Criticality	3.00	0.00	10.00	19
Severity	3.16	0.00	10.00	19
Likelihood	1.53	0.00	7.00	19

Inlet Exhaust System

Inlet Exhaust System: Tappet Clearance Setting	Average	Minimum	Maximum	Count
Criticality	2.84	0.00	8.00	19
Severity	3.11	0.00	8.00	19
Likelihood	1.63	0.00	6.00	19

Inlet Exhaust System

Inlet Exhaust System: Bend valve stem	Average	Minimum	Maximum	Count
Criticality	3.26	0.00	10.00	19
Severity	3.53	0.00	10.00	19
Likelihood	1.74	0.00	7.00	19

Inlet Exhaust System

Inlet Exhaust System: Tappet clearance	Average	Minimum	Maximum	Count
Criticality	2.68	0.00	8.00	19
Severity	2.89	0.00	10.00	19
Likelihood	2.00	0.00	7.00	19

Inlet Exhaust System

Inlet Exhaust System: Valve seat clearance	Average	Minimum	Maximum	Count
Criticality	3.21	0.00	10.00	19
Severity	3.05	0.00	10.00	19
Likelihood	4.21	0.00	48.00	19

Inlet Exhaust System

Inlet Exhaust System: Tappet Clearance Setting	Average	Minimum	Maximum	Count
Criticality	2.47	0.00	8.00	19
Severity	2.47	0.00	8.00	19
Likelihood	1.58	0.00	6.00	19

Inlet Exhaust System

Inlet Exhaust System: Bend valve stem	Average	Minimum	Maximum	Count
Criticality	2.74	0.00	10.00	19
Severity	2.79	0.00	10.00	19
Likelihood	1.58	0.00	7.00	19

Inlet Exhaust System

Inlet Exhaust System: Tappet clearance	Average	Minimum	Maximum	Count
Criticality	2.32	0.00	8.00	19
Severity	2.42	0.00	10.00	19
Likelihood	1.74	0.00	7.00	19

Inlet Exhaust System

Inlet Exhaust System: Valve seat clearance	Average	Minimum	Maximum	Count
Criticality	2.68	0.00	10.00	19
Severity	2.74	0.00	10.00	19
Likelihood	1.26	0.00	6.00	19

Alternator

Alternator: AVR failure	Average	Minimum	Maximum	Count
Criticality	3.37	0.00	10.00	19
Severity	3.58	0.00	10.00	19
Likelihood	2.63	0.00	8.00	19

Alternator

Alternator: Exciter failure	Average	Minimum	Maximum	Count
Criticality	3.89	0.00	10.00	19
Severity	3.26	0.00	10.00	19
Likelihood	2.26	0.00	8.00	19

Alternator

Alternator: Rotor bearing failure	Average	Minimum	Maximum	Count
Criticality	3.58	0.00	10.00	19
Severity	3.79	0.00	10.00	19
Likelihood	2.05	0.00	8.00	19

Alternator ⓘ

Alternator: Rotor alignment fault	Average	Minimum	Maximum	Count
Criticality	3.47	0.00	10.00	19
Severity	3.63	0.00	10.00	19
Likelihood	1.89	0.00	7.00	19

Alternator ⓘ

Alternator: No air gap	Average	Minimum	Maximum	Count
Criticality	3.37	0.00	10.00	19
Severity	3.11	0.00	10.00	19
Likelihood	1.89	0.00	6.00	19

Alternator ⓘ

Alternator: Alternator alignment fault	Average	Minimum	Maximum	Count
Criticality	3.42	0.00	10.00	19
Severity	3.74	0.00	10.00	19
Likelihood	1.63	0.00	7.00	19

APPENDIX 6: DFTA STRUCTURE

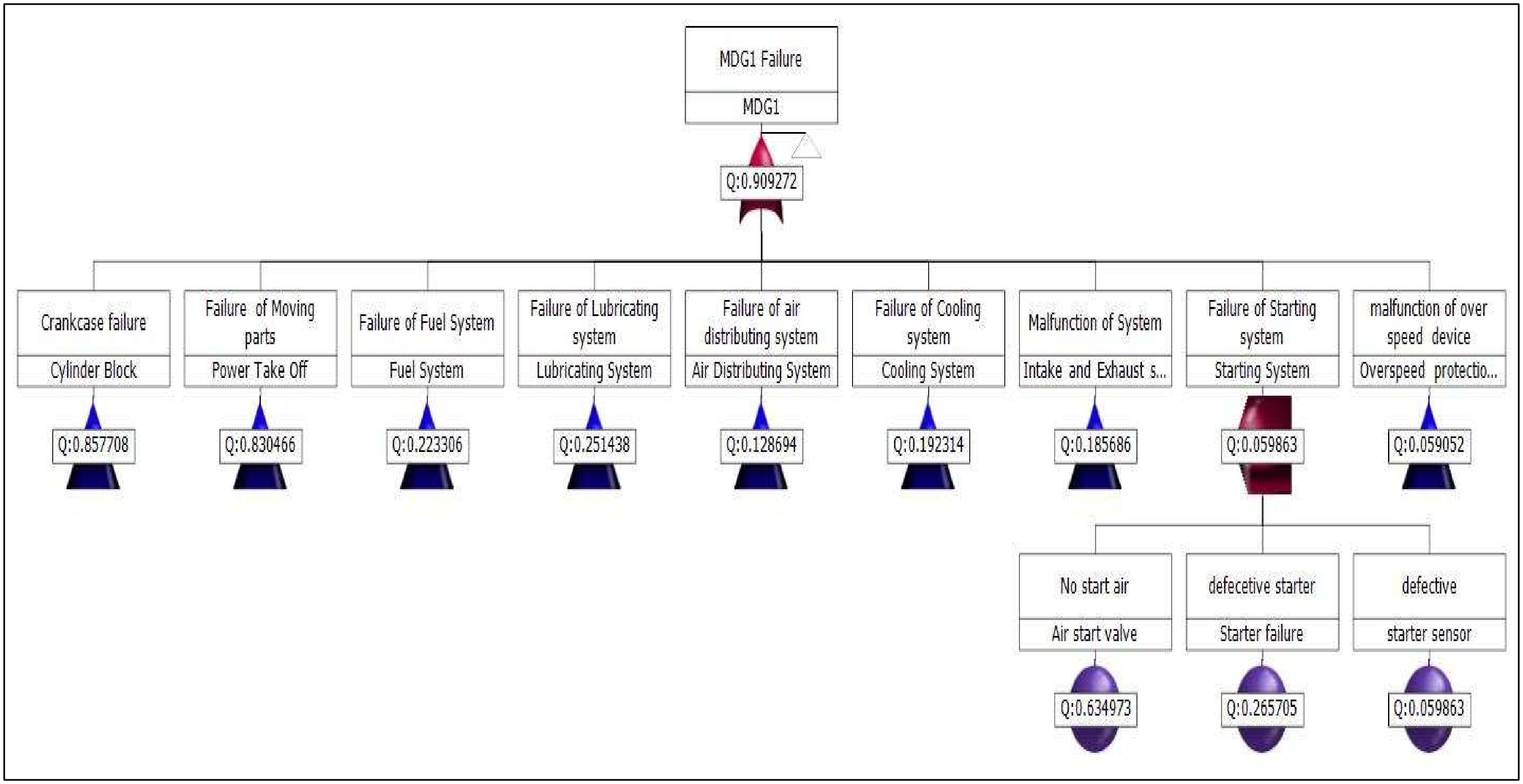


Figure 69:MDG 1 DFTA Structure

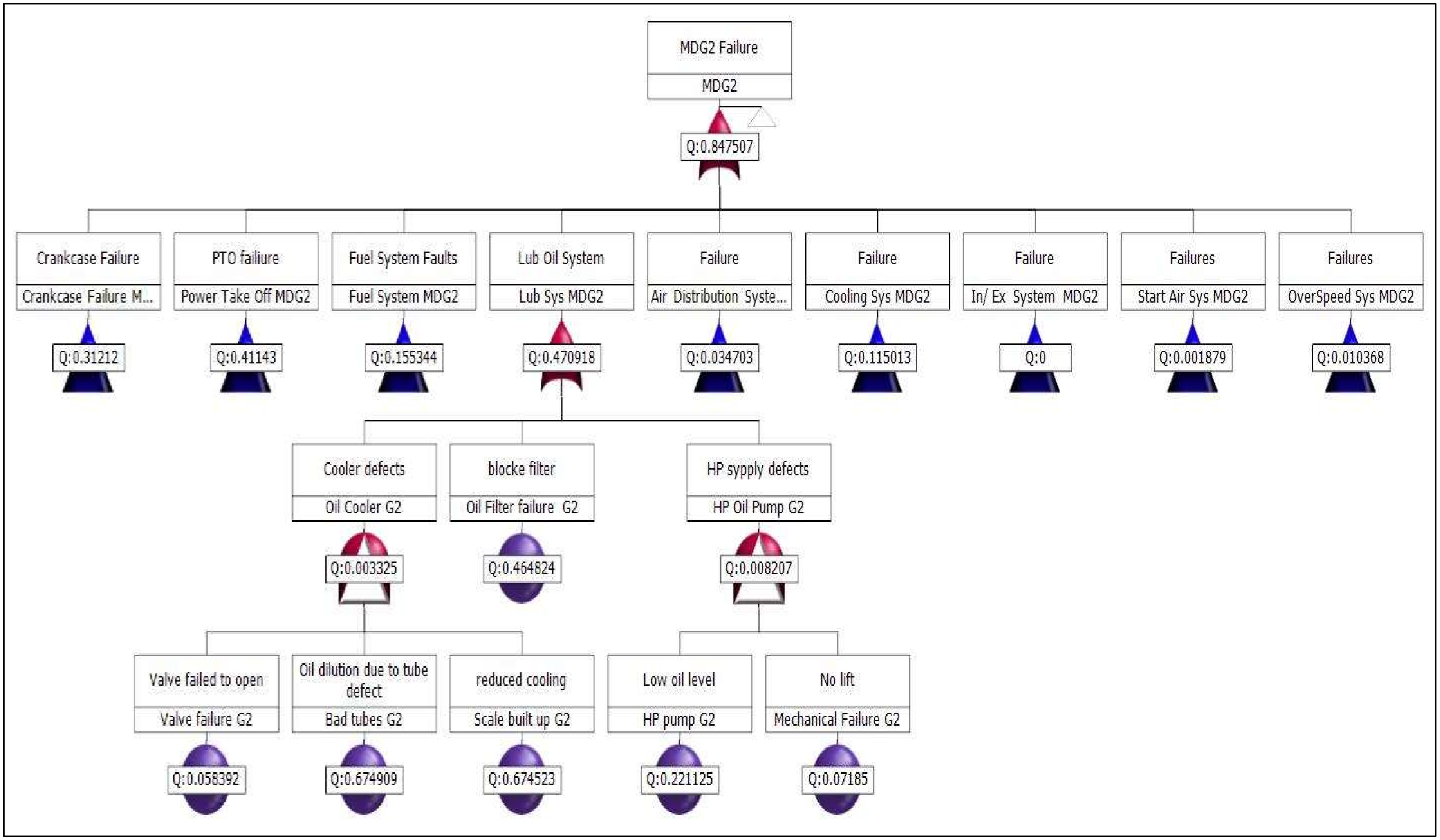


Figure 70:MDG 2 DFTA Structure

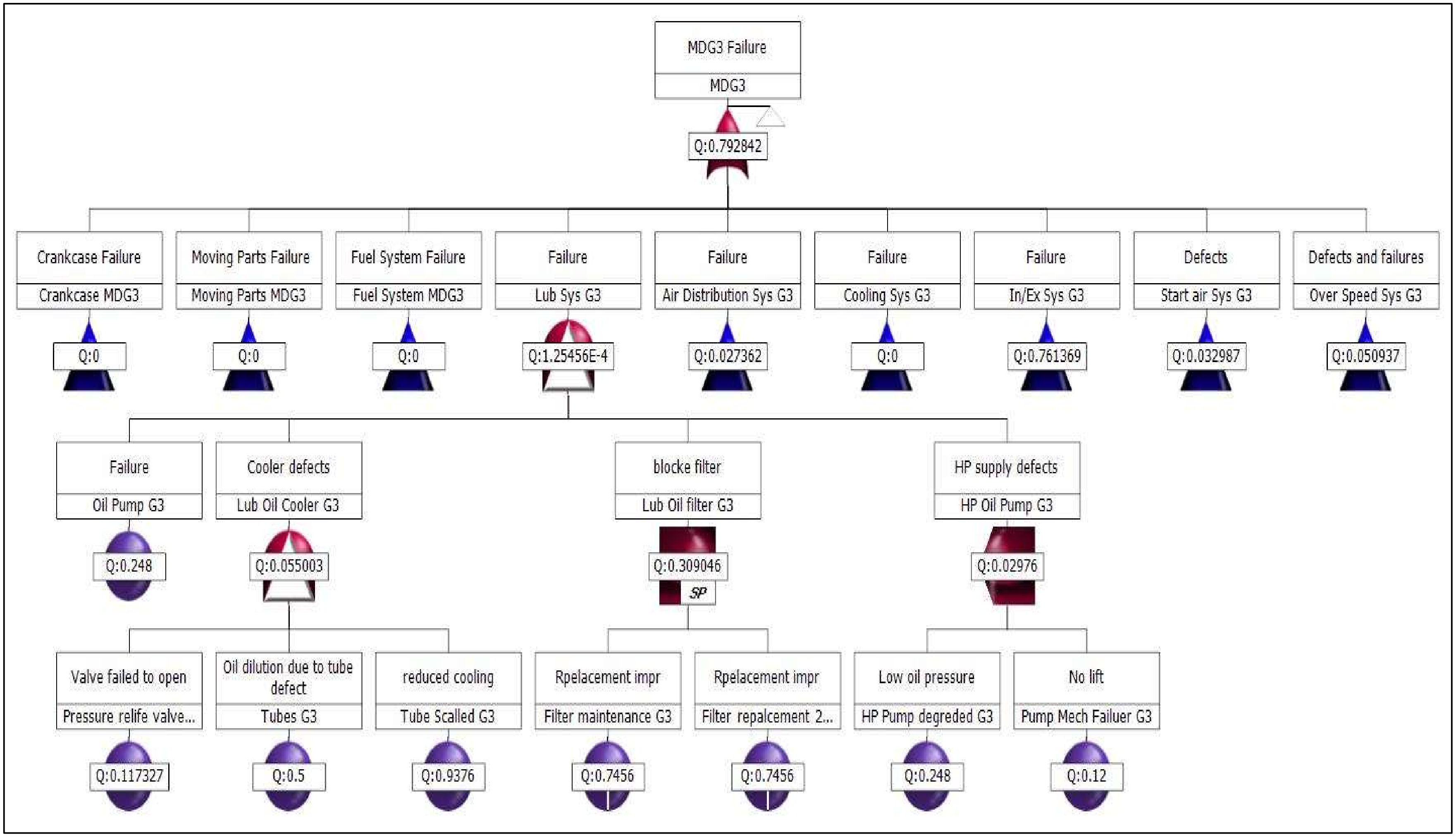


Figure 71:MDG 3 DFTA Structure

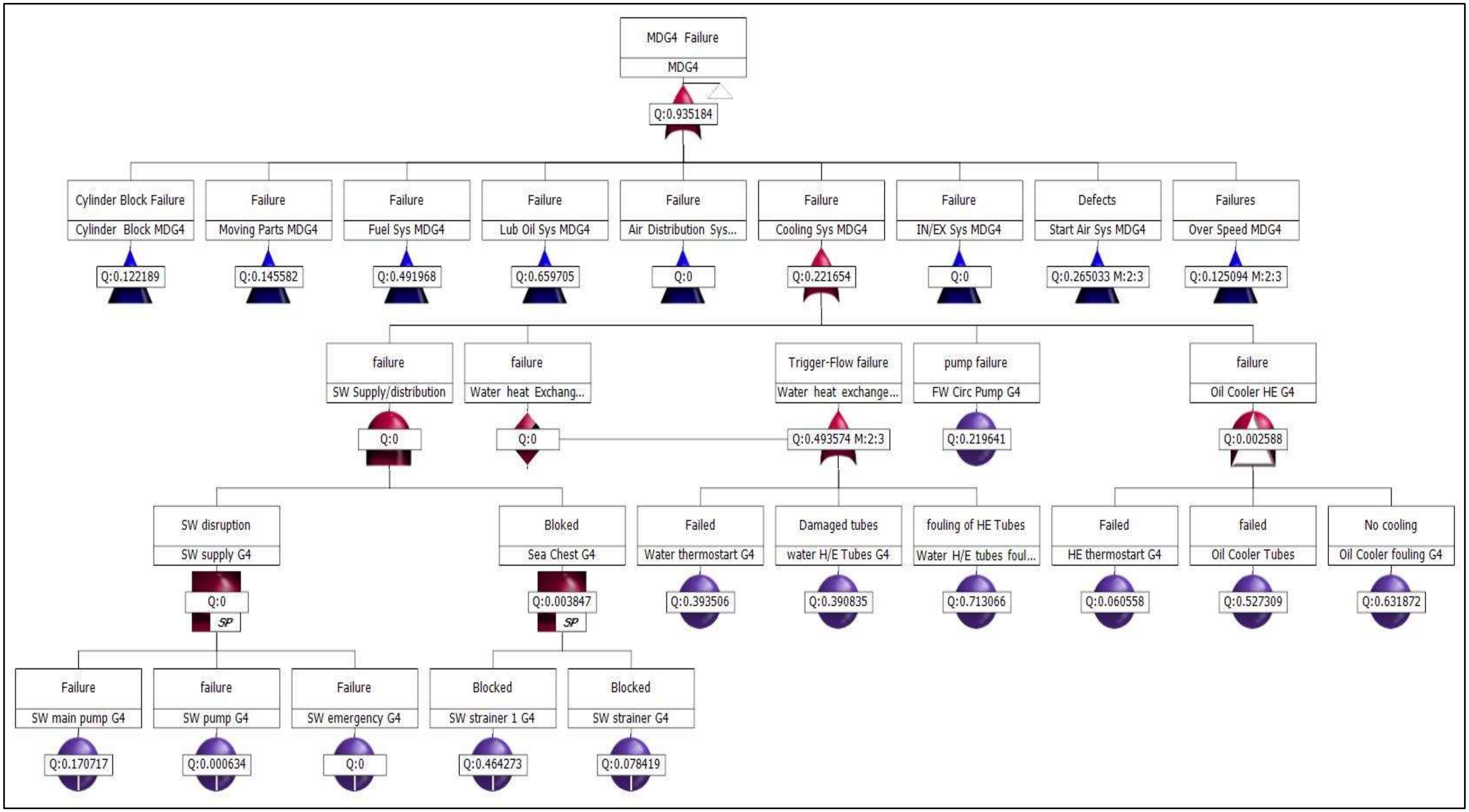


Figure 72: MDG 4 DFTA Struct

APPENDIX 7: COMPLETE FMECA TABLE

ALL DGs	Subsystem	Component	Function	Description of Failure			Effects of Failure				Safe Guards		Criticality	Severity	Likelihood	RPN	Mission Criticality
				Mode	**Causes**	**Detection**	**Local**	**Global**	**Influence/factors**	**TTR**	**Prevention**	**Mitigation**	**Min 1 Max10**	**Min1 Max 10**	**Min 1 Max 10**	**CxSxL**	
1	**Cylinder Block**	Crankcase	1. Housing of Engine parts	Cracking	1. Overheating 2.Excessive Vibration 3. Failure of Piston/Connect Rod/Valves 4. Loss Cyleder heard bolts. 5. Lose Foundatiion bolt	1.Temperature Checks 2. Vibration Measurements	Lost of DG	Reduced PGS Availability and reliability	1. Extended Downtime 2. High Cost 3. No spare parts 4. Risk of Engine room fire. 5. Risk to personnel safety	1-3months	1. Install Engine seat 2. Instal vibration monitoring and alarm 3. Introduce remote virbration alert at FSGs 4. Reduced Inspection Intervals	1. Improve exhaust gas and temperature monitoring 2. Provide better vibration damping	**8**	**7**	**4**	**224**	**65**
		Cylinder liner failure	1. Housing of piston and accesseis 2. Provides a gliding surface for the piston	1. Cracks 2. Scuffing 3. Seizure	1. High Temperature operation 2. Lubrication Failure 3. Water ingress 4. Piston or rings failure	1.High operating temperature. 2. Increase lub oil consumption 3. High Exhaust temperature	1. Cylinder liner damage 2. Piston and rings damage 3. Overheating 4. Degraded perfomance	1.High Fuel Consumption 2.Degarded perfomance 3. reduced system PGS avaialability	1. Extended downtime 2. High Cost 3. Require specialist 4. Risk to personnel safety	1wk-3months(depending spare parts availability)	1. Operating Temperaure Monitoring 2. Exhauste Temperature Monitoring. 3.Lub Oil level Checks 4. Lub Oil condition monitoring	1. Reduced load 2. Increase watch keeping monitoring intervals	**8**	**6**	**4**	**192**	**55**
		Cylinder head bolts	1. Securing cylinder head to the crankcase	1. Loose 2. Not firm	1. High Vibration 2. Wrong torque 3. High temperature stress 4. Material Failure	1. Lub oil leakages 2. Combustion gas leakage	1. Risk of damege to cylinder 2. Damage to piston,rings and cylinder 3. Damage to O-rings and gaskets.	1. Increased Fuel Consumtion 2. Incread Lub oil consumption 3. Degraded perfaomance 4. Risk of gas burn to personnel 5. Degraded perfoamce and reduced system availalbility	1. Difficult to detect 2. High occurance frequenecy	1-3hrs	1. Physical Monitoring 2. Replace bolts with better ones	1. shutdown check and retightend 2. Increased watch keeping monitoring	**7**	**6**	**8**	**336**	**100**

		Top Cylider gasket	1. Gas and water tight cealing	1. Burnt 2. Materian Failure	1. Overheating	1.Oil contamination 2. Gas leakage 3. Overheating	1. Oil aand water mixing 2. damage to cylinder liners 3. Lose of gas and tight cealing	1. Incomplet compustion 2. Increased fuel and oil consumption 3.Reduced DG avaialbility	1. Difficult to detect 2. High occurance frequenecy	10-24hrs	1. Improve DG condition monitroing. 2. Install water sensor in sump. 3. Increase oil quality checks	1. Reduce load 2. Shutdown DG	**7**	**6**	**5**	**210**	**60**
		Vibration Dampers	1. Absorving engine vibration 2. foundation	1. Cracks 2. Compression	1. Excessive engine vibration 2. Engine overload 3. Improper installation	1. Visual inspection 2. Increase vibration	1. Crack damage	1. increased engine vibration 2. Vibration effects on other engine parts	1. Engine may need to be lifted 2. Eninge balancing	10-24hrs	1. Ensure to instal the right dampars 2. Monitoring	1. Monitoring	**5**	**5**	**4**	**100**	**26**
		Engine Seat	1. Absorving engine vibration 2. foundation	1. Braking 2. Deformation 3. Corrosion	1. High vibration 2. incorrect installation 3. High stress	1. Visual inspection 2. Increase vibration	1. Poor engine balance	1. increased engine vibration 2. Vibration effects on other engine parts	1. Engine may need to be lifted 2. Eninge balancing	10-24hrs	1.Proper engine mounting 2 Corrosion control	Installing vibration dampers	**4**	**4**	**4**	**64**	**14**
		Cylinder head O-ring	Water and air tight sealing	Deformation	1. Excessive Temperatures	Temperature checks/sensors	1. Oil aand water mixing 2. damage to cylinder liners 3. Lose of gas and tight cealing	Reduced DG reliability and availibility	1. Increased risk of Common cause Faiure 2. Difficulty to dictate	2 wk-2 months	1. Introduced alarm system. 2. Check quality of O-rings. 3. Count over heating frequency and periods	1. Monitor DG vibration 2. Reduce inspection intervals	**7**	**6**	**5**	**210**	**60**
2	**Power Take Off**	Crank Shaft	Converting reciprocating movement and Transmiting of engine Torque	1. Surface roughness 2. Mis alignment	1. High Vibration 2. Lose of Lubrication 3. High Stress due to pison or conect rod failure	1	1. Degraded perfomance 2. Lost of DG	Reduced System availablility	1. Long Down time 2. High Repair Cost 3. Require OEM intervention/specialist intervention	1 month	1. Improve DG condition monitroing. 2. Consider oil particle checks	1. Reduce source of engine vibration 2. Reduce/ prevent DG overheating	**8**	**7**	**3**	**168**	**47**
		Journal Bearing	Enable friction free rotational movement	Friction and seizure	1. Lubrication Failure 2. Overheating 3. Cranshaft alignment 4. High Stress due to pison or conect rod failure	1. Oil particle analysis 2. Inspection 3.	1. Degraded perfomance 2. Excessive operating Temperature/ seizure	1. Seizure 2. Lost of DG	1. Long Down time 2. High Repair Cost 3. Require OEM /specialist intervention	6hrs-2 days(with spare availability) 1-2 months (OEM to supply spares)			**7**	**7**	**4**	**196**	**56**

3	**Cooling System**	Heat Exchanger Tubes	Jacket water cooling	1. Scale build up 2. Leakages	1. Materila Failure 2. Corrosion 3. water impurities	1. Temperature Sensor	1. Lost of cooling 2. Degraded perfomemance	Reduced System availablility	1. Increased risk of failure to other systems 2. Difficulty to dictate and repair	30min-6hrs	1. Use of additives 2. Replacing Zinc anodes as at and when due. 3.Improve inspection 4. Checking for sea water conataminati on	1. Replace with high quality tubes 2. Improved monitoring of Zinc anode depletion	**5**	**6**	**7**	**210**	**60**
		Sea Chest	Sea water Fitlteration	1. Blockage 2. Corrosion	1. Debris 2. Corrosion	1. Flow meter 2. Inspection	1. Lost of cooling 2. Risk of blockage in cooler fins. 3. Over heating	1. DG overheat 2. Common Cause Component failures	1. Power destrubtion 2. May affect other DG sea water line	30min - 1hr	1. Flow meter 2. Inspection. 3. Use of Zinc Anodes	1. Redesign 2. Emegency sea water line 3. Duplex systems	**6**	**6**	**4**	**144**	**40**
		FW HE Tubes	Heat Transfer	1. Scale build up 2. Leakages	1. Corrosion 2. Scalling		1. Leakeges 2. Mixing of fresh and sea water	1. Over heating 2. Degraeded perfomance	1. Difficult to detect 2. High occurance frequenecy	5-24hrs	1. Use of additives 2. Replacing Zinc anodes as at and when due. 3.Improve inspection 4. Checking for sea water conataminati on		**5**	**5**	**5**	**125**	**34**
		FW Thermostart	Temperature control	1. Failed Closed	1. Functiona failure 2. Stucked due to debri or scale	1. Excessive Temperature Rise 2. Tempreture checks	1. No water flow	1. Over heating 2. Degraeded perfomance	1. DG needs to taken offline to repaire	2-4hrs	1. Use of additives 2. Replacing Zinc anodes as at and when due. 3.Improve inspection 4. Checking for sea water contaminatio n	1. Shutdown DG and remove thermostart	**6**	**6**	**4**	**144**	**40**
		Charge air Cooler	Cooling of compressed charge air	1. Scale build up 2. Internal Leakages	1. Scalling 2. Corrosion 3. Thermostat failure	1. Black smoke 2. Increased fuel consumption 3. High exhaust temperature	1. Internal leakage 2. No cooling	1. Overheating 2. Increase fuel 3. Reduced load ability	1. Difficult to dictate. And repair	2hrs-4weeks (depending on availability)	1. Use of zinc anodes 2.Routine inspection	Shutdonw DG	**5**	**5**	**4**	**100**	**26**
		Lub Oil Cooler	Cooling of circulating lub oil	1. Scale build up 2. Internal Leakages	1. Scalling 2. Corrosion 3. Thermostat failure	1. Circulating water pressure 2. reduced perfomance	1. No tempretature transfre	1. Overheating		2hrs-4weeks (depending on availability)	1. Use of zinc anodes 2.Routine inspection	Shutdown DG	**5**	**5**	**4**	**100**	**26**

		FW circulation pump	High pressure freshwatre water circulation to cylinder jackets	1. No water supply 2. Drop in pressure	1. Impler failure 2. Mechanical Failure 3.V- Belt failure	1. Temperature checks 2. Low circulation pressure 3. Excessive temperature rise	1. No or drop in circulation water pressure	1. Over heating 2. Degraeded perfomance	1. DG needs to taken offline to repaire	2hrs-4weeks	1. V-belt checks 2. flow monitoring	1. Shutdown DG	**7**	**6**	**4**	**168**	**47**
		Oil Cooler thermostart	Temperature control	1. Failed Closed	1. Spring or diaphragm failure 2. Scale/corrosion	1. Excessive Temperature Rise 2. Tempreture checks	1. High lub oil temperature	1. DG overheat 2. Increased risk of Common Cause Component failures	1. May lead to DG seizure	2-4hrs	1. Oil tempertaure alarrm 2. Water flow meter	1. Shutdown DG and remove or replace thermostart	**6**	**5**	**4**	**120**	**32**
		SW pump assembly	Circulating cooling SW	1. No SW supply 2. Drop in pressure	1. Shaft wear 2. Mechanical seal failure 3. Casing wear	1. Visual inspction 2. Pressure sensors	1. Damage pump 2. Pump material debris	1. DG overheat 2. Increased risk of Common Cause Component failure	1. May lead to DG seizure	2-4hrs	1. Do not run pump dry 2. Ensure adequet supply of SW at all times	1. Shut down DG	**7**	**6**	**4**	**168**	**47**
		SW pump impeller	Pressurised sea water supply	1.Impler blades brake or corrosion 2. Pump casing wear	1. Running dry or insuffiecinet water. 2. Wear	1. Temperature checks 2. Low circulation pressure 3. Excessive temperature rise	1. Temperature rise	1. Overheating 2. Increase fuel and oil consumption 3. High exhaust gas tempertaure	Ease of detection	1-6hrs	1. Use of non return valve down street of pump 2. Flow meter 3. Esnure sufficinet water supply before running pump	1. Shutdown DG and replace impleer	**6**	**6**	**4**	**144**	**40**
4	**Fuel Supply System**	Fuel supply pump pulley bolts	Fuel supply to injector nozzels	1. loose Bolts 2. Brake	1. Vibration	1. On occuraance. 2. Inspection	1. degraded perfomace. 2. Hunting	1. Reduced system availability. 2. Hazard Risk	1. Difficult to dictate. 2. Increase fuel consumption	1-3 hrs	1. Change pump to gear type 2. Inspection	1. Vibration monitoring 2. Replaace bolts 3. Improve monitoring	**6**	**6**	**4**	**144**	**40**
		Fuel supply pump drive	Power transmission to pump plungers	1. Gear tooth alignment. 2. Gear tooth failure	1. Vibration. 2. Camshfat timing	1. Failure to start. 2. Degraded perfomance 3. Cannot attain load speed	1. Degraded perfomance. 2.Hunting	1. Reduced system availability	1. Increase fuel consumption. 2. Possible low voltage/frequnecy risk	1-7 hrs	1. Reduce engine vibration	1. Vibration monitoring 2. Replace bolts 3. Improve monitoring	**6**	**6**	**4**	**144**	**40**

		High pressure Fuel supply pipe	High pressure fuel supply to injector nozzles	1. leakage 2. loose	1. loose banjor bolt 2. Failed seal	1. Fuel leakage	1. Fuel leakge 2. Loss of cylidenr power	1. Degraded perfoamnce. 2. Fuel spill	1. No significant issues	30min-2hrs	1. Monitoring	Re tightend	**5**	**5**	**4**	**100**	**26**
		Fuel return line	Excess fuel return	1. leakage 2. loose	1. loose banjor bolt 2. Failed seal	1. Fuel leakage	1. Pressure lose	1. Fuel leakages	1. No significant issues	30min-2hrs	1. Monitoring	Re tightend	**3**	**3**	**4**	**36**	**6**
		High pressure Fuel supply pump	High pressure fuel supply to injector nozzles	1. Loose mounting bolts. 2. Driver failure	1. Speed compartability 2. Load mismatche 3. Frequent drive gear failure	1. Failure to start. 2. Low speed.	1. Degraded perfomance. 2.Hunting	1. Reduced system availability	1.Possible low voltage/frequnecy risk	1-2hrs	1. Reduce engine vibration	.1.Vibration monitoring 2. Replace bolts 3. Improve monitoring	**6**	**6**	**4**	**144**	**40**
		Fuel Quality	Power means	1. Loss of power 2. Eratic opertaion 3.Filter blockage 4. Sludge accumualtion in tanks	1, Low grade bunker fuel. 2. Fuel contermination in storage. 3. High moisture content	1. Fuel quaility certificate and test 2. Fuel tank drains, 3. Routine fuel water content test.	1.Degraded perfomance. 2. Fuel contamination 3. Filter blockage	1. PGS will be unavailability 2. Entire fuel system may need to be decontermina ted	1. May require fuel system evacuation 2. Extended tank cleaning and defueling process	1-2weeks	1. Strict Compliance with OEM fuel quality standards. 2. Ensure fuel quality certificate is genuine . 3. Conduct fuel lab test before embarking. 4. Fuel purification system	1. Duplex filter 2. Emergency fuel tank 3. Avoild going low on fuel levels 4. Ensure service tanks are always above 30% capacity.	**6**	**6**	**6**	**216**	**62**
		Primary Fuel Filter	Protecting fuel system from impurities and water	1.Reduced fuel flow 2. Blockages	1. Low grade or dirty fuel 2. Low fuel tank level	1. Low fuel pressure 2. Dirty filters	1. Reduced fuel flow 2. Reduced power 3. Allowing dirty fuel to secondry filters	1. Degraded perfomance. 2.Hunting	1. Increased filter change frequnecy 2. Need to evacuate fuel from system	30min-24hrs	1. Strict Compliance with OEM fuel quality standards. 2. Fuel purification system 3. Avoid running low on fuel 4. Duplex filter	1. Swap duplex flter	**5**	**5**	**5**	**125**	**34**

		Secondry Fuel Filter	Protecting fuel system from impurities	1. Flow loss 2. Blockage	1. Dirty Fuel 2. Sludge accumualtion 3. Bacteria attack on filter elements	1. Fuel Flow meter 2. Visuall inspection 3. Pressure sensors	1. Reduced fuel flow	1. Degraded perfomance. 2.Hunting 3. Damage to injevctor nozzles	1. Increased filter change frequnecy 2. Need to evacuate fuel from system	30-2hrs	1. Ensure Primary filters are always in good condition 2. Monitoring fuel flow 3. Change filtres once there is indiication of reduced fuel flow	1. Swap duplex flter	**3**	**4**	**4**	**48**	**9**
		Dirty Fuel Tanks	Holding fuel	1. Pressence of particulate matter in fuel 2. Blockages in fuel filters. 3. Low pressure in fuel system	1. Sludge accumulation 2. Dirty fuel bunker	1. Taking of fuel samples 2. Fuel test 3. Pressure drops	1. Blockages	1. Degraded perfomance. 2. Filter blockage 3. Damage to injector nozzles	1. Increased filter change frequnecy 2. Need to evacuate fuel from system		1. Ensure fuel quality 2. Provision of filteration system at fuel dumps.	1. Ensure fuel quality 2. Provision of filteration system at fuel dumps.	**4**	**6**	**5**	**120**	**32**
5	**Air Distrubution System**	Turbo charger	Supply of compressed air	1.Oil leakage 2. stiifness	1. Seal failure 2. Bearing failure 3. Lubrication failure	1. Oil leakages 2. High Temperature 3. Black smoke	1. High Tempertaure 2. incomplete combustion 3. Air stavation	1. Degraded perfomance 2. Increased fuel consumption	1.No significant issue with replacememnt 2. D	5hrs- 24 hrs(with spare available)	1. Monitoring 2. Charge air flow sensor	1. Shutdown DG	**6**	**6**	**4**	**144**	**40**
		Air filter	Charge air filteration	1. Restricted air flow	1. Blockage 2. Dirt/dust accumualation 3. Over usage	1. Black smoke 2. Increased fuel consumption 3. Load shading	1. High Tempertaure 2. incomplete combustion 3. Air stavation	1. Degraded perfomance. 2.Reduced system availabilityy	1.Late detection may lead bigger problems	1-2hrs	1. Monitoring 2. Ensure engine room air quality	1. Replace with anaother filter	**4**	**4**	**4**	**64**	**14**
6	**Lubricating System**	Oil Filter	Removing lub oil impuirities	1. Leakages 2. Blockages 3. Broken housing	1. Over use 2. Debri 3.Material failure	1. Oil leakage 2. Visual Inspection	1. Lub oil leakage	1. Overheat		2-10 hrs	1. Monitoring 2. Replace with a better filtre housing	1. Shutdouwn DG	**4**	**4**	**2**	**32**	**4**
		Lub oil inlet Hose	Pressurised Lub oil supply	1. Leakages 2. Broken housing	1. Broken seal 2. Loose bolt	1. Visual inspection 2. Oil Leakge 2. Monitoring	1. Lub oil leakage	1. Increase lub oil consumption due to oil leakage 2. Lub oil in bilge engine room bilge	No significant issue	30min - 1hr	1. Monitoring 2. Retightened hose or replace hoe if needed	1. Retightend 2. Shutdown DG if necessary	**3**	**3**	**5**	**45**	**8**

		Oil Pump	1. Pressursing and circulating lubricating oil	1. Not pumping oil 2. Rudecde pressure 3. Over Pressure	1. Broken shaft 2. Damage pumping gears 3. Obstructed suction 4. broken driving gear	1. Pressure sensor 2. Monitoring	1. No significant effect	1. Engien Overheating 2. Seizure	1. Require require extended downtime		1. Improved maintenance 2.ensure clear oil passage	1.Early detection of faults. 2. Ensure good oil quality	**5**	**4**	**2**	**42**	**7**
7	**Inlet/Exh System**	Valve Seat	Provides air tight sealing for valve head on cylinder head manfold	1. Air leakages2. 2. Valve spring	1. Not lapping due to soot accumalation 2. Valve clearance	1. Air leakages 2. Black exhasut 3. High exhuast temperature	1.High temperature 2. Poor scavenging	1. Degraded perfomamnce , 2. Increased fuel consumption 3. high Exhasut tempertaure	1. If all cylinders are affected may require decarbonisation and griding.	1-2wks	1. Esnure correct valave clearance 2. Monitoring exhaust gas temeparure and colour	Check and reset valve clearance	**3**	**3**	**2**	**18**	**0**
		Tappet	1. Control valve movement	1. Clearance	1. Wrong clearance	1. Noisy operation 2. Difficulty starting DG 3. Black smoke	1. Increased fuel consumption . 2. Noisy operation	1. Degraded perfaomnce 2. Reduced load capacity 3. Reduce system reliability	1. May lead to increased fuel consumption	1-4hrs	1. Monitoring 2. Tappet clearance setting	1. Tappet clearance	**4**	**4**	**2**	**32**	**4**
		Valve Stem	1. Suport valve head 2. Provides support for valve springs 3.Limits valve travel	1. Bend 2. Break	1. Excessive temprature 2. Excessive stress 3. Engine Overload 4. improper timing	1. Noisy operation 2. Rdeuced Perfomance 3. difficulty starting	1. Valve will not open. 2. Valve will close	1. Starting difficulty 2. damage to other components	1. May lead to increased fuel consumption	3-24 hrs	1. Monitoring 2.		**3**	**3**	**2**	**18**	**0**
8	**Alternator**	**Stator/rotor**	Eletricity generation	1. Rotor Bearing failure 2. Insolation breakdown 3.Burnt alternator 4.Prime mover and alternator alighnment	1. Wear and tear 2. Lack of Lubrication 3. Moisture accumualtion 4. Heater failure 5. Rubbing 6. External eletric faults	1. Noisy operation 2. Dificulty starting 3. High alternator operating temperature 4. Vibration	1.Unstable output. 2. No output	1. No output 2. Reduced DG availability	1. Extended repaire time 2. Require taken out for rewinding	6hrs-4wks	1. Heating 2. Inspetion 3. Condition Monitoring	1. Shut down DG 2. Ensure alternotor windings a heated regularly	**5**	**5**	**3**	**75**	**18**
				Vibration	Misalingment, defective mounts,bearing fault,overload	1.Noisy operation 2, Vibration		1. Stiffness 2. Difficulty to start	1. Difficult to dictate cause		1. Monitoring		**5**	**5**	**2**	**50**	**10**

				1.Automatic Voltage Regulator failure	Integrated circuit failure due to overlaod or missuse or age	1. Phase lose 2.Load unbalance 3. Unstable output	1. Unstable output	1. No load sharing 2. Black out 3. Power surge	1. Difficult to dictate			Shutdown DG	**5**	**5**	**3**	**75**	**18**
				1.Exciter failure	Internal electric failure	1. No output	Unstable output	1. Under voltage	Difficult to dictate	6hrs -2days		Shutdown DG	**5**	**4**	**3**	**60**	**13**
				Air gap failure	1.Rubbing 2. Foreing body	1. test for insolation breakdown	1. Overheating 2. Fire 3. Sparks	1. Lost of output	Alternator may need replace	7 days-1 month	1. Preheating alternator	1. Frequent insolation breakdown tests	**4**	**4**	**2**	**32**	**4**
				Alignment	1. Bearing Failure 2.loose bolts	1. Visual inspction 2. difficulting starting 3. Increase operating temprature	1. Overheating 2. Fire 3. Sparks	1. Damage to crankshaft oil seal 2. Increase engine load	Alternator/rotor may need replace	1day - 1 month	1. Monitoring		**5**	**5**	**2**	**50**	**10**

APPENDIX 8: FAILURE RATE SENSITIVITY VALUES (FOR INCREASE BETWEEN 10 AND 30 %)

ALL	Failure Type	Action taken	Frequency																											
Component			G1	G2	G3	G4		G1	G2	G3	G4	G3 -10%	G3+10%	G3+20%	G3+30%		G1-10%	G1+10%	G1+20%	G1+30%		G2-10%	G2+10%	G2+20%	G2+30%		G4-10%	G4+10%	G4+20%	G4+30%
Turbo charger	black smoke	replaced, repaired	8	10	12	12		62.5	78.1	93.8	93.8	89.0625	103.125	112.5	121.875		56.25	68.75	75	81.25		70.3125	85.9375	93.75	101.5625		84.375	103.125	112.5	121.875
Lub oil cooler	oil leakage	1. replaced 2. cleaned and zinc anode replaced*	16	18	15	16		125.0	140.6	117.2	125.0	111.3281	128.9063	140.625	152.3438		112.5	137.5	150	162.5		126.5625	154.6875	168.75	182.8125		112.5	137.5	150	162.5
	external leakage		10	8	8	12		78.1	62.5	62.5	93.8	59.375	68.75	75	81.25		70.3125	85.9375	93.75	101.5625		56.25	68.75	75	81.25		84.375	103.125	112.5	121.875
Oil valve	failed	remove/repaired	1	1	2	1		7.8	7.8	15.6	7.8	14.84375	17.1875	18.75	20.3125		7.03125	8.59375	9.375	10.15625		7.03125	8.59375	9.375	10.15625		7.03125	8.59375	9.375	10.15625
Cylinder head	oil leakage 1.Fresh water leakage from A2 exhaust 2. Unable to start	1.Liner,Oring replaced(G1&G3) 2. Cylinder replaced(G3&G2) replaced gasket (G3)	20	19	19	21		156.3	148.4	148.4	164.1	141.0156	163.2813	178.125	192.9688		140.625	171.875	187.5	203.125		133.5938	163.2813	178.125	192.9688		147.6563	180.4688	196.875	213.2813
		Guide bushing	20	14	20	20		156.3	109.4	156.3	156.3	148.4375	171.875	187.5	203.125		140.625	171.875	187.5	203.125		98.4375	120.3125	131.25	142.1875		140.625	171.875	187.5	203.125
		O-ring	28	32	23	23		218.8	250.0	179.7	179.7	170.7031	197.6563	215.625	233.5938		196.875	240.625	262.5	284.375		225	275	300	325		161.7188	197.6563	215.625	233.5938
		Holding bolts	18	17	17	16		140.6	132.8	132.8	125.0	126.1719	146.0938	159.375	172.6563		126.5625	154.6875	168.75	182.8125		119.5313	146.0938	159.375	172.6563		112.5	137.5	150	162.5
Cylinder jacket/sleeve	scuffed 4 cracked 2	replaced	11	12	11	12		85.9	93.8	85.9	93.8	81.64063	94.53125	103.125	111.7188		77.34375	94.53125	103.125	111.7188		84.375	103.125	112.5	121.875		84.375	103.125	112.5	121.875
Piston	Rings	Replaced	12	13	13	14		93.8	101.6	101.6	109.4	96.48438	111.7188	121.875	132.0313		84.375	103.125	112.5	121.875		91.40625	111.7188	121.875	132.0313		98.4375	120.3125	131.25	142.1875
	cooling/crown		8	13	15	7		62.5	101.6	117.2	54.7	111.3281	128.9063	140.625	152.3438		56.25	68.75	75	81.25		91.40625	111.7188	121.875	132.0313		49.21875	60.15625	65.625	71.09375
ConRod	bent		7	9	8	9		54.7	70.3	62.5	70.3	59.375	68.75	75	81.25		49.21875	60.15625	65.625	71.09375		63.28125	77.34375	84.375	91.40625		63.28125	77.34375	84.375	91.40625
	Gudgeon pin		8	6	8	6		62.5	46.9	62.5	46.9	59.375	68.75	75	81.25		56.25	68.75	75	81.25		42.1875	51.5625	56.25	60.9375		42.1875	51.5625	56.25	60.9375
Drive belt	failed	replaced	8	8	9	11		62.5	62.5	70.3	85.9	66.79688	77.34375	84.375	91.40625		56.25	68.75	75	81.25		56.25	68.75	75	81.25		77.34375	94.53125	103.125	111.7188
	Torn(wear)	replace	11	5	9	3		85.9	39.1	70.3	23.4	66.79688	77.34375	84.375	91.40625		77.34375	94.53125	103.125	111.7188		35.15625	42.96875	46.875	50.78125		21.09375	25.78125	28.125	30.46875
Mech Injector pump	1. Cracked bolts 2. Broken bolts 3. Broken shims	1. Replace bolt and drive(G1,G3) 2. Replace bolt, pulley, and set injector timing(G1,2) 3. Replaced shims	16	12	12	13		125.0	93.8	93.8	101.6	89.0625	103.125	112.5	121.875		112.5	137.5	150	162.5		84.375	103.125	112.5	121.875		91.40625	111.7188	121.875	132.0313
	Drive	defects	22	20	21	24		171.9	156.3	164.1	187.5	155.8594	180.4688	196.875	213.2813		154.6875	189.0625	206.25	223.4375		140.625	171.875	187.5	203.125		168.75	206.25	225	243.75
Injector Pump	failure	failure	30	28	22	28		234.4	218.8	171.9	218.8	163.2813	189.0625	206.25	223.4375		210.9375	257.8125	281.25	304.6875		196.875	240.625	262.5	284.375		196.875	240.625	262.5	284.375
Air Starter	failed Stater starting sensor	repaired x 3 replaced x1	16	16	16	16		125.0	125.0	125.0	125.0	118.75	137.5	150	162.5		112.5	137.5	150	162.5		112.5	137.5	150	162.5		112.5	137.5	150	162.5
Governor failure	1.Failure 2. Hunting		24	20	24	24		187.5	156.3	187.5	187.5	178.125	206.25	225	243.75		168.75	206.25	225	243.75		140.625	171.875	187.5	203.125		168.75	206.25	225	243.75
Intercooler	1. High exhaust temp 2. leakages 3. Overheating	1.Cleaned* 2. Retightened" 3. Replaced gasket!	11	13	16	11		85.9	101.6	125.0	85.9	118.75	137.5	150	162.5		77.34375	94.53125	103.125	111.7188		91.40625	111.7188	121.875	132.0313		77.34375	94.53125	103.125	111.7188

HP fuel line	leakages	Retightened	28	24	30	31		218.8	187.5	234.4	242.2	222.6563	257.8125	281.25	304.6875		196.875	240.625	262.5	284.375		168.75	206.25	225	243.75		217.9688	266.4063	290.625	314.8438
freshwater impeller	wear	replaced	26	21	21	23		203.1	164.1	164.1	179.7	155.8594	180.4688	196.875	213.2813		182.8125	223.4375	243.75	264.0625		147.6563	180.4688	196.875	213.2813		161.7188	197.6563	215.625	233.5938
Freshwater thermostat	failure	removed	8	8	8	8		62.5	62.5	62.5	62.5	59.375	68.75	75	81.25		56.25	68.75	75	81.25		56.25	68.75	75	81.25		56.25	68.75	75	81.25
freshwater pump	1.leakages, worn out pulley belt 2. Pipe	replaced	10	17	15	14		78.1	132.8	117.2	109.4	111.3281	128.9063	140.625	152.3438		70.3125	85.9375	93.75	101.5625		119.5313	146.0938	159.375	172.6563		98.4375	120.3125	131.25	142.1875
	pulley		4	4	5	4		31.3	31.3	39.1	31.3	37.10938	42.96875	46.875	50.78125		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625
Sea water valve	failed	Replaced	3	4	3	2		23.4	31.3	23.4	15.6	22.26563	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875		28.125	34.375	37.5	40.625		14.0625	17.1875	18.75	20.3125
Sea water impeller	failed	Replaced	30	19	27	23		234.4	148.4	210.9	179.7	200.3906	232.0313	253.125	274.2188		210.9375	257.8125	281.25	304.6875		133.5938	163.2813	178.125	192.9688		161.7188	197.6563	215.625	233.5938
Sea water pump case	failed	replaced	7	9	10	12		54.7	70.3	78.1	93.8	74.21875	85.9375	93.75	101.5625		49.21875	60.15625	65.625	71.09375		63.28125	77.34375	84.375	91.40625		84.375	103.125	112.5	121.875
Sea water pump	1.failed 2.blockage*	Replaced " Cleared*	6	3	4	3		46.9	23.4	31.3	23.4	29.6875	34.375	37.5	40.625		42.1875	51.5625	56.25	60.9375		21.09375	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875
Sea chest	cleared		20	17	20	20		156.3	132.8	156.3	156.3	148.4375	171.875	187.5	203.125		140.625	171.875	187.5	203.125		119.5313	146.0938	159.375	172.6563		140.625	171.875	187.5	203.125
Injector nozzles	1.failed 2.hard starting	1.Replaced 2.eplacement(12)(serviced , replaced 3)*	20	30	24	18		156.3	234.4	187.5	140.6	178.125	206.25	225	243.75		140.625	171.875	187.5	203.125		210.9375	257.8125	281.25	304.6875		126.5625	154.6875	168.75	182.8125
Gear train for injector pump drive	Broken		4	3	3	5		31.3	23.4	23.4	39.1	22.26563	25.78125	28.125	30.46875		28.125	34.375	37.5	40.625		21.09375	25.78125	28.125	30.46875		35.15625	42.96875	46.875	50.78125
Starting air line	leakages	Retightened	2	1	1	2		15.6	7.8	7.8	15.6	7.421875	8.59375	9.375	10.15625		14.0625	17.1875	18.75	20.3125		7.03125	8.59375	9.375	10.15625		14.0625	17.1875	18.75	20.3125
Exhaust gas temp sensor	failed	replaced	4	3	3	5		31.3	23.4	23.4	39.1	22.26563	25.78125	28.125	30.46875		28.125	34.375	37.5	40.625		21.09375	25.78125	28.125	30.46875		35.15625	42.96875	46.875	50.78125
Multiple sensor failure	failed	remodification	1	3	1	1		7.8	23.4	7.8	7.8	7.421875	8.59375	9.375	10.15625		7.03125	8.59375	9.375	10.15625		21.09375	25.78125	28.125	30.46875		7.03125	8.59375	9.375	10.15625
Crankshaft	damages	replace/repaired	6	4	3	3		46.9	31.3	23.4	23.4	22.26563	25.78125	28.125	30.46875		42.1875	51.5625	56.25	60.9375		28.125	34.375	37.5	40.625		21.09375	25.78125	28.125	30.46875
Crankshaft pulley belt	won	replaced	2	6	3	7		15.6	46.9	23.4	54.7	22.26563	25.78125	28.125	30.46875		14.0625	17.1875	18.75	20.3125		42.1875	51.5625	56.25	60.9375		49.21875	60.15625	65.625	71.09375
balance shaft	failure		6	5	5	4		46.9	39.1	39.1	31.3	37.10938	42.96875	46.875	50.78125		42.1875	51.5625	56.25	60.9375		35.15625	42.96875	46.875	50.78125		28.125	34.375	37.5	40.625
	alignment		4	3	4	3		31.3	23.4	31.3	23.4	29.6875	34.375	37.5	40.625		28.125	34.375	37.5	40.625		21.09375	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875
Crank case	failed	replaced	3	2	3	2		23.4	15.6	23.4	15.6	22.26563	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875		14.0625	17.1875	18.75	20.3125		14.0625	17.1875	18.75	20.3125
Crank case	Cracked	Repair	4	4	4	4		31.3	31.3	31.3	31.3	29.6875	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625
Lub Temp sensor	failed 2.leakage	1.Replaced 2. replaced gaskets*	3	2	0	2		23.4	15.6	0.0	15.6	0	0	0	0		21.09375	25.78125	28.125	30.46875		14.0625	17.1875	18.75	20.3125		14.0625	17.1875	18.75	20.3125
Heat exchanger	Overheating	1.Heat exchanger back flushed 2.fresh water supply Hose reconnected	28	30	29	20		218.8	234.4	226.6	156.3	215.2344	249.2188	271.875	294.5313		196.875	240.625	262.5	284.375		210.9375	257.8125	281.25	304.6875		140.625	171.875	187.5	203.125
	tubes	internal leakages	12	18	12	8		93.8	140.6	93.8	62.5	89.0625	103.125	112.5	121.875		84.375	103.125	112.5	121.875		126.5625	154.6875	168.75	182.8125		56.25	68.75	75	81.25
Emergency Cooling failure	Failed		7	8	5	6		54.7	62.5	39.1	46.9	37.10938	42.96875	46.875	50.78125		49.21875	60.15625	65.625	71.09375		56.25	68.75	75	81.25		42.1875	51.5625	56.25	60.9375
Lub Oil line	blocked	cleared	3	3	2	3		23.4	23.4	15.6	23.4	14.84375	17.1875	18.75	20.3125		21.09375	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875
Zinc Anode	1. Depleted 2.Replaced(lu b oil cooler)	Replaced(all)	8	8	8	8		62.5	62.5	62.5	62.5	59.375	68.75	75	81.25		56.25	68.75	75	81.25		56.25	68.75	75	81.25		56.25	68.75	75	81.25
tappet	Tappet clearance overdue	clearance adjusted(Mar)	30	30	30	32		234.4	234.4	234.4	250.0	222.6563	257.8125	281.25	304.6875		210.9375	257.8125	281.25	304.6875		210.9375	257.8125	281.25	304.6875		225	275	300	325

Exhaust Manifold	Constricted due to broken studs & heat seal	Replacement studs & seal	1	1	2	1		7.8	7.8	15.6	7.8	14.84375	17.1875	18.75	20.3125		7.03125	8.59375	9.375	10.15625		7.03125	8.59375	9.375	10.15625		7.03125	8.59375	9.375	10.15625
Freshwater pipe	leakage	repaired	1	0	1	1		7.8	0.0	7.8	7.8	7.421875	8.59375	9.375	10.15625		7.03125	8.59375	9.375	10.15625		0	0	0	0		7.03125	8.59375	9.375	10.15625
Transmission gear	3		4	4	4	4		31.3	31.3	31.3	31.3	29.6875	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625
fuel tank	dirty/sludge		12	12	12	12		93.8	93.8	93.8	93.8	89.0625	103.125	112.5	121.875		84.375	103.125	112.5	121.875		84.375	103.125	112.5	121.875		84.375	103.125	112.5	121.875
bad fuel			10	10	10	10		78.1	78.1	78.1	78.1	74.21875	85.9375	93.75	101.5625		70.3125	85.9375	93.75	101.5625		70.3125	85.9375	93.75	101.5625		70.3125	85.9375	93.75	101.5625
Fuel Filter Sec	leakages		16	16	16	16		125.0	125.0	125.0	125.0	118.75	137.5	150	162.5		112.5	137.5	150	162.5		112.5	137.5	150	162.5		112.5	137.5	150	162.5
fuel filter Sec	Clogged	rectified	26	26	26	26		203.1	203.1	203.1	203.1	192.9688	223.4375	243.75	264.0625		182.8125	223.4375	243.75	264.0625		182.8125	223.4375	243.75	264.0625		182.8125	223.4375	243.75	264.0625
Fuel Filter Pir	leakages		16	14	16	17		125.0	109.4	125.0	132.8	118.75	137.5	150	162.5		112.5	137.5	150	162.5		98.4375	120.3125	131.25	142.1875		119.5313	146.0938	159.375	172.6563
fuel filter Pri	clogged		24	24	24	24		187.5	187.5	187.5	187.5	178.125	206.25	225	243.75		168.75	206.25	225	243.75		168.75	206.25	225	243.75		168.75	206.25	225	243.75
Fuel Supply pump	failure		26	20	18	15		203.1	156.3	140.6	117.2	133.5938	154.6875	168.75	182.8125		182.8125	223.4375	243.75	264.0625		140.625	171.875	187.5	203.125		105.4688	128.9063	140.625	152.3438
fuel hand pump	failure		8	12	12	12		62.5	93.8	93.8	93.8	89.0625	103.125	112.5	121.875		56.25	68.75	75	81.25		84.375	103.125	112.5	121.875		84.375	103.125	112.5	121.875
Lub oil pump	defective		4	4	4	4		31.3	31.3	31.3	31.3	29.6875	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625
Lub oil filter	defective base	replaced	10	10	12	13		78.1	78.1	93.8	101.6	89.0625	103.125	112.5	121.875		70.3125	85.9375	93.75	101.5625		70.3125	85.9375	93.75	101.5625		91.40625	111.7188	121.875	132.0313
Journal bearing cooling			3	2	2	3		23.4	15.6	15.6	23.4	14.84375	17.1875	18.75	20.3125		21.09375	25.78125	28.125	30.46875		14.0625	17.1875	18.75	20.3125		21.09375	25.78125	28.125	30.46875
main bearing	No/poor cooling	repaired/replaced	4	3	3	3		31.3	23.4	23.4	23.4	22.26563	25.78125	28.125	30.46875		28.125	34.375	37.5	40.625		21.09375	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875
	Failure	replaced	3	2	2	2		23.4	15.6	15.6	15.6	14.84375	17.1875	18.75	20.3125		21.09375	25.78125	28.125	30.46875		14.0625	17.1875	18.75	20.3125		14.0625	17.1875	18.75	20.3125
Valve (inlet/exhaust)	clearance/ carbon		12	14	16	13		93.8	109.4	125.0	101.6	118.75	137.5	150	162.5		84.375	103.125	112.5	121.875		98.4375	120.3125	131.25	142.1875		91.40625	111.7188	121.875	132.0313
valve spring	weak/broken		8	8	7	9		62.5	62.5	54.7	70.3	51.95313	60.15625	65.625	71.09375		56.25	68.75	75	81.25		56.25	68.75	75	81.25		63.28125	77.34375	84.375	91.40625
Air filter	clogged		23	23	23	23		179.7	179.7	179.7	179.7	170.7031	197.6563	215.625	233.5938		161.7188	197.6563	215.625	233.5938		161.7188	197.6563	215.625	233.5938		161.7188	197.6563	215.625	233.5938
Oil Thermostat	failure		1	0	2	1		7.8	0.0	15.6	7.8	14.84375	17.1875	18.75	20.3125		7.03125	8.59375	9.375	10.15625		0	0	0	0		7.03125	8.59375	9.375	10.15625
Intercooler Thermostat	failure		3	4	3	4		23.4	31.3	23.4	31.3	22.26563	25.78125	28.125	30.46875		21.09375	25.78125	28.125	30.46875		28.125	34.375	37.5	40.625		28.125	34.375	37.5	40.625
Intercooler	fouled/failure		11	12	12	12		85.9	93.8	93.8	93.8	89.0625	103.125	112.5	121.875		77.34375	94.53125	103.125	111.7188		84.375	103.125	112.5	121.875		84.375	103.125	112.5	121.875
Overspeed device			16	12	13	10		125.0	93.8	101.6	78.1	96.48438	111.7188	121.875	132.0313		112.5	137.5	150	162.5		84.375	103.125	112.5	121.875		70.3125	85.9375	93.75	101.5625
Engine Seizure								215.9				0					194.31	237.49	259.08	280.67		0					0			
Damage to piston/conrod								273.5				0					246.15	300.85	328.2	355.55		0					0			
												0					0					0					0			
Total failure			836	816	823	807						0					0					0					0			

APPENDIX 9: DSS STRUCTURE

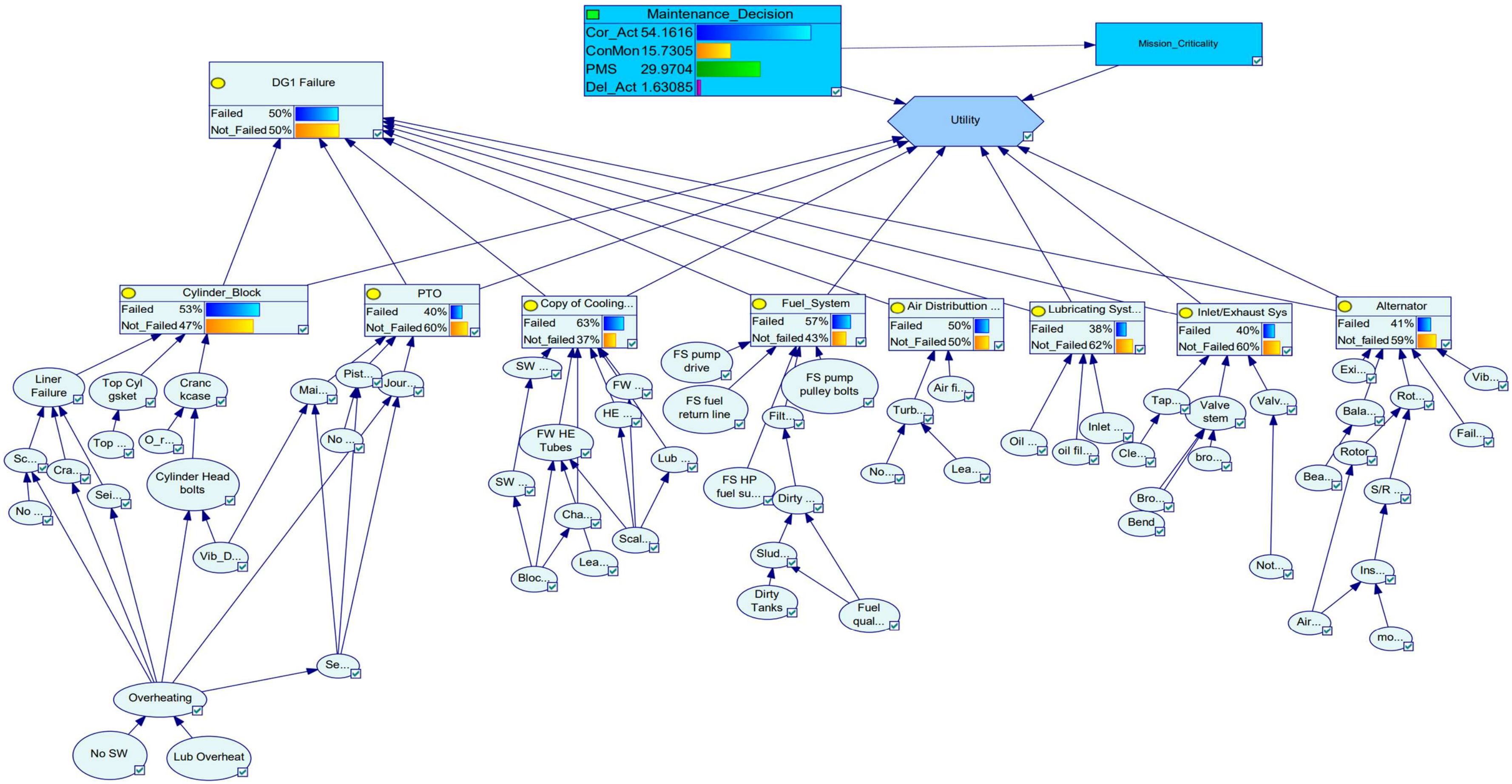


Figure 73:MDG1 DSS STRUCTURE

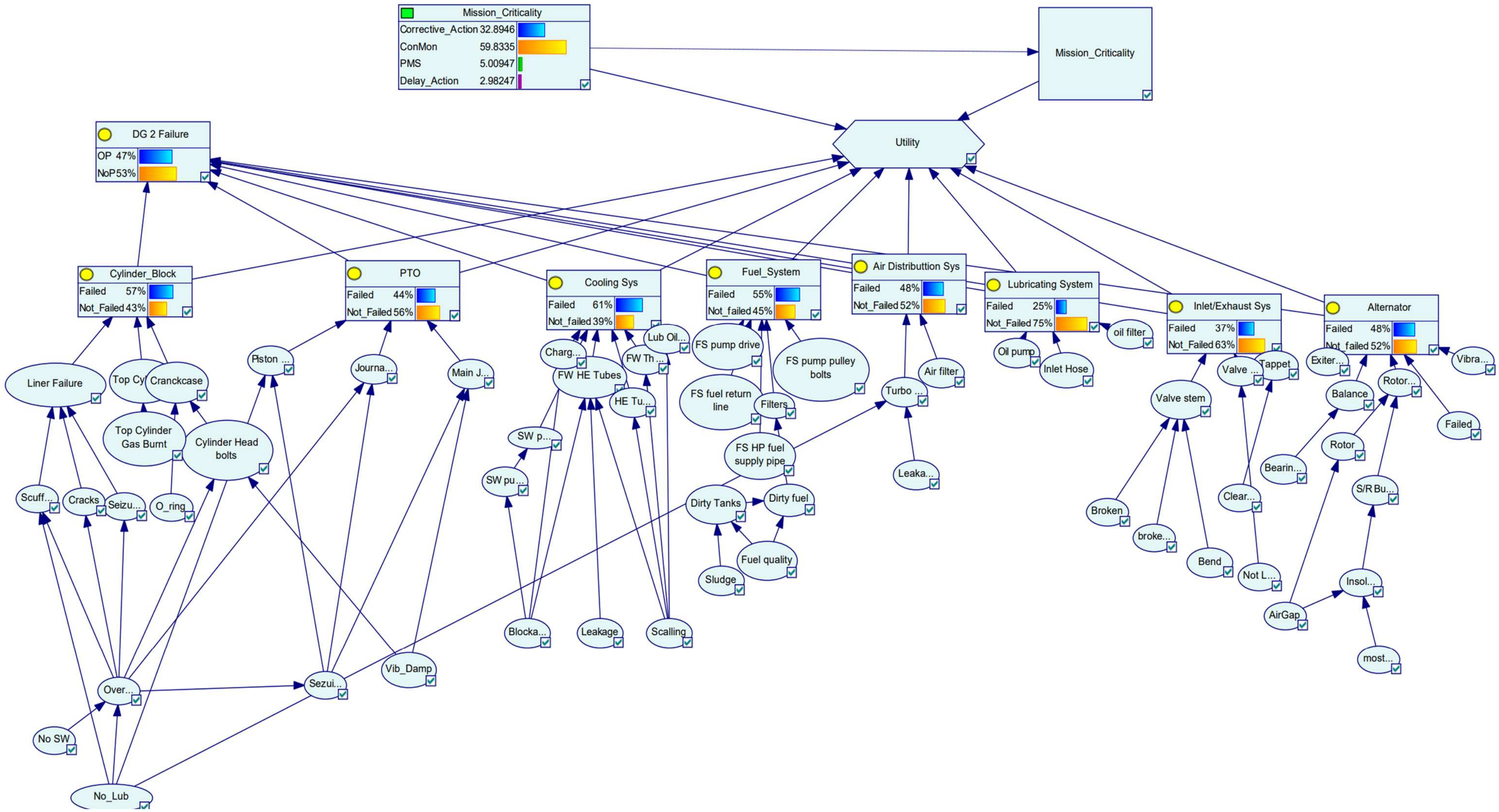


Figure 74:MDG 2 DSS STRUCTURE

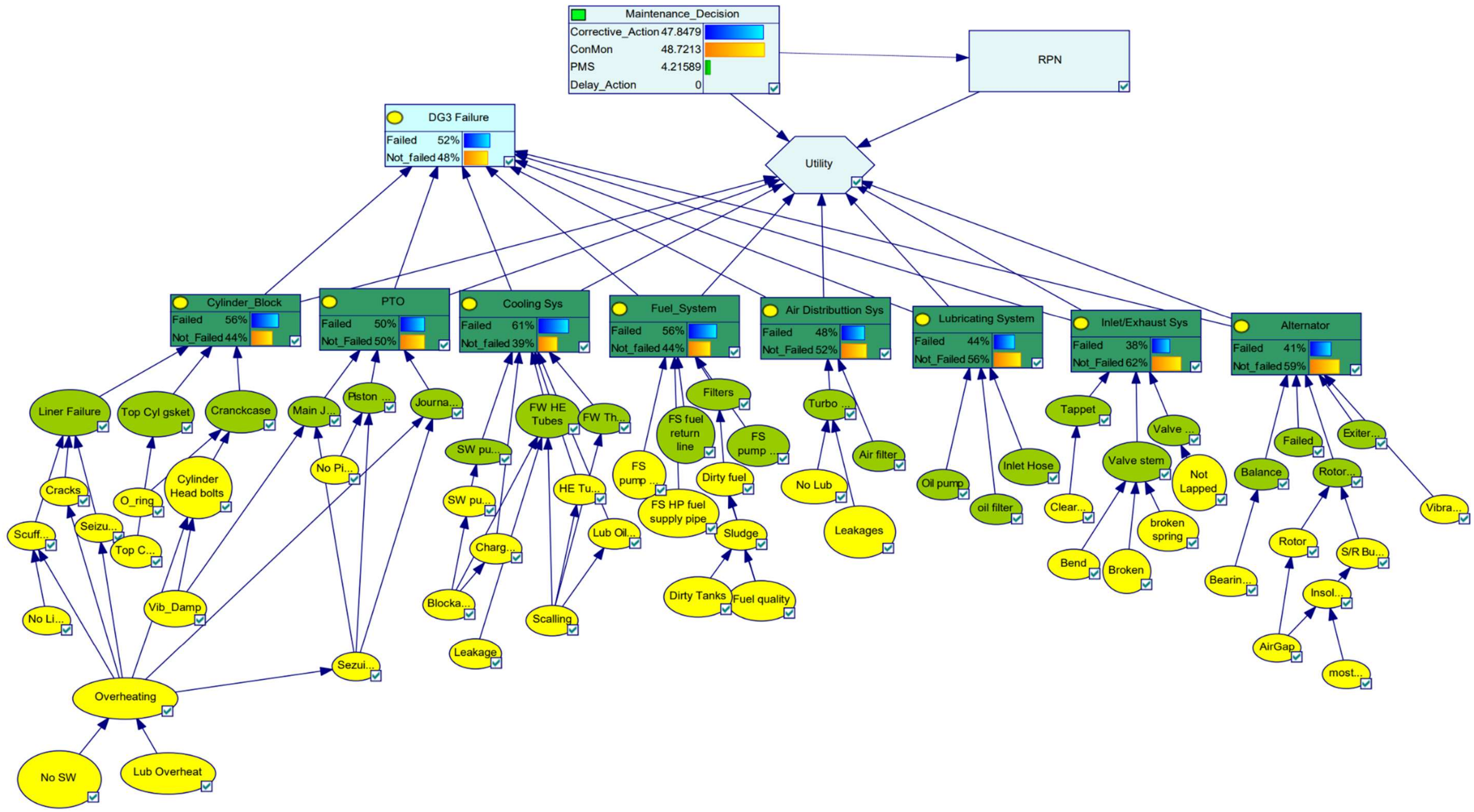


Figure 75:MDG3 DSS STRUCTURE

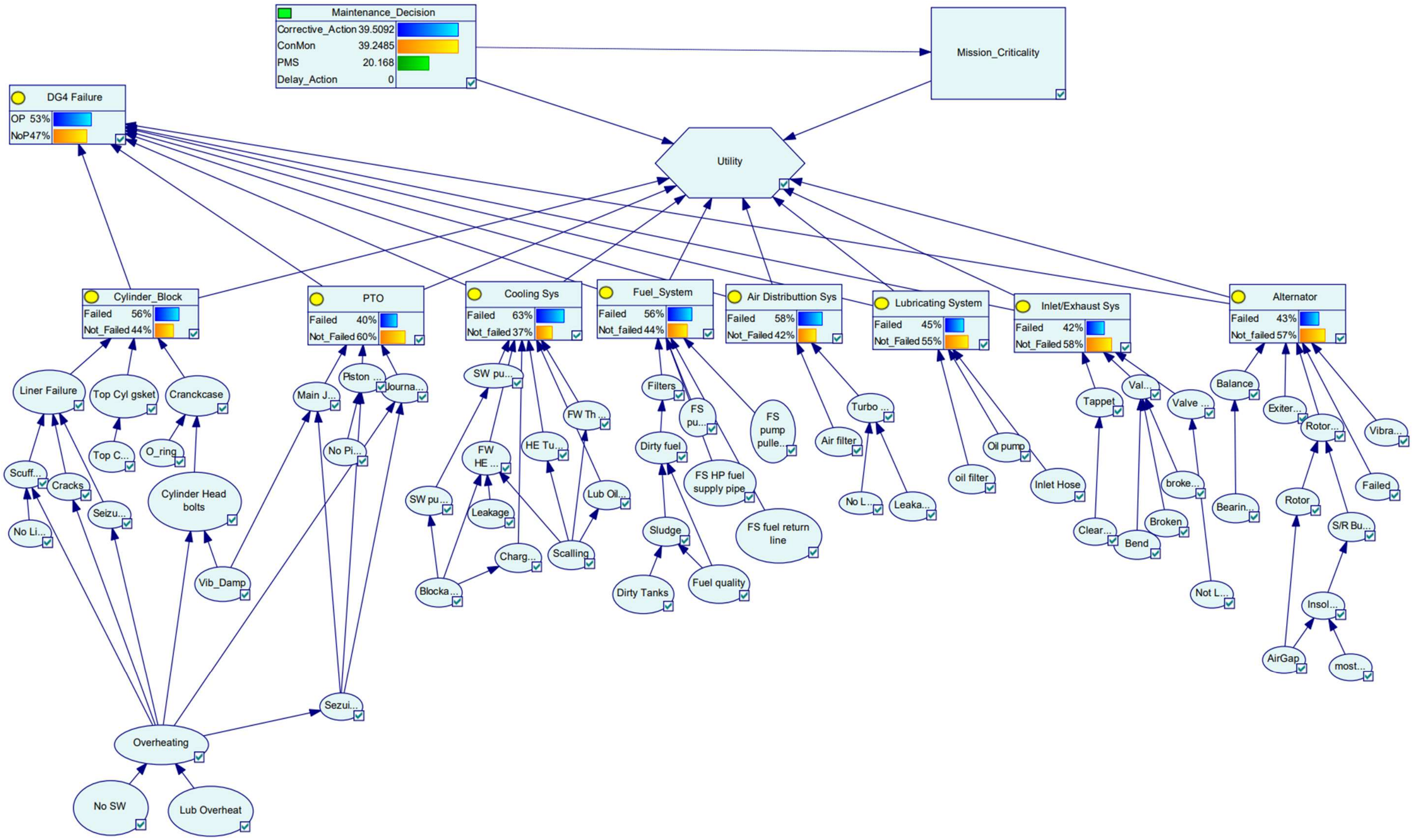


Figure 76;MDG 4 DSS STRUCTURE