Performance assessment modelling of a low-speed two-stroke marine engine

By

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Abstract

This thesis aims to develop a new method to assess, process, diagnose and predict the performance of a low-speed two-stroke (LS2S) marine engine.

Performance monitoring and maintenance decision making are intertwined elements of machinery management and critical for trouble-free ship operations. With the evolution of sensor technology, improved data transfer capability, machine learning algorithms and better knowledge management, there is a gradual move away from fixed-interval maintenance actions towards predictive maintenance to extend the time between overhauls.

In this study, a Bayesian Network (BN) model has been developed for performance assessment of a low-speed two-stroke marine engine used for ship propulsion. The overarching objective of the model is to evaluate the health of each cylinder of LS2S engine as performance can vary significantly from one cylinder to another. The results from combustion performance, wear assessment and post-combustion fouling combine to indicate an engine's operational health.

The BN model receives operational inputs from key engine performance parameters identified through a literature search. The conditional probability tables are mainly developed through expert judgements, and partially through various data sources. To address the challenge of converting the engine's operational data into suitable prior probabilities for BN input, a fuzzy model is developed to accommodate and convert raw subjective data from domain experts, which has been further fine-tuned through the evidential reasoning approach. Moreover, the original BN network is expanded to integrate various features of the BN, fuzzy mode and evidential reasoning to produce a larger comprehensive BN-based decision making toolkit for diagnostics and health assessment. Finally, based on the comprehensive static BN, a novel predictive assessment tool using dynamic BN methodology for a low-speed two-stroke engine is proposed and applied through a case study.

The models developed in this study are expected to be utilised by ship operators, with their graphical interface and quantitative outputs facilitating the engine performance management and supplementing existing engine monitoring methodologies. Secondly, with the frequent processing of engine data through this model, an engine operational profile can be developed and compared with the shop test data, calm weather operations, rough weather operations, cargo voyage, ballast voyage and so forth to create a bespoke predictive health assessment tool.

Acknowledgements

First and foremost, I would like to thank my supervisor, Professor Zaili Yang, for not only his guidance, advice and supervision, but also for his patience, encouragement and not losing hope in me. He helped me keep my focus through his selfless support and commitment. I wish to extend my sincere thanks to my co-supervisors, Dr Chia-Hsun Chang and Dr Zhuohua Qu, for providing me with valuable advice by examining the progress of my research.

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Most importantly, I am indebted to my parents for their unwavering support and prayers, and for giving me every possible opportunity to explore and flourish.

I embarked this journey with my wife alongside me; without her support, it would not have been possible. Her patience and understanding coupled with her excellent culinary skills were important motivational factors.

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Abbreviations

Al + Si	Aluminium + Silicon (Catalyst fines present in residual fuels)
BN	Bayesian Network
CBM	Condition-Based Maintenance
CCAI	Calculated Carbon Aromaticity Index
CDO	Cylinder Drain Oil
CIMAC	International Council on Combustion Engines
CLO	Cylinder Lube Oil
CM	Condition Monitoring
CPT	Conditional Probability Table
CSM	Continuous Survey Machinery (Cycle)
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Network
DM	Distillate Marine
DoB	Degree of Belief
ER	Evidential Reasoning
Fe	Iron
FEAP	FOBAS Engine Assessment Programme
FOBAS	Fuel Oil Bunker Analysis & Advisory Service
FQS	Fuel Quality Settings
GUI	Graphical User Interface
GT	Gross Tonne
HSFO	High Sulphur Fuel Oil
ICP	Inductively Coupled Plasma
IDS	Intelligent Decision Systems (software)
ISM	International Safety Management
ISO	International Organisation for Standardisation
KPI	Key Performance Indicator

LJMU	Liverpool John Moores University
LR	Lloyd’s Register
LS2S	Low-Speed Two-Stroke
MARPOL	The International Convention for the Prevention of Pollution from Ships
MCBM	Machinery Condition-Based Maintenance
MCDM	Multi-Criteria Decision Making
MCR	Micro Carbon Residue
MIP	Mean Indicated Pressure
MMS	Maintenance Management System
MPMS	Machinery Planned Maintenance Scheme
NO_x	Nitrogen Oxides
OEM	Original Equipment Manufacturer
PHM	Prognostics and Health Management
PM	Predictive Maintenance
P_{max}	Maximum Pressure (during a combustion cycle)
PQ	Particle Quantifier
RPM	Revolution Per Minute
P_{scav}	Scavenge Air Pressure
P_{comp}	Compression pressure (before fuel injection around top dead centre during a combustion cycle)
RCM	Reliability Centred Maintenance
RM	Residual Marine
RTF	Run-To-Failure
SFOC	Specific Fuel Oil Consumption
SMS	Safety Management System
SO_x	Sulphur Oxides
TBM	Time-Based Maintenance (Fixed Interval)
TBN	Total Base Number

TPT	Transition Probability Table
T_{scav}	Scavenge Air Temperature
ULSFO	Ultra Low Sulphur Fuel Oil
VIT	Variable Injection Timing
VLSFO	Very Low Sulphur Fuel Oil
WMC	Water Mist Catcher

1 Introduction

This chapter describes the research background and explains the principal objectives developed by investigating and browsing related literature. The applied methods constitute the final models and highlight the novelty of the research in the academic field.

1.1 Research background

In marine operations, loss of propulsion is considered a significant hazard that can jeopardise the ship's safety. Reliable engine performance is vital in reducing the risk posed by the loss of propulsion. An analysis of marine accident investigation indicates that machinery failure is responsible for around 24% of marine accidents in the UK merchant fleet for ship sizes over 100 Gross Tonnes (GT) (Douglas, 2007).

The majority of the world fleet of ships greater than 10,000 GT are fitted with Low-Speed Two-Stroke (LS2S) engines as prime movers (Sea-web, 2020). LS2S engine manufacturers have made substantial efforts to improve reliability and availability through better control systems, robust designs and improved component materials. However, due to the hostile and variable conditions under which marine engines operate, the existing barriers and maintenance strategies sometimes fall short in preventing breakdown or emergency repair scenarios.

In their bi-annual report, the Swedish Club (2018) reported that the number of machinery claims is around 47% of the insurance underwriters' total claims, as shown in Figure 1.1.

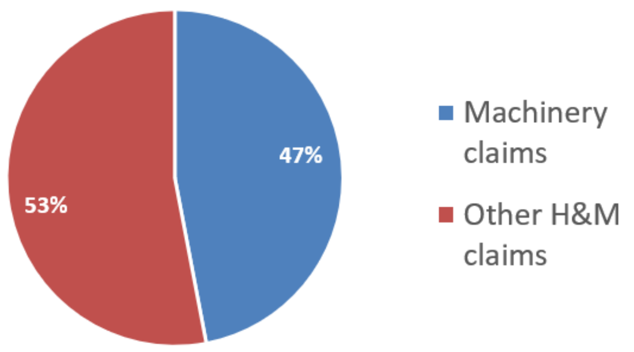


Figure 1.1: Hull and Machinery (H&M) claims by number (2015-2017)
As adopted from: The Swedish Club (2018)

Out of the total machinery claims, 28% were related to main engine damage, which is also the highest in cost at around USD 650,000 per claim. These figures are just the tip of the iceberg compared to the overall costs a ship operator faces during the emergency breakdown of critical machinery equipment such as the main engine.

Furthermore, the Lloyd’s Register (LR) fuel-testing business, FOBAS (Fuel Oil Bunker Analysis and Advisory Service), regularly deals with fuel-related operational issues reported by ships on their fuel-testing programme (LR, 2019). The investigative cases are divided into four broad failure modes, i.e. ‘sludging’, ‘fuel injection equipment failure’, ‘cylinder component damage’ and ‘other’ which include material, corrosion and few undefined cases (Figure 1.2).

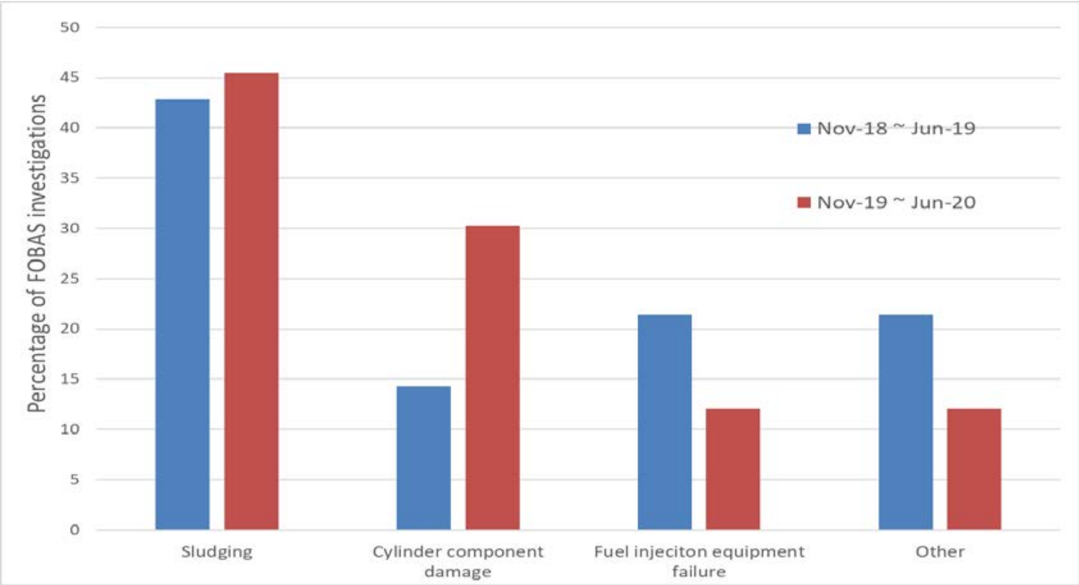


Figure 1.2: Percentage distribution of fuel-related investigations
Source: FOBAS (2020)

The above figure compares the data for two specific periods. November 2019 to June 2020 saw an increase in the number of cases of cylinder component damage in diesel engines. All of the cases were reported to the ships’ large two-stroke main engines (FOBAS, 2020). An investigation into the cases to determine the root cause mainly indicated that there was no single factor, but a combination of factors that result in failure. For example, in one of the cases, the ship experienced excessive wear on cylinder components, high soot/fouling of scavenge space, and broken piston rings in cylinders 1, 2, 3, 4, and 6 of the LS2S engine. A picture of the cylinder 4 piston ring pack taken from the scavenge space is shown in Figure 1.3.

Figure 1.3: Piston ring pack condition of cylinder 4
Source: FOBAS (2020)

This figure shows sticking piston rings in the ring groove and heavy fouling due to unburnt fuel or excessive lubricant feed rate. The ship was recommended several actions to rectify the situation, including opening up the cylinders and checking the liner condition and replacing them as required. Moreover, the condition of fuel injectors, fuel quality and Cylinder Lube Oil (CLO) feed rate was also questioned. The ship was taken out of service for a few days, causing its operator additional monetary loss in port fees and cargo delay on top of the repair bill (FOBAS, 2020). These cases, although few and far between, with around 0.2~0.3% of total marine fuel bunkering (FOBAS, 2020), point to the lack of an integrated approach where most of the engine's operational parameters are not viewed collectively by evaluating the respective inter-dependencies.

Moreover, the literature review conducted during the course of the study indicates that many studies addressing the issue of marine engine health management consider only a limited number of parameters, so the work needs to be expanded to integrate more health indicators for better diagnostic and predictive assessments (Wang, Chen and Guan, 2021).

1.2 Market analysis of LS2S engines

Diesel engines on a ship serve various functions, from an emergency power source to propelling the ship across the oceans. Engine applications on ships have been divided into three broad categories based on engine speeds in Revolutions Per Minute (RPM) as follows (Chell, 2007):

- Low-speed: <200 RPM
- Medium-speed: 200~1000 RPM
- High-speed: >1000 RPM

High-speed engines are smaller in size and power than the other types, and are usually used for emergency onboard applications. Medium-speed engines are either auxiliary engines generating electricity for various onboard consumers or are used for main propulsion. On the bigger ships, low-speed engines are usually installed as prime movers. The majority of the high- and medium-speed engines operate on a four-stroke (two crankshaft revolutions to complete a combustion cycle) principle whilst low-speed engines are usually two-stroke (one crankshaft revolution to complete a combustion cycle), as shown in Figure 1.4.

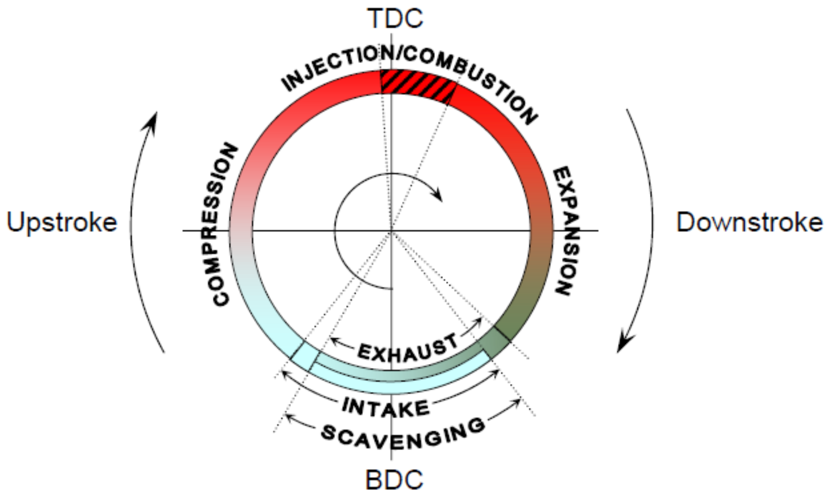


Figure 1.4: Schematic of a typical two-stroke diesel engine cycle
Source: Douglas (2007)

There are mainly four stages, i.e. compression, fuel injection/combustion, expansion and scavenging. The piston at BDC (Bottom Dead Centre) is at rest for a very short time when scavenging ports at the lower end of the liner are uncovered, and exhaust valve is open to replace the hot gases with the fresh charge air. Piston upward movement starts with closing of exhaust valve followed by covering of scavenge ports, initiating compression. A few degrees before TDC (Top Dead Centre), fuel injection starts and fuel under high pressure and temperature self-ignites, causing a ‘bang’ pushing the piston down with force, generating the power.

A cross-section of the typical LS2S engine design is shown in Figure 1.5. These engines are unique because of the uniflow scavenging arrangement and crosshead design, enabling complete segregation of cylinder liner/combustion space and crankcase through the diaphragm. The last few decades have seen insignificant design changes to LS2S engines. Even though the introduction of renewable fuels such as methane, propane, methanol and ammonia has brought complexity to the fuel systems of LS2S engines with regard to burning non-conventional fuels efficiently, the basic structure and design of these engines remain pretty much the same.

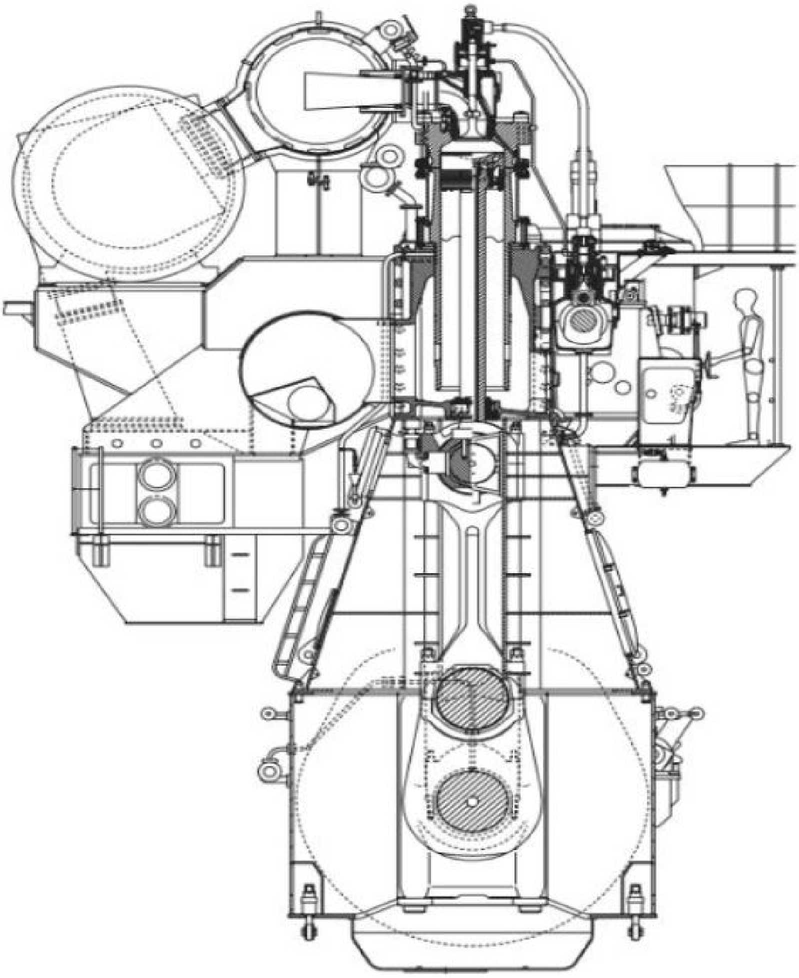


Figure 1.5: Cross-section of a typical LS2S (cross-head) engine
Source: Tsaganos et al (2018)

A low-speed engine market analysis is performed through Sea-web (2020) data by filtering records of 139,872 ships. Figure 1.6 shows the distribution based on ship sizes in Gross Tonne (GT) and types of prime movers installed in the world fleet today.

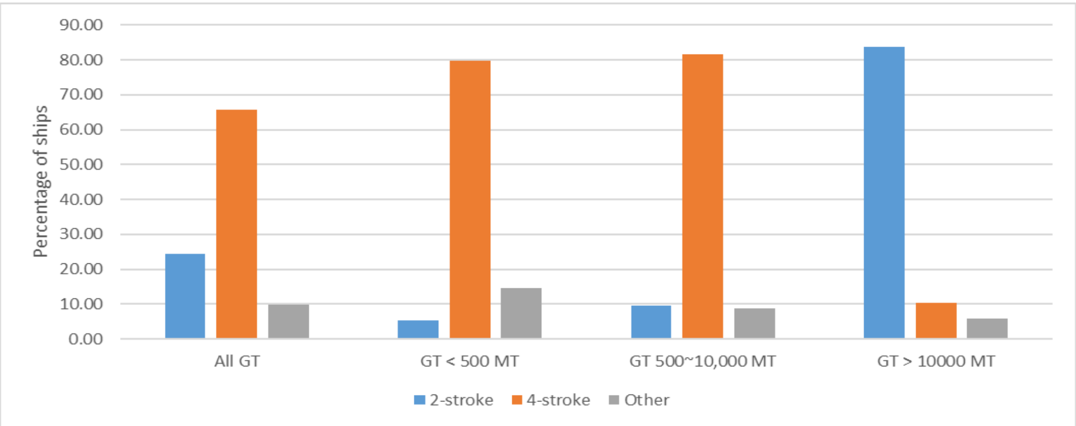


Figure 1.6: World fleet percentage distribution of prime movers
Source: Sea-web (2020)

These results indicate that, overall, medium/high-speed four stroke engines are installed in 65% of the world fleet, whilst 25% have LS2S engines and 10% have 'Others', which includes propulsion options such as gas turbines, electric (Azimuth), steam turbines, hybrid solutions and others. Further drilling down the data shows that around 79% of the ships are below 10,000 GT in size. Smaller ships with specific power/speed requirements and lower engine-headroom mainly have four-stroke engines as prime movers.

However, the landscape quickly changes for ships greater than 10,000 GT, with low-speed cross-head design two-stroke engines installed in around 84% of these ships. Kyrtatos et al (2016) have argued that better thermal efficiency and fewer moving parts are the key reasons for the significant uptake of LS2S engines in bigger ships. Furthermore, these engines are low and variable speed, and reversible, hence reducing the complexity by eliminating the need to integrate reduction gears and controllable pitch propellers in the power transfer and shafting system (Tsaganos et al., 2018). Compared to the other engine types and prime movers, LS2S engines boast superior power to weight ratio and thermal efficiency, as shown in Figure 1.7.

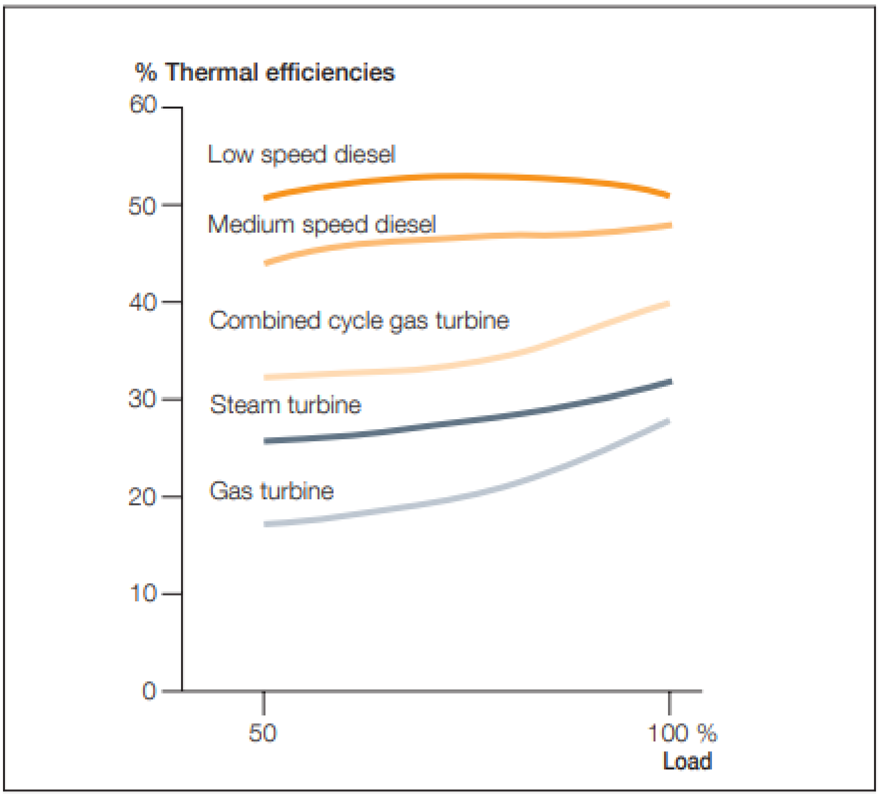


Figure 1.7: Typical part-load efficiencies of prime movers
Source: MAN-ES (2013a)

The Swedish club (2018) also categorised the prime movers into low-speed (two-stroke) and medium/high-speed (four-stroke) engines in their main engine damage report. The insurance underwriters highlighted that the majority (71%) of their registered fleet are fitted with low-speed engines as prime movers whilst the rest (29%) are medium/high-speed engines. The claims frequency is 2.5 times higher for medium/high engines however the cost per claim is significantly higher for LS2S engines, as per Figure 1.8.

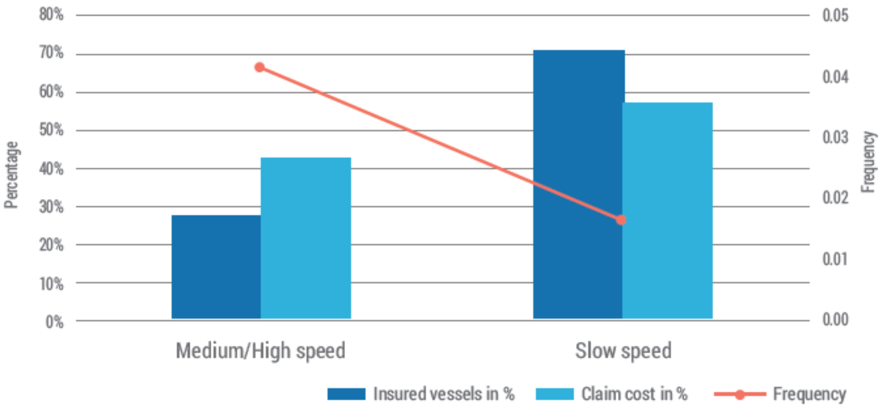


Figure 1.8: Main engine claims by engine speed, 2015-2017
Source: The Swedish club (2018)

It can be inferred from Figure 1.8 that by virtue of lower claims frequency, LS2S engines indicate better reliability and could be one of the reason for being a preferred choice as prime mover for larger ships. Further market analysis of LS2S engine (excluding gas engines) application in the maritime sector is performed in Table 1.1 (Sea-web, 2020).

Table 1.1: Analysis of LS2S engine distribution on types and sizes

Engine type	Engine designer	No. of cylinder	Stroke*	Bore Diameter (centimetre)	Concept**
X-head two-stroke main engines	MAN-ES (86%)	5 (10.6%)			
		6 (59.7%)	G (10.7%)		
			S (48.5%)	30 (0.04%)	
				35 (2.4%)	
				40 (0.89%)	
				42 (3.3%)	
				46 (5.14%)	
				50 (18.0%)	MC (9.2%)
					ME (8.8%)
				60 (12.8%)	
				70 (5.07%)	
				80 (0.56%)	
				90 (0.24%)	
			L (0.23%)		
			K (0.13%)		
		7 (9.0%)			
		8 (1.8%)			
		9 (1.7%)			
		10 (0.7%)			
		11 (1.4%)			
		12 (1.1%)			
	WinGD & J-Eng (14%)				

*Stroke/bore ratio (K – short, L – long, S – super long, G – 'Green' ultra-long)

** E – Electronically & C – Camshaft

The three main LS2S engine designers in the marine industry are MAN-ES, WinGD (former Sulzer/Wartsila) and J-Eng (former Mitsubishi/MHI) (Tsaganos et al., 2018). MAN enjoys the greater market share of around 86% whilst the rest (14%) is split between WinGD (10%) and J-Eng (4%) (Sea-web, 2020). All three Original Equipment Manufacturers (OEMs) produce engine designs in various configurations of stroke/bore ratios and a varying number of cylinder to meet specific operator requirements for power and size. The data (as per Table 1.1) indicates that the MAN6S50 MC & ME design is the most popular LS2S marine engine.

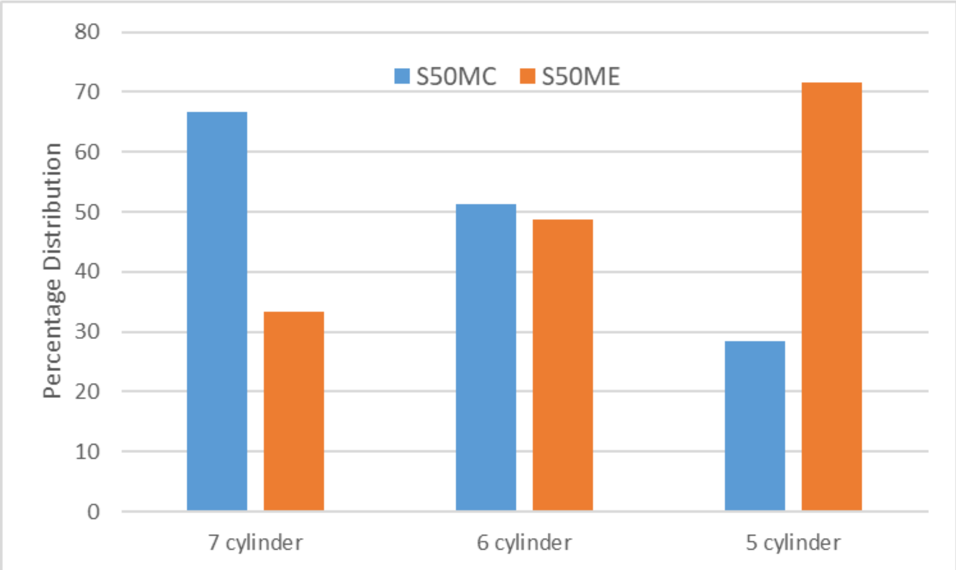


Figure 1.9: Percentage split between ME & MC engine types of MAN-ES in the last 10 years
Source: Sea-web (2020)

Figure 1.9 provides the further distribution of MAN's ME and MC designs for 5-, 6- and 7-cylinder engine ships launched in the last 10 years. It appears that there is increasing uptake in the 5-cylinder ME designs, and there is almost a 50/50 split for the ME/MC 6-cylinder engine arrangement. In this project, for the main case study, a ship fitted with a MAN 6S50-MC engine has been used, which is also the most widely used engine at 9.2%, as per Table 1.1.

The analysis performed above indicates that the LS2S engine is the most important onboard asset with distinctive advantages such as simple operation and design, making it the preferred choice for the main propulsion of larger ships. Nevertheless, LS2S engine failures are not uncommon, albeit they are less frequent compared to the four-stroke engine. However, if/when failures occur, they could potentially result in significant safety and economic implications.

1.3 Research aim and objectives

Given the importance of the LS2S engine as prime mover on a ship, it is essential to investigate how the current engine health assessment methodology can become a proactive one. Based on the above discussions, the aim of the research is:

To develop a user-friendly tool that will enable ship operators to proactively monitor the LS2S engine performance and would result in improved maintenance decision making.

To achieve the aim of the research, the study focuses on the following three objectives;

1. Develop understanding of the LS2S engine marine application, conventional maintenance and corresponding performance assessment methodologies by performing a thorough literature review and market analysis.

2. Develop a proactive LS2S engine performance assessment methodology through the use of operational indicators.

3. Develop a predictive assessment capability for LS2S engines which can support timely operational adjustments and maintenance tasks.

1.4 Research novelty

In the process of achieving the research objectives outlined in section 1.2, the study produced models to assess the marine engine's performance with the following key novel features:

1. The BN model's development to assess the LS2S engine's health using the operational indicators is a unique methodology for scholars to utilise the model as a knowledge management and machine learning vehicle
2. In this research, a fuzzy rule-base and subsequently fuzzy evidential reasoning method is used for converting LS2S engine operational data into a probability distribution for the first time (to the researcher's best knowledge), to use as BN model input.

The application of a dynamic BN to assess the LS2S engine's performance further exploits the model's ability to predict the performance degradation over a specific time period. This feature is coupled with assigning certain limits to help ship operators plan the maintenance action and eventually utilise the component's remaining useful life to the maximum.

1.5 Research framework

Figure 1.10 shows the research framework divided into three stages: i) literature review, ii) performance/health assessment modelling and iii) development of the capability to perform predictive health assessment. The work is divided into eight inter-linked chapters, as described below and shown in Figure 1.10. The models developed in this research are built around industry data and expert judgements, which involved engaging a panel of experts.

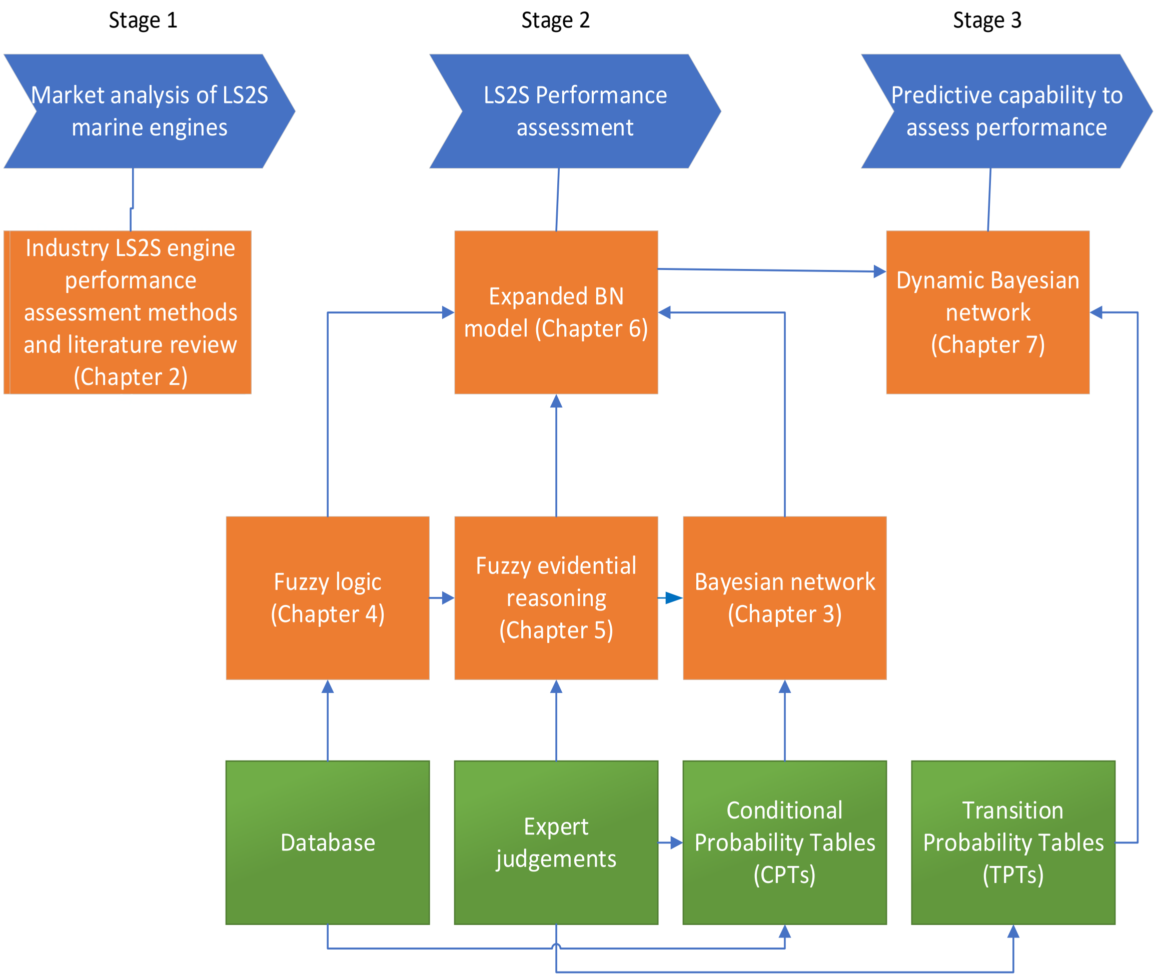


Figure 1.10: Research methodology framework

The following paragraphs provide a brief description of each chapter.

Chapter 1 introduces the basic information about the research, its objectives, contribution to knowledge, framework and novelty. The state of the LS2S engine market and fundamental drivers behind this engine type's popularity as the prime mover has also been highlighted. Overall, combining these important features demonstrates the necessity of conducting the research.

Chapter 2 analyses the prevailing maritime maintenance methods, academic research in the field of marine engine technology and corresponding performance assessment of LS2S engine. This chapter also proposes a framework to address the identified gaps in the research.

Chapter 3 develops a technical BN model by conducting a review of the key LS2S engine operational indicators with the primary aim of assessing the engine's health. To develop the BN conditional probability tables for intermediate and leaf nodes, a combination of expert judgements and real data is used. Sensitivity analysis is performed, which shows the comparative importance of a few parameters, followed by a case study to demonstrate the BN model's functionality.

Chapter 4 addresses the critical issue of assigning the prior probabilities to the BN model's parent nodes, which require conversion from real operational values into probability distributions. To achieve this objective, fuzzy logic is used to model each parent node of the BN developed. Multiple influencing factors are modelled through fuzzy logic control. A modified fuzzy logic controller was employed by removing the defuzzification step because of the BN model's requirement to have inputs as unconditional probability distributions for input variables.

Chapter 5 is intended to further improve the precision of the fuzzy model's output by replacing the conventional 'max-min' approach with Evidential Reasoning (ER).

Chapter 6 develops a novel expanded BN by integrating key features of the BN, fuzzy model and fuzzy-ER model. The expanded BN provides a more holistic view of the LS2S engine's operational health through a directed acyclic graph (DAG), making it far easier for the ship's operator to navigate and identify the issues.

Chapter 7 adds a temporal dimension to the expanded BN model using the smart algorithm and transition probabilities derived from expert judgements. The exciting feature of the model is the potential for LS2S health prediction, which is demonstrated through a case study.

Chapter 8 concludes the research by providing a summary, limitations of the study and future direction in this area.

2 Low-speed two-stroke engine maintenance and performance: Literature review from both practical and theoretical perspectives

Marine diesel engines have been the prime movers for merchant ships for more than a century (Woodyard, 2004). They are robust, reliable and have proven their worth across hundreds of thousands of nautical miles. This chapter to focus on the current maintenance strategies for LS2S engine, corresponding technology status and operational performance assessment in the maritime industry.

2.1 Maintenance management strategies

In the era of cost-saving, low freight rates and increased environmental awareness, ship operators are making every effort to reduce maintenance costs, minimise failure probability and maximise availability. Maintenance of machinery equipment is part of the necessary costs which can be up to 20% of the total operational expenditure of the ship (Wang, Chen and Guan, 2021). Run-to-Failure (RTF) used to be a maintenance strategy, but this has been eventually eclipsed by a Time-Based (preventive) Maintenance (TBM) strategy for critical equipment. TBM is still popular and widely used in the maritime sector; however, there is a natural evolution towards Predictive Maintenance (PM) becoming an industry norm, as shown in Figure 2.1.

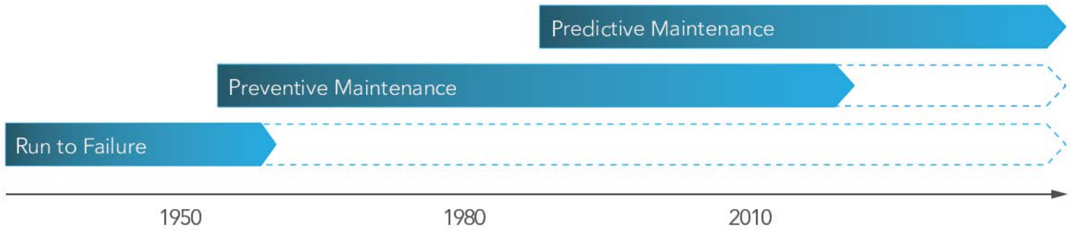


Figure 2.1: Evolution of maintenance practices
Source: Knutsen, Manno and Vartdal (2014)

One of the reasons for PM uptake as a maintenance model is that the RTF and TBM strategies can be inherently uneconomical. Using an RTF strategy would mean fewer maintenance events; however, operational costs can be extremely high when a failure eventually occurs. However, where the consequences of failures are slight and quick identification/repair is possible, RTF could be a suitable maintenance plan. In contrast, a TBM strategy would mean better asset availability through regular maintenance and low failure probability. However, overall maintenance costs could be high, making it unattractive, especially where a machinery system has in-built redundancy (Tan et al., 2020).

In most industries, including the maritime sector, there has been an evolution of maintenance strategies from a ‘fail and fix’ to a ‘predict and prevent’ approach (Medina-Oliva et al., 2014). Condition-Based Maintenance (CBM) is the terminology frequently used in the industry which fulfils the criteria mentioned above where decisions are made based on machinery condition, forming an integral part of PM strategy.

A PM strategy can achieve these goals through reliability analysis, condition assessment and an effective decision-making process. Figure 2.2 indicates how a maintenance interval extension can be achieved through condition monitoring and early response to random problems before costly secondary damage occurs (Toms and Toms, 2008).

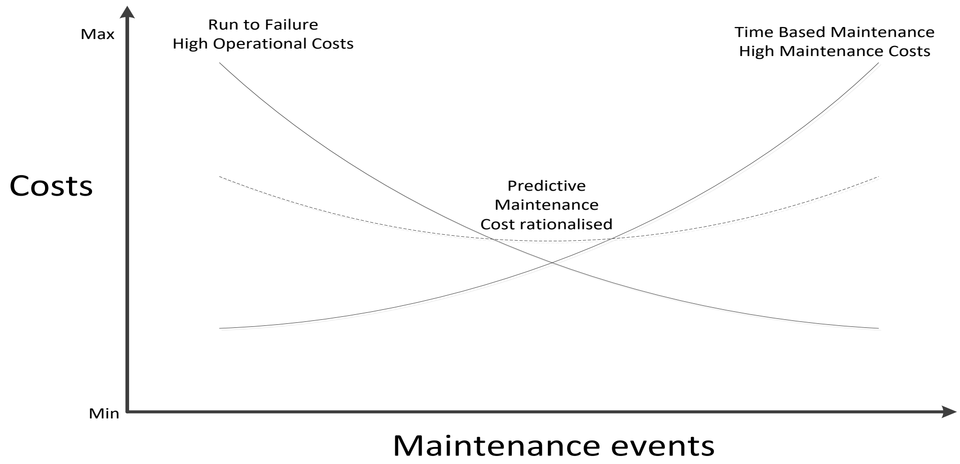


Figure 2.2: Predictive maintenance trades-off operational and maintenance requirements for lower overall costs
Source: Toms and Toms (2008)

Figure 2.3 provides an overview of various maintenance strategies and corresponding interlinks.

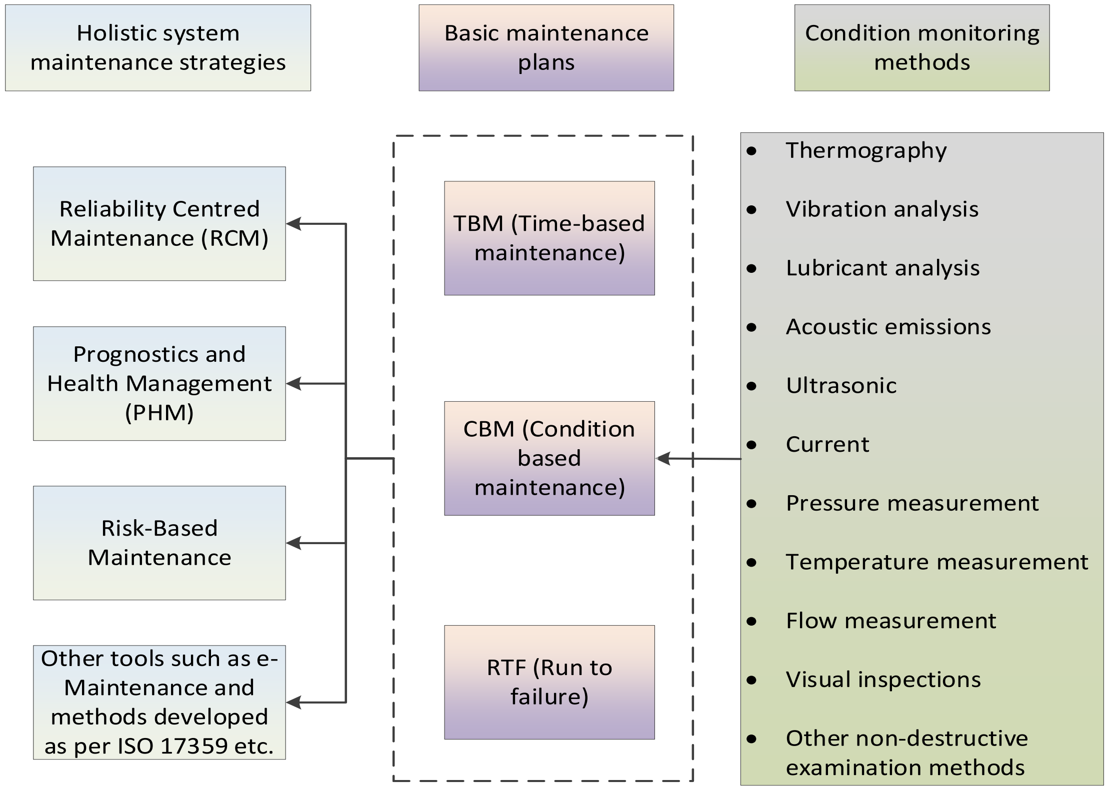


Figure 2.3: Overview of maintenance management strategies

In summary, there are three basic maintenance plans, i.e., TBM, CBM & RTF. TBM is usually dictated by the machinery maintenance manual where a defined time-frame is given to carry out an inspection or maintenance activity based on running hours. An RTF is normally applied to non-critical and low impact machinery to extract maximum life out of an equipment / component. Whilst maintenance decision making under CBM naturally depend on the data generated from condition monitoring methods listed on the right hand column of Figure 2.3.

As the systems are becoming more complex, holistic maintenance strategies such as Reliability Centred Maintenance (RCM) are being introduced which are built around selecting and implementing the best parts of all three basic maintenance plans for a given system or component (Wang and Trbojevic, 2007). These strategies are not only an attempt to optimise the use of resource in machinery maintenance but also take into account system's functionality, availability, reliability, and corresponding impact of various interdependencies between operational parameters.

Kernel of such comprehensive maintenance strategies are condition monitoring enabling the experts to diagnose and predict through data analytics and smart algorithms. For example, RCM produced excellent results in the aviation industry which prompted other high-performance industries to adopt it as a maintenance management method (Mokashi, Wang and Verma, 2002). However, such maintenance strategies can be resource intensive and asset operators consider return-on-investment or cost-benefit-analysis before opting for such options.

One of the pillars of these holistic frameworks is taking the maximum out of the useful equipment life and performing maintenance action at the right time, before a failure occurs. Moubray (1997) coined the idea of a P-F curve to estimate the time between Potential (P) failure and Functional (F) failure. The time between the two points is termed the P-F interval, which forms an essential basis for any RCM programme. The concept was to develop a strategy to ensure that potential failures are picked up at an early stage before they become functional failures.

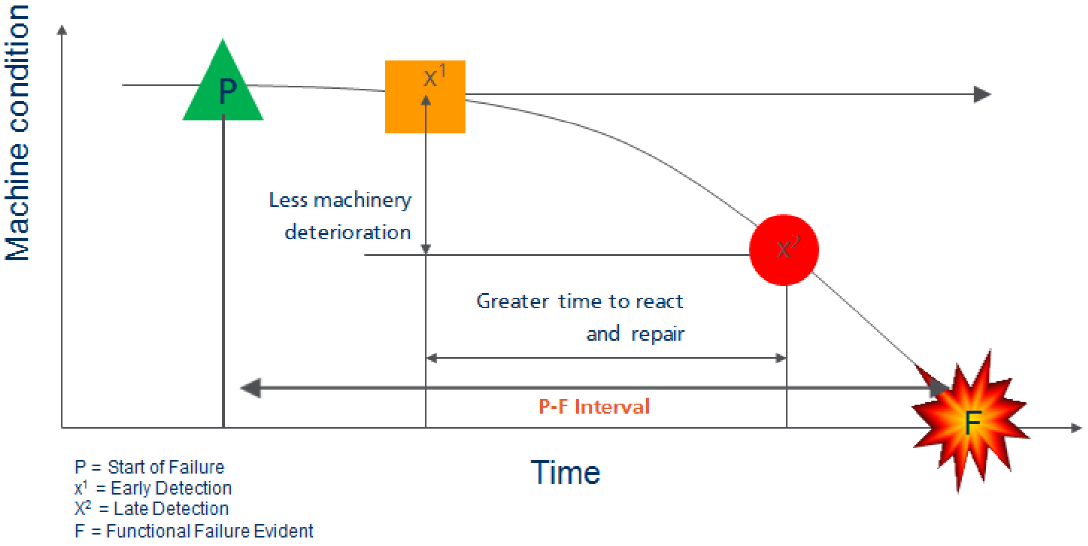


Figure 2.4: P-F curve
Source: Moubray (1997)

The concept presented in Figure 2.4 shows that the detection of propagating failure at point X^2 means there is little time to react and take mitigating action. Hence, with more comprehensive modelling and diagnostic capability, the optimum point for detecting incipient failure should be around X^1. Moubray (1997) also introduced the term ‘functional context’, meaning that the optimal intervention to return the machinery to a satisfactory state depends on the context.

For example, on the one hand, the operator would like to prolong the asset’s life without intervention as intervention earlier than needed is unlikely to be cost-effective, which also carries the risk of failures at the initial stage of operational life. Secondly, it is crucial to recognise the type of failure mode, where some failures may require priority actions to fix them immediately after their detection; however, there may be failure modes with predictable patterns where the operator can be more confident of delaying the maintenance action to prolong the life of the equipment or a component.

Moreover, an assumption is made in Figure 2.4 about the system or equipment's condition deteriorating gradually unless an intervention like a maintenance action is performed. Grall, Berenbuer and Dieulle (2002) proposed a similar concept to the P-F curve, where a stochastic deterioration model is trained through parametric learning to optimise the condition-based maintenance policy and reduce cost. However, these models are unable to consider the imperfect maintenance actions and probable flaws in the inspection regime, introducing additional complexity into the process.

2.1.1 Selecting a suitable maintenance strategy

The important factors for the ship operator to select a suitable maintenance strategy are cost, safety, availability, reliability, and acceptability risk levels associated with the machinery downtime (Asuquo et al., 2019). A few ship operators take a progressive, long-term view of investing in advanced machinery condition monitoring equipment, while others may rely on basic engine monitoring methods and conventional time-based maintenance.

Lee et al (2013) used a maintenance transformation map to depict the suitability of various strategies based on the uncertainty and complexity of the system under study, as shown in Figure 2.5. For highly complex and critical systems such as nuclear power plants, preventative maintenance may be effective; however, ships with a comparatively simple system configuration are likely to exhibit low operational uncertainty, making them a right candidate for CBM or Prognostics & Health Management framework.

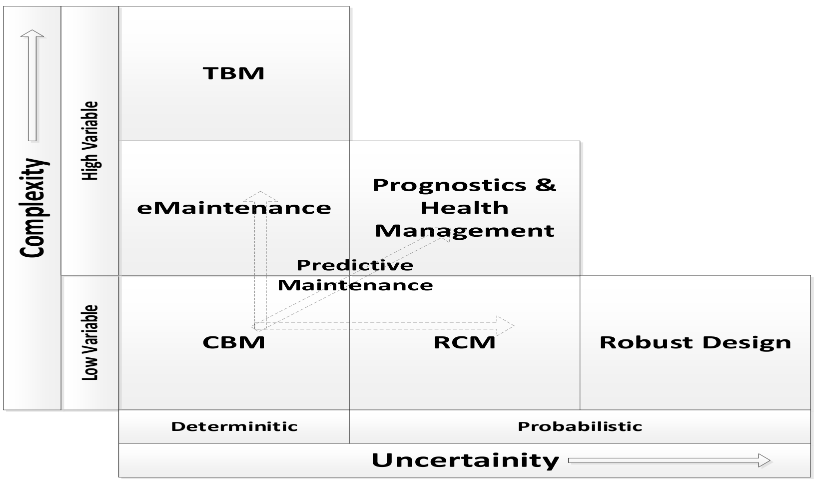


Figure 2.5: Maintenance transformation map
Source: Lee et al (2013)

Ahmadi et al (2009) used the relatively simple formulation of 'cost' and 'severity of consequence' to set the criteria, as shown in Figure 2.6. For example, low-cost machines and systems with low consequences from failure are likely to operate under the RTF maintenance strategy. The other end of the scale sees that comprehensive and careful planning is required to deal with complex machinery systems with potentially high severity of consequence from a failure.

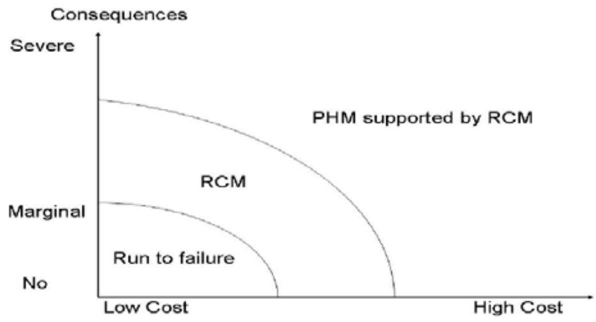


Figure 2.6: Approach selection criteria
Source: Ahmadi et al (2009)

Asuquo et al (2019) developed a Multi-Attribute Group Decision-Making model to select an appropriate maintenance strategy, ranking CBM as the most effective maintenance strategy followed by planned (fixed time interval) maintenance with RTF ranked last. Based on '*what gets measured gets done*', improvement in the machinery condition depends on the frequent collection, monitoring and processing of performance data for maintenance action planning, making it an integral part of the CBM framework.

2.1.2 Ship classification and regulatory frameworks concerning maintenance

Classification rules and international maritime regulatory frameworks primarily address a ship's safety, the wellbeing of its crew, environmental protection and risk mitigation. Machinery performance, maintenance and operations have been left to ship operators to set the performance standards they want to attain. However, as a minimum, section 10 of International Safety Management (ISM code, 2010) requires ships to maintain the machinery equipment, and they should carry a Maintenance Management Plan (MMS) within the company's Safety Management System (SMS) framework. The statement provides an overarching objective without going into specific pathways.

Ship classification societies issue a set of prescriptive rules for the ships under their class to comply, which are aligned with the SOLAS (Safety of Life At Sea, 1974) guidelines concerning one failure criterion, i.e. a single component failure should not cause a ship to lose critical systems which include the critical machinery equipment such as LS2S engines. Compliance with the class rules ensures that ships meet minimum machinery component safety requirements and encourage safe machinery operation by setting a few critical operational limits. For example, classification rules for safe operations set the maximum fuel system temperature at 150°C at engine inlet (Rulefinder, 2020). If the fuel system temperature is allowed to go beyond 150°C, then there are risks to the piping and components, which are not designed to withstand too high temperature conditions.

Performance assessment of the machinery equipment is not an area generally targeted through class rules. However, with the introduction of high-performing systems and technologies, the emphasis is shifting from a prescriptive ‘rule-based’ approach to a ‘goal-based’ approach. Rapid digitalisation and improved ship-to-shore data transfer capabilities bring new opportunities in the field of online condition monitoring, fault detection and prognosis like the LR maintenance optimisation tool (ALLASSETS, 2020).

Furthermore, LR has developed specific descriptive notes for ships’ machinery maintenance management wishing to go above and beyond minimum class requirements. The following planned maintenance schemes are available for LR classed ships as part of the Continuous Survey Machinery (CSM) cycle (ShipRight, 2019):

- MPMS (Machinery Planned Maintenance Scheme)
- MCM (Machinery Condition Monitoring)
- MCBM (Machinery Conditioned-Based Maintenance)
- RCM (Reliability Centred Maintenance).

MCM, MCBM and RCM descriptive notes are comprehensive and require some form of data collection and analysis. For example, Figure 2.7 provides a general layout of the LR-MCM framework.

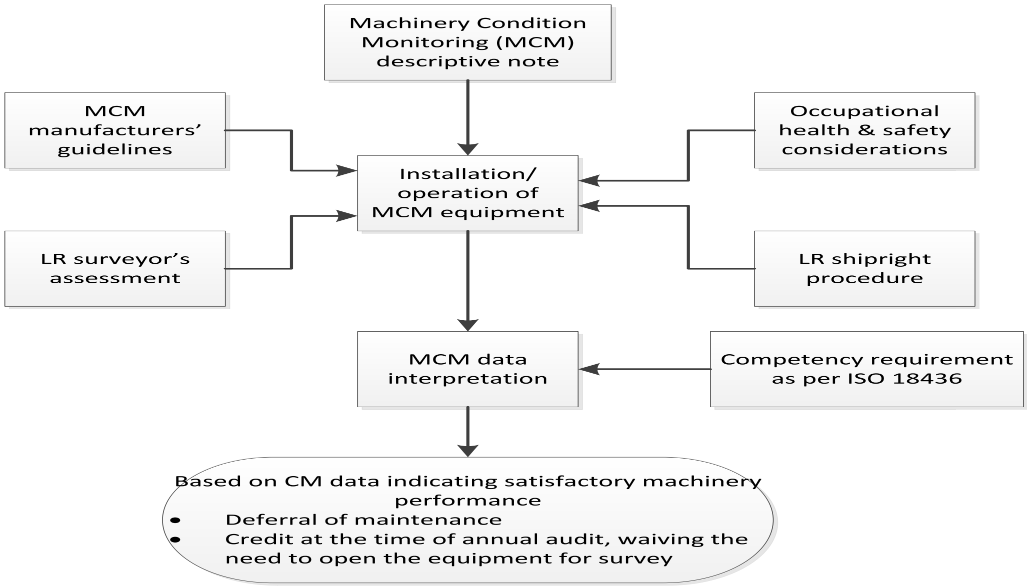


Figure 2.7: Generic layout for LR MCM descriptive notation

The ship operator needs to submit the MCM plan to the class society for approval. The condition monitoring needs to fulfil various procedural and safety requirements imposed by class and equipment manufacturers. Moreover, data from the Condition Monitoring (CM) equipment needs to be interpreted/verified by an ISO 18436 (2014) qualified professional. The advantage for a ship demonstrating the satisfactory condition of its machinery equipment through CM results is that it can be eligible for time credit at the annual survey, avoiding intrusive machinery inspection (ShipRight, 2019). The operator may decide the number of machines included in the scheme; the remaining items not subject to condition monitoring are dealt with under MPMS/CSM.

A more comprehensive and resource intensive descriptive note is RCM. Various studies have been performed to demonstrate the suitability of RCM as a maintenance management methodology in the marine context – notably proposed by Wang et al (2010).

Figure 2.8 shows the distribution of LR-classed ships on various maintenance management schemes.

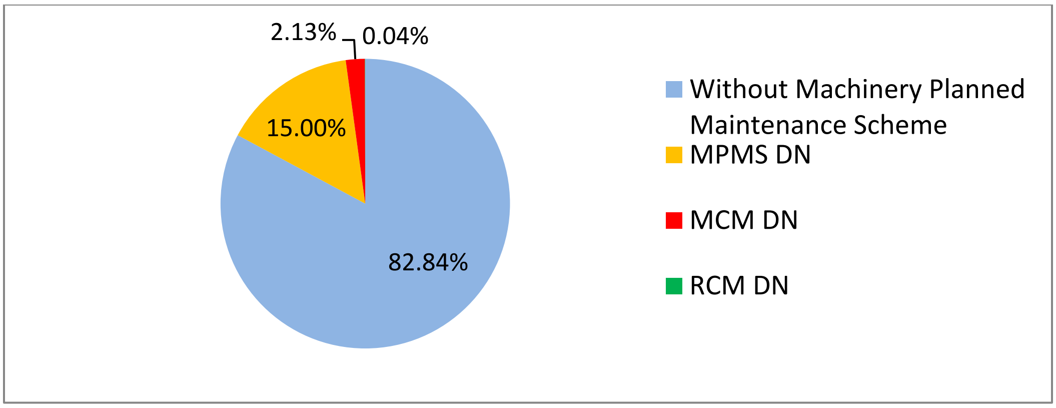


Figure 2.8: Percentage distribution of LR-classed ships on various descriptive notes
Source: ShipRight (2015)

The results indicate that just around 2% of LR-classed ships utilise condition-based monitoring and maintenance schemes. Interestingly, no LR-classed commercial ship utilises the RCM and MCBM descriptive notes. Only a few LR-classed naval ships employ the RCM methodology for onboard asset management. There could be various reasons for this low take-up of MCM, MCBM and RCM descriptive notes, such as:

- Application of MCM, MCBM and RCM descriptive notes is considered resource-intensive (Panić, Ćelić, and Cuculić, 2018), coupled with the level of redundancy in ship machinery systems, making it difficult for commercial ship operators to present a business case to implement more advanced maintenance management strategies.

- Apparent lack of condition monitoring and maintenance management application expertise available in the maritime sector.
- Potential benefits have not been fully realised by various stakeholders.
- Cost benefits of condition monitoring and condition-based maintenance have been documented through various studies and projects; however, scepticism remains over the professed numbers.
- Embedded conservatism of the marine industry. Moreover, this is a kind of paradigm shift for an industry used to prescriptive rules – "tell me what to do" – to a goal-based approach – "tell me what to achieve".

Nevertheless, there is an increasing focus on combining the salient features of descriptive notes with the digital product solution portfolio to utilise the prevailing opportunity in data transfer, sensor technology and machine learning.

Other transport modes and power-generation sectors have witnessed a tremendous uptake of condition-based machinery management processes, diagnostics and prognostics over the years, prompting the International Organisation for Standardisation (ISO) to publish an international standard setting out principles and guidelines for a condition-based maintenance/monitoring programme. Figure 2.9 provides an overview of the ISO 17359 (2011) "*Condition monitoring and diagnostics of machines – General guidelines*" standard and the typical steps involved in establishing the machinery system's condition-monitoring process.

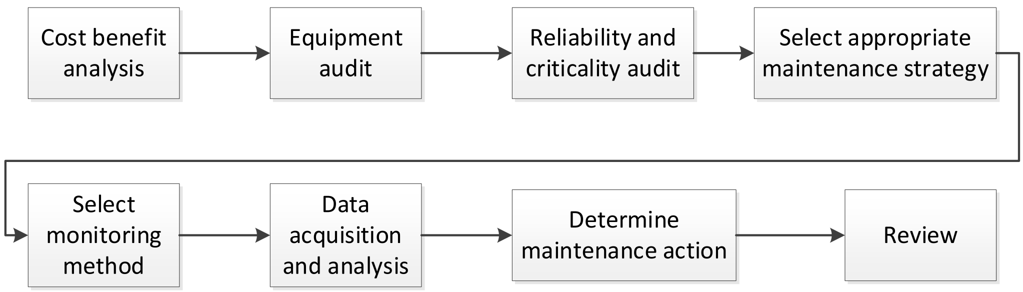


Figure 2.9: An overview of the condition monitoring process
Source: ISO 17359 (2011)

This standard forms the basis of various maintenance management methodologies for machinery equipment. LR refers to the principles described in ISO 17359 (2011) for their MCBM (Machinery Condition-Based Maintenance) and RCM descriptive notes to facilitate ship operators in complying with and exceeding the requirements for class rules on machinery maintenance (ShipRight, 2019).

2.2 Condition assessment of marine diesel engines

The most critical asset onboard ships is an LS2S engine installed as a prime mover. As described in section 1.2, these engines carry several advantages such as excellent efficiency even at low load, capacity to burn low-grade fuels, and a simple shafting arrangement due to reversible and variable speed operations. However, engine failures are not uncommon due to a lack of condition based assessment and subsequent maintenance decision making (Espadafor et al., 2014), resulting in high costs of unplanned maintenance. Hence, there is a need to better understand how marine diesel engines are assessed during operations for performance, fault identification and maintenance requiring a review of the following key aspects:

- Review of scientific work in the academic sphere
- Review of conventional engine monitoring practices
- Review of engine designer guidelines on condition assessment.

2.2.1 Review of the literature

A systematic review is needed to effectively assess the research performed in the field of marine diesel engine condition assessment and monitoring. Hence, a process used by Wang et al (2020) has been adopted. The approach generally follows the pattern shown in Figure 2.10.

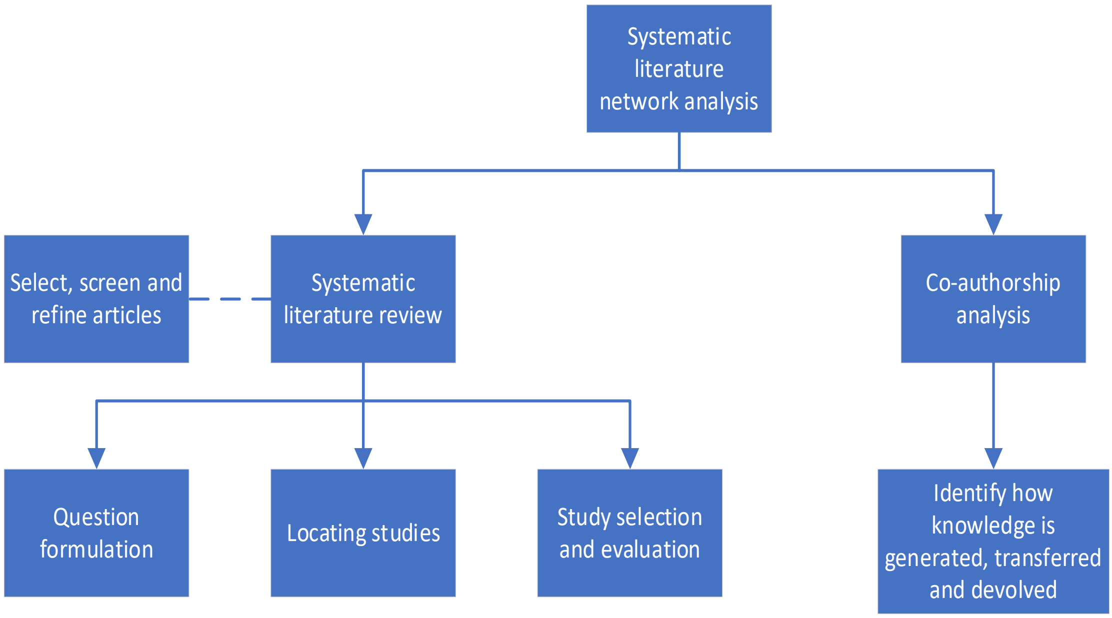


Figure 2.10: Systematic literature network analysis
Source: Wang et al (2020)

The process is mainly comprised of a systematic literature review and co-authorship analysis. For this study, the objective is to review the advantages, disadvantages and suitability of the various engine condition assessment techniques applied to the marine diesel engines, hence co-authorship analysis has been excluded to manage the scope. The systematic literature review is comprised of three main aspects, i.e. question formulation, locating studies, and study selection & evaluation.

As a first step, the researcher formulated the question, keywords or main theme of interest. To limit the number of search outcomes, only a couple of keywords are carefully selected, which are ‘condition monitoring’ and ‘marine diesel engine’, to sufficiently capture the field of interest. The second step is the identification and selection of a research platform to locate the studies. ‘Web of Science’, which contains the world’s best scientific and technical research articles, has been selected as the search engine. The two keywords are combined with the AND operator by selecting ‘Topic’ as the field of search.

The results produced 104 articles and proceedings papers from 1971 onwards. To ensure quality and relevance, papers published in peer-reviewed journals were retained as that type of journal is respected in the scientific community. Applying this criterion reduced the number of papers to 62 relevant papers. It was observed that almost 80% of the selected papers were published in or after 2010. Thus, papers published before 2010 were excluded, and further applying the additional criterion of selecting papers only published in English reduced the number to 46. These 46 papers were thoroughly screened and reviewed and out of that four papers were further excluded because they were primarily relevant to marine fuel production and its impact, reducing the number to 42. The distribution of the reviewed papers based on the publication year is shown in Figure 2.11, indicating significant work in the last decade, and, out of these papers, almost 50% have been published in the last three years. There are only two papers in the year 2021 because this part of the literature research was conducted at the beginning (February) of 2021.

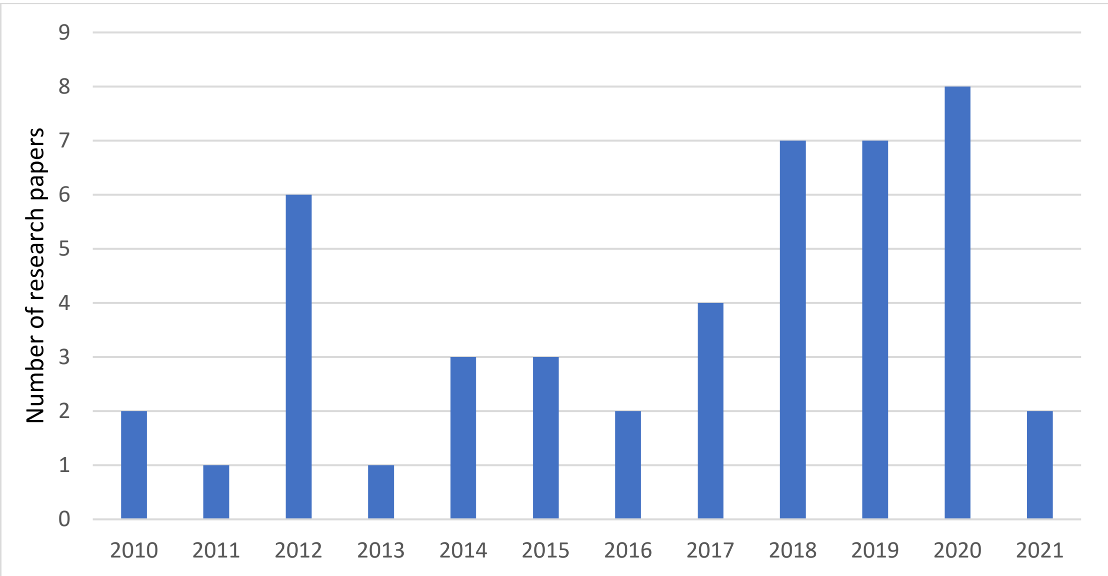


Figure 2.11: Distribution of papers by year of publication

These articles mainly originate from Europe and Asia, as per Figure 2.12. The majority of the Asian (around 80%) articles are from Chinese universities and institutions, which shows the popularity of this research area in the country. The work in Europe is evenly distributed in various countries, such as Spain, Poland, the UK, Greece and others.

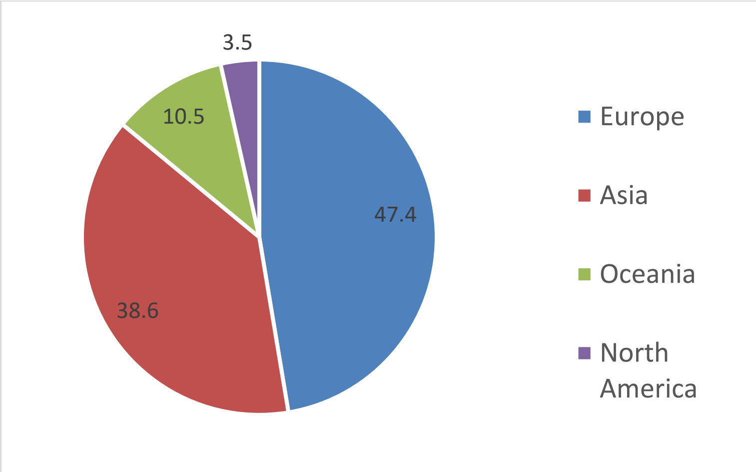


Figure 2.12: Distribution of articles by geographic location

A further point of interest is to evaluate the distribution of research activity in condition monitoring of medium/high-speed engines compared with the low-speed engines used in maritime operations. Figure 2.13 shows that the majority of the papers (around 60%) address medium/high-speed four-stroke engines whilst 30% discuss the various condition assessment methodologies for the LS2S engines. One of the potential reasons for this distribution could be the higher failure rate of the medium-speed marine engines, as shown in Figure 1.8.

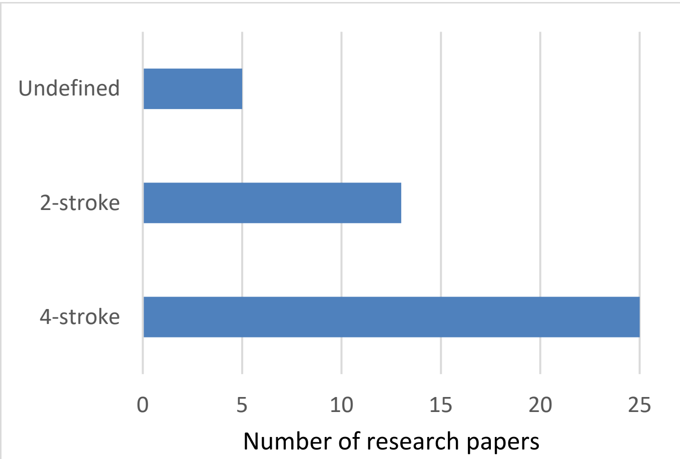


Figure 2.13: Categorisation of papers based on engine type

There were a few papers where the term marine diesel engine was used without defining the engine type. Moreover, one paper specifically developed a methodology applicable to both two- and four-stroke engines.

The papers are further distributed at component/system level, as shown in Figure 2.14, which shows that around 60% of the papers target a particular component or system such as fuel, lubes and combustion whilst the rest, model the engine's general operations.

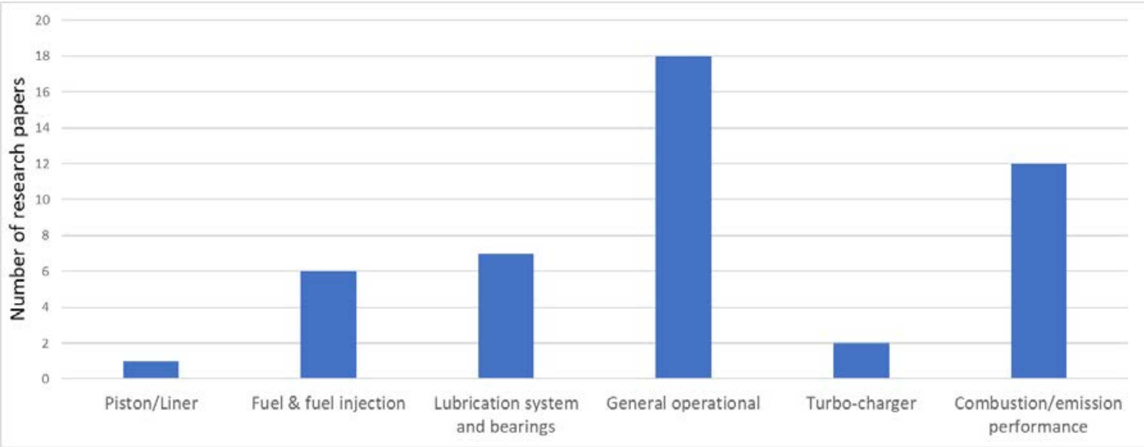


Figure 2.14: Distribution of papers addressing engine component/system level

Lastly, these papers have been distributed based on the type of data source used, as shown in Figure 2.15.

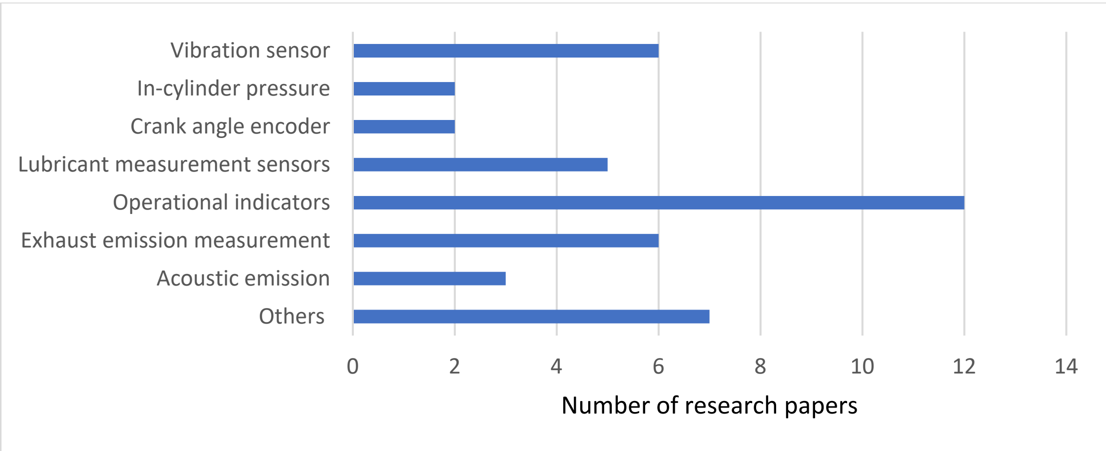


Figure 2.15: Distribution of data source

The graph shows the extensive use of sensor technology in condition monitoring of marine diesel engines, especially at the research phase. Similarly, around 28% of the research articles suggest the use of operational parameters for engine condition monitoring.

Apart from the abovementioned points, there are a couple of general observations as follows;

- There is an apparent lack of research on low-speed two-stroke engine performance assessment compared to four-stroke engines.

- The recent research focus has been on the trials of sensor technology in engine fault diagnosis however some of the research fails to take a holistic view of the system and interdependencies of the operational parameters.

2.2.2 Conventional monitoring methods of LS2S engines

On a traditional ship, engine performance monitoring is performed through temperature and pressure gauges and associated control system (Lamaris and Hountalas, 2010). Based on a parameter's criticality, specific temperature, flow or pressure is also measured through sensors sending signals to a central engine control room. Specific OEM or user-defined limits are applied on various systems to alert the engineers onboard. Figure 2.16 provides a flowchart describing a generic monitoring process of key LS2S engine performance parameters.

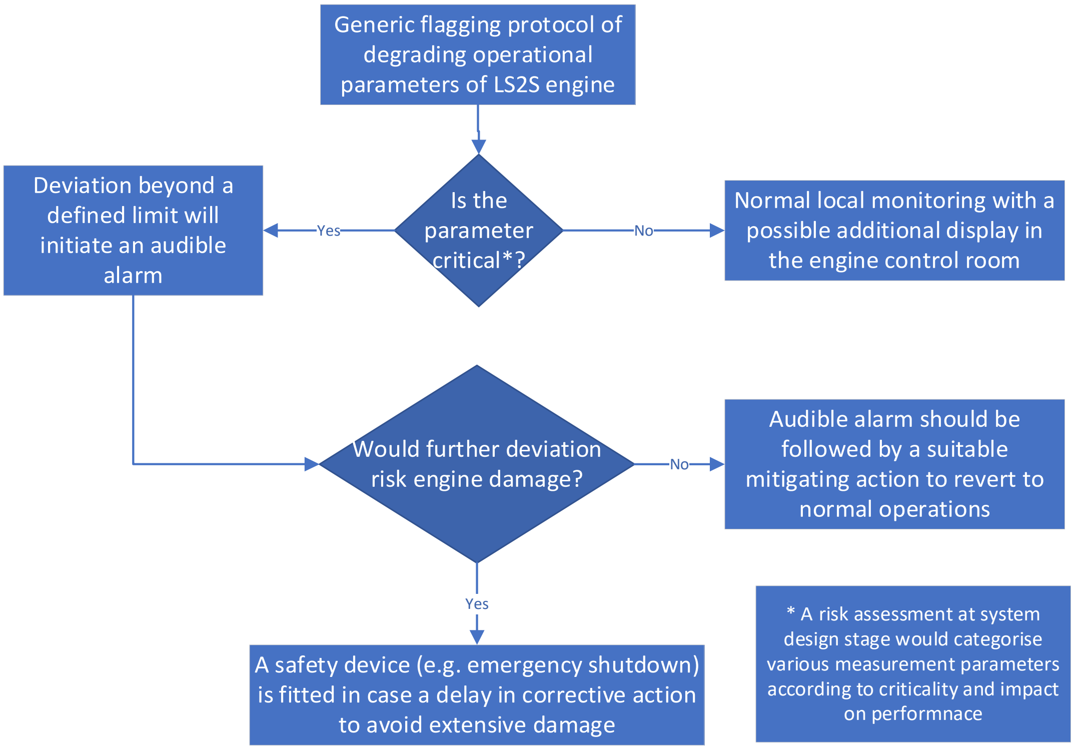


Figure 2.16: Machinery key performance indicators measurement flowchart

For example, system lube oil pressure is a critical parameter and lubrication failure has been considered by the Swedish Club report on Hull and Machinery claims to be the most expensive cause of damage to the engine (The Swedish Club, 2018). Suppose the typical system lube oil pressure for an LS2S engine is 4 bar. If the pressure reaches 3.7 bar, an alarm is sounded, initiating engine slowdown after a delay of 60 seconds. If the pressure remains low, the engine is shut down after a further 90 seconds. This safety feature is integrated into the engine’s control system to avoid triggering a catastrophic chain of events if there is a loss of hydrodynamic lubrication in the engine’s bottom-end and cross-head bearings.

Similarly, monitoring the combustion performance is one of the critical areas to ensure smooth engine operations. There are several pressure and temperature measurement locations for local and remote monitoring of the engine (Griffiths, 2006). Moreover, some of the newer engine designs have devices installed to continuously monitor the cylinder peak pressures and the Mean Indicated Pressure (MIP) from each cylinder. This information can be very useful in power balancing the engine for better operation and reducing fuel consumption. However, these are separate pieces of information/data which need to be viewed holistically to form an opinion about the engine’s health and diagnose any incipient failures, which can be a challenge.

Alongside these measurement devices, staff onboard also rely on their engineering knowledge and experience to diagnose/monitor machinery performance through visual inspections, unusual sounds and vibration levels (Chell, 2007). It is imperative for competent engineers to make decisions based on the available data and their cognitive abilities. Ship staff utilising the latest tools and methods in parallel with the engineering knowledge and skills would improve the early detection of operational problems.

Shipowners and operators tend to rely on engine manufacturers for guidance and maintenance decision making. Generally, engine maintenance manuals suggest fixed time maintenance, which is carried out at specific fixed intervals; however, it has been realised that replacing a machinery component after its prescribed number of ‘running hours’ is not an optimum use of resources. For example, MAN-ES issued a service letter, SL12-552/HWC (MAN-ES, 2012), stating that opening-up main engine bearings for the survey is expensive, time-consuming and carries the risk of damage by disturbing a bearing that is performing well. Dirt, debris and mistakes during reassembly can lead to damage. The engine designer encouraged the use of a condition monitoring system instead.

Figure 2.17 provides an overview of the performance management tools usually available to onboard engineers operating an LS2S engine.

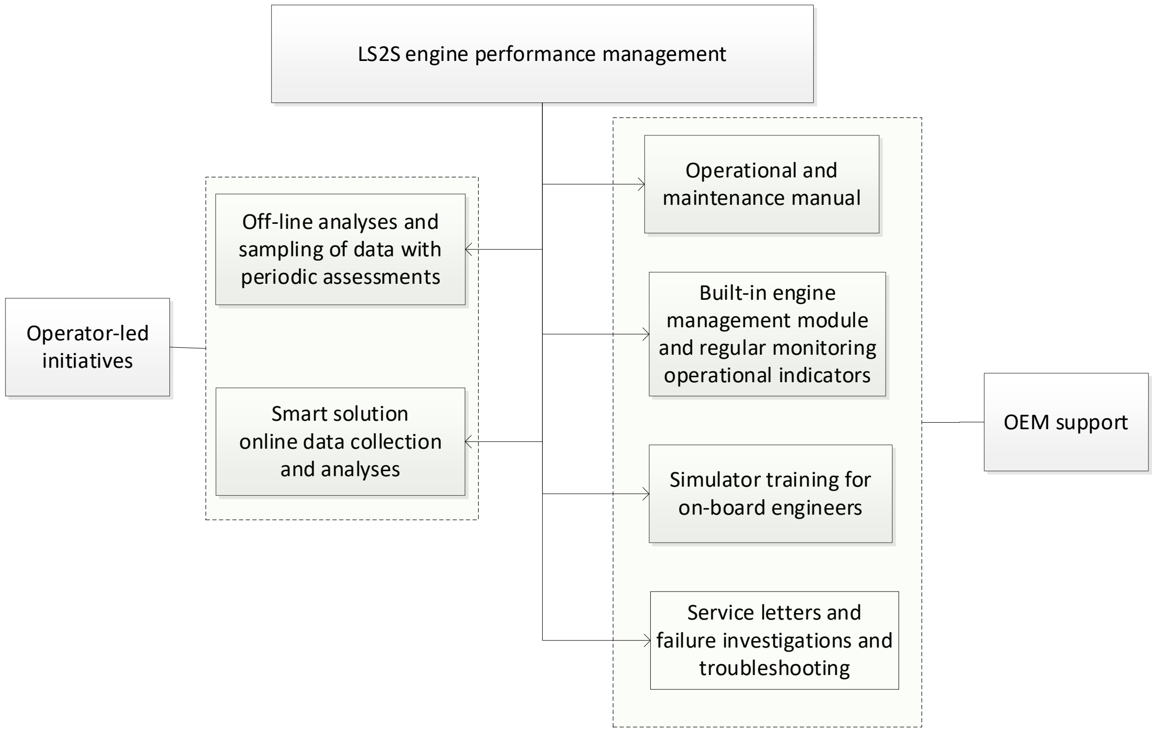


Figure 2.17: Performance management of LS2S marine engines

Generally, the performance management is split into two broad categories, i.e. OEM support and ships' operator-led initiatives. The following two sections further describe these aspects.

2.2.2.1 Engine manufacturers

It is important to note that LS2S engine designers and engine manufacturers/builders are not the same in the maritime context. MAN-ES, WinGD and J-Eng are engine designers and, due to the majority of the large-scale ship building shifting to the Far East (Japan, South Korea and China), the engine designers have given licenses to the local ship builders in major ship-building hubs in these countries to manufacture the LS2S engines (MAN-ES, 2021; WinGD, 2021a; J-Eng, 2021). Hence, the same engine model, type and size can be built in various countries as per designer specifications. Each engine builder has their own quality assurance procedures; on top of that they strictly follow the engine designer specifications. Hence, the LS2S engines, when new, are under warranty from the engine builder and not directly from the engine designer.

Moreover, a number of after-sales support activities are also performed by the engine builder in collaboration with the engine designer. Traditionally, such support comes in the form of engine operations and maintenance manuals to provide essential guidance for a planned maintenance system for the LS2S engine. Similarly, the OEMs have designed a few pre-emptive methods to monitor the engine's critical performance aspects and improve diagnostic capability. The data received from these tools can be used for maintenance action planning. Introducing new engine design features to onboard engineers by conducting training courses forms a vital support mechanism for ship operators.

Overall, the support extended by the engine designers to ship operators to monitor the engine performance covers most bases, yet the ship operators might want to do more in this area and further seek support from independent third-party consultancy services.

2.2.2.2 Independent performance analyses

To further improve the asset availability, reliability and performance, few ship operators choose to seek support from independent consultancies and CM equipment manufacturers. Various methodologies are employed which generate performance data and corresponding trends through sensors or offline information and sampling. By processing the data, practical actions to improve the performance are fed back to the ship. However, implementing these practical actions requires caution and should be complemented by counter checking whether the machinery in question shows symptoms of the issues highlighted in the shore-based reporting tool, as there is the possibility of faulty sensors and poor sampling, which can mislead the diagnosticians and experts, causing them to reach an incorrect conclusion.

2.2.2.3 Summary of research gaps

The research indicates that the LS2S engine is the prised onboard asset with distinctive propulsion advantages such as simple operation and design. Nevertheless, LS2S engine failures are not uncommon so when and if a failure occur, that could cause significant safety and economic implications. The statutory and classification frameworks usually address high level safety of the machinery and without going into the precise guidance on performance and maintenance methods to be applied and left to ship operators. This leaves a practical gap for ship operators to fill through proactive asset management.

The literature review conducted during the course of the study indicates an apparent lack of research on low-speed two-stroke engine performance assessment compared to four-stroke engines. Moreover, many studies addressing the issue of marine engine health management consider only a limited number of parameters, so the work needs to be expanded to integrate more health indicators for better diagnostic and predictive assessments (Wang, Chen and Guan, 2021). Finally, the recent research focus has been on the trials of sensor technology in engine fault diagnosis however some of the research fails to take a holistic view of the system and interdependencies of the operational parameters.

The following section further expands on the need of the research and proposes a way forward.

2.3 Research justification

The literature review performed in section 2.2.1 found numerous studies encompassing the performance assessment of various fuels and emission measurements from marine diesel engines; however, there appears to be insufficient literature addressing the operational health of the LS2S engine by taking a wide-ranging health parameters as the basis.

For example, Kökkülünk, Parlak and Erdem (2016) evaluated the power drop and increased fuel consumption in an LS2S marine engine by investigating the operational parameters of scavenge air pressure/temperature, fuel injection timing/pressure and compression pressures. However, the study was unable to address the impact of cylinder lubrication, fuel quality and maintenance level in evaluating degradation and increased fuel consumption.

From the practical aspect, research also indicates that the marine industry, in general, is not at an advanced stage of adopting condition-based maintenance decision making, and still relies heavily on traditional time-based maintenance and reactive actions in case of an unexpected failure. Moreover, the pace of adoption of new CM methods is slow (Panić, Ćelić, and Cuculić, 2018), indicating a conservative approach towards change. This mindset appears to suggest that ship operators need facilitation and guidance to fully realise the benefits before a commercial decision is made to invest in innovative system design, process or equipment.

Nevertheless, independent consultancies like LR's *i4 insight* (www.i4-insight.com) provide the support services whereby sensor-generated data streamed to shore-based data warehouses is processed and analysed. This process can identify the issues and probable solutions, directing the ship's resources to where they are needed most. Moreover, the reliability of sensors have also been questioned. For example, in an attempt to assess engine cylinder pressures, Wang, Chen and Guan (2021) have argued that direct pressure sensors are prone to defects hence they relied on engine angular speed measurement as feature extraction tool for cylinder pressures. Table 2.1 compares some of the pros and cons of using such systems.

Table 2.1: Brief evaluation of online condition monitoring

Advantages	Disadvantages
• Evaluation of incoming data by shore-side condition monitoring system/experts with exposure to similar data is likely to help in more accurate diagnosis and prognosis for machinery equipment. • Reduced annual Operational expenditure due to optimised use of resources.	• Faulty sensors producing erroneous information, which may lead to an incorrect condition assessment • Reliance on satellite data streaming and communications • Cyber security risks (MAN-ES, 2020a) • Taking the maintenance decision-making responsibility away from the ship's staff may induce a sense of unaccountability and loss of interest. • The initial cost of sensor installation may be high.

Moreover, there is a hybrid approach where data collected from a ship is sent ashore where subject matter experts analyse it in an offline format. The data is evaluated and sent back to the ship's staff, where it is further discussed, obtaining tangible feedback by involving them in the decision-making process. The model proposed in this study is based on a similar concept. This would entail ships sending various samples (fuels, lubes & cylinder drain oil) with main engine operational data at the time of sampling. The samples are analysed in the lab, and the data evaluated and processed through a computational model which determines various aspects of the engine performance. The resultant recommendations are then sent to the ship staff for further feedback and implementation.

2.3.1 Characteristic analysis of the research

The research performed in this study has three key challenges as follows;

1. Collection of data and its quality
2. Complexity and uncertainty of engine operations
3. Model validation through onboard application.

The issues related to the collection of data and its quality has been briefly highlighted in section 3.2.4. The required operational data for specific performance aspects of LS2S engine was unavailable through a single source. Primarily, researcher used the data generated from his workplace business stream detailed in chapter 3 and 4, yet there were gaps which were filled through seeking 'expert judgements' from a panel of industry experts.

Secondly, the LS2S engine performance assessment require deep understanding of the combustion/ignition behaviour of various fuel types, interaction of cylinder lubricant with the combustion products, tribological behaviour of the lubricant under stress, engine settings, quality of fuel and lubricant and so forth. One of the key feature of the research is pre-assigned dependency analysis of various interlinked operational factors of a large two-stroke engine. To perform this function, either data is relied upon or expert judgements have been used to establish relationships in quantitative terms.

The model is validated through the sensitivity analysis in chapter 3, 6 and 7 and case studies. However, to demonstrate the model functionality, it is imperative that the model is actually applied to the ship operations. A practical approach has been proposed in section 7.6.

2.4 A proactive engine performance management framework

This study proposes a new approach from a widely applied LS2S engine management method to a proactive approach, as shown in Figure 2.18.

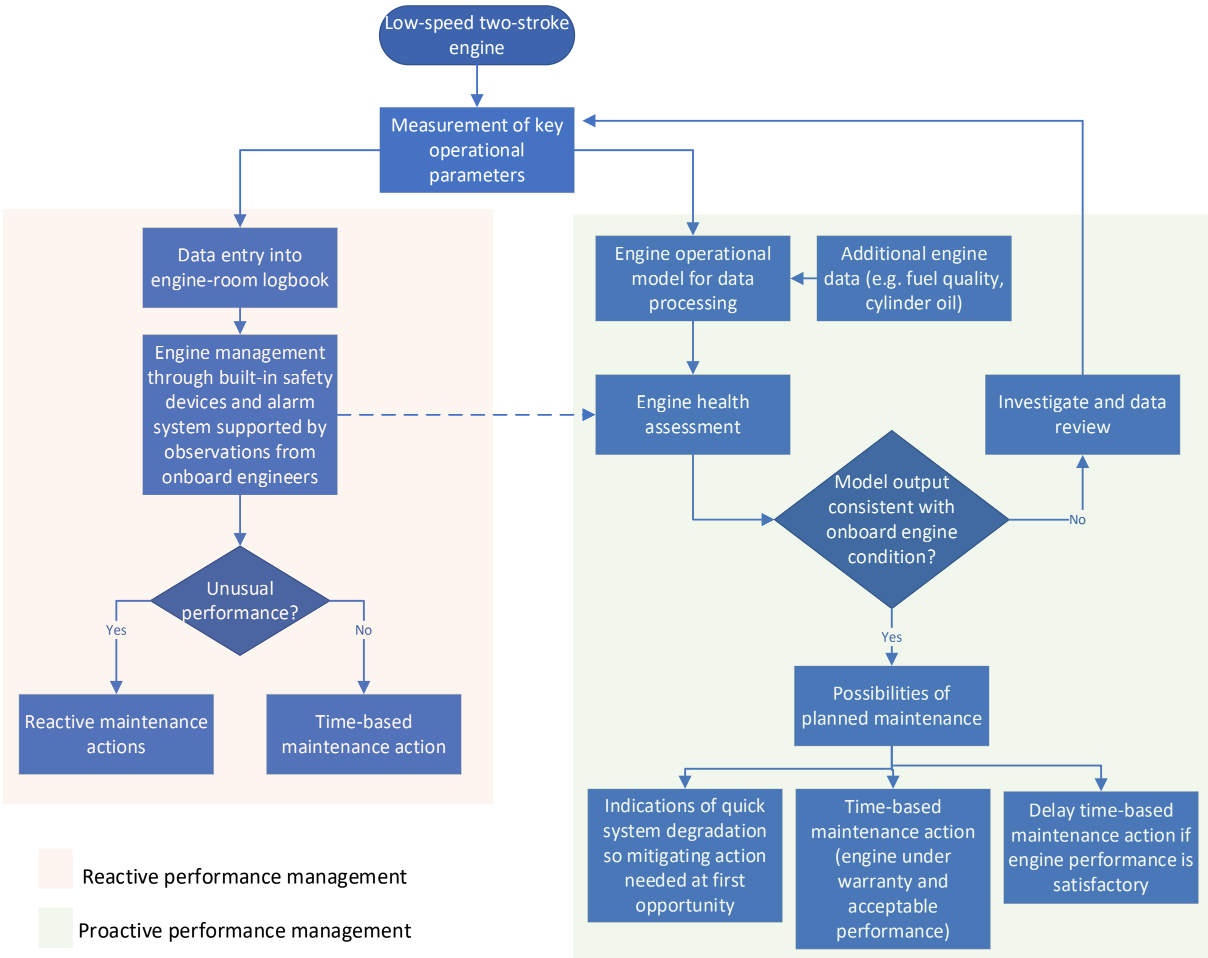


Figure 2.18: The proposed approach for the LS2S engine performance management

Conventionally, the ships collect critical LS2S data, and this is entered into the engine room logbook followed by a review from onboard engineers or the technical superintendent. However, mainly, the collected data is not viewed holistically; hence there is a risk of an oversight in detecting a failure-in-progress. If the engine is operating without any apparent issues, then time-based maintenance actions are planned, otherwise an emergency maintenance action needs to be performed. This approach is likely to be uneconomical and not the best use of resources. On the right of Figure 2.18 (shaded green) is a proactive approach which has the following salient features:

- Easy to use an offline system to enter engine operational data which produces a quantified engine health factor.
- Incorporates a validation phase, i.e. an onboard review would be needed if there is a discrepancy between model output and actual engine performance.
- Allows the ship to possess a better diagnostic capability hence reducing the risks of emergency repairs.
- Three planned maintenance options to choose from: i) planned maintenance at the first available opportunity in the case of quickly degrading performance, ii) the ship can still choose a conventional time-based maintenance action as per OEM guidelines or iii) a decision to delay the planned maintenance action as engine performance is satisfactory (though this may require a no-objection from stakeholders such as engine manufacturer and ship classification society).

The kernel of this approach is the requirement of additional data (such as fuels and cylinder drain oil) and an intelligent engine model with quantitative output.

There are various facets of engine operational performance that need to be assessed separately or collectively to create an engine's overall performance profile. Figure 2.19 lists a comprehensive list of operational data points split into ‘Direct measurements’ and ‘Calculations & observations’. These 36 parameters has been extracted from the MAN Service letter (MAN-ES, 2014b) and sample submission form used for the FOBAS Engine Assessment Programme (FEAP, 2017).

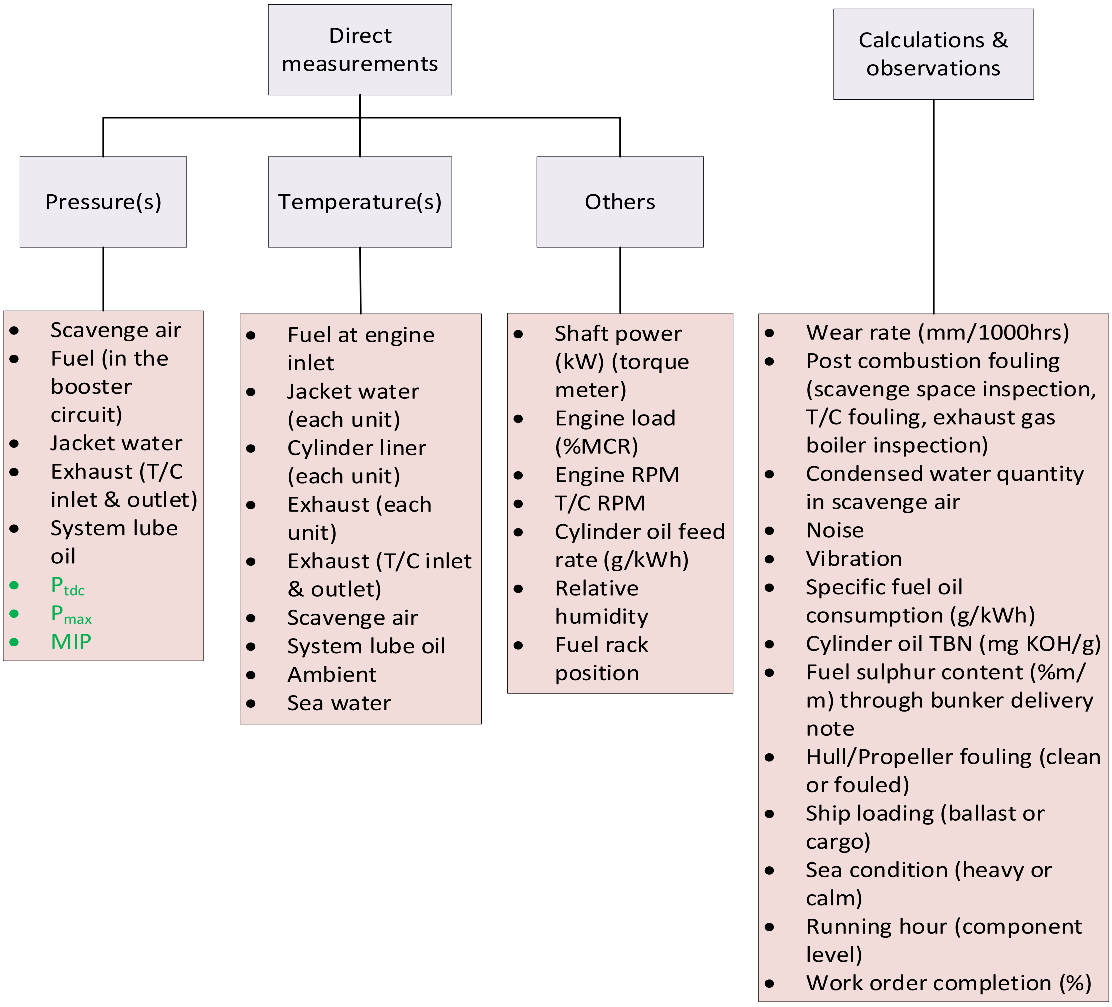


Figure 2.19: Key LS2S engine operational measurements and observations

The direct measurements have been divided into three categories, i.e. pressure, temperature and others. Capturing the parameters listed under direct measurements into the engine room logbook is an everyday watchkeeping practice. Similarly, some of the indirect measurements and observations are routinely logged to assess the LS2S engine condition. It can be observed that three data points highlighted in *green* under the 'pressure' category of Figure 2.19, i.e. P_{comp} (Compression Pressure), P_{max} (Maximum Pressure during combustion cycle) and MIP (Mean Indicated Pressure), are not normal continuous measurement parameters for slightly older LS2S engine designs as these are taken with special equipment to draw power cards, peak pressures and compression pressures. Nevertheless, there are non-intrusive methods (Dong, Nguyen and Lee, 2020; Jafri et al., 2021) using an acoustic measurement technique which may improve the ability to monitor the in-cylinder pressures continuously with the right level of confidence.

This study utilises a combination of directly and indirectly measured parameters to develop the LS2S engine model. The selection process depends on the model's objective, which mainly revolves around two primary themes: i) cylinder component wear and ii) combustion and post-combustion fouling. The rationale for selecting a set of parameters out of 36 outlined in Figure 2.19 have been detailed in section 3.2.

However, it is equally important to reason why some of the operational parameters have not been considered. It is imperative to note the model objective in order to understand the rationale. Moreover, only key parameters are considered to avoid computations becoming intractable. Following paragraphs discuss some of the excluded parameters;

Fuel pressure – Sufficient fuel pressure in the booster circuit is important to maintain required flow rate and quantity to the engine especially during heavy fuel oil consumption. The injection pressure produced by high pressure pumps for the injectors ensures correct atomisation which is partly covered in the study through the review of the fuel quality and combustion conditions. Moreover, low booster circuit fuel pressure due to filter blockages or other similar reasons are coupled with the alarm system hence do not directly impact the engine performance.

Jacket water & liner temperatures – Huge variations in the liner temperatures between various cylinders impact the performance. In this study though, exhaust emission from individual cylinders have been considered to reflect each unit's thermal performance. Furthermore, it has been suggested that inclusion of this parameters in future studies would benefit to improve the model sensitivity and precision in predicting LS2S engine performance.

System lube oil pressure & temperature – In LS2S engines, the function of system lube oil is relatively different compared to a four-stroke engine where it also comes in contact with the combustion products. In LS2S engine, the system oil remains relatively clean due to cross-head construction. Hence this parameter is excluded because it does not have a direct impact on the combustion performance and also if there are issues with the lube pressure then a very sensitive alarm and engine shutdown system is incorporated to protect the asset. Although lube oil thermal degradation is not unlikely as lubricant also functions as piston cooling agent in most modern engine types which require close monitoring.

Engine load (and RPM) – This aspect has been indirectly considered through 'engine settings' and parameters such as scavenge air pressure which depends on the engine load. Greater the load, higher will be the operational pressures and temperatures of the LS2S engine.

Noise and vibration – Although there are onboard equipment available to measure the levels of noise and vibration, conventionally any noticeable variations can easily be observed by the experienced onboard engineers. Certain engines may be additionally fitted with vibration dampers for smooth operations. Vibration in itself is a complex subject as on a ship there may be numerous sources of vibration including engines hence to keep the model simple, vibration has not been considered.

Specific fuel oil consumption (SFOC) – To calculate the SFOC, additional pieces of measurement equipment are needed i.e., torque meter and fuel mass flow meter. Most ship are not installed with such equipment although this can be a useful indicator to determine the engine performance. Moreover, SFOC is predominantly an indicator of engine’s operational efficiency which has been partly covered through determining the level power output optimisation, hence not been considered.

2.5 Conclusion

The literature review indicates that 84% of the ocean-going ships greater than 10,000 Gross Tonne are equipped with LS2S engines as the prime mover. The data indicates that these engines are relatively more reliable compared to medium-speed four-stroke engines; however, LS2S engine breakdown presents a grave concern such as loss of propulsion, which can be a critical safety issue during manoeuvring and in restricted waters and channels. Moreover, engine performance is intertwined with the ship operator’s onboard maintenance strategy. Data suggests that most ship operators do not utilise any form of condition monitoring method, and a time-based maintenance strategy dominates the marine industry. However, slowly, there is a move towards conditioned-based maintenance decision making.

The literature review identifies an opportunity where LS2S engine performance monitoring can be performed through readily available data. This practical model processes the information to produce a health assessment factor which can then be utilised to assist in the maintenance action planning to move away from a reactive to a proactive approach. Moreover, the same approach can be applied to other onboard machinery equipment for performance and maintenance management.

The following chapters explain the background, methodology and application of the model developed in this study.

3 A novel Bayesian Network (BN) model for LS2S engine performance assessment

The objective of this chapter is to develop an LS2S engine performance assessment model as part of the proposed proactive performance management framework (refer to Figure 2.24). A novel BN model is proposed to capture the complex relationship between various operational parameters, specifically the combustion performance of LS2S engines. This model not only intends to serve as an engine performance assessment tool but also due to its graphical nature, can also be a knowledge management platform.

This chapter has been divided into five sections. Section 3.1 describes the background, applications and key features of the BN models. Section 3.2 introduces the BN model for LS2S engines. In section 3.3, BN model validation and sensitivity analyses are performed. BN model application is demonstrated through a case study in section 3.4. Finally, the chapter is summarised in section 3.5.

3.1 Bayesian Network

The BN is based on Bayes’ theorem, named after Thomas Bayes. Bayes’ theorem was proposed in 1763 based on probability theory. BNs are models which combine knowledge representation in graphic form (shows the relationship of direct dependence) and probabilistic form, as highlighted in Figure 3.1. (Bouaziz, Zamani and Duvivier, 2013).

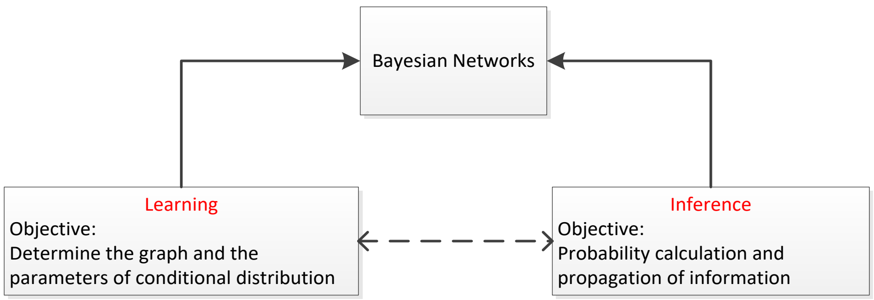


Figure 3.1: Generic BN for learning and inference
Source: Bouaziz, Zamani and Duvivier (2013)

The use of BN’s stochastic capabilities to solve real-world problems are wide ranging and multi-disciplinary from banking, medicine, robotics, geology, ecology and so forth (Pourret, Naim and Marcot, 2008). For example, Sohn and Lee (2013) used BN analysis to predict early-stage entrepreneurial attitudes, activities and aspirations and how these are affected over time. Ferreiro et al (2012) applied a BN to replace corrective maintenance with a predictive maintenance strategy and estimated the brake wear of an aircraft.

In the maritime domain quite a few studies have been performed on aspects such as navigational safety, reliability of structures and machinery equipment, and ship operational management as detailed in section 3.1.1. Some of these studies also compared the use of BN with other stochastic modelling methods and found salient BN features more promising. Manolis (2019) analysed historical data about marine traffic in the Aegean Sea using the BN model to improve safety. This study also considered linear regression and neural network as potential alternative methods to BN; however, it was found that linear regression and neural networks present 60% and 35% more computational error respectively compared to the BN model.

Moreover, Yu et al (2021) developed a collision risk evaluation model between ships and offshore installations using rule-based BN reasoning. The study developed conditional probability tables through a set of rules derived from objective data and expert judgements and compared the model output with the Fuzzy Logic Analysis. The study found that although the outputs from both the models are fairly consistent, the BN model demonstrates distinct benefits such as better sensitivity to minor change in risk, fast computing ability due to widely available software packages, and a user friendly interface.

Similarly, Bow-Tie models have been in use to identify hazards in risk analysis. Comparing this method with the BN, Khakzad, Khan and Amyotte (2013) highlighted that BN identifies common failures and also measures the conditional dependencies whereas the Bow-Tie method has shown limitations in assessing probability of failure. On other hand, BN is relatively complex and requires more expertise (Khakzad, Khan and Amyotte, 2013).

Moghaddam et al (2019) analysed the efficacy of various mathematical models including BN and Artificial Neural Network (ANN) to forecast the groundwater levels in aquifers. Out of those, BN was found to be most accurate predictive model.

Further description of the advantages and limitations of the BN will be provided in section 3.1.2.

3.1.1 Previous research

This section presents a few research applications of the BN in the maritime domain.

Yu et al (2020) presented a novel BN learning model integrating with the Evidential Reasoning (ER) approach to develop ship collision avoidance model near offshore wind farms. The researchers of the study were faced with the problem of limited historic data rendering conventional quantitative risk analysis methodologies impractical. Moreover, a data driven model was needed which can effectively handle multiple data sources of automatic identification system, expert judgements, and historic data. ER was used to process the expert judgements whilst BN learning was an overarching platform to effectively manage the multiple data sources.

Abaei et al (2018) proposed a novel BN methodology integrating hydrodynamic analysis to perform reliability assessment of marine floating structures controlled by mooring lines. The study indicates that due to the stochastic nature of the maritime environment, a probabilistic assessment model such as BN is better for inspection and monitoring of the systems. Moreover the research reviewed a few traditional methodologies and found BN as efficient and more promising.

Similarly, Baksh et al (2018) performed a comprehensive safety assessment by considering risks such as collision, grounding and floundering of ships navigating through the Northern Sea route. The study discussed various maritime accident models and risk assessment methodologies such as fault tree and event tree analysis however BN is preferred mainly because it is easy to update prior probabilities which is key in modelling accident scenarios.

Moreover, the BN developed in the above study is quite large comprising of 70 nodes/parameters which would have been a challenge to handle in other risk models. The study uses a combination of expert judgements and historic data to develop probability distributions for the five specific regions of the Arctic sea. The study performed a sensitivity analysis where variance in the prior probability of root nodes and corresponding variance on the target nodes was assessed which is useful for the risk analysis and decision making to focus on areas requiring particular attention.

Lazakis et al (2016) developed a reliability and availability assessment platform for various onboard machinery equipment including diesel engines using the BN approach. The BN model considered the probabilities of various failure modes associated with an LS2S engine and calculated the asset's subsequent availability. Although the study considers the inter-causal relationships that exist between various sub-systems and at the component level, the BN output does not fully reflect and take into account the engine's current operational health.

In the same vein, Wang, Chen and Guan (2021) provided the detailed review of various diagnostic models used for marine diesel engines and found that uncertainty quantification related to the engine’s operational conditions are not well addressed in the literature especially in the area of engine health assessment. The study proposed a BN inference based approach as a promising solution to address such a gap. The study used operational information under fault and normal conditions from a four-stroke medium-speed marine diesel engine as training and testing datasets. The study also found that for a larger system like a marine diesel engine with multiple influencing factors, it is impractical to predict an assets' end-of-life. However prediction may be relatively straightforward when considering small scale/standalone gears or a pump based on data. Moreover, the study uses a single indicator for prediction but suggested that future studies should consider multiple health indicators to improve the accuracy of the predictive performance assessments.

Overall, the above literature review shows the efficacy of the BN compared to few other tools used in the context of risk analysis, multi-criteria decision making, performance management, and predictive assessments covering wide variety of industry applications, in particular the maritime industry. Moreover, due to the distinct features of this study, i.e., large number of inter-dependent operational factors, uncertain and dynamic operating environment, handling of live data stream, bi-directional analysis requirement, need for a user-friendly interface, etc., requires a method which is capable of addressing these concerns effectively.

ANN has few similarities with the BN in terms of graphical representation i.e., it consist of three layers input, hidden and output layer (Moghaddam et al., 2019). Moreover, the ANN require large data to train the model which is not too dissimilar for BN however ANN has a limitation in terms of bi-directional analysis which can be performed through the BN.

The use BN as risk and uncertainty treatment method is not uncommon however there is a need to further exploit BN's capability in maritime machinery performance assessment and support predictive maintenance in maritime domain.

3.1.2 Advantages and limitations of the BN

Several studies (e.g., Khakzad, Khan and Amyotte, 2013; Uusitalo, 2007) have described the BN's advantages and limitations. A few advantages are briefly listed below:

- BN enhances the process by representing event scenarios visually and in a strictly logical way. The Graphical User Interface (GUI) thus improves the exchange of knowledge between experts and assessment teams and facilitates communication with non-professionals, leading to improved communication.
- Suitable for data analysis, especially under uncertainty.
- Suitable for small and incomplete data.
- Utilises causal relationship among knowledge, theories and hypotheses to build models.
- Makes structural learning possible.

- Provides a fast response and, technically, it is more robust than traditional tools.
- BN is able to handle large systems and associated variability.
- Can be applied to decision making and diagnostic purposes.

It has a few limitations, as follows:

- Incorporates expert judgement; however, it might be difficult for a group of experts to quantify a probability, especially those working with real or experimental data.
- Moreover, it requires more expertise than other techniques, such as fault tree analysis.
- A common criticism of the Bayesian approach is that it requires too much information in the form of prior probabilities and that this information is often difficult or impossible to obtain in risk assessment (Yang et al., 2008).

The studies also indicate that researchers need to pay attention to ensure unnecessary nodes or influencing factors are excluded which can potentially distort the results obtained and confuse the issues to be addressed. Additionally, the conditional probability data required for child nodes must not be irrelevant and substantiated wherever possible.

3.1.3 BN inference

There is a wide range of BN applications – medical sciences, criminology, linguistics, risk and safety assessment, and robotics are just a few examples. Creating a model is the first step to address any real-world problem (Pourret, Naim and Marcot, 2008). These models can be multifunctional and help evaluate, maintain, simulate, predict, diagnose and even make everyday decisions. On a more general basis, subject matter experts with knowledge and the data collected either from operations or observations can be combined to create a model to help stakeholders decide or take appropriate action, as described in Figure 3.2.

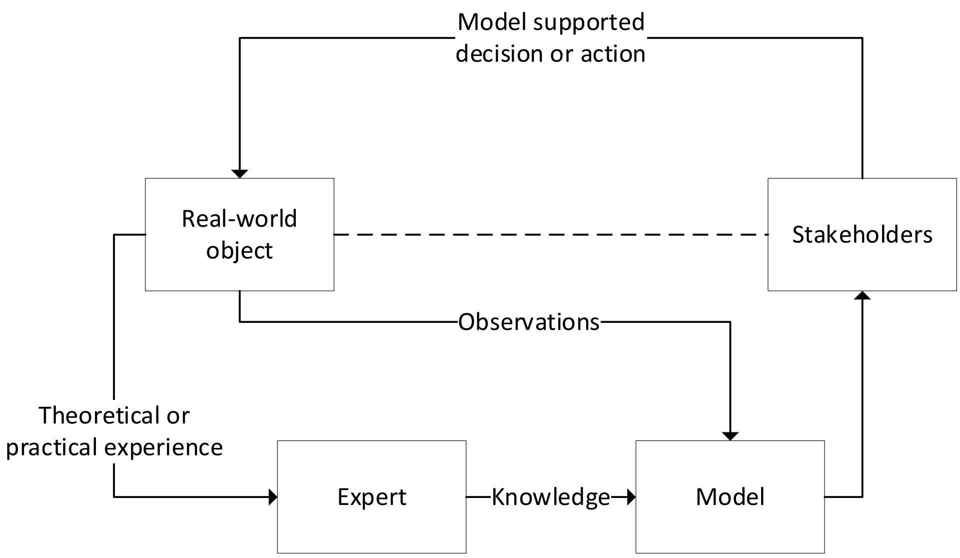


Figure 3.2: Construction and use of a model
Source: Pourret, Naim and Marcot (2008)

The BN inference process is based on input data and collected evidence put through an inference engine to integrate reasoning and establish causal relationships between various parameters. The reasoning can be a top-down or bottom-up approach, i.e. updating evidence from root nodes to leaves, and leaves to root nodes, respectively.

For example, marine heavy fuel oils from the South African port of Cape Town exhibit some unusual characteristics for parameters, like Micro Carbon Residue (MCR) and Calculated Carbon Aromaticity Index (CCAI). Based on the FOBAS (2020) data, typical MCR and CCAI values for Cape Town fuels are 16 mass %[1] and 860 respectively. With no prior information on the origin, four fuel samples were tested in the lab, as per Table 3.2, to determine which sample was more likely to represent Cape Town's fuel.

Table 3.1: MCR and CCAI results for general Cape Town fuels

Sample	Input data	Inferred information
1	MCR = 8 mass % & CCAI = 840	Fuel is not from Cape Town
2	MCR = 16 mass % & CCAI = 840	Fuel is unlikely to be from Cape Town
3	MCR = 16 mass % & CCAI = 860	Fuel is likely to be from Cape Town
4	MCR = 20 mass % & CCAI = 860	Fuel is unlikely to be from Cape Town

[1] ‘mass %’ represents the percentage by mass of a component out of total mass of the body (of gas, liquid or solid)

In the above example, there are some prior beliefs about the specific fuel characteristics from Cape Town. However, to determine whether the fuel samples tested in the lab have been sent from Cape Town or not, a probabilistic inference needs to be performed. Moreover, if the model is quantified with assigned probabilities, it improves confidence in the inference process.

To process the evidence and likelihood, a BN theorem is used. Alaei and Yazdizadeh (2013) expressed the theorem in descriptively, as below:

$$Posterior = \frac{Liklihood \ \times Prior}{Evidence}$$

Zhang et al (2013) represented Bayes theory by a parameter, 'γ', given observed (evidence), 'x', as follows:

$$P\langle \gamma | x \rangle = \frac{P(\gamma) P\langle x | \gamma \rangle}{P\ (x)}$$

Here:

"|" is a symbol of conditional probability

P (γ) describes the prior probability of γ

P ($\gamma|x$) describes the posterior probability of γ given the condition that x occurs

P ($x|\gamma$) is the likelihood distribution (occurrence probability of x given γ occurs)

P (x) is a normalising constant.

The Bayes theorem can handle multiple parameters (causes) given multiple observations (effects), e.g. for n observations $x = (x_1,\ldots, x_n)$ the posterior probability for γ is expressed as:

$$P\langle \gamma | x_1, \ldots, x_n \rangle = \frac{P(\gamma) P\langle x_1, \ldots, x_n | \gamma \rangle}{P\ (x_1, \ldots, x_n)}$$

An important BN inference feature is the model's ability to update as new evidence or data becomes available. Hence, the BN inference becomes quite useful for predictive analysis where direct measurements are unavailable or complex.

The BN is a specifically useful tool for qualitative and quantitative assessment under uncertainties. There are specific terms used when developing probabilistic modelling, and these are briefly described in Table 3.1.

Table 3.2: Important terms used in BN probability theory

Term	Description

Probability	Frequency of occurrence of an event (with values generally expressed between 0 and 1).
Conditional probability	A probability computed under the assumption that some condition holds.
Unconditional probability	A probability computed under the assumption that no condition holds.
Prior probability	A probability before a Bayesian update.
Posterior probability	A probability computed by a Bayesian update.
The likelihood of the evidence	One of the terms in Bayes' theorem: the probability of the evidence conditioned on a hypothesis.
Normalising constant	The denominator of Bayes' theorem, used to normalise the result to be a probability.

3.1.4 Qualitative features of BNs

The BN technique builds graphical networks known as Directed Acyclic Graphs (DAGs). Acyclic means such graphs do not have cycles; an example is chain graphs. These networks express dependence and independence statements. The BN supports deductive (causal), adductive (diagnostic) and inter-causal reasoning (Kjærulff and Madsen, 2005). The following example illustrates these types of reasoning through DAGs.

A ship's overall performance depends on numerous factors such as maintenance, leading to frequent machinery breakdowns and reputation loss if poorly managed. Similarly, an insufficiently developed Safety Management System (SMS) may have a similar impact.

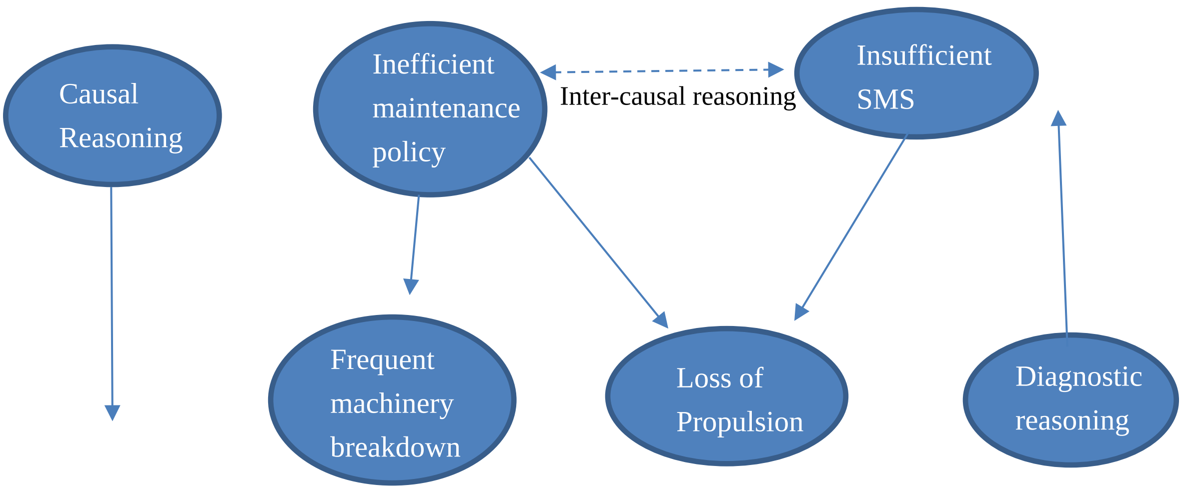


Figure 3.3: BN adductive, deductive and inter-causal reasoning

As shown in Figure 3.3, causal reasoning attempts to point towards the consequences that facilitate the prospective analysis. In contrast, diagnostic reasoning helps determine the root cause analysis or retrospective analysis and, finally, a graphical interface makes it easier to make inter-causal reasoning.

3.1.4.1 Types of nodes and arcs

Nodes describe system variables, whereas arcs represent the cause and effect relationship (Cai et al., 2012). The relationship between variables and arcs helps to pull together different kinds of cognition described as recorded knowledge, domain knowledge and expert opinion. Kjærulff and Madsen (2005) categorised three main classes of nodes, represented in Figure 3.4.

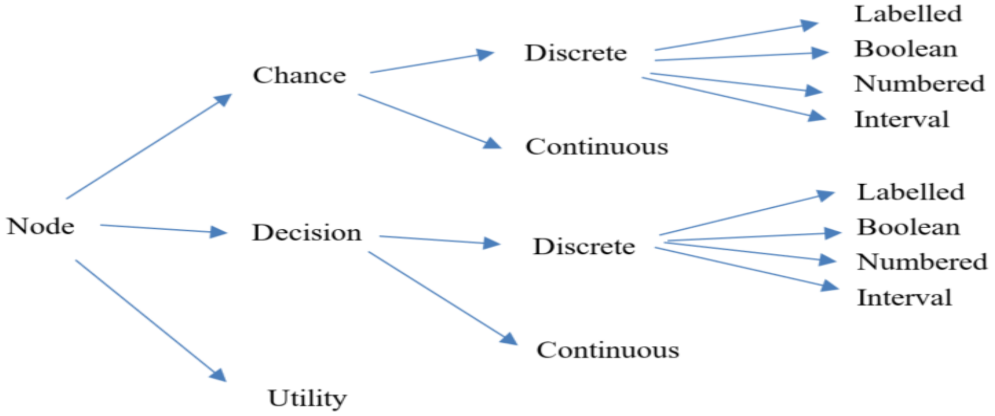


Figure 3.4: Taxonomy for nodes/variables
Source: Kjærulff and Madsen, 2005

There are nodes representing chance variables in a probabilistic network, nodes for decision variables, and utility functions. Chance and decision variables can either be discrete or continuous. Discrete nodes are further distinguished by the terms Labelled, Boolean, Numbered and Interval. Table 3.3 provides examples of each discrete variable.

Table 3.3: Discrete variables of each type of node

Labelled	Poor, Good, Excellent
Boolean	True, False
Numbered	1, 5, 9, 13
Interval	[10-15]

On the other hand, a continuous node would represent any variable with undefined boundaries.

From the graphical representation perspective, arcs are used to show the probabilistic dependence among 'parent' and 'child' nodes. Usually, an arc points from parent to child node. More specifically, a DAG with multiple nodes would contain root nodes, intermediate nodes and leaf nodes. Nodes without parents are described as root nodes, and nodes without a child are termed leaf nodes. A node with a parent and child node is an intermediate node.

A simple DAG of a parent and child node relationship is exemplified in Figure 3.5, showing a causal dependence between bunker hose failure and oil spill. Failure of the hose is a parent node (cause) and oil spill (effect) is a child node. For simplification, hose failure has been considered a root node, and the oil spill is a leaf node when assessed independently. The probability distribution of a child node is conditional, whereas the parent node has an unconditional probability.

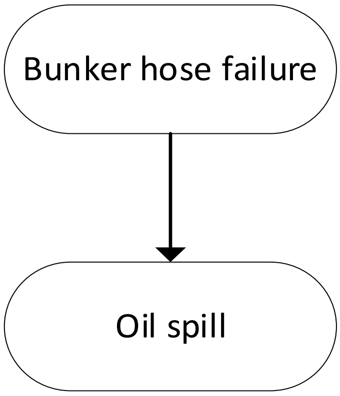


Figure 3.5: Parent and child node relationship

3.1.4.2 Types of connections

Dependence and independence properties of the joint probability among nodes are graphically represented by three primary causal connections (Kjærulff and Madsen, 2005). These are serial connections, diverging connections and converging connections (see Figure 3.6).

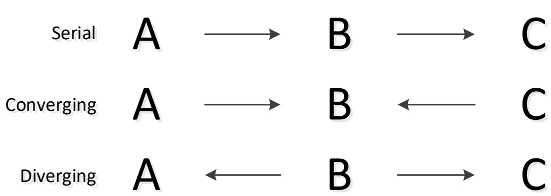


Figure 3.6: Basic causal connections

i) <u>The serial connection:</u> Figure 3.7 illustrates the serial connection with an example of a malfunction of the main lube oil pump resulting in low lube oil pressure in the engine, alerting the engineers through an alarm.

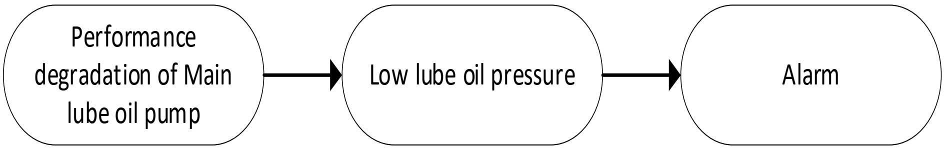


Figure 3.7: Nodes having a serial connection

ii) The diverging connection: This type of connection has been exemplified by a common operational issue, i.e. loss of fuel purifier seal (Figure 3.8). Loss of water seal (for water-seal purifiers) would trigger an alarm and initiate a shutdown sequence to ensure fuel is not lost to the sludge tank. In this case, the initiation of the purifier shutdown sequence does not influence the alarm and vice versa.

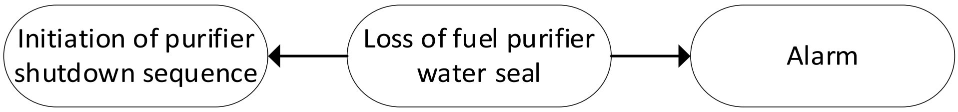


Figure 3.8: Nodes having a diverging connection

iii) The converging connection: Figure 3.9 indicates nodes having a converging connection where satisfactory fuel injector performance depends on the regular maintenance/overhaul of fuel injectors and the fuel quality in use.

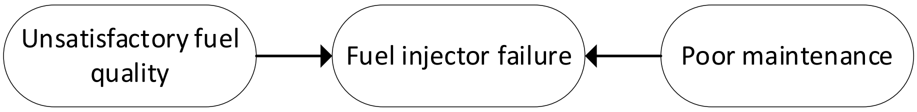


Figure 3.9: Nodes having a converging connection

However, with any DAG, the nodes and arcs required to exhibit logical connections and their links should be validated. The process is generally performed through applying the principle of direct-dependent separation (D-separation), which can be defined as two nodes, A and C, are D-separated (conditionally independent) to B if all paths from node A to node C are blocked (Pristrom et al., 2016). Given the three connection types described above:

For the serial connection (A → B → C), evidence can pass through from A to C only if B is not observed to be in a specific state. A similar concept applies to the diverging connection (A ← B → C), where evidence may pass through B if it is not observed. A and C are then D-separated by B. However, the converging connection (A → B ← C) is different from the above two cases as information does not flow from A to C if B is not observed. However, knowledge about B's state enables information to flow from A to C, making them conditionally dependent.

Let us consider the example in Figure 3.9, where a converging connection indicates that the fuel injector's failure is an observed event. Maintenance and fuel quality are the events impacting the fuel injector’s performance; however, if the injector failure is unknown, then there is not going to be any flow of information, i.e. both fuel quality and unsatisfactory maintenance are conditionally independent. However, suppose the fuel injector fails due to poor fuel quality. In that case, the conditional probability assigned to poor maintenance is significantly altered based on the new evidence that poor maintenance is unlikely to have caused the injector failure, which opens up the flow of information between these two nodes, i.e. poor maintenance and unsatisfactory fuel quality. The model created for this study has been D-separation tested to ensure that the BN is simplified without unnecessary nodes.

Secondly, with the BN graphical structure's actual construction, the BN has the advantage that it represents the real-world environment rather than a mere reasoning scheme in isolation. For DAG development, once the variables (parameters) of interest are identified, and their rationale is documented, the process of connecting the variables by understanding the interdependencies can begin to construct a qualitative network. The graphical representation makes it easy for the developer to explain qualitative relationships and corresponding influences, and make adjustments with knowledge and evidence.

The first stage is to determine which nodes are considered root nodes, i.e. other parameters do not influence the root nodes or variables. The model is built in a hierarchical way, i.e. top-level nodes followed by the second layer of sub-systems or processes influenced by the root nodes and a third layer which is a further synthesis of middle nodes to represent a final output. There can be a single middle layer or multiple layers and this depends on the system under study.

Thus, if the root nodes are defined at level-1, then nodes influenced by root nodes can be termed as level-2 nodes of the second stage. Any node at level-2 has its parent(s) in level-1 that directly influence that particular node which is represented by linking them with arcs to establish a parent-child link. This process is repeated for the next level until all the variables have a place in the graph and all parent-child links are accounted for. The final layer is most likely to have one or multiple leaf nodes without a child node, although intermediate layers may also contain leaf nodes.

Similarly, it is essential to note that a single node can be a part of two levels. For example, consider Figure 3.8: ‘Loss of fuel purifier water seal’ is the root node placed at level-1, which activates an ‘alarm’ and ‘initiation of purifier shutdown sequence’ at level-2 directly influenced by the level-1 node. Furthermore, in some designs, ‘initiation of shutdown sequence’ may also initiate the ‘alarm’; hence, these two nodes are also connected in the next, third, stage. Hence, the ‘alarm’ node at the second stage becomes the level-3 node at the third stage.

It is important to note that DAG development is a subjective process because the nodes are identified through the subjective judgements of the individuals constructing the graph. Nevertheless, the process can be considered reliable because for any node, once the direct influences on it are known, all other potential influences become irrelevant (Yang, 2008).

3.1.5 Quantitative Features of the BN

Once the DAG is developed, the next step is assigning the states to the selected nodes. Furthermore, Conditional Probability Tables (CPTs) are developed to compute posterior probabilities for intermediate and leaf nodes.

Example: Consider a bunker hose/coupling failure scenario during the bunkering operation on a ship. The hose/coupling failure would likely cause an oil spill, graphically presented in Figure 3.5.

There are two states (Yes and No) for both parent and child node. Table 3.4 displays the conditional dependencies of the oil spill on the event, hose/coupling failure. During the bunkering operation, if the hose fails then an oil spill occurs; however, if there is no hose failure, then the probability of an oil spill is minimal.

Table 3.4: CPT for oil spill scenario

	Bunker hose/coupling failure	
	Yes	No
Oil spill – Yes	1	0.05
Oil spill – No	0	0.95

An advantage of the BN is that beliefs and probabilities can be updated once new evidence is available. This feature also signifies the importance of defining the scope of a model. Therefore, Downey (2011) rightly points out that the assigning of Bayesian probability depends on one’s state of knowledge.

3.1.6 Sensitivity analysis

The term sensitivity analysis refers to a process of identifying the most influential parameter of a BN and assessing its effects on other parameters (HUGINEXPERT, 2017). Jones et al (2009) and Pristrom et al (2016) used the following three axioms to validate the BN model:

1. Any increase/decrease in the probability distribution of parent nodes should have a proportional effect on the posterior probabilities of child nodes.
2. Influence of changes in the parent node probability should keep consistency with the probability of child node.
3. Where there are multiple parent nodes (n) influencing a child node, then their total influence should be higher than the one generated by the same change of n-1 root nodes.

In essence, any positive or negative change to the parent node's subjective probability should have a consistent and proportional effect on the child nodes' posterior probabilities. This is exemplified in section 3.3.1, where the model has been checked to comply with the above mentioned three conditions.

3.2 BN Model for LS2S engine

The following objective of this chapter is achieved in this section:

Propose and implement a proactive performance assessment technique.

3.2.1 Basic steps

The diagnostic and health assessment model for the LS2S marine engine is based on a simple five-step process, as shown in Figure 3.10, requiring integration of qualitative and quantitative features of the BN discussed in the previous section.

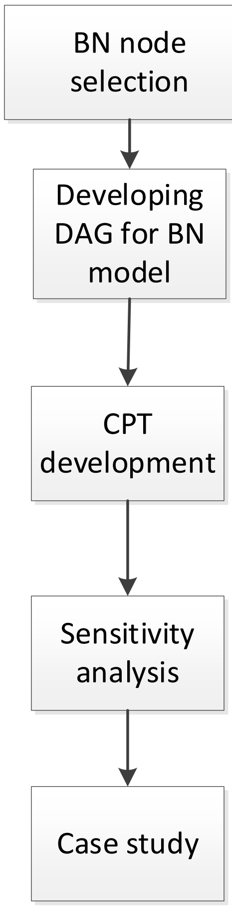


Figure 3.10: BN model methodology steps

Step 1: This involves identifying and selecting key LS2S engine operational performance parameters as BN nodes.

Step 2: The nodes selected in step 1 are logically connected to develop a Direct Acyclic Graph (DAG) to demonstrate the BN model's qualitative feature.

Step 3: This step demonstrates the quantitative feature by developing the conditional probability tables (CPTs) for each intermediate and leaf node. Development of CPTs involves data collection and obtaining quantitative feedback from the panel of experts.

Step 4: Sensitivity analysis is performed to test the BN model's functionality to ensure that the model behaves as expected.

Step 5: The final step involves demonstrating how the BN model works with a real case study.

3.2.2 BN node selection

The first step is the BN node selection performed through a literature review and researcher's industry knowledge. Corresponding parameters have been outlined in Figure 2.25. This section provides details of the nodes required to capture the LS2S engine's operational health, combustion performance and wear of cylinder components. In this model, there are three sets of nodes, as displayed in Figure 3.11. Each set is described in the following sub-sections.

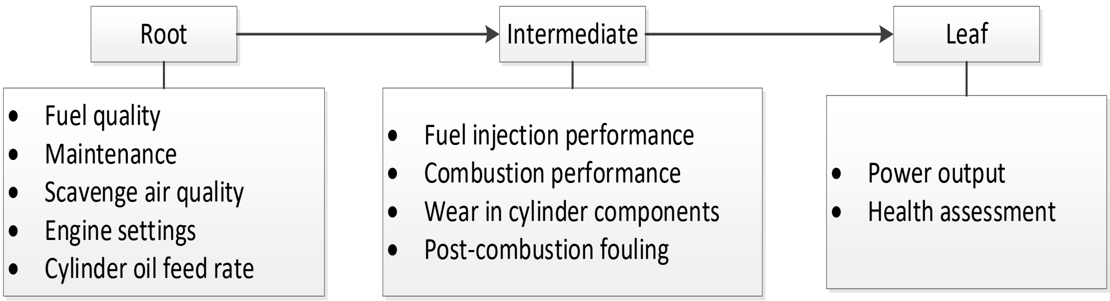


Figure 3.11: Sets of nodes for the model

3.2.2.1 Parent nodes

3.2.2.1.1 Fuel quality

In their 2018 failure investigation report, the Swedish Club analysed insurance claims and found that poor fuel management was one of the top three causes of damage to machinery, with an average cost per claim of USD 344,069 for the period 2015-2017. Alagumalai (2014) highlighted fuel ignition characteristics and viscosity as key parameters affecting the combustion performance in internal combustion engines.

Due to the shipping industry's international nature, fuel quality can vary significantly from one region to another and even from one port to another in the same region. Globally, marine fuels are purchased on international marine fuel quality standard ISO 8217 (Fisher and Lux, 2004). This standard provides essential information, limits and suitable test methods to evaluate various marine fuel quality parameters such as viscosity, density, pour point and elemental concentrations. A ship draws manifold drip samples during a bunkering procedure and sends one representative sample to an accredited lab for testing. The sample is analysed as per ISO 8217 (2017) parameters, and the ship is advised based on the results. However, the quality of the fuel ‘as supplied’ can be different from the quality of fuel at the engine inlet. This is because the fuel should pass through onboard settling, separation and filtration stages in the process of separating the impurities of water, abrasive elements of aluminium + silicon and other sediments before being injected into the engine for combustion (Fisher and Lux, 2004). In this study, where engine combustion performance is the focus, fuel quality at engine inlet has been considered rather than fuel as loaded.

Marine fuels are divided into two main categories, i.e. RM (Residual Marine) and DM (Distillate Marine) fuels (ISO 8217). Ships mainly burn RM grade fuels for large two-stroke engines as a more cost-effective option compared with DM fuels. RM fuels come in various viscosity grades and usually require heating at certain temperatures to achieve correct injection viscosity. Apart from having the knowledge and understanding of the various fuel quality parameters, it is crucial to assess the ignition characteristics of RM grade fuels. An initial assessment can be made through the CCAI index; however, more precise information by obtaining the ECN (Estimated Cetane Number) value can be sought by analysing the fuel for a non-routine Fuel Ignition Analyser (FIA) test (Leigh-Jones, 2005).

For this study's purpose, the fuel quality has been assigned two states, ‘satisfactory’ and ‘unsatisfactory’. For the users to assess whether the quality of fuel in use is satisfactory or unsatisfactory, input data for the following five key fuel quality parameters is needed:

- Viscosity at the engine inlet
- The concentration of catalyst fines (Aluminium + Silicon)
- CCAI
- Water content
- Ash content.

3.2.2.1.2 Engine maintenance

Poor maintenance can significantly impact engine operational performance, leading to increased risk of functional failure. The Swedish Club (2018) has ranked insufficient maintenance/repair as the second major reason for reported machinery failures. Similarly, Duran, Uriondo and Moreno-Gutierrez (2012) performed emission measurements on marine engines to evaluate the impact of poor maintenance on combustion, and the results also indicated an increase in nitrogen oxides (NOx) and carbon monoxide (CO) emissions.

As per the literature review of Chapter 2, a preventative or fixed-time interval maintenance approach is prevalent in the maritime domain. This is also generally supported by the equipment manufacturers indicating the running hours of particular components before replacement is considered necessary unless some form of condition monitoring is applied (Griffiths, 2007). For this study's purpose, the level of maintenance is mainly judged by the outstanding maintenance actions for the specific engine sub-component and availability of the asset. Availability is a measure of how often the system is alive and available for service. The formula used to assess the availability is expressed as uptime/(uptime + downtime) (Barringer, 1997). In this context, it is the data which would indicate the number of (propulsion) days spent at sea and the number of days lost due to unavailability of the main engine due to unexpected failure. This node has been assigned two states, ‘unsatisfactory’ and ‘satisfactory’, with the assessment criteria using ‘work order status’ and ‘availability of the asset’.

3.2.2.1.3 Engine settings

With the advent of sophisticated control instrumentation, the more conventional mechanical control systems of two-stroke marine engines have gradually been replaced with electronic controls and ‘intelligent’ systems (Griffiths, 2006). Nevertheless, the engine control systems' primary objective remains the same, which is to achieve optimised efficiency for given conditions. Through these ‘adjustable’ operational settings for a two-stroke engine, mainly the timings for fuel injection, exhaust valve and CLO injection are optimised for specific conditions of engine load and fuel/lube quality. In the older designs with mechanical controls, getting the balance right for optimised engine operations was relatively challenging, as compared to newer electronically controlled system designs that make it easier to fine-tune the engine operations with little human intervention (Griffiths, 2006). Either way, non-optimal engine settings have the potential for engine wear, poor combustion and high deviation in observable indicators such as P_{max} (maximum pressure during a combustion cycle), P_{comp} (Compression pressure), MIP (Mean indicated pressure) and exhaust temperatures. Moreover, Wang, Chen and Guan (2021) have argued that the MIP and other cylinder pressure data from a marine engine is key to develop a performance assessment model.

These indicators have been used in this study to assess the engine settings as being ‘satisfactory’ or ‘unsatisfactory’. Three criteria for this parameter are listed as follows:

- $P_{max} – P_{comp}$
- MIP deviation
- Exhaust temperature deviation.

3.2.2.1.4 Scavenge air quality

Scavenge air quality is the function of scavenge air temperature, pressure and level of moisture carried into the cylinder liner for combustion. Scavenge air quality significantly impacts the quality of combustion of two-stroke engines (Rolsted et al., 2016). The engine operations manual provides the information about the corresponding scavenge air pressure proportional to the load that the engine is operating on. Lower pressures and air density can potentially lead to incomplete fuel combustion. Similarly, scavenge temperature is dictated by the ambient temperature, humidity and performance of the scavenge air cooler. Optimally low temperature would significantly help increase the air density going into the combustion chamber and hence facilitate the combustion process. The third factor is the level of scavenge air dryness and performance of the water mist catcher fitted after the scavenge air cooler. Air containing a higher concentration of water droplets going through the scavenge ports and being deposited on the liner surface has a higher propensity to condense and mix with acidic combustion products, forming acids that cause corrosive wear (Karvounis et al., 2018). Different engine manufacturers provide guidance to calculate the expected amount of water which can be separated from scavenge air under different operational circumstances. Hence, the difference (ΔQ - tonne/24 hr) between the calculated and actual amount of water collected over a 24-hour period can be used as input to indicate the performance of the water separator. This node has been assigned two states, ‘satisfactory’ and ‘unsatisfactory’, with the following criteria:

- Scavenge air pressure
- Scavenge air temperature
- Water mist catcher performance.

3.2.2.1.5 Cylinder Lube Oil (CLO) feed rate

Cylinder lubrication of a two-stroke cross-head engine is through a separate cylinder lubrication system where the lubricant is injected at every stroke through multiple lubricating quills mounted radially around the cylinder liner (Griffiths, 2006). The lubricant is usually high in Total Base Number (TBN) to neutralise the acidic components formed during the combustion process. Implementation of MARPOL Annex VI Reg. 14.1.3 from 1st January 2020 permitting ships to burn fuels outside emission control areas with a maximum sulphur content of 0.50 mass % (MARPOL, 2009) results in a significant reduction in sulphur oxide emissions. During combustion, the fuel sulphur is oxidised and oxygen in the air reduced to form sulphur dioxide (Fogh et al., 2016).

$S + O_2 \rightarrow SO_2$ (Some of the sulphur dioxide (SO_2) is further oxidised into sulphur trioxide $2SO_2 + O_2 \rightarrow 2SO_3$.)

The sulphur trioxide reacts with water/moisture to form sulphuric acid.

$SO_3 + H_2O \rightarrow H_2SO_4$

The acidity on the liner walls needs to be neutralised through alkalinity, which is achieved through the calcium carbonate buffer of cylinder oil.

$H_2SO_4 + CaCO_3 \rightarrow CaSO_4 + CO_2 + H_2O$

Therefore, the feed rate of the lubricant is carefully adjusted to keep liner wear to a minimum by monitoring various factors including TBN reserve and iron (Fe) content in cylinder drain oil samples (Fogh et al., 2016). Lower than required feed rate is likely to cause adhesive wear and risk of corrosive wear, and excessive feed rate would cause deposits on cylinder components due to possible burning of excessive lubricant, which may result in a phenomenon called cylinder liner clover leafing in reference to the wear pattern (Griffiths, 2006). Hence, a balanced feed rate, the uniform circumferential spread of cylinder lubricant within the liner, and appropriate TBN with good detergency and dispersancy is needed to maintain a decent operational condition in order to increase the cylinder liner's remaining useful life. This area has been the subject of a continued investigation by engine manufacturers and researchers attempting to optimise and control various parameters to strike that balance and achieve the best results. This node also has two states, 'satisfactory' and 'unsatisfactory' feed rates, which are based on the assessment of 'Fe' content and 'TBN' of cylinder drain oil from each cylinder.

3.2.2.2 Intermediate nodes

3.2.2.2.1 Fuel injection performance

This node is the function of a high-pressure fuel pump and injector performance. The fuel pump generates high pressure to the injector at the correct timings. The injector needle momentarily lifts, introducing fine fuel mist into the combustion chamber (Chell, 2007). There can be various inter-related operational issues impacting the desired functionality, hence performance of pump and injector has been considered as a single unit in this study.

Fink et al (2016) looked at the Internal Diesel Injector Deposit (IDID) issue and how it is linked with the quality of fuel in use with operating conditions, including the level of maintenance. Marine residual fuels containing high sediments and abrasive elements can cause severe damage to the sliding surfaces of the barrel and plunger assembly and needle valve of the fuel injector. Similarly, delayed or incorrect maintenance can result in fuel pump and injector issues such as fuel dribbling, 'carbon trumpet' formation, and partial blockage of nozzle holes, impacting the spray pattern. Subsequently, poor fuel injection can severely impact the combustion in the engine (Griffiths, 2006). There are two states for this node, 'Satisfactory' and 'Unsatisfactory'.

3.2.2.2.2 Combustion performance

The combustion performance assessment is the lynchpin of the model. In the literature, there are numerous combustion performance modelling methods and experimental studies to evaluate the interdependence of various factors in the diesel engine. For example, Kowalski (2014) performed an experimental study to determine how combustion is affected by the engine settings (injection timings) and performance of the fuel pumps/injectors in marine diesel engines. Stengel et al (2016) used different fuel types to evaluate the impact of fuel qualities on combustion and emission performance. The study concludes that combustion performance is not only dependent on the fuel being used but also on the engine settings.

Moreover, fuel quality in terms of aromaticity/ignition characteristics, water content and level of abrasives can have a high degree of influence on the combustion quality (Wright, 2005). There can be other influencing factors on combustion, such as changeover process between different fuels and load profile; however, a careful analysis of data and consultation with subject matter experts indicates that the selected nodes would suffice in exhibiting key combustion performance indicators of LS2S engines. This node has been given two states, 'satisfactory' and 'unsatisfactory'.

3.2.2.2.3 Post-combustion fouling

The level of post-combustion fouling is directly linked to the quality of combustion and also to the cylinder lubrication settings for each cylinder in a two-stroke engine. There is always a level of post-combustion fouling, mainly due to the type of marine heavy fuel oil in use. However, higher levels of fouling can have a significant impact on the performance of the exhaust valve, turbocharger and other components in the exhaust stream (Leigh-Jones, 2005). Moreover, there is an inherent dispersancy characteristic in CLO to cope with the products of post-combustion fouling to a certain degree. However, if the level of fouling is too high, then the lubricant is going to struggle to perform its primary function satisfactorily – which is to create a film between the sliding surfaces in order to reduce frictional losses and wear. This node has two states, 'nominal' and 'excessive' fouling.

3.2.2.2.4 Wear in cylinder components

Yan et al (2015) described in their research that excessive wear and friction between cylinder components are the cause of more than half of the faults in marine diesel engines. Similarly, the Swedish Club (2018) in their report mentioned that, for LS2S engines, around 39% (Figure 3.12) of the claims for main engine damage related to wear/damage of cylinder components.

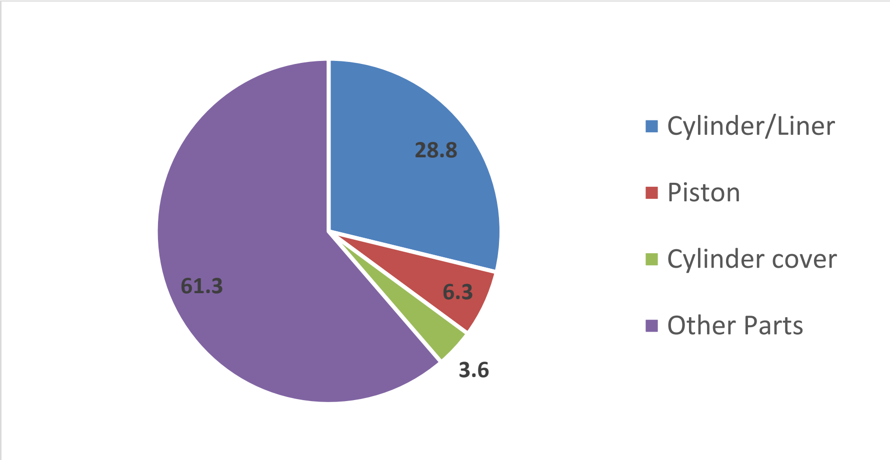


Figure 3.12: Percentage distribution of the number of claims relating to main engine damage
Source: the Swedish Club (2018)

Subarshan and Bhaduri (1983) classified the wear in the cylinder liners into two categories, physical mechanisms and chemical corrosion. The two mechanisms can be in action independently or at the same time depending on the operational conditions, design and maintenance of the engine. More specifically, the wear in the cylinder components of a large two-stroke engine can be divided into three broad categories, as described in Figure 3.13.

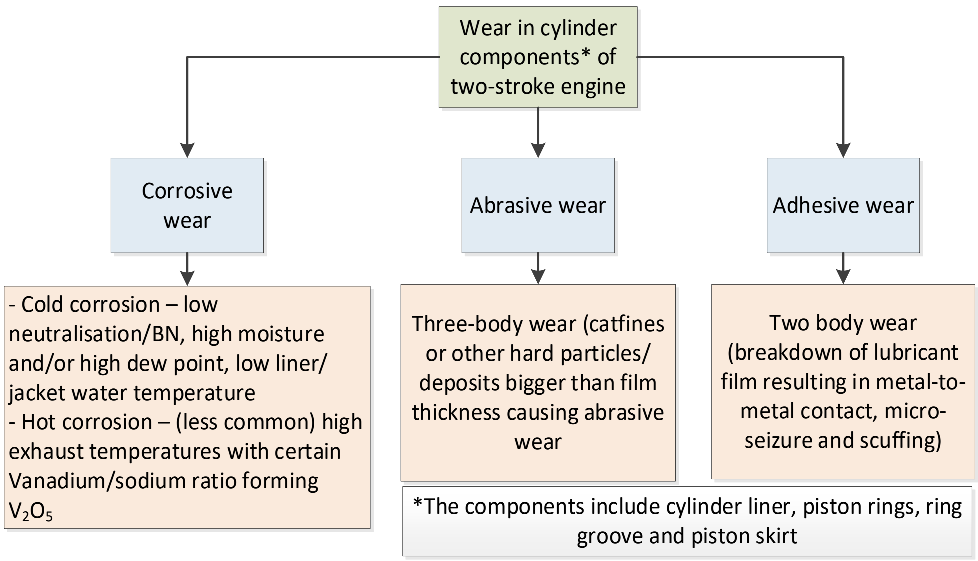


Figure 3.13: Types of wear within two-stroke cylinder components

The mechanism of cold corrosion has been briefly described in the above section under ‘cylinder oil feed setting’. The level of corrosive wear can be reduced by carefully adjusting the operational parameters. Rolsted et al (2016) proposed a number of ways to tackle the issue, one of which is by increasing the liner temperature through design modifications. However, in view of the 0.50% sulphur fuels in use from 1st January 2020, MAN-ES (2020) through their service letter (SL2020-692/KAMO) advised ships to deactivate the load-dependent cooling system to operate at lower liner temperatures effectively.

Since the implementation of MARPOL Annex VI Reg. 14.1.3 from 1st January 2020, FOBAS (2020) has observed a spike in the number of ships reporting excessive liner scuffing, which can be symptomatic of adhesive or two-body wear. Mainly, adhesive wear is the lubrication failure causing metal-to-metal contact, which can be further exacerbated into three-body wear through micro-seizure peeling-off of Fe particles from rubbing surfaces.

Abrasive wear is mainly associated with the catalyst fines (abrasive elements of aluminium + silicon) particles which, if larger than the thickness of the oil film between piston rings and liner and in higher concentration[2], would have devastating consequences and could result in costly damage to the cylinder liner and pistons.

An accurate wear evaluation through physical measurement of engine cylinder components is beneficial. Engine manufacturers such as WinGD suggest guiding limits for wear rate of 0.03~0.10 mm per 1,000 running hrs for cylinder liners as acceptable (WinGD, 2021). Wear rate is simply obtained by subtracting running diameter with the non-running diameter of the liner surface and dividing the result with the liner total running hours. To get the result in mm/1000 hours, multiply it by 1000. Similarly wear rate of piston rings can be measured.

These periodic physical measurements are essential; however, they are not straightforward and are usually possible when a cylinder is opened up for overhaul. In the interim, non-intrusive techniques such as regular drain oil analysis and monitoring the condition through scavenge port inspection are becoming a standard best practice approach recommended by engine manufacturers (Fogh et al., 2016). Although both physical measurements and non-intrusive methods are considered as primary methods to determine the wear of cylinder components, this model intends to provide a quick wear assessment based on the key indicators of combustion performance and CLO feed rate. Nevertheless, any non-intrusive wear assessment method would benefit from and should be complemented with the physical measurements to confirm and

[2] Most engine manufacturers recommend that the catalyst fines concentration in the fuel should be less than 15 mg/kg at engine inlet, although recently engine manufacturers have started to ask that the catalyst fines concentration be as low as practically possible.

validate the results. This node has been assigned two states, i.e. ‘normal’ and ‘excessive’ wear.

3.2.2.3 Leaf nodes

3.2.2.3.1 Engine power output (effective)

This node is influenced by the combustion performance and engine settings. Due to the low-speed of large two-stroke engines, a fixed-pitch propeller is usually directly connected with the engine crankshaft through an intermediate shaft; hence, engine rpm (revolutions per minute) is controlled to maintain specific ship speed with a governor controlling the fuel rack to adjust the engine RPM. The shaft load on the engine varies due to external factors such as hull & propeller fouling, laden or ballast voyage, and sea-state. However, for the purpose of this study, the focus is on the engine performance-related aspects that impact the power output from an engine. The power output can be directly measured by indicator diagrams (P_{max}, P_{comp} and MIP) and then compared against the baseline data which is gathered during engine shop test and sea trials. Any deviations from the baseline would indicate the performance levels of the engine in terms of power output against standard conditions. This is considered as one of the outputs of the model with two states, ‘Optimum’ and ‘non-optimum’.

3.2.2.3.2 Engine health

This node takes input from the level of post-combustion fouling and wear of the cylinder components. This node has two states, ‘Satisfactory’ and ‘Unsatisfactory’. The level of operational efficiency would define this state. Based on the level of health of the engine and indicators highlighted in the model, the operators are guided to make the adjustments and then reassess and improve the ‘engine health’ score.

3.2.3 BN graphical structure

Uusitalo (2007) identified a number of software tools available to help develop the BN model out of which HUGINEXPERT (HUGINEXPERT, 2017) has been selected for use in this study because of its ease of use and the clarity of information displayed. The nodes identified in previous sections have been arranged into a DAG, as shown in Figure 3.14. Moreover, a D-separation test has been carried out to ensure there are no superfluous nodes, and the overall model is simple.

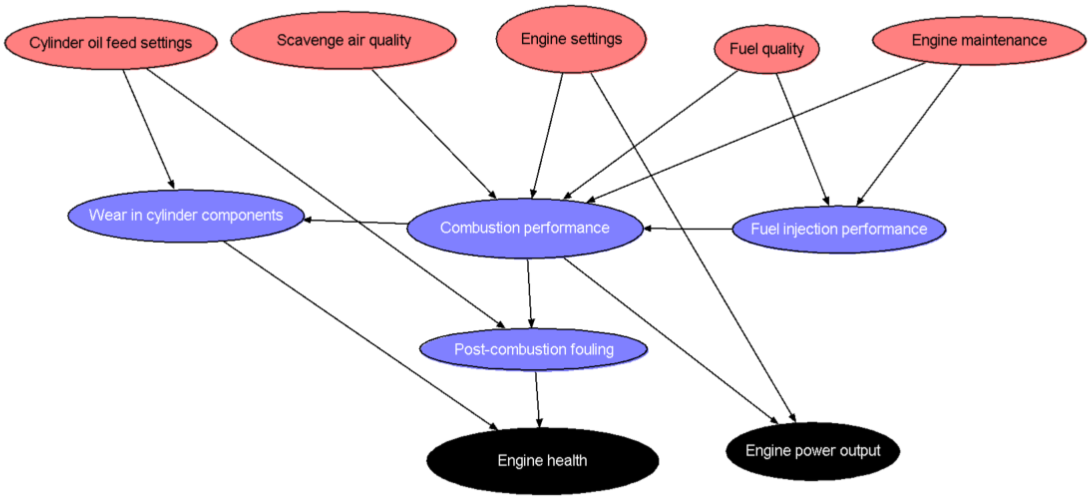


Figure 3.14: DAG for engine health assessment and engine power output

The diagram is colour coded with parent nodes, intermediate and leaf nodes in red, blue and black respectively. The next stage is gathering the evidence and operational data-based information to develop the intermediate and leaf node conditional probability distributions.

3.2.4 Conditional probability data

In order to create relevant conditional probability tables (CPTs), relevant data is needed. For the purpose of this study, multiple avenues have been explored rather than relying on a single source of data. The main reason is that the data on specific combustion performance parameters and their interdependence is based on established inter-causal reasoning rather than in the form of probabilities of occurrence, failures or success.

High accuracy and minimal uncertainty of data is significant to the model's integrity. Pegoraro, Uysal and van der Aalst (2021) has described three possible sources of data uncertainty, i.e., incorrectness, coarseness and ambiguity. Incorrectness is simply the error(s) creep into the data at data entry stage or faults in the information system. Coarseness is caused by the system limitation in the way data is recorded in the database, e.g., a missing field which could limit the analysis and interpretation capacity.

For example, when recording the fuel analysis results, if a parameter such as acid number results are missing, then a fuel specialist will still be able to interpret the results however if the acid number results are available then it could have further reduced the uncertainty in the data and improved the interpretation. Finally, ambiguity can stem from the type of data and subsequent interpretation, such as interpreting the linguistic variables into a quantitative output. Authors stressed the need to change the inherent causes of implicit uncertainty into explicit uncertainty to achieve procedural transparency.

All types of data are susceptible to above uncertainties and data used in this study is no exception. Certain measures have been taken to ensure that the data used remain accurate as far as practically possible. Following paragraphs elaborate the sources of data used in this study and further commentary on the data accuracy.

The following sources of data inference have been utilised to create suitable CPTs:

1. Expert judgement
2. FOBAS Engine Assessment Programme (FEAP)
3. FOBAS fuel quality data.

Firstly, expert judgements have been used to assign probabilities due to the lack of objective data. Some work is performed through the panel of experts in the verification of the weightage and probability values assigned to various interdependent parameters.

The niche engineering field and the nature of the study, focusing on one particular piece of machinery equipment (LS2S engine) installed on large ships, considerably restricted the availability of relevant experts in this area. The primary criterion for the expert identification and selection is the individual expert’s level of knowledge and experience of LS2S engine watch keeping, maintenance, design, troubleshooting and operations. Various LR and LJMU channels were used to identify the experts fulfilling the general criteria. LJMU’s ethical approval process was strictly followed before approaching the experts.

To ensure consistency and minimise ambiguity when receiving feedback from the panel of experts, each expert first received an email, followed by a phone call, from the researcher. These experts were sent a questionnaire detailing the background of the research methodology and were requested to provide individual input in the form of conditional probability. Each result was then reviewed and it has been assessed that the data is robust because the inputs from the experts are generally consistent.

However, on a couple of occasions, deviations were detected between the expert judgements; this was addressed by contacting the individual experts and asking them to reconsider their score and whether the assigned value may have been generated through a lack of clarity on the question itself. Furthermore, these results were verified through the sensitivity analysis and in line with the real-world application experience.

Expert judgements have been used whilst developing chapters 3, 5 and 7. In total, 13 experts were engaged in the study.

Table 3.5 provides the full list of these experts. Some of these experts were engaged for all three research chapters whilst a few others were only requested to provide judgements on a specific research area. The suitability of an expert for a specific area of study and the number of experts needed for a reasonable level of data were discussed and agreed with the research supervisory team.

For the BN conditional probability data collection, 10 experts (1 ~10 of Table 3.6) were engaged. A copy of the questionnaire sent to these 10 experts is provided in Appendix B. Consideration has been given regarding whether to use a weightage scheme in order to prioritise the judgements of individual experts; however, considering all the experts are well experienced and qualified, they have been assigned the equal weighting.

Table 3.5: Introduction to the domain experts consulted for the study

Expert	Experience (Years)	Education (Level)	Expertise
1	29	Master’s	Condition monitoring and condition-based maintenance in the maritime industry. The expert worked as a lead tribologist in marine consultancy services of a classification society and, during that time, he developed practical application to assess machinery health including LS2S engines. Currently heads an engineering consultancy in this area.
2	18	Master’s	Currently a senior surveyor in a marine and offshore organisation with extensive operational seagoing experience of maintenance and watch keeping of LS2S engines.
3	24	PhD	Currently working in a classification society as a team leader responsible for the safety and operational availability of the critical machinery assets of ships and offshore platforms. He also has extensive onboard experience sailing on oil tankers and cargo ships and in the process gained valuable operational experience of LS2S engines
4	25	Bachelor’s	Expert 4 currently works for an engine manufacturer and designer. As a marine engineer, the expert has extensive engine operations and maintenance, and troubleshooting experience.
5	30+	Master’s	Expert 5 is an ex-chief engineer currently working in a classification society as a senior specialist in piping and machinery, and is an authority on plan approval. His operational, maintenance and troubleshooting experience of LS2S engines is extensive.
6	28	PhD	Expert 6 is an ex-seagoing engineer with experience as senior researcher in a classification society. He then joined an LS2S engine designer as chief engineer on a large engines project. The expert is currently working for a large ship operator as a fleet energy efficiency manager.
7	30+	Master’s	Expert 7 is a veteran marine engineer with extensive onboard experience. For the last 15 years, he has worked in a classification society leading a team of experts on the MARPOL regulatory regime, and is also expert in the field of innovative exhaust gas scrubber technology with a strong connection to the LS2S engine technology.
8	18	Master’s	Expert 8 is also a marine engineer currently working as a marine and offshore surveyor responsible for the safety, availability and

			reliability of the assets. He has extensive operational experience of LS2S engines.
9	25	Master’s	A lead project manager in a marine and offshore company responsible for new construction from the design stage to the operation of the marine and offshore assets. He has extensive marine experience of LS2S engines from working on oil tankers and general cargo ships.
10	30+	PhD	A marine engineer currently working as a senior lecturer in a renowned university and also represents his country of residence in the International Maritime Organisation plenary discussions on energy efficiency and pollution prevention.
11	25	Master’s	Expert 11 has an extensive industry experience gained whilst serving on oil tankers and bulk carriers as a marine engineer. For the last 12 years, he has been working in a classification society in the marine consultancy department as a lead specialist helping ship operators with asset management and supporting their operations through fuel and lube testing.
12	24	Bachelor’s	Expert 12 is currently serving as an onboard chief engineer on a large oil tanker. He has extensive experience of operations, maintenance, watch keeping and troubleshooting on a variety of two-stroke engine designs and power outputs.
13	30+	HND	With 43 years of industry experience, expert 13 is currently working for a European shipping operator in a leading position. He spent 30 years as an onboard chief engineer, mainly as chief engineer, and is now serving as technical superintendent responsible for a number of onboard change management programmes such as 1st January 2020 implementation of low sulphur fuels

The second data source used for the study is FEAP which is a diagnostic tool to assess the health of LS2S engines. The researcher is the product manager responsible for the development and service delivery of this subscription-based service (LR, 2021). The data extracted is primarily based on the correlations, such as, there is a strong relationship between the level of calcium and a high TBN of the cylinder lubricant. If the concentration of calcium in the cylinder drain oil (CDO) sample is higher than that of the CLO, then this is likely to indicate the possible burning of CLO during combustion, which is indicative of poor combustion conditions and excessive feed rate due to corresponding high TBN reserve. An example is shown in Figure 3.15.

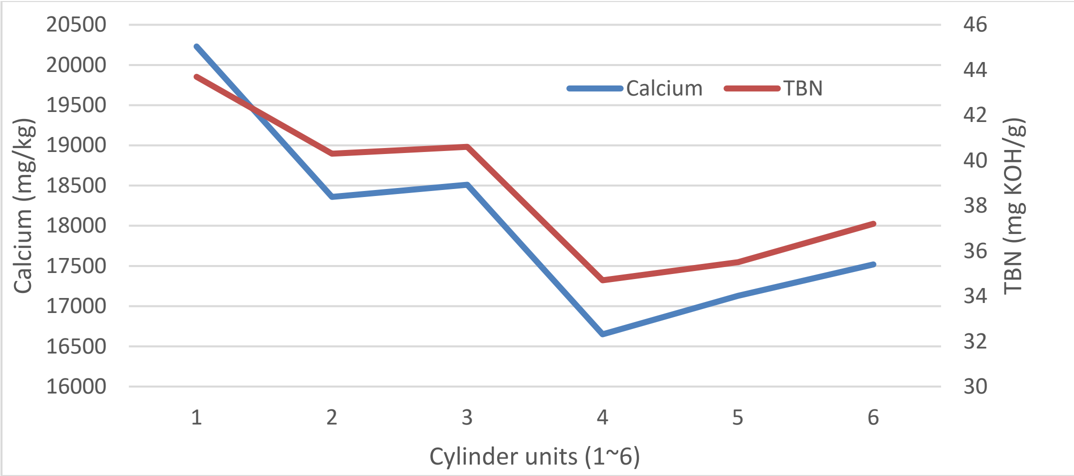


Figure 3.15: Relation between calcium and TBN
Source: FEAP (2017)

Similarly, soot in the CDO analysis would indicate less than perfect combustion, which may cause wear in the cylinder components (Figure 3.16).

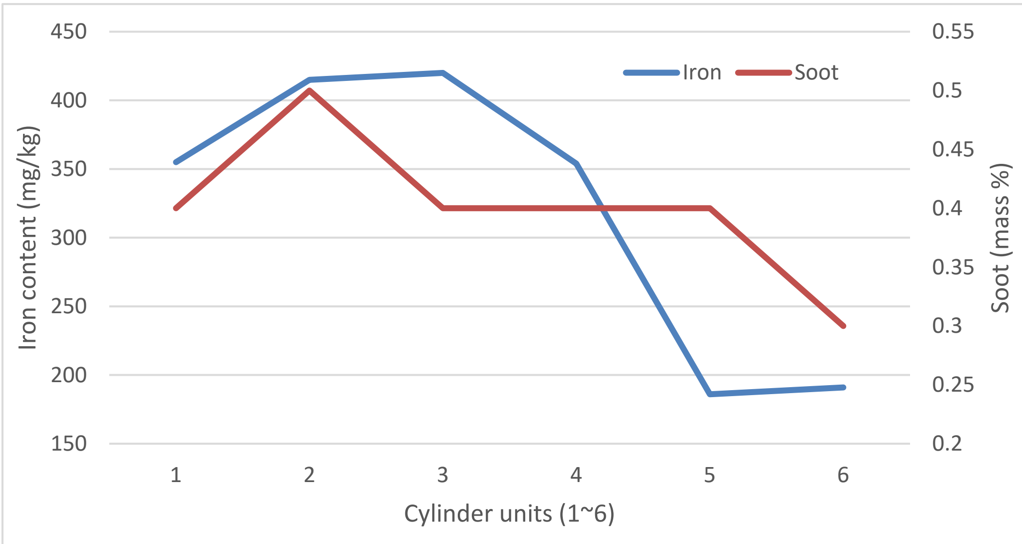


Figure 3.16: Relation between iron and soot
Source: FEAP (2017)

There are a few parameters with direct dependence and some with indirect dependence. A matrix has been created to capture the complexities that exist between these parameters. Then, the relevant probabilities of occurrence have been assigned based on the level of correlation found in the past FEAP reports.

Finally, FOBAS (2020) fuel data[3] has also been utilised where the influence of fuel quality on fuel system components needs to be established. The accuracy of the

[3] The Fuel Oil Bunker Analysis and Advisory Service (FOBAS) is part of LR Marine Consultancy

analysis and data is primarily ensured through the testing labs compliant to ISO 17025. Although there remains a risk of incorrect entry, however considering the amount of data and mainly averages instead of individual numbers used for the study, the impact of any incorrect entry is absorbed by the large database. Moreover, the data is regularly shared, compared and recognised as representative of the bunker industry by the industry forums and expert working groups such as ISO TC28/SC4/WG6 and CIMAC WG7.

3.2.4.1 Assignment of the data to the nodes

The root nodes (fuel quality, engine settings, scavenge air quality, cylinder oil feed rate and engine maintenance) basically represent the operational inputs, and there are going to be variations based on the operational condition of the engine. Nevertheless, to convert the quantitative and qualitative information emanating from operational parameters representing the root nodes of the model into appropriate prior probability value is not straightforward. Hence, the focus of the next chapter is how to convert the onboard data collected from the ship and use it to work out the probability of root nodes. For this chapter, the probability values for the root nodes are directly interpreted from the available operational data by the user to test the response and functionality of the model against various scenarios.

3.2.4.1.1 Fuel injector performance

Conditional probabilities of these nodes have been established through the data and expert judgements. The table below shows the relevant conditional probabilities for the nodes described in Table 3.6.

Table 3.6: Fuel injection performance CPT

Engine maintenance	Satisfactory		Unsatisfactory	
Fuel quality	Satisfactory	Unsatisfactory	Satisfactory	Unsatisfactory
Satisfactory	0.9	0.3	0.31	0.12
Unsatisfactory	0.1	0.7	0.69	0.88

As shown in Figure 3.14, fuel quality and maintenance are the main factors impacting the fuel injection performance. The analysis of FOBAS (2020) data[4] indicates that the quality of fuel has slightly more influence than the maintenance levels on the

established almost 40 years ago. FOBAS tests more than 50,000 fuel samples a year, with a significant number of fuel-related failure investigations dealt every year.

[4] The quality of data depends on the accuracy of information reported by the ships registered on FOBAS programme.

functionality of fuel injectors, which is reflected in the above table. Fuel quality parameters such as incorrect viscosity, high levels of abrasive elements and high sediments in the fuel at engine inlet can result in unsatisfactory fuel injection performance.

In the period between 2012 and 2017, approximately 70% of the reported issues with fuel injectors/pumps have been associated with poor fuel quality with no outstanding planned maintenance schedule. Here, 30% of the cases were eliminated as having no direct evidence or only inconclusive evidence to relate the operational problem to the quality of the fuel after investigative fuel analysis; hence, the probabilities of 0.7 (unsatisfactory) and 0.3 (satisfactory) have been assigned (highlighted green in Table 3.6). Other probabilities have been assigned for this node from the experts' judgements. For example, on the condition that the engine is poorly maintained and the fuel quality is unsatisfactory, the 10 experts assigned the probability values shown in Figure 3.17.

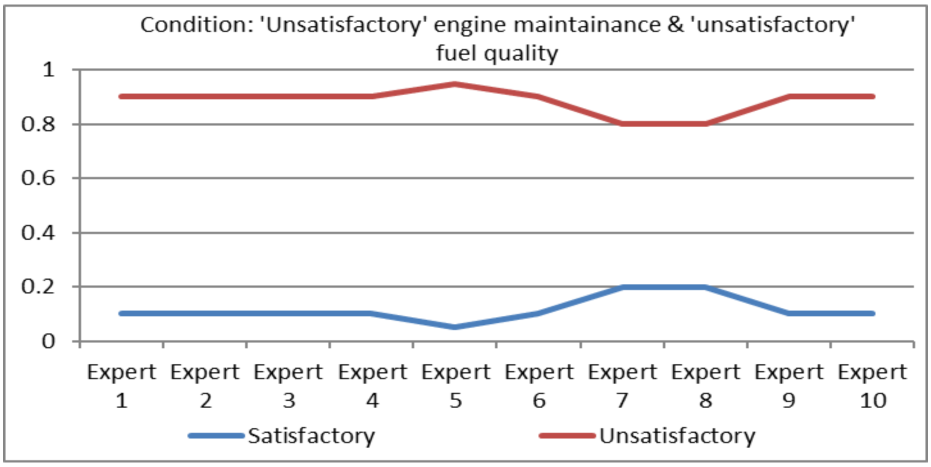


Figure 3.17: Experts' input for fuel injection performance (1)

Taking the average of these results gave a probability of poor injector performance of 0.88 and good performance of 0.12. Similarly, if the engine is well maintained and the fuel quality is satisfactory, then the results in Figure 3.18 are derived from relevant expert judgements.

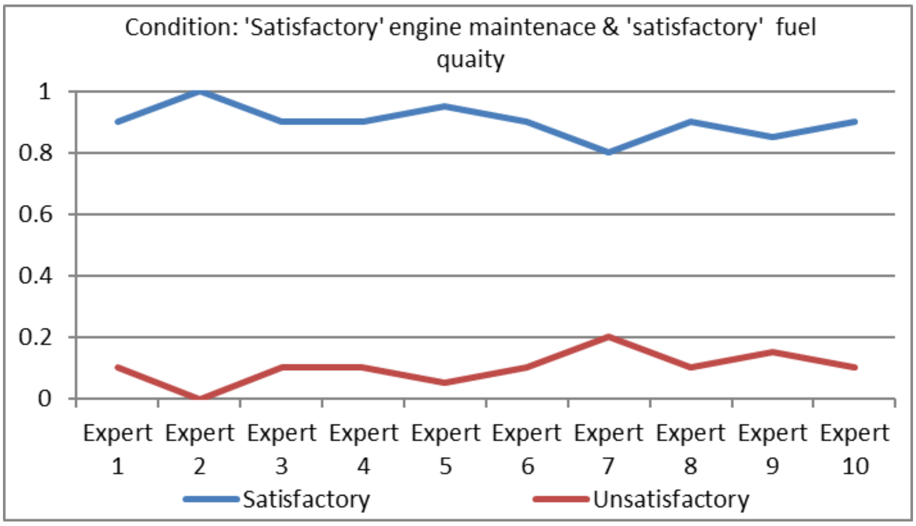


Figure 3.18: Experts' input for fuel injection performance (2)

This clearly shows that the injection performance is likely to be satisfactory (0.9), and the probability of unsatisfactory performance is 0.1. Similarly, for the fourth condition, see Figure 3.19.

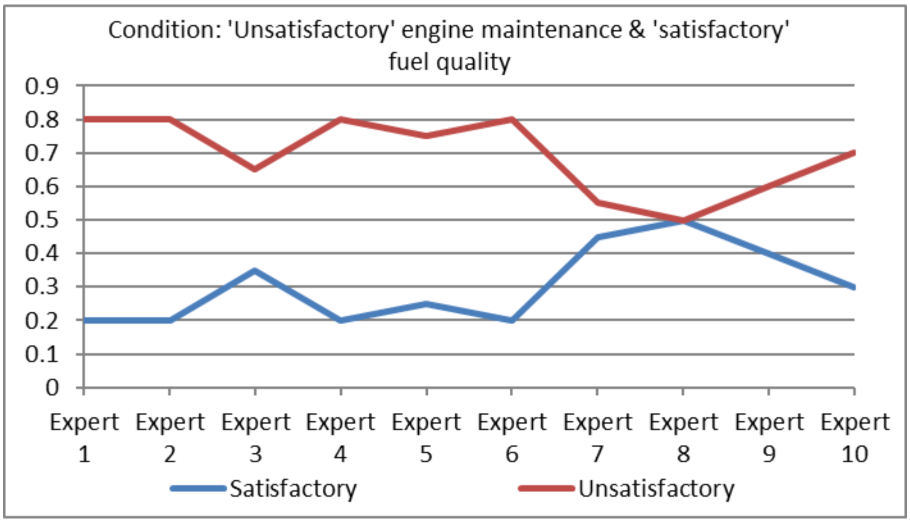


Figure 3.19: Experts' input for fuel injector performance (3)

3.2.4.1.2 Combustion performance

Combustion is a complex chemical and physical reaction taking place in a confined space under immense pressure and temperature. Precise assessment of combustion performance is not straightforward, hence requiring a holistic approach where key engine performance indicators are evaluated to make an informed judgement. Five parent nodes (variables) directly impact the combustion performance, each with two states, creating 32 (2^5) probable conditions to investigate. Considering the large number of variables involved, a mathematical approach (Alyami et al., 2014) has been used instead of including this node in the questionnaire for experts to produce

(32 × 2 = 64) probability values. Moreover, the inclusion of a combustion performance CPT would have made the questionnaire too complex to follow.

The approach involves assigning each of the five parent nodes of ‘combustion performance’ a weight and creating a matrix. The total weight of all five parameters should be equal to 1. The weight has been assigned to each parameter based on the level of operational impact on combustion performance. Experts 1, 7 and 10 with their relevant experiences and slightly diverse backgrounds were separately requested to provide a priority order from 1~5, where 5 is ‘most important’ and 1 ‘least important’. All three experts considered fuel quality to be the most critical aspect and engine maintenance to be the least important to impact combustion performance, as shown in Figure 3.20.

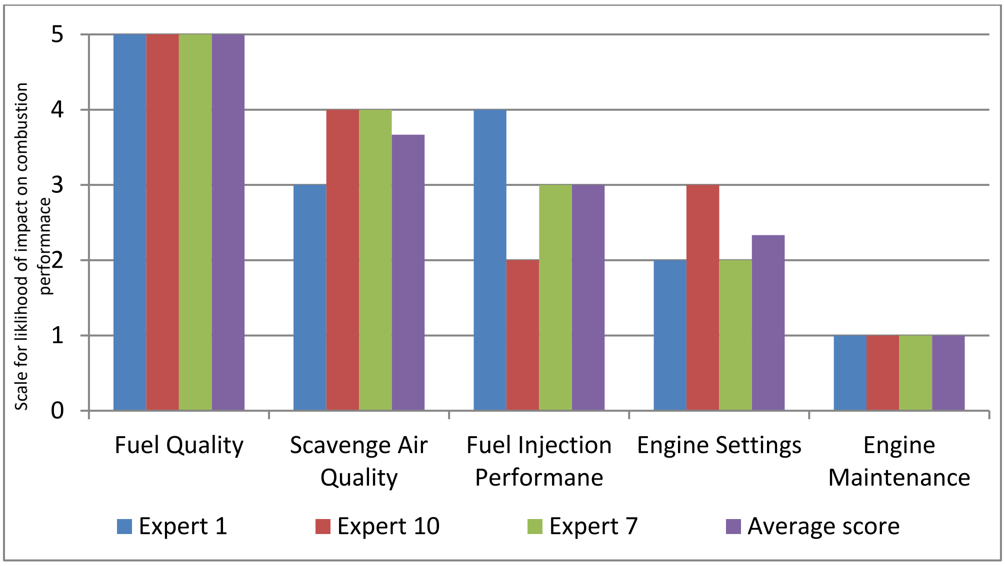


Figure 3.20: Weightage scheme for combustion performance (parent nodes)

The following values have been derived after taking into account the above results:

Table 3.7: Weighted means for the parent nodes to assess combustion performance

	Fuel quality	Scavenge air quality	Fuel injection performance	Engine settings	Engine maintenance
Average score	5	3.7	3.0	2.3	1
Weighted (ς) distribution*	0.33	0.24	0.20	0.16	0.07

* $\sum_{i=5} \varsigma = 1$

Each parent node can have a positive or negative impact on combustion performance. For example, if the fuel quality is ‘satisfactory’, fuel injection performance is ‘satisfactory’, engine settings are ‘satisfactory’, scavenge air quality is ‘satisfactory’, and the engine maintenance is 'satisfactory', then the probability of 'satisfactory' combustion performance is 1 and 'unsatisfactory' is 0. However, if all these parameters have a negative impact, then the probability of 'unsatisfactory' combustion performance is 1 and 'satisfactory' is 0. All the other conditions fall in between these two extremes. As an example, consider the following scenario:

Table 3.8: Weighted means for a particular scenario

Fuel quality	Scavenge air quality	Fuel injection performance	Engine settings	Engine maintenance
Unsatisfactory	Satisfactory	Unsatisfactory	Satisfactory	Satisfactory
-0.33	0.24	-0.20	0.16	0.07

If we add the positive values where X > 0:

X = 0.24 + 0.16 + 0.07 = 0.57

This result represents the conditional probability of 'satisfactory' combustion performance for the conditions described above as 0.57 and 'unsatisfactory' as 0.53. Similarly, all 64 probability values have been calculated and described in Appendix C.

3.2.4.1.3 Wear in cylinder component

This intermediate node has two parent nodes, combustion performance and cylinder oil feed rate. FEAP (2017) data indicates that, for 80% of the cases, wear has been found to be excessive where combustion is unsatisfactory, and there is 'unsatisfactory' CLO feed rate which results in a belief degree of 0.8 (excessive wear) and 0.2 (normal wear). Other probabilities in Table 3.9 have been derived from the expert panel.

Table 3.9: CPT of wear in cylinder components

CLO feed rate	Satisfactory		Unsatisfactory	
Combustion performance	Satisfactory	Unsatisfactory	Satisfactory	Unsatisfactory
Normal	0.89	0.64	0.35	0.2
Excessive	0.11	0.36	0.65	0.8

Figure 3.21, Figure 3.22 and Figure 3.23 provide the beliefs from the experts regarding the other three scenarios.

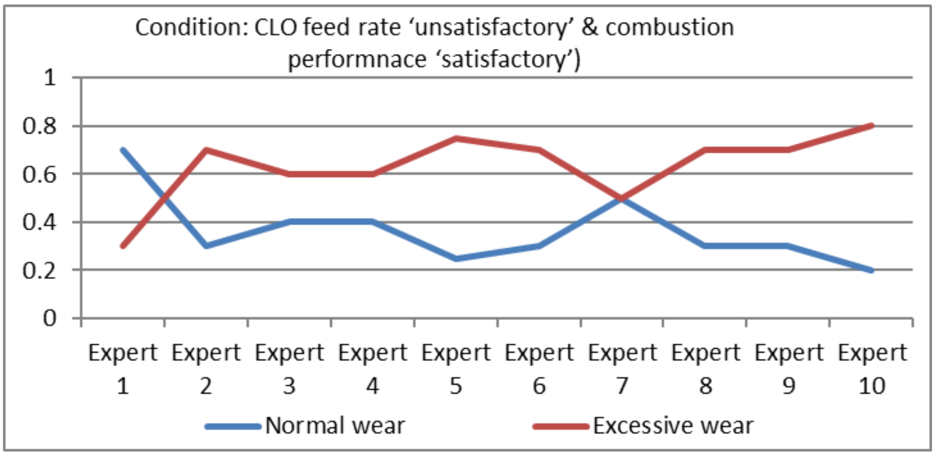


Figure 3.21: Experts’ input for wear in cylinder components (1)

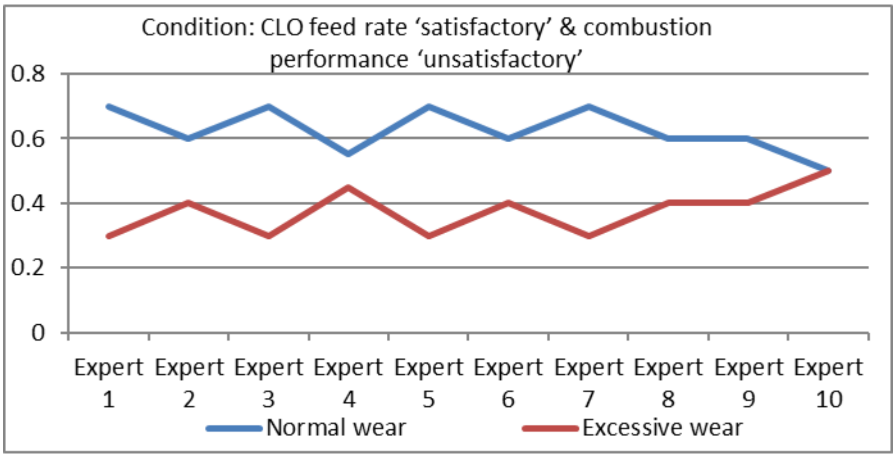


Figure 3.22: Experts’ input for wear in cylinder components (2)

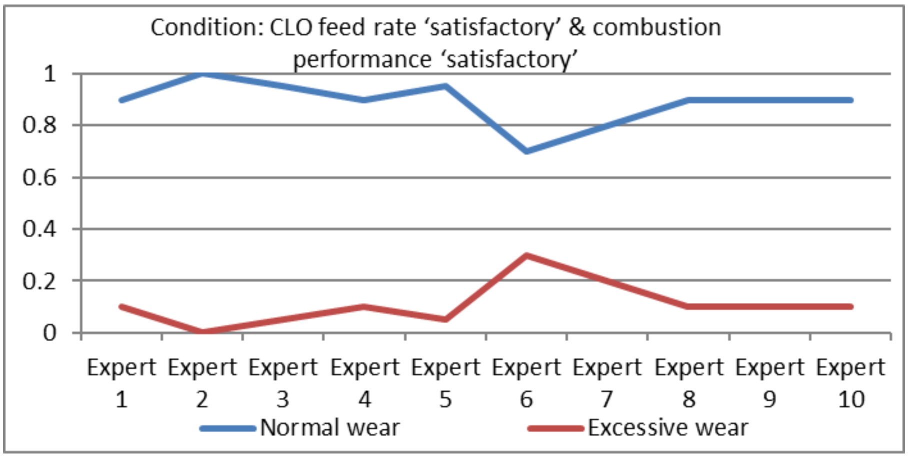


Figure 3.23: Experts’ input for wear in cylinder components (3)

3.2.4.1.4 Engine power output

Under the optimised LS2S engine settings, the Specific Fuel Oil Consumption (SFOC) and emissions would be ‘low’ compared to non-optimised engine settings. ‘Clean burn’ is linked with optimum engine settings through Variable Ignition Timings (VITs) or Fuel Quality Settings (FQSs) to suit variable ignition characteristics and operating conditions (WinGD, 2021). The CPT shown in Table 3.10 has been developed through expert judgements depicted in Figure 3.24 to Figure 3.28.

Table 3.10: Engine power output CPT

Engine settings	Satisfactory		Unsatisfactory	
Combustion performance	Satisfactory	Unsatisfactory	Satisfactory	Unsatisfactory
Optimum	0.9	0.33	0.33	0.13
Non-optimum	0.1	0.67	0.67	0.87

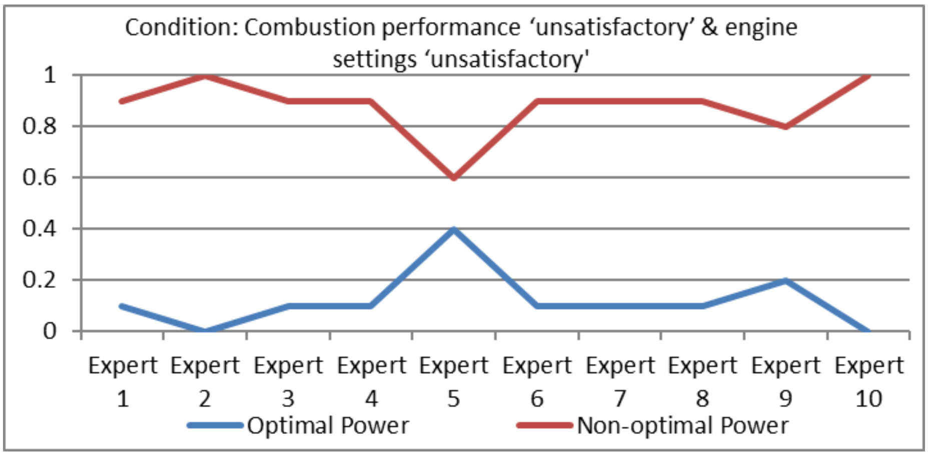


Figure 3.24: Experts' input on engine power output (1)

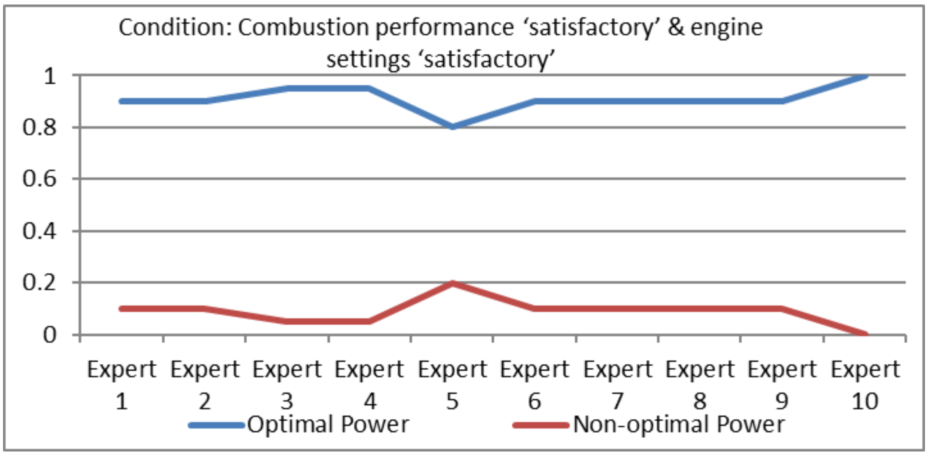


Figure 3.25: Experts' input on engine power output (2)

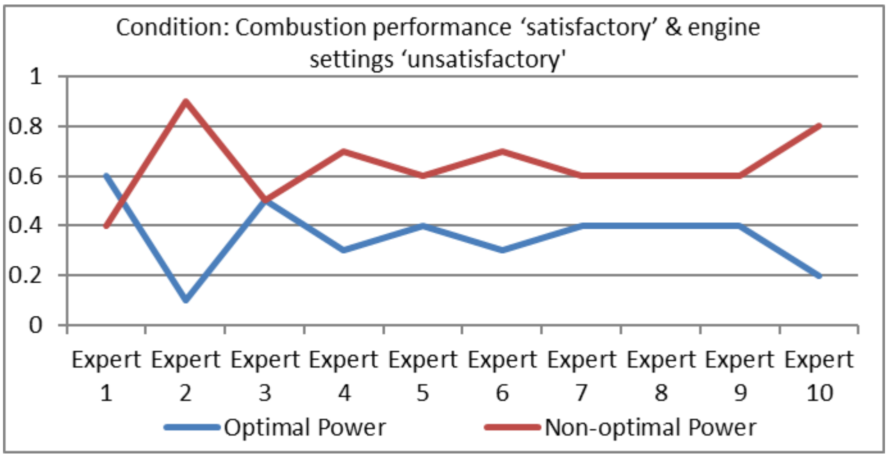


Figure 3.26: Experts’ input on engine power output (3)

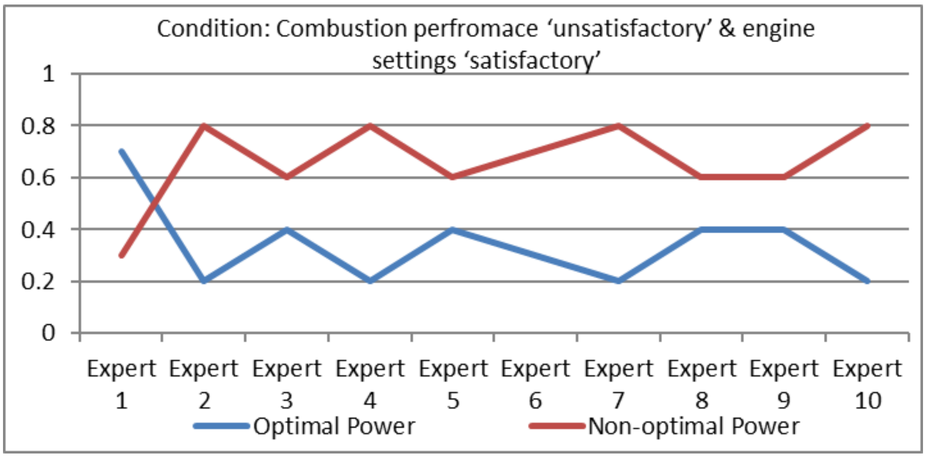


Figure 3.27: Experts’ input on engine power output (4)

3.2.4.1.5 Post-combustion fouling

Some fouling is inevitable, especially during heavy fuel oil consumption in main engines; however, the situation is exacerbated if poor combustion conditions exist. The levels of fouling need to be monitored, and root cause investigation should be performed if excessive fouling is observed followed by conventional best practice approaches such as frequent soot blowing and water washing. Table 3.11 provides the CPT based on expert judgements displayed in Figure 3.28 to Figure 3.31.

Table 3.11: Post-combustion fouling CPT

CLO feed rate	Satisfactory		Unsatisfactory	
Combustion performance	Satisfactory	Unsatisfactory	Satisfactory	Unsatisfactory
Excessive	0.13	0.71	0.34	0.85
Nominal	0.87	0.29	0.66	0.15

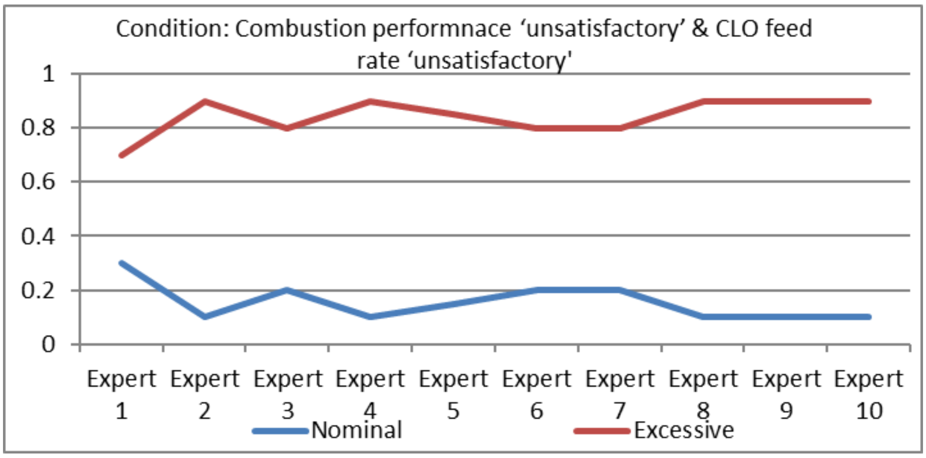


Figure 3.28: Experts’ input on post-combustion fouling (1)

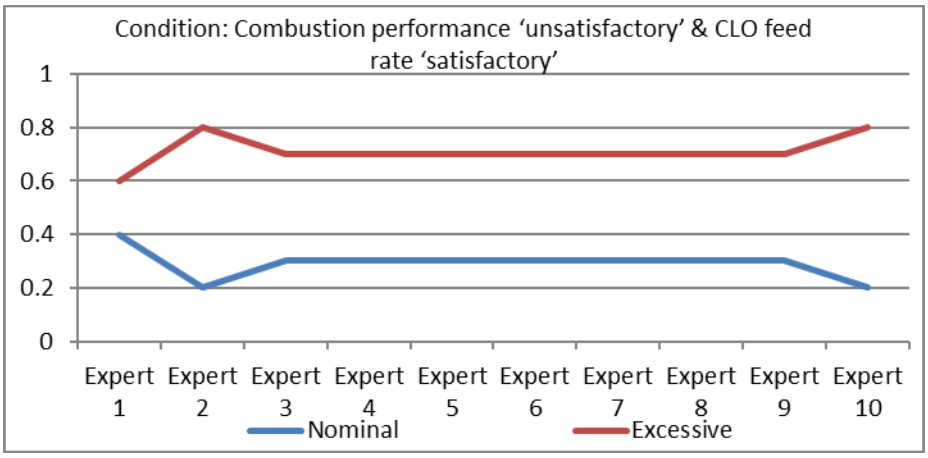


Figure 3.29: Experts’ input on post-combustion fouling (2)

Figure 3.30: Experts’ input on post-combustion fouling (3)

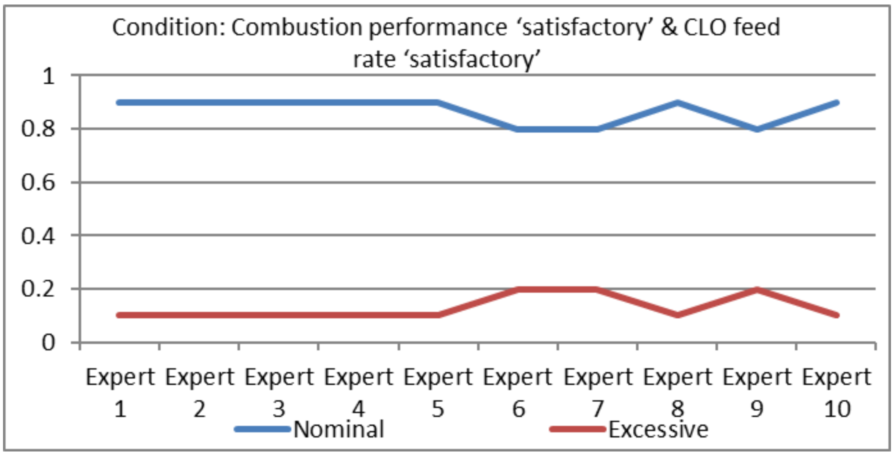


Figure 3.31: Experts’ input on post-combustion fouling (4)

3.2.4.1.6 Health assessment

The engine’s health is an aggregate measure of wear in cylinder components and fouling of the engine components. This gives the onboard engineers a quick indication of the engine’s operational performance. These probabilities have been assigned through the judgements from expert panel. Table 3.12 displays the CPT based on expert judgements given in Figure 3.32 to Figure 3.35

Table 3.12: CPT for engine health assessment

Post-combustion fouling	Excessive		Nominal	
Wear in cylinder components	Normal	Excessive	Normal	Excessive
Satisfactory	0.33	0.08	0.88	0.32
Unsatisfactory	0.67	0.92	0.12	0.68

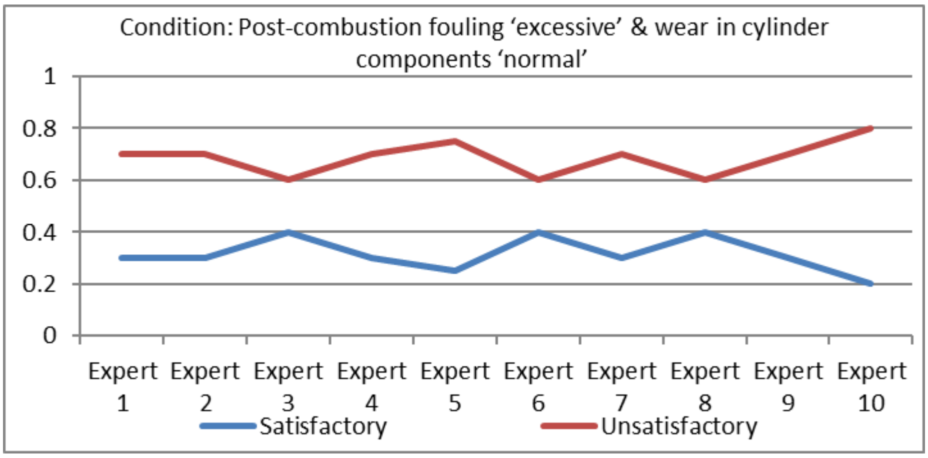


Figure 3.32: Experts’ input on engine health assessment (1)

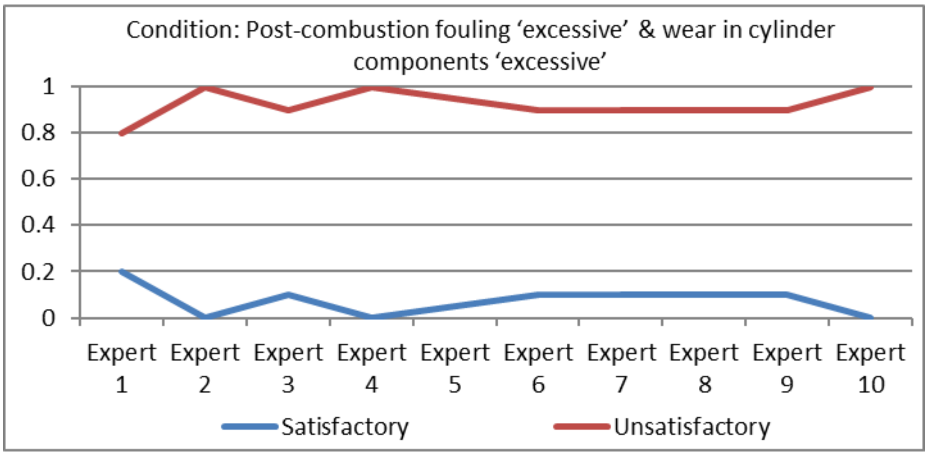


Figure 3.33: Experts' input on engine health assessment (2)

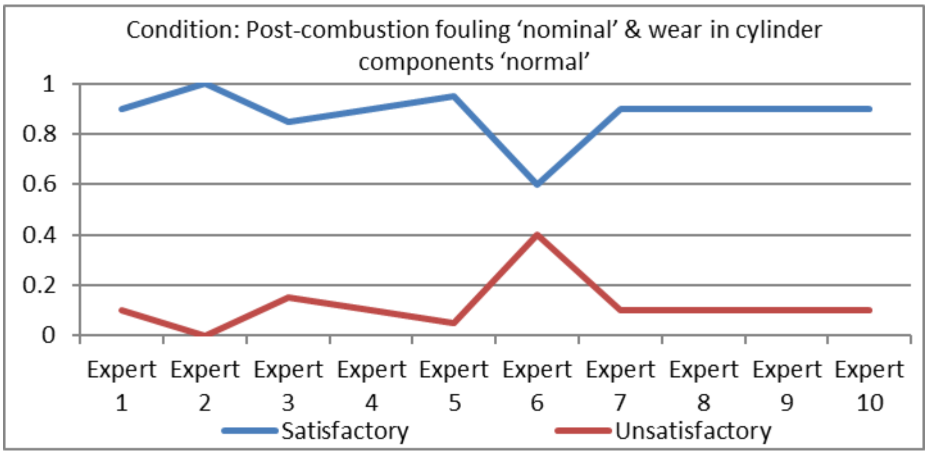


Figure 3.34: Experts' input on engine health assessment (3)

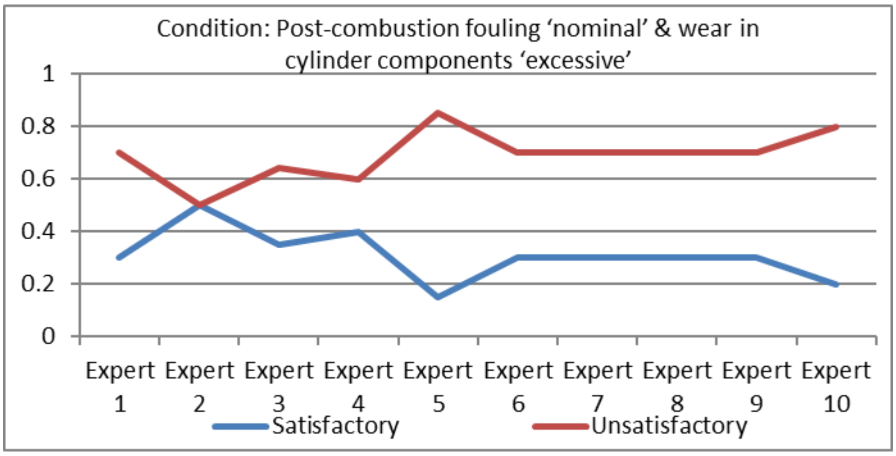


Figure 3.35: Experts' input on engine health assessment (4)

3.3 Model functionality and validation

There are three key measurable or observable engine performance indicators of interest, i.e. wear in cylinder components, post-combustion fouling and optimum engine power output under given conditions. Cylinder component wear rate can be assessed either through analysis of wear metals in scavenge drain oil samples or by taking physical measurements during scavenge port inspections or at the time of cylinder overhauls. Excessive post-combustion fouling can manifest itself in the form of turbocharger surging, loss of performance, lower than expected steam generation from exhaust gas economiser, and high soot levels in the cylinder drain oil analysis. The power output reading is usually taken from the torque meter; however, an important factor is to evaluate the difference (expected power – actual power) to determine any loss in performance under given conditions.

During long voyages, with limited resources and increasing commercial pressures to meet deadlines, it is not always possible for a ship's staff to make frequent checks to determine wear and post-combustion fouling. Hence, this model helps the operators to perform non-invasive assessment and follow up with physical measurements, monitoring, and corrective actions as and when required. This model also serves as a knowledge management tool with a graphical depiction of the inter-causal relationship that exists between various factors affecting engine performance.

Figure 3.36 shows the base model with likelihood windows. The output of the model depends on the inputs to the parent nodes. To begin with, the likelihoods of various states of parent nodes are weighted equally. Based on the assessment of the information about level of maintenance, fuel quality, engine settings, scavenge air quality and CLO feed rate, unconditional probabilities need to be determined for each node. Moreover, the BN model is flexible and allows the probability values of child nodes to be changed if there is a particular need.

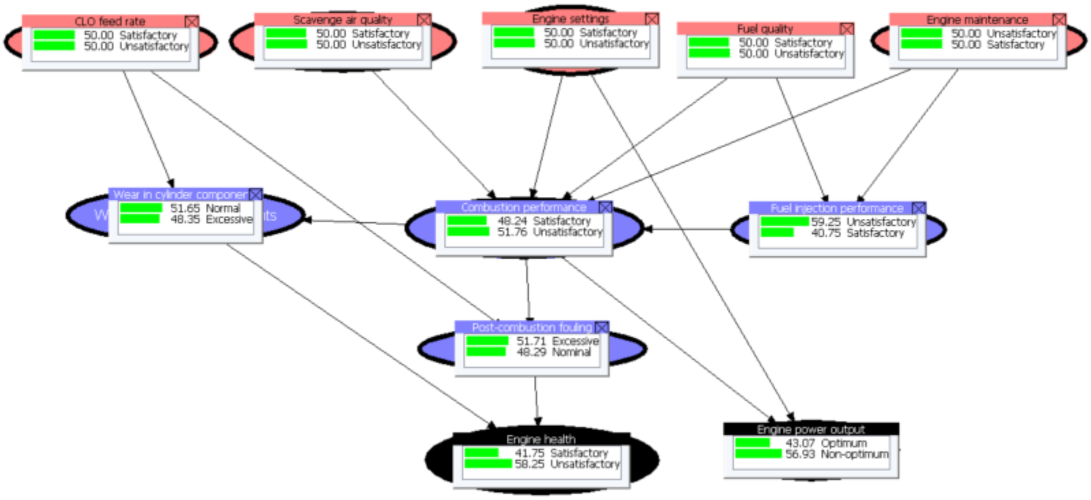


Figure 3.36: BN model with the likelihood

Figure 3.37 indicates the perfect scenario, where all the indicators are positive and the engine operating condition is in a highly desirable mode. This has a positive impact on all the indicators, with a high probability of the engine running under optimum conditions with a satisfactory health rating.

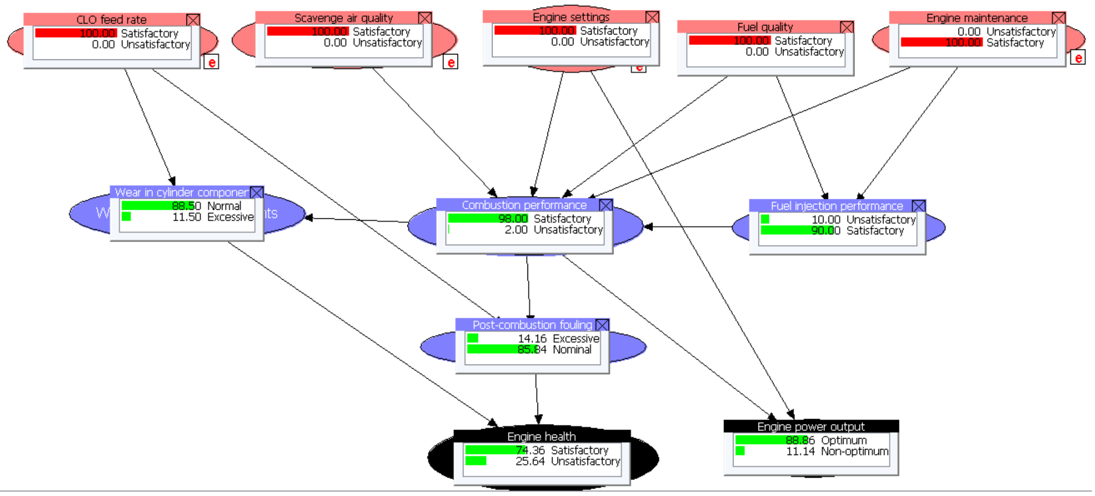


Figure 3.37: Model with a perfect (positive) score for parent nodes

Similarly, the model is tested with the opposite end of the scale, where all the parent nodes exhibit a negative impact on the engine operations, as shown in Figure 3.38. This results in high wear of cylinder components, excessive post-combustion fouling and unsatisfactory power output, subsequently generating a poor engine health rating.

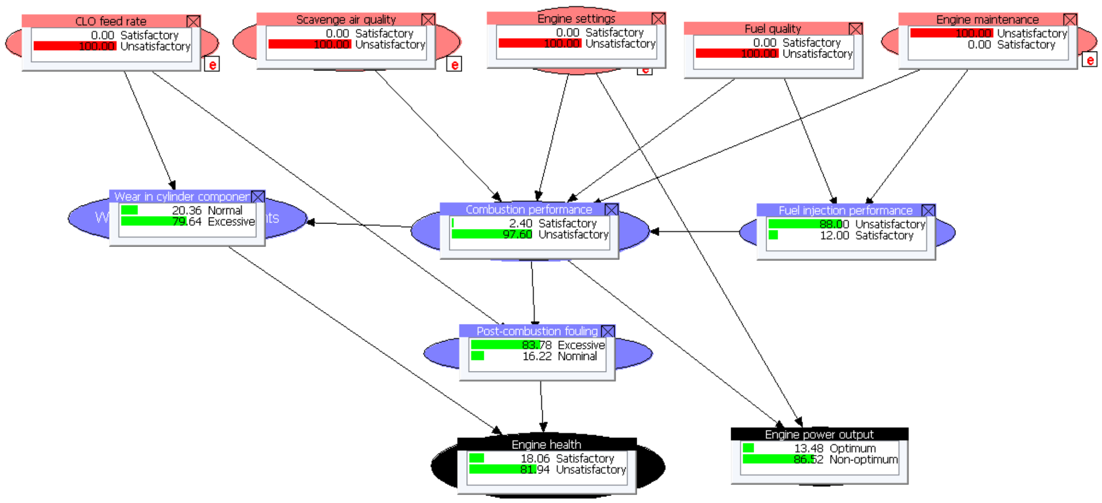


Figure 3.38: Model with an imperfect (negative) score for parent nodes

3.3.1 Sensitivity analysis

As described in section 3.1.5, the BN is tested on three axioms in order to perform sensitivity analysis.

Axiom 1: Table 3.13 indicates that the BN behaves as expected and changing the value of each parent node changes the belief of the variable, as it would in real life. If the unconditional probability of engine settings change from 'satisfactory' to 'unsatisfactory', then posterior probability of 'unsatisfactory' combustion increases from 0.44 to 0.60. Similarly, the impact of fuel quality and maintenance on combustion performance have been given in Table 3.13.

Table 3.13: Test of axiom 1 for combustion performance

Engine settings	Combustion performance
Satisfactory	Unsatisfactory
0	0.60
0.5	0.52
1	0.44
Fuel quality	Combustion performance
Unsatisfactory	Unsatisfactory
0	0.31
0.5	0.52
1	0.72
Engine maintenance	Combustion performance
Unsatisfactory	Unsatisfactory
0	0.44
0.5	0.52
1	0.59

Axiom 2: This axiom is satisfied by showing that the change in the influence of the parent node is consistent with the probability of the child node. Figure 3.39 shows the changes of probabilities for the node ‘combustion performance’ in accordance with the changes made to its parent variables, ‘scavenge air quality’, ‘engine settings’, ‘fuel quality’, ‘engine maintenance’ and ‘fuel injection performance’. The graph indicates consistent changes for ‘poor combustion’ due to change of probabilities of ‘scavenge air quality’ = ‘unsatisfactory’, ‘engine settings’ = unsatisfactory’, ‘fuel quality’ = ‘unsatisfactory’, ‘engine maintenance’ = unsatisfactory’, and ‘fuel injection performance’ = ‘unsatisfactory’. Similar deviations can be seen for the other intermediate node as per Figure 3.40 which shows the functionality of a child node ‘excessive wear’ as a function of CLO feed rate and combustion performance.

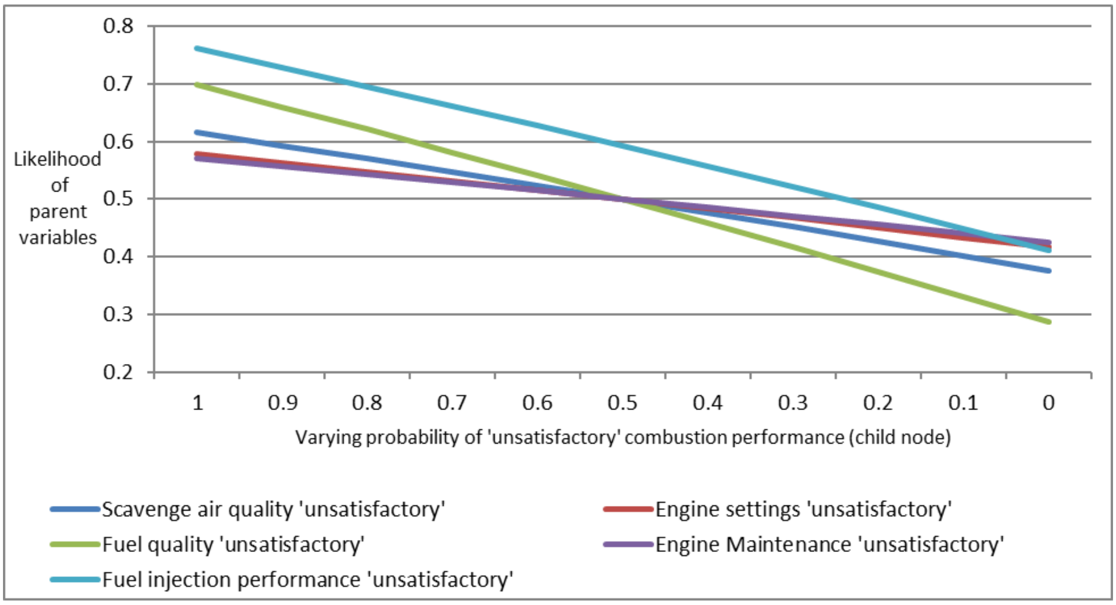


Figure 3.39: Test of axiom 2 for the node 'combustion performance'

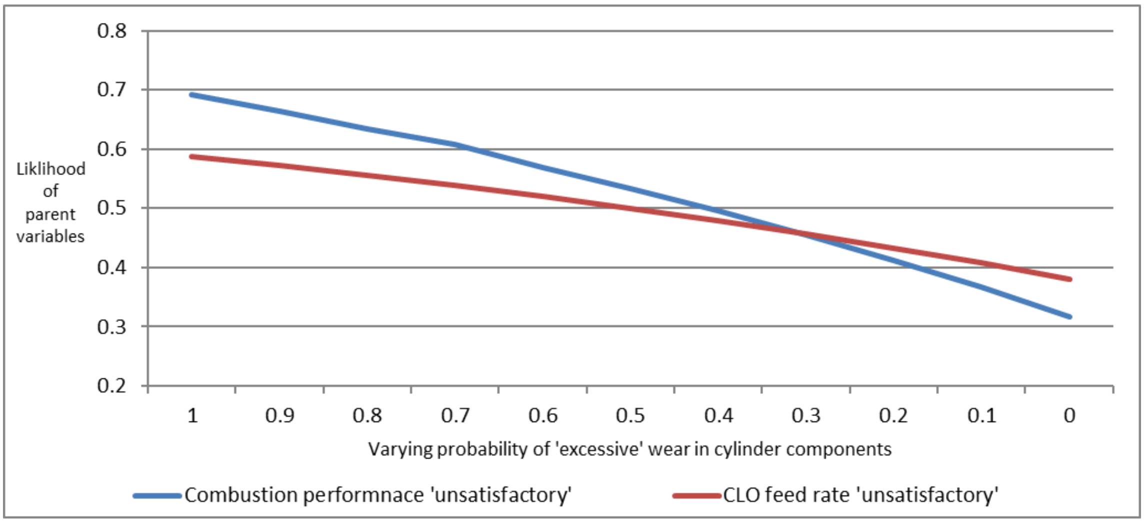


Figure 3.40: Test of axiom 2 for the node 'wear in cylinder components'

Axiom 3: This last axiom requires the combined influence of parent nodes ‘n’ to be higher than the one generated by the same change of n-1 root nodes. Under the perfect conditions of ‘scavenge air quality = satisfactory’, ‘engine settings = satisfactory’, ‘fuel quality = satisfactory’, and ‘engine maintenance = satisfactory’, the posterior probability of ‘combustion performance = satisfactory’ is 0.98, as can be seen from Figure 3.37.

To satisfy axiom 3 (i.e. effect of n-1), assigning the ‘engine settings = unsatisfactory’ would result in a change of posterior probability for ‘combustion performance = satisfactory’, as 0.82 from 0.98, as seen in Figure 3.41.

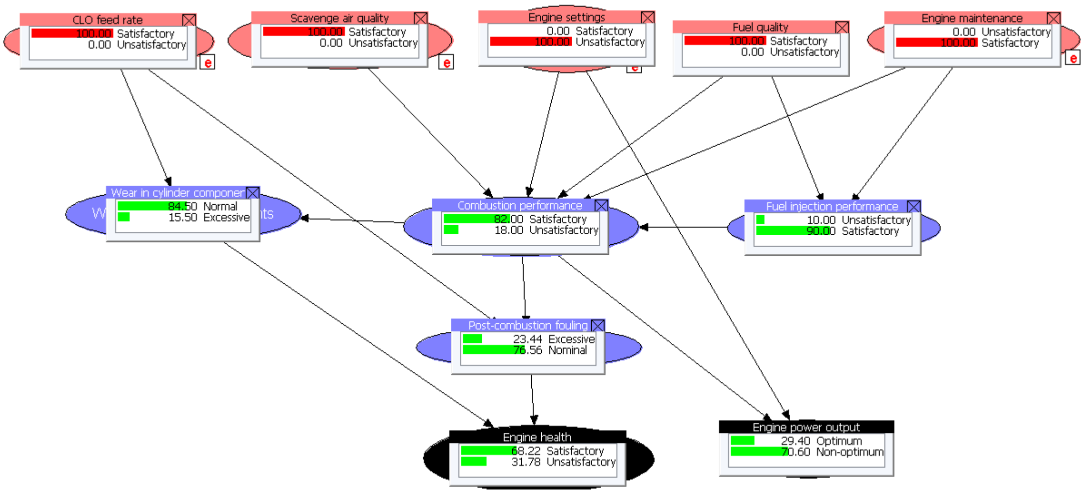


Figure 3.41: Test of axiom 3

In a similar way, more scenarios have been tested using both the newly proposed BN model and the established FEAP (2017) to check the robustness of the BN model. The results from the two methods maintain consistency. For example, the effect on 'post-combustion fouling' when parent node inputs are changed individually, and their combined impact, can be observed from Table 3.14.

Table 3.14: Impact of 'Combustion performance'

Parent nodes for 'combustion performance'	Influence on 'post-combustion fouling = excessive'
Scavenge air quality = unsatisfactory (1)	0.28
Engine settings = unsatisfactory (1)	0.23
Fuel quality = unsatisfactory (1)	0.40
Engine maintenance = unsatisfactory (1)	0.25
CLO feed settings = unsatisfactory (1)	0.35
Combined	0.84

Table 3.14 also provides an indications of the parent nodes having a greater impact on the child node, i.e., fuel quality impose by far the greatest impact on post-combustion fouling and engine settings has the smallest impact in comparison. This kind of analysis also helps the model operator to focus on improving particular area of the performance to have greater improvements.

3.4 Case study

In this section, model validation is performed through a real case study. A bulk carrier on the FEAP (2017) analysis programme reported operational problems with its two-stroke main engine (J-Eng 6UEC60LSII-ECO). The ship reported excessive wear at the cylinder liner, as shown in Figure 3.42.

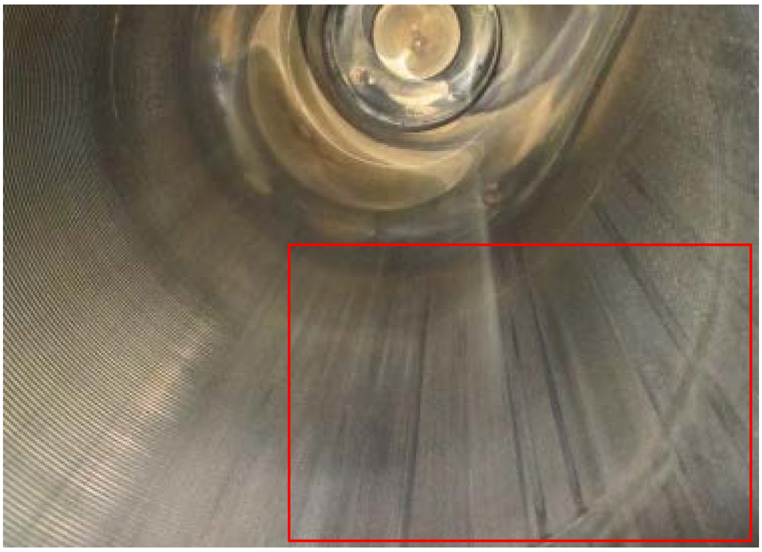


Figure 3.42: Inside view of the affected cylinder liner showing wear pattern

The picture shows vertical sliding marks on one side of the liner surface. To diagnose the reported problem, operational data is processed and placed as input to the BN model. The information received from the ship is placed and analysed in Table 3.15, with corresponding prior probabilities for each parent node derived by converting corresponding quantitative and qualitative operational data into probability distributions.

Table 3.15: Operational variables input and assessment table for the case study

Parameters	Information received from the ship	Qualitative assessment	Corresponding likelihoods
Fuel Quality	Fuel analysis report suggests a low concentration of abrasive catalyst fines at the engine inlet. Other fuel quality parameters comply with Table 2 of the ISO 8217 standard. Fuel sulphur content = 2.23 mass %.	Overall satisfactory quality fuel; however, the viscosity of the fuel is on the higher side for engine inlet.	Satisfactory = 0.70 Unsatisfactory = 0.30
Engine Settings	High deviation in P_{max} and exhaust temperature for cylinder 3. Also, the deviation was high for	Minor corrections were not made to adjust the P_{max}; however, MIP was	Satisfactory = 0.60 Unsatisfactory = 0.40

	cylinder 1 P_{comp} (as shown in Figure 3.44).	consistent for all cylinders.	
Engine Maintenance	Apparently, no outstanding activity (work order) within a planned maintenance scheme.	Machinery maintenance appears to be satisfactory; however, there were recent reports of engine operational issues with perceived links to the unsatisfactory maintenance management	Satisfactory = 0.58 Unsatisfactory = 0.42
Scavenge air quality (temperature/pressure)	Scavenge air temperature and pressure are 45^0C and 1.73 bar respectively.	The optimum temperature should be around 40^0C. Scavenge pressure is satisfactory for the corresponding load on the engine.	Satisfactory = 0.72 Unsatisfactory = 0.28
CLO feed rate	The feed rate is set at 1.04 g/kWh.	Considering the operational circumstances, the CLO feed rate was deemed to be excessive.	Satisfactory = 0.22 Unsatisfactory = 0.78

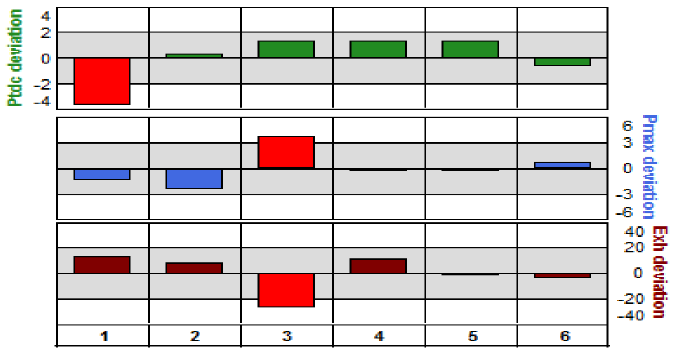


Figure 3.43: Data received from the ship on P_{comp}, P_{max} and exhaust gas temperature deviations for the six-cylinder LS2S engine

Once these prior probabilities are placed in the model, the results are obtained, as shown in Figure 3.44.

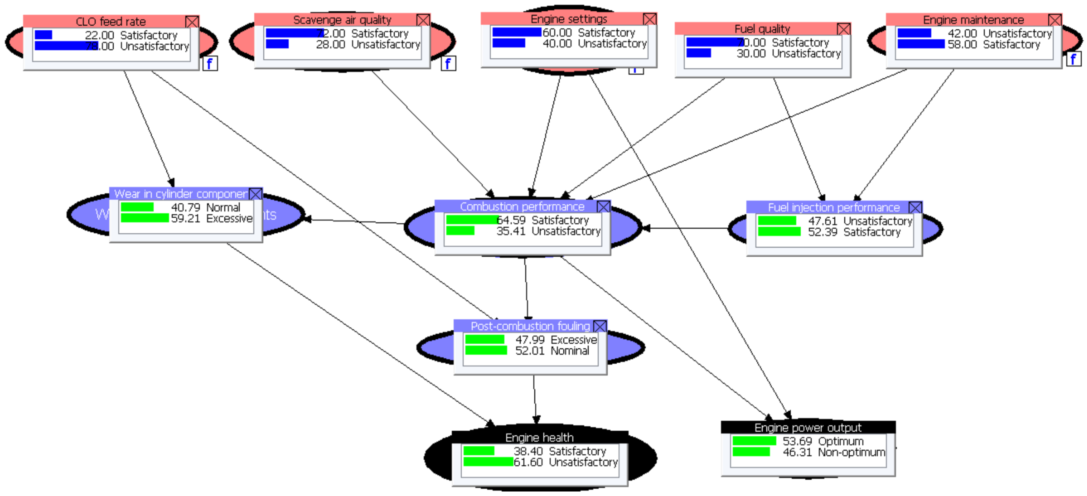


Figure 3.44: BN model for the case study

The processing of the data through the model provides valuable insight into various engine KPIs. The combustion performance appears to be predominantly satisfactory, given good fuel quality and relatively better maintenance and engine settings. However, the cylinder oil feed rate is non-optimal, which has resulted in the above normal wear, explaining the reported operational problem and resulting in the predominantly unsatisfactory engine health rating. The following photographs received from the ship indicate a relatively low rate of post-combustion fouling.

Figure 3.45: Pictures through scavenge ports indicating level of fouling

However, on the piston topland, there is an indication of fouling (grey layer – the picture on the right) which appears to be through the burning of excessive CLO. This also confirms that the engine has been running with a relatively high cylinder oil feed rate. In this case, feed rate optimisation would likely result in a low wear rate and reduce the fouling observed on the piston.

3.5 Conclusion

Combustion in a large two-stroke marine diesel engine is a complex phenomenon, even more so during heavy fuel oil consumption, making it extremely difficult to predict and prevent consequences from poor combustion. However, there are indicators, the logical analysis of which can provide reasonably accurate information about the key performance parameters.

The literature review indicated the suitability of the BN to serve as a stochastic model to capture the operations of dynamic systems such as onboard a ship with an LS2S engine. A user-friendly BN model has been developed and described in section 3.2, which provides the ship's staff with LS2S engine health assessment and facilitates in maintenance decision making. The study utilises the judgements from 10 industry experts to create BN conditional probability tables. The model is also put through the validation phase to check for its sensitivity, i.e. how the model outputs change with the changes in input, by using three axioms described in section 3.3. Finally, a real-life case study is presented where the BN model is employed as a retrospective analysis tool to determine the root cause of the problem and also whether the model output matches the initially reported problem of excessive wear rate of cylinder liner and components.

The model can be used as both a prospective and a retrospective tool, as shown in the case study. Currently, the model's limitation is that the operators themselves need to interpret the operational data to form judgements in order to generate prior probabilities for BN parent nodes. This is likely to generate different results for similar operational conditions based on the users' experience and viewpoint. This can be addressed by providing interpretation guidelines for the users, although a better solution is to create a further probabilistic model where input operational data is processed and directly fed into the BN model as parent node probabilities, subsequently eliminating the human element. This particular issue is addressed in the next chapter.

4 Use of fuzzy rule-base to elicit probabilities in the BN model of LS2S engine performance assessment

It has been the intention of this study to create a dynamic model capable of processing the key operational parameters for two-stroke engine performance assessment. The major challenge has been to address how the multiple sets of quantitative and qualitative operational information are amalgamated and converted into an appropriate quantitative feed for the BN model. An attempt has been made to address the issue by applying fuzzy set theory to all five BN parent nodes, namely scavenge air quality, fuel quality, maintenance, cylinder oil feed rate and engine settings.

A fuzzy control model has been chosen to address the challenge described in the above paragraph because it is one of the most suitable methods to address uncertainty and combine various indicators. Fuzzy control model accommodates various sources of information, allows logical inference to process the information (Jantzen, 2013) and can provide output in the probability format which can be used in the Bayesian model as input.

4.1 Fuzzy modelling

Fuzzy logic theory was formalised in 1965 and has emerged over the years as a useful tool for modelling processes which are relatively complex for conventional methods (like probability theory) or when the available information is uncertain or inexact (Wang and Trbojevic, 2007).

Fuzzy logic can handle problems with inaccurate and insufficient data. The method is concerned with the formal principles of approximate reasoning, i.e. description of the relationship between complexity and uncertainty, and it is said that, with the increase in complexity, certainty decreases. The basic concept of fuzzy set theory is linguistic variables. The significance of these variables is that they facilitate the gradual transition between states and therefore are able to deal with the observation and measurement of uncertainties (Klir, 1995).

Fuzzy logic starts with the concept of a fuzzy set. In a fuzzy set, the boundaries are not precise, contrary to the classical notion of a set, i.e. the membership of a fuzzy set is not a matter of affirmation or denial but a matter of degree. A fuzzy set assigns the grades to membership between 0 and 1; 1 corresponds to full membership and 0 means no membership (Klir, 1995). For example, let ‘*x*’ be the height of a person, and a person is termed as ‘tall’ if $x \geq 176$ centimetres. In the case of classical set theory, everyone with a height of 176 cm and above is going to be a full member of the (crisp) set of ‘tall’ people. However, fuzzy sets seem a natural choice for representation where membership of the set can vary from 0 to 1 and all in between (gradual rather than abrupt), as shown in Figure 4.1 (Jantzen, 2013).

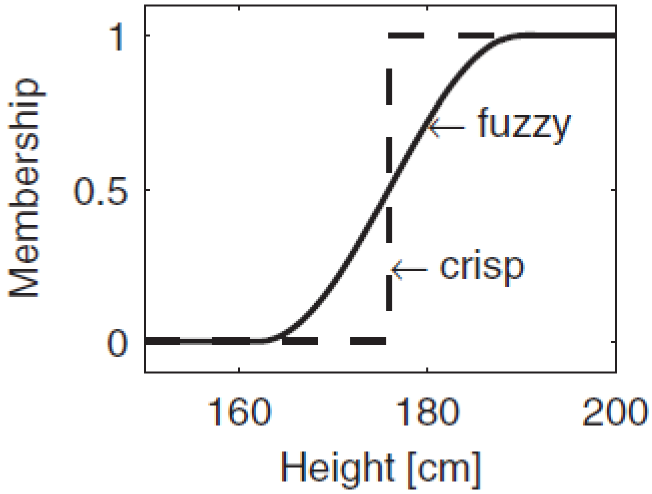


Figure 4.1: Two definitions of the set of tall men, a crisp set and a fuzzy set
Source: Jantzen (2013)

4.2 Membership functions

Fuzzy membership can be represented as either continuous or discrete functions. Example of continuous membership functions are trapezoidal and triangular membership functions. Trapezoidal membership is a piecewise continuous membership function controlled by four parameters/breakpoints as a ≤ b ≤ c ≤ d. Triangular membership is a form of trapezoidal membership function where b = c.

For example, a comfortable room temperature is considered to be around 22˚C, as shown in Figure 4.2.

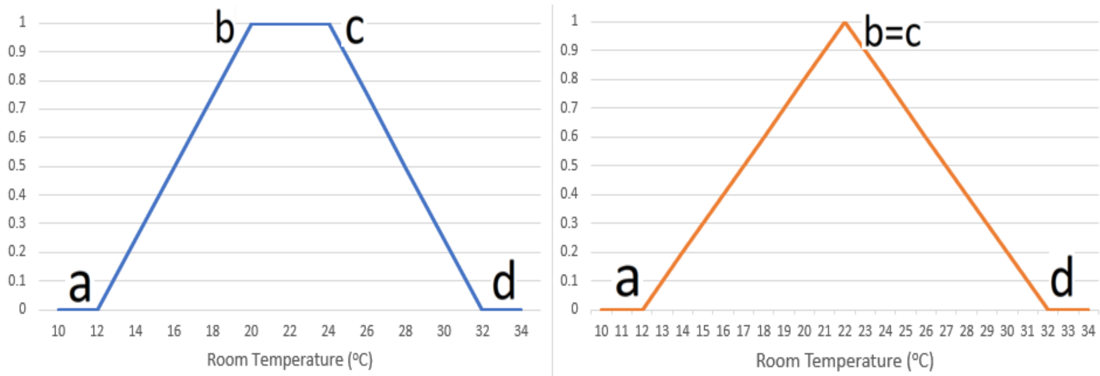


Figure 4.2: Trapezoidal (left) and triangular (right) membership functions for comfortable room temperature

Trapezoidal membership gives a wider range from 20~24^{o}C whilst triangular function only points to a single value of 22^{o}C. However, the continuous membership function for comfort is going to vary depending on the beliefs or what is considered as comfortable. In this research, both triangular and trapezoidal membership functions have been used depending on a particular context and available data.

4.3 Fuzzy control model

Information flow through the fuzzy control model as input variables goes through three major transformations before coming out as results. The three stages are fuzzification, fuzzy inference and defuzzification, as shown in Figure 4.3.

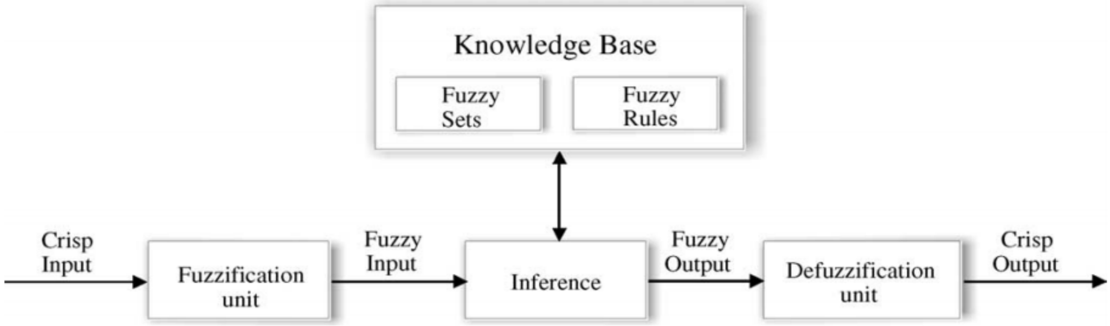


Figure 4.3: Structure of a typical fuzzy model
Source: Konstandinidou et al (2006)

4.3.1 Fuzzification

In the first stage, inputs are taken from variables and converted to appropriate fuzzy sets to express the uncertainties associated with the measurements (Das, Panja and Chakrabarty, 2014). In fuzzy modelling, membership functions are used to describe the membership of a variable to a fuzzy set. There are various functions, and the simplest is the triangular membership function which has predominantly been used in this study.

4.3.2 Fuzzy inference

The inference process assigns one fuzzy output set to each fuzzy rule-base. Then, the degree of truth for the activation of each rule is computed and applied to the conclusion part (then part) of the rule. Based on the degree of truth of each part of the rule, a *max-min* inference technique is used (Konstandinidou et al., 2006). The truth value of a rule is determined from the combination of the information associated with each rule and this is determined by taking the minimum rule antecedent. If any fuzzy output is the consequence of more than one rule, then that output is determined by the maximum truth value of all the rules that include this as a consequent. The result of the rule evaluation is a set of fuzzy conclusions that need to be defuzzified (Andrew and Moss, 2002).

4.3.3 Defuzzification

The purpose of defuzzification is to convert each conclusion obtained by the inference engine, which is expressed in terms of a fuzzy set, to a single real number (Klir and Yuan, 1995). There are various defuzzification methods in the literature. Jensen (2013) compared various methods based on their universe of discourse and showed how these methods could yield slightly varied results.

However in this chapter, the aim is to develop a fuzzy model to compute prior probability values which can be achieved at the fuzzy inference stage, practically eliminating the need for defuzzification of the input variables.

4.4 A fuzzy model for engine performance assessment

The description provided in section 3.2.2 details the rationale for the node selection. However, processing these operational parameters through a fuzzy model requires defining a set of criteria against which the operational data is assessed and categorised. Upcoming sections 4.4.1 to 4.4.5 will provide the details of these quantitative limits fixed to develop fuzzy membership functions.

Table 4.1 briefly outlines the key variables and their states under consideration in this section.

Table 4.1: Input model variables

Operational parameter (consequent)	Antecedents (factors affecting the parameter)	States of antecedents	States of consequents
Scavenge air quality	Air pressure	1) Low & 2) Satisfactory	1) Satisfactory & 2) Unsatisfactory
	Air temperature	1) Low, 2) Satisfactory & 3) High	
	Performance of Water Mist Catcher (WMC)	1) Satisfactory & 2) Unsatisfactory	
Fuel quality (at engine inlet)	Catalyst fines level	1) Satisfactory & 2) High	1) Satisfactory & 2) Unsatisfactory
	Viscosity	1) Low, 2) Satisfactory & 3) High	
	Water	1) Satisfactory & 2) High	
	Ash content	1) Satisfactory & 2) High	
	Combustion performance (CCAI)	1) Satisfactory & 2) High	
Engine maintenance	Work orders completion	1) Satisfactory & 2) Unsatisfactory	1) Satisfactory & 2) Unsatisfactory
	Availability of the asset	1) Satisfactory & 2) Unsatisfactory	
CLO feed settings	Fe content	1) Satisfactory & 2) High	1) Satisfactory & 2) Unsatisfactory
	TBN	1) Low, 2) Satisfactory & 3) High	
Engine settings	$P_{max} – P_{comp}$	1) Low, 2) Satisfactory & 3) High	1) Satisfactory & 2) Unsatisfactory
	MIP deviation	1) Unsatisfactory & 2) Satisfactory	
	Exhaust (temp) Deviation	1) Unsatisfactory & 2) Satisfactory	

4.4.1 A fuzzy model for scavenge air quality

Scavenge air to the main engine is supplied by the turbocharger(s) fitted on the exhaust side of the engine. The air is drawn through a filter into the turbocharger compressor, then passed through the air cooler, water mist catcher and set of non-return valves, before entering the scavenge air receiver, as per Figure 4.4.

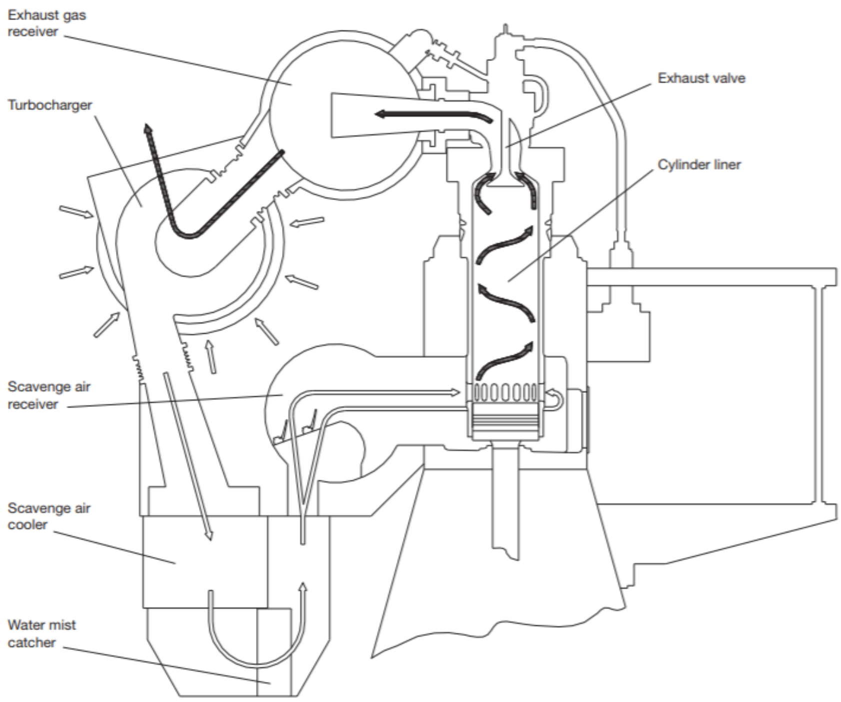


Figure 4.4: Scavenge air system
Source: MAN-ES, (2014a)

Scavenge air at optimum pressure, temperature and with minimum moisture levels contributes to good combustion conditions in the two-stroke engine (Griffiths, 2006). Pressure and temperature have a direct relationship; hence, air going into the engine at the right temperature and appropriate pressure provides sufficient mass of oxygen to facilitate complete combustion. Lower pressure and higher temperature risk incomplete combustion and higher exhaust temperature (Griffiths, 2006).

Hence, for this study, the quality of the scavenge air has been assessed by processing the temperature and pressure in the scavenge air receiver, and performance of the water mist catcher indicating dryness of the air by following the process shown in Figure 4.5.

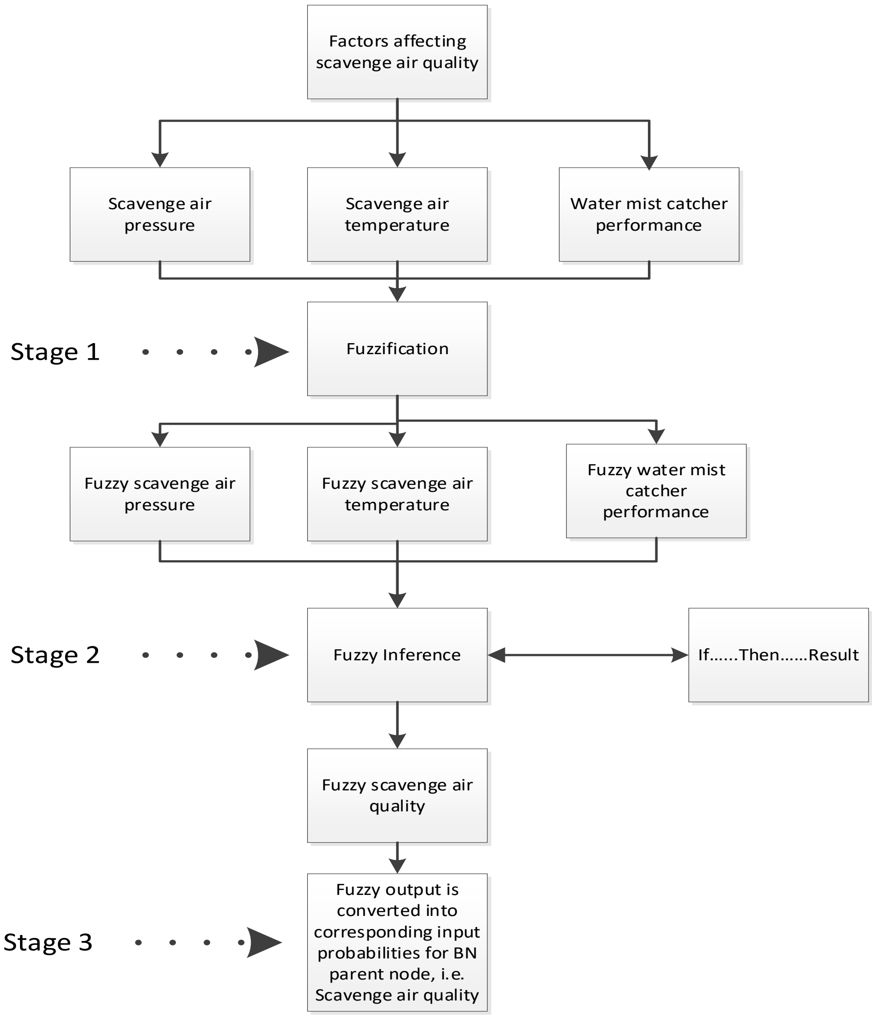


Figure 4.5: Fuzzy model for scavenge air quality

Three fuzzy sets are developed with corresponding linguistic terms to fuzzify the engine's operational data with the fuzzy 'IF-THEN' rules to establish whether the scavenge air quality is 'satisfactory' or 'unsatisfactory'.

4.4.1.1 Fuzzification of input variables

Quantitatively, pressure and temperature are direct operational measurements; however, determining the level of scavenge air 'dryness' entering cylinder liners for combustion is not straightforward. Pressurised scavenge air going into the scavenge space goes through the scavenge air cooler, Water Mist Catcher (WMC)/separator and non-return valves/flaps before entering the scavenge space. In order to achieve a quantitative measurement, the WMC performance has been used as an indicator where the difference between actual water collected and expected (as per the engine operations manual) would be used to determine its effectiveness. The following sub-sections provide the details of the fuzzification steps for the three variables.

4.4.1.2 Scavenge air pressure

During normal operations, there is an approximately linear relationship between the effective power/engine load vs scavenge air pressure for a typical two-stroke engine (Zhu et al., 2020). This is also reflected from the analysis of the FEAP (2017) dataset repository, where a good correlation between the load and the corresponding scavenge air pressures has been observed, as per Figure 4.6.

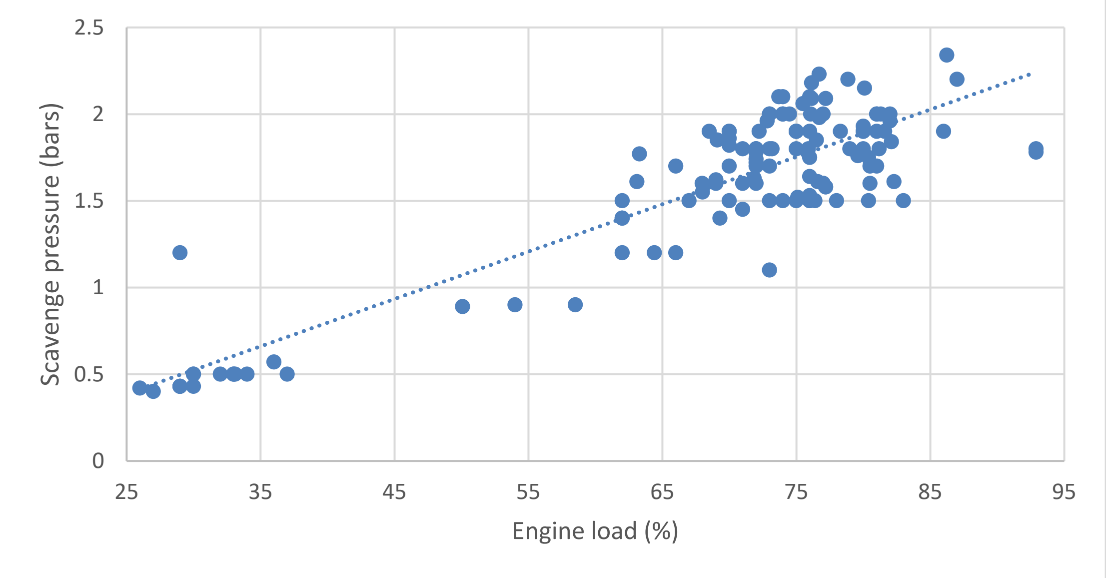


Figure 4.6: Correlation between scavenge pressure and engine load
Source: FEAP (2017)

The critical factor is to determine whether the operational data, i.e. scavenge air pressure, is sufficient for the engine load it is operating on. There could be several reasons for lower than expected pressure, such as post-combustion fouling degrading the turbocharger performance, partially-blocked air suction filter, fouled scavenge air cooler, leaky scavenge space, and malfunctioning non-return valves. If the scavenge pressure is low for the prevailing operating conditions, then it negatively impacts combustion performance.

For the purpose of this study, percentage deviation (ΔP_{scav}) from the optimum scavenge air pressure for the given load has been used for fuzzy modelling where two fuzzy sets, ‘Low’ and ‘Satisfactory’, are developed with fuzzy membership varying from 0 to 1. The current operational reading of scavenge air pressure needs to be compared with the corresponding values provided in the operations manual for the same loading conditions to compute the percentage deviation. For example, if an engine is operating at 70% load with scavenge pressure of 1.9 bar but the engine operations manual indicates the ideal pressure to be around 2.1 bar, then this represents a deviation of around 9.5%.

To establish whether fuzzy membership functions for scavenge air pressure deviation (ΔP_{scav}) are assigned 'satisfactory' or 'low', the study takes guidance from international standard ISO 15550 (2016) addressing general requirements for power measurements of internal combustion engines. Table 4 (section 2) of the standard provides the permissible deviations ranges for various pressure measurements. A couple of parameters, 'inlet depression (ΔP_d)' and 'boost pressure drop through the air cooler (ΔP_{ba})', are considered to be relevant. ΔP_d provides a permissible pressure variation at the inlet of the turbocharger of ±5%, and ΔP_{ba} is allowable pressure drop across the air cooler of ±10 %. These two key points of the scavenge air system have been combined to develop a limit for use as the acceptability criterion for the scavenge pressure being low or satisfactory.

$\Delta P_{scav} = \Delta P_{ba} + \Delta P_d$

$\Delta P_{scav} = 10 + 5 = 15\%$

The graph shown in Figure 4.7 reflects the above calculation, suggesting if ΔP_{scav} exceeds 15% or more then scavenge pressure would be considered 'low' with 100% belief degree and vice versa.

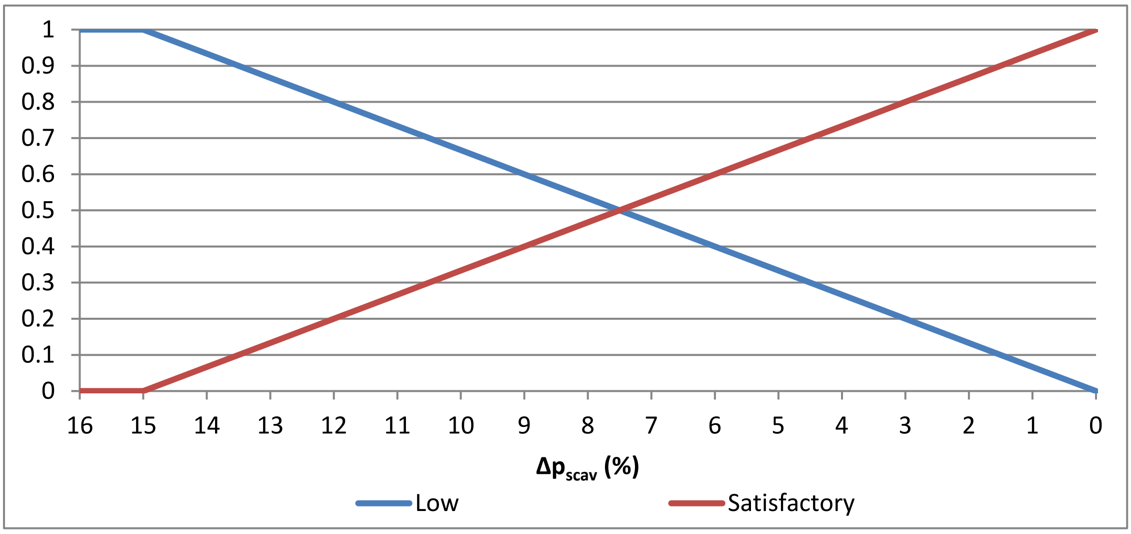


Figure 4.7: Fuzzy membership of scavenge air pressure

Similarly, for the case described above, ΔP_{scav} of 9.5% would result in a fuzzy membership of 0.63 as 'low' and 0.37 as 'satisfactory'.

4.4.1.3 Scavenge air temperature

Scavenge air temperature is mainly a function of ambient temperatures and the efficiency of the scavenge air cooler. The temperature is kept within a specific operating range, as a high scavenge temperature could result in poor combustion performance (low air density), and an excessively low temperature could cause thermal shock to cylinder components (Wright, 2005). The density of air (ρ_{scav}) going into the engine increases or decreases depending on the temperature of the air, as it has an inverse relationship:

$T_{scav} \propto 1 / \rho_{scav}$

During normal operation, the amount of air is kept above the minimum required levels, i.e. stoichiometric air/fuel ratio which is a theoretical condition where all the oxygen in the air inlet is consumed leaving combustion without any oxygen with maximum CO_2. The actual air/fuel ratio can be two to three times more than the stoichiometric air/fuel ratio (Wright, 2005). The excess air facilitates the combustion process; however, its drawback is that there are increased NOx emissions (Kaltoft, 2011).

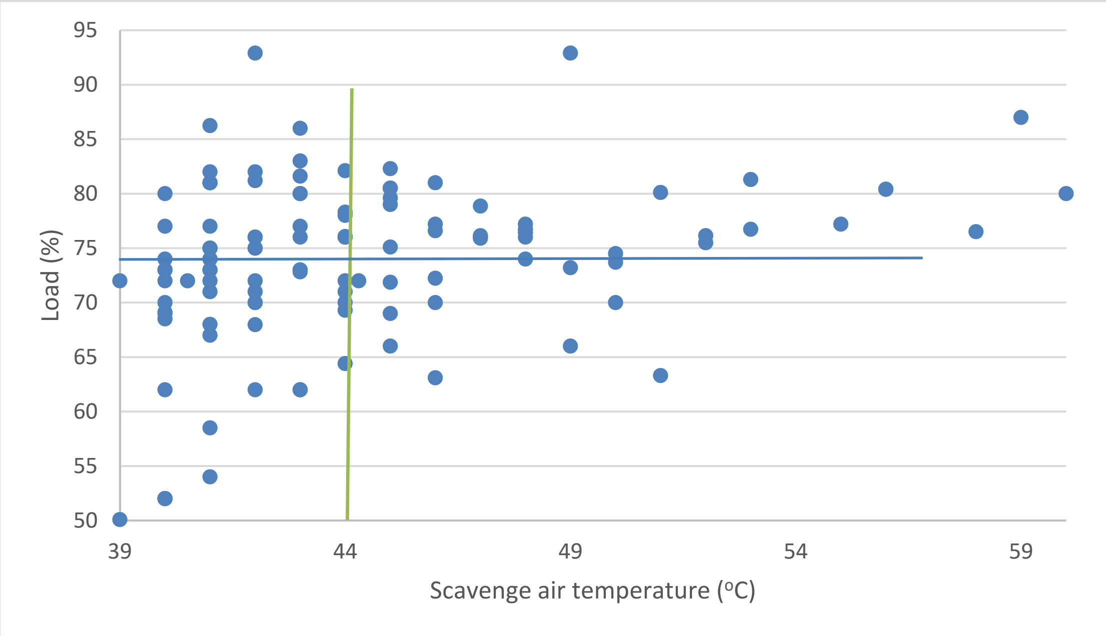


Figure 4.8: Temperature vs Load
Source: FEAP (2017)

Figure 4.8 is based on the FEAP (2017) data showing the scavenge air temperature variations with the engine load (>50%). The vertical green line on the graph indicates the average scavenge air temperature (44ºC) whilst the blue line is corresponding average load (74%) for the chosen data range. At low load (<50%) operations (slow steaming), the average scavenge temperature drops to 40ºC at an average load of 31%. Based on these numbers and from the engine designer's guidance (MAN-ES, 2010), it has been established that an average acceptable scavenge air temperature is 42ºC, subject to ambient conditions and cooler efficiency. Moreover, the lower and upper quartiles of the data set (Figure 4.8) are around 34 and 50ºC, respectively. Based on the data, three fuzzy sets have been defined, i.e. ‘Low’, ‘Satisfactory’ and ‘High’, as per Figure 4.9.

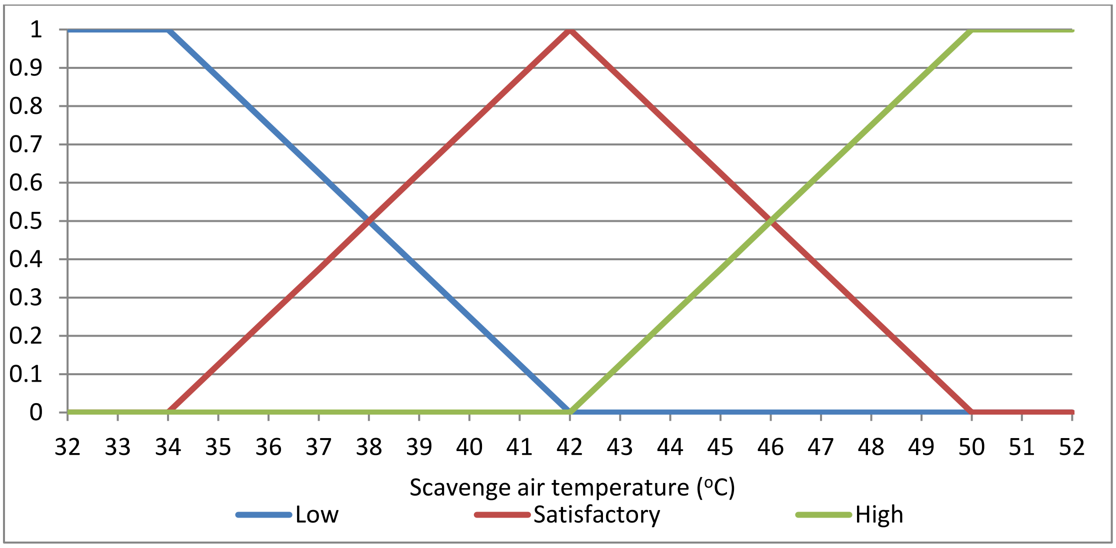


Figure 4.9: Fuzzy membership of scavenge air temperature

Fuzzy scavenge air temperature is determined based on the operational input from the engine, which can determine the level of membership to a fuzzy set. For example, if the scavenge air temperature is around 46^{o}C, then the fuzzy scavenge air temperature is assigned a fuzzy membership of 0.5 ‘satisfactory’ and 0.5 ‘high’.

4.4.1.4 Performance of WMC

The primary function of the WMC is to remove the water mist from the scavenge air to avoid carry-over of high moisture content into the scavenge space, potentially disrupting the lubricant film and leading to the formation of acids contributing to cold corrosion (Griffiths, 2006). The amount of water condensation would mainly depend on the ambient temperature, relative humidity, scavenge air temperature, scavenge air pressure, engine size and load. It is difficult to directly measure the acceptable humidity levels for the air going into the combustion chamber. MAN-ES (2011) evaluates the WMC efficiency as a function of the air velocity passing through it. Various WMC designs are tested for efficiency in a research facility under varying air quality conditions. In order to address this unknown factor, i.e. which WMC design is fitted on an engine, this study instead proposes a measurement method by computing the difference between the actual amounts of water condensed during certain operating conditions and corresponding calculated amount as per the engine maker’s guidelines.

The water vapour in the air intake can be calculated from relative humidity (ϕ) which is given as (Balmer, 2011);

$$\phi = \frac{p_w}{p_{sat}}$$

Here p_w is the actual partial pressure of water vapour and p_{sat} is the saturation pressure of the water vapour at a certain temperature. On ships, relative humidity readings can be directly taken from a psychrometer placed on the bridge or other suitable location.

The humidity ratio τ of the air is given as (Balmer, 2011);

$$\tau = \frac{m_w}{m_a}$$

here m_w is the mass of water vapour present in the air and m_a is the mass of dry air. These two measures are related by the following equation (Balmer, 2011);

$$\tau = 0.622 \left(\frac{\phi\, p_{sat}}{p_m - \phi\, p_{sat}}\right)$$

where p_m is the atmospheric pressure which is the sum of p_a (partial pressure of dry air) and p_w (partial pressure of water vapour). Along with relative humidity, atmospheric pressure is also a known value through onboard barometers. p_{sat} in the above equation can be determined through the following Arden Buck equation (Kaplya, Kaplya and Silaev, 2020);

$$p_{sat} = a_1\, exp\left[\frac{a_2 - T/a_3}{a_4 + T}\, T\right]$$

The values of the constants a_1, a_2, a_3, and a_4 in this equation for any temperature (T) > 0^oC have been given as 6.11, 18.678, 234.5 and 257.14 respectively (Kaplya, Kaplya and Silaev, 2020). From the equations above, the humidity ratio τ in kg of water/kg of dry air can be determined using the information from measurement devices and formula for p_{sat}.

Furthermore, MARPOL (2009) section 5.12.4 of NOx technical code provides a humidity correction factor to apply for engines with an intermediate cooler. The formula given in the section yield the humidity (H_{sc}) of charge air in g water per kg dry air as follows;

$$H_{sc} = 6.22 \,.\, p_{sc} \,.\, 100/(p_c - p_{sc})$$

Here p_{sc} is the saturation vapour pressure of the charge air and p_c is the charge air pressure.

Hence for the actual calculations, if we know the specific fuel consumption (g/kWh), engine operational load, and the energy content (MJ/kg) of the fuel, the amount of fuel consumed by the engine in kg per hour is calculated. It is estimated that the amount of fuel is approximately 2% of the amount of dry air, so this will yield the amount of air in kg/h. The amount of condensate should be the amount of water vapour in the intake air minus the amount of water vapour in the scavenge air.

This study intends to use MAN-ES engine as a case example hence to simplify; the MAN-ES 6S50MC-C engine operations manual is consulted which provides a simplified approach by graphical representation of the above calculations. For data privacy issues, these graphs cannot be reproduced here however the following calculations have been made to produce a number of results to define the fuzzy membership functions for WMC performance in removing the condensate from scavenge air.

To calculate the WMC performance, the difference between the calculated condensed water ($M_{condens}$) and actual amount (M_{actual}) of water collected over a 24-hour period is used. The following formula is employed to calculate the $M_{condens}$ during operation;

$$M_{condens} = Engine\ Load \times (M_{amb} - M_{scav})$$

Where

M_{amb} is the amount of water vapour in the intake air in ambient conditions

M_{scav} is the amount of water vapour in the scavenge air

M_{amb} and M_{scav} are determined from relative humidity and scavenge pressure curves or calculated as per formulas provided in the above paragraphs.

For example, for a 6S50MC-C engine operating at 90% load (around 8964 kW) under ambient temperature of 30°C with a relative humidity of 70%, the scavenge pressure and temperature for this load is 3.5 bar and 42°C, respectively. M_{amb} and M_{scav} have been computed as 0.23 and 0.16 kg/h, respectively. Using the following equation:

$$M_{condens}^{calc} = Engine\ Load \times (M_{ambient} - M_{scavenge})$$

$$M_{condens}^{calc} = 8965 \times (0.23 - 0.16)$$

$$M_{condens}^{calc} = 627\ kg/h\ OR\ 15\ tonne/day$$

Suppose, actual water collected in the scavenge condensate tank is 13 tonnes in 24 hour period, then $\Delta M_{condens}$ would be 2 tonnes/day. The higher the $\Delta M_{condens}$, the higher the inefficiency of the WMC, which increases the risk of water carry over to the scavenge space. Unusual results can be used as prompts for the ship's staff to investigate the reason, such as scavenge drain blockage, possible water leaks from the scavenge cooler or damaged WMC. It has been realised that these calculations may lack precision, so a tolerance of up to ±10% is applied.

The assignment of fuzzy membership functions to WMC performance being 'satisfactory' or 'unsatisfactory' would be inconsistent. This is because the amount of water condensed and separated is predominantly a function of engine size/power and ambient conditions. To demonstrate the functionality of this fuzzy model, a medium-sized MAN 6S50MC-C two-stroke X-head engine is chosen, though the membership functions would require adjustments for significantly larger or smaller engine sizes. To establish fuzzy membership functions typically for the 6S50MC-C engine, a simulation approach has been adopted where a set of plausible scenarios are developed at various ambient and operational conditions, as per Table 4.2.

Table 4.2: M_{conden} calculations for a 6S50MC-C engine

Scenario	Power (kW)	T_{scav} (°C)	P_{scav} (bars)	T_{amb} (°C)	Rel. humidity (%)	M_{scav} (kg/h)	M_{amb} (kg/h)	M_{conden} (kg/h)	$M^{calc}_{condens}$ (tonne/ day)	20% of M^{calc}_{conden}
1	5000	39	2	35	60	0.2	0.21	50	1.2	0.24
2	6000	41	2.2	35	70	0.19	0.235	270	6.48	1.296
3	7000	42	2.5	40	80	0.18	0.34	1120	26.88	5.376
4	8000	45	3	35	80	0.19	0.24	400	9.6	1.92
5	9000	45	3.2	40	60	0.175	0.25	675	16.2	3.24

These scenarios reflect a range of loading conditions, from near 100% to around 50% load with corresponding rate of condensation varying from 1.2 tonnes/day to 26 tonnes/day. Assuming there is an error margin of ±10% in these estimates and another 10% associated with the potential WMC inefficiency would result in total margin of around 20% of $M^{calc}_{condens}$. For this particular engine size, this results in a range from 0.24 to around 5 tonnes/day. So this range forms the basis of perceived difference in estimated value to actual condensate quantity collected onboard. In view of this, Figure 4.10 presents the fuzzy membership functions defined for this parameter.

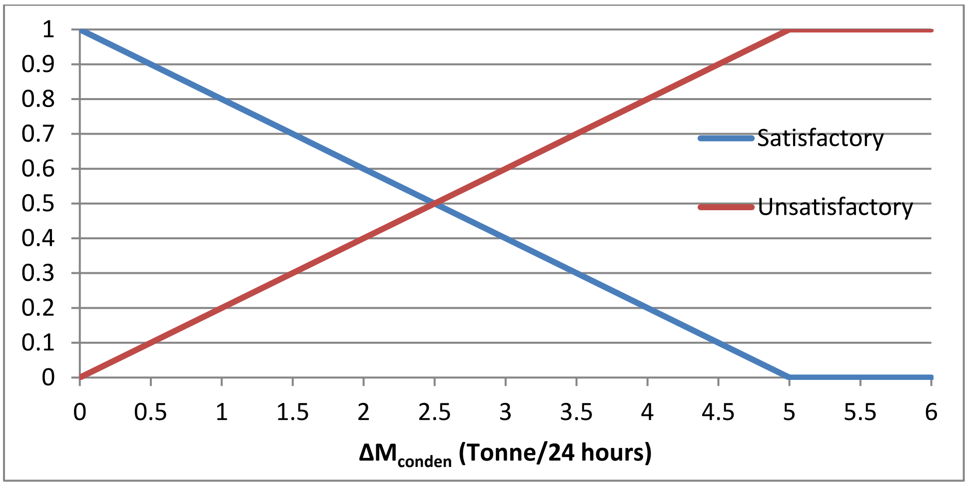


Figure 4.10: Fuzzy membership for WMC performance assessment

This means that, if the difference ($\Delta M_{conden} = M^{calc}_{condens} - M^{actual}_{condens}$) is 4 tonnes/day, then WMC performance would be assigned 'satisfactory' as 0.2 and 'unsatisfactory' 0.8.

4.4.1.5 Fuzzy inference

The next step in the process is the development of the fuzzy rule-base. Considering there are three antecedents (IF part) with 2 × 2 × 3 states resulting in 12 rules as shown in Table 4.3, the THEN part of the rule-base reflects whether the scavenge air quality is 'satisfactory' or 'unsatisfactory'.

For each rule, the consequent part is established by assigning the three antecedents equal weights, which means IF two out of the three antecedents are pointing towards 'satisfactory' scavenge air quality THEN the consequent part of the rule is also 'satisfactory'. For example, IF the air pressure is 'satisfactory', the temperature is 'low', and WMC performance is 'satisfactory' THEN scavenge air quality is 'satisfactory'.

Table 4.3: Fuzzy rule-base for scavenge air quality

Rule No.	IF			THEN
	Air Pressure	Temperature	WMC	Scavenge air quality
1	Low	Low	Satisfactory	Unsatisfactory
2	Low	Low	Unsatisfactory	Unsatisfactory
3	Low	Satisfactory	Satisfactory	Satisfactory
4	Low	Satisfactory	Unsatisfactory	Unsatisfactory
5	Low	High	Satisfactory	Unsatisfactory
6	Low	High	Unsatisfactory	Unsatisfactory
7	Satisfactory	Low	Satisfactory	Satisfactory
8	Satisfactory	Low	Unsatisfactory	Unsatisfactory
9	Satisfactory	Satisfactory	Satisfactory	Satisfactory
10	Satisfactory	Satisfactory	Unsatisfactory	Satisfactory
11	Satisfactory	High	Satisfactory	Satisfactory
12	Satisfactory	High	Unsatisfactory	Unsatisfactory

Fuzzy model functionality for the scavenge air quality has been demonstrated through an example. Table 4.4 shows the typical operational data for a ship installed with a MAN 6S50MC-C two-stroke marine engine.

Table 4.4: Input operational variables

List of parameter	Unit	Value
Effective Power	kW	8000
Corresponding Scavenge air pressure as per the manual	Bar	3.0
Actual Scavenge air pressure	Bar	2.8
Scavenge air temperature	^{o}C	44
Condensed scavenge cooler water collected (actual)	tonne/24H	7.5
Condensed scavenge cooler water (as per section 4.4.1.4)	tonne/24H	9

Placing these operational values into the fuzzy models developed in sections 4.4.1.2, 4.4.1.3 and 4.4.1.4 would result in Table 4.5 showing the fuzzy membership for all three variables.

Table 4.5: Fuzzy membership for individual fuzzy sets

Air pressure	
Low	0.44
Satisfactory	0.56
Temperature	
Low	0
Satisfactory	0.75
High	0.25
WMC performance	
Satisfactory	0.7
Unsatisfactory	0.3

For the operational scenario developed in this section and corresponding fuzzy membership in Table 4.5, eight rules out of 12 from Table 4.3 were activated. These rules have been summarised in Table 4.6 with their corresponding 'truth' values.

Table 4.6: Set of fuzzy rule-base to determine scavenge air quality

Rule No.	IF				THEN
	Air Pressure	Temperature	WMC	Min-value	Scavenge air quality
3	Low (0.44)	Satisfactory (0.75)	Satisfactory (0.70)	0.44	Satisfactory
4	Low (0.44)	Satisfactory (0.75)	Unsatisfactory (0.30)	0.30	Unsatisfactory
5	Low (0.44)	High (0.25)	Satisfactory (0.70)	0.25	Unsatisfactory
6	Low (0.44)	High (0.25)	Unsatisfactory (0.30)	0.25	Unsatisfactory
9	Satisfactory (0.56)	Satisfactory (0.75)	Satisfactory (0.70)	0.56	Satisfactory
10	Satisfactory (0.56)	Satisfactory (0.75)	Unsatisfactory (0.30)	0.30	Satisfactory
11	Satisfactory (0.56)	High (0.25)	Satisfactory (0.70)	0.25	Satisfactory
12	Satisfactory (0.56)	High (0.25)	Unsatisfactory (0.30)	0.25	Unsatisfactory

Using the first step in fuzzy 'max-min' operations as described in section 4.3.2, a minimum value from each rule is extracted and also shown in Table 4.6. Out of these eight activated rules, the THEN parts of rules 3, 9, 10 & 11 indicate a 'satisfactory' outcome whilst rules 4, 5, 6 & 12 represent an 'unsatisfactory' outcome, as follows:

Satisfactory = {0.44, 0.56, 0.30, 0.25}

Unsatisfactory = {0.30, 0.25, 0.25, 0.25}

The next step is to take a maximum value from each set of corresponding consequents, i.e. max (0.44, <u>0.56</u>, 0.30, 0.25) and max (<u>0.30</u>, 0.25, 0.25, 0.25), resulting in probability values for scavenge air quality as 'satisfactory' 0.56 and 'unsatisfactory' 0.30. However, there remains an unassigned probability value of 0.14 {1 − (0.56 + 0.30)} which needs to be addressed. A simple rounding off approach has been used, i.e. unsatisfactory (x) scavenge air quality with fuzzy membership value of 0.30 would equate to:

$x = \frac{0.30}{0.56+0.30}$ Where $x \leq 1$

$x = 0.35$

Hence, the conditional probability for scavenge air quality is ‘unsatisfactory’ 0.35 and ‘satisfactory’ 0.65.

4.4.2 A fuzzy model for fuel quality (at engine inlet)

For developing this fuzzy model, five parameters (viscosity, CCAI, ash, catalyst fines and water content) have been considered to determine the fuel quality at the engine inlet with the potential to affect the combustion in the LS2S engine directly. A similar approach to that outlined in Figure 4.5 has been adopted to develop the fuzzy model for fuel quality evaluation.

The CCAI is a calculated value from viscosity and density of the fuel (ISO 8217, 2017) and can be considered as a screening tool for an early indication of potential ignition delay in residual fuel oils (Fisher and Lux, 2004). There are more sophisticated testing methods such as FIA-100 FCA (Fuel Combustion Analyser) (Fueltech, 2021) to determine the combustion characteristic of the fuel; however, routine fuel analysis does not include such methods, hence the CCAI has been considered for swift evaluation.

Similarly, unsuitable injection viscosity, excessive water and abrasives of catalyst fines can severely impact the combustion and contribute to the wear of the cylinder components (Fisher and Lux, 2004). Moreover, higher levels of ash in the fuel, which represents the non-hydrocarbon components, would contribute towards excessive post-combustion fouling. Higher levels of fouling can negatively impact the turbocharger and exhaust valve performance.

4.4.2.1 Fuzzification of fuel input parameters

In this step, fuzzy membership functions are developed for each of the five factors impacting the fuel quality at the engine inlet. To establish the baselines, the FOBAS (2020) database is mainly used.

4.4.2.2 CCAI (combustion performance)

This study is based around the premise that an RM grade fuel is being burnt in an LS2S engine. For residual fuel oils, the CCAI used to be considered as a reliable indicator of combustion performance for straight-run heavy fuels (i.e. ignition delay is a direct function of aromaticity indicated by higher density and low viscosity). However, with the changes in the marine fuel market and increased demand, more blended fuels have entered the supply chain, which has reduced confidence in the CCAI in terms of representing the combustion performance of the fuel (CIMAC 2011). Nevertheless, the CCAI is still considered as an index and screening tool to determine the levels of aromaticity where a high CCAI value could highlight an ignition delay characteristic of the fuel. Hence, there are two linguistic variables associated with CCAI, 'High' and 'Satisfactory'.

To establish a quantitative baseline, first, FOBAS (2020) data has been reviewed on latest marine fuel quality. Most of the graphs used in section 4.4 have been derived from FOBAS (2020) data (from Dec 2019 to May 2020) and divided into three main categories based on sulphur content as follows:

1. Ultra-Low Sulphur Fuel Oil (**ULSFO**) with sulphur ≤ 0.10 mass %
2. Very-Low Sulphur Fuel Oil (**VLSFO**) with sulphur between 0.11% ~ 0.50 mass %
3. High Sulphur Fuel Oil (**HSFO**) with sulphur > 0.50 mass %.

HSFO are mainly residual fuels with higher viscosity and density; hence, they exhibit high CCAI values. ULSFO are usually light residual with higher paraffinic blends whilst VLSFO exhibit wide variability, from heavy distillates to heavy fuels. After the implementation of MARPOL Annex VI Reg. 14.1.3 from 1st January 2020 (MARPOL, 2009), HSFOs have been replaced with VLSFOs to be burnt outside emission control areas unless the ship is fitted with an exhaust gas cleaning system.

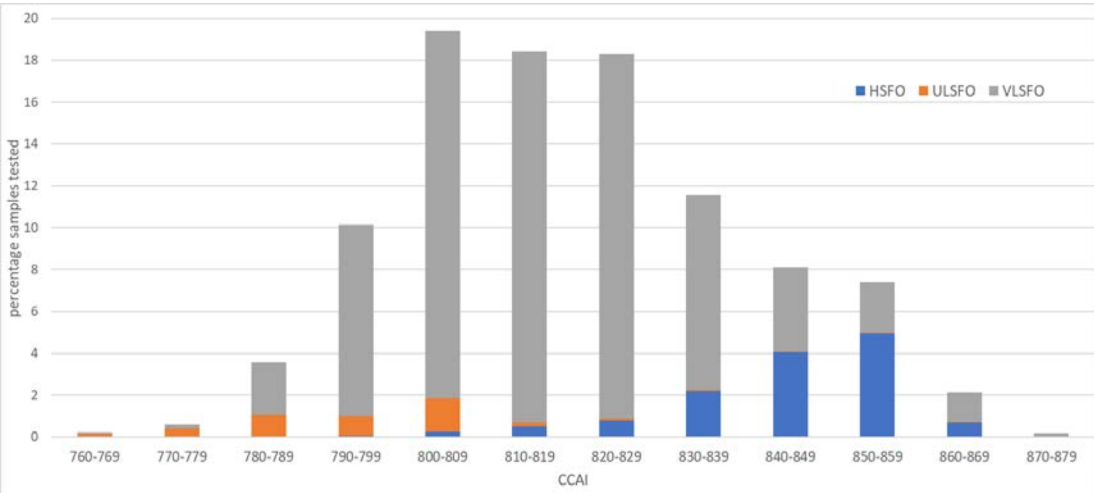


Figure 4.11: CCAI distribution of samples tested
Source: FOBAS (2020)

Figure 4.11 is based on the FOBAS (2020) data for the first five months of 2020. It can be observed that around 94% of all fuel types fall between a CCAI value of 790 and 860, which shows wide variability compared to pre-2020 data, which indicates that around 70% of fuel samples fall in a narrow range of 840~860. FOBAS (2020) data also indicates that the likelihood of engines requiring particular attention for their fuel combustion performance increases when the CCAI value is above 860. However, recent use of VLSFO fuels indicates that even lower CCAI values of 850 and less can cause combustion problems. Nevertheless, there is a cumulative risk with the increase in a fuel's aromaticity. Considering the latest data, the likelihood of the CCAI being judged as 'High' would increase from 0% at a CCAI of 830 to 100% at 870 with a linear relationship, and vice versa for 'satisfactory', as per Figure 4.12.

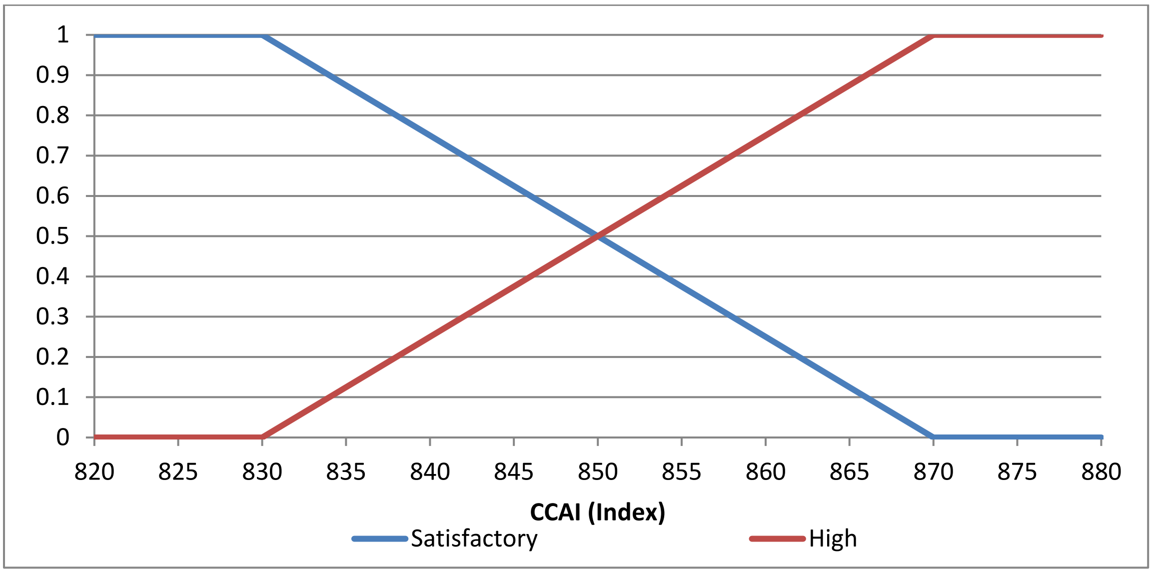


Figure 4.12: Fuzzy membership for evaluation of CCAI

For example, if the CCAI is 845, then a corresponding fuzzy membership of 0.625 'Satisfactory' and 0.375 'High' would be assigned.

4.4.2.3 Viscosity

Correct injection viscosity is an essential parameter during heavy fuel oil consumption. For a typical two-stroke engine, the recommended injection viscosity is around 10~15 cSt (Fisher and Lux, 2004), and this is usually maintained through a viscosity controller. The following graph shows the typical injection viscosities for various fuel blends with a maximum allowance of 2~20 cSt. Figure 4.13 presents the heating requirement to achieve the required engine inlet viscosity for the corresponding standard tested viscosity of the fuel. For example, to achieve 12 cSt viscosity at engine inlet, a fuel with the viscosity of 200 cSt (@50 ^{o}C) is required to be heated to around 123^{o}C.

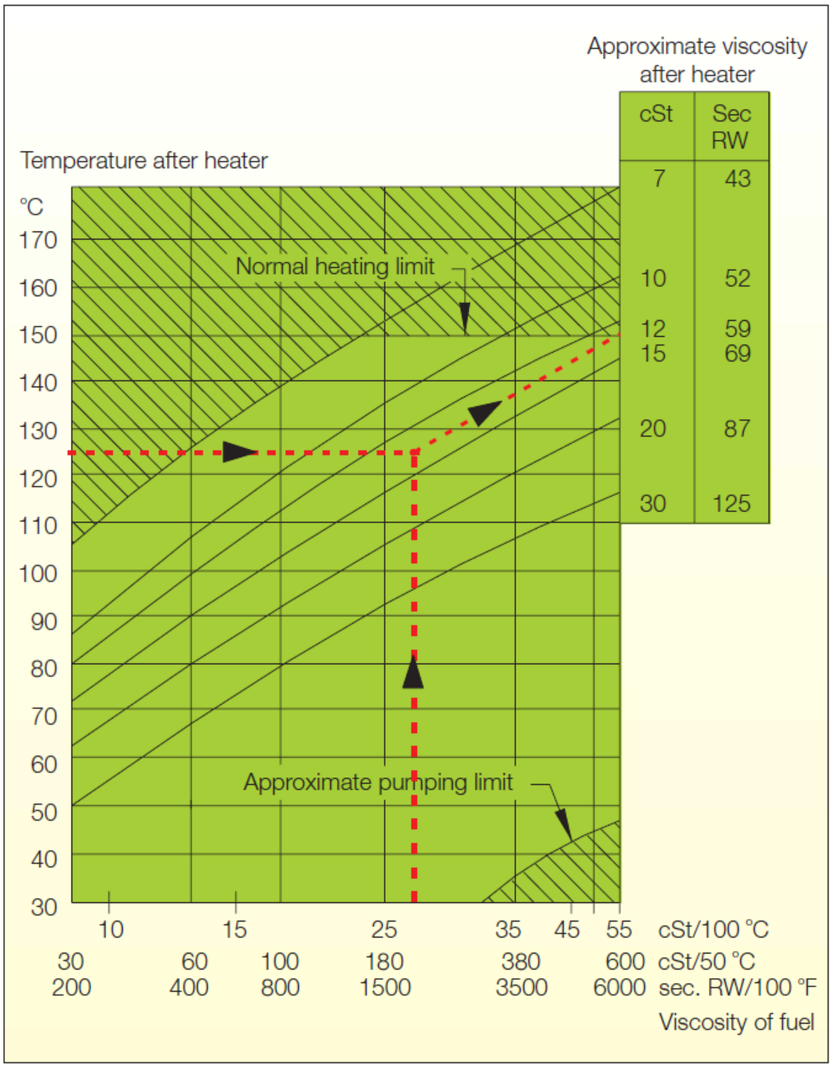


Figure 4.13: Heating chart for heavy fuel oil
Source: MAN-ES (2014)

Maintaining higher than recommended viscosity at engine inlet could result in poor atomisation at fuel injectors, resulting in fuel impingement and increased levels of unburnt fuel. Conversely, too low viscosity points to overheating of fuel, loss of energy and insufficient fuel penetration within the combustion chamber, resulting in poor combustion. Hence, it is essential to maintain viscosity within a specific range for good combustion performance.

Recent FOBAS (2020) data indicates the wide variations in the viscosity of marine fuels delivered to ships. For example, before the introduction of VLSFO, the data suggests that around 56% of residual fuels fell in the range of 300~380 cSt (@50°C); however, this has now been reduced to 16% for the same viscosity range, as shown in Figure 4.14.

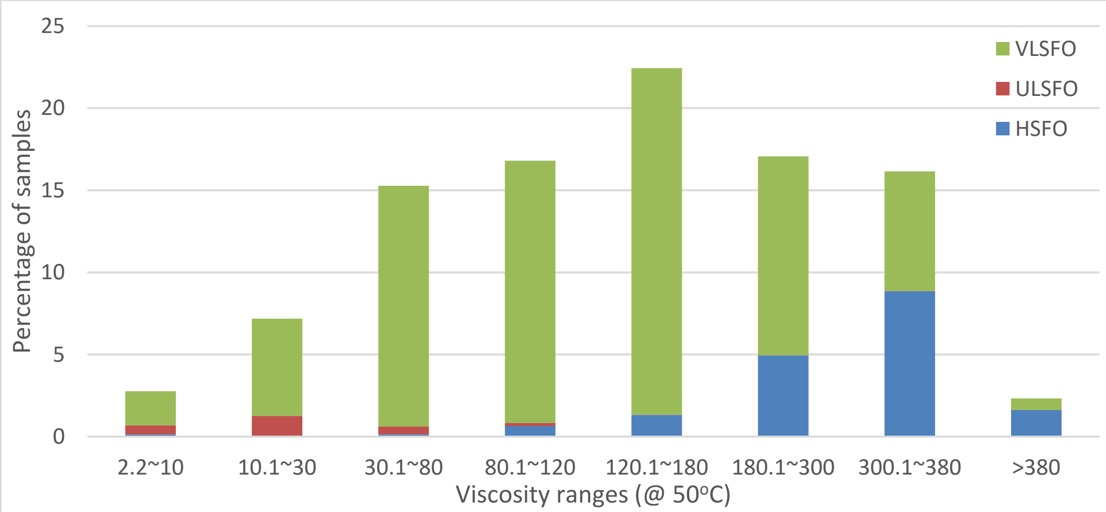


Figure 4.14: Viscosity distribution of the samples tested
Source: FOBAS (2020)

Moreover, an increasing number of samples being tested are from a lower viscosity range, which indicates an increased risk of fuel overheating if the operational adjustments are not made. In view of the above commentary, three fuzzy membership functions have been defined for viscosity at engine inlet, ‘Low’, ‘Satisfactory’ and ‘High’, as per Figure 4.15.

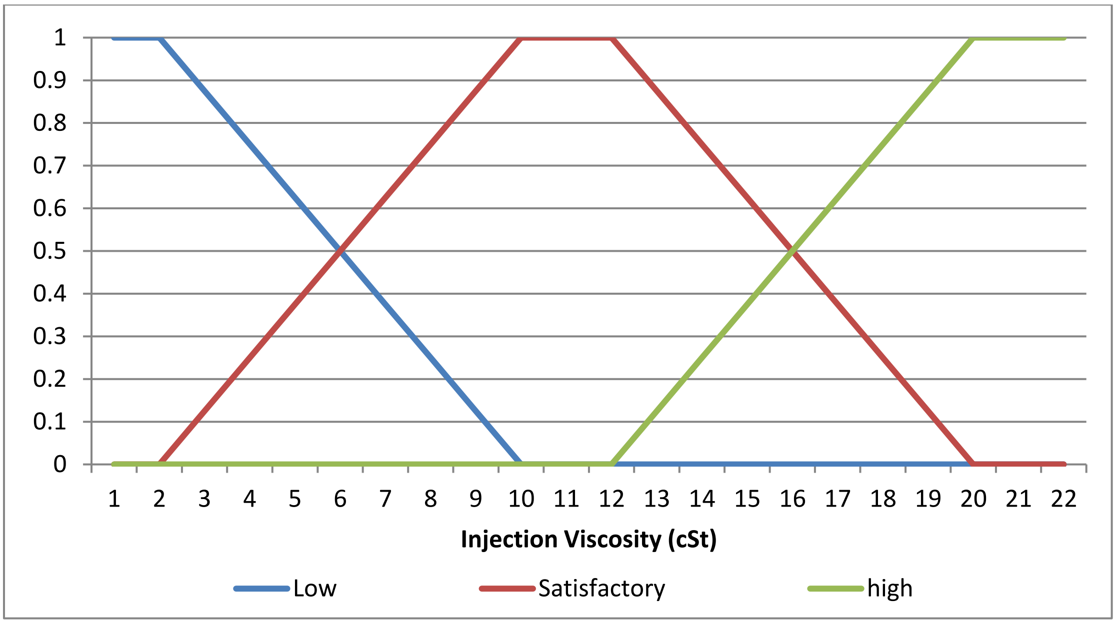


Figure 4.15: Fuzzy membership of viscosity evaluation

The corresponding values have been assigned from the FOBAS data, OEM guidelines (Figure 4.13) and experience of the fuel problems reported by ship operators. For example, the viscosity of 16 cSt at engine inlet would mean fuzzy membership of 0.5 ‘Satisfactory’ and 0.5 ‘High’.

4.4.2.4 Catalyst fines

Catalyst fines are abrasive particles formed of aluminium + silicon, which usually originate from the catalytic cracking process in the refinery (Leigh-Jones, 2008). In the international marine fuel standard, the concentration of these catalyst fines has been limited to a maximum of 60 mg/kg (ISO 8217:2017). These particles are nevertheless present in heavy marine fuels and have the potential to cause abrasive wear at the fuel pumps/injectors and cylinder components. The fuel is processed onboard to remove these abrasive particles through settling and separation processes.

Figure 4.16 is based on the FOBAS (2020) data showing the catalyst fines distribution amongst various fuel types. Generally, particular attention would be needed to operate an onboard separation plant under optimum conditions when catalyst fines levels exceed 40~45 mg/kg. The graph indicates that around 5% of samples are above 45 mg/kg compared to 8.5% samples (for the same criteria) in the pre-2020 data set.

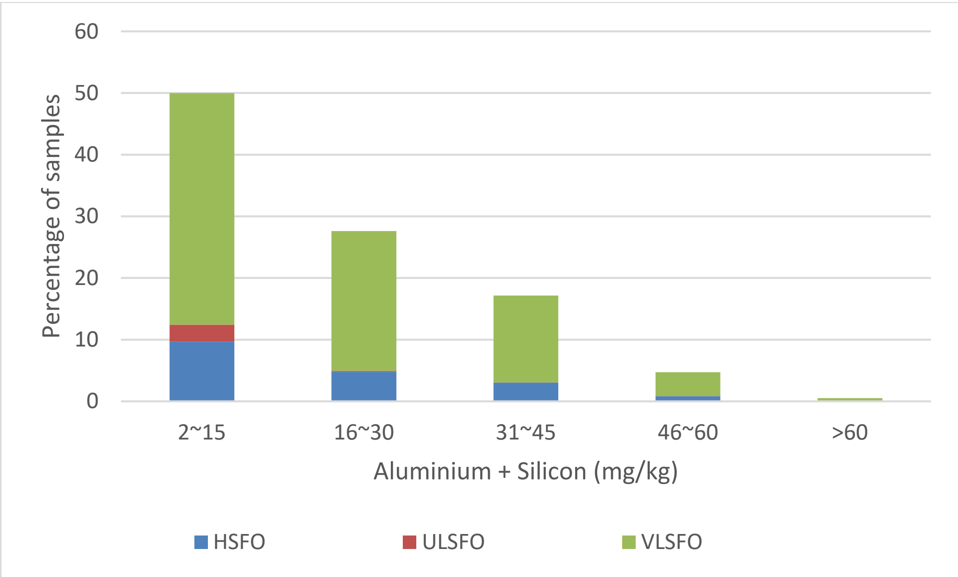


Figure 4.16: Catalyst fines levels in manifold drip samples tested by FOBAS
Source: FOBAS (2020)

Engine manufacturers recommend that the concentration of these catalyst fines should be as low as practically possible (preferably below 10 mg/kg); however, they should not be more than 15 mg/kg at engine inlet (CIMAC, 2006). Figure 4.17 indicates the fuzzy memberships for the corresponding states of ‘Satisfactory’ and ‘High’. For example, catalyst fines (Al + Si) concentration of 12 mg/kg would correspond to the fuzzy membership of 0.6 ‘Satisfactory’ and 0.4 ‘High’.

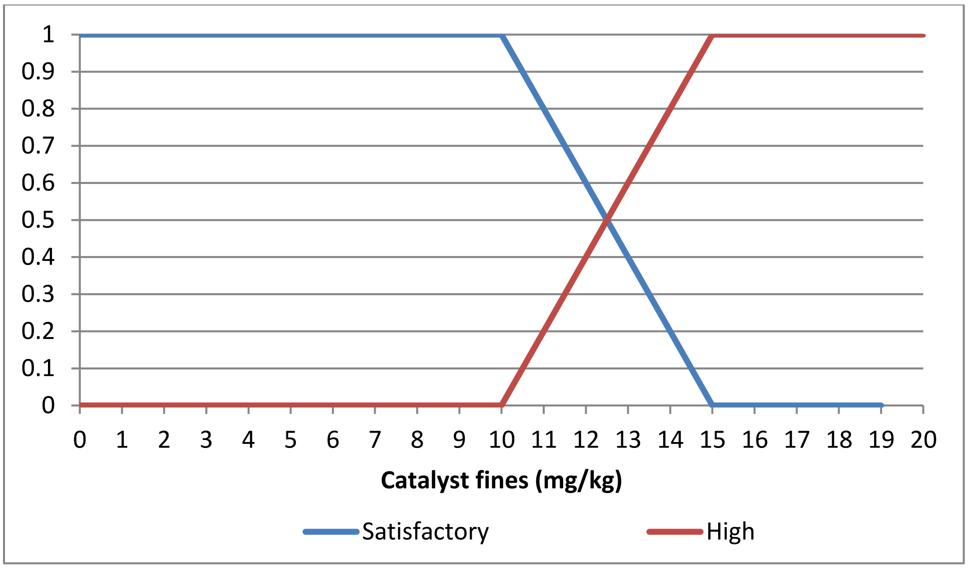
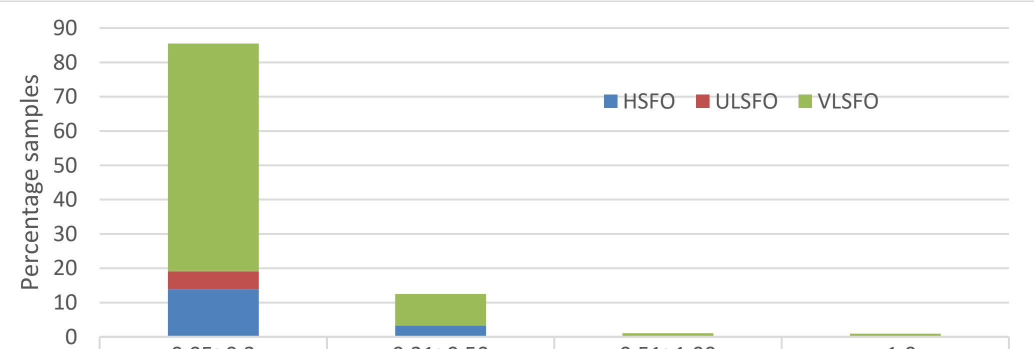


Figure 4.17: Fuzzy membership for abrasive catalyst fines levels

4.4.2.5 Water

The concentration of water in the fuel is another parameter which has a limit of 0.50% vol. as supplied in the table 2 of ISO 8217 for residual marine fuel grades. High water in the fuel can lead to poor combustion conditions and subsequently lower than expected calorific value of the fuel. There can be few possibilities of high water at engine inlet such as leaking steam heating coils, condensation in the tank, leak from adjacent (ballast) tank, or deliberate mixing (Leigh-Joes, 2008). It is essential to determine the nature of the water in the fuel in order to establish its source. A higher concentration of sodium in the fuel would be a good indicator that the water is likely to be saline in nature, and hence the focus can turn towards curbing seawater contamination in the fuel. The risk of high water in the fuels 'as supplied' is relatively low, as can be seen from Figure 4.18.



	0.05~0.2	0.21~0.50	0.51~1.00	>1.0
VLSFO	66.39142738	9.166396066	0.723662847	0.565941458
ULSFO	5.218722457	0.07422183	0.037110915	0.060305237
HSFO	13.88412117	3.24256622	0.324720508	0.310803915

Figure 4.18: Water (volume %) distributions based on samples tested
Source: FOBAS (2020)

Around 85% of fuel samples tested contained water equal to or below 0.2% vol. However, there remains a small risk of around 2% of fuels exceeding the 0.5% vol. limit of the ISO 8217 standard. The CIMAC (2006) guidelines indicate that most engine manufacturers allow water content of up to 0.2% to 0.3% at engine inlet; however, lower the better. In view of the above, two fuzzy membership functions 'Satisfactory' and 'High', have been defined, as per Figure 4.19.

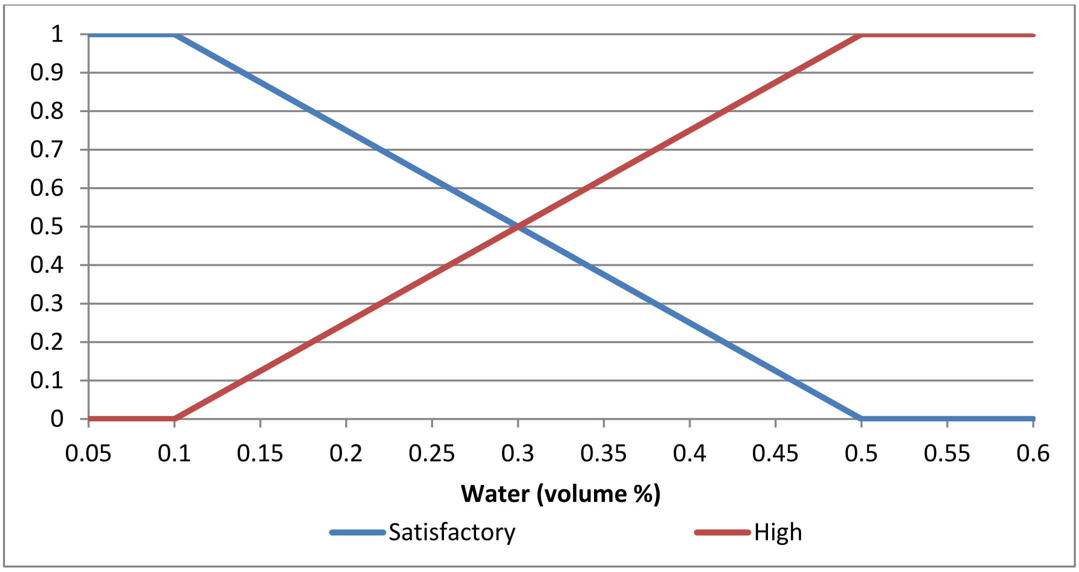


Figure 4.19: Fuzzy membership of water level at the engine inlet

For example, fuzzification of the water content of 0.25 volume % would correspond to the fuzzy membership of 0.625 'Satisfactory' and 0.375 'High'.

4.4.2.6 Ash

Ash content in the fuel is the summation of elemental concentration in the fuel. There is an ash content limit of 0.10 mass % within the ISO 8217:2017 standard for most of the residual grades. High ash would present the challenge of increased post-combustion fouling and performance degradation of the turbocharger and exhaust gas heat exchanger. However, it is expected that ash content for an engine inlet sample would be lower compared to the manifold drip sample because of the fuel processed onboard through settling and separation processes.

Higher ash content in marine fuels could also be a precursor of a group of elements such as calcium, zinc and phosphorus, indicating the presence of used lubricant oil (ULO). A higher concentration of ULO can severely impact the performance of the separator plant. Moreover, naturally, fuels from certain regions of the world could contain higher elemental concentrations of vanadium and nickel. FOBAS (2020) data as per Figure 4.20 indicates that, from samples tested since 1st of January 2020, around 0.16% of fuels exceeded the 0.10 mass % ash content limit provided in ISO 8217 (Table 2) compared to 0.30% of fuels exceeding it in the previous year.

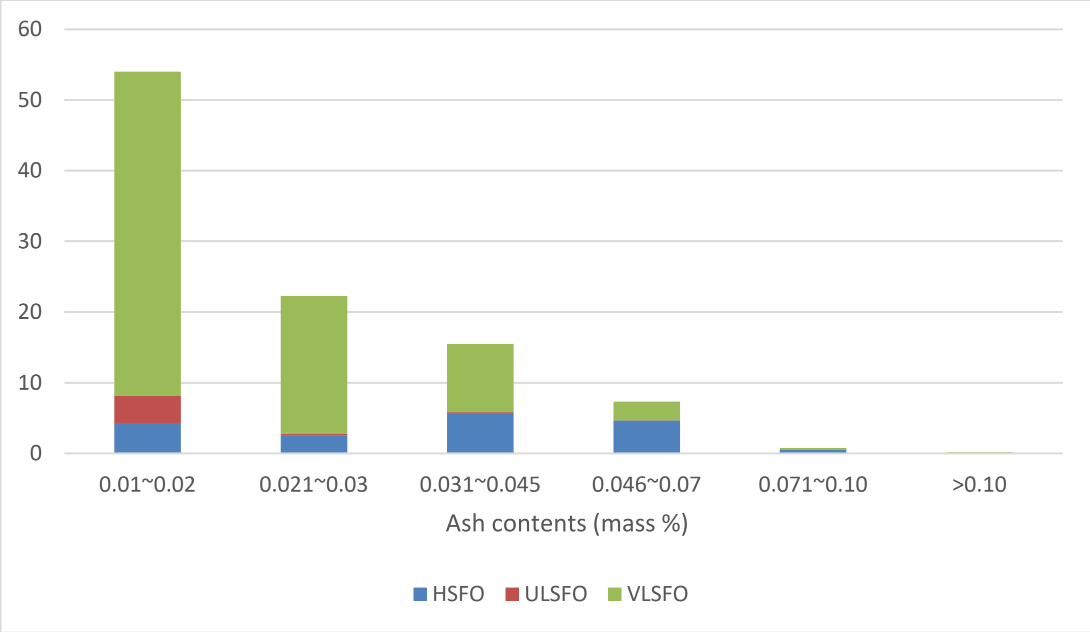


Figure 4.20: Ash distribution amongst various fuel types
Source: FOBAS (2020)

Hence the likelihood of ships bunkering fuels with higher ash is low, and, in view of the data, fuzzy membership functions have been defined as per Figure 4.21.

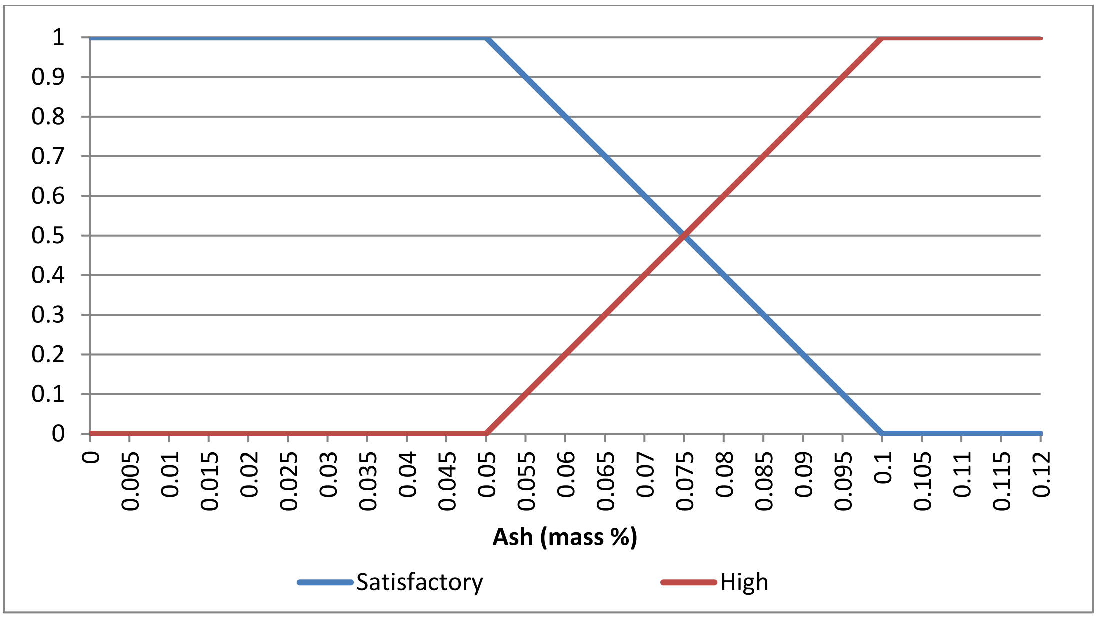


Figure 4.21: Fuzzy membership of ash content in fuel

For example, the ash content of 0.06 mass % would result in fuzzy membership of 0.8 'Satisfactory' and 0.2 'High'.

4.4.2.7 Fuzzy inference

The next stage is the fuzzy inference. A set of 'IF-THEN' rules has been developed to combine the selected parameters and produce the output for fuzzy fuel quality membership for the states ‘satisfactory’ and ‘unsatisfactory’. The number of rules in total is 48 ($2^4 \times 3^1$), i.e. four parameters with two states and one parameter with three states. The THEN (consequent) part of the rules which represent fuel quality has two states, ‘satisfactory’ or ‘unsatisfactory’. Each rule has been assessed to assign a particular state by virtue of assessing its antecedent part. For example, IF catalyst fines are ‘Low’, water is ‘Low’, ash is ‘Low’, CCAI is ‘High’ and Viscosity is ‘Low’, THEN fuel quality is deemed ‘Satisfactory’. The rationale is similar to what was developed in section 4.4.1.5, where each antecedent is assigned equal weight and this, by virtue of the number of antecedents being positive or negative, would determine the consequent state of ‘satisfactory’ or ‘unsatisfactory’. This results in the consequent part of 21 rules as ‘Satisfactory’ and 27 rules as ‘Unsatisfactory’ fuel quality described in Table 4.7.

Table 4.7: Fuzzy rule-base for fuel quality

Rule No.	IF					THEN
	Catalyst fines	Water	Ash	CCAI	Viscosity	Fuel Quality
1	High	High	High	High	High	Unsatisfactory
2	High	High	High	High	Satisfactory	Unsatisfactory
3	High	High	High	High	Low	Unsatisfactory
.	..	..	..	..	..	..
.	..	..	..	..	..	..
23	High	Satisfactory	Satisfactory	Satisfactory	Satisfactory	Satisfactory
24	High	Satisfactory	Satisfactory	Satisfactory	Low	Satisfactory
25	Satisfactory	High	High	High	High	Unsatisfactory
.	..	..	..	..	..	..
.	..	..	..	..	..	..
46	Satisfactory	Satisfactory	Satisfactory	Satisfactory	High	Satisfactory
47	Satisfactory	Satisfactory	Satisfactory	Satisfactory	Satisfactory	Satisfactory
48	Satisfactory	Satisfactory	Satisfactory	Satisfactory	Low	Satisfactory

Once the rule-base is developed, the next step is to use the fuel quality data for the parameters defined in this section to identify the corresponding fuzzy membership functions for each fuzzy set. The process is the same as defined in section 4.4.1.5, where final probability values are determined by using the ‘max-min’ function.

4.4.3 CLO feed rate

CLO (Cylinder Lube Oil) feed rate is one of the critical factors which can impact not only the two-stroke engine performance but also the operational cost of the ship. This is the reason why the optimum CLO feed rate is critical in maintaining the engine's cleanliness and also ensuring reduced maintenance and operational expenditure. CLO feed rate is the function of engine load, fuel sulphur content, and other operational conditions such as the 'running-in' process after cylinder(s) overhaul.

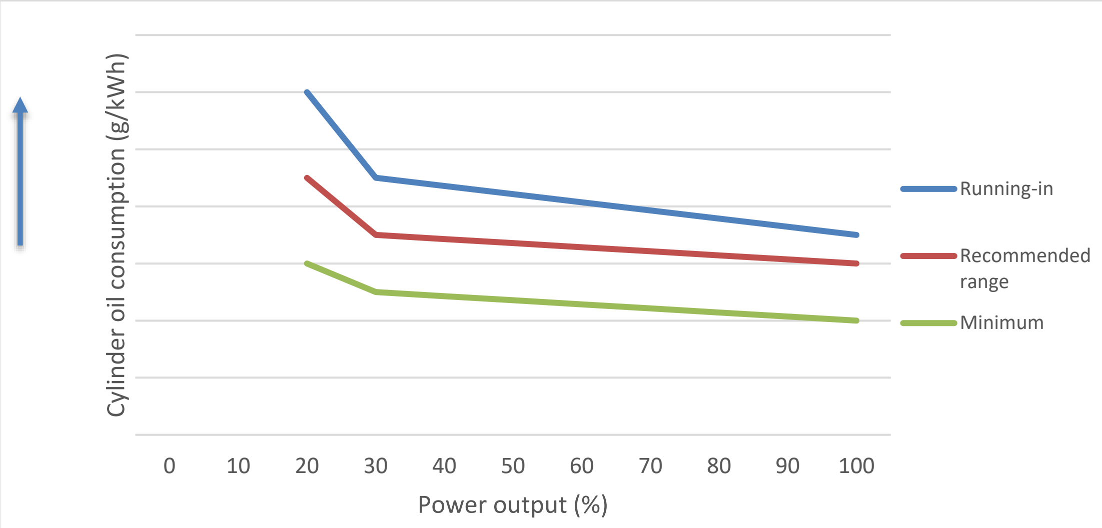


Figure 4.22: CLO feed settings
Source: Griffiths (2006)

Figure 4.22 shows the key settings in this respect. Engine designers do provide detailed guidelines, especially after the cylinder overhaul, the length of time the CLO feed settings need to be kept at higher levels for 'running-in' of piston rings and liner. Another important factor influencing performance is the CLO injection timing, i.e. injection should take place when the piston is passing over the quills. The injection control system has the inputs of engine speed and piston location to adjust to varying load and engine speeds. There could be occasions where, due to system malfunction, the injection timing goes out of sync, which can negatively impact the tribological behaviour of the piston rings and liners. However, due to the low likelihood of this and to keep the model simple, it has been assumed that CLO injection timings are satisfactory; hence, they are not considered in the performance assessment.

During normal running conditions, it is not straightforward to determine whether the CLO feed rate is optimum or not. The decision to make adjustments to the CLO feed rate requires operational knowledge and analyses of cylinder drain oil samples from the two-stroke engine. There are multiple operational indicators and elemental concentration in the drain oil analysis combined with engineering knowledge enabling the ship operators to make an informed opinion regarding whether the CLO feed rate is insufficient, sufficient or excessive. However, for simplicity, there are two major indicators in use, which are Fe and TBN of the scrape-down sample collected from each cylinder. CIMAC (2017) recommendations provide guidance as to what are considered as optimum and non-optimum levels of Fe and TBN, as shown in Figure 4.23:

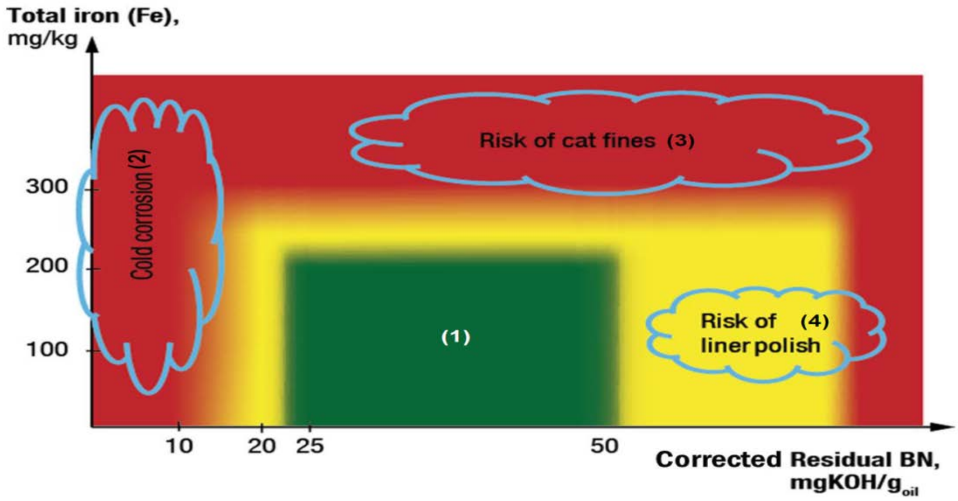


Figure 4.23: CIMAC recommendations for two-stroke engine lubrication
Source: CIMAC (2017)

The graph has been divided into four distinct sections, as described in Table 4.8:

Table 4.8: Fe-TBN graph (risk matrix)

Area	Risk	Description
1	-	Fe & TBN results from a cylinder(s) fall in this area would indicate current settings are satisfactory.
2	Cold corrosion	This is indicated by low residual TBN requiring an increase in feed rate or change to higher TBN oil. Prolonged operation with low TBN could result in excessive chemical (corrosive) wear.
3	Catalyst fines	The most likely reason for high Fe content when TBN is satisfactory is abrasive (three-body) or adhesive (two-body) wear. Abrasive wear could be due to higher catalyst fines levels in the fuel, and adhesive wear can have various reasons including micro-seizure due to lubrication breakdown.
4	Liner polish	This is indicated by high residual TBN of drain oil, which may require lowering the cylinder oil feed rate or switching to lower TBN oil. Prolonged operation with high TBN levels could result in excess calcium carbonate and fouling, which can hamper the piston ring operation.

Performing a diagnosis through an ‘Fe vs TBN’ chart can be too simplistic; hence, other operational factors need to be viewed in conjunction with the information gained by Fe & TBN test results to establish an opinion.

It should be noted that the graph (Figure 4.23) and associated assessment criteria is generally acceptable by all three LS2S OEMs however with lower sulphur fuels and lower cylinder oil TBNs, the limits applied in Figure 4.23 can vary. One of the reasons for allowing ‘controlled corrosion’ to take place is to avoid a bore-polishing effect, i.e. where the liner surface becomes so smooth that it loses the ability to retain the cylinder lubricant on its surface, causing the breakdown of the lubricant film. This study focuses on the MAN-ES two-stroke engines, which are installed in the majority of the world’s fleet for main propulsion. Figure 4.24 shows FEAP (2017) data of around 4000 samples.

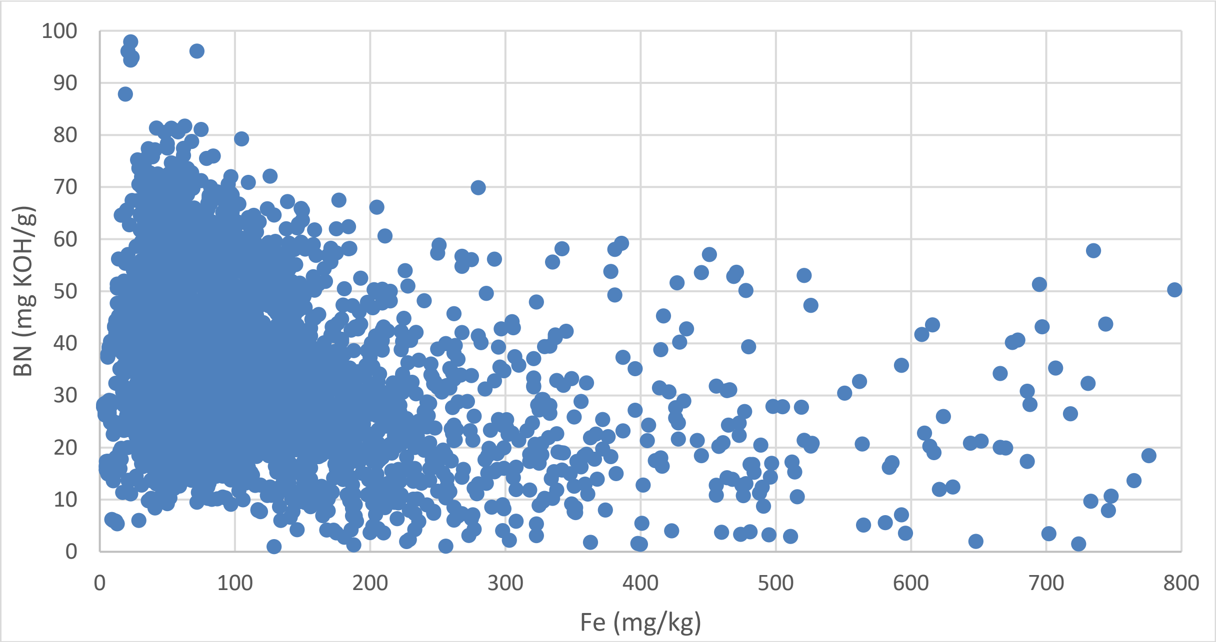


Figure 4.24: Fe vs TBN data
Source: FEAP (2017)

The breakdown of FOBAS data with reference to Figure 4.23 is as follows:

1. 57% of samples tested fell in the green zone (area 1)
2. 21% indicated cold corrosion (area 2)
3. 6% showed signs of abrasive wear (area 3)
4. and 15% indicated excessive TBN levels with lower Fe content representing a risk of bore polishing (area 4).

There are a large proportion of samples indicating signs of cold corrosion; however, the data is predominantly based on HSFO usage and, with lower sulphur content (0.50

mass %) fuels being widely used since January 2020, it is expected that there are going to be more results in areas 3 and 4 due to reduced neutralising demand, which poses an increased risk of bore polishing. The steps of developing the fuzzy model where Fe and TBN have been considered as the main driving factor for optimised CLO feed rate are similar to those described in Figure 4.5.

4.4.3.1 Iron

Iron (Fe) in the scrape-down cylinder oil sample can be of two forms, i.e. Fe from corrosive wear and abrasive/adhesive wear. The corrosive Fe is likely to be in the form of soluble iron-sulphide formed due to cold corrosion on the liner and piston rings. The abrasive Fe is magnetic and formed of relatively larger-size particles. Fe is determined in the lab by the use of an ICP (Inductively Coupled Plasma) method where particles greater than 7 μm are not detected; hence, further PQ (Particle Quantifier) analysis is performed in order to determine the magnetic Fe, and then the assessment is made by reviewing the ICP and PQ analysis to form an opinion on the proportion of whether the wear is corrosive or abrasive (Toms and Toms, 2008).

The data set used in Figure 4.24 indicates that Fe content has lower, median and upper quartiles of 54, 87 and 144 respectively, with the upper limit generally kept at 200 mg/kg, as per CIMAC (2017) guidelines. Figure 4.25 below has been developed with two states for Fe concentration in the drain oil samples, i.e. ‘Satisfactory’ and ‘High’, which is based on FOBAS data and industry guidelines.

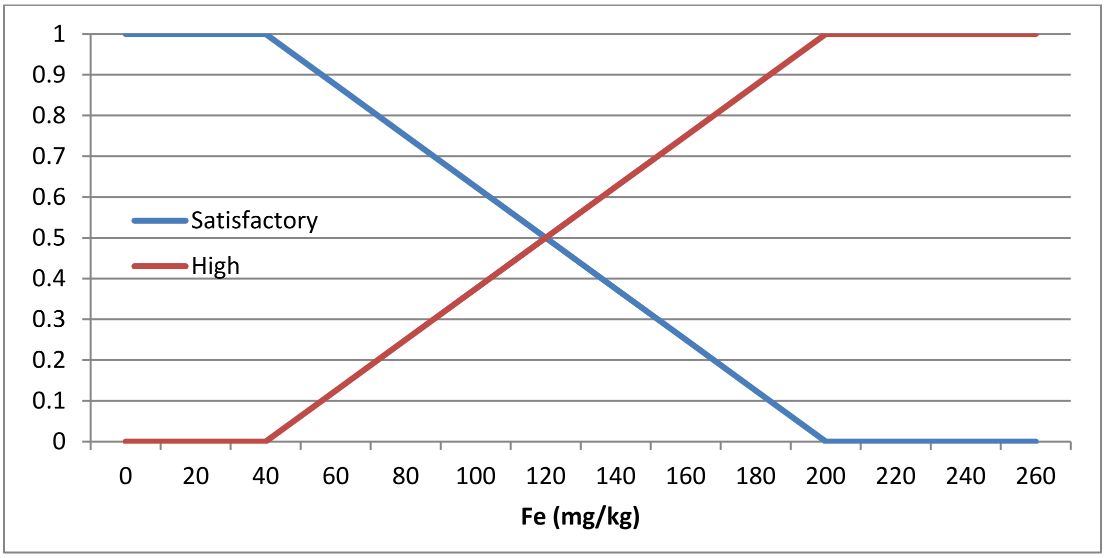


Figure 4.25: Fuzzy membership of drain oil samples Fe content

4.4.3.2 TBN

In this context, TBN is derived by testing the cylinder oil drain samples from each cylinder of the two-stroke engine, which indicates the residual or remaining TBN after the CLO neutralises the acidic components formed during combustion to protect the liner from acidic corrosion. On a general principle, higher than expected ΔTBN (TBN $_{\text{(fresh CLO)}}$ – TBN $_{\text{(scrape-down CLO)}}$) would indicate insufficient feed rate or a need to replace the CLO with higher TBN oil. Similarly, lower ΔTBN may indicate excessive neutralising buffer or over-lubrication. However, ΔTBN would vary based on operational conditions, type of fuel in use and TBN of the oil in use. For example, for ULSFO (0.10 mass % sulphur fuel), the ΔTBN could be high; however, that would not necessarily mean over-lubrication and vice versa. Thus, ideally, a bespoke scale would be needed to define whether TBN levels are 'low', 'satisfactory' or 'high'.

For the purpose of this study, a direct TBN value is used to model the fuzzy membership instead of ΔTBN, as direct measurements are well understood and easily interpreted by operators. The states 'low', 'satisfactory' and 'high' have been assigned to the TBN of the tested cylinder drain oil in view of the MAN-ES generic guidelines for the use of high sulphur fuels and FEAP (2017) data. The data suggests lower and upper quartiles as 25 and 44, respectively. Hence, a 100% 'satisfactory' fuzzy membership function has been established for this range, as per Figure 4.26. This is also in line with the CIMAC guidelines for a satisfactory TBN level.

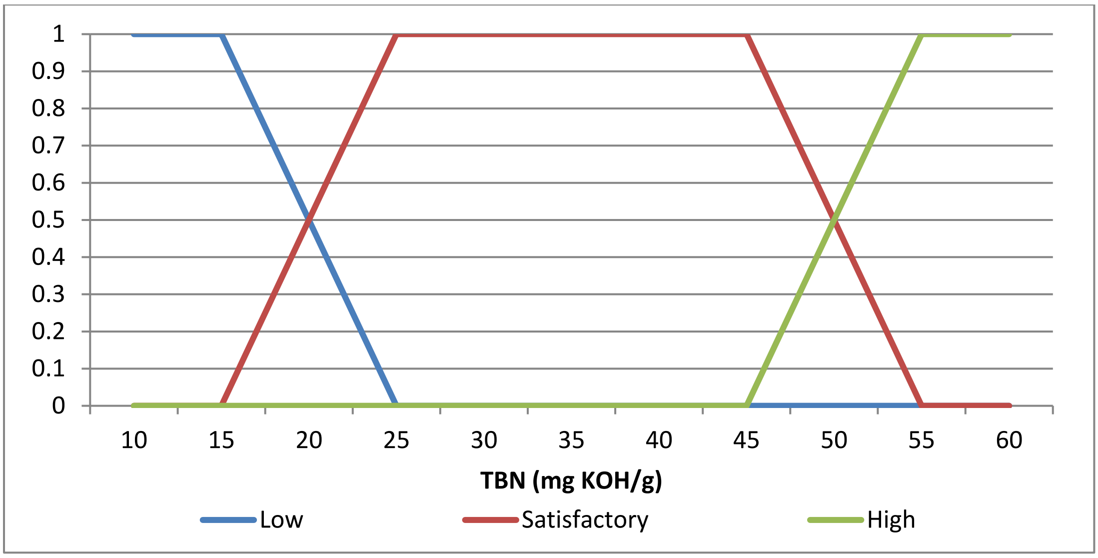


Figure 4.26: Fuzzy membership of TBN in cylinder drain oil

4.4.3.3 Fuzzy inference

A set of 'IF-THEN' rules has been developed to combine the selected parameters (Fe & TBN) to produce an output for cylinder oil feed rate membership for states 'optimal' and 'non-optimal'. The number of rules in total is 6 ($2^1 \times 3^1$), as per Table 4.9.

Table 4.9: Fuzzy rule-base for CLO feed rate

Rule No.	IF		THEN
	Fe	TBN	CLO feed rate
1	Satisfactory	Low	Satisfactory
2	Satisfactory	Satisfactory	Satisfactory
3	Satisfactory	High	Satisfactory
4	High	Low	Unsatisfactory
5	High	Satisfactory	Unsatisfactory
6	High	High	Unsatisfactory

It can be observed from the table above that the consequent part of the rule-base is 'optimal' if the Fe content remains within the acceptable range. This has been adopted in view of the feedback from the FEAP (2017) reporting where ships are adjusting feed rate predominantly based on the wear rate, even though the TBN could fall in area 2 or 4 of Figure 4.23.

The next step is the determination of a final value using a conventional fuzzy 'max-min' approach, as described in section 4.4.1.5, for quantitative assessment.

4.4.4 Engine Settings

To determine whether engine settings are optimum is a complex problem and requires a deep understanding of the engine design features and operating conditions. Various engine manufacturers use different processes to optimise the engine output. For example, WinGD RT-Flex engines are installed with the WinGD Engine Control System (WECS), which has the capability to optimise the cylinder pressures by adjusting the fuel injection timings and exhaust valve opening and closing timings (Griffiths, 2006). In this study, the MAN-ES engines are considered mainly due to their widespread application and significant market share. MAN-ES also supply engine tuning system called PMI (Performance Measurement Indicator) (MAN-ES, 2020b) connected to the engine control systems.

There are many facets of engine settings which would require an understanding of operating conditions and the engine type. Considering the variability and in the context of this study, three operational indicators have been selected to model the engine settings, as follows:

1. Pressure rise (P_{max} - P_{comp})
2. MIP (Mean Indicated Pressure) deviation
3. Deviation from mean exhaust temperatures.

4.4.4.1 Pressure rise (P_{max} - P_{comp})

P_{max} is the maximum pressure within the combustion chamber at any point during a stroke, which usually occurs just after the fuel is injected and combustion occurs. P_{comp} is the maximum compression pressure in the cylinder around the top dead centre (TDC). The difference between the P_{max} and P_{comp} can be an important indicator of prevailing combustion conditions. For example, low P_{max} – P_{comp} may indicate poor fuel ignition quality, unsatisfactory injector/pump performance, fuel starvation or retarded/too late ignition. At normal running conditions, a low P_{max} – P_{comp} would prompt adjustments by slightly advancing the fuel timings and vice versa. Similarly, high P_{max} – P_{comp} may indicate an early injection. There could be situations where both P_{max} and P_{comp} are low, which could indicate blow-by, exhaust valve malfunction or leakage, low scavenge pressure or change in combustion space volume. Similarly, high P_{max} and high P_{comp} could be an indicator of engine overload (Chell, 2007).

One of the ways to improve the P_{max} – P_{comp} variations is by adjusting the injection timings. These adjustments to the fuel injection timings can be through Variable Injection Timing (VIT), which is an additional control mechanism installed on MAN-ES engines to fine-tune fuel injection timings. Newer engines are installed with electronic VIT controls; however, older designs are fitted with mechanical VIT units (Griffiths, 2006). Based on the power diagram (electronic or mechanical), if P_{max} is excessively high or low compared with the shop test or baseline for corresponding load and operating conditions whilst P_{comp} is satisfactory, then VIT adjustment would seem necessary. Moreover, it is recommended to overhaul the fuel pumps when the index has increased by about 10%.

The FEAP (2017) data has been analysed, and a trend can be observed towards lower pressure differences at higher loads and vice versa, as per Figure 4.27.

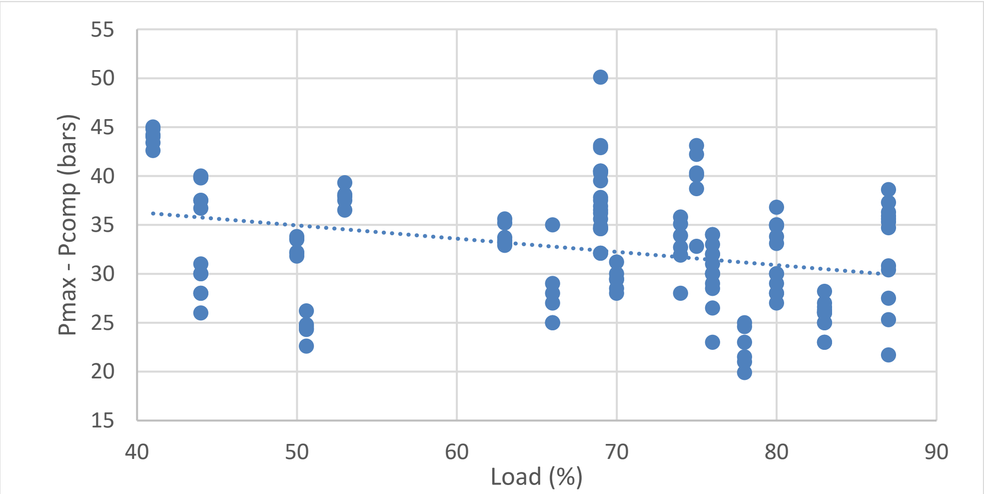


Figure 4.27: P_{max} - P_{comp} relation vs engine load
Source: FEAP (2017)

The $P_{max} - P_{comp}$ data is divided into upper, median and lower quartiles with results of 28, 32 and 36 bar respectively. This forms the ‘satisfactory’ range for the corresponding membership functions with ‘high’ and ‘low’ defined as per Figure 4.28.

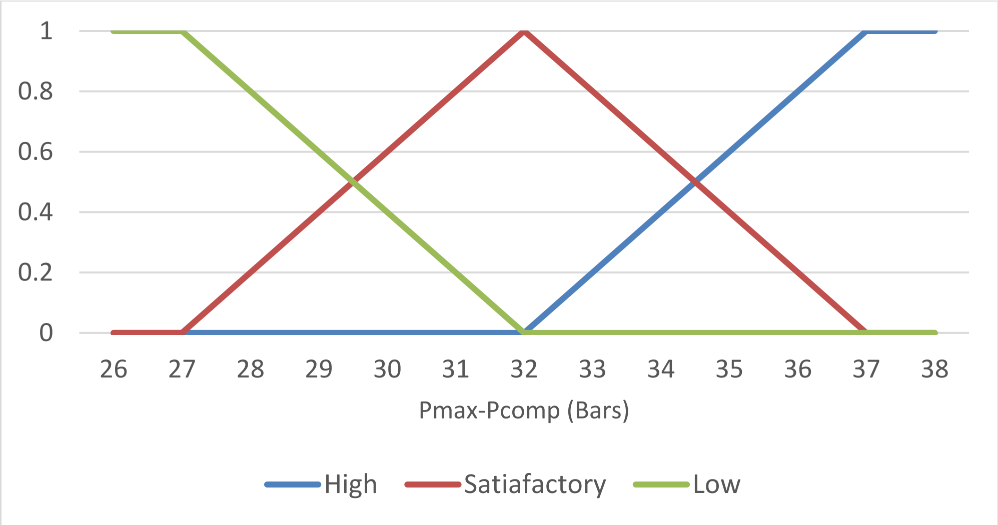


Figure 4.28: Fuzzy membership of the difference between the maximum and compression pressure

4.4.4.2 MIP deviation

Mean Indicated Pressure (MIP) is a measurement taken from each cylinder of the engine during manual or electronic performance assessment under normal operating conditions. The direct MIP measurements are obtained by first measuring the mean height (area of the diagram (mm^2) / height of the diagram (mm)) of the power diagram and multiplying it with the indicator spring constant (N/m^2 per mm) to obtain a mean indicator pressure (N/m^2) (Griffiths, 2006). The manual method of taking power cards lacks precision, especially when identifying the TDC (Top Dead Centre) accurately; however, electronic built-in or portable pressure analysers (e.g. https://iconresearch.co.uk/diesel-engine-analysis/doctor-portable) are widely in use, bringing confidence in the final measurements. MIP is an important indicator to power balance the engine, and high deviation between various cylinders would indicate imbalance and may require ship staff to take mitigating action to make adjustments. The FEAP (2017) data (Figure 4.29) indicates predominantly a linear relationship between the MIP and the engine load.

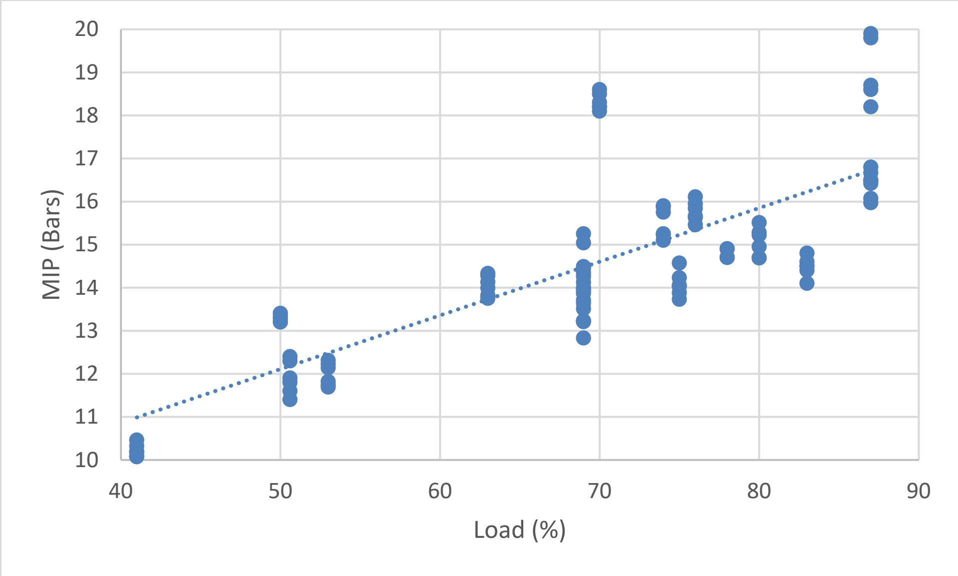


Figure 4.29: MIP vs engine load graph
Source: FEAP (2017)

The data is analysed to establish fuzzy sets for MIP deviations and it was found that the average standard deviation is 0.3 bar with a maximum deviation between cylinders is 1.4 bar. Two fuzzy sets have been defined as 'Satisfactory' and Unsatisfactory', as shown in Figure 4.30.

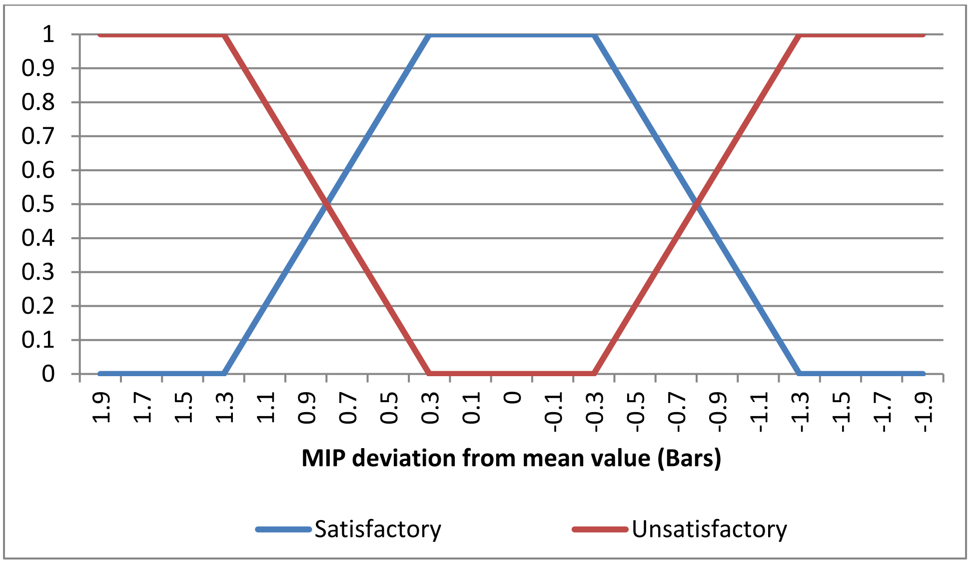


Figure 4.30: Fuzzy membership of mean indicated pressure

Based on the data, a deviation of 0.3 bar from average MIP value for individual cylinders has been assigned as 'satisfactory' whilst the maximum permissible deviation is 1.3 bar.

4.4.4.3 Exhaust deviation

The low exhaust temperature deviations between different cylinders of an engine could be a precursor to better combustion conditions. FEAP (2017) data suggests some correlation between the engine load and the exhaust temperatures. As per Figure 4.31, the deviation remains more inconsistent throughout various load ranges, which is mainly a function of operating conditions and status of engine maintenance.

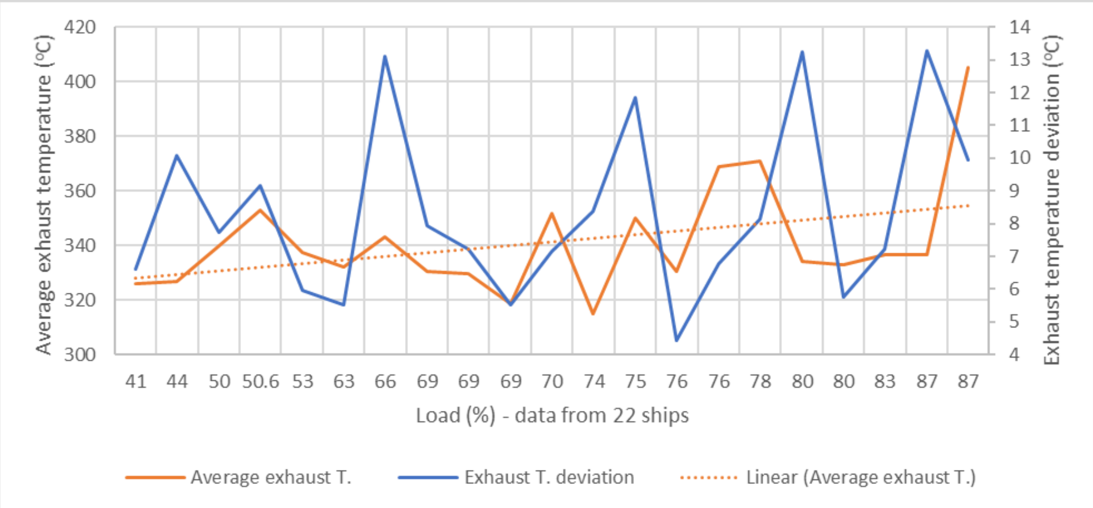


Figure 4.31: Exhaust temperatures & deviations vs Load
Source: FEAP (2017)

The deviation in the exhaust temperature is vital in determining whether the engine settings are appropriate for the prevailing operating conditions. The data suggests that, on average, there remains an 8ºC deviation from the mean exhaust temperatures of all cylinders under certain operating conditions, with the maximum deviation observed at around 14ºC and the minimum at 4ºC. Hence, 4 to 14ºC has been used as a transition range from 100% satisfactory to 100% unsatisfactory, as per Figure 4.32.

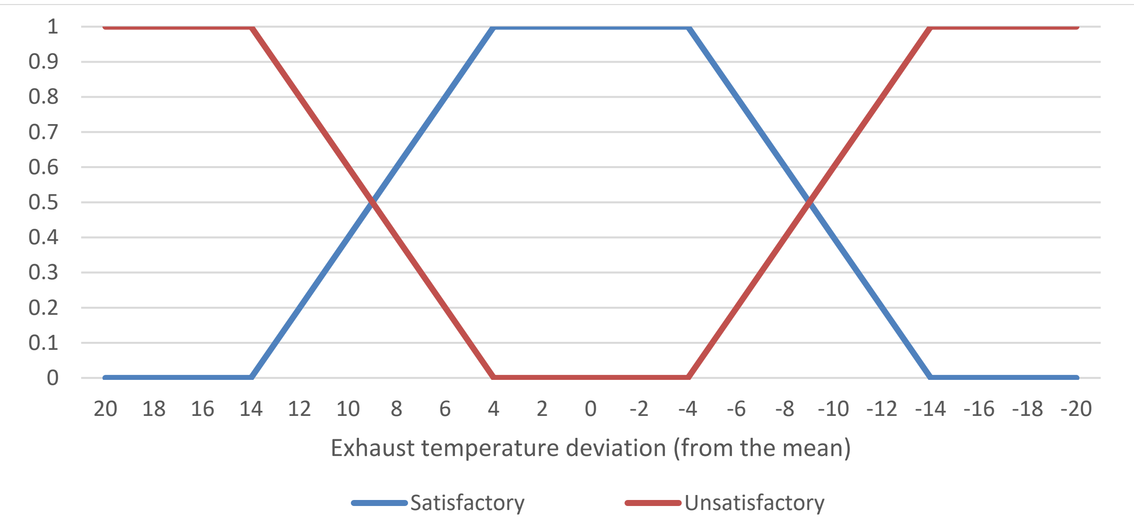


Figure 4.32: Fuzzy membership of exhaust deviation

4.4.4.4 Fuzzy inference

A set of 'IF-THEN' rules has been developed to process the inputs from exhaust deviation, P_{max} - P_{comp} and MIP deviation to produce the output for the membership functions of 'engine settings' as being 'satisfactory' and 'unsatisfactory'. The number of rules in total is 12 ($3^1 \times 2^1 \times 2^1$). To assign a 'state' to the consequent part of the rule-base, i.e. 'satisfactory' or 'unsatisfactory', the same approach has been used as defined in section 4.4.1.5, i.e. by assigning equal weighting to the antecedent parts. For example, IF the P_{max} - P_{comp} is 'satisfactory' and MIP deviation is 'unsatisfactory', and Exhaust deviation is 'unsatisfactory', THEN engine settings would be deemed 'unsatisfactory'. The details of the fuzzy rule-base are given in Table 4.10.

Table 4.10: Fuzzy rule-base for engine settings

Rule No.	IF			THEN
	P_{max} - P_{comp}	MIP dev.	Exhaust dev.	Engine settings
1	High	Unsatisfactory	Unsatisfactory	Unsatisfactory
2	High	Unsatisfactory	Satisfactory	Unsatisfactory
3	High	Satisfactory	Unsatisfactory	Unsatisfactory
4	High	Satisfactory	Satisfactory	Satisfactory
5	Satisfactory	Unsatisfactory	Unsatisfactory	Unsatisfactory
6	Satisfactory	Unsatisfactory	Satisfactory	Satisfactory
7	Satisfactory	Satisfactory	Unsatisfactory	Satisfactory
8	Satisfactory	Satisfactory	Satisfactory	Satisfactory
9	Low	Unsatisfactory	Unsatisfactory	Unsatisfactory
10	Low	Unsatisfactory	Satisfactory	Unsatisfactory
11	Low	Satisfactory	Unsatisfactory	Unsatisfactory
12	Low	Satisfactory	Satisfactory	Satisfactory

This is followed by the conventional 'max-min' approach, as defined in section 4.4.1.5, to determine a prior probability for the BN model. It is important to note that, through this method, the assessment of a single cylinder can be made, prompting the ship operator to focus on the individual cylinder performance where the deviation has been observed.

4.4.5 Maintenance condition

From a regulatory perspective, section 10 of the International Safety Management (ISM code, 2010) requires ships to maintain the machinery equipment, and they should carry an MMS within the company's Safety Management System (SMS) framework. Equally, the monetary benefits of maintaining good machinery health are significant. The assessment of machinery condition onboard is a multifaceted issue mainly because there are a number of maintenance strategies to choose from and ship operators employ what they deem suitable for their ship's operation. One of the crucial factors is the quality of maintenance directly linked to the crew competence and prevailing top-down support and facilitation provided from the organisation. In one of their recent reports, The Swedish Club (2021) observes that around 50% of the engine damage cases occur right after a maintenance action is performed which points to the incorrect maintenance actions during assembly of critical engine components. This subject requires a holistic assessment of the human factor, which is currently outside the scope of this study. Nevertheless, it is a critical quality parameter to ensure adequate maintenance management.

In order to cover the most common maintenance scenarios and perform a quantitative assessment, this study utilises the concept of availability formula and upkeep of the work orders, as described in the following sections.

4.4.5.1 Work order

Many ships employ a process where a MMS (or in some cases PMS (Planned Maintenance System)) generates work orders for all the critical machinery components as per the original equipment manufacturer (OEM) guidelines, or they can be based on in-house technical requirements. Work order generation at fixed intervals serves as a prompt for the onboard engineers to assess the condition of the machinery or take action as per OEM guidelines. Hence, for the purpose of this study and to assess the engine maintenance, total work orders need to be identified with the number of incomplete work orders. It has been realised that not all work orders carry the same importance for the main engine; nevertheless, these numbers would also assist in gaining an overall view of the level of importance given to engine maintenance.

Two key required values are 1) total number of work orders and ii) number of completed work orders for a specific point in time. The fuzzy set has two states, 'complete' and 'incomplete'. The researcher contacted a large ship operator to gain access to some anonymous data and formulate fuzzy membership on work orders. Unfortunately, due to company's strict data protection policy, they refused to divulge the required information. Nevertheless, a general note was shared by the contact in the company indicating that anything less than 50% completion is considered unacceptable. Hence Figure 4.33 is based on that piece of information. Nevertheless, it is recommended that the future studies and model users (ship operators) to consider adjusting the criteria by using the real data and even implement a stricter work order completion standard in the fuzzy membership function.

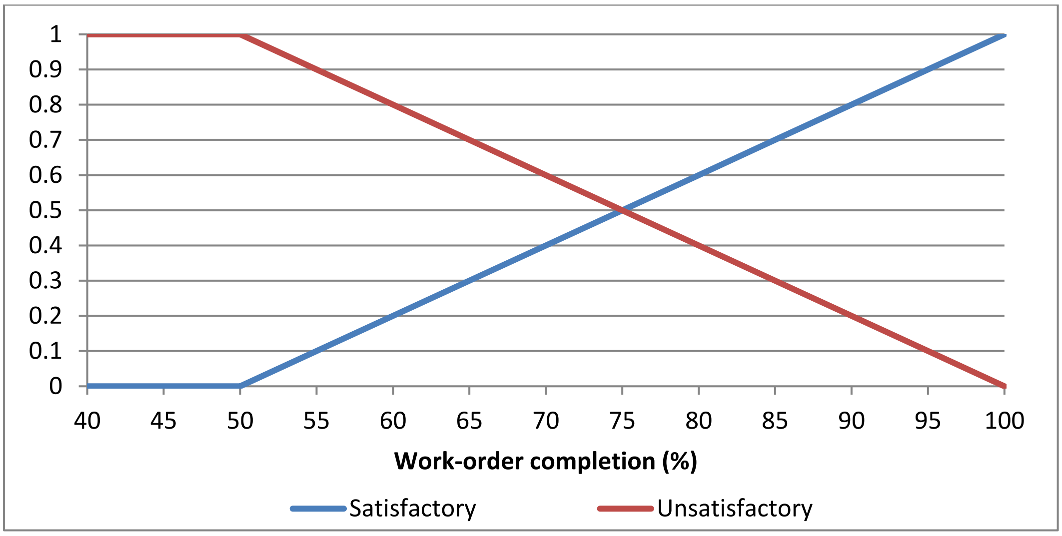


Figure 4.33: Fuzzy membership of work orders

4.4.5.2 Availability of the asset

Availability is a measure of how often the system is alive and available for service. The general formula used for this purpose is as follows (Barringer, 1997):

$$Availability = \frac{\text{Uptime}}{\text{Total time of operations (uptime+ downtime)}}$$

'Uptime' usually refers to the duration when the asset is able to perform its intended function whilst 'downtime' refers to the opposite condition. In most cases, the unavailability of the LS2S main engine (on demand) means a loss of propulsion incident due to the direct shafting arrangement. Although the frequency of such incidents is low; nevertheless, the consequences can be severe.

Aziz et al (2019) modelled four operational risks, namely fire & explosion, loss of main engine, power failure, and manoeuvrability failure. The study reported the potential loss of propulsion due to main engine failure frequency at 6.3/year where the engine is either completely stopped or slowed down.

LR (2020) fleet data analysis is performed to assess the failure rate of the LS2S engines for the period 2009 to 2018. The results indicate an average reported failure rate of around 3.5%, witnessing a decline over this period as shown in Figure 4.34.

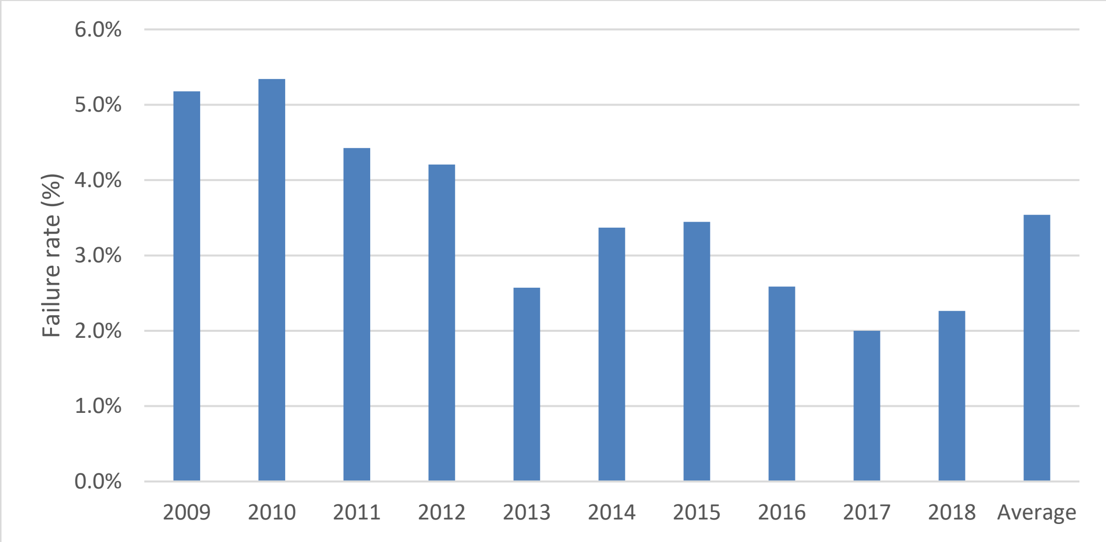


Figure 4.34: LR fleet data analysis for two-stroke engine failure rate
Source: LR (2020)

For example, LR recorded 511 failure incidents related to LS2S main engines out of 12,146 registered ships operating worldwide in the year 2012, which gave a failure percentage of 4.2%. Based on the above and using an average of 3.5%, the engine available range has been assigned on a sliding scale from 100% as ‘satisfactory = 1’ to 96.5% availability as ‘unsatisfactory = 1’ as shown in the Figure 4.35.

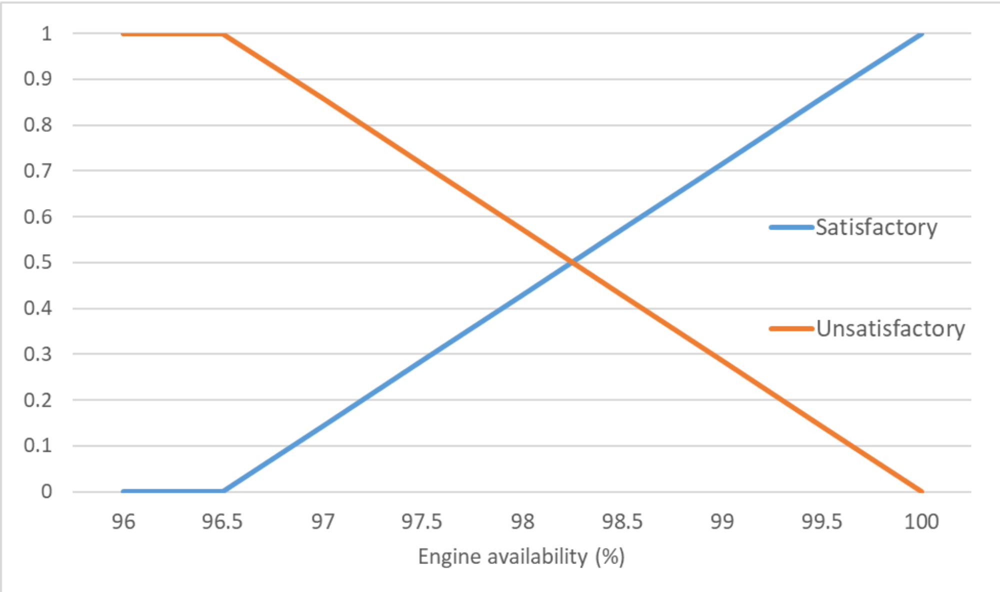


Figure 4.35: Fuzzy membership of availability of the asset

For the purpose of this study, and using ‘Availability’ as an input variable, a ship operator needs to calculate (on average) the number of days their ship spent at sea (i.e. required availability) and the number of days lost at sea (if any) due to malfunction of the two-stroke main engine. For example, if a ship has a sailing time of 180 days a year and she has lost five days due to unexpected repair of the main engine, then availability can be calculated by using the following formula:

$$Availability = \frac{\text{Uptime (total sailing days } - \text{ days lost due to unavailability)}}{\text{Total time of operations (total sailing days)}}$$

$$availability = \frac{180 - 5}{180}$$

This gives an availability of 0.972 (97.2%), which results in fuzzy membership of 'acceptable' as 0.2 and 'unacceptable' as 0.8, as per Figure 4.35.

4.4.5.3 Fuzzy inference

For this particular parameter, there are only four possible rule scenarios, as described in Table 4.11.

Table 4.11: Fuzzy rule-base for maintenance management

Rule No.	IF		THEN
	Work orders	Availability	Maintenance
1	Satisfactory	Satisfactory	Satisfactory
2	Satisfactory	Unsatisfactory	Unsatisfactory
3	Unsatisfactory	Satisfactory	Satisfactory
4	Unsatisfactory	Unsatisfactory	Unsatisfactory

Rules 1 and 4 are straightforward to interpret as both antecedents are either satisfactory or unsatisfactory. For rules 2 and 3, the availability of the asset is considered pivotal because there could be situations where work orders are complete, yet the engine is experiencing breakdowns because the maintenance actions undertaken are insufficient due to human factors or poor quality of spare parts. Using the same 'max-min' function, the fuzzy inference is performed to evaluate the efficacy of maintenance management and is demonstrated in the following section.

4.5 Case study

A Handymax bulk carrier registered on the FEAP (2017) programme sent main engine data and samples for analysis. The ship has a six-cylinder MAN 6S50MC-C engine installed, driving a fixed-pitch propeller. At the time of sample collection, the reported engine load was 78% with torque meter reading at 6900 kW. The remaining operational data and results of the sample(s) analysis related to the key parameters are provided in Table 4.12.

Table 4.12: Operational data from the bulk carrier

Key parameters	Contributory factors		Results
Fuel quality (at engine inlet)	Catalyst fines (mg/kg)		10
	Viscosity (cSt)		13
	Ash content (mass %)		0.02
	CCAI (Viscosity 346 cSt & Density 989 kg/m^3)		851
	Water content (volume %)		0.05
Scavenge air quality	Pressure (Bar)	Actual	2.4
		Ideal	2.6
	Temperature (^{o}C)		45
	WMC performance	$M_{condens}^{calculated}$ (tonne/24 hours)	2.5*
		$M_{condens}^{actual}$ (tonne/24 hours)	2
Engine settings	P_{max} - P_{comp} (Bar)	Cylinder 1	21.5
		Cylinder 2	21
		Cylinder 3	23
		Cylinder 4	24.6
		Cylinder 5	25
		Cylinder 6	19.9
	Exhaust temperature (^{o}C) (Mean = 371)	Cylinder 1	373
		Cylinder 2	376
		Cylinder 3	362
		Cylinder 4	361
		Cylinder 5	372
		Cylinder 6	382
	MIP (Bar) (Mean = 14.8)	Cylinder 1	14.9
		Cylinder 2	14.9
		Cylinder 3	14.7

		Cylinder 4		14.7
		Cylinder 5		14.7
		Cylinder 6		14.9
Engine maintenance	Availability	The average number of days spent at sea in a year		180
		Number of days lost during the year due to unavailability of the asset		2
	Work orders	Total work orders	Cylinder 1	14
			Cylinder 2	14
			Cylinder 3	14
			Cylinder 4	14
			Cylinder 5	14
			Cylinder 6	14
		Completed work orders	Cylinder 1	12
			Cylinder 2	13
			Cylinder 3	12
			Cylinder 4	13
			Cylinder 5	14
			Cylinder 6	12
	Fe (mg/kg)	Cylinder 1		95
		Cylinder 2		108

Cylinder oil feed rate settings		Cylinder 3	86
		Cylinder 4	317
		Cylinder 5	138
		Cylinder 6	134
	TBN (mg KOH/g)	Cylinder 1	29.3
		Cylinder 2	24.1
		Cylinder 3	28.3
		Cylinder 4	29.9
		Cylinder 5	24.9
		Cylinder 6	24.4

*The value is derived by the approach described in section 4.4.1.5 and based a relative humidity of 75% and an ambient temperature of 30ºC.

From Table 4.12, it can be observed that there are six model outputs, i.e. one for each single cylinder. The computations for fuel and scavenge air quality are common for all cylinders, whilst cylinder oil feed rate, engine maintenance and engine settings need to be calculated for each cylinder separately. Table 4.13 provides the fuzzy membership values of fuel quality and scavenge quality after performing a fuzzy 'max-min' inference function as detailed in section 4.4.1 and 4.4.2.

Table 4.13: Fuzzy outputs for fuel and scavenge air quality

Main parameters	Contributory factors	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Fuel quality (at engine inlet)	Catalyst fines	-	1	0	1.0	0.0
	Viscosity	-	0.875	0.125		
	Ash	-	1	0		
	CCAI	-	0.475	0.525		
	Water	-	1	0		
Scavenge air quality	Pressure	0.51	0.49	-	0.58	0.42
	Temperature	-	0.63	0.37		

	WMC performance	-	0.90	0.10		

The consequent (THEN) parts of the fuzzy rule indicate that fuel quality, in this case, is considered 100% satisfactory whilst scavenge air quality is 58% satisfactory and 42% unsatisfactory.

Table 4.14 provides the fuzzy output specifically for cylinder 1 after performing fuzzy inference for the rest of the parameters. The fuzzy outputs after the inference processes for cylinders 2, 3, 4, 5 and 6 are provided in Appendix D.

Table 4.14: Cylinder 1 – fuzzy outputs for engine settings, maintenance and cylinder oil feed rate settings

Key parameters	Contributory factors	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Engine settings	$P_{max} - P_{comp}$ (Bar)	1	0	-	1	0
	Exhaust temperature (ºC) (Mean value = 371)	-	1	0		
	MIP (Bar) (Mean value = 14.8)	-	1	0		
Engine maintenance	Availability	-	0.8	0.2	0.70	0.30
	Work orders	-	0.71	0.29		
Cylinder oil feed rate	Fe (mg/kg)	-	0.66	0.34	0.66	0.34
	TBN (mg KOH/g)	0.47	0.53	-		

The THEN parts of the rule-base provided in Table 4.13 and Table 4.14 are the final outputs from this fuzzy model, which can now be used as input in the BN model developed in Chapter 2 with the results shown in Figure 4.36.

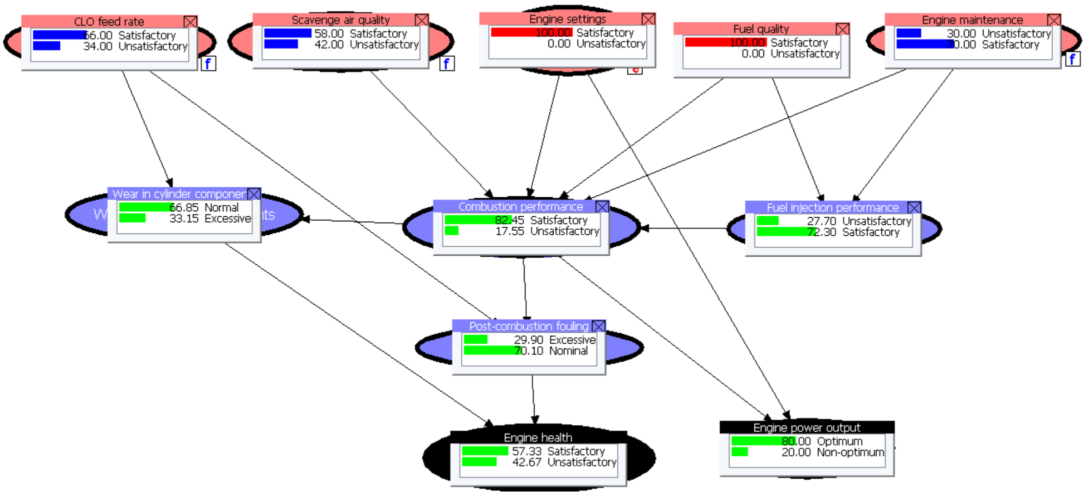
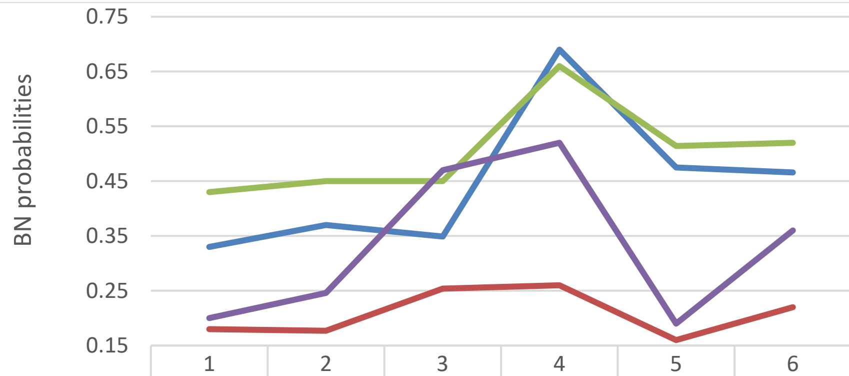


Figure 4.36: BN model assessment for cylinder 1

The fuzzy outputs have been used as inputs for BN model parent nodes, as shown in the above figure for cylinder 1 assessment. Similarly, for the remaining cylinders (2~6), the BN DAGs are shown in Appendix E. Each BN model has a number of intermediate and leaf nodes which require consideration to compare the results between various cylinders and also assess the performance of individual cylinders. Figure 4.37 provides a summary of key results from all six cylinders for key nodes of the BN model from this case study.



	1	2	3	4	5	6
Excessive 'wear'	0.33	0.37	0.349	0.69	0.475	0.466
Unsatisfactory 'combustion'	0.18	0.177	0.254	0.26	0.16	0.22
Unsatisfactory 'engine health'	0.43	0.45	0.45	0.66	0.514	0.52
Non-optimum 'power output'	0.2	0.246	0.47	0.52	0.19	0.36

Figure 4.37: Summary of BN outputs for all cylinders

These results indicate that cylinder 4 is not performing well, mainly due to the high wear rate. One reason for excessive wear is the possibility of a cylinder going through a 'running-in' process after an overhaul which can last up to 500 running hours. In the case of cylinder 4, it was last overhauled 1,800 running hours ago, and, ideally, there should not be any excessive wear taking place. With the low likelihood of abrasive wear (low catalyst fines levels in fuel), the possibility of corrosive wear is also low, as wear in other cylinders is low. It appears that some form of adhesive wear is taking place due to lubrication breakdown. This needs to be further assessed onboard through scavenge port inspection.

Cylinders 1 and 5 appear to be performing better than the rest. Overall, the engine health is around 50% which, by reviewing other parameters, seems satisfactory. However, there is a need for frequent sampling and data collection to establish a baseline of the engine health acceptability values. Different two-stroke engines can respond differently to the various inputs. Moreover, shop test data and trials performed on new engines further need to be considered for benchmarking and evaluating the engine’s health. The results and interpretation performed through this case study show good correlation with the FEAP (2017) assessment and reporting system.

4.6 Conclusion

Combustion in an engine is a complex reaction taking place under intense heat and pressure. There are numerous operating variables which are carefully monitored and controlled to ensure engine performance indicators remain optimised; hence, asset life is prolonged and unplanned maintenance actions are avoided. An integrated approach can help to achieve these objectives by effectively processing the engine operational data. This chapter follows on from the previous chapter where a BN model was proposed to assess the two-stroke engine performance. However, a gap was identified in terms of the model’s inability to process the operational data systematically, rather than the operator assigning a prior probability value to the BN model parent nodes. This chapter attempts to address this issue by proposing a fuzzy model to process the five parent nodes (parameters) of the BN model.

In order to define fuzzy membership functions, industry data has been used, such as fuel and lube oil analysis detailed in section 4.4. The conventional fuzzy ‘max-min’ function is used for inference without the use of a defuzzification step to align with the proposed modus operandi. The functionality of the fuzzy model is then demonstrated by a real case study in section 4.5, with results providing a good correlation with the FEAP (2017) reporting protocol.

One of the downsides of the conventional fuzzy ‘max-min’ approach is the lack of sensitivity to sufficiently respond to the variations of the input variables. Moreover, there remains a question mark over the conventional use of fuzzy rule-base development where consequent parts of each rule may be assigned a single ‘state’, which is unlikely to capture the conditionality of each rule in the output comprehensively. These drawbacks need to be addressed to ensure the model is further fine-tuned.

5 Use of evidential reasoning to fine-tune the belief structure in the fuzzy rule-base to improve expert judgements in fuzzy BN reasoning

It has been the intention of this study to create a dynamic model capable of processing the key operational parameters for two-stroke engine performance assessment. The major challenge has been to address how the multiple sets of quantitative and qualitative operational information are amalgamated and converted into an appropriate quantitative feed for the BN model. The previous chapter provides a fuzzy set approach applied to all five BN parent nodes, namely scavenge air quality, fuel quality, maintenance, cylinder oil feed rate and engine settings.

The fuzzy set approach has been chosen to address the multi-attribute issue described as above because it is one of the most suitable methods to address uncertainty by employing linguistic variables and a knowledge-based reasoning process. It accommodates various sources of information, allows logical inference and provides output in the probability format, which can be directly used in the Bayesian model as input.

However, the traditional fuzzy ‘max-min’ inference method adopted in the last chapter appears to have the tendency to lose useful information (Yang et al., 2009). Furthermore, the stability of the output through ‘max-min’ inference is questionable. Additionally, the Fuzzy Rule-Base (FRB) consequent part may not always be able to reflect the variability in the antecedent (Yang et al., 2009). To overcome these issues, in the current chapter, an Evidential Reasoning (ER) approach has been discussed and applied as an attempt to improve fuzzy inference. The results from both fuzzy inference processes are compared and analysed.

5.1 Evidential reasoning

Evidential Reasoning (ER) is a method of drawing likely conclusions from a set of information which can be incomplete or uncertain. The theory of evidence was first introduced by Dempster in 1967, and it was further developed by his student Shafer in 1976. Therefore, ER is also commonly known as Dempster-Shafer theory (D-S theory) (Maistralis, 2007).

D-S theory uses a number between 0 and 1 to represent the Degree of Belief (DoB), which could be divided into multiple grades such as low, average, high and very high (Zhang et al., 2016). For example, the quality of the fuel entering the engine could be evaluated as 60% acceptable and 40% unacceptable based on the available data and expert judgements. One of the significant advantages of ER is its ability to process unassigned DoB, which could be due to uncertain data or insufficient expertise in the field (Lee and Yang, 2018). In the example above, there could be a scenario where fuel quality is considered as 60% acceptable and 20% unacceptable, and the remaining 20% can be processed as unassigned DoB within the ER algorithm. Furthermore, Zhang et al (2016) listed a few advantages such as the ER model's ability to deal with both quantitative and qualitative criteria under uncertainty through a systematic process which yields consistent results, and, secondly, the use of IDS (Intelligent Decision System) software (Yang and Xu, 2000), which is designed to present information graphically for various applications. Similarly, there has been some criticism of the method in terms of its apparent inability to address the issue of conflicting evidence (Qin, Xi and Pedrycz, 2020).

Most practical ER applications are concerned with addressing the issue of multi-criteria decision making (MCDM) under uncertainty by utilising expert judgement in the form of belief functions (Yang and Xu, 2002). There have been a number of applications of evidential reasoning. For example, Zeng, Wang and Zheng (2006) carried out an information technology project by developing an aggregative risk assessment, and Liu et al (2002) used an ER approach to analyse the safety of an engineering system. Moreover, there has been focused research within the maritime sector to employ the ER approach under the MCDM paradigm. Table 5.1 provides an overview of some of the key ER applications in the maritime context.

Table 5.1: ER research studies in the maritime context

Study	Topic	Technical model	Key outcome
Asuquo et al (2019)	Marine machinery management	ER combined with Analytical Hierarchy Process	A condition-based decision-making tool to assess crane machinery health condition based on the lubricant/grease analysis data taking into consideration various uncertainty scenarios.
Jiang et al (2019)	Marine navigational safety	Fuzzy Evidential Reasoning	Decision-making tool for cable-laying operation to select the most appropriate route considering safety and environmental factors.

Lee and Yang (2018)	Maritime operations	Fuzzy evidential reasoning for MCDM	A knowledge-based decision-making tool to select the most suitable ship for a particular voyage considering corresponding multi-attributes.
Wu et al (2017)	Maritime safety (human factors)	ER-based CREAM (cognitive reliability and error analysis method) approach	A human reliability analysis model to estimate the human error probability (HEP) in a ship capsize (prospective) scenario addressing the inherent uncertainty within marine accident propagation.
Zhang et al (2016)	Marine navigational safety	ER-based FRB	Navigational risk assessment of an inland-waterway by dividing the Yangtze river into three regions and evaluating and comparing the safety of the regions.
Yang et al (2009)	Maritime security	Fuzzy evidential reasoning	Four Security Control Options (SCOs) were evaluated and prioritised using the FRB-ER approach.

The studies conducted by Jiang et al (2019), Zhang et al (2016) and reported by Lee and Yang (2018) demonstrate similarities in terms of helping decision makers to determine the most appropriate or safe option based on subjective and incomplete data. The output is a utility value calculated for each option, where a higher value would indicate a better choice compared to other competing options. Yang et al (2009) followed a similar approach to evaluate various security threats and developed a corresponding ranking scheme for security control options. The work of Asuquo et al (2019) is interesting as it combines various factors such as design, historical trends, operating environment, similar machines and human factors to develop a machinery condition monitoring tool with a diagnostic capability. The study seems well rounded and effectively addresses issues such as lack of guidance from equipment manufacturer and gaps in available data, yet it appears to have overlooked the possibility of including the analysis of a fresh lubricant/grease sample to improve confidence in the baseline, which currently depends on the expert judgement in the study.

One of the major advantages of the ER is that the approach can address the incompleteness in the data or information through the degree of belief concept (Yang et al., 2019) which is especially useful in handling uncertainty in real world applications. Moreover, the approach provides the flexibility to the decision makers to produce outcomes not only in subjective (verbal descriptors) form but also in a quantitative (specific numbers) way (Yang et al., 2018).

A fuzzy ER approach which has been employed by most of the studies mentioned in Table 5.1 has the advantage over fuzzy logic and the ER approach in terms of how the input variables are described. Fuzzy logic uses membership functions whilst ER utilises the belief degree; however, the fuzzy ER model synthesises the fuzzy membership functions and combines them with the belief degree, improving the overall precision of input variables (Jiang et al., 2019). ER and fuzzy ER models share the same functional aspects like the description of output variables, handling of incomplete information, and use of extended IF-THEN rules (Jiang et al., 2019).

In chapter 4, fuzzy models for each key parameter have been developed as operational benchmarks to process the raw data from various LS2S engine parameters. However, fuzzy inference process and rule-base appears to lack the required sensitivity for a multicriteria context. From the literature review, it appears that ER is well suited to integrate with the proposed fuzzy model framework and address the apparent lack of certainty in the fuzzy rule-base through the use of expert judgements. More specifically the ER model improves the fuzzy rule-base by assigning different weight to the antecedent of each rule which is a realistic representation of the real world scenarios.

5.2 ER algorithm

The ER algorithm is used to capture the non-linear relationships between the set of rules. This aim is achieved by combining all the outputs from each rule to generate a conclusion. The kernel of the approach is the use of extended IF-THEN rules with the main steps described as follows.

The first step is assigning the relative weight (ω) to the antecedents A_k (where K = 1, 2, …, L) and mainly under the premise $\sum_{K=1}^{L} \omega = 1$. Assigning of the weights is performed through expert judgement as it is understood that the impact of the various parameters on overall performance or outcome is unequal in real-world scenarios, hence this needs to be reflected in the model.

The second step is calculating the degree of belief (β_k) based on knowledge of antecedents (A_k) for consequents (D_k). This is mainly carried out by taking the relative weights assigned to the antecedents in step one. A belief structure similar to the one proposed by Alyami et al (2014) has been taken as a reference to model the THEN part in the extended rule-base. For example, IF ‘air pressure’ is **Low**, ‘temperature’ is **Low**, and ‘water mist catcher (WMC)’ performance is **Unsatisfactory**, THEN ‘scavenge quality’ is 0% **Satisfactory** and 100% **Unsatisfactory**.

The third step is calculating the weight of each rule Θ_k for a specific operational scenario. This is performed by multiplying the corresponding antecedent mass distribution to generate a crisp number for the rule R_k. The impact of a rule in the final outcome is proportional to its weight. For all activated rules, the condition $\sum_{K=1}^{N} \Theta = 1$ applies.

The fourth step is comprised of a recursive process of synthesising the activated rules by taking values from two rules at a time, starting by calculating the mass distribution of D_k for each rule R_k. This is the product of the weight of each rule and degree of belief. Suppose M_1^j and M_2^j (j = 1, 2) are the individual degrees that support the hypothesis and α_1^j & α_2^j (j = 1, 2) represents the extent to which the selected rule belongs to the consequent part of the rule-base. The relative weight (ω) of the antecedents for each rule has already been calculated in step one, so the following needs to be calculated for both rules being synthesised (Zhang et al., 2016):

$$M_1^j = \alpha_1^j \times \omega_1 \ \ \& \ \ M_2^j = \alpha_2^j \times \omega_2 \qquad (1)$$

Suppose that H_1 and H_2 are the remaining unassigned belief values, then these can be calculated as:

$$H_1 = \overline{H_1} + \widetilde{H_1} \quad and \quad H_2 = \overline{H_2} + \widetilde{H_2} \qquad (2)$$

Where $\overline{H}$ represents the degree of belief in the assessment whilst $\widetilde{H}$ is caused due to the possible incompleteness, which can be described as follows:

$$\overline{H}_1 = 1 - \omega_1 \ \text{ and } \ \overline{H}_2 = 1 - \omega_2 \qquad (3)$$

$$\widetilde{H_1} = \omega_1 \left(1 - \left(\alpha_1^1 + \alpha_1^2 \right)\right) \qquad (4)$$

$$\widetilde{H_2} = \omega_2 \left(1 - \left(\alpha_2^1 + \alpha_2^2 \right)\right) \qquad (5)$$

In the case where there is no incomplete or unassigned degree of belief, then:

$\alpha_1^j + \alpha_1^j = 1$; Hence, $H_1 = \overline{H_1}$ & $H_2 = \overline{H_2}$ respectively.

Suppose α^m ($m = 1, 2$) represents the non-normalised aggregated degree of belief assigned to the consequent part of the rule-base. If a^1 and a^2 represent the two consequents for a parameter:

$$a^1 = \frac{a^{1\prime}}{1-H_u'} \ \& \ a^2 = \frac{a^{2\prime}}{1-H_u'} \tag{6}$$

Where

$$H_u' = K\ (\bar{H}_1 \times \bar{H}_2) \tag{7}$$

And

$$a^{1\prime} = K\ (M_1^1 \times M_2^1 + M_1^1 \times H_2 + M_2^1 \times H_1)\ \&\ a^{2\prime} = K\ (M_1^2 \times M_2^2 + M_1^2 \times H_2 + M_2^2 \times H_1) \tag{8}$$

K in the above equations is a normalising constant and is determined as:

$$K = \left[1 - \sum_{T=1}^{2} \times \sum_{R=1}^{2} (M_T^1 M_R^2)\right]^{-1} \tag{9}$$

Thus, in the above scenario:

$$K = [1 - (M_1^1 M_2^2 + M_2^1 M_1^2)]^{-1} \tag{10}$$

Using the formulas mentioned, rules R_1 and R_2 have been synthesised to determine the mass distribution (values) of a^1 and $a^2$of the consequent part. This process completes the first phase as now the same process needs to be repeated using these outputs, and combine them with the next activated rule, e.g. R_3. Similarly, the output from this is combined with the other rules one at a time, which represents a recursive process.

5.3 Fuzzy ER approach for two-stroke engine health monitoring

This chapter builds on the work performed in previous chapters where a BN model is combined with the fuzzy model to assess the overall two-stroke engine health rating. The focus of this chapter would improve the fuzzy inference process through ER and evaluate the difference in terms of model effectiveness and accuracy. A 12-step workflow diagram has been presented for this chapter as per Figure 5.1.

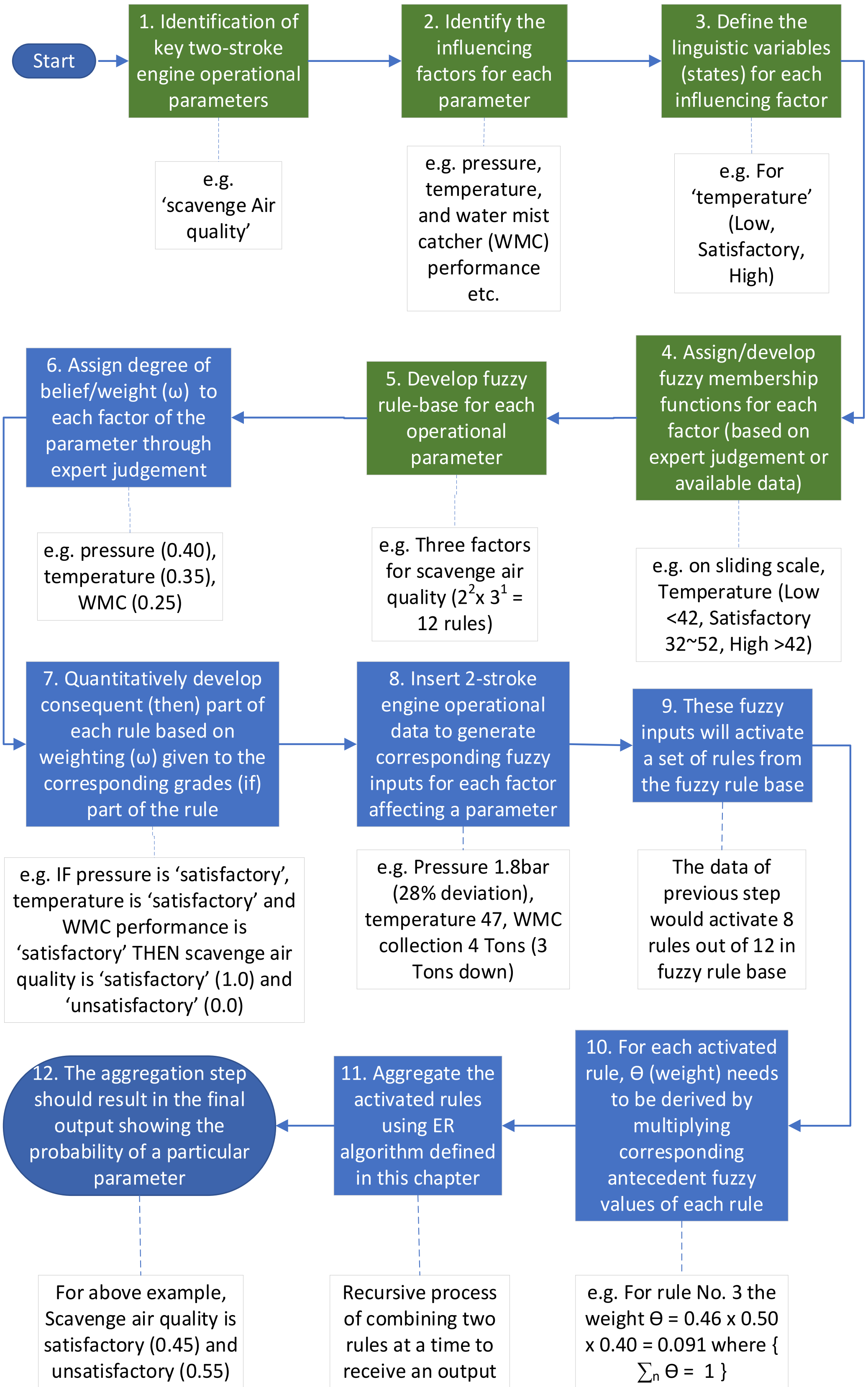


Figure 5.1: Flow diagram of the ER model

The steps one to five (shaded green) in the above figure have been presented in chapter 4. Steps six to twelve present a fuzzy inference process through the ER algorithm, which is discussed in the following sections.

5.3.1 Assigning belief degree (Step 6)

The factors impacting a parameter output have unequal influence. For example, the impact of low scavenge air pressure on the overall quality of scavenge air may be slightly higher compared to that of incorrect scavenge air temperature. In the absence of a data set to assign appropriate weights to each factor to reflect the scale of impact on a specific parameter, six subject matter experts have been engaged to provide expert judgements.

Table 3.5 provides the list of experts and from that list, experts 1, 4, 5 and 6 were re-contacted for this area of the study, whilst two new experts, 11 and 12, were contacted due to their particular operational experience. These experts have been chosen based on their knowledge and experience of the design, operations and maintenance of LS2S engines.

These experts were contacted individually via an email sent by the researcher. The email contained a brief introduction and background of the enquiry. With a few experts, a follow-up call was made where individuals sought clarification. The experts were requested to provide their individual input to assign their degree of belief (β) to factors μ_m (m = 1, 2..., k), where k is the total number of factors impacting a parameter.

Where $\sum_{m=1}^{k} \beta_m = 1$ (m = 1, 2…, k)

A greater value of β assigned would reflect more importance has been given to that factor compared to others. Table 5.2 provides a summary of the judgements received from the experts.

Table 5.2: Expert judgements from six experts

Parameter	Factors affecting the parameter	Exp. 1	Exp. 4	Exp. 5	Exp. 6	Exp. 11	Exp. 12
Scavenge air quality	Scavenge air pressure	0.2	0.5	0.35	0.45	0.4	0.5
	Scavenge air temperature	0.5	0.4	0.35	0.4	0.4	0.2
	Water mist catcher performance	0.3	0.1	0.3	0.15	0.2	0.3
Fuel quality (at engine inlet)	Catalyst fines	0.3	0.5	0.2	0.25	0.3	0.25
	Water	0.22	0.2	0.2	0.15	0.2	0.15
	Ash	0.12	0.1	0.15	0.15	0.1	0.1
	Viscosity	0.27	0.1	0.25	0.2	0.25	0.3
	CCAI	0.09	0.1	0.2	0.25	0.15	0.2
Maintenance management	Work order (TBM routine)	0.1	0.5	0.5	0.6	0.35	0.8
	Availability of the asset	0.9	0.5	0.5	0.4	0.64	0.2
Engine settings (indicators)	$P_{max} - P_{comp}$	0.3	0.5	0.35	0.45	0.25	0.5
	MIP deviation	0.3	0.25	0.35	0.25	0.4	0.3
	Exhaust temperature deviation	0.4	0.25	0.3	0.3	0.35	0.2
CLO feed rate	Fe content	0.7	0.5	0.4	0.35	0.35	0.3
	TBN	0.3	0.5	0.6	0.65	0.6	0.7

The next step is to aggregate these judgements to produce a single value for each factor μ. In order to undertake this step, the evidential reasoning model described in section 5.2 has been used. The first step here is the estimation of weights in the judgements of various experts.

Due to variations in experts' professional roles, experiences and education levels, judgements from specific individuals may carry more weight compared to other experts in the panel. In order to address this variability in a systematic fashion, a classification scheme like the one proposed by Lavasani et al (2012) has been introduced. To estimate the weight, each expert is assessed against three performance indicators: 1) education, 2) professional experience and 3) leadership role in their respective organisations. Table 5.3 provides the constitution of the classification scheme.

Table 5.3: Weighting score of different experts

Criteria	Classification	Score
Education Level (EL)	PhD	5
	Master	4
	Bachelor	3
	HND	2
	School-level	1
Professional Experience (PE)	≥ 30 Years	5
	20 - 29	4
	10 - 19	3
	6 - 9	2
	≤ 5	1
Organisational Responsibility (OR)	Executive/Principal	5
	Lead	4
	Senior	3
	Engineer	2
	Technician	1

An individual expert i 's weight (w_i) is obtained by first estimating individual scores (S_i) by using equations 11 and 12.

$$S_i = \text{EL of expert}_i + \text{PE of expert}_i + \text{OR of expert}_i \tag{11}$$

$$w_i = \frac{S_i}{\sum_{i=1}^{n} S_i} \tag{12}$$

Where $\sum_{i=1}^{n} w_i = 1$ (n = 1, 2…, 6)

Based on the classification provided in Table 5.3, each expert's score and subsequent weight has been estimated and shown in Table 5.4.

Table 5.4: Weight estimation of each expert

Expert number	Education	Experience (years)	Responsibility	Score (S)	Weightage (w_i)
1	Master	20-29	Executive	5+4+4 = 13	0.183
4	Bachelor	20-29	Lead	4+4+3 = 11	0.155
5	Master	>30	Senior	3+5+4 = 12	0.169
6	PhD	20-29	Lead	4+4+5 = 13	0.183
11	Master	20-29	Lead	4+4+4 = 12	0.169
12	Bachelor	20-29	Senior	3+4+3 = 10	0.141
					Total = 1

ER is a recursive process and its functionality has been demonstrated by aggregating the expert judgements for scavenge air quality. To begin with, the judgements from experts 11 & 4 are taken (from Table 5.2) for each factor, pressure (*P*), temperature (*T*) and water mist catcher (*C*), and presented as follows:

$\beta_{11}^{P} = 0.40 \quad \beta_{11}^{T} = 0.40 \quad \beta_{11}^{C} = 0.20$

$\beta_{4}^{P} = 0.50 \quad \beta_{4}^{T} = 0.40 \quad \beta_{4}^{C} = 0.10$

The weights of experts 11 and 4 (from Table 5.4) are:

$w'_{11} = 0.169$

$\mathrm{w}'_{4} = 0.155$

Normalised weights of both experts are as follows:

$w_{11} = w'_{11} \,/\, (w'_{11} + w'_{4}) = 0.5216$

$w_{4} = w'_{4} \,/\, (w'_{11} + w'_{4}) = 0.4784$

Suppose M_R^j ($j = P, T, C$) are the individual degrees that support the hypothesis:

$M_{11}^{P} = \beta_{11}^{P} \times w_{11}$ = 0.40 x 0.5216 = 0.2086

$M_{11}^{T} = \beta_{11}^{T} \times w_{11}$ = 0.40 x 0.5216 = 0.2086

$M_{11}^{C} = \beta_{11}^{C} \times w_{11}$ = 0.20 x 0.5216 = 0.1057

$M_4^P = \beta_4^P \times w_4$ = 0.50 x 0.4784 = 0.2392

$M_4^T = \beta_4^T \times w_4$ = 0.40 x 0.4784 = 0.1914

$M_4^C = \beta_4^C \times w_4$ = 0.10 x 0.4784 = 0.0478

Suppose H_{11} and H_4 are the individual belief values for M_{11}^m and M_4^m (m = *P, T, C)*. Then, H_{11} and H_4 can be expressed as follows:

$$H_{11} = \overline{H_{11}} + \widetilde{H_{11}} \, and \qquad H_4 = \overline{H_4} + \widetilde{H_4}$$

Where $\overline{H}$ represents the degree of belief in the assessment whilst $\widetilde{H}$ is caused due to the possible incompleteness, which can be described as follows:

$\overline{H}_{11} = 1 - \mathrm{w}_{11}$ and $\overline{H}_4 = 1 - \mathrm{w}_4$

$\widetilde{H_{11}} = \mathrm{w}_{11} \, (1 - (\beta_{11}^P + \beta_{11}^T + \beta_{11}^C))$

$\widetilde{H_4} = \mathrm{w}_4 \, (1 - (\beta_4^P + \beta_4^T + \beta_4^C))$

As

$\beta_{11}^P + \beta_{11}^T + \beta_{11}^C = 1$ & $\beta_4^P + \beta_4^T + \beta_4^C = 1$ hence, $H_{11} = \overline{H_{11}}$ & $H_4 = \overline{H_4}$ respectively:

$\overline{H}_{11} = 1 - \mathrm{w}_{11}$ = 1 – 0.5216 = 0.4784

$\overline{H}_4 = 1 - \mathrm{w}_4$ = 1 – 0.4784 = 0.5216

The next step is to determine the value of K (constant):

$$K = [1 - \sum_{T=1}^{3} \times \sum_{R=1}^{3} (M_T^{11} M_R^4)]^{-1}$$

For the case above,

$$K = [1 - (M_{11}^P M_4^T + M_{11}^P M_4^C + M_{11}^T M_4^P + M_{11}^T M_4^C + M_{11}^C M_4^P + M_{11}^C M_4^T)]^{-1}$$

Inserting the values in the above equation:

$$K = 1.1838$$

Suppose $\beta_{11,4}^m$ (m = *P, T, C)* represents the non-normalised aggregated degree of belief assigned where $\beta_{11,4}^P$ represents the ‘pressure’, $\beta_{11,4}^T$ represents the ‘temperature’ and $\beta^{C}_{11,4}$ represents the ‘WMC performance’ for scavenge air quality, then:

$\beta^{P}_{11,4} = \frac{a^{P\prime}}{1-H'_u}$, $\beta^{T}_{11,4} = \frac{a^{T\prime}}{1-H'_u}$, $\beta^{C}_{11,4} = \frac{a^{C\prime}}{1-H'_u}$

Where

H'_u = K ($\bar{H}_{11} \times \bar{H}_4$)

H'_u = 0.2952

And

$a^{P\prime} = K\ (M^{P}_{11} \times M^{P}_{4} + M^{P}_{11} \times H_4 + M^{P}_{4} \times H_{11})$ = 0.3232

$a^{T\prime} = K\ (M^{T}_{11} \times M^{T}_{4} + M^{T}_{11} \times H_4 + M^{T}_{4} \times H_{11})$ = 0.2843

$a^{C\prime} = K\ (M^{C}_{11} \times M^{C}_{4} + M^{C}_{11} \times H_4 + M^{C}_{4} \times H_{11})$ = 0.0973

Placing these values into the following equation:

$\beta^{P}_{11,4} = \frac{a^{P\prime}}{1-H'_u}$, $\beta^{T}_{11,4} = \frac{a^{T\prime}}{1-H'_u}$, $\beta^{C}_{11,4} = \frac{a^{C\prime}}{1-H'_u}$

$\beta^{P}_{11,4}$ = 0.4585, $\beta^{T}_{11,4}$ = 0.4033, $\beta^{C}_{11,4}$ = 0.1381

Hence, inserting the values into the above equations would give aggregated judgements ($\beta^{P}_{11,4}$, $\beta^{T}_{11,4}$ and $\beta^{C}_{11,4}$) for experts 11 and 4. The next step is to combine these three values with the expert judgements of the other experts, one by one, as a recursive process until all six experts are weighted to determine the final score for ω_P, ω_T and ω_C. In order to facilitate the computation, IDS software has been used to provide the final aggregated result for the scavenge air quality, as shown in Figure 5.2.

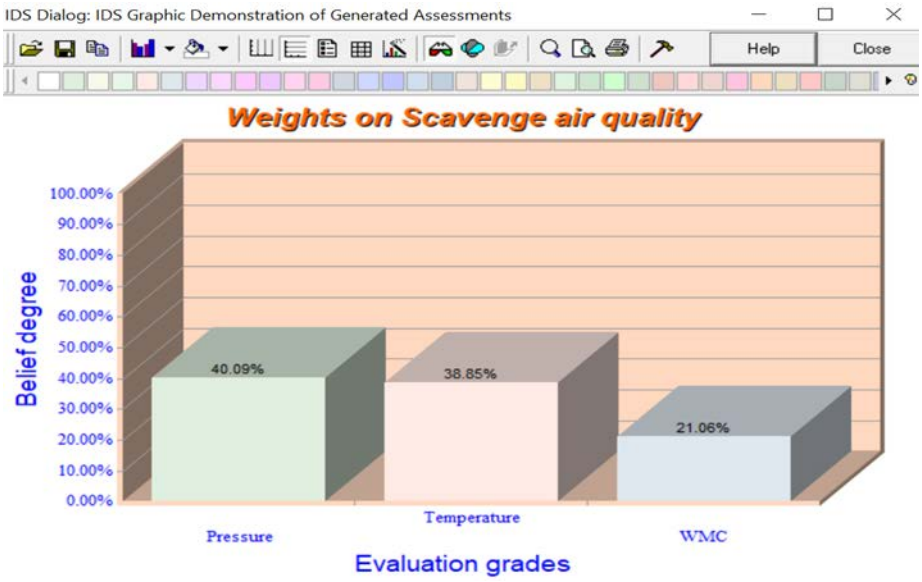


Figure 5.2: IDS-assisted aggregation of expert judgement (IDS software)

Similarly, the rest of the parameters have been computed, and the final aggregation has been summarised in Table 5.5.

Table 5.5: Summary of the aggregated expert judgement results

Parameter	Factors affecting the parameter	Expert judgements through evidential reasoning
Scavenge air quality	Scavenge air pressure	0.4009
	Scavenge air temperature	0.3885
	Water mist catcher performance	0.2106
Fuel quality (at engine inlet)	Catalyst fines	0.3093
	Water	0.1849
	Ash	0.1158
	Viscosity	0.2294
	CCAI	0.1606
Maintenance management	Work order (planned maintenance routine)	0.4507
	Availability of the asset	0.5493
Engine settings (indicators)	$P_{max} - P_{comp}$	0.3953
	MIP deviation	0.3041
	Deviation in exhaust temperature	0.3006
Cylinder oil feed rate settings	Fe content	0.4344
	TBN	0.5656

5.3.2 Quantitative assessment of the consequent parts of the FRB (Step 7)

This step follows on from the previous step, where antecedents of each FRB have been assigned a weight through expert judgement. This next step involves using these values to assign the weights to the consequent parts of the FRB. Yang et al (2009) constructed an FRB for maritime security assessment with the belief structure which follows a proportionality principle, i.e. if all the antecedents in an FRB point to a 'positive' outcome, then it can be deduced with 100% certainty that the consequent is also 'positive'.

For example, there are three factors affecting the scavenge air quality. The antecedents of the rule-base are scavenge air pressure ω_P (0.4009), scavenge temperature ω_T (0.3885), and water mist catcher performance ω_C (0.2106), affecting scavenge air quality being 'satisfactory' ε_S^s or unsatisfactory ε_u^s, which are a consequent part. IF the pressure is '**Acceptable**', temperature is '**Acceptable**' and water mist catcher performance is '**Satisfactory**', THEN scavenge air quality is '**Satisfactory**' with a belief degree of 1 and '**Unsatisfactory**' as 0. Similarly, IF the pressure is '**Low**', temperature is '**Low**' and water mist catcher performance is '**Satisfactory**', THEN scavenge air quality is estimated as follows:

$\varepsilon^s = \omega_C = 0.2106$

$\varepsilon^u = \omega_P + \omega_T = 0.4009+0.3885 = 0.7894$

In the case above, two antecedents (pressure & temperature) pointed to an unsatisfactory outcome, hence the consequent part is formed by adding the prior weights assigned to these factors, whilst the WMC performance was satisfactory, which is reflected as the sole contributor of the THEN part being 'satisfactory'.

The rest of the FRB has been developed on these lines and is described in Table 5.6:

Table 5.6: Modified FRB for scavenge air quality

Rule No.	IF (Antecedents)			THEN (Consequent) - Scavenge quality	
	Air Pressure (ω_P)	Temperature (ω_T)	WMC (ω_C)	Satisfactory (ε^s)	Unsatisfactory (ε^u)
1	Low	Low	Satisfactory	0.2106	0.7894
2	Low	Low	Unsatisfactory	0	1
3	Low	Satisfactory	Satisfactory	0.5991	0.4009
4	Low	Satisfactory	Unsatisfactory	0.3885	0.6115
5	Low	High	Satisfactory	0.2106	0.7894
6	Low	High	Unsatisfactory	0	1
7	Satisfactory	Low	Satisfactory	0.6115	0.3885
8	Satisfactory	Low	Unsatisfactory	0.4009	0.5991
9	Satisfactory	Satisfactory	Satisfactory	1	0
10	Satisfactory	Satisfactory	Unsatisfactory	0.7894	0.2106
11	Satisfactory	High	Satisfactory	0.6115	0.3885
12	Satisfactory	High	Unsatisfactory	0.4009	0.5991

Similarly, FRBs for the other four parameters (Fuel quality, Maintenance management, Engine settings & Cylinder oil feed rate) have been developed and described in Appendix F.

5.3.3 Fuzzy inference and rule activation (steps 8 & 9)

In order to demonstrate the new fuzzy inference process using the ER algorithm, this section uses a scenario to initiate the processing of operational data from an LS2S engine. For the ease of reference, this section continues the use of scavenge air quality as a reference parameter. Table 5.7 shows the typical operational data during a voyage for a MAN 6S50MC two-stroke main engine:

Table 5.7: Operational data to assess scavenge air quality

	Units	Operational input
Effective power	kW	6000
Scavenge air pressure (calculated)	Bar	2.7
Scavenge air pressure (actual)	Bar	2.5
Scavenge air temperature	°C	42
Condensed scavenge cooler water (calculated)	tonne/24H	6
Condensed scavenge cooler water (actual)	tonne/24H	4

Let ϕ_i^j represents the fuzzy membership values for antecedents (*j*) with corresponding state *i*. Placing these operational values into the fuzzy model developed in chapter 4 (section 4.4.1) would result in fuzzy memberships as per Table 5.8:

Table 5.8: Corresponding fuzzy membership values for the case

Antecedents of FRB	Fuzzy membership values
Air pressure	
Low (ϕ_L^P)	0.49
Satisfactory (ϕ_S^P)	0.51
Temperature	
Low (ϕ_L^T)	0
Satisfactory (ϕ_S^T)	1
High (ϕ_H^T)	0
Water mist catcher	
Satisfactory (ϕ_S^C)	0.6
Unsatisfactory (ϕ_U^C)	0.4

The conditions described above activated four rules (from Table 5.8), which have been summarised in Table 5.9 as follows:

Table 5.9: Activated fuzzy rules for the case

Rule no.	IF (Antecedents)			THEN (Consequent) - Scavenge quality	
	Air Pressure (ω_P)	Temperature (ω_T)	WMC (ω_C)	Satisfactory (ε^s)	Unsatisfactory (ε^u)
3	Low	Satisfactory	Satisfactory	0.5991	0.4009
4	Low	Satisfactory	Unsatisfactory	0.3885	0.6115
9	Satisfactory	Satisfactory	Satisfactory	1	0
10	Satisfactory	Satisfactory	Unsatisfactory	0.7894	0.2106

5.3.4 Assigning weight (ϴ) to each rule (step 10)

In the context, different activated rules are going to have different levels of importance in the aggregated outcome. Hence, the weight Θ_k (k = 3, 4, 9, 10) of each rule is calculated by taking the corresponding antecedent fuzzy membership values. For example, the weight of rule 3 has been calculated as follows:

$\Theta_3 = \phi_L^P \times \phi_S^T \times \phi_S^C$

$\Theta_3 = 0.49 \times 1 \times 0.6 = 0.296$

Similarly, the weights of the other three rules have been calculated as $\Theta_4 = 0.197$, $\Theta_9 = 0.304$ and $\Theta_{10} = 0.203$. It is important to note that for activated rules (K = 1, 2, 3, …, L), following condition applies:

$$\sum_{L=1}^{k} \Theta_k = 1$$

5.3.5 Application of ER algorithm to aggregate the activated rules (steps 11 & 12)

As described in section 5.1 of this chapter, ER is a useful aggregation methodology to use in the multi-criteria decision analysis. For the case developed in section 4.5, there are four activated rules, as per Table 5.9. The ER is a step-wise recursive process where two rules are aggregated first and the output thereof combined with the third rule and so forth.

In view of the above, activated rules 3 and 4 have been taken, with the following results:

$\varepsilon_3^s = 0.5991$ $\qquad$ $\varepsilon_3^u = 0.4009$

$\varepsilon_4^s = 0.3885$ $\qquad$ $\varepsilon_4^u = 0.6115$

Where each $\varepsilon_R^{s\ OR\ u}$ (R = 1, 2) represents the extent to which the selected rule belongs to the consequent part of the rule-base. Moreover, from section 5.3.4, the weight of each rule can be derived and are as follows:

$\Theta'_3 = 0.296$

$\Theta'_4 = 0.197$

However, these weights need to be normalised. Where $\sum_{m=1}^{k} \Theta_m = 1$ (m = 1, 2) which results in:

$\Theta_3 = \Theta'_3 / (\Theta'_3 + \Theta'_3) = 0.6$

$\Theta_4 = \Theta'_4 / (\Theta'_4 + \Theta'_4) = 0.4$

Suppose M_R^j (j = 1, 2) are the individual degrees that support the hypothesis:

$M_3^s = \varepsilon_3^s \times \Theta_3 = 0.5991 \times 0.6 = 0.36$

$M_3^u = \varepsilon_3^u \times \Theta_3 = 0.4009 \times 0.6 = 0.24$

$M_4^s = \varepsilon_4^s \times \Theta_4 = 0.3885 \times 0.4 = 0.16$

$M_4^u = \varepsilon_4^u \times \Theta_4 = 0.6115 \times 0.4 = 0.24$

Suppose H_3 and H_4 are the individual remaining unassigned belief values for M_3^m and M_4^m (*m = satisfactory, unsatisfactory*). Then, H_3 and H_4 can be expressed as follows:

$$H_3 = \overline{H_3} + \widetilde{H_3} \quad \textit{and} \quad H_4 = \overline{H_4} + \widetilde{H_4}$$

Where $\overline{H}$ represents the degree of belief in the assessment, whilst $\widetilde{H}$ is caused due to the possible incompleteness, which can be described as follows:

$\overline{H}_3 = 1 - \Theta_3$ and $\overline{H}_4 = 1 - \Theta_4$

$\widetilde{H_3} = \Theta_3\,(1 - (\varepsilon_3^s + \varepsilon_3^u))$

$\widetilde{H_4} = \Theta_4\,(1 - (\varepsilon_4^s + \varepsilon_4^u))$

As $\varepsilon_3^s + \varepsilon_3^u = 1$ & $\varepsilon_4^s + \varepsilon_4^u = 1$ hence, $H_3 = \overline{H_3}$ & $H_4 = \overline{H_4}$ respectively;

$\overline{H}_3 = 1 - \Theta_3 = 1 - 0.6 = 0.4$

$\overline{H}_4 = 1 - \Theta_4 = 1 - 0.4 = 0.6$

The next step is to determine the value of K (constant):

$$K = [1 - \sum_{T=1}^{2} \times \sum_{R=1}^{2} (M_T^1 M_R^2)]^{-1}$$

$$K = [1 - (M_3^s M_4^u + M_4^s M_3^u)]^{-1}$$

Inserting the values in the above equation:

$$K = [1 - (0.13)]^{-1}$$

K = 1.14

Suppose ε^m (*m = satisfactory, unsatisfactory*) represents the non-normalised aggregated degree of belief assigned to the consequent part of the rule-base. Here, ε^s

represents the satisfactory and ε^u represent the unsatisfactory outcome for scavenge air quality:

$$\varepsilon^s = \frac{\varepsilon^{s\prime}}{1-H_u'} \qquad \& \qquad \varepsilon^u = \frac{\varepsilon^{u\prime}}{1-H_u'} \tag{i}$$

Where

H_u' = K ($\bar{H}_3 \times \bar{H}_4$) = 0.27

And

$\varepsilon^{s\prime} = K\ (M_3^s \times M_4^s + M_3^s \times H_4 + M_4^s \times H_3)$

$\varepsilon^{s\prime} = 0.38$

&

$\varepsilon^{u\prime} = K\ (M_3^u \times M_4^u + M_3^u \times H_4 + M_4^u \times H_3)$

$\varepsilon^{u\prime} = 0.34$

Hence, from equation (i):

ε^s = 0.53

ε^u = 0.47

This completes the first phase. The next phase is to combine the outcome of rules 3 & 4 with the next activated rule, rule 9, and repeat the same process until the last activated rule, which in this case is rule 10, to receive a final assessment. The same process is simulated and processed through the IDS software, with the result shown in Figure 5.3.

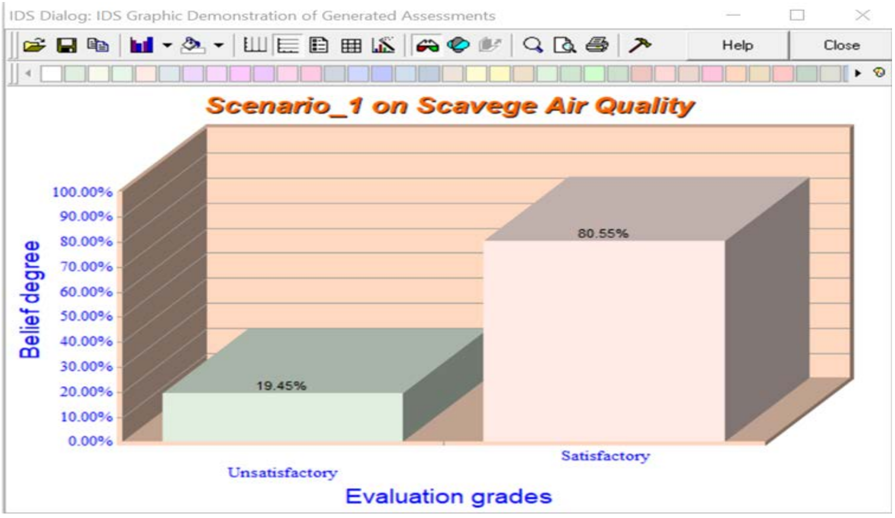


Figure 5.3: IDS result of the scenario on scavenge air quality

Thus, the final probability for satisfactory scavenge air quality is **0.8055** and unsatisfactory is **0.1945**, compared to the values of **0.56** (satisfactory) and **0.44** (unsatisfactory) obtained through the conventional fuzzy max-min approach for the same operational input. This indicates a significant difference in the two sets of results. However, if the raw input data is observed closely, ER inference results are clearly more plausible, considering scavenge air temperature (100%), pressure (51%) and WMC (60%) are 'satisfactory', which, combined with consequent weights for the activated rules, shows the high probability of scavenge air quality being 'satisfactory'. Further simulated runs are performed in the following section to gauge quantitative variances between the two inference techniques.

5.4 Comparison between fuzzy inference processes

In this section, a comparison is made between the 'max-min' fuzzy inference process adopted in chapter 4 and the ER approach employed in this chapter. For this purpose, scavenge air pressure, fuel quality and engine settings have been considered by varying the input of one factor while keeping the other factors constant.

Firstly, the impact of varying temperatures on the scavenge air quality is evaluated by creating a scenario where scavenge air pressure, estimated and actual condensate quantities, and engine load are fixed, as per Table 5.10.

Table 5.10: Operational data related to scavenge air quality

	Units	Operational input
Effective power	kW	6000
Corresponding scavenge air pressure as per the manual	Bar	2.6
Actual scavenge air pressure	Bar	2.5
Scavenge air temperature	^{o}C	Variable (34~50)
Condensed scavenge cooler water collected (actual)	tonne/24H	2
Condensed scavenge cooler water (determined from operations manual for given conditions)	tonne/24H	2.5

The results from the two inference techniques are plotted in Figure 5.4.

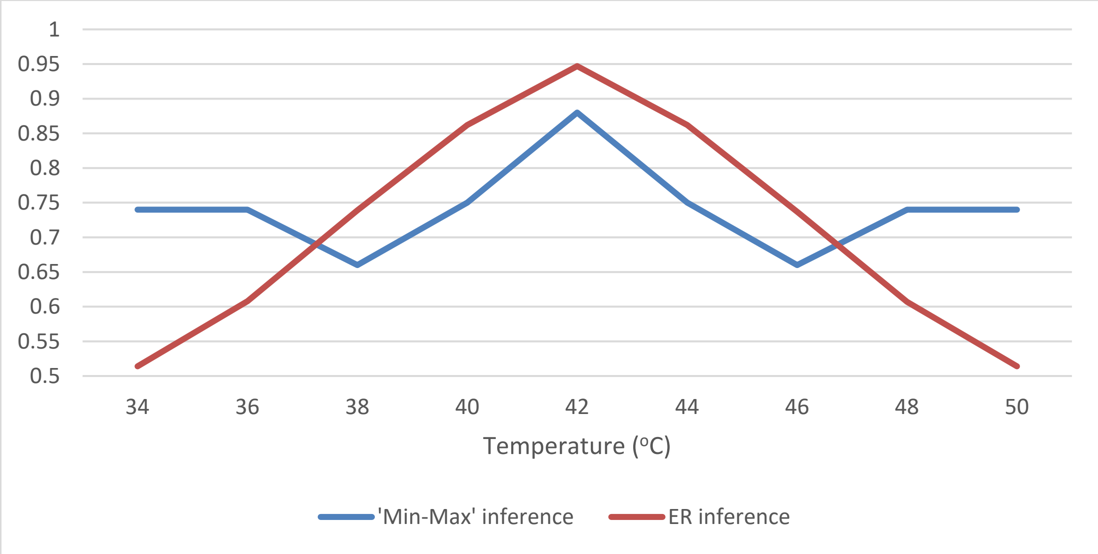


Figure 5.4: ‘Satisfactory’ scavenge air quality (variable temperature)

The ER inference curve indicates a relatively stable output and better reflects the fuzzy set developed for the scavenge air temperature in section 4.4.1.3. The curve for the conventional fuzzy ‘max-min’ inference tends to follow the ER inference curve, though there appears to be an anomaly at point temperatures 36~38 & 46~48°C. For example, at 38°C, eight rules are activated from the fuzzy rule-base as shown in Table 5.11:

Table 5.11: Activated fuzzy rule-base at 38°C

Pressure	Temperature	WMC Performance	THEN (Min value)
Low 0.26	Low 0.50	Satisfactory 0.90	Unsatisfactory 0.26
Low 0.26	Low 0.50	Unsatisfactory 0.10	Unsatisfactory 0.10
Low 0.26	Satisfactory 0.50	Satisfactory 0.90	Satisfactory 0.26
Low 0.26	Satisfactory 0.50	Unsatisfactory 0.10	Unsatisfactory 0.10
Satisfactory 0.74	Low 0.50	Satisfactory 0.90	Satisfactory 0.50
Satisfactory 0.74	Low 0.50	Unsatisfactory 0.10	Unsatisfactory 0.10
Satisfactory 0.74	Satisfactory 0.50	Satisfactory 0.90	Satisfactory 0.50
Satisfactory 0.74	Satisfactory 0.50	Unsatisfactory 0.10	Satisfactory 0.10

The next stage is taking a maximum value from both sets of satisfactory {0.26, 0.50, 0.50, 0.10} and unsatisfactory {0.26, 0.10, 0.10, 0.10} outcomes, which results in 0.50 and 0.26 respectively. Normalising these values to address incompleteness, the final probability value for ‘satisfactory’ is 0.66 and ‘unsatisfactory’ is 0.34. The model should follow a trajectory where a further peripheral evaluation point of 36°C should result in inferior scavenge air quality, i.e. lower probability value for the state ‘satisfactory’. However, as Figure 5.4 indicates, instead, the scavenge air quality seems to have improved at 36^{o}C. There are eight activated rules for the temperature of 36^{o}C, as per Table 5.12:

Table 5.12: Activated fuzzy rule-base for 36^{o}C

Pressure	Temperature	WMC Performance	THEN (Min value)
Low 0.26	Low 0.75	Satisfactory 0.90	Unsatisfactory 0.26
Low 0.26	Low 0.75	Unsatisfactory 0.10	Unsatisfactory 0.10
Low 0.26	Satisfactory 0.25	Satisfactory 0.90	Satisfactory 0.25
Low 0.26	Satisfactory 0.25	Unsatisfactory 0.10	Unsatisfactory 0.10
Satisfactory 0.74	Low 0.75	Satisfactory 0.90	Satisfactory 0.74
Satisfactory 0.74	Low 0.75	Unsatisfactory 0.10	Unsatisfactory 0.10
Satisfactory 0.74	Satisfactory 0.25	Satisfactory 0.90	Satisfactory 0.25
Satisfactory 0.74	Satisfactory 0.25	Unsatisfactory 0.10	Satisfactory 0.10

The above table provides a set of satisfactory {0.25, 0.74, 0.25, 0.10} and unsatisfactory {0.26, 0.10, 0.10, 0.10} outcomes which, by using ‘max’ function, results in 0.74 and 0.26 respectively. The ‘min’ function used in rule number 5 (highlighted green) on the list generated a higher number (0.74) in Table 5.12 compared to (0.50) for the same rule in Table 5.11. This unstable output seems to be one of the drawbacks of the fuzzy ‘max-min’ inference technique, which has been addressed by developing a fuzzy ER inference model.

Secondly, probability values for the fuel quality have been evaluated by varying the CCAI input into both fuzzy ‘max-min’ and fuzzy ER models for the operational fuel quality data, as per Table 5.13:

Table 5.13: Operational data related to fuel quality at the engine inlet

	Units	Operational input
Viscosity	cSt	13
Catalyst fines	mg/kg	14
Water	volume %	0.05
Ash	mass %	0.02
CCAI	Index	Variable (830~870)

The operational data generated a set of values which have been plotted on the graph shown in Figure 5.5.

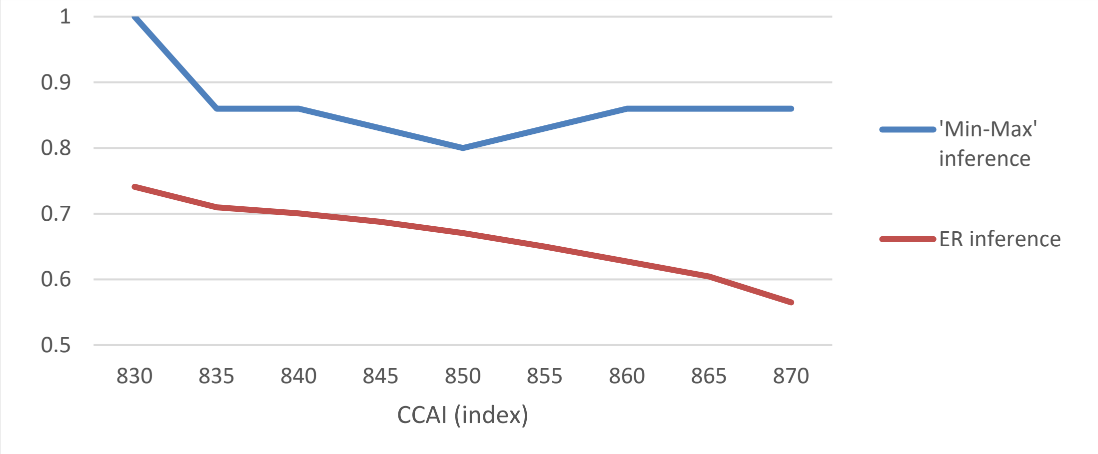


Figure 5.5: Satisfactory fuel quality (varying CCAI)

Similar to the scavenge air quality example (Figure 5.4), the fuzzy ER inference curve on the graph follows conventional wisdom where increasing CCAI value means the likelihood of inferior-quality fuels. However, the ‘max-min’ inference curve remains on a downward trend, from 830 to 850; however, then an upward trend can be observed, from 850 to 860, before it flattens out. This is a similar issue as demonstrated and explained in Figure 5.4, which has been discussed in the above paragraph.

Finally, ‘engine setting’ has been chosen to demonstrate the difference between the two models. Table 5.14 provides the set of parameters where exhaust deviations have been kept as a variable.

Table 5.14: Operational data for engine settings

	Units	Operational input
$P_{max} - P_{comp}$	Bar	31
MIP deviation	Bar	0.1
Exhaust deviation	^{o}C	Variable (3~15)

The two fuzzy inference techniques provide the results depicted in Figure 5.6.

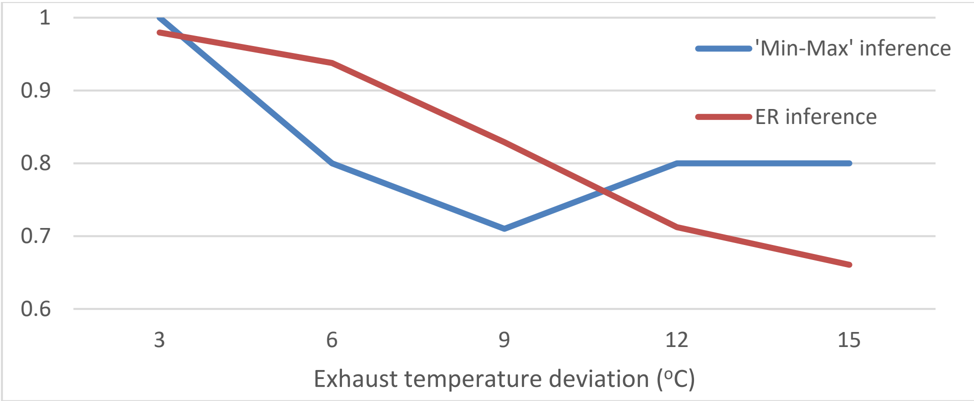


Figure 5.6: Satisfactory engine settings (varying exhaust deviations)

Once again, in this simulation, ER inference appears to demonstrate better stability in terms of output compared to the ‘max-min’ function, where a gradual increase in exhaust temperature deviations should result in lower probability of ‘satisfactory’ engine settings.

5.5 Case study

In this section, the model developed in section 5.3 is applied to the same case study discussed in section 4.5 to make further comparisons. The operational data in the case study is based on a ship registered with FEAP (2017) and provided in Table 4.12. The prior probabilities for parent nodes of the BN model are computed where two parameters (fuel and scavenge air quality) are common for all cylinders, and shown in Table 5.15, whilst the remaining three parameters (CLO feed rate, maintenance management and engine settings) are calculated for each cylinder separately.

Table 5.15: Fuzzy ER inference outputs for fuel and scavenge air quality

Main parameters	Contributory factors	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Fuel quality (at engine inlet)	Catalyst fines	-	1	0	0.923	0.077
	Viscosity	-	0.875	0.125		
	Ash	-	1	0		
	CCAI	-	0.475	0.525		
	Water	-	1	0		
Scavenge air quality	Pressure	0.51	0.49	-	0.668	0.332
	Temperature	-	0.63	0.37		
	WMC performance	-	0.90	0.10		

Similarly, Table 5.16 provides the fuzzy ER outputs for the remaining three parameters for the six individual cylinders.

Table 5.16: ER fuzzy outputs for engine settings, maintenance and cylinder oil feed rate settings

Parameter	State	Cylinder					
		1	2	3	4	5	6
Engine settings	Satisfactory	0.60	0.59	0.44	0.40	0.60	0.36
	Unsatisfactory	0.40	0.41	0.56	0.60	0.40	0.64
CLO feed rate	Satisfactory	0.92	0.84	0.95	0.57	0.75	0.74
	Unsatisfactory	0.08	0.16	0.05	0.43	0.25	0.26
Maintenance management	Satisfactory	0.78	0.86	0.78	0.86	0.92	0.78
	Unsatisfactory	0.22	0.14	0.22	0.14	0.08	0.22

The results provided in Table 5.15 and Table 5.16 are taken as prior probabilities for the BN model and used to measure key performance indicators of LS2S engine. The BN model for cylinder 1 based on the above results is shown in the following figure, Figure 5.7, whilst the rest of the BN models (for cylinders 2~6) are displayed in Appendix G.

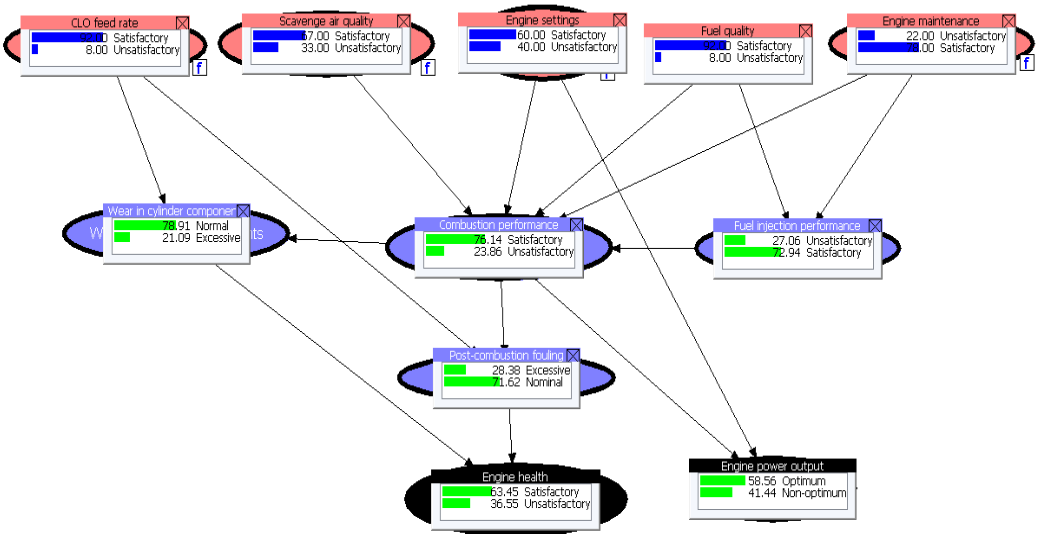


Figure 5.7: BN model assessment for cylinder_1 based on fuzzy ER prior probabilities

Figure 5.8 shows the key LS2S engine performance indicators resulting from the BN when using input from the fuzzy ER inference technique.

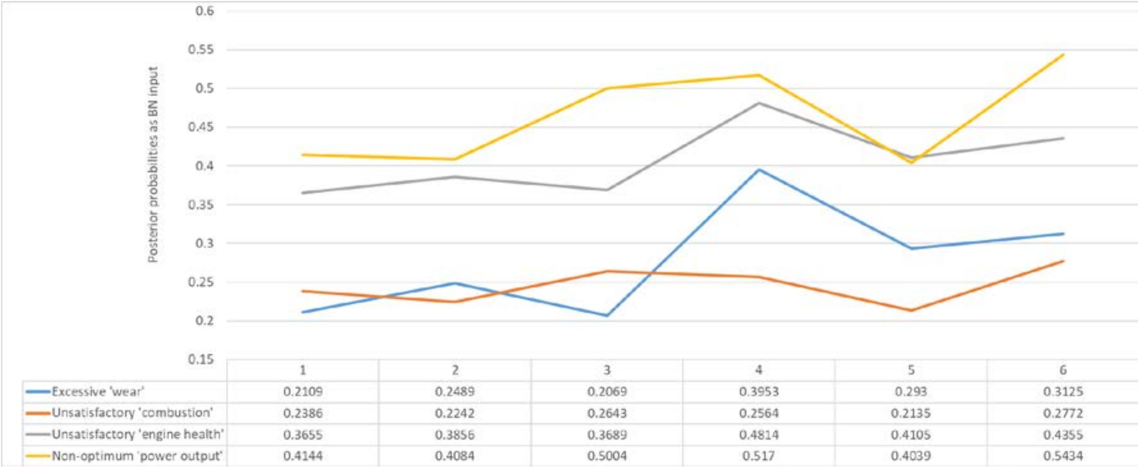


Figure 5.8: Summary of BN model output (using fuzzy ER input)

The outputs from the BN model using two different fuzzy models are not overly dissimilar. The results show unsatisfactory performance for cylinders 4 and 6, with a number of factors affecting the outcome. For example, for cylinder 6, it appears that the poor engine settings (compared to other cylinders) have contributed towards the unsatisfactory combustion performance and power output. The impact of the different fuzzy models on the final outcome has been further elaborated in Figure 5.9.

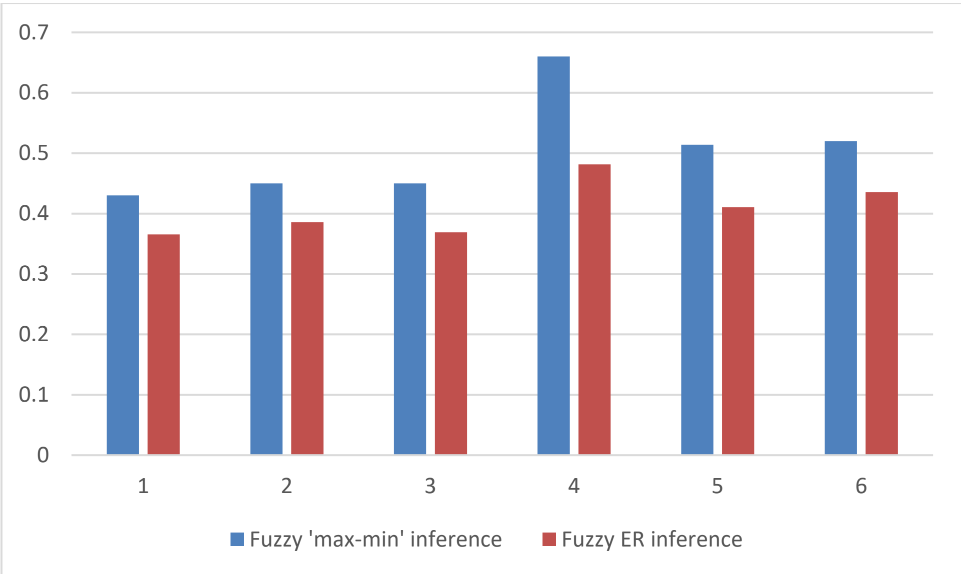


Figure 5.9: Comparisons of posterior probability (rating) of 'unsatisfactory' engine health

There appears to be a good consistency between the results from Fuzzy ER inference for all cylinders and lower values compared to ‘max-min’ inference. The reason seems to be the improved sensitivity of the model introduced through the expert judgements giving certain factors within a parameter more importance than others, which was not the case with the fuzzy ‘max-min’ inference approach, where all the factors were given equal weight.

5.6 Conclusion

The fuzzy ER model developed in this chapter is an attempt to improve further the precision and sensitivity of the input variables of the BN model. The key steps involved assigning weights to antecedents and consequents by utilising the expert judgements to develop modified fuzzy sets. The ER algorithm is then used to aggregate the results from the various activated rules as opposed to conventional fuzzy ‘max-min’ inference.

A comparative analysis is performed between the two different fuzzy inference methods in section 5.4, followed by a case study in section 5.5.

6 Comprehensive BN with advanced ability of dealing with uncertainty in data

This chapter presents a novel approach to determine the LS2S engine health by integrating the salient features of the BN model (Chapter 3), fuzzy rule-base (Chapter 4) and fuzzy ER (Chapter 5). The proposed methodology is an extension of the initial BN health assessment model by bringing in the factors influencing the parent nodes. This process provides an opportunity to calculate the LS2S engine health assessment in a unique format and compare the outputs from two different methodologies whilst using the same inputs, generating a comparison of model effectiveness.

6.1 Model inputs

The BN model developed in Chapter 3 for LS2S engine health assessment considers five parent nodes, namely fuel quality, engine settings, maintenance management, scavenge air quality and cylinder oil feed rate, as key operational indicators to influence the engine combustion performance and subsequently engine health. However, prior probabilities are needed for these parent nodes associated with a particular scenario from actual operational data such as temperatures and pressures. This issue is addressed systematically in chapters 4 and 5 using fuzzy membership functions for each parent node and through evidential reasoning. Hence, this expanded model has been built on three inputs, as described in Figure 6.1.

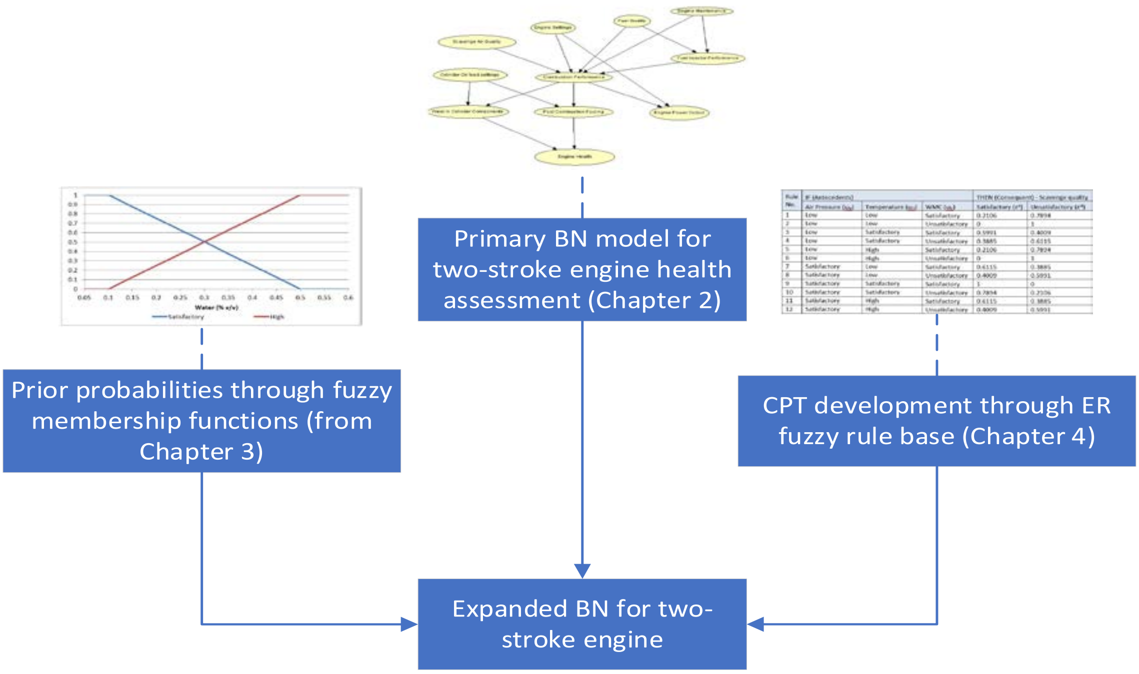


Figure 6.1: Inputs for developing the expanded BN model

A simple five-step process is followed to develop a comprehensive BN model:

1. Develop the expanded direct acyclic graph (DAG) for two-stroke engine assessment
2. Establish conditional probability tables (CPTs)
3. Use a systematic method to determine the probabilities for parent nodes
4. Perform sensitivity analysis
5. Verify and compare the model through a case study.

6.1.1 DAG structure

Table 4.1 provides a list of factors which impact the parent nodes of the BN model, and also explains the rationale in the corresponding sections. For example, there are three conditionally independent factors of scavenge air temperature, pressure and performance of water mist catcher which impact the quality of scavenge air going into the LS2S engine. As these factors have a direct correlation, hence the current BN model is expanded to establish these factors as parent nodes of scavenge air quality. Similarly, the other four key parameters are treated as shown in Figure 6.2. In contrast to Chapter 3, where HUGINEXPERT was used to develop the BN model, this chapter uses NETICA (https://www.norsys.com/download.html), for the reason that the expanded BN model exceeds the size limitation of the free HUGINEXPERT downloadable version. Secondly, NETICA's full accessibility version is by far the most economical option for educational use.

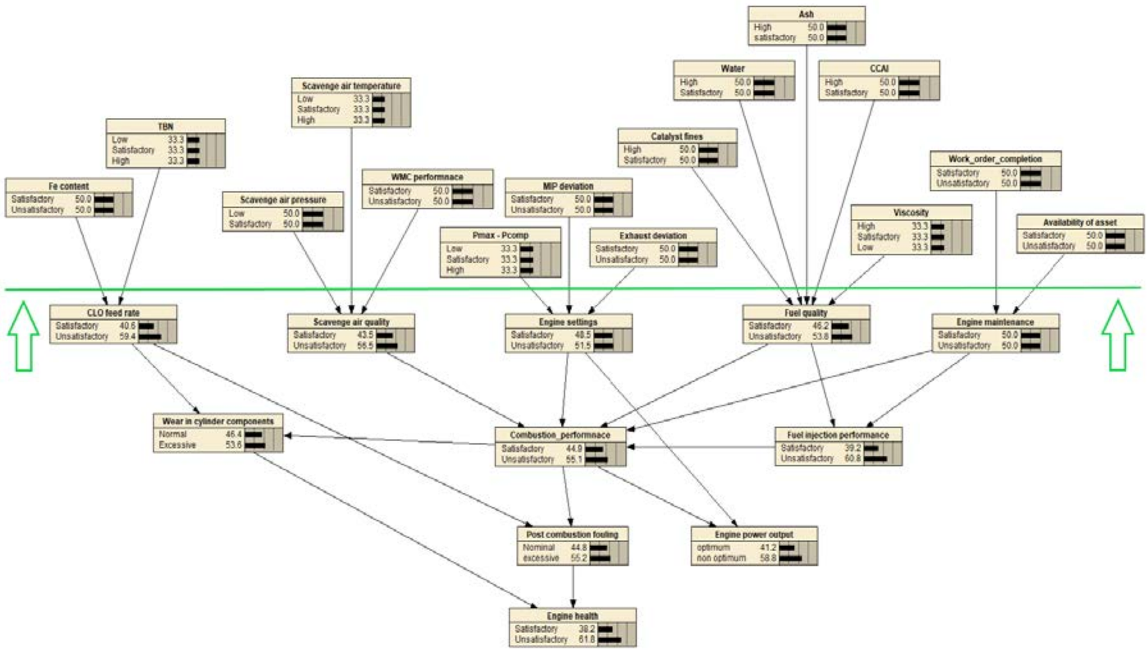


Figure 6.2: Expanded BN model for two-stroke engine health assessment

In Figure 6.2, the area of the diagram shown above the 'green' line contains the nodes that have been newly added to the DAG.

6.1.2 CPT development

The conditional dependence of various factors follows the principles of 'IF-THEN' rules. Yang, Bonsall and Wang (2008) proposed a fuzzy rule-based Bayesian reasoning (FuRBaR) approach to develop the CPTs through the fuzzy rule-base, which has been followed in this study. The modified fuzzy rule-base developed through the evidential reasoning approach appears most suited to describe the conditional dependence with the newly included nodes on the existing nodes. For example, IF the air pressure is 'low' and the temperature is 'high' and the WMC performance is 'unsatisfactory', THEN scavenge air quality is assigned a posterior probability value of 1 'unsatisfactory' and 0 'satisfactory'. The complete CPT for scavenge air quality has been given in Table 5.6.

Similarly, the other four CPTs for fuel quality, maintenance management, cylinder oil feed rate and engine settings have been developed and described in Appendix F.

6.1.3 Unconditional probabilities

In the expanded BN model, there are 15 parent nodes requiring unconditional probabilities to be computed. This issue was addressed in Chapter 4 using fuzzy membership functions and described in detail in section 4.4. The main challenge has been to process the direct operational measurements from the LS2S engine into suitable probabilities for the node, such as the probability of pressure being 'satisfactory' or 'unsatisfactory'. The functionality of the model has been elaborated in the case study.

One of the main differences between the current chapter and chapters 4 and 5 is the probability computation method for the five key nodes. Chapter 4 uses fuzzy 'max-min' inference whilst, in Chapter 5, a fuzzy evidential reasoning methodology has been employed. This chapter, although it follows on from the previous two chapters, uses a Bayes rule to determine the probabilities as these five key nodes are no longer parent nodes in the expanded BN model.

6.2 Model functionality

Figure 6.3 indicates the perfect scenario where all the parent nodes are assigned 100% satisfactory prior beliefs under the assumption that the engine is operating in a highly desirable mode.

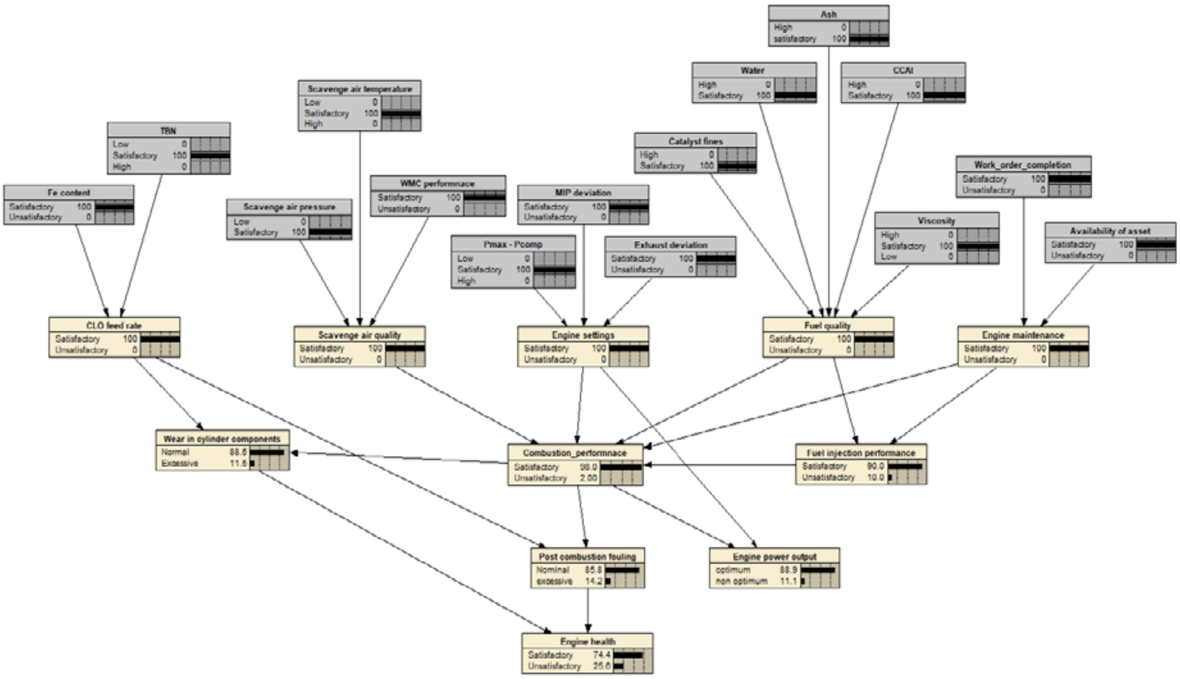


Figure 6.3: Expanded BN with a 'perfect' scenario

In contrast, the model is tested with 100% negative prior beliefs for all the parent nodes, as shown in Figure 6.4. This results in high wear of cylinder components, excessive post-combustion fouling and unsatisfactory power output, subsequently generating a poor engine health rating.

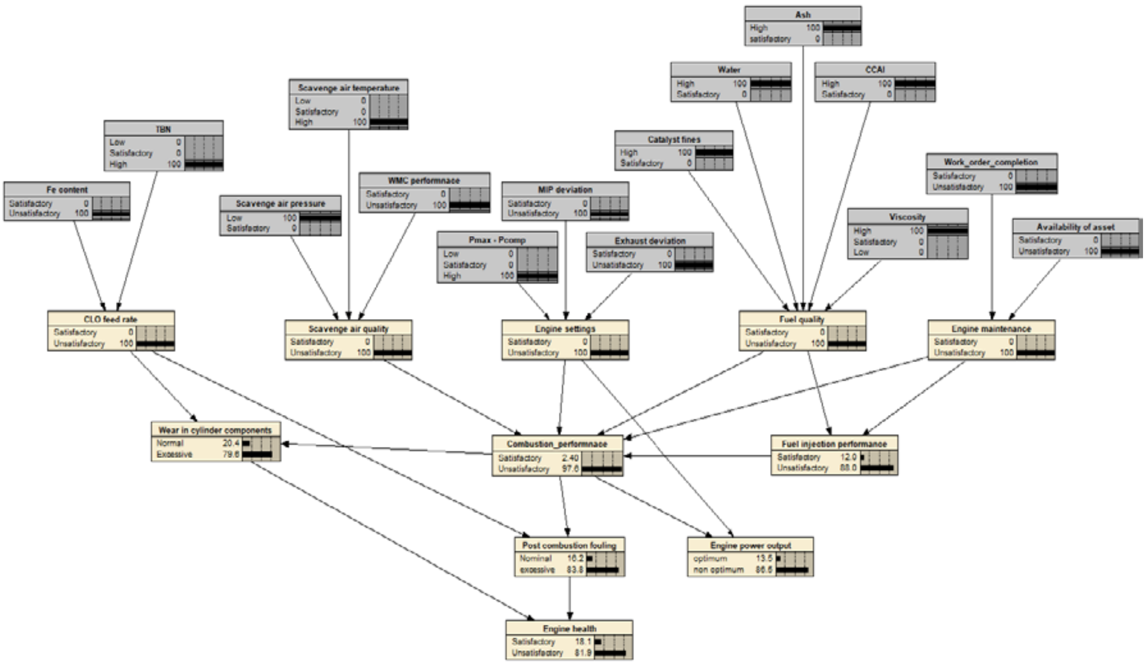


Figure 6.4: Expanded BN with ‘imperfect’ scenario

These results are in line with the initial results described in section 3.3 for perfectly ‘perfect’ and perfectly ‘imperfect’ scenarios.

6.3 Sensitivity analysis

The expanded BN model requires further validation; hence, the approach used in section 3.1.5 has been re-utilised for sensitivity analysis as per Pristrom et al (2016). The model is tested against the following three axioms:

1. Influence of changes in the parent node probability should keep consistency with the probability of child nodes.
2. Any increase/decrease in the probability distribution of parent nodes should have a proportional effect on the posterior probabilities of child nodes.
3. Where there are multiple parent nodes (n) influencing a child node, then their total influence should be higher than the one generated by the same change of n-1 root nodes.

Axiom 1: This axiom is satisfied by showing that the change in the influence of the parent node is consistent with the probability of the child node. Figure 6.5 shows the change of probabilities for the node ‘engine maintenance’ in accordance with the changes to its parent variables, ‘availability of asset’ and ‘work order completion’. The graph indicates consistent changes in unsatisfactory parent node states for ‘availability’ and ‘work order completion’ against unsatisfactory engine maintenance, satisfying axiom 1.

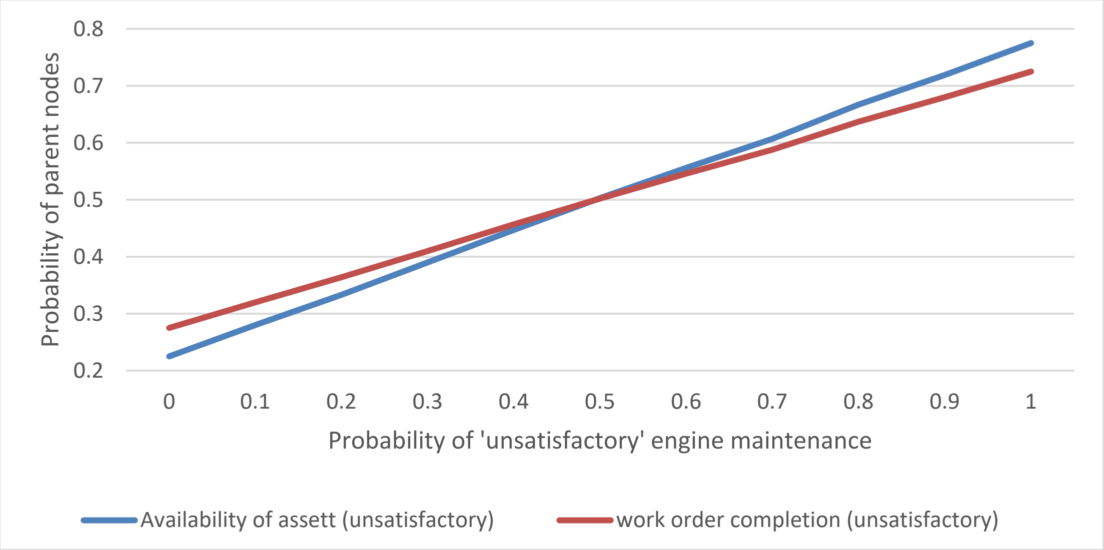


Figure 6.5: Test of axiom 1 for the node 'engine maintenance.'

Axiom 2: Table 6.2 indicates that the BN behaves as expected and changing the value of each parent node changes the belief of the variable, as it would in real life. These results also indicate a different impact on fuel quality according to the weightage assigned to them through expert judgement in Chapter 4. For example, catalyst fines have a higher impact (30%) on fuel quality being unsatisfactory compared to CCAI value (16%).

Table 6.1: Test of axiom 2 for fuel quality

Catalyst fines (high)	Fuel quality (Unsatisfactory)
0	0
0.5	0.155
1	0.309
Water (high)	
0	0
0.5	0.092
1	0.185
Ash (high)	
0	0
0.5	0.0579
1	0.116
CCAI (high)	
0	0
0.5	0.08
1	0.161
Viscosity (High or Low)	
0	0
0.66	0.153
1	0.229

Axiom 3: This last axiom requires the combined influence of parent nodes, ‘n’, to be higher than the one generated by the same change of n-1 root nodes. For example, scavenge air is a parent node (evidence) for combustion performance with root nodes (sub-evidence) of pressure, temperature and WMC performance. When each piece of sub-evidence is individually added i.e., scavenge pressure is ‘satisfactory’, temperature is ‘satisfactory’ and WMC performance is ‘satisfactory’, then the probability of ‘satisfactory’ combustion performance is 0.48, 0.51 and 0.47 respectively. However, when scavenge air quality is placed as ‘satisfactory’ in the model, then ‘satisfactory’ combustion performance is 0.58. Similarly, further tests are

conducted on other intermediate and leaf nodes, and the results are in harmony with axiom 3.

6.4 Case study

To demonstrate the functionality of the expanded BN model for LS2S engine health assessment, the case study discussed in section 4.5 is utilised. The first step in the process is to determine the prior probabilities for the parent nodes of the expanded BN model. As described in section 4.4, the fuzzy membership functions developed in Chapter 4 have been used to convert the operational measurements into probability values for a particular parameter. Table 6.3 and Table 6.4 (for cylinder 1) provide those prior probability values for the case study developed in section 4.5, which is used as input for the expanded BN model.

Table 6.2: Fuzzy outputs for fuel and scavenge air quality

Key parameter	Parent nodes	Operational measurement	Corresponding fuzzy membership value		
			Low	Satisfactory	High OR Unsatisfactory
Fuel quality (at engine inlet)	Catalyst fines	10 mg/kg	-	1	0
	Viscosity	13 cSt	-	0.875	0.125
	Ash	0.02 mass %	-	1	0
	CCAI	851	-	0.475	0.525
	Water	0.05 volume %	-	1	0
Scavenge air quality	Pressure	2.4 bar	0.51	0.49	-
	Temperature	45°C	-	0.63	0.37
	WMC performance	0.5 tonne (ΔCondensation)	-	0.90	0.10

Table 6.3: Fuzzy outputs for engine settings, maintenance and CLO feed rate (cylinder 1)

Key parameter	Parent nodes	Operational measurement	Corresponding fuzzy membership value		
			Low	Satisfactory	High OR Unsatisfactory
Engine settings	$P_{max} - P_{comp}$ (Bar)	21.5 bar	1	0	-
	Exhaust temperature (Mean value = 371)	373 (deviation of 2^{o}C)	0	1	0
	MIP (Mean value = 14.8)	14.9 (deviation of 0.1 bar)	0	1	0
Engine maintenance	Availability	98.9%	-	0.7	0.3
	Work-order completion	85.7%	-	0.71	0.29
Cylinder oil feed rate	Fe	95 mg/kg	-	0.66	0.34
	TBN	29.3 mg KOH/g	-	1	-

Once these values are inserted into the BN model developed in section 6.1, it produces the result for cylinder 1, as shown in Figure 6.6.

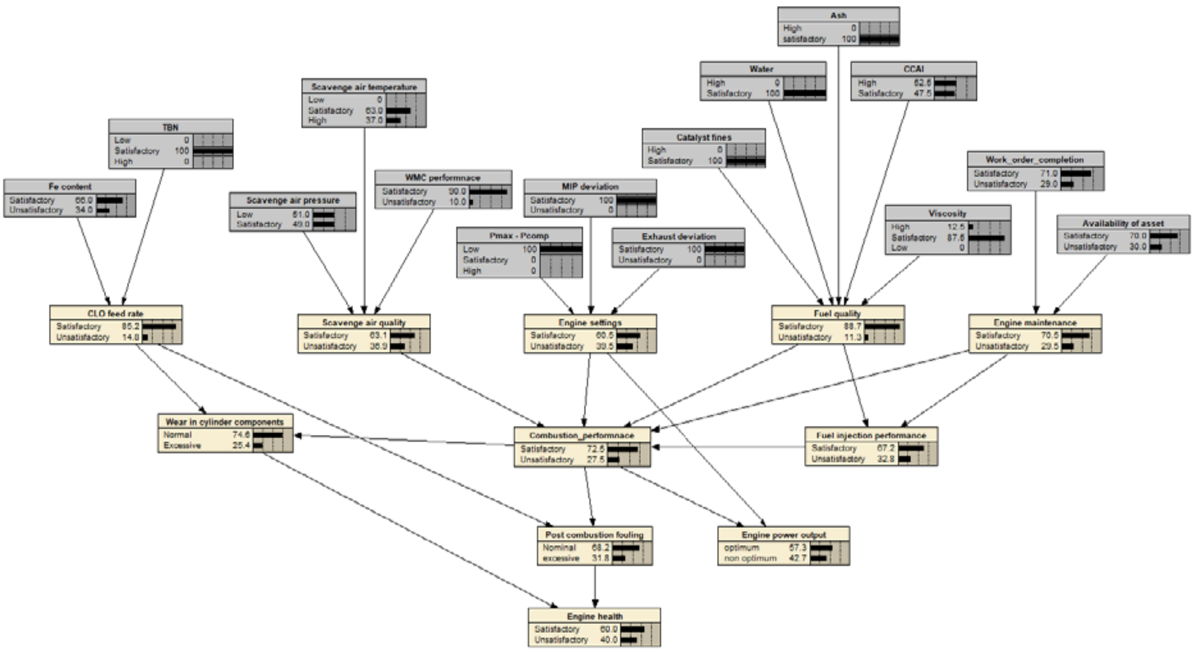


Figure 6.6: BN health assessment for cylinder 1

Similarly, the expanded BNs have been developed for cylinders 2 to 6 and displayed in Appendix H.

These results closely correlate with the model outputs of fuzzy ER and fuzzy 'max-min' inferences, albeit with slight variations, as shown in Figure 6.7.

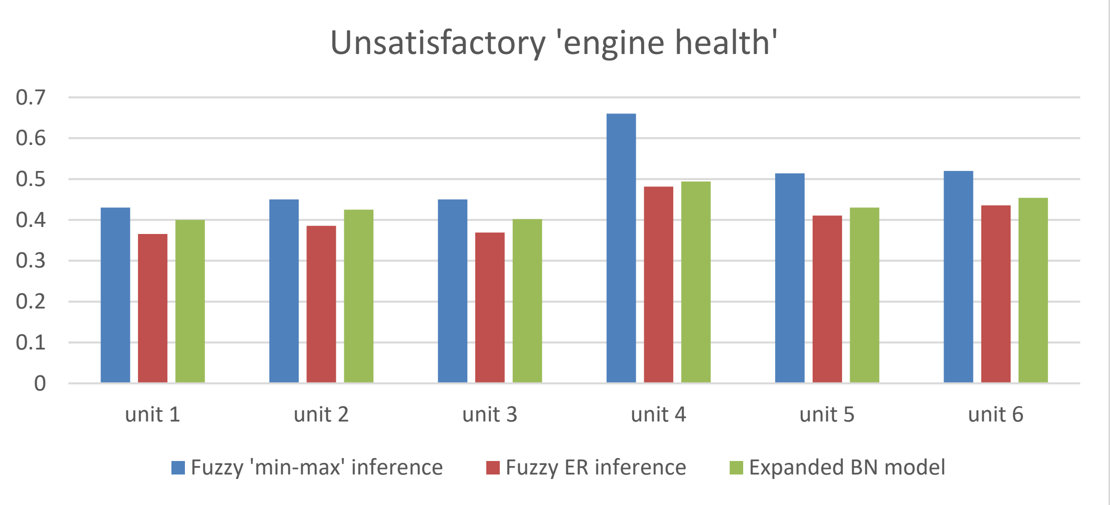


Figure 6.7: Comparison of various inference methodologies to compute the posterior probability for the case study

It appears there is a better correlation between the results from the expanded BN model and fuzzy ER inference mechanism. Statistically, the expanded BN also points towards the inherent poor performance of cylinder 4. Overall, the results are in line with the expected outcomes.

6.5 Conclusion

A novel approach has been used to fuse features of various models developed in this study to improve diagnostic capability, probabilistic quantification and graphical interface for the LS2S engine health assessment model. The key steps in developing an expanded BN model involve processing the operational data into probabilities through fuzzy membership functions and the use of a modified fuzzy ER rule-base for CPT development. Sensitivity analysis backed up by a case study shows promising results and correlation. However, as highlighted in the previous chapter, further work is needed to develop a baseline for the model outputs in order to establish a traffic light system.

7 Incorporating a Dynamic Bayesian Network (DBN) to improve model efficiency

The BN models are based on direct acyclic graphs (DAGs) to facilitate reasoning under uncertain conditions (Ramirez and Utne, 2015). The BN model developed in Chapter 3 of this study has been further expanded to include operational factors and presented in Chapter 6. However, one of the drawbacks of the conventional BN model is that it represents a static condition and would only reflect the output for a particular time slice (Wu et al., 2018). The Dynamic Bayesian Network (DBN) addresses this issue by bringing in the temporal dimension in the BN, which can be extremely useful to understand and model component/machinery degradation as a function of time, maintenance actions and operational factors (Weber and Simon, 2016).

Moreover, DBNs by virtue of being graphical in nature are useful tools to represent diverse and uncertain conditions by reducing complexity for decision makers in an interlinked system (Khan, Khan and Veitch, 2020). This chapter attempts to integrate the temporal dimension to the BN model for LS2S engine performance assessment to capture dynamic operational conditions and associated complexity.

7.1 Dynamic Bayesian Network (DBN)

A DBN is an extension of an ordinary BN which accommodates the changes occurring over a time period (discrete time-slices) (Cai et al., 2013). As a minimum, there should be two time slices in a DBN model to reflect the temporal evolution, such as shown in Figure 7.1, which is comprised of current time, *t*, and a future time slice, *t+1*.

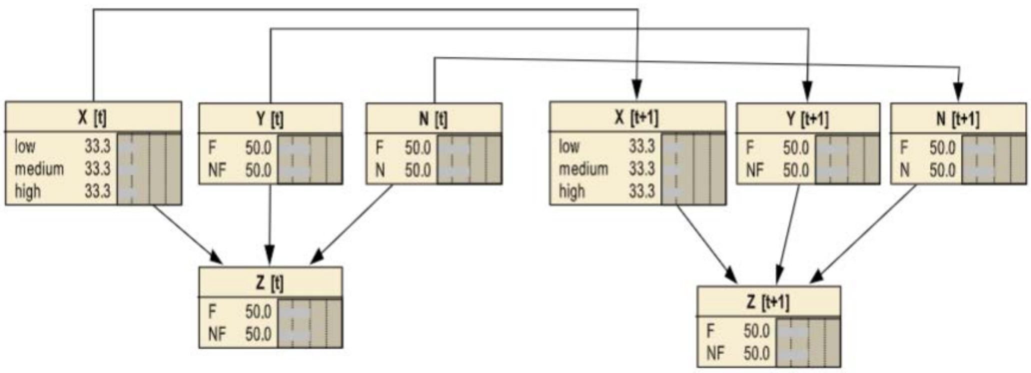


Figure 7.1: DBN with two time slices
Source: Wang et al (2017)

The variables *Z* (leaf/target node) is connected with *X*, *Y* and *N* (parent nodes) through intra-slice arcs in each time slice (*t* & *t+1*), whilst inter-slice (temporal) arcs connect the nodes X_t, Y_t and N_t with X_{t+1}, Y_{t+1} and N_{t+1}. Above is an example of dynamic BN inference known as *prediction* where analysis moves forward from the current time step, *t*, to a future time step, *t+1* (Ramirez and Utne, 2015). The other two DBN inference types are *filtering* and *smoothing*. Filtering is computing the system state at the current time step, *t*, whilst smoothing is determining the state at previous time steps, *t-1* (Ramirez and Utne, 2015). The DBN also supports the temporal and non-temporal nodes in the same model (Khan, Khan and Veitch, 2020); e.g., in the above example *X*, *Y* & *N* are temporal nodes whilst node Z is not, although the posterior probability of node Z could automatically change, moving from $Z_t \rightarrow Z_{t+1}$ due to the changing probability of its parent temporal nodes.

For a BN model, a conditional probability table would be required to demonstrate the conditional dependence between variables. However, the DBN introduces an additional complexity, requiring Transition Probability Tables (TPTs) for nodes with temporal arcs to demonstrate probabilistic temporal dependence between different time slices.

To develop TPTs, the literature review indicated a number of standalone and hybrid statistical methodologies which can broadly be divided into four categories:

1. Expert elicitation
2. Empirical (operational) data
3. Statistical and mathematical model simulations
4. Combination of any of the above.

Ramirez and Utne (2015) used parametric models, simulating the changing conditions of the system over time, complemented with Monte-Carlo simulation. Similarly, Jiang and Lu (2020) utilised a Poisson distribution equation to determine the probabilities at multiple discrete time slices. However, the aforementioned approach assumes constant average changes over time, which may not be applicable in specific applications.

There are three DBN inference types: smoothing (past (*t-1*)); filtering (present (t_0)); and prediction (future (*t+1*)). In simple terms, *t-n* (*n = 1, 2,.. k*) smoothing can be used for system diagnostics whilst *t+n* (*n = 1, 2, ….k*) prediction can be utilised for prognostics.

Jiang and Lu (2020) also performed a sensitivity analysis on the DBN model to determine the degree of influence of the specific nodes on the target node(s) largely responsible for significant variations. Moreover, Murphy (2002) provided a detailed overview of BDN learning, inference and combination of algorithms which can be applied based on the context and problem statement.

Weber and Simon (2016) considered various modelling options such as the use of Dynamic Fault Trees (DFTs) which also have a graphical base however DFTs show limitation in terms of being a binary state representation and hence cannot easily model a multi-state system. The study found DBNs as particularly useful in that respect with machinery degradation assessment taking into account operational factors with multiple states.

7.2 DBN applications

There have been a number of exciting and diverse DBN applications in recent times. Wu et al (2018) used DBN inference to evaluate the environmental impact of dredging on seagrass. For example, Tobon-Mejia, Medjaher and Zerhouni (2012) used DBN to diagnose and predict the wear in a machining tool. Qian, Zhang and Zhang (2020) employed a DBN for risk assessment and comparison of five key areas of Northwest Arctic navigational safety at different times over the past 10+ years. Nie et al (2019) used a DBN, logistics regression and a deterministic method to estimate the effects of rainfall intensity on slope failure (sliding) and make a comparison between the results. Tran, Arteaga and Aoues (2020) modelled the degradation patterns of timber structures to determine the reliability aspects using a DBN. Most of these studies found unique features of the DBN such as temporal dimension, graphical representation and ease of development through available software packages quite useful.

Table 7.1 provides the key features of various studies performed where a DBN is used as the primary research model, and comparisons have been made.

Table 7.1: DBN studies in the field of marine and offshore environment

	Title	Industry (subject)	Software used	Transition CPT	Time series	Comments
1	Reliability and availability modelling of subsea Xmas tree system using DBN with different maintenance methods (Wang et al., 2020a)	Oil & gas upstream (Subsea maintenance methods)	NETICA	Algorithm + data (from Kohda and Cui, 2007)	Months (0~300)	The study modelled the reliability and availability of the asset with various 'perfect' and 'imperfect' repair scenarios coupled with preventative maintenance (fault tree analysis).
2	Maritime accident risk estimation for sea lanes based on a DBN (Jiang and Lu, 2020)	Maritime (Navigational safety)	NETICA	Combination of expert judgements, data and algorithms	Year (0~9)	
3	A DBN model for ship-ice collision risk in the Arctic waters (Khan, Khan and Veitch, 2020)	Maritime (Navigational safety)	GeNIe	Data and literature research	In hours (0~7)	Varying temporal connection (arcs) for the same node.
4	A DBN based methodology for fault diagnosis of a subsea Christmas tree (Liu et al., 2020)	Oil & gas upstream (subsea safety and degradation)	NETICA	OREDA and statistical tools	In hours (1~ 10000) evaluation at every 1000 hours	Use of parent/root as non-temporal nodes and intermediate/leaf nodes forming the temporal plate (fault tree).
5	A DBN structure for joint diagnostics and prognostics of complex engineering systems (Lewis and Groth, 2020)	Nuclear (system safety of sodium fast reactor)	GeNIe	Simulated data from infrastructure model (Python)	--	A set of anchor (root) and terminal (leaf) nodes with intermediate (temporal) nodes as a source of changing system information (PHM).

6	Use of DBN for life extension assessment of ageing systems (Ramirez and Utne, 2015)	Oil & gas upstream (machinery degradation model)	--	Parametric modelling + data (complimented with Monte-Carlo simulation)	Years (30~50)	An integrated maintenance, cost and risk assessment model for standby and continuous operating machinery.
7	Dynamic risk assessment of natural environment based on DBN for key nodes of the Arctic Northwest passage (Qian, Zhang and Zhang, 2020)	Maritime (Navigational safety)	--	Objective training data set (EM algorithm)	Monthly (July to December)	Risk estimation from July to December for five indexes. Better fusion is achieved through DBN of dynamic reasoning from multi-source information compared to other methods (OOBN, Fuzzy Analytical Hierarchy Process and TFSS).
8	DBN based approach for risk analysis of subsea wellhead fatigue failure during service life (Yuanjiang et al., 2019)	Oil & gas upstream (Subsea safety)	GeNIe	Expert judgement and fuzzy theory	Months (from 0 to 36)	
9	Probabilistic framework to evaluate the resilience of engineering systems using BN and DBN (Kammouh, Gardoni and Cimellaro, 2020)	Resilience engineering (transportation systems)	GeNIe	Literature research and fuzzy theory	t = 1, 2, 3, …., T	
10	A DBN modelling of human factors on offshore blowouts (Cai et al., 2013)	Offshore engineering (human factors)	NETICA	Expert judgements	Weeks (0 to 50)	Fault tree and pseudo fault tree.

11	A DBN framework for spatial deterioration modelling and reliability updating of timber structures subjected to decay (Tran, Bastidas-Arteaga and Aoues, 2020)	Civil engineering (reliability and inspection)	--	Data + statistical tools	Year (0 to 40)	Parametric learning of decay process over time.

The above examples of DBN industrial applications are wide-ranging and also show how integrating the time dimension improves the effectiveness of the conventional BN model. There does not seem to be a standardised DBN model development process, and these studies have adopted a few unique pathways suited to specific applications. Some of the important considerations from the above studies are summarised as follows:

- Parameter learning and assigning the suitable nodes a temporal dimension would mainly depend on the time slices, i.e. whether hours, days, months or years have been considered for time granularity.
- The key is to formulate a suitable method to establish transition probability tables (TPTs). A statistical modelling technique (such as Gaussian, Poisson or Monte-Carlo distribution) combined with the expert judgements and real data have commonly been used. However, the decision on which method to employ would be based on the system boundaries, DBN structure and availability/unavailability of data.
- Software – there are multiple options (listed in column 4 of Table 7.1) to select from, most providing acceptable DBN functionality; however, the decision could come down to the data-handling capacity and functionality as DBNs (depending on time slices) can quickly become intractable.
- DBN sensitivity analysis could be used to gauge the proportional impact of specific parameters on output and vice versa.
- Further developing the DBN capability to function as a diagnostic and prognostic tool in certain applications would require a few key failure modes and operational limits to be defined for comparison.

7.2.1 Advantages and limitations of BDN

This section presents a short summary of the benefits and limitations of DBNs taken from Weber and Simon (2016) and the papers presented in Table 7.1;

- DBNs are graphical models which are extremely useful to capture diverse and uncertain conditions and reducing complexity for decision makers. Moreover, there are number of software packages available to facilitate the development.
- DBNs have the flexibility to process variables with multiple states as oppose to some other methodologies where only binary states can be processed.
- To model highly random and complex systems, DBNs can provide the necessary compactness to reduce the modelling difficulty.
- BDN are quite useful in handling multiple components in a system and integrating in the impact exogenous variables on the model output.
- Comparing to a static BN model, DBN can deal with the cycled correlation in the networks to a degree.

There are a couple of key limitations found in the literature as follows;

- For the larger DBNs with significant number of (unrolled) time slices, the computation and data handling capacity can become an issue.
- The BDN inference works well as long as any new evidence introduced for a variable maintains independence between variables. However, if dependence is introduced through a new evidence then computing problem may appear prompting the use of specific algorithms for inference.

7.3 Proposed DBN for engine health assessment

For the BDN model development, the selection of appropriate time granularity is a critical aspect to demonstrate the model's effectiveness. In the case of LS2S engine operational modelling, the elapsed time between two consecutive data points should not be too large which poses the risk of losing important information. There are systems for various selected parameters where data can be collected every minute or hour through sensors or onboard monitoring devices; however, access to such data is usually limited to ship operators.

FOBAS receives regular LS2S engine operations data from ships which can be used; however, data collection and samplings are typically months apart, which cannot be confidently used to fully represent the dynamic conditions for two-stroke engine operations. In view of the above, a 24-hour time interval has been considered appropriate to model the engine operations through a DBN which is also aligned with the onboard *noon-figures* routine for detailed entry into the engine-room logbook. It is understood that each engine is different, and, with changing operational conditions, the variations may not be insignificant. However, in this study, an average rate of change is to be considered over 24 hours; however, the operator potentially using this assessment model in future would have the liberty to adjust the rate of change based on prevailing operational conditions relying on live data and fine-tuning the time granularity.

Figure 7.2 presents the flow chart adopted to develop the DBN model for LS2S engine assessment.

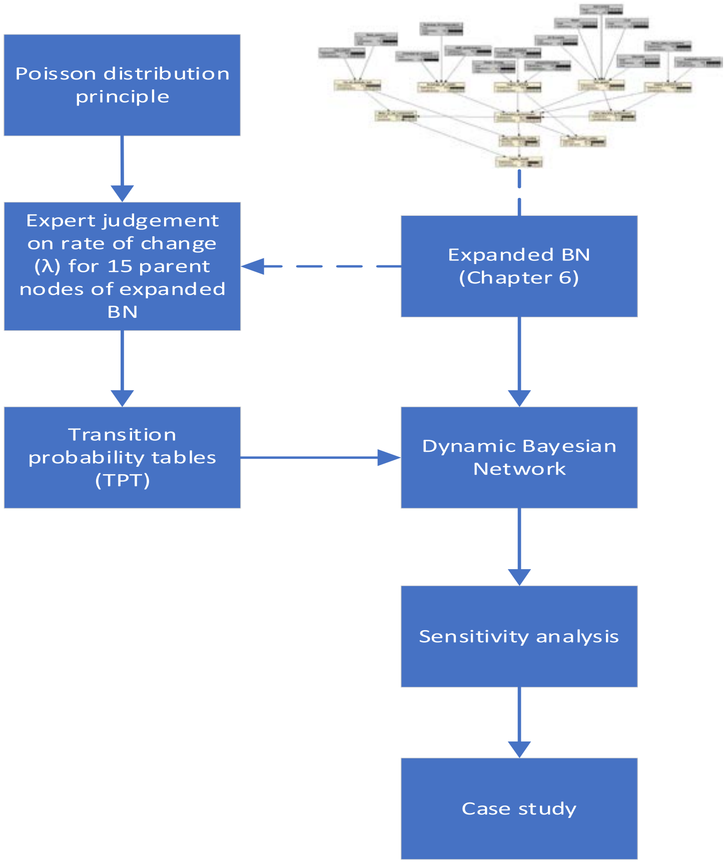


Figure 7.2: Dynamic Bayesian Network for two-stroke engine health assessment

There are four key steps, namely: i) establishing the transition probability tables, ii) generating a DBN from the expanded BN by utilising a suitable software package, iii) sensitivity analysis and, finally, iv) demonstrating DBN functionality through a case study.

7.3.1 Transition probability tables (TPTs)

There are a number of approaches to establish TPTs, as highlighted in Table 7.1. A 24-hour time interval has been selected to establish the TPTs which aligns with the *noon-figures*. To keep the model output generic, a group of experts have been requested to provide expert judgements on average deviations of various engine parameters over the prescribed period.

Hence, an approach has been adopted which combines an algorithm with the expert judgement. The deviation in two-stroke engine parameters for a defined time period can be random, and, considering the probabilistic nature of the TPT development, a suitable probability distribution would need to be selected to combine with the expert judgements.

Poisson distribution is a discrete probability distribution named after French mathematician Simeon-Denis Poisson. It is suitable for describing a number of random events occurring in unit time. In view of the above, the approach adopted by Jiang and Lu (2020) has been considered a suitable candidate which assumes the influencing parameters (occurrences) as random events which follows a Poisson distribution. The study assumed that the average deviation of a parameter per unit time is λ; the probability that an influential factor occurs n times is:

$$P\{N(t+\Delta t)-N(t)=n\} = \frac{e^{-\lambda\Delta t}(\lambda\Delta t)^n}{n!} \quad (1)$$

If a parameter's output condition changes to fully satisfactory (*S*) at time *t* with the quantitative representation of 1, then the probability that the parameter remains unsatisfactory (*U*) from time *t* to $t+\Delta t$ (i.e. no change, 0) can be calculated as:

$$P\{N(t,t+\Delta t)=U\,|N(t)=S\} = \frac{P\{N(t)=U, N(t,t+\Delta t)-N(t)=0\}}{P\{N(t)=U\}}$$

$$= \frac{P\{N(t)=U\} * P\{N(t,t+\Delta t)-N(t)=0\}}{P\{N(t)=U\}}$$

$$= P\{N(t,t+\Delta t)-N(t)=0\} \quad (2)$$

Using equation 2 to calculate the values from equation 1:

$$P\{N(t,t+\Delta t) - N(t)=0\} = \frac{e^{-\lambda\Delta t}(\lambda\Delta t)^0}{0!} = e^{-\lambda\Delta t} \quad (3)$$

If a parameter condition is satisfactory (*S*) at time *t*, the probability that the parameter condition remains satisfactory (*S*) from time *t* to $t+\Delta t$ (1) can be calculated as:

$$P\{N(t,t+\Delta t)=S|N(t)=S\} = \frac{P\{N(t)=1, N(t,t+\Delta t)-N(t)=1\}}{P\{N(t)=1\}}$$

$$= \frac{P\{N(t)=1\} * P\{N(t,t+\Delta t)-N(t)=1\}}{P\{N(t)=1\}}$$

$$= P\{N(t,t+\Delta t)-N(t)=1\} \quad (4)$$

Using equation 4 to calculate the values from equation 1:

$$P\{N(t,t+\Delta t) - N(t)=1\} = \frac{e^{-\lambda\Delta t}(\lambda\Delta t)^1}{1!} = \lambda\Delta t e^{-\lambda\Delta t} \quad (5)$$

For any influential factor, the probability distribution of the next state depends only on the current state and not on the sequence of preceding events. Assuming that a parameter's present state is unsatisfactory ($X_t = U$), then the probability of the parameter being satisfactory at $t+1$ ($P(X_{t+1} = S \mid X_t = U)$) can be calculated through the use of a Bayesian algorithm equation:

$$P(X_{t+1} = S|X_t = U) = \frac{P(X_{t+1} = S, X_t = U)}{P(X_t = U|X_{t+1} = S) * P(X_{t+1} = S) + P(X_t = U|X_{t+1} = U) * P(X_{t+1} = U)}$$

Here, the value of denominator is equal to 1, hence:

$$= P(X_{t+1} = S, X_t = U)$$

Inserting this into equation 5:

$$= P(X_{t+1} = S, X_t = U) = \lambda * (1)e^{-\lambda*(1)} = \lambda e^{-\lambda} \tag{6}$$

As:

$$P(X_{t+1} = S|X_t = U) + P(X_{t+1} = U|X_t = U) = 1$$

So:

$$P(X_{t+1} = U|X_t = U) = 1 - \lambda e^{-\lambda} \tag{7}$$

Conversely,

$$P(X_{t+1} = S|X_t = S) = \frac{P(X_{t+1}=S, X_t=S)}{P(X_t=S|X_{t+1}=S)*P(X_{t+1}=S)+P(X_t=S|X_{t+1}=S)*P(X_{t+1}=S)}$$

Here, the value of the denominator is equal to 1, hence:

$$= P(X_{t+1} = S, X_t = S)$$

Similarly, using equation 3:

$$= P(X_{t+1} = S, X_t = S) = e^{-\lambda*(1)} = e^{-\lambda} \tag{8}$$

$$P(X_{t+1} = U|X_t = S) + P(X_{t+1} = S|X_t = S) = 1$$

So:

$$P(X_{t+1} = U|X_t = S) = 1 - e^{-\lambda} \tag{9}$$

Hence, four probabilistic conditions (equations 6 to 9) have been derived and listed as follows;

$$P(X_{t+1} = S, X_t = U) = \lambda e^{-\lambda}$$

$$P(X_{t+1} = U | X_t = U) = 1 - \lambda e^{-\lambda}$$

$$P(X_{t+1} = S, X_t = S) = e^{-\lambda}$$

$$P(X_{t+1} = U | X_t = S) = 1 - e^{-\lambda}$$

In the expanded BN shown in Figure 6.2, there are 15 parent nodes which would change between time slices, each requiring a TPT.

These factors (parent nodes) also possess dissimilar 'rates of change' (λ) and some do not change at all for a given time frame, such as CCAI value, whilst others would frequently change, such as MIP deviation, depending on the operational conditions. Moreover, a few of these changes might be positive (improvements) whilst others are negative (degrading performance). Table 7.2 provides the list of the parameters in the DBN with the temporal dimension and associated description.

Table 7.2: List of parent nodes of the DBN with the temporal dimension

	Parameter	Measurement over a time slice
1	Scavenge air pressure	Quantifiable (part of the noon-figures). This would vary based on operating conditions such as engine load, T/C performance, and air flow resistance in the scavenge system.
2	Scavenge air temperature	Quantifiable (part of the noon-figures). This would vary based on ambient condition and efficiency of the scavenge cooler.
3	Exhaust temp deviation	Quantifiable. It is an integral part of regular record keeping (measurement can be either be through local thermometers or remote sensors connected to engine control system).
4	Viscosity of fuel	Quantifiable: readings through viscosity controller and gauges at the fuel inlet.
5	Fe content	This is not a regular 24-hour reading unless the ship is fitted with an online condition monitoring device (e.g. liner scan) or carries an onboard testing device. However, there can be a trajectory of increasing Fe content to indicate the failure propagation (distinguishing between magnetic Fe and total Fe through onboard testing can be tricky).

6	TBN	Similar to the Fe content and could be determined through onboard testing of drain oil samples; however, not a regularly tested parameter.
7	Water mist catcher performance	Water mist catcher performance can be determined by measuring the amount of water collected and comparing this with the expected water collection as described in the engine's operations manual.
8	$P_{max} – P_{comp}$	These pressure measurements are not continuously measured on older engines, however, on newer designs, cylinder pressures are continuously measured through sensor technology.
9	MIP deviation	Similar as item 8 (above).
10	Catalyst fines in fuel	Usually measured in the bunker drip sample and ships sometimes taking system samples and sending for analysis. However, these are not regular 24-hour measurement parameters.
11	Water in fuel	Same comments as item 10 regarding catalyst fines.
12	Ash content of the fuel	Should remain constant; however, there may be an unlikely scenario of minor deviation where a small quantity of inorganic sediment which has been settled in the tank bottoms can make its way to the engine inlet in poor weather. For simplicity, the ash content in fuel has been considered unchanged for the same fuel in use over a 24-hour period.
13	CCAI of fuel	Should remain constant over a 24-hour period assuming a homogenous blend of fuel is in use.
14	Work order completion	No expected deviation in a normal 24-hour period of operation.
15	Asset availability	No expected deviation in a normal 24-hour period of operation.

In Table 7.2, the parameters have been divided into three categories:

- Orange shaded: These are the parameters whose values are likely to deviate in a 24-hour period depending on the operational conditions, and corresponding measurements are part of the regular noon-figures.
- Blue shaded: These are the parameters whose values are likely to deviate in a 24-hour period depending on the operational conditions; however, corresponding measurements are not part of the regular noon-figures.
- Green shaded: These are the parameters whose values are unlikely to deviate in 24-hour engine operations; hence, they are considered as constant.

In view of the above, the blue-shaded parameters are more complex than the rest to define the corresponding rate of change, λ. A group of subject matter experts have been contacted to gather their expert judgements on the orange- and blue-shaded parameters.

7.3.2 Expert judgement

To determine the deviation in the operational parameters (parent nodes) over a specific period of time is inherently variable and would depend on the prevailing operating conditions. However, in this study, a group of experts are requested to provide input based on their experience of operation, design and maintenance of LS2S engines as percentage deviation, 'λ' (from satisfactory/ideal operation), over 24-hour engine operations under insignificant changes in conditions. The rationale for using percentage deviation instead of direct parameter measurement is to introduce consistency in the model output. Nevertheless, it has been realised that the criteria of the deviations need to be fine-tuned by developing certain operational scenarios which can even be engine- or ship-specific. This study is based on an overall performance assessment and considers a generic condition to test the model.

Six experts were selected from Table 3.5 who were considered suitable to provide expert judgement in this area of study. These were experts 4, 5, 6, 7, 11 and 13.

Due to variations in their professional roles, experiences and education levels, judgements from specific individuals would be preferred compared to those from others. In order to address this variability in a systematic fashion, a classification scheme was adopted similar to the one proposed in Table 5.3 with a slight variation, assigning professional experience more weight compared to education level and organisational responsibility, due to the nature of the expert elicitation and context of this particular area of study. Table 7.3 provides the constitution of the classification scheme.

Table 7.3: Classification scheme to assign weights to experts

Criteria	Classification	Score
Education Level (EL)	PhD Master Bachelor HND School-level	5 4 3 2 1
Professional Experience (PE)	≥ 30 Years 20 - 29 10 - 19 6 - 9 ≤ 5	10 8 6 4 2
Organisational Responsibility (OR)	Executive Lead Senior Engineer Technician/Worker	5 4 3 2 1

Individual expert i 's weight (w_i) is obtained by first estimating individual scores (S_i) by using following equations;

S_i = EL of expert$_i$ + PE of expert$_i$ + OR of expert$_i$

$$w_i = \frac{S_i}{\sum_{i=1}^{n} S_i}$$

Where $\sum_{i=1}^{n} w_i = 1$ (n = 1, 2…, 6)

Based on the classification provided in Table 7.3, each expert's score and subsequent weight has been estimated and is shown in Table 7.4.

Table 7.4: Weight estimation of each expert

Expert number	Education	Experience (years)	Responsibility	Score (S)	Weightage (w_i)
4	Bachelor	22 (20-29)	Senior	3+8+3 = 14	0.143
5	Masters	32 (≥ 30)	Senior	4+10+3 = 17	0.173
6	PhD	26 (20-29)	Executive	5+8+5= 18	0.184
7	Master	31 (≥ 30)	Senior	4+10+3 = 17	0.173
11	Master	22 (20-29)	Lead	4+8+4 = 16	0.163
13	HND	43 (≥ 30)	Lead	2+10+4 = 16	0.163
					Total = 1

The results in Table 7.4 suggest there is an insignificant difference in the overall weightage of the six experts providing the expert judgements. Table 7.5 summarises the judgements received from the individual experts.

Table 7.5: Expert judgements for selected parameter deviation (in percentage) over 24-hour two-stroke engine operations

	Parameter	Expert 4	Expert 5	Expert 6	Expert 7	Expert 11	Expert 13
1	Scavenge air pressure	2	3	1	2	6	2
2	Scavenge air temp.	3	3	1	4	4	3
3	Exhaust temp deviation	2	7	3	1	5	2
4	Viscosity of fuel	6	4	3	1	8	2
5	Fe content	1	-	1	-	0.5	-
6	TBN	1	-	4	-	1	-
7	WMC performance	3	1	4	3	10	5
8	$P_{max} – P_{comp}$	2	5	2.5	2	3	-
9	MIP deviation	4	2	1	2	6	1
10	Catalyst fines in fuel	4	-	0.5	-	10	-
11	Water in fuel	1	1	1.5	-	1	-

From Table 7.5, it can be seen that experts 5, 7 and 13 have refrained from providing judgements about certain parameters, citing the high associated uncertainty, and they questioned if there is sufficient evidence of significant changes in the parameter over a short period of time. Moreover, expert 7 commented in his response that usually the ranges could better depict the operating envelopes as fixed values can be open to interpretation. Expert 13 also highlighted that an important assumption is that the same fuel is in use and a change of fuel from high sulphur to low sulphur can significantly change the operating conditions.

To combine these judgements, a simple aggregation approach adopted by Pristrom et al (2016) has been used. If the judgement of expert '*i*' is represented by x_i and the combined weight of all six experts is x, then:

$$x = w_1 \times x_1 + w_2 \times x_2 + w_3 \times x_3 + w_4 \times x_4 + w_5 \times x_5 + w_6 \times x_6$$

where w_i is the weight of each expert derived as per Table 7.4. For example, scavenge air temperature deviation has been assigned by six experts as 3, 3, 1, 4, 5 and 3 percent respectively. Thus, the aggregate final percentage deviation for scavenge air temperature will be as follows:

$$x_{scave\ temp} = w_1 \times x_1 + w_2 \times x_2 + w_3 \times x_3 + w_4 \times x_4 + w_5 \times x_5 + w_6 \times x_6$$

$$= 0.163 \times 4 + 0.173 \times 3 + 0.173 \times 4 + 0.143 \times 3 + 0.163 \times 3 + 0.184 \times 1$$

$$x_{scave\ temp} = 2.97$$

Similarly, the final values of the other parameters have been defined as detailed in Table 7.6.

Table 7.6: Aggregated percentage deviation from expert elicitation

	Parameter	Expert 4	Expert 5	Expert 6	Expert 7	Expert 11	Expert 13	Aggregate (percentage)	Aggregate (λ) (Decimal)
1	Scavenge air pressure	0.29	0.52	0.18	0.35	0.98	0.33	2.64	0.0264
2	Scavenge air temperature	0.43	0.52	0.18	0.69	0.65	0.49	2.97	0.0297
3	Exhaust temp deviation	0.29	1.21	0.55	0.17	0.82	0.33	3.37	0.0337
4	Viscosity of fuel	0.86	0.69	0.55	0.17	1.31	0.33	3.91	0.0391
5	Fe content	0.14	-	0.18	-	0.08	-	0.41	0.0041
6	TBN	0.14	-	0.73	-	0.16	-	1.04	0.0104
7	Water mist catcher performance	0.43	0.17	0.73	0.52	1.63	0.82	4.31	0.0431
8	$P_{max} – P_{comp}$	0.29	0.87	0.46	0.35	0.49	-	2.45	0.0245
9	MIP deviation	0.57	0.35	0.18	0.35	0.98	0.16	2.59	0.0259
10	Catalyst fines in fuel	0.57	-	0.09	-	1.63	-	2.30	0.023
11	Water in fuel	0.14	0.17	0.28	-	0.16	-	0.76	0.0076

The remaining four parameters, shaded GREEN in Table 7.2, have been considered constant with zero deviation over a 24-hour period. The next stage is to establish the TPTs for each of these parameters to develop the DBN using equations 6 to 9 provided in section 7.3.1.

Scavenge air pressure: The aggregate deviation as per Table 7.6 is 0.0264 and using the equations from section 7.3.1, the transition probabilities have been computed as per Table 7.7:

Table 7.7: TPT for scavenge air pressure

't'	't+1	
	Low	Satisfactory
Low	$1 - \lambda e^{-\lambda} = 0.974$	$\lambda e^{-\lambda} = 0.026$
Satisfactory	$1 - e^{-\lambda} = 0.026$	$e^{-\lambda} = 0.974$

For a parameter with three states such as scavenge air temperature with the deviation of 2.97%, the TPT is as per Table 7.8.

Table 7.8: TPT for scavenge air temperature

't'	't+1		
	Low	Satisfactory	high
Low	$1 - \lambda e^{-\lambda} = 0.971$	$\lambda e^{-\lambda} = 0.029$	0
Satisfactory	$0.50(1 - e^{-\lambda})$ $= 0.014$	$e^{-\lambda} = 0.971$	$0.50(1 - e^{-\lambda}) = 0.014$
High	0	$\lambda e^{-\lambda} = 0.029$	$1 - \lambda e^{-\lambda} = 0.971$

Here, it has been considered that there is an equal probability of change from a 'satisfactory' state to a couple of unwanted states, i.e. 'low' or 'high', from 't' to 't+1', which is dictated by the prevailing operational circumstances. Moreover, the likelihood of a parameter state such as 'low' scavenge air temperature at 't' to shift to the other end of the scale into 'high' at 't+1' is de minimis and vice versa; hence, the corresponding value has been assigned as '0'. This is particularly valid in view of the relatively short time period under consideration. TPTs for the other 13 operational parameters have been derived and given in Appendix I.

Similar to Chapter 6, the DBN is also developed using NETICA software. The expanded BN structure with existing arcs and CPTs for a single slice is used to integrate the TPTs and unroll with multiple time slices. As discussed at the start of this chapter, the parent nodes of the BN model have the temporal dimension whilst the probabilities of child and leaf nodes within different time slices change as normal posterior probabilities, as can be seen in Figure 7.3.

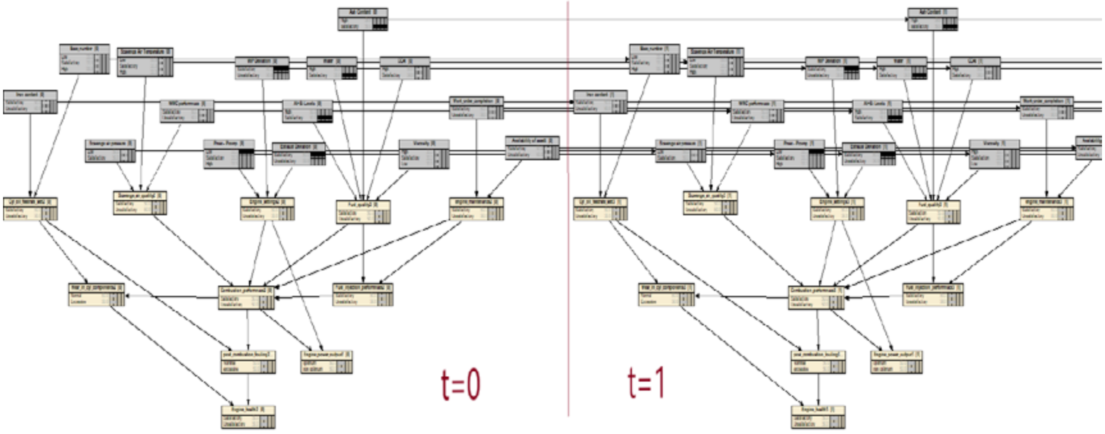


Figure 7.3: DBN for LS2S engine health assessment (at two time slices, '0' and '1')

7.4 Sensitivity analysis

Sensitivity analysis has been performed for the BN developed in Chapter 3 using the criteria defined by Pristrom et al (2009). For the DBN, similar principles can be applied to observe the effects of small changes to the input parameter to output (Kammouh, Gardoni and Cimellaro, 2020). There may be two primary axioms to analyse, as per below:

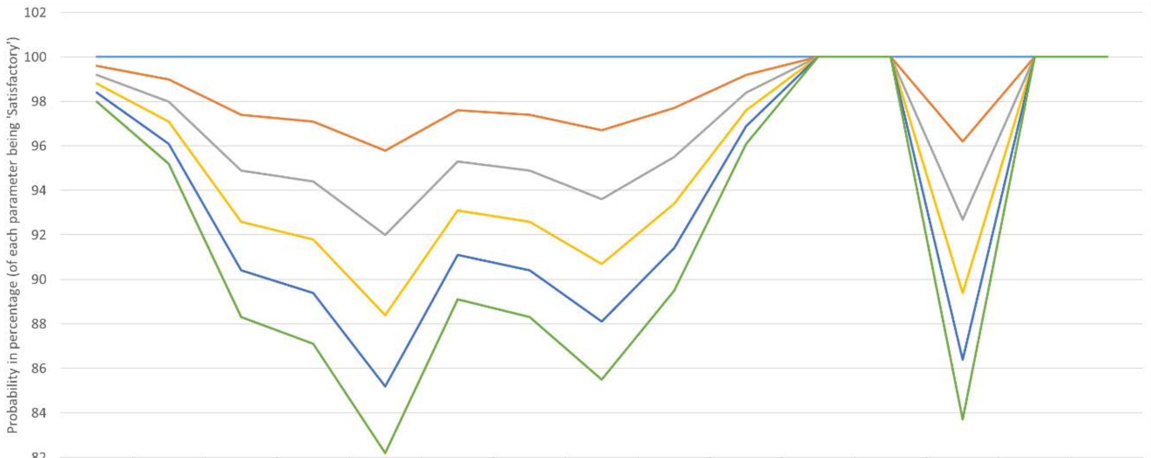
1. When the DBN is time expanded, the sensitivity of the parent node(s) (with temporal dimension) should be proportional to the changes made to the initial (t_0) temporal clone.
2. Evaluate the changes in target/leaf node(s) in different time slices to determine which parent node has a greater degree of influence.

In essence, any positive or negative change to the subjective probability of the parent node should have a consistent and proportional effect on the posterior probabilities of the child nodes.

Axiom 1: Each parameter (parent node) is assessed for its performance when the DBN is time expanded in the NETICA software. Throughout this section, the DBN is expanded, with each time slice representing a 24-hour period. Hence, six time slices have been used in this section to model five days of engine operations, which is a typical voyage length in days at a nominal speed of 15 knots between two of the busiest ports in the world, Singapore to Hong Kong[5]. For t_0 to t_5, the results are given

[5] http://ports.com/sea-route/port-of-singapore,singapore/port-of-humen,hong-kong/.

in Figure 7.4 for axiom 1.

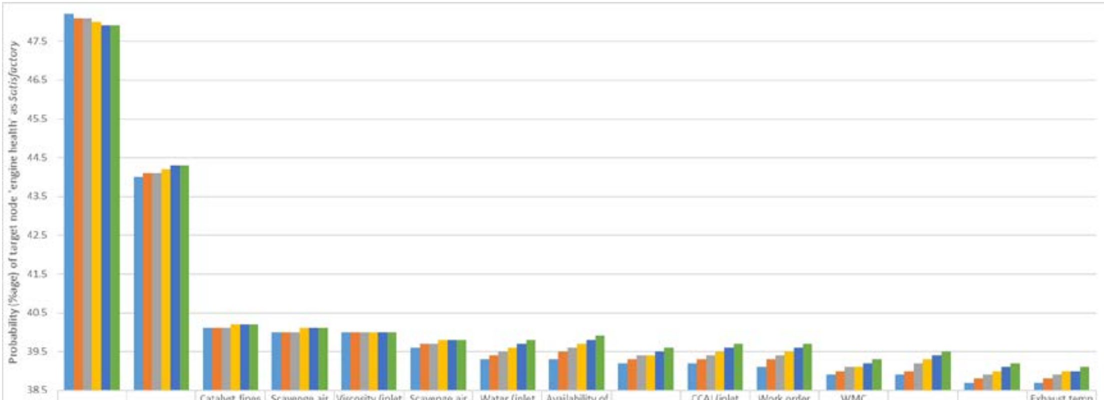


	Iron content	Base number	Scavenge Air pressure	Scavenge Air Temperarture	WMC Performnace	Pmax-Pcomp	MIP Deviation	Exhaust temp deviation	Al+Si	Water	Ash	CCAI	Viscosity	Work order completion	Availability of assett
0	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
1	99.6	99	97.4	97.1	95.8	97.6	97.4	96.7	97.7	99.2	100	100	96.2	100	100
2	99.2	98	94.9	94.4	92	95.3	94.9	93.6	95.5	98.4	100	100	92.7	100	100
3	98.8	97.1	92.6	91.8	88.4	93.1	92.6	90.7	93.4	97.6	100	100	89.4	100	100
4	98.4	96.1	90.4	89.4	85.2	91.1	90.4	88.1	91.4	96.9	100	100	86.4	100	100
5	98	95.2	88.3	87.1	82.2	89.1	88.3	85.5	89.5	96.1	100	100	83.7	100	100

Figure 7.4: Change in probability of each parent node state 'Satisfactory' over six time slices

These results reflect the variations in the various parameters, which also reflect and are in-line with the deviations derived through expert judgements in Table 7.6. For example, WMC performance, viscosity and exhaust temperature are the top three parameters for most variability, with average deviations of 3.6%, 3.2% and 2.9% respectively during each time slice. Other parameters like ash, CCAI, work order completion and availability of asset do not change throughout the period under study.

Axiom 2: The second axiom would evaluate the degree of influence on the target node of the different parent node(s) over various time slices. For this purpose, all 15 parent nodes are individually tested by giving a maximum ‘satisfactory’ score to each parameter and giving all other nodes a fixed (balanced) prior probability. The target node selected to check the influence of parent nodes is the ‘engine health’ being *satisfactory*. This exercise also reveals the parent nodes which have the most influence on the target node and how the posterior probability of the target node changes with time. Figure 7.5 shows the results of the DBN model simulation run in NETICA.



	TBN	Fe content	Catalyst fines (inlet fuel)	Scavenge air temperarture	Viscosity (inlet fuel)	Scavenge air pressure	Water (inlet fuel)	Availability of assett	Pmax-Pcomp	CCAI (inlet fuel)	Work order completion	WMC performnace	Ash (inlet fuel)	MIP deviation	Exhaust temp deviation
t(0)	48.2	44	40.1	40	40	39.6	39.3	39.3	39.2	39.2	39.1	38.9	38.9	38.7	38.7
t(1)	48.1	44.1	40.1	40	40	39.7	39.4	39.5	39.3	39.3	39.3	39	39	38.8	38.8
t(2)	48.1	44.1	40.1	40	40	39.7	39.5	39.6	39.4	39.4	39.4	39.1	39.2	38.9	38.9
t(3)	48	44.2	40.2	40.1	40	39.8	39.6	39.7	39.4	39.5	39.5	39.1	39.3	39	39
t(4)	47.9	44.3	40.2	40.1	40	39.8	39.7	39.8	39.5	39.6	39.6	39.2	39.4	39.1	39
t(5)	47.9	44.3	40.2	40.1	40	39.8	39.8	39.9	39.6	39.7	39.7	39.3	39.5	39.2	39.1

Figure 7.5: Degree of influence on target node over five time slices of parent nodes

These results indicate that the parameter TBN is most influential on the target node, i.e., engine health, and any small changes to the TBN in the DBN have a more significant influence on engine health than any other parameter. The second most influential parameter is the Fe content, which seems to suggest that ‘CLO feed rate’ as a child node of ‘TBN’ and ‘Fe content’ could be the most influential intermediate node in the DBN. The above graph also suggests that, for the least influential parameters, such as ‘MIP deviation’ and ‘exhaust temperature deviations’ tends to improve over time; however, for the most influential parameter, ‘TBN’, there is a slight degradation over time. The apparent skewness of these results is caused by the TPTs of the parent nodes.

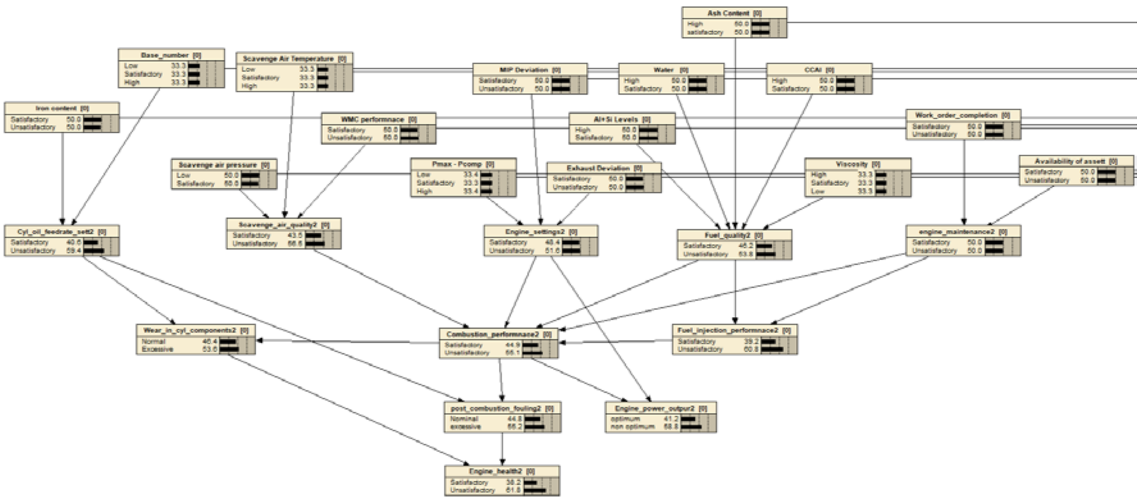


Figure 7.6: DBN model at time slice t_0 and all parent nodes assigned a balanced prior probability distribution

For example, when all the parameter states are given equal prior probability distribution, as per Figure 7.6, the probability of engine health appears to marginally improve in subsequent time slices (blue line), as per Figure 7.7. Similarly, the model is tested with the parent nodes either 100% ‘satisfactory’ (orange line) or 100% ‘unsatisfactory’ (grey line), as also shown in Figure 7.7.

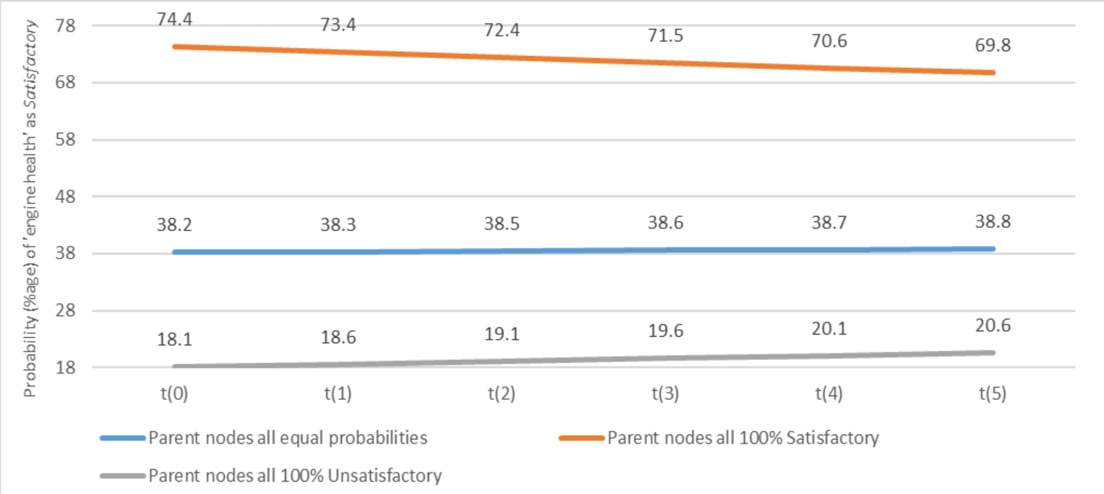


Figure 7.7: 'Satisfactory' engine health under various input scenarios

These results are interesting to show how the model reacts to various extreme inputs and the resultant output over the specified time period. They also indicate almost linear trends for all three input scenarios. The slope of the orange line (all the parent nodes are ‘satisfactory’) is higher at 0.9 compared to the slope of the grey line at 0.5 (all the parent nodes are unsatisfactory) and the blue line at 0.125 (all the parent nodes have been given equal prior probabilities). These initial observations seem to be in line with the expected behaviour of a machinery system in an actual application. The model indicates a degradation from a highly desirable state unless corrective actions are taken to maintain high performance which would entail fresh model inputs based on new information. Similarly, there is a slow recovery from an extremely poor operational condition which is not unexpected through either ship staff making incremental adjustments or likely (organic) improvements in the operational conditions from extremely poor conditions having a positive impact on engine health.

The model can be unrolled to as many time slices (days) as possible or reduced to a minimum of one-day operation, which would be a two time slice model.

As a predictive tool, the DBN can be further expanded to determine a probable time frame where performance degradation would be at a level where, unless intervention is made, there is a higher risk of breakdown. However, this requires zones/limits to be defined, as described in Figure 7.8.

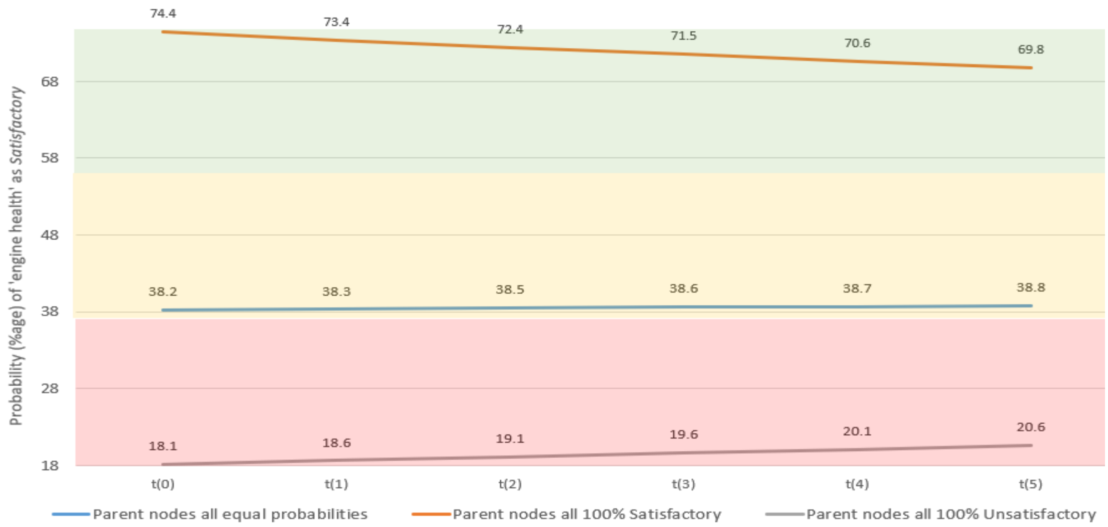


Figure 7.8: Traffic light system for engine health assessment

As can be seen from Figure 7.8, the engine is operating between two extreme probability values for 'satisfactory' engine health of 18.1% to 74.4%. Thus, the graph has been divided into three colour-coded zones as follows:

1. GREEN: Engine's operating levels are 'satisfactory', and the general recommendation would be to continue to operate with a usual best practice approach.
2. AMBER: Engine is operating at lower 'satisfactory' levels, requiring caution, and further investigation is needed to determine the parameter most in need of improvement to bring the rating back up to the GREEN zone.
3. RED: Engine is operating at 'unsatisfactory' levels, requiring immediate action to investigate and improve the situation, as continuous operation in the RED zone could result in a machinery breakdown.

The three colour-coded operating zones have been given equal space on the graph outlined as follows;

P {max(satisfactory)} = 74.4%

P {min(satisfactory)} = 18.1%

P {max(satisfactory)}- P {min(satisfactory)} = 56.3

The three zones are equally weighed; hence, 56.3/3 = 18.7% assigned to each zone.

This means that the GREEN operating zone covers probabilities above 55.6%, AMBER is between 37% and 55.6% and RED is below 37%.

The above quantitative limits for the three engine operational ranges can be further fine-tuned through onboard engine data analytics as these can be moving targets mainly depending on the engine type/design, running hours, operating conditions and so on.

The model developed in the section above has been tested using the case study discussed in previous chapters.

7.5 Case study

In order to demonstrate the model's functionality, the case study developed in the previous chapter has been used where prior probabilities for the BN model for a six-cylinder engine were derived from the fuzzy-ER approach. Table 7.9 shows all the prior probabilities of the case study for the LS2S engine's cylinders 1 to 6. These probabilities have been used in the DBN developed in this chapter as input for time slice t(0) to compute the probability of 'satisfactory' engine health at subsequent time slices. To design the case study, a five-day engine operation has been modelled to evaluate engine performance.

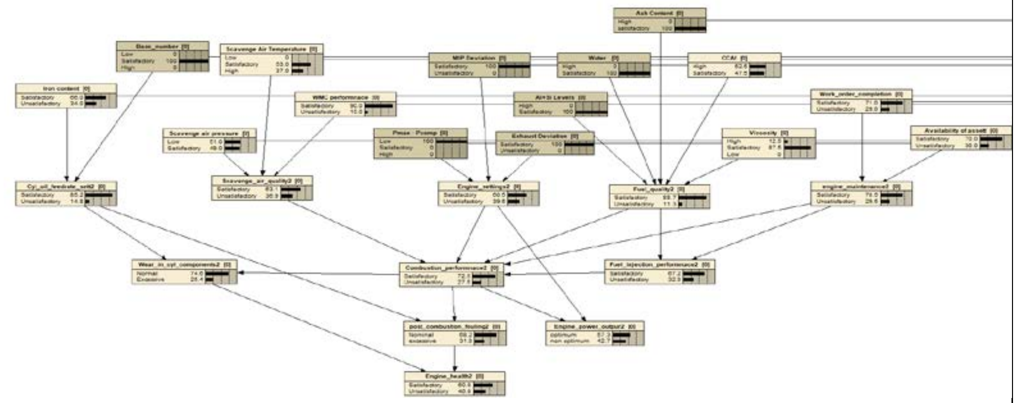
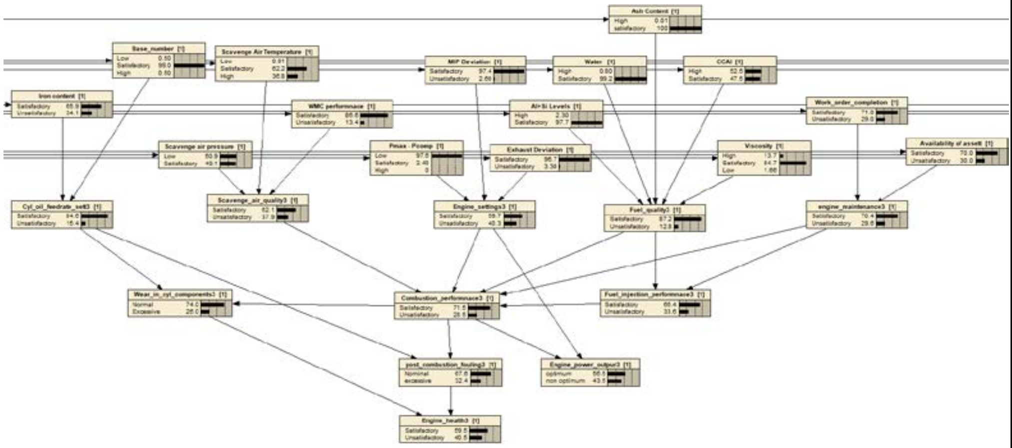
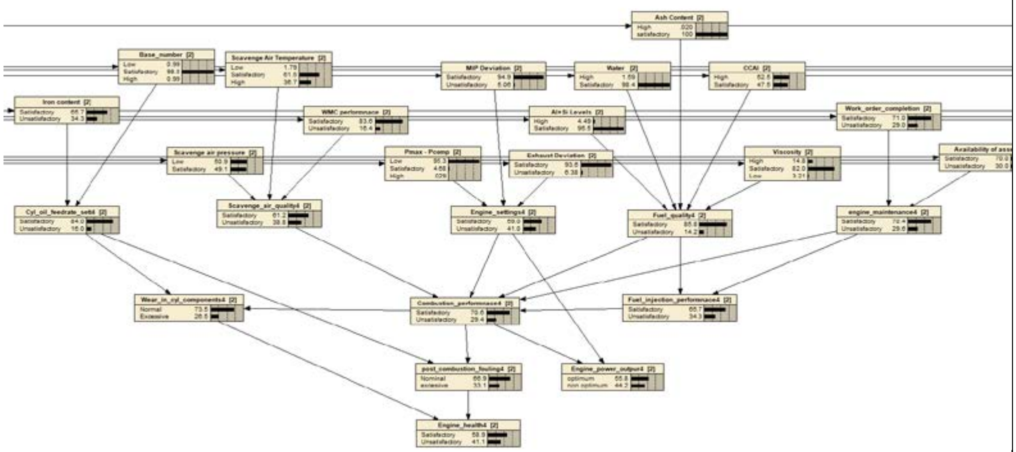
Table 7.9: Prior probabilities from a case study from Chapter 5 to be used as input to the DBN at t(0)

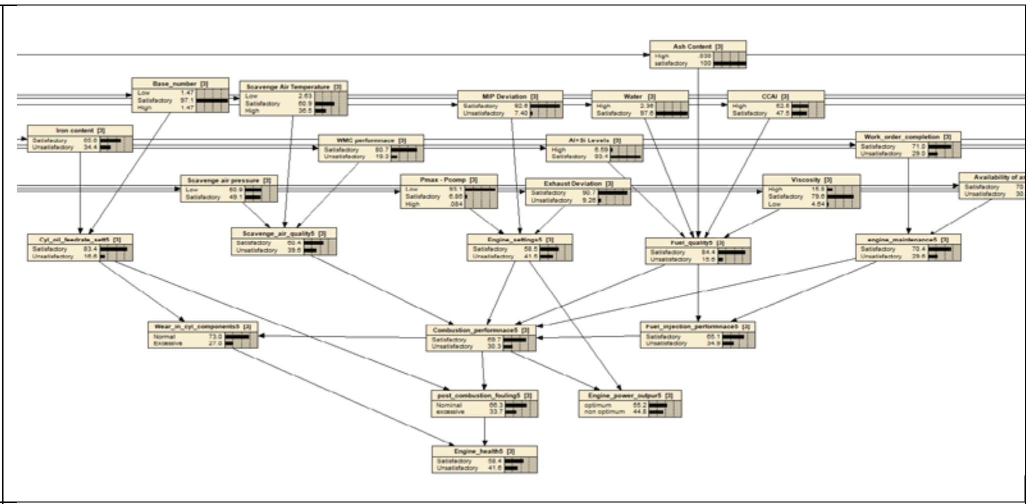
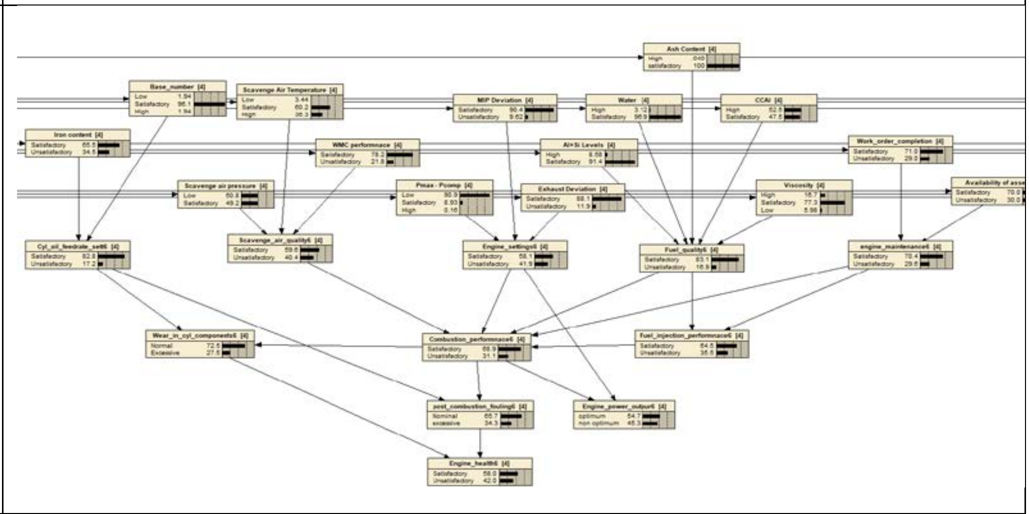
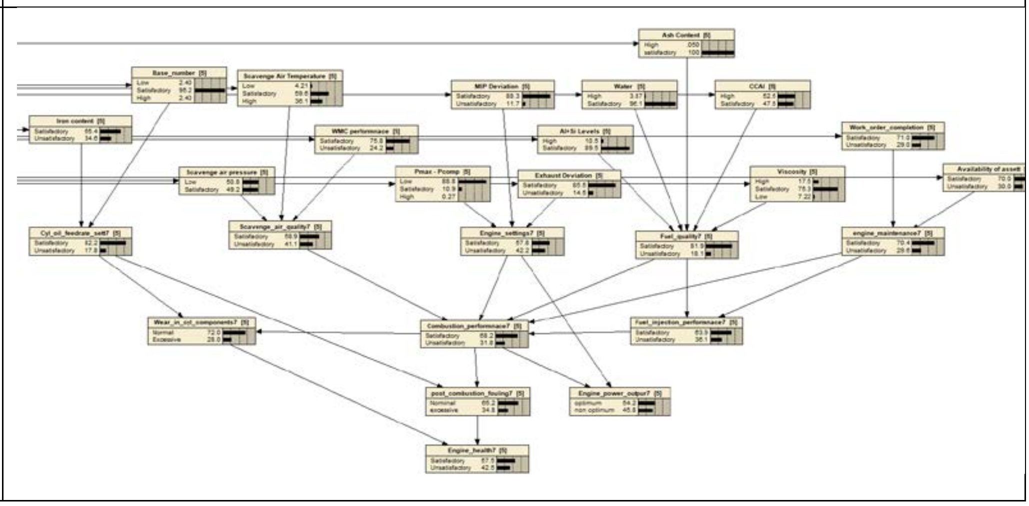
	Parameter	State	Probability in percentage for six cylinders					
			1	2	3	4	5	6
1	Scavenge air pressure	Low	51	51	51	51	51	51
		Satisfactory	49	49	49	49	49	49
2	Scavenge air temperature	Low	0	0	0	0	0	0
		Satisfactory	63	63	63	63	63	63
		High	37	37	37	37	37	37
3	Exhaust temp dev.	Satisfactory	100	90	50	40	100	30
		Unsatisfactory	0	10	50	60	0	70
4	Fuel inlet Viscosity	Low	0	0	0	0	0	0
		Satisfactory	87.5	87.5	87.5	87.5	87.5	87.5
		High	12.5	12.5	12.5	12.5	12.5	12.5
5	Fe content	Satisfactory	66	57.5	71.2	0	38.8	41.3
		Unsatisfactory	34	42.5	28.8	100	61.2	58.7
6	TBN	Low	0	9	0	0	1	6
		Satisfactory	100	91	100	100	99	94
		High	0	0	0	0	0	0
7		Satisfactory	90	90	90	90	90	90

	WMC performance	Unsatisfactory	10	10	10	10	10	10
8	$P_{max} – P_{comp}$	Low	100	100	100	100	100	100
		Satisfactory	0	0	0	0	0	0
		High	0	0	0	0	0	0
9	MIP deviation	Satisfactory	100	100	100	100	100	100
		Unsatisfactory	0	0	0	0	0	0
10	Catalyst fines	Satisfactory	100	100	100	100	100	100
		High	0	0	0	0	0	0
11	Water	Satisfactory	100	100	100	100	100	100
		High	0	0	0	0	0	0
12	Ash	Satisfactory	100	100	100	100	100	100
		High	0	0	0	0	0	0
13	CCAI	Satisfactory	47.5	47.5	47.5	47.5	47.5	47.5
		High	52.5	52.5	52.5	52.5	52.5	52.5
14	Work order completion	Satisfactory	71	85	71	86	100	71
		Unsatisfactory	29	14	29	14	0	29
15	Asset availability	Satisfactory	70	70	70	70	70	70
		Unsatisfactory	30	30	30	30	30	30

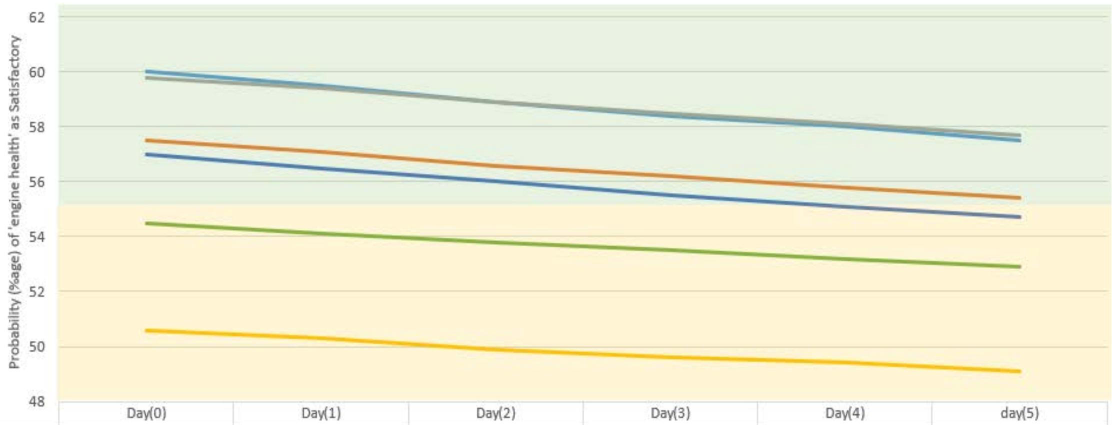
The unconditional probabilities for cylinder 1 are used as input in the DBN created in NETICA, which generated six time slices modelling five days of engine operation. Table 7.10 provides a snapshot of each time slice for cylinder 1.

Table 7.10: DBN time slices for cylinder 1

Time slice	DBN graphical model
Day 0	
Day 1	
Day 2	

Day 3	
Day 4	
Day 5	

Similarly, the other five cylinders are also modelled, and a final value for 'satisfactory' engine health was computed, as summarised in Figure 7.9 below.



	Day(0)	Day(1)	Day(2)	Day(3)	Day(4)	day(5)
Unit 1	60	59.5	58.9	58.4	58	57.5
Unit 2	57.5	57.1	56.6	56.2	55.8	55.4
Unit 3	59.8	59.4	58.9	58.5	58.1	57.7
Unit 4	50.6	50.3	49.9	49.6	49.4	49.1
Unit 5	57	56.5	56	55.5	55.1	54.7
Unit 6	54.5	54.1	53.8	53.5	53.2	52.9

Figure 7.9: Engine operation over a five-day period

The results from all cylinders have been categorised using GREEN, AMBER and RED criteria developed in the previous section. There are a few observations to make, as follows:

- Most cylinders are operating in the satisfactory GREEN zone; however, cylinders 4 and 6 fell into the AMBER zone, requiring attention.
- Cylinder 5 is predicted after two days of operation to fall into the AMBER zone, whilst cylinder 2 operates in the GREEN zone; however, the trend suggests that, if the engine operated for an extended period, cylinder 2 could also cross into the AMBER zone.
- The model output suggests that cylinders 1 and 3 are the most satisfactory operating cylinders. Cylinder 1 at day(0) is at the most satisfactory condition; however, it has a steeper slope compared to cylinder 3, which means that operating conditions are likely to deteriorate rapidly for cylinder 1 compared to cylinder 3.

These results show that the BDN is a useful method and quick indication tool for the engine operators to determine and even predict the performance of the engine, giving ample time for them to ensure operations are maintained in the GREEN zone for the upcoming voyage for all the cylinders.

7.6 Model validation and onboard application

Overall, the model is validated through sensitivity analyses presented in chapters 3, 6 and 7. Moreover, case studies have been developed to demonstrate the functionality of the models. However, to acquire a comprehensive model validation, the model needs to be applied onboard to assess the LS2S engine operational performance. Following are few key practical steps to achieve this objective;

- The first step would be to integrate the various models into a single software package which could be capable of receiving input onboard engine data management system and manual input from the operator
- The developed software needs to be installed on the engine room PC
- Then model needs to be suitably trained through actual data generated from the asset to benchmark e.g., what is ‘acceptable’ and ‘unacceptable’.
- If the DBN developed in current chapter is used, then additionally operator needs to select appropriate time granularity to perform either retrospective or prospective LS2S engine assessment. One of the validation pathways is to train the model with historic data and then roll forward to a point of potential failure or incident which may have actually happened. Secondly, the model can point to an issue with a certain cylinder which then needs to be inspected to verify the model output.

For the model application on a ship, there could be a number of design configurations so each system is considered on its merits. Griffiths (2006) presents on page 184, a typical LS2S engine control system. The engine control room has two operational panels i.e., main operational panel and a backup which is usually a PC.

For the practical application of this model, it has been envisaged that the backup operational panel (a PC) receiving a direct feed of engine data is installed with the software constituting the BN model as per design shown in Figure 7.10. The direct feed coupled with the data from parameters requiring manual input can be added by the staff to the computer to yield an engine health factor with a set of practical actions to improve the LS2S operational score / performance.

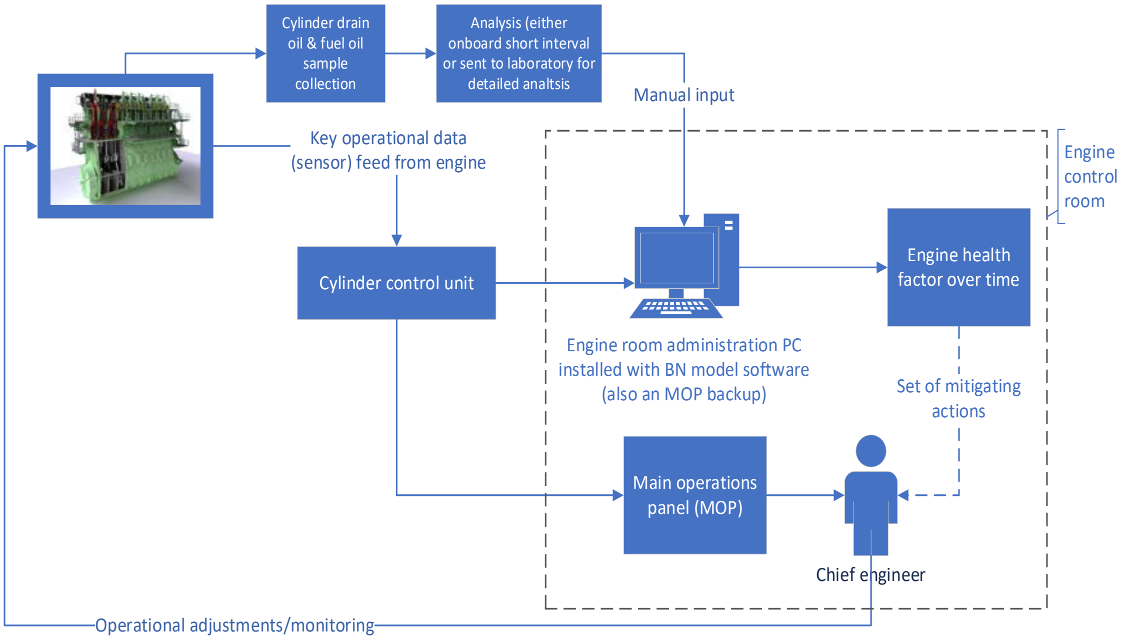


Figure 7.10: Proposed model integration with the onboard engine control systems

The model do not intend to replace or contradict any existing OEM control system but to provide additional complementary information and support for the onboard engineers to maintain optimum operational health of the LS2S engine. In case the model outputs are not aligned with the prevailing operational conditions of the engine, then further investigation should be performed to determine the reason for the apparent contradiction.

7.7 Conclusion

In this chapter, a fundamental limitation of the conventional BN models has been addressed through the use of a Dynamic Bayesian Network (DBN). A key challenge in developing an operational DBN model is the development of transition probability tables (TPTs). In this study, it has been observed that changes in the engine operational parameters can occur randomly, which follows the Poisson distribution. The average deviations in each parameter are not a straight calculation; hence, a group of subject matter experts were requested to provide expert judgements. TPTs were developed for each of the 15 parent nodes. To evaluate the model functionality, a sensitivity analysis was performed, followed by a case study.

One of the key benefits of using the novel DBN is that it uses a traffic light system which would indicate where the engine is operating in terms of its operational health. Moreover, it provides a predictive capability to the operator to judge how different cylinders might behave during a forthcoming voyage by identifying lower- and higher-risk cylinders. Furthermore, this can assist the operator in making operational adjustments to ensure trouble-free engine operations.

8 Conclusion and recommendations

8.1 Research summary

The research thesis has primarily been developed around five technical chapters and one chapter on literature review to achieve the research objectives. This section briefly explains the summary of the research process.

In chapter 2 of the study, a review of the large two-stroke engine market, onboard application, manufacturers, maintenance methods, criticality of asset, and consequences of failure were discussed. Moreover, a comparative analysis is performed to assess the engine health from various industry guidelines, standards, and regulatory framework perspectives. One of the main contribution of this chapter is the review of the current onboard processes and procedures which are predominantly deemed reactive and a proposed proactive methodology based on operational indicators (refer to Figure 2.24). The proposed technology is targeted for ship's staff to facilitate in their day-to-day operational management of the LS2S engine.

In chapter 3, various stochastic models were considered for the proposed proactive LS2S engine health assessment methodology however the BN model was selected and presented (refer to Figure 3.14) due to its distinct features to handle a large number of parameters and varying conditions. Multiple data sources were used including the judgements from 10 industry experts to create CPTs. The model is also put through the validation phase and its functionality is shown by a case study. The case study demonstrated that the model output closely matches with the investigation performed to determine the probable causes of failure. The inputs to the BN model vary with the prevailing operating conditions of the LS2S engine. The inputs are crisp values from engine data however these require to be converted into probability distributions for each parent node. It was left to the BN model operator to input a value based on his/her experience. However, this can introduce inconsistencies in the model output when used for the same operating conditions.

To address this issue, chapter 4 attempts to standardise and introduces a consistent method to process the engine operational data into probabilities for BN input by using fuzzy logic control. Firstly, each parent node is broken down into multiple influencing factors or antecedents (refer to Table 4.1). Each antecedent with multiple 'states' was assigned fuzzy membership functions based on real data from the industry. A set of antecedents were combined with fuzzy 'IF-THEN' rules. The conventional fuzzy 'max-min' function is used for inference without the defuzzification step for a direct BN input. The functionality of the fuzzy model is then demonstrated by a real case study in section 4.5, with results providing a good correlation with the FEAP (2017) reporting protocol. Nevertheless, there remains some criticism of fuzzy ‘max-min’ inference as not sufficiently sensitive to the variations in the input variables. Moreover, assigning a single ‘state’ to the consequent part of a conventional fuzzy rule does not reflect the real world scenarios.

To improve the precision and sensitivity of the input variables to the BN model, the ER algorithm is introduced in chapter 5 to develop a fuzzy ER model. The key steps involved assigning weights to antecedents and consequents of fuzzy rule-base by utilising the expert judgements to develop modified fuzzy sets. The ER algorithm is then used to aggregate the results from various activated rules as opposed to conventional fuzzy ‘max-min’ inference. A comparative analysis is performed between the two fuzzy inference methods where fuzzy ER was found to be more sensitive to the variations as compared to the ‘max-min’ inference which suggests a better quantitative precision has been achieved through this model.

Chapter 6 attempts to fuse together salient features of all the previous technical chapters (refer to Figure 6.1) to create a comprehensive performance assessment BN model to improve diagnostic capability, probabilistic quantification and graphical user interface. Operational information for 15 root nodes is processed to compute prior probability values through the fuzzy membership functions and ER is used to derive CPTs for intermediate and leaf nodes of expanded BN. Finally the model output i.e. posterior probabilities are calculated through the Bayes theorem. Sensitivity analysis backed up by a case study shows promising results and correlation.

The final technical chapter, 7, is one of the most important chapters of the study which proposes a DBN model to predict the LS2S engine health through a temporal dimension in the conventional BN model. During the development the fifteen transition probability tables i.e. how selected engine performance indicators change over a certain time period, it was assumed that the events occur randomly following a Poisson distribution. Expert judgements have been used to derive the rate of change for the time period which has been set at 24 hours of normal operations. To evaluate the model functionality, a sensitivity analysis was performed, followed by a case study. A traffic light system has been introduced in the DBN model to indicate where the engine is operating in terms of its operational health. DBNs capability to perform a prospective analysis, facilitates the operator to judge how different LS2S engine cylinders might behave during a forthcoming voyage by identifying lower-, medium- and higher-risk cylinders.

8.2 Research contribution and conclusion

This research provides important insights and contributions for both ship operators and machine learning practitioners. A few key contributions have been outlined as follows;

1. To the researcher's best knowledge, key LS2S engine performance indicators such as combustion, cylinder component wear, power output and fouling have been combined for the first time to assess LS2S engine health.
2. The inter-dependencies of various operational indicators have been modelled and combined with the BN graphical nature is expected to improve LS2S engine operational management and knowledge.
3. The model presents a fuzzy logic method to compute the unconditional probabilities by processing LS2S engine raw data and further refining the output by evidential reasoning.
4. It is the first attempt to model LS2S engine performance through a dynamic Bayesian network for predictive assessment. This would encourage ship operators to take pre-emptive action based on model output to improve the score, subsequently avoiding potential operational issues.

The following paragraphs presents the conclusion on each of the three objectives set out in the first chapter.

Objective 1: Develop understanding of the LS2S engine marine application, conventional maintenance and corresponding performance assessment methodologies by performing a thorough literature review and market analysis.

This objective is achieved in Chapter 2 although subsequent chapters also contain relevant information so understanding was developed over the course of the research. The literature review indicates that in the maritime domain, there has been 50% more diagnostic and performance assessment modelling of four-stroke engines compared to LS2S engines. Secondly, although a few studies have utilised operational indicators to model the engine performance, nevertheless to create a more holistic framework, there is a need to consider more operational indicators. Engine manufacturer, classification societies, regulators, flag States, standardisation bodies, ship owners and operators, fuel and lube suppliers, and charterers, all view onboard asset management from a particular perspective. There is a need to develop an unbiased performance based framework where asset's safety and conditioned based maintenance decision making would be a priority. Moreover, current performance assessment, data processing and maintenance activities are deemed reactive hence to optimise the use of resources, a proactive performance assessment methodology has been proposed (refer to Figure 2.24).

Objective 2. Develop a proactive LS2S engine performance assessment methodology through the use of operational indicators.

This objective has been achieved in chapters 3, 4, 5 and 6. A novel methodology has been proposed where LS2S engine operational indicators are processed through fuzzy evidential reasoning and used as input into a BN model. Each technical chapter complements the others where chapter 6 fuses the features developed in previous chapters into a single comprehensive BN model. Robustness of the model has been verified through real case studies which indicate satisfactory correlation. One of the important feature of the model is the identification of the parameters having greater impact on the engine performance compared to others prompting the ship operator to pay extra attention to those aspects. Overall results indicate that the this objective has been satisfactorily achieved.

Objective 3. Develop a predictive assessment capability for LS2S engines which can facilitate scheduling timely operational adjustments and maintenance tasks.

This final objective is achieved in chapter 7. Incorporating a temporal dimension to BN enables both prospective and retrospective performance assessment. To further make the model user friendly, a traffic light system is introduced which enables the operator to identify a particular cylinder of the engine whether operating in GREEN, AMBER or RED zone.

In conclusion, the main focus of the study has been the practical application of the model with the aim to improve overall ship safety through better performance assessment and maintenance decision making of the LS2S engines. The risks to larger vessels are ever present as witnessed in the recent case of the Ever Given (ABC News, 2021) involved in an incident in Suez Canal where direct and indirect costs are expected to run into billions of dollars. The unique feature of this model is that it attempts to take into account the conditional dependencies of parameters and is flexible in terms of updating beliefs, and even adding/removing nodes to fit specific scenarios or prevailing conditions.

8.3 Research applicability

The applicability of the model developed is the main driver of the research. The following are a few key points in this regards:

- This model can become an integral part of an onboard maintenance strategy such as RCM, CBM, PHM or resilience framework. It is also envisaged that the systematic use of this model is going to build an engine’s operational profile, and trend analysis can be performed by viewing the engine inputs and outputs.

- Ship operators should be able to use this model either as a standalone performance assessment tool or it could complement the OEMs digital data assessment solutions such as WiDE (WinGD, 2018) and PMI (MAN-ED, 2021a). However, the latter would require some additional integration work to go through a validation and system compatibility assessment.
- Graphical nature of the model can serve as a knowledge management tool which can be particularly useful for young engineers learning their trade onboard ships.
- The model will flag the performance issues early on, leaving the ship operator with ample time to react. The DBN model can be used for prognostics and carrying out timely maintenance actions.
- Although the proposed model is LS2S engine specific, a few operating limits and scenarios can easily be transposed to fit any other onboard machinery equipment.
- Another possible application is to present the model output to classification surveyors gaining possible exemption in the CSM cycle (refer to section 2.1.2). However, this requires an understanding/acceptance beforehand from the ship classification society.
- One possible model application is to trial a feature-extraction from model's 'power output' node, SFOC reduction to demonstrate overall CO_2 and EEXI (Energy Efficiency Existing Ship Index) improvements to demonstrate compliance (Psaraftis, Zis and Lagouvardou, 2021) with expected implemented date of 1st November 2022 (LR, 2021a). However this idea should be complemented with the installation of telemetry system such as fuel mass flow meter and torque meters for validation and precision.

8.4 Limitation of the research

There are few limitations which came to light during the period of research as outlined below:

- The model effectiveness largely depends on the quality of the input data and operators familiarity and understanding with the model interface. An error at data entry stage may lead to incorrect assessment and subsequent interpretation, though this limitation can be addressed to a degree by linking the model with the OEM solutions such as WiDE (WinGD, 2018) and PMI (MAN-ES, 2020b).
- LS2S engines installed with exhaust gas recirculation (EGR) to reduce NOx are not within the scope of this model however with some amendments, this limitation can be removed.

- The model is insensitive to human factors e.g. quality of maintenance actions performed to mitigate a deteriorating situation would depend on a number of factors requiring Human Reliability Analysis which is outside the scope of this study.
- LS2S engines on newer ships are under warranty from engine manufacturers for a specified time period. To retain the warranty, ship operators tend not to divert from engine manufacturers guidelines particularly on maintenance schedules. Hence, even if the LS2S assessment indicates satisfactory performance, the ship operator may still replace or overhaul a cylinder to follow the fixed time interval maintenance approach.
- Models output may be unreliable where ship is not operating in steady-state conditions, i.e., extreme weather or ship under distress.
- Outputs from the model are in the form of probabilities assigned to linguistic variables (e.g., 'satisfactory' and 'unsatisfactory') associated with each parameter, which require benchmarking such as described in section 7.3.2. Although these outputs can be made bespoke through the ship's staff generating recursive outputs and comparing with the actual operating conditions and shop test data. This exercise should result in creating a set of quantitative limits to categorise the output into acceptable and unacceptable categories. An attempt has been made to generate generic operating limits through this model, however as each LS2S engine can respond differently even under similar operating conditions; hence, a bespoke approach may be considered by the operator to suit their asset. For example, an engine's design limits the cylinder liner iron wear to as low as practically possible; however, a particular engine type would allow slight corrosive wear in order to maintain porosity on the liner surface to facilitate lubricant retention and avoid bore polishing. Variations such as these can be accommodated on a case-by-case basis to adjust the model to suit the operational and design requirements.
- In the study, a model validation has been performed through sensitivity analysis and case studies. Although a system integration process (section 7.6) has been proposed for future onboard applications, yet current model validation status may not be considered as comprehensive. Furthermore, model validation steps outlined section 7.6 needs to be followed to improve confidence in model output and enhance technology readiness levels.

8.5 Recommendations for future work

It is not possible to envisage all possible future directions of the research. Here are a few possible research areas;

- The study successfully included a number of operational indicators for LS2S engine which have not been considered before. There remain few additional operational factors (considered peripheral) which have been excluded to avoid model becoming intractable such as jacket water temperature, machinery running hours since last overhaul, turbo charger performance, system lube oil, vibration, sea conditions, torque measurement. However with the industrial software applications, using the proposed network, the BN should be updated with these additional nodes.
- A set of practical recommendations or guidance document would be useful based on model diagnostics to help the ship operator point in the right direction for any additional onboard monitoring and maintenance activity as a mitigating action.
- Future studies can also explore the monetary benefits through a 'cost benefit analysis' to compare short and long term benefits of using and not using the proposed performance assessment model.
- The model has been developed considering a residual marine fuel being burnt in the LS2S engine however future work should consider to adjust the model for use of alternative fuels such as Methanol, Ammonia, Hydrogen, renewable LNG and others.
- LS2S engines of similar design/type and age can produce different results mainly because of the unique operating conditions, maintenance regime, different manufacturers, and quality control placing various stress levels causing the field behaviours to vary significantly over time. Hence, future work can focus on fine-tuning to develop bespoke limits of the GREEN, AMBER and RED zones in the DBN model through machine learning and data analytics. Moreover, technologies such as digital twin is an area gaining traction (LR, 2018) hence the proposed model aligns well with the concept and further integration work is recommended.
- A natural progression would be to integrate the models developed in the study to produce a single software which can serve as a Blackbox solution for the ship operator.

8.6 A final remark

The technology landscape is fast changing in communications, sensors, big data, artificial intelligence, and machine learning coupled with a global drive to decarbonise all transport modes including shipping. The adoption of new technology or the use of renewable fuels is not a default choice in a very traditional maritime industry. Fresh ideas and innovative solutions are needed to drive the change which has become a necessity primarily due to stricter maritime regulations, regional demands, monetary pressures, health and safety of people and the environment. All stakeholders in the maritime industry need to collaborate and demonstrate the required leadership to drive and accomplish the change for a better and safe future.

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Appendix A – Publications arisen from the thesis

Usman, M., Saeed, F., Yang, Z. (2016) Changing role of Classification Societies in managing onboard machinery equipment through descriptive notes. Proceedings of Liverpool John Moores University Faculty Research Week, 9th – 13th May 2016. [Available at: https://www.ljmu.ac.uk/research/centres-and-institutes/fet-research-week]

Usman, M., Yang, Z., Shorten, D. (2017) Development of Bayesian Network (BN) model to estimate health factor for predictive maintenance strategy of large two-stroke marine engine. Proceedings of 'The First World Congress of Condition Monitoring', 13th – 16th June 2017, London

Usman, M., Yang, Z. (2019) Combining Fuzzy Modelling and Bayesian Network (BN) Approach to Assess Two-Stroke Engine Performance. Proceedings of 29th CIMAC Congress, 10th – 14th June 2019, Vancouver

Usman, M., Qu, Z., Chang, C-H., Yang, Z. (2020) A new fuzzy approach for two-stroke engine operational health analysis. Proceedings of 30th European Safety and Reliability Conference and 15th Probabilistic Safety Assessment and Management Conference, 1st – 5th November 2020, Venice

Usman, M., Yang, Z. (2021) Development of a Bayesian Network (BN) model to estimate operational health of large two-stroke marine engines. Proceedings of the Institute of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment (submitted and under review)

Appendix B – Questionnaire to subject matter experts to gather judgements for BN model CPTs

LIVERPOOL JOHN MOORES UNIVERSITY
PARTICIPANT INFORMATION SHEET

Title of Project:
Development of Bayesian Network (BN) model to estimate two stroke marine engine health factor for predictive maintenance strategy

Name of Researcher and School/Faculty:
Muhammad Usman – School of engineering, technology and maritime operations

You are being invited to take part in a research study. Before you decide it is important that you understand why the research is being done and what it involves. Please take time to read the following information. Ask us if there is anything that is not clear or if you would like more information.

1. What is the purpose of the study?
The purpose of this study is to develop a proactive Bayesian network model where combustion performance of a large two stroke engine is evaluated and maintenance actions are recommended based on the holistic view of the systems.

2. Do I have to take part?
No. It is up to you to decide whether or not to take part. You are free to withdraw at any time and without giving a reason. A decision to withdraw will not affect your rights/any future treatment/service you receive.

3. What will happen to me if I take part?
This questionnaire should not take more than an hour to fill out. Once the feedback is collected from all other participants, the probabilities will be assessed and if there are significant variations between the two or more expert opinions then another request will be sent out to individuals to review their rankings to normalise the output.

4. Are there any risks / benefits involved?
There are no apparent risks. Participants are likely to benefit from the experience from others in the pool as anonymous feedback will be shared between the participants.

5. Will my taking part in the study be kept confidential?
Please note that any information collected as a part of the study will be used for analysis and will be treated confidentially, stored securely on password-protected computers or in a locked cabinet. Only the researcher and his supervisory team will have direct access to it. Any personal information will be retained for a period of 2-4 years after analysis when it will then be destroyed.

This study has received ethical approval from LJMU's Research Ethics Committee

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If you have any concerns regarding your involvement in this research, please discuss these with the researcher in the first instance. If you wish to make a complaint, please contact researchethics@ljmu.ac.uk and your communication will be re-directed to an independent person as appropriate.

Introduction

This research is titled "Development of Bayesian Network (BN) model to estimate two stroke marine engine health factor for predictive maintenance strategy". Primary objective of this study is to investigate and develop a monitoring tool to assess the health factor of large two-stroke marine diesel engines. Bayesian network due to its numerous advantages have been selected to model various engine operational parameters. Brief description of the BN has been provided in the appendix A.

This document has been divided into eight sections as per figure 1. Section 1 provides the details of the selected nodes and DAG (direct acyclic graph) of the model. Sections 2 to 6 contain the conditional probability tables for different variables which require filling out by the participants. Section 7 has not been made part of this questionnaire and will be assessed once probability data for section 2 to 6 are available whilst last section is for overall comments on the model and any recommendations. References and appendix A (description of bayesian network) have been provided at the end of the document.

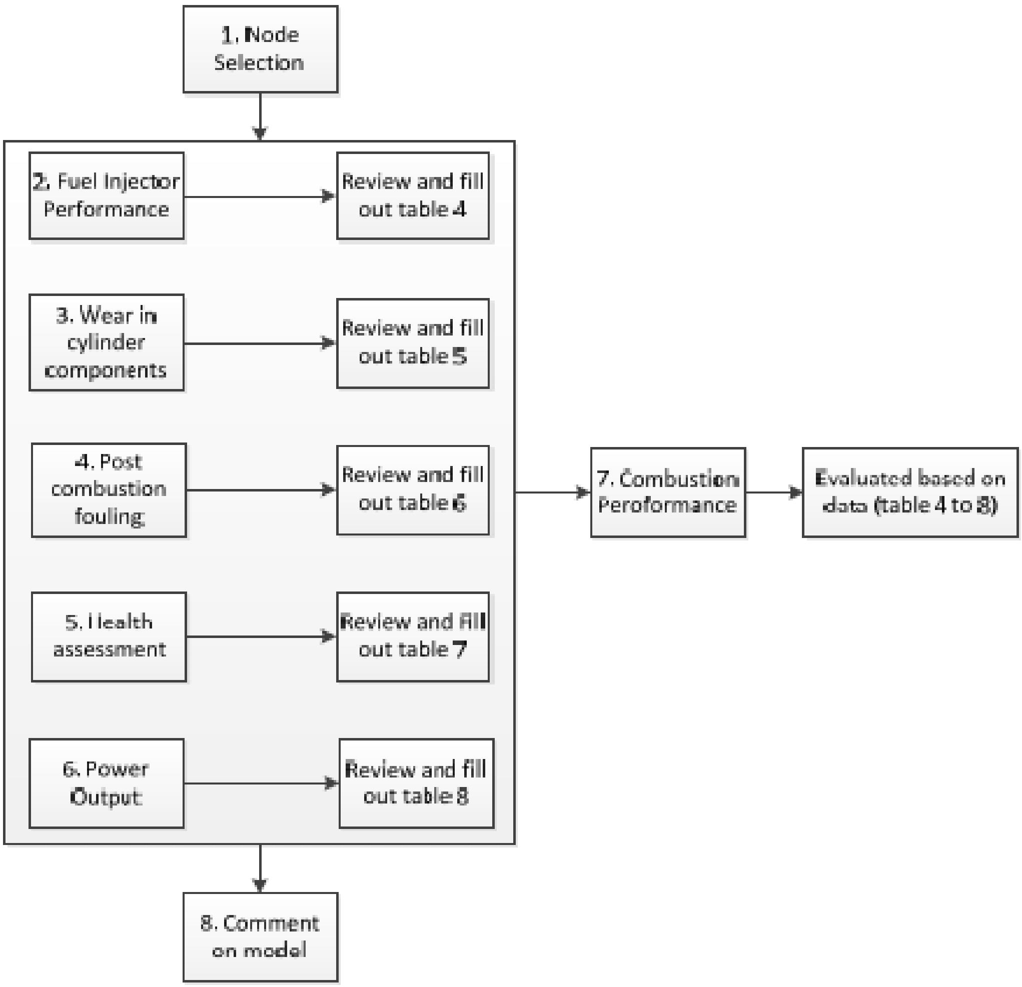

Figure 1: Questionnaire layout

1. Node selection

First step is the node selection for BN model. Figure 1 shows the DAG (Direct acyclic Graph) developed for this study showing inter-causal relationship between various engine parameters.

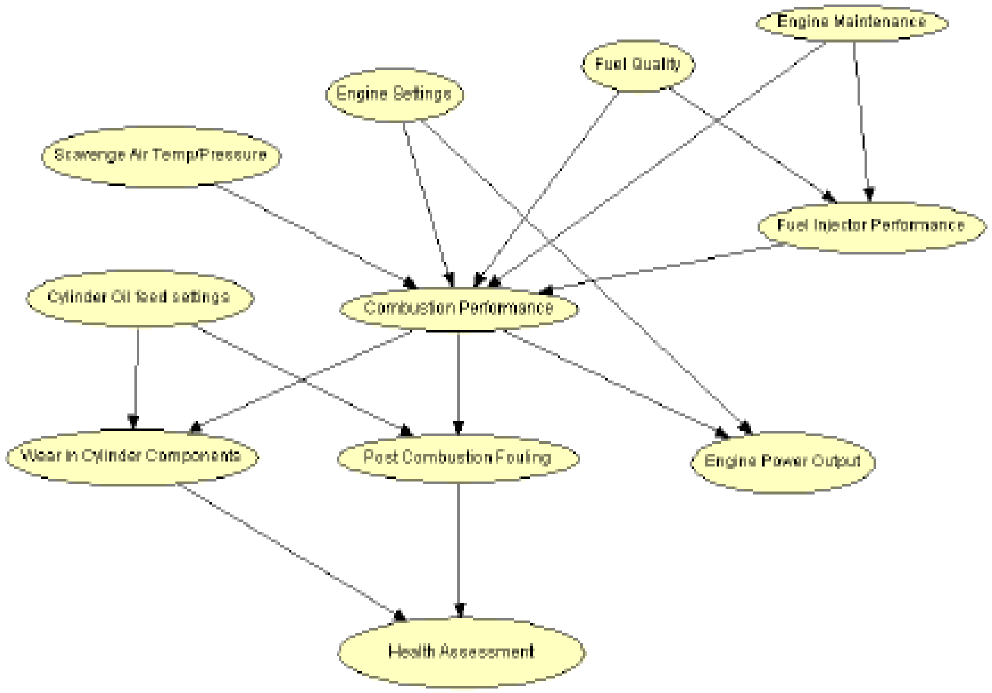

Figure 2: DAG for 2-stroke engine health assessment

Combustion is at the heart of how engine is performing. Parent nodes such as scavenge air temperature, engine settings, fuel quality and engine maintenance will be assigned unconditional probability to test the model however direct input from the engine operational parameters are substituted to provide probabilities as model inputs to check the engine performance. Each node needs to have a CPT (Conditional Probability Table) to show various conditional and unconditional dependencies. Factors such as fuel injector performance, combustion performance wear in cylinder components, and post combustion fouling are intermediate nodes whilst power output and health assessment are leaf nodes.

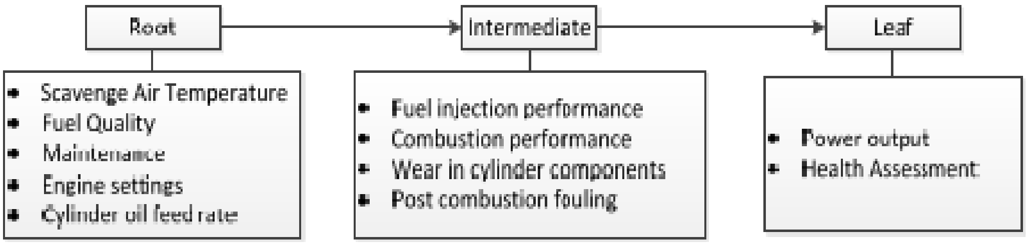

Figure 3: Node types

Further details of these nodes have been provided in following table;

Table 1: Root nodes and their description

	Node	State(s)	Child Node(s)	Brief Description
1	Scavenge Air Quality	(2) Satisfactory / Unsatisfactory	(1) Combustion Performance	Includes the pressure and temperature of scavenge air
2	Engine settings	(2) Optimal / non-optimal	(2) Combustion Performance / Engine Power Output	Dictated by various operational requirements, engine setting / level of deviations from norm
3	Fuel Quality	(2) Satisfactory / Unsatisfactory	(2) Fuel Injector performance / Combustion Performance	For the purpose of this study, use of heavy fuel oil (HFO) has been considered for use in the engine
4	Maintenance	(2) Poorly Maintained / Well Maintained	(2) Fuel Injector performance / Combustion Performance	How well the maintenance programme is run to keep up the machinery in working order
5	Cylinder oil feed rate	(2) Optimal / non-optimal	(2) Wear in Cylinder Component / post combustion fouling	Adjusted by HFO's sulphur content and BN of the lubricant in use, getting the right balance is not easy

Remaining 6 nodes are either intermediate or leaf nodes as described in table below.

Table 2: Intermediate and leaf nodes with brief description

	Nodes	State(s)	Parent Node(s)	Child Node(s)	Brief Description
6	Fuel Injector Performance	(2) Satisfactory / Unsatisfactory	(2) Fuel Quality / Engine Maintenance	(1) Combustion Performance	Critical in maintaining good atomisation and better fuel consumption
7	Combustion Performance	(2) Satisfactory / Unsatisfactory	(5) Nodes 1, 2, 3, 4 & 6 (as per serial number of list above)	(3) Engine Power Output / post Combustion Fouling / wear in cylinder components	Lynchpin of the engine health assessment
8	Wear in Cylinder Components	(2) Normal / Excessive	(2) Cylinder oil feed setting / combustion Performance	(1) Health Assessment	Qualitative assessment through parent nodes however further accuracy can be achieved by analysing CDO samples
9	Post Combustion Fouling	(2) Heavy / Nominal	(2) Combustion Performance / cylinder oil feed rate	(1) Health Assessment	Exhaust valves, manifold, turbocharger and exhaust uptake are affected. Heavy fouling may also cause sparking or uptake fire
10	Engine Power output	(2) Optimal / non-optimal	(2) Combustion Performance / engine settings	(0)	Well-tuned engine for clean burn will improve SFOC and power output
11	Health Assessment	(2) Satisfactory / Unsatisfactory	(2) Post Combustion Fouling / Wear in cylinder components	(0)	Engine health assessment followed by fault detection

2. Fuel Injector Performance

Some of the conditional probability values have been taken from the FOBAS database. For example, below table shows the relevant conditional probabilities for fuel injector performance.

Table 3: Fuel injector performance CPT

Engine Maintenance	Poorly Maintained		Well Maintained	
Fuel Quality	Satisfactory	Unsatisfactory	Satisfactory	Unsatisfactory
Satisfactory				0.70
Unsatisfactory				0.30

Fink et al, (2016) looked at the Internal Diesel Injector Deposit (IDID) issue and how it is linked with the quality of fuel in use with operating conditions. Moreover, analysis of FOBAS data[1] indicates that the quality of fuel has slightly more influence than the maintenance levels on functionality of fuel injectors which is reflected in the above table. Fuel quality parameters such as incorrect viscosity, high levels of abrasive elements and high sediments in the fuel at engine inlet can result poor fuel injector performance. In the last 5 years, approximately 70% of the reported issues on fuel injectors/pumps have been associated with the poor fuel quality with no outstanding maintenance. Here 30% of the cases were eliminated as having no direct or inconclusive evidence to relate the operational problem with the quality of the fuel after investigative fuel analysis. Nevertheless, few probabilities need to be assigned through expert judgment because there is lack of objective data.

In view of the above, please provide assessment and guiding values needed in the following tables.

Note: Total probability for a single if-then scenario should be equal to '1.0' as can be observed from the first row of the table below with the values of 0.7 and 0.3.

Table 4: CPT inference for Fuel injector performance

If	..and	Then
Engine is well maintained	Fuel quality is unsatisfactory	Fuel injector performance is poor (0.7) (As per above explanation) Fuel injector performance is good (0.3)
Engine is well maintained	Fuel quality is satisfactory	Fuel injector performance is poor ……. Fuel injector performance is good …….
Engine is poorly maintained	Fuel quality is unsatisfactory	Fuel injector performance is poor ……. Fuel injector performance is good …….
Engine is poorly maintained	Fuel quality is satisfactory	Fuel injector performance is poor ……. Fuel injector performance is good …….

[1] The data reliability depends on the accuracy of information reported by the ship staff under FOBAS fuel testing programme.

3. Wear in cylinder components:

Subarshan and Bhaduri (1983) classified the wear in the cylinder liners into two categories i.e. Physical mechanisms and chemical corrosion. Both mechanisms can be in action independently or at same time depending on the operational variables, design and maintenance of the engine. Furthermore, in specific, the types of corrosion which takes place in the large 2 stroke engine, wear can be divided into 3 main categories as described in figure below

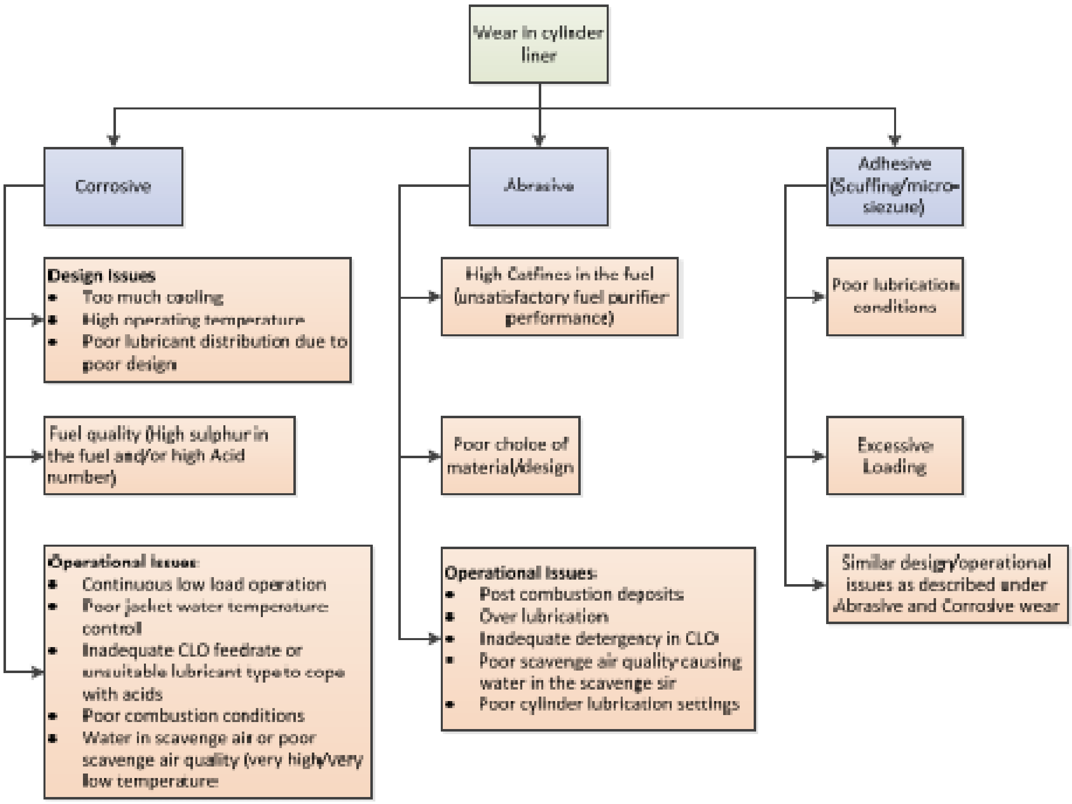

Figure 2: Types of wear within 2 stroke cylinder components

Abrasive wear is mainly associated with the catfines (abrasive elements of Aluminium + Silicon) particles which if larger than the thickness of oil film between piston rings and liner and in higher concentration[2] would have devastating consequences and could result in costly damage to the cylinder liner and pistons. Similarly, cold corrosion is an issue increasingly coming into focus which is the function of the base number of cylinder lubricant, scavenge air quality (temperature and pressure), and cylinder liner temperature. Rolsted et al, (2016) proposed ways to tackle the issue and one of which is by increasing the liner temperature through design change. Considering temperature control is mainly a function of engine

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[2] Most engine manufacturers recommend catfines concentration in the fuel should be less than 15 mg/kg at engine inlet. Although, recently engine manufacturers have started to ask the catfine concentration to be as low as practically possible.

design, addressed by the engine manufacturer, hence this has not been considered in this study.

FOBAS data indicates that for 80% of the cases dealt under FOBAS ENGINE programme, wear have been found to be excessive where both combustion is unsatisfactory with higher than required cylinder oil feed rate. That gives the belief of 0.8 as excessive wear under poor combustion with higher than required feed rate. Similarly, other probabilities need development.

Table 5: CPT inference for 'Wear in Cylinder Components'

If	..and	Then
Cylinder oil feed is non-optimal	Combustion is unsatisfactory	wear would be Normal (0.2) wear would be Excessive (0.8)
Cylinder oil feed is non-optimal	Combustion is satisfactory	wear would be Normal .... wear would be Excessive ....
Cylinder oil feed is optimal	Combustion is unsatisfactory	wear would be Normal .... wear would be Excessive ....
Cylinder oil feed is optimal	Combustion is satisfactory	wear would be Normal .... wear would be Excessive ....

4. Post Combustion Fouling:

Some fouling is inevitable especially during HFO consumption at main engine however situation exacerbates if poor combustion conditions exist with incorrect/excessive cylinder oil feed rate. The probabilities need to be assigned by the experts with extensive knowledge and experience of the marine engine operation on heavy fuel oil operation. The levels of fouling needs to be monitored and investigation should be made to determine the root cause. In case of heavy fouling, best practice approach such as frequent soot blowing and water washing is recommended.

Table 6: CPT inference for 'post combustion fouling'

If	..and	Then
Combustion Performance is unsatisfactory	Cylinder oil feed rate is non-optimal	Post combustion fouling would be heavy .... Post combustion fouling would be nominal ....
Combustion Performance is unsatisfactory	Cylinder oil feed rate is optimal	Post combustion fouling would be heavy .... Post combustion fouling would be nominal ....
Combustion Performance is satisfactory	Cylinder oil feed rate is non-optimal	Post combustion fouling would be heavy .... Post combustion fouling would be nominal ....
Combustion Performance is satisfactory	Cylinder oil feed rate is optimal	Post combustion fouling would be heavy .... Post combustion fouling would be nominal ....

5. Health assessment

Engine health measure is combined relationship of wear and fouling of cylinder components providing a quick indication to the engineers about the engine's operational performance.

Table 7: CPT inference for 'Health Assessment'

If	..and	Then
Post combustion fouling is heavy	Cylinder wear is normal	Engine health would be Satisfactory ……. Engine health would be unsatisfactory …….
Post combustion fouling is heavy	Cylinder wear is excessive	Engine health would be Satisfactory ……. Engine health would be unsatisfactory …….
Post combustion fouling is Nominal	Cylinder wear is normal	Engine health would be Satisfactory ……. Engine health would be unsatisfactory …….
Post combustion fouling is Nominal	Cylinder wear is excessive	Engine health would be Satisfactory ……. Engine health would be unsatisfactory …….

6. Power Output

Reasonable specific fuel oil consumption (SFOC) during engine operation would be indicative of high rate of energy conversion through efficient fuel combustion. 'Clean burn' is linked with optimum engine settings through VIT (Variable Ignition Timings) or FQS (Fuel Quality Settings) to suite variable ignition characteristics and operating conditions (Wartsila 2014).

Table 8: CPT inference for 'Engine Power output'

If	..and	Then
Combustion performance is unsatisfactory	Engine settings are optimal	Engine power output is optimal …… Engine power output is non-optimal ……
Combustion performance is unsatisfactory	Engine settings are non-optimal	Engine power output is optimal …… Engine power output is non-optimal ……
Combustion performance is satisfactory	Engine settings are optimal	Engine power output is optimal …… Engine power output is non-optimal ……
Combustion performance is satisfactory	Engine settings are non-optimal	Engine power output is optimal …… Engine power output is non-optimal ……

7. Combustion performance

Combustion performance is by far the most complex probability table in view of the various parent nodes of parameters affecting the combustion within the engine. CPTs for the combustion performance will be developed based on the cumulative impact of above CPTs and the available data from other sources.

8. Any other comments

Please provide any comments you may have on the DAG (figure 1) and overall assessment of the model.

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Appendix C – Conditional probability table for combustion performance (CP)

	Fuel quality	Scavenge air quality	Fuel injector performance	Engine settings	Engine maintenance	CP unsatisfactory	CP satisfactory
1	FS (0.3)	AS (0.25)	IP (-0.15)	SO (0.2)	MP (-0.1)	0.27	0.73
2	FS (0.3)	AU (-0.25)	IP (-0.15)	SO (0.2)	MP (-0.1)	0.51	0.49
3	FS (0.3)	AS (0.25)	IP (-0.15)	SN (-0.2)	MP (-0.1)	0.43	0.57
4	FS (0.3)	AU (-0.25)	IP (-0.15)	SN (-0.2)	MP (-0.1)	0.67	0.33
5	FS (0.3)	AS (0.25)	IG (0.15)	SO (0.2)	MP (-0.1)	0.07	0.93
6	FS (0.3)	AU (-0.25)	IG (0.15)	SO (0.2)	MP (-0.1)	0.31	0.69
7	FS (0.3)	AS (0.25)	IG (0.15)	SN (-0.2)	MP (-0.1)	0.23	0.77
8	FS (0.3)	AU (-0.25)	IG (0.15)	SN (-0.2)	MP (-0.1)	0.47	0.53
9	FU (-0.3)	AS (0.25)	IP (-0.15)	SO (0.2)	MP (-0.1)	0.6	0.4
10	FU (-0.3)	AU (-0.25)	IP (-0.15)	SO (0.2)	MP (-0.1)	0.84	0.16
11	FU (-0.3)	AS (0.25)	IP (-0.15)	SN (-0.2)	MP (-0.1)	0.76	0.24
12	FU (-0.3)	AU (-0.25)	IP (-0.15)	SN (-0.2)	MP (-0.1)	1	0
13	FU (-0.3)	AS (0.25)	IG (0.15)	SO (0.2)	MP (-0.1)	0.4	0.6
14	FU (-0.3)	AU (-0.25)	IG (0.15)	SO (0.2)	MP (-0.1)	0.64	0.36
15	FU (-0.3)	AS (0.25)	IG (0.15)	SN (-0.2)	MP (-0.1)	0.56	0.44
16	FU (-0.3)	AU (-0.25)	IG (0.15)	SN (-0.2)	MP (-0.1)	0.8	0.2
17	FS (0.3)	AS (0.25)	IP (-0.15)	SO (0.2)	MW (0.1)	0.2	0.8
18	FS (0.3)	AU (-0.25)	IP (-0.15)	SO (0.2)	MW (0.1)	0.44	0.56
19	FS (0.3)	AS (0.25)	IP (-0.15)	SN (-0.2)	MW (0.1)	0.36	0.64
20	FS (0.3)	AU (-0.25)	IP (-0.15)	SN (-0.2)	MW (0.1)	0.6	0.4
21	FS (0.3)	AS (0.25)	IG (0.15)	SO (0.2)	MW (0.1)	0	1
22	FS (0.3)	AU (-0.25)	IG (0.15)	SO (0.2)	MW (0.1)	0.24	0.76
23	FS (0.3)	AS (0.25)	IG (0.15)	SN (-0.2)	MW (0.1)	0.16	0.84
24	FS (0.3)	AU (-0.25)	IG (0.15)	SN (-0.2)	MW (0.1)	0.4	0.6
25	FU (-0.3)	AS (0.25)	IP (-0.15)	SO (0.2)	MW (0.1)	0.53	0.47
26	FU (-0.3)	AU (-0.25)	IP (-0.15)	SO (0.2)	MW (0.1)	0.77	0.23
27	FU (-0.3)	AS (0.25)	IP (-0.15)	SN (-0.2)	MW (0.1)	0.69	0.31
28	FU (-0.3)	AU (-0.25)	IP (-0.15)	SN (-0.2)	MW (0.1)	0.93	0.07
29	FU (-0.3)	AS (0.25)	IG (0.15)	SO (0.2)	MW (0.1)	0.33	0.67
30	FU (-0.3)	AU (-0.25)	IG (0.15)	SO (0.2)	MW (0.1)	0.57	0.43
31	FU (-0.3)	AS (0.25)	IG (0.15)	SN (-0.2)	MW (0.1)	0.49	0.51
32	FU (-0.3)	AU (-0.25)	IG (0.15)	SN (-0.2)	MW (0.1)	0.73	0.27

Appendix D – Fuzzy outputs (for engine settings, maintenance, and cylinder oil feed rate for cylinders 2~6 as per section 4.5)

Cylinder_2

Main parameters	Sub parameters	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Engine settings	$P_{max} – P_{comp}$ (Bar)	1	0	-	0.9	0.1
	Exhaust temperature (ºC) (Mean value = 371)	-	0.9	0.1		
	MIP (Bar) (Mean value = 14.8)	-	1	0		
Engine Maintenance	Availability	-	0.8	0.2	0.70	0.30
	Work-orders	-	0.71	0.29		
Cylinder Oil feed rate	Fe (mg/kg)	-	0.66	0.34	0.57	0.43
	BN (mg KOH/g)	0.47	0.53	-		

Cylinder_3

Main parameters	Sub parameters	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Engine settings	$P_{max} – P_{comp}$ (Bar)	1	0	-	1	0
	Exhaust temperature (ºC) (Mean value = 371)	-	1	0		
	MIP (Bar) (Mean value = 14.8)	-	1	0		
Engine Maintenance	Availability	-	0.8	0.2	0.70	0.30
	Work-orders	-	0.71	0.29		

Cylinder Oil feed rate	Fe (mg/kg)	-	0.66	0.34	0.71	0.29
	BN (mg KOH/g)	0.47	0.53	-		

Cylinder_4

Main parameters	Sub parameters	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Engine settings	$P_{max} - P_{comp}$ (Bar)	1	0	-	1	0
	Exhaust temperature (°C) (Mean value = 371)	-	1	0		
	MIP (Bar) (Mean value = 14.8)	-	1	0		
Engine Maintenance	Availability	-	0.8	0.2	0.70	0.30
	Work-orders	-	0.71	0.29		
Cylinder Oil feed rate	Fe (mg/kg)	-	0.66	0.34	0.0	1.0
	BN (mg KOH/g)	0.47	0.53	-		

Cylinder_5

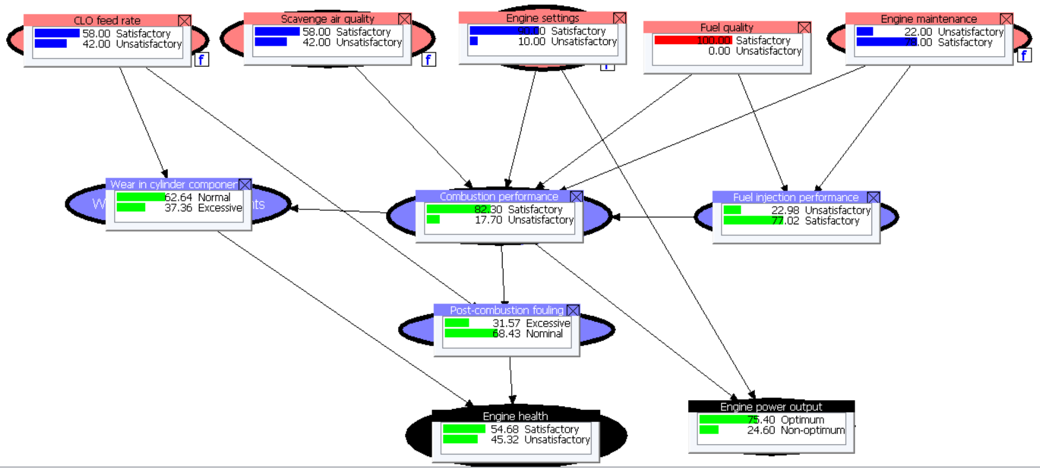
Main parameters	Sub parameters	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Engine settings	$P_{max} - P_{comp}$ (Bar)	1	0	-	1	0
	Exhaust temperature (ºC) (Mean value = 371)	-	1	0		
	MIP (Bar) (Mean value = 14.8)	-	1	0		
Engine Maintenance	Availability	-	0.8	0.2	0.70	0.30
	Work-orders	-	0.71	0.29		
Cylinder Oil feed rate	Fe (mg/kg)	-	0.66	0.34	0.39	0.61
	BN (mg KOH/g)	0.47	0.53	-		

Cylinder_6

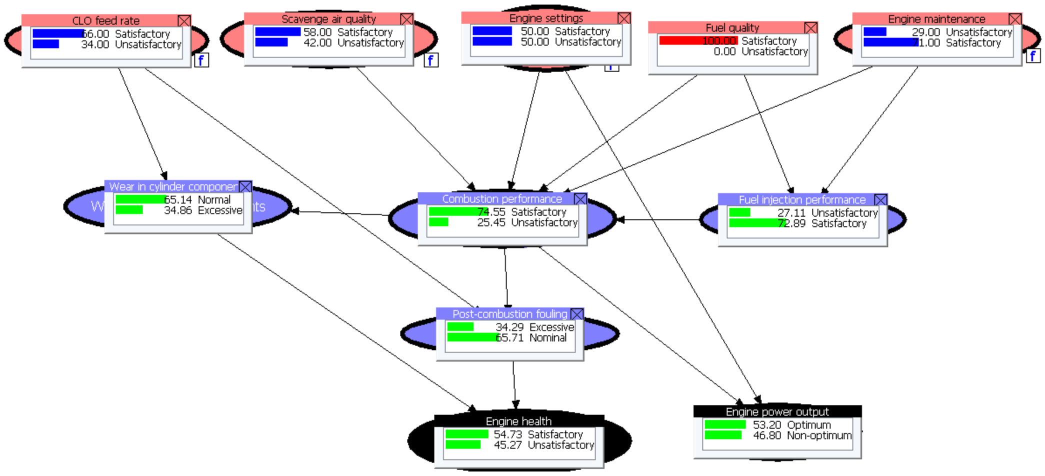
Main parameters	Sub parameters	States (IF part)			States (THEN part)	
		Low	Satisfactory	High OR Unsatisfactory	Satisfactory	Unsatisfactory
Engine settings	$P_{max} - P_{comp}$ (Bar)	1	0	-	1	0
	Exhaust temperature (ºC) (Mean value = 371)	-	1	0		
	MIP (Bar) (Mean value = 14.8)	-	1	0		
Engine Maintenance	Availability	-	0.8	0.2	0.70	0.30
	Work-orders	-	0.71	0.29		
Cylinder Oil feed rate	Fe (mg/kg)	-	0.66	0.34	0.41	0.59
	BN (mg KOH/g)	0.47	0.53	-		

Appendix E – BN model outputs for cylinders 2~6 (Chapter 4)

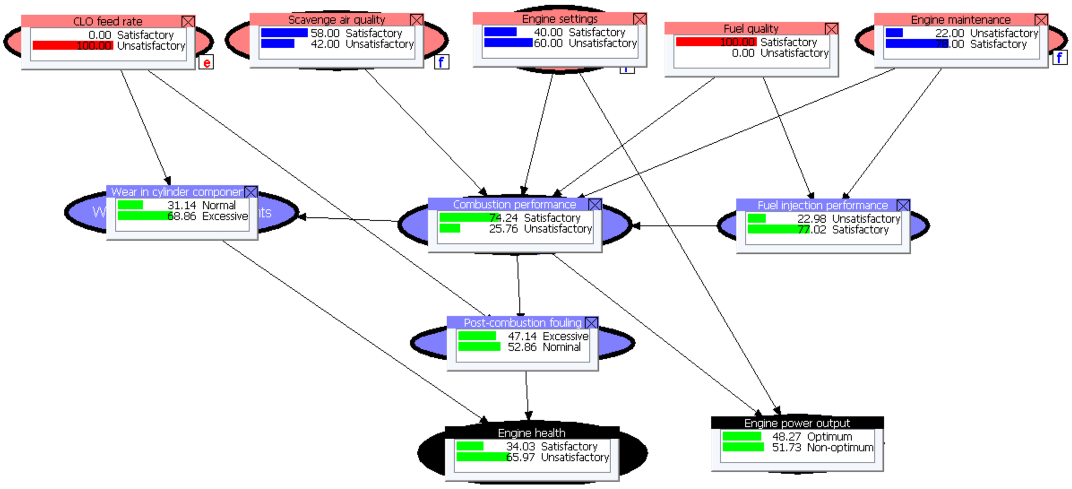
Cylinder_2:



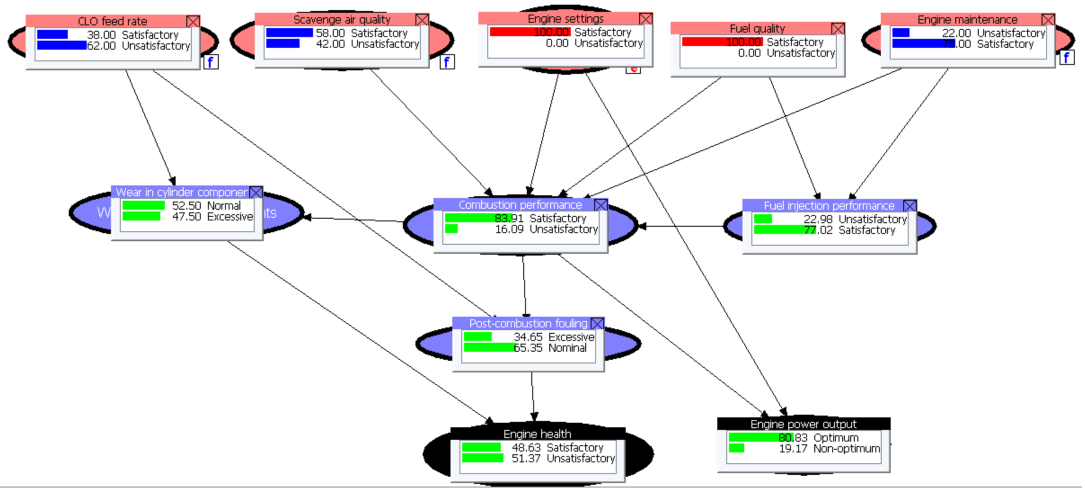
Cylinder_3:



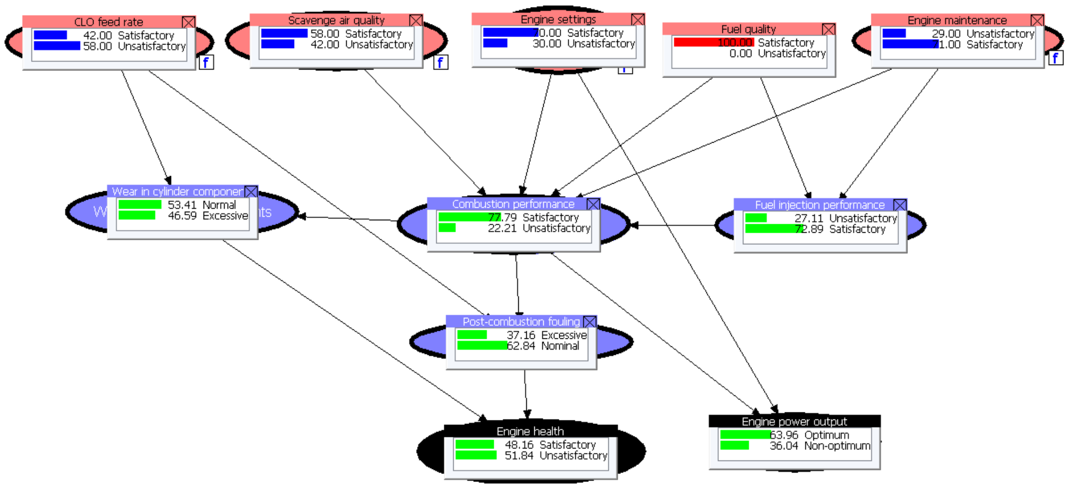
Cylinder_4:



Cylinder_5:



Cylinder_6:



Appendix F – Modified fuzzy rule-base for parameters

Fuel quality

IF (ω)					THEN (Fuel quality)	
Catalyst fines (0.3093)	Water (0.1849)	Ash (0.1158)	CCAI (0.1606)	Viscosity (0.2294)	Satisfactory	Unsatisfactory
High	High	High	High	High	0	1
High	High	High	High	Acceptable	0.2294	0.7706
High	High	High	High	Low	0	1
High	High	High	Acceptable	High	0.1606	0.8394
High	High	High	Acceptable	Acceptable	0.39	0.61
High	High	High	Acceptable	Low	0.1606	0.8394
High	High	Acceptable	High	High	0.1158	0.8842
High	High	Acceptable	High	Acceptable	0.3452	0.6548
High	High	Acceptable	High	Low	0.1158	0.8842
High	High	Acceptable	Acceptable	High	0.2764	0.7236
High	High	Acceptable	Acceptable	Acceptable	0.5058	0.4942
High	High	Acceptable	Acceptable	Low	0.2764	0.7236
High	Acceptable	High	High	High	0.1849	0.8151
High	Acceptable	High	High	Acceptable	0.4143	0.5857
High	Acceptable	High	High	Low	0.1849	0.8151
High	Acceptable	High	Acceptable	High	0.3455	0.6545
High	Acceptable	High	Acceptable	Acceptable	0.5749	0.4251
High	Acceptable	High	Acceptable	Low	0.3455	0.6545
High	Acceptable	Acceptable	High	High	0.3007	0.6993
High	Acceptable	Acceptable	High	Acceptable	0.5301	0.4699
High	Acceptable	Acceptable	High	Low	0.3007	0.6993
High	Acceptable	Acceptable	Acceptable	High	0.4613	0.5387
High	Acceptable	Acceptable	Acceptable	Acceptable	0.6907	0.3093
High	Acceptable	Acceptable	Acceptable	Low	0.4613	0.5387
Acceptable	High	High	High	High	0.3093	0.6907
Acceptable	High	High	High	Acceptable	0.5387	0.4613
Acceptable	High	High	High	Low	0.3093	0.6907
Acceptable	High	High	Acceptable	High	0.4699	0.5301
Acceptable	High	High	Acceptable	Acceptable	0.6993	0.3007

Acceptable	High	High	Acceptable	Low	0.4699	0.5301
Acceptable	High	Acceptable	High	High	0.4251	0.5749
Acceptable	High	Acceptable	High	Acceptable	0.6545	0.3455
Acceptable	High	Acceptable	High	Low	0.4251	0.5749
Acceptable	High	Acceptable	Acceptable	High	0.5857	0.4143
Acceptable	High	Acceptable	Acceptable	Acceptable	0.8151	0.1849
Acceptable	High	Acceptable	Acceptable	Low	0.5857	0.4143
Acceptable	Acceptable	High	High	High	0.4942	0.5058
Acceptable	Acceptable	High	High	Acceptable	0.7236	0.2764
Acceptable	Acceptable	High	High	Low	0.4942	0.5058
Acceptable	Acceptable	High	Acceptable	High	0.6548	0.3452
Acceptable	Acceptable	High	Acceptable	Acceptable	0.8842	0.1158
Acceptable	Acceptable	High	Acceptable	Low	0.6548	0.3452
Acceptable	Acceptable	Acceptable	High	High	0.61	0.39
Acceptable	Acceptable	Acceptable	High	Acceptable	0.8394	0.1606
Acceptable	Acceptable	Acceptable	High	Low	0.61	0.39
Acceptable	Acceptable	Acceptable	Acceptable	High	0.7706	0.2294
Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	1	0
Acceptable	Acceptable	Acceptable	Acceptable	Low	0.7706	0.2294

Maintenance

IF (ω)		THEN (Maintenance)	
Work orders (0.4507)	Availability (0.5493)	Satisfactory	Unsatisfactory
Complete	Acceptable	1	0
Complete	Unacceptable	0.4507	0.5493
Incomplete	Acceptable	0.5493	0.4507
Incomplete	Unacceptable	0	1

Engine settings

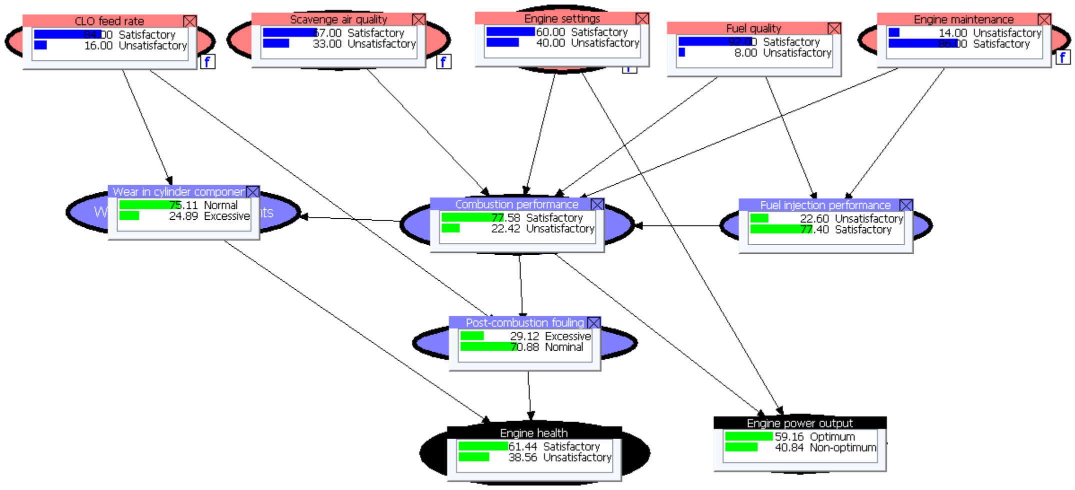
IF (ω)			THEN (Engine settings)	
P_{max} - P_{comp} (0.3953)	MIP Dev (0.3041)	Exhaust Dev (0.3006)	Satisfactory	Unsatisfactory
High	Unsatisfactory	Unsatisfactory	0	1
High	Unsatisfactory	Satisfactory	0.3006	0.6994
High	Satisfactory	Unsatisfactory	0.3041	0.6959
High	Satisfactory	Satisfactory	0.6047	0.3953
Acceptable	Unsatisfactory	Unsatisfactory	0.3953	0.6047
Acceptable	Unsatisfactory	Satisfactory	0.6959	0.3041
Acceptable	Satisfactory	Unsatisfactory	0.699	0.3006
Acceptable	Satisfactory	Satisfactory	1.0000	0
Low	Unsatisfactory	Unsatisfactory	0.6047	0.3953
Low	Unsatisfactory	Satisfactory	0.3006	0.6994
Low	Satisfactory	Unsatisfactory	0.3041	0.6959
Low	Satisfactory	Satisfactory	0.6047	0.3953

Cylinder oil feed rate

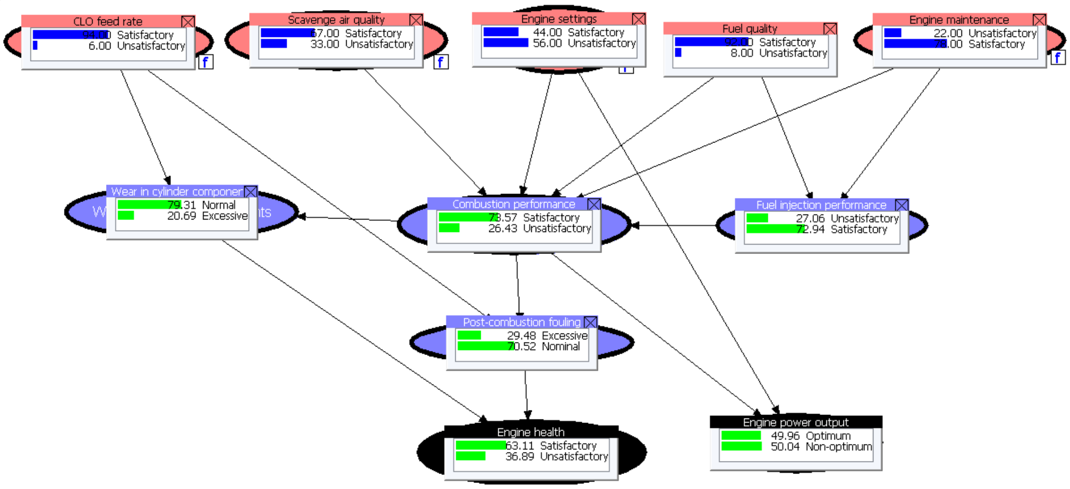
IF (ω)		Then (Cylinder oil feed rate)	
Fe (0.4344)	TBN (0.5665)	optimal	non-optimal
Satisfactory	low	0.4344	0.5656
Satisfactory	Satisfactory	1	0
Satisfactory	high	0.4344	0.5656
high	low	0	1
high	Satisfactory	0.5656	0.4344
high	high	0	1

Appendix G – BN model outputs (based on fuzzy ER inference) for cylinders 2~6

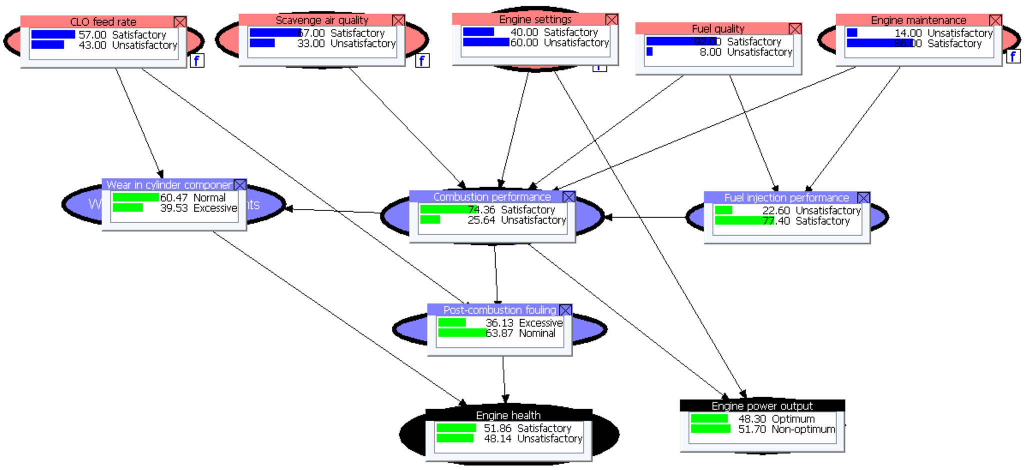
Cylinder 2



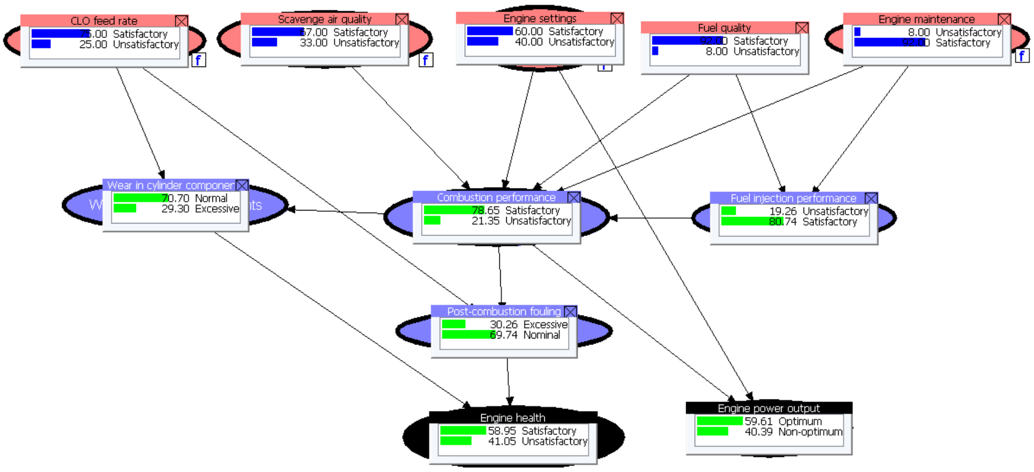
Cylinder 3



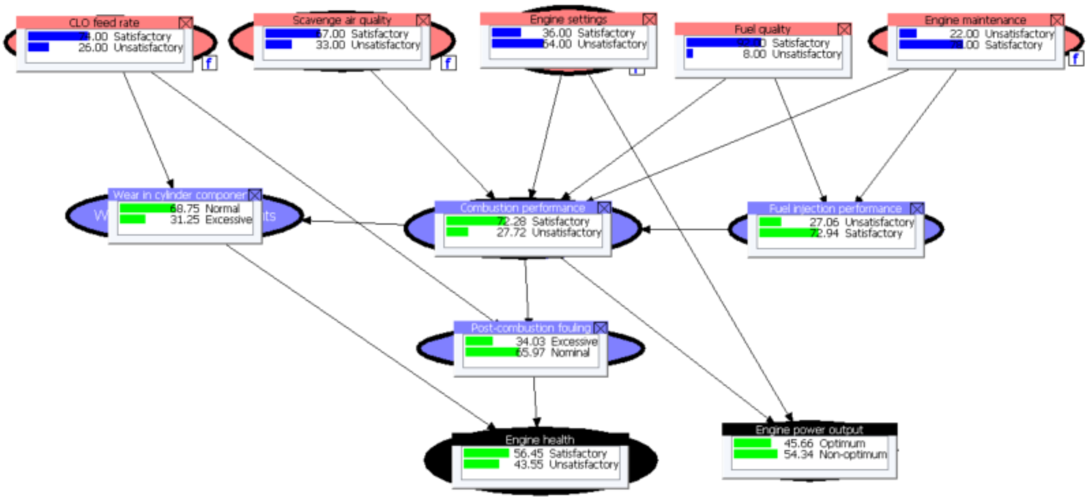
Cylinder 4



Cylinder 5

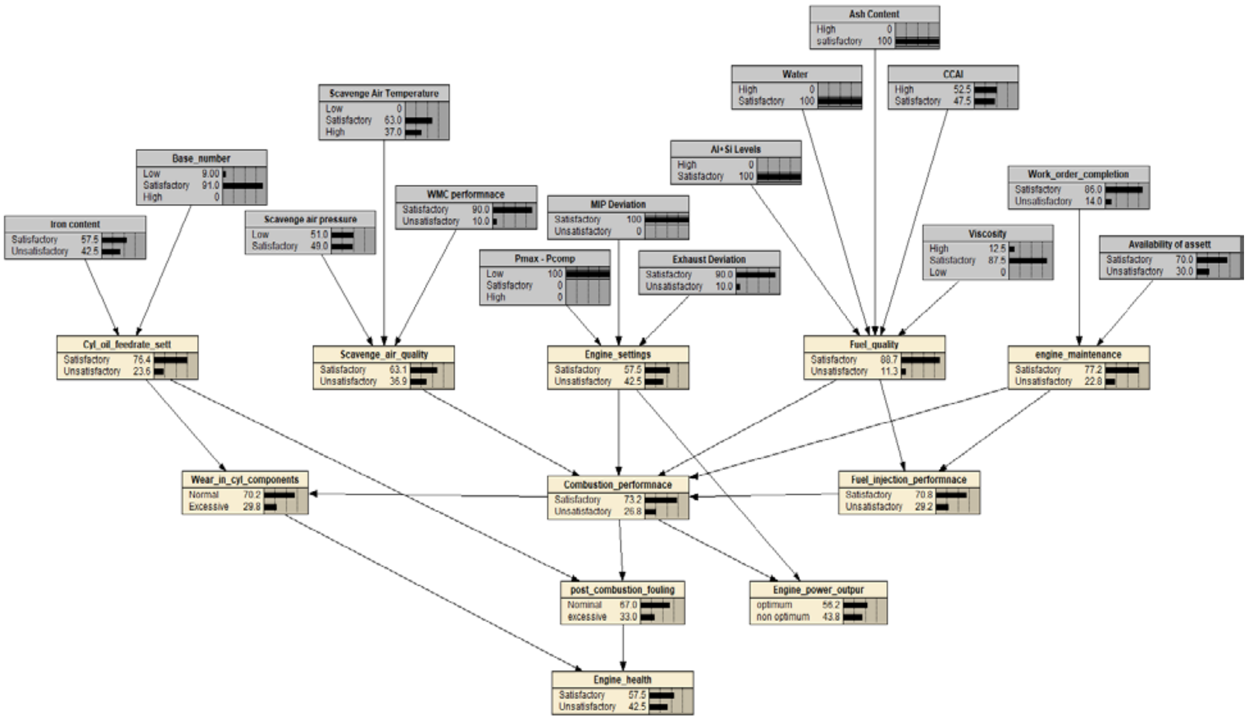


Cylinder 6

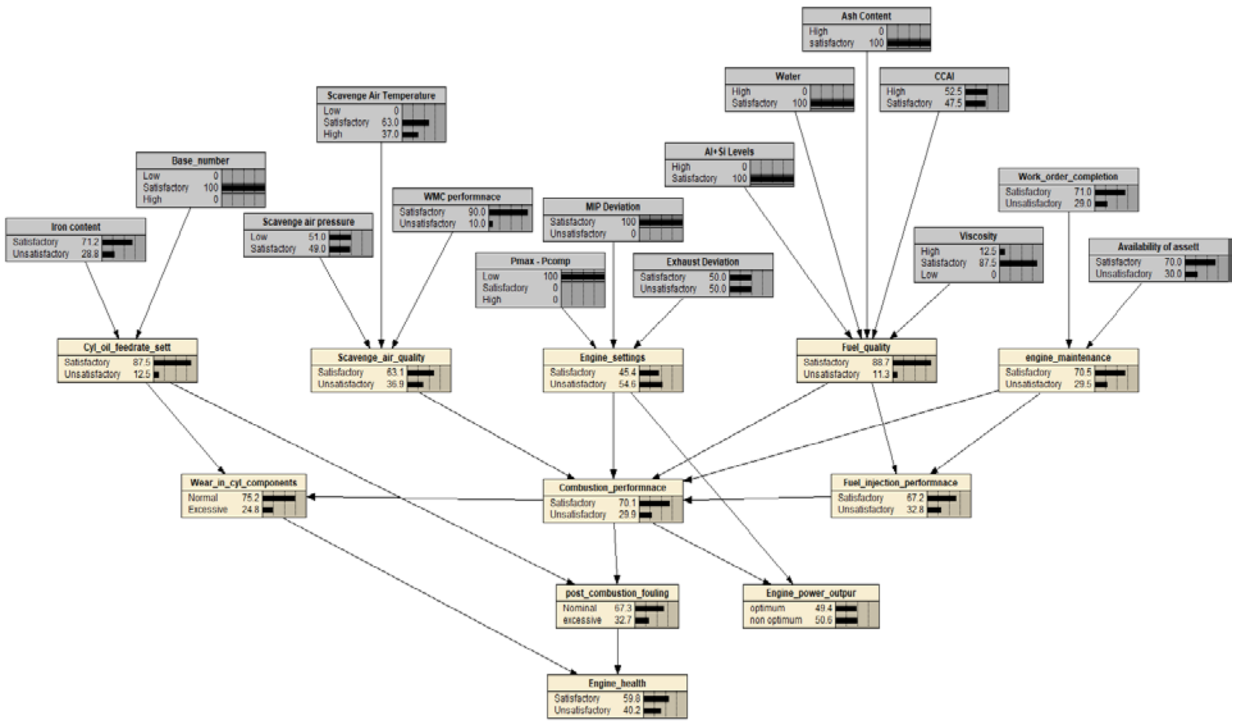


Appendix H – Expanded BN DAGs for cylinders 2~6

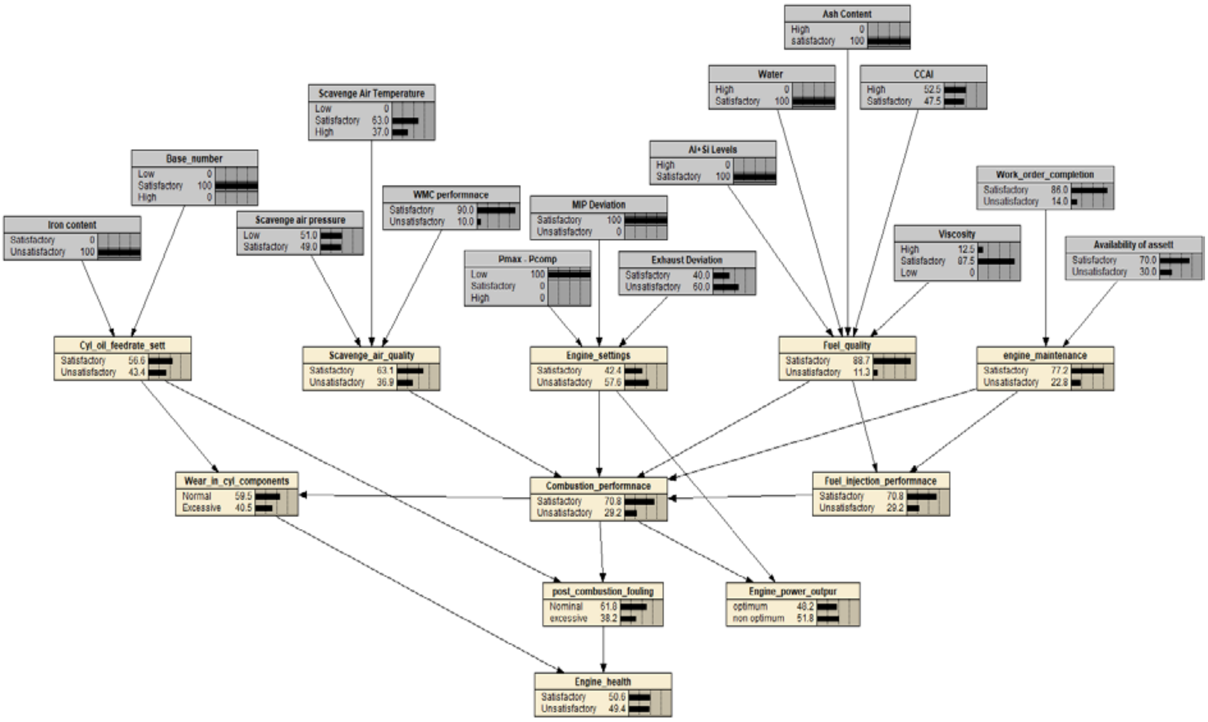
Cylinder 2



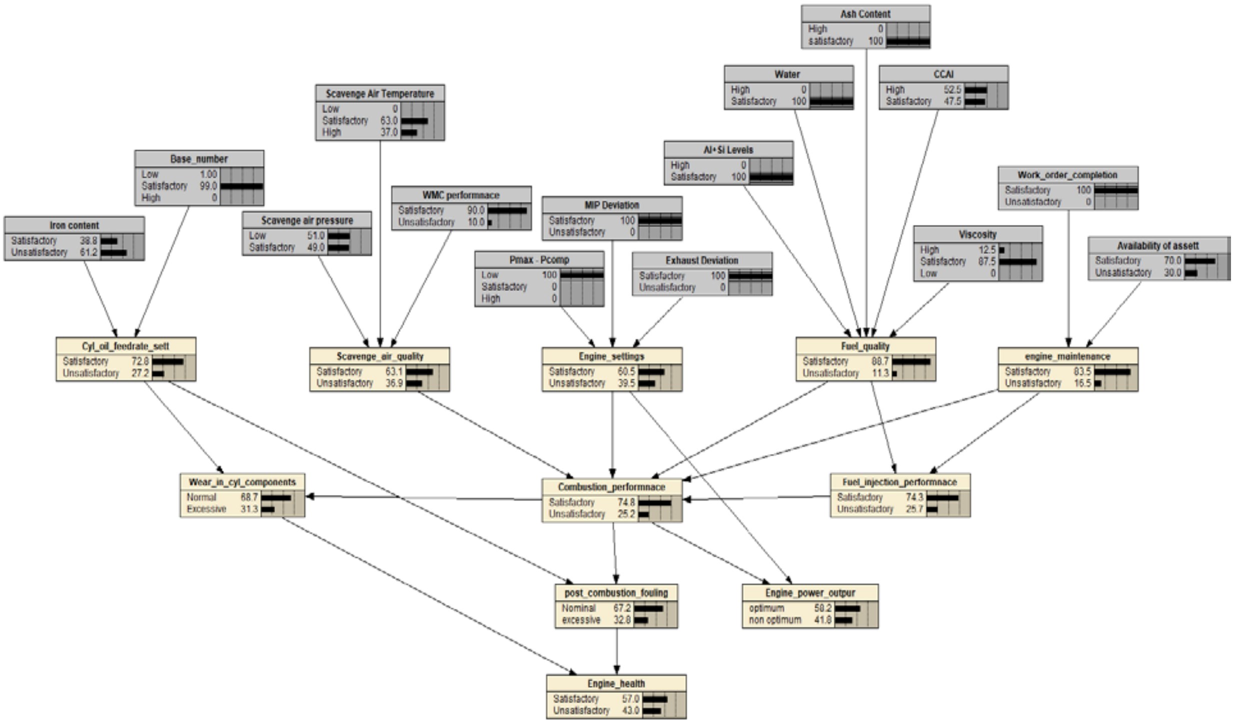
Cylinder 3



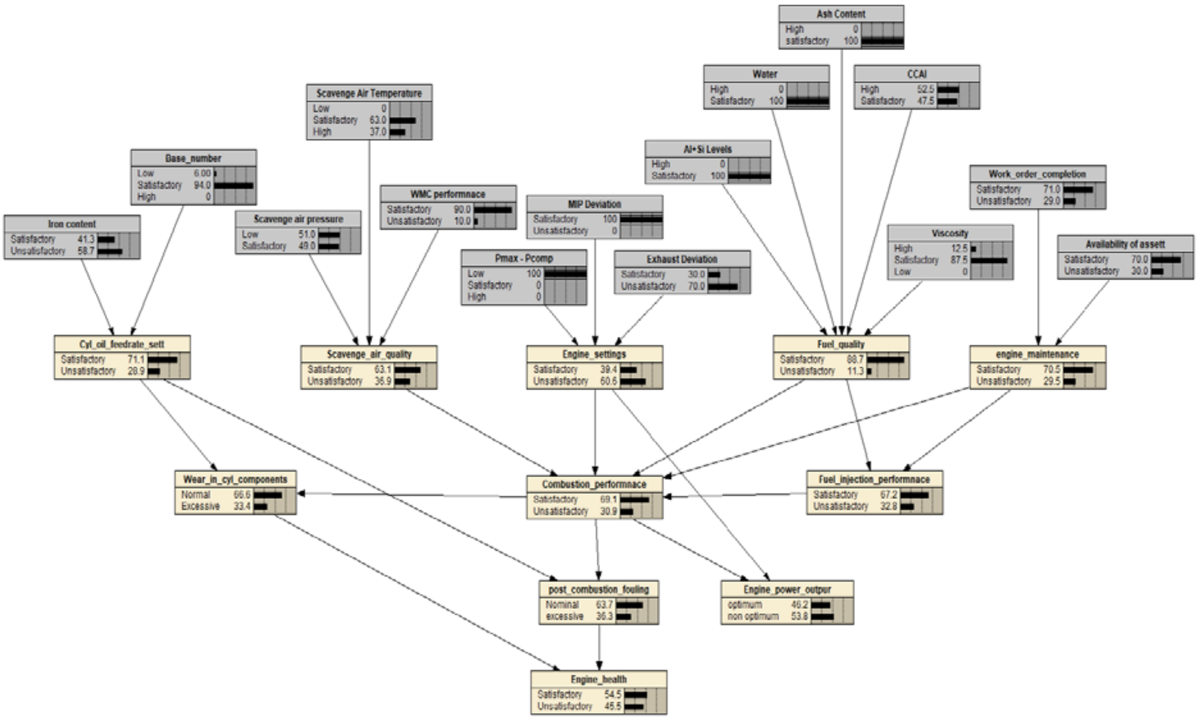
Cylinder 4



Cylinder 5



Cylinder 6



Ash Content
High 0
satisfactory 100
Water
High 0
Satisfactory 100
CCAI
High 52.5
Satisfactory 47.5
Scavenge Air Temperature
Low 0
Satisfactory 63.0
High 37.0
Al+Si Levels
High 0
Satisfactory 100
Base_number
Low 6.00
Satisfactory 94.0
High 0
WMC performnace
Satisfactory 90.0
Unsatisfactory 10.0
MIP Deviation
Satisfactory 100
Unsatisfactory 0
Work_order_completion
Satisfactory 71.0
Unsatisfactory 29.0
Iron content
Satisfactory 41.3
Unsatisfactory 58.7
Scavenge air pressure
Low 51.0
Satisfactory 49.0
Viscosity
High 12.5
Satisfactory 87.5
Low 0
Availability of assett
Satisfactory 70.0
Unsatisfactory 30.0
Pmax - Pcomp
Low 100
Satisfactory 0
High 0
Exhaust Deviation
Satisfactory 30.0
Unsatisfactory 70.0
Cyl_oil_feedrate_sett
Satisfactory 71.1
Unsatisfactory 28.9
Scavenge_air_quality
Satisfactory 63.1
Unsatisfactory 36.9
Engine_settings
Satisfactory 39.4
Unsatisfactory 60.6
Fuel_quality
Satisfactory 88.7
Unsatisfactory 11.3
engine_maintenance
Satisfactory 70.5
Unsatisfactory 29.5
Wear_in_cyl_components
Normal 66.6
Excessive 33.4
Combustion_performnace
Satisfactory 69.1
Unsatisfactory 30.9
Fuel_injection_performnace
Satisfactory 67.2
Unsatisfactory 32.8
post_combustion_fouling
Nominal 63.7
excessive 36.3
Engine_power_outpur
optimum 46.2
non optimum 53.8
Engine_health
Satisfactory 54.5
Unsatisfactory 45.5

Appendix I – TPTs for parent nodes

Exhaust temperature deviation (λ = 3.37%)

‘t’	‘t+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.967	0.033
Satisfactory	0.033	0.967

Viscosity at engine inlet (λ = 3.91%)

‘t’	‘t+1		
	Low	Satisfactory	high
Low	0.962	0.038	0
Satisfactory	0.019	0.962	0.019
High	0	0.038	0.962

Fe content of cylinder drain (λ = 0.41%)

‘t’	‘t+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.996	0.004
Satisfactory	0.004	0.996

TBN of cylinder drain oil (λ = 1.04%)

‘t’	‘t+1		
	Low	Satisfactory	high
Low	0.99	0.01	0
Satisfactory	0.005	0.99	0.005
High	0	0.01	0.99

WMC performance (λ = 4.31%)

't'	't+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.958	0.041
Satisfactory	0.041	0.958

$P_{max} - P_{comp}$ (λ = 2.45%)

't'	't+1		
	Low	Satisfactory	high
Low	0.976	0.024	0
Satisfactory	0.012	0.976	0.012
High	0	0.024	0.976

MIP deviation (λ = 2.59%)

't'	't+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	0.974	0.025
Satisfactory	0.025	0.974

Catalyst fines levels in fuel (λ = 2.30%)

't'	't+1	
	High	Satisfactory
High	0.977	0.022
Satisfactory	0.022	0.977

Water in fuel (λ = 0.76%)

't'	't+1	
	High	Satisfactory
High	0.992	0.008
Satisfactory	0.008	0.992

Ash content (λ = 0%)

't'	't+1	
	High	Satisfactory
High	1	0
Satisfactory	0	1

CCAI (λ = 0%)

't'	't+1	
	High	Satisfactory
High	1	0
Satisfactory	0	1

Work order completion (λ = 0%)

't'	't+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	1	0
Satisfactory	0	1

Availability of asset (λ = 0%)

't'	't+1	
	Unsatisfactory	Satisfactory
Unsatisfactory	1	0
Satisfactory	0	1