University of Strathclyde

Department of Naval Architecture, Ocean and Marine Engineering

# Combination of Reliability Tools and Artificial Intelligence in a Hybrid Condition Monitoring Framework for Ship Machinery Systems

**by**

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

Doctor of Philosophy

Glasgow, UK

**2018**

Declaration of Authenticity and Author's Rights

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



Signed: 

Date: 09/07/2018

# Acknowledgements

I would like to express my sincere gratitude and appreciation to Dr. Iraklis Lazakis for supervising and funding this research study. Special thanks must be directed to INCASS EU FP7 project and Danaos Shipping Co Ltd. for organising and supporting the data acquisition process of this study. Windforce Maritime Enterprises Inc. is also gratefully acknowledged for their technical feedback and constructive discussions. I would like to thank Dr. Victoria Catterson from the University of Strathclyde as well for her valuable input regarding neural networks. Special thanks also go to all my colleagues and friends for their suggestions, inspiration and support. Finally, I would like to thank my family, Thomas, Kathleen, Lisa and my partner Eirini for their continuous support and encouragement throughout my study. I could not have completed this thesis without their support.

# Research Outputs

The following research outputs have been published as part of this research work.

### Journal publications

Raptodimos, Y. & Lazakis, I. 2018. Using artificial neural network-self-organising map for data clustering of marine engine condition monitoring applications. *Ships and Offshore Structures*, 13, 649-656

Lazakis, I., Raptodimos, Y. & Varelas, T. 2018. Predicting ship machinery system condition through analytical reliability tools and artificial neural networks. *Ocean Engineering*, 152, 404-415

Raptodimos, Y. & Lazakis, I. 2018. Application of NARX neural network for predicting marine engine performance parameters. *Ships and Offshore Structures,* (Submitted-Under review)

### Book chapter

Raptodimos, Y. & Lazakis, I. 2017. Fault tree analysis and artificial neural network modelling for establishing a predictive ship machinery maintenance methodology. *Operations Research & Information Science in e-Maritime (ORISMA).* Danaos Management Consultants SA, Piraeus, Greece

### Conference publications

Raptodimos, Y. & Lazakis, I. 2018. Implementing unsupervised learning algorithm for marine engine data clustering applications. *International Conference on Smart Ship Technology*. Royal Institution of Naval Architects, 23-24 January, London, United Kingdom

Raptodimos, Y. & Lazakis, I. 2017. Fault tree analysis and artificial neural network modelling for establishing a predictive ship machinery maintenance methodology. *International Conference on Smart Ship Technology*. Royal Institution of Naval Architects, 24-25 January, London, United Kingdom

Raptodimos, Y. & Lazakis, I. 2016. An artificial neural network approach for predicting the performance of ship machinery. *International Conference on Maritime Safety and Operations*. 13-14 October, Glasgow, United Kingdom

Dikis, K., Lazakis, I., Michala, A.L, Raptodimos, Y. & Theotokatos, G. 2016. Dynamic risk and reliability assessment for ship machinery decision making. *European Safety and Reliability Conference*. 25-29 September, Glasgow, United Kingdom

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# Table of Contents

## List of Figures

# List of Tables

# Nomenclature

| | |
|---|---|
| ABS | American Bureau of Shipping |
| AHP | Analytic Hierarchy Process |
| AI | Artificial Intelligence |
| AIC | Akaike Information Criterion |
| AICC | Akaike Information Criterion with a Correction |
| AM | Asset Management |
| ANN | Artificial Neural Network |
| APE | Absolute Percentage Error |
| ART | Adaptive Resonance Theory |
| B/C | Benefit/Cost Ratio |
| BBN | Bayesian Belief Networks |
| BDC | Bottom Dead Centre |
| BCM | Business Centred Maintenance |
| BIC | Bayesian Information Criterion |
| BS | British Standard |
| CapEx | Capital Expenditure |
| CBA | Cost-Benefit Analysis |
| CBM | Condition Based Maintenance |
| CFW | Cooling Fresh Water |
| CMMS | Computerised Maintenance Management System |
| CW | Cooling Water |
| DNV | Det Norske Veritas |
| FFNN | Feed-Forward Neural Network |
| FMEA | Failure Modes and Effects Analysis |
| FMECA | Failure Modes Effects and Criticality Analysis |
| FO | Fuel Oil |
| FPSO | Floating Production Storage and Offloading |
| FR | Failure Rate |
| FRACAS | Failure Reporting, Analysis and Corrective Action System |
| FSA | Formal Safety Assessment |
| FT | Fault Tree |
| FTA | Fault Tree Analysis |
| GDP | Gross Domestic Product |
| GT | Gross Tonnage |
| IACS | International Association of Classification Societies |
| ILS | Integrated Logistic Support |
| IMO | International Maritime Organisation |
| IMs | Importance Measures |
| INCASS | Inspection Capabilities for Enhanced Ship Safety |
| ISM | International Safety Management |

| | |
|---|---|
| ISO | International Standards Organisation |
| IUMI | International Union of Marine Insurance |
| JCFW | Jacket Cooling Fresh Water |
| LO | Lubrication Oil |
| LSA | Logistic Support Analysis |
| LSTM | Long-Short Term Memory |
| MAPE | Mean Absolute Percentage Error |
| MAT | Maintenance Assistant Tool |
| MCI | Machinery Condition Indicator |
| MLP | Multilayer Perceptron |
| MoD | Ministry of Defence |
| MTBF | Mean Time Between Failure |
| NAR | Nonlinear Autoregressive |
| NARX | Nonlinear Autoregressive with exogenous input |
| OCIMF | Oil Companies International Marine Forum |
| OEM | Original Equipment Manufacturer |
| OpEx | Operational Expenditure |
| PAND | Priority AND |
| PAS | Publicly Available Specification |
| PCO | Piston Cooling Oil |
| PMS | Planned Maintenance System |
| RBD | Reliability Block Diagram |
| RBF | Radial Basis Function |
| RBI | Risk Based Inspection |
| RBM | Risk Based Maintenance |
| RCM | Reliability Centred Maintenance |
| RCP | Relevant Condition Parameter |
| RNN | Recurrent Neural Network |
| ROI | Return on Investment |
| RTF | Run to Failure |
| SEQ | Sequence Enforcing |
| SOM | Self-Organising Map |
| TDC | Top Dead Centre |
| TMSA | Tanker Management Self-Assessment |
| TPM | Total Productive Maintenance |
| UK | United Kingdom |
| UNCTAD | United Nations Conference on Trade and Development |
| US | United States |
| USD | United States Dollar |

# Abstract

Inadequate ship machinery maintenance can increase equipment failure posing a threat to the environment, affecting performance, having a great impact in terms of business losses by reducing ship availability, increasing downtime and moreover increasing the potential of major accidents occurring and endangering lives on-board. With high cost of ownership and overburdened crew, ship maintenance has become one of the major challenges in the marine industry. Though the industry is still predominantly reliant on a time-based, prescriptive approach to maintenance, technological advances, heightened expectation and competitive requirements as to ship availability and efficiency and the influence of the data revolution on vessel operations, have resulted in considerable interest in advanced maintenance techniques and favour a properly structured condition-based maintenance regime. In this respect, this thesis develops a hybrid framework oriented towards ship machinery condition monitoring utilising a combination of reliability tools (Fault Tree Analysis, Failure Modes & Effects Analysis, Reliability Block Diagrams) and data-driven approaches based on artificial neural networks (Self-Organising Maps, Nonlinear Autoregressive, Multilayer Perceptron). The above assist in identifying critical ship machinery systems and components and subsequently monitoring their condition through the employment of data clustering, time series forecasting, diagnostic and health assessment, leading to advisory generation of appropriate maintenance actions and recommendations. The above framework is applied to the case study of a Panamax container ship main engine for system, subsystem and component level and the results are validated with actual data recorded onboard. Sensitivity and cost benefit analysis are also presented. Key results include amongst others the identification of critical systems through a systematic approach, the ability of the Self-Organising Map to cluster data and monitor the status of the main engine and the forecasting capabilities of the Nonlinear Autoregressive time series neural networks to analyse available main engine data with high forecasting accuracy.

**Keywords:** Artificial neural networks, data analysis, reliability tools, condition monitoring, predictive maintenance, maritime industry

# 1 Introduction

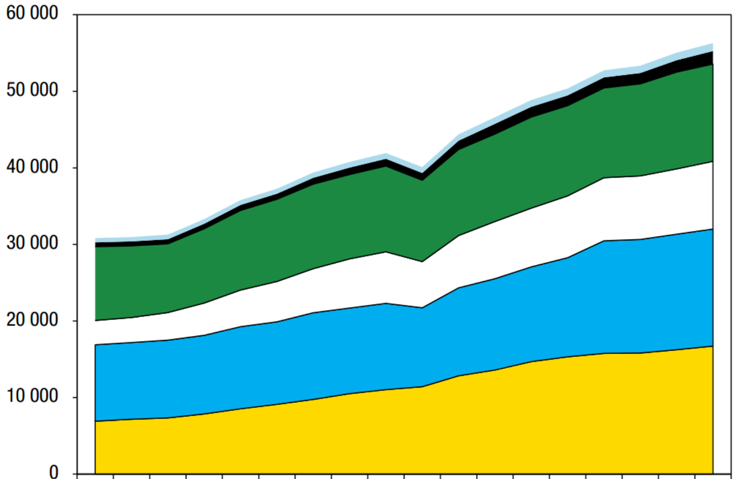
## 1.1 Chapter outline

In this chapter, background information related to the thesis is presented. Initially, a brief introduction into the maritime industry and maintenance is presented alongside key challenges in the shipping maintenance sector. An outline of the chapters encompassing the thesis is also described to introduce the reader to the core structure of the thesis.

## 1.2 An introduction to maritime maintenance

Shipping is the most important mode of transport for international merchandise trade. The marine industry is responsible for the transportation of the vast majority of the merchandise worldwide, as over 80% of global trade by volume is carried on board ships, emphasising the importance of maritime transport for trade and development (UNCTAD, 2017). The world fleet in terms of gross tonnage, consists of bulk carriers (34.6%), oil and chemical tankers (25.9%) and container ships (17.4%), with the remaining ship types consisting mostly of general cargo, Ro-Ro cargo, gas tankers, offshore vessels and passenger ships (Equasis, 2016). For the fifth year in a row, world fleet growth has been decelerating as the maritime transport sector continues to face the prolonged effects of the economic downturn of 2009. Nonetheless, the supply of ship-carrying capacity increased faster than demand, leading to a continued situation of global overcapacity and downward pressure on freight rates and earnings. Bearing in mind projected growth in world Gross Domestic Product (GDP) and merchandise trade and the downside risks to the global economy and trade policy, various estimates of future seaborne trade growth have been put forward and all appear to converge on continued growth in world seaborne trade in 2017.

In 2016, demand for shipping services improved moderately with world seaborne trades expanding by 2.6%, up from 1.8% in 2015. Global shipping ton-miles reached 55,057 estimated billions, indicating an increase of 3.2% over the previous year, as observed in Figure 1.1 which represents the world seaborne trade in cargo ton-miles by type of cargo from 2000 until 2017 (UNCTAD, 2017). In its latest report, UNCTAD, forecasts world seaborne trade to increase by 2.8% in 2017, with total volumes reaching 10.6 billion tons. Furthermore, UNCTAD projects world seaborne trade volumes to expand at a compound annual growth rate of 3.2% between 2017 and 2022.




| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016[a] | 2017[b] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Chemicals | 552 | 562 | 593 | 606 | 625 | 651 | 689 | 724 | 736 | 765 | 824 | 864 | 889 | 908 | 914 | 953 | 991 | 1 039 |
| Gas | 576 | 591 | 611 | 662 | 719 | 736 | 833 | 913 | 956 | 958 | 1 147 | 1 344 | 1 346 | 1 347 | 1 392 | 1 422 | 1 563 | 1 706 |
| Oil | 9 631 | 9 352 | 8 971 | 9 698 | 10 393 | 10 729 | 11 036 | 11 011 | 11 200 | 10 621 | 11 237 | 11 417 | 11 890 | 11 779 | 11 717 | 12 013 | 12 638 | 12 701 |
| Container | 3 170 | 3 271 | 3 601 | 4 216 | 4 785 | 5 269 | 5 757 | 6 422 | 6 734 | 6 030 | 6 833 | 7 469 | 7 673 | 8 076 | 8 237 | 8 302 | 8 529 | 8 845 |
| Other (minor bulks and other dry cargo) | 9 998 | 10 023 | 10 167 | 10 275 | 10 729 | 10 782 | 11 330 | 11 186 | 11 272 | 10 325 | 11 504 | 11 927 | 12 375 | 12 952 | 14 707 | 14 836 | 15 097 | 15 298 |
| Five main dry bulks | 6 896 | 7 158 | 7 331 | 7 852 | 8 527 | 9 107 | 9 745 | 10 503 | 11 028 | 11 400 | 12 824 | 13 596 | 14 691 | 15 312 | 15 768 | 15 813 | 16 239 | 16 710 |

Figure 1.1 World seaborne trade in cargo ton-miles by cargo type 2000-2017 (UNCTAD, 2017)

All the above evidently indicate the continuing growth of the seaborne trade and the maritime industry’s significant role in transportation of goods and passengers worldwide. However, projected growth in world seaborne trade remains subject to uncertainty and several downside risks. In this context and considering the emerging trends currently shaping the outlook for seaborne cargo flows in combination with technological advancements, the safe, efficient and environmentally friendly operation of ships is extremely important.

Shipowners and operators always seek the best performance from their ships, and this is most likely to occur when the ships are in good working condition. To keep any ship in good condition, maintenance must be considered. Inadequate maintenance can increase equipment failure posing a threat to the environment, affecting performance, having a great impact in terms of business losses by reducing ship availability, increasing downtime and moreover increasing the potential of major accidents occurring and endangering lives onboard. Major marine accidents and incidents such as Piper Alpha in 1988, Erika in 1999 and Prestige in 2002 are attributed to lack of correct maintenance procedure and poor maintenance (Paté-Cornell, 1993, Ringbom, 2001, Wirtz et al., 2007).

Poor maintenance can lead to situations such as dangerous work environments, lack of functional backup systems and crew fatigue from the need to carry out emergency repairs. In this respect, maintenance is an important contributor to reach the intended life-time of technical capital assets and is defined as a combination of all the technical and associated administrative activities required to keep equipment, installations and other physical assets in the desired operating condition or to restore them to this condition (BS, 1993). Maintenance deals with systems that are subject to deterioration and failure with usage and age. For systems such as aircrafts, submarines, nuclear, ships, it is extremely important to avoid failure during actual operation because it can be dangerous or disastrous. Therefore, maintenance on them is a necessity since it can improve system and asset reliability (Wang, 2002).

Maintenance tasks affect the reliability and availability standards of the shipping industry as well and are important factors in the lifecycle of a ship that can minimise down-time and reduce operating costs (Lazakis and Olcer, 2015). Routine and periodic maintenance accounts for approximately 20% of a ship’s operational expenses (Stopford, 2009). According to the latest survey by Stephens (2017), vessel operating costs are expected to rise by 2.1% in 2017 and 2.4% in 2018, with repairs, maintenance and spare parts being the cost categories which are likely to increase most significantly in both years by 2%.

The fact that repairs, maintenance and spares emerged as the items with the largest projected cost increases in both 2017 and 2018 was predictable in that they are two items of expenditure on which shipowners and operators might conceivably have economised or delayed in previous years, and such economies cannot be sustained over longer periods without impacting safety.

In the context of safety, the European Maritime Safety Agency (EMSA, 2017) indicated in its recent report that the main location of marine casualties and incidents was the engine room for cargo ships and passenger ships. Additionally, 71% of accidental events were linked to shipboard operations as a contributing factor over the examined period of 2011 to 2016. Furthermore, from a total of 1170 accidental events analysed, equipment failure is the second biggest contributing factor, with human erroneous action being the primary factor. Moreover, Figure 1.2 illustrates the contributing factor most quoted per category of accidental event. As illustrated, for the category of equipment failure, maintenance was quoted as the main contributing factor.

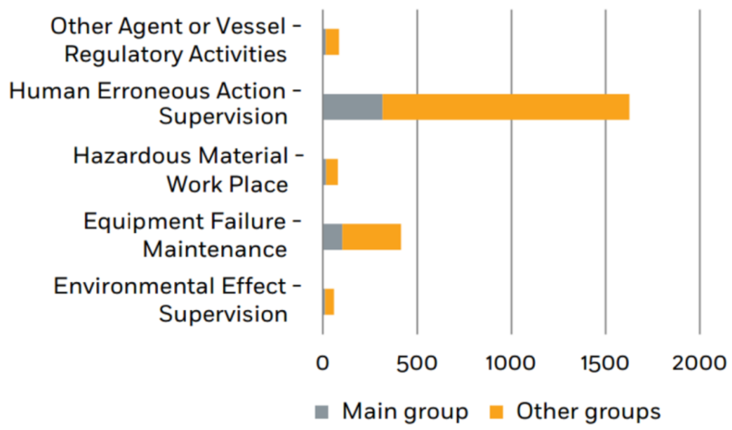



Figure 1.2 Groups of contributing factors for accidental events (EMSA, 2017)

Additionally, according to the latest report published by Allianz (2017) regarding the review of trends and developments in shipping losses and safety, foundered, wrecked/stranded, fire/explosion, collision and machinery damage were the most frequent causes of losses at sea over the past decade. In terms of all casualties including total losses, machinery damage is the main cause of shipping incidents globally (32%). This value can also be observed in the casualty and world fleet statistics report of the International Union of Marine Insurance (IUMI, 2015), for an examined period of 14 years (2000-2014), in which machinery represents over 35% the cause for all serious losses for all vessel types above 500 GT (Figure 1.3).

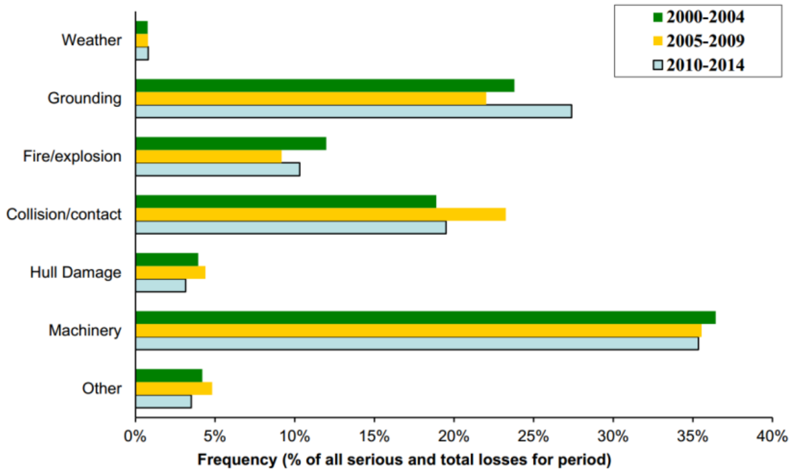



Figure 1.3 Ship serious losses by cause for all vessel types above 500 GT (IUMI, 2015)

In the same report produced by Allianz, crew negligence and inadequate vessel maintenance are two increasing areas of risk in the current economic shipping environment, especially if shipowners select to recruit crew with less experience and fewer qualifications/training in order to increase savings or choose to stretch maintenance work to the longest possible interval. Negligence/poor maintenance is also mentioned as one of the top causes of liability loss in the marine sector, so vigorous inspection and maintenance regimes are crucial.

The importance of maintenance is also demonstrated by the fact that it is the only shipboard activity to have one whole element assigned to it in the ISM code (IMO, 1993). For systems onboard ships, it is extremely important to avoid failures during actual operation since it can be dangerous or disastrous in terms of performance, safety and economic losses. The performance of the vessel generally deteriorates with time as a result of fouling or degradation of machinery systems and components. Unwanted failures result in economic impact in the form of higher maintenance costs and lower machine reliability and availability. With reduced manning levels and the ever-increasing competition, ship maintenance has become one of the major challenges in the marine industry. Moreover, technological advances, overburdened crew and high cost of ownership have resulted in considerable interest in advanced maintenance techniques (INCASS, 2015c).

Consequently, the maritime industry is seeking increased reliability, maximum uptime and optimal operational efficiency, as well as ensuring safe and sustainable environmental performance in harsh environments. It is only recently that new approaches investigating the enhancement of ship's reliability, availability and profitability have been considered according to Lazakis and Olcer (2015). The outcome of this study indicated that preventive maintenance is still the preferred maintenance approach by ship operators, closely followed by predictive maintenance; hence avoiding the ship corrective maintenance framework and increasing overall ship reliability and availability.

Though the industry is still predominantly reliant on a time-based, prescriptive approach to maintenance, there are several factors challenging the long-held norm. In most ships, the current machinery maintenance regime is in line with the original equipment machinery manufacturer's recommendations. In this case, maintenance is based upon running hours or calendar time scheduling. This form of maintenance scheduling usually leads to the *'over-maintenance'* of machinery. This increases direct and indirect maintenance costs by increasing voluntary production losses, speeding aging due to excess dismantling and re-assembly, and increasing the risks of damage through human error (Reason and Hobbs, 2003).

The increasing complexity of shipboard systems, heightened expectation and competitive requirements as to ship availability and efficiency and the influence of the data revolution on vessel operations, favour a properly structured Condition Based Maintenance (CBM) regime (Tinsley, 2016). This may not replace all planned maintenance, but it can possibly reduce downtime, inspection and unnecessary servicing work. Moreover, shifting from scheduled, rule-based maintenance to a data-driven, risk-based approach can lead to more accurate and timely maintenance, resulting in lower costs, greater availability of ship systems and increased safety.

Compared to other industrial sectors, the maritime sector lacks the element of applying and implementing technologically advanced tools with real-time monitoring. Classification Societies encourage condition monitoring techniques onboard ships, offer guidelines but do not oblige ship operators or owners to implement such techniques in their operation and maintenance strategy (Lloyd's Register, 2013). Maintenance decisions are often based on experience and the preventive maintenance activities of the Planned Maintenance System (PMS). For effective utilisation of data, skilled personnel are required to handle and analyse the data.

In addition, the issue of availability of powerful tools and methods are required for analytics, data exploration and visualisation to support streams of sensor data and heterogeneous data. Shipping companies also lack the long-term vision of such maintenance strategies and expect a quick return of investment and avoid realising that maintenance is not a one-time activity for continuous improvement; but is a long-term and continuous improvement activity (Lazakis and Ölçer, 2015).

Furthermore, compared to other industrial applications, data pooling in the shipping industry is not always possible as similar equipment operating in different conditions may have different failure patterns (Lazakis et al., 2018). Ships operate in different and changing environmental conditions, making it difficult to use failure data from one ship to another. Therefore, maintenance and degradation behaviour in marine systems also depends on the operational profile of the vessel and as a result, the use of similar data may be ineffective for sister ships. Another issue is the constant appearance of new equipment, which makes historical records obsolete.

Moreover, data is not collected in a standardised way that could lead to more informed and effective decision making. The question of how much data, which data, and how often this should be collected and how has also emerged; as although companies adopt CBM schemes, there seems to be an issue in processing, analysing and utilising the recorded operational data (Raptodimos et al., 2016). Therefore, it is vital that ship managers/operators identify the essential information required and decide which maintenance approach is the most efficient to follow.

Bearing all the above in mind, an effective maintenance system should be capable of monitoring the operating conditions of ship machinery and equipment, predict their future state to prevent fatal breakdowns and issue advanced warnings of potential faults. In this respect, the proposed condition monitoring framework employs a hybrid approach to initially identify critical ship machinery systems and components through reliability modelling and tools and subsequently monitors and assesses their condition through the employment of artificial intelligence for data clustering, forecasting and diagnostic analysis, leading to appropriate maintenance actions and suggestions.

## 1.3 Thesis layout

The thesis layout introduces the reader to the flow and structure of each chapter of the thesis. The thesis is structured into 9 chapters, demonstrated in Figure 1.4 and summarised below.

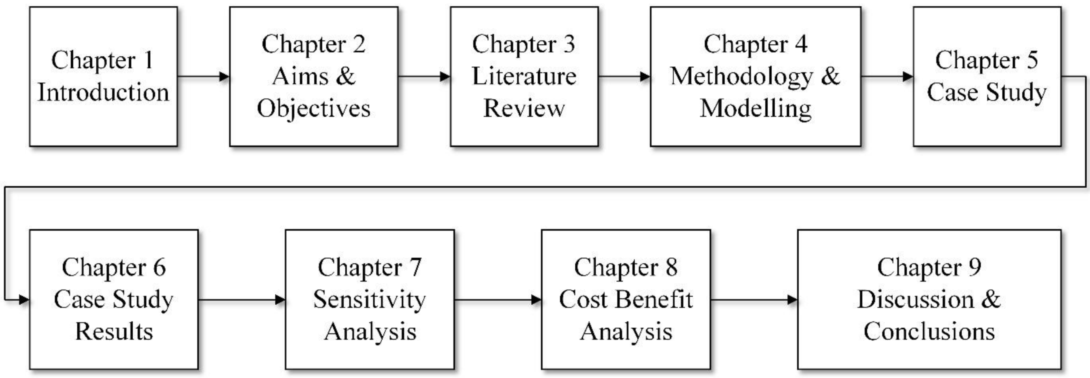


Figure 1.4 Thesis structure

*Chapter 1: Introduction*

This chapter sets out the wider context for the thesis. An initial introduction regarding the maritime industry is provided alongside some critical characteristics of maintenance in the shipping sector which deliver the incentive for the proposed research framework.

*Chapter 2: Aim & Objectives*

This chapter consists of the research question, main aim and objectives of the thesis. The objectives provide a description of the key research challenges to be tackled in order to achieve the main aim of the thesis.

*Chapter 3: Literature and Critical Review*

The research background through an extensive literature and critical review is presented. This chapter provides an overview of topics related to maintenance, condition monitoring, reliability tools and artificial neural networks. The review aims to identify research gaps in order to understand and develop the main research concept.

*Chapter 4: Methodology & Modelling*

Considering the identified gaps in the existing literature, this chapter focuses on the description of the considered and developed tools and methods by presenting their modelling principles. The structure and functionality of the proposed methodology are also explained which includes stages related to identification of critical systems, data collection, data preparation, time series forecasting analysis, diagnostic and health assessment analysis and advisory generation of maintenance actions and activities.

*Chapter 5: Case Study*

The specifications of the examined case study by implementing the proposed and developed methodology are presented in this chapter. Initially, the developed Fault Tree and Failure Modes and Effects Analysis (FMEA) model for the ship main engine case study is presented in order to identify the main engine critical systems and their relevant parameters to be monitored. After identifying the input data, the analysis of the data is described for the developed Self-Organising Map (SOM), Nonlinear Autoregressive (NAR), Nonlinear Autoregressive with Exogenous Input (NARX), ANN Multilayer Perceptron (MLP) neural network models, system Reliability Block Diagram (RBD) health assessment tool and Maintenance Assistant Tool (MAT).

*Chapter 6: Case Study Results*

This chapter presents the results of the above case study application. The outcomes of each part of the proposed methodology are assessed both as independent and integrated tools. The results and their assessment present and validate the applicability and accuracy of the methodology.

*Chapter 7: Sensitivity Analysis*

In this chapter, sensitivity analysis is performed in the case of the NARX model. A base case is established considering the initial results from the previous section and variations to the NARX inputs are implemented to examine the performance of the developed NARX model. Overall, the sensitivity analysis demonstrates that the suggested methodology performs efficiently under several variations in the input data.

*Chapter 8: Cost-Benefit Analysis*

A cost-benefit analysis is performed to demonstrate the costs and benefits associated with applying the proposed condition monitoring framework against a traditional ship machinery PMS scheme over a ship lifecycle of 25 years.

*Chapter 9: Discussion & Conclusions*

This chapter includes the discussion and conclusions section of the overall thesis, assessing and providing an in-depth summary of the key research findings and presents the novelty of the thesis. Furthermore, concluding statements are provided in this chapter summarising the key learning points of the conducted research. Finally, recommendations for future research are also presented.

## 1.4 Chapter summary

In this chapter, a brief introduction into the maritime industry and maintenance was presented. Various challenges and issues that currently exist in maritime maintenance were described. Furthermore, an outline of the chapters comprising the thesis was also presented to introduce the reader into the core structure of the thesis. In the following chapter, the research question, main aim and objectives of the thesis are presented, reflecting the aspirations and expectations of the undertaken research.

# 2 Aim & Objectives

## 2.1 Chapter overview

This chapter focuses on the research question and the description of the main aim and objectives of the present thesis.

## 2.2 Research question

The research question of the present thesis is formulated as:

*How to develop and implement a hybrid condition monitoring strategy in the maritime industry based on reliability tools and data-driven artificial intelligence methods for assessing and predicting the present and future status of machinery systems?*

## 2.3 Aim & objectives

The main aim of the thesis is to develop an efficient and robust predictive condition monitoring framework for application on ship machinery systems through the combination of reliability tools and data-driven models based on artificial neural networks.

The objectives through which the main aim of the thesis will be achieved are listed below:

1. Identify the gaps in the literature and issues in maritime maintenance and condition monitoring by conducting a detailed literature and critical review pertinent to the research topic.
2. Focus on the identified research gaps to propose an innovative condition monitoring framework methodology for the maritime industry and demonstrate the various elements that it consists of in full depth.

3. Collect data for analysis through ship onboard measurement campaigns to demonstrate the proposed methodology.
4. Demonstrate the applicability of the developed methodology for the main engine system of a container ship.
5. Validate key aspects of the methodology and demonstrate the performance of the methodology under different circumstances through a sensitivity analysis.
6. Perform a cost-benefit analysis to investigate and assess the value associated with implementing the developed condition monitoring framework.

## 2.4 Chapter summary

In this chapter, the research question of the present thesis has been formulated and the thesis main aim and objectives have been identified and described. The following chapter presents the literature and critical review undertaken to identify maritime maintenance practices and applications, research activities and existing gaps.

# 3 Literature and Critical Review

## 3.1 Chapter overview

In this chapter, the overall literature and critical review is demonstrated. The literature review starts by referring the reader to the background of maintenance, specifically its evolution from a *"necessary evil"* towards treating maintenance as a mature partner in business strategy development. Secondly, maintenance types such as corrective, preventive and predictive are analysed and compared, followed by a descriptive analysis of the various maintenance concepts including Condition Based Maintenance (CBM), Reliability Centred Maintenance (RCM) and Total Productive Maintenance (TPM) amongst others. Maintenance within the maritime sector is also examined with regards to existing regulatory elements, maintenance activities and research trends. Finally, Artificial Neural Networks (ANNs) are presented and a comprehensive review of multi-sectoral studies is also presented regarding their application within the context of CBM. The existing gaps are identified and lay the foundations for the introduction and development of the innovative methodology suggested in this thesis.

## 3.2 Maintenance background

Competition, cost effectiveness and safety have asked for better maintenance. According to British Standards (1993), maintenance can be defined as a combination of all the technical and associated administrative activities required to keep equipment, installations and other physical assets in the desired operating condition or to restore them to this condition. Most authors in maintenance management literature, one way or another, agree on defining maintenance as the "*set of activities required to keep physical assets in the desired operating condition or to restore them to this condition*" (Pintelon and Parodi-Herz, 2008). Maintenance management has undergone considerable change in the past few years. There is more awareness of the failure characteristics of components and maintenance is now aimed at, based on the operating context, preserving the functions of assets rather than their condition

(Mokashi et al., 2002b). The history and evolution of maintenance in the form of important milestones is described below.

Engineering has evolved since the industrial revolution, but it is safe to say that the most dramatic changes have occurred in the last fifty years (Garg and Deshmukh, 2006). Prior to the Second World War, machinery was generally very rugged and relatively slow running with instrumentation and control systems developed at a basic level. Downtime was not usually a critical issue and it was adequate to maintain machinery and equipment on a breakdown basis. After the 1950's with the rebuilding of industry, there was an increasing intolerance of downtime and the cost of labour became increasingly significant leading to a surge in mechanisation and automation. Furthermore, machinery manufactured was of lighter construction and operated at higher speeds, meaning that they wore out more rapidly and were seen as less reliable. It was recognised that some failures of mechanical components had a direct relation with the time or number of cycles in use, based on physical wear of components or age-related fatigue characteristics. The main concern was how to determine, based on historical data, the adequate period to perform preventive maintenance. Production demanded better maintenance actions which eventually led to the development of planned preventive maintenance involving overhauls based upon a time interval or hours of operation (Brown and Sondalini, 2014).

In the 1960's the aviation industry introduced the Boeing 747 and in its search for improved reliability, questioned the current maintenance strategies of that time and the established assumption that older equipment is more likely to fail. First operations research models for maintenance appeared in the 1960's and in the 1970's condition monitoring came forward, focusing on techniques which predict failures using information on the actual state of equipment which proved to be more effective than the large time-based preventive maintenance programs (Dekker, 1996). At this point, the effectiveness of applying preventive maintenance actions started to be questioned as a common concern about *"over-maintaining"* grew rapidly. Moreover, as the insidious belief on preventive maintenance benefits was put at risk, new precautionary, predictive maintenance techniques emerged. This meant a gradual, though not complete switch to inspection and CBM actions. In the late 1970s and early 1980s, these techniques were only reserved to high-risk industry applications such as aviation or nuclear power plants (Pintelon and Parodi-Herz, 2008).

In the beginning of the 1980's minicomputers with dedicated programs were developed giving higher freedom for the maintenance department to systematise, plan and check-up maintenance activities. At this time, the backbone of Computerised Maintenance Management System (CMMS) was established, consisting of functionality for scheduling, plant inventory, stock control, cost and budgeting and maintenance history (Kans, 2009). In addition, plant and systems became increasingly complex, the demands of the competitive marketplace and intolerance of downtime increased, and maintenance costs continued to rise. Along with the demands for greater reliability at a lower cost came new awareness of failure processes, improved management techniques and new technologies to allow an understanding of machine and component health. Environmental and safety issues became paramount and the study of risk became very important.

In the late 1980s and early 1990s a different footprint on maintenance development occurred with the emergence of life cycle engineering. Here maintenance requirements were already under consideration at earlier product stages such as design or commission. As a result, instead of having to deal with built-in characteristics, maintenance turned out to be active in setting design requirements for installations and became partly involved in equipment selection and development. All this led to a different type of precautionary, proactive maintenance (Fedele, 2011). According to Arunraj and Maiti (2007), maintenance policies can be categorised into four generations. The fourth generation is the most recent one, which focuses on failure eliminations and concentrates on reducing the proportion of equipment failures and overall levels of failure probability. Figure 3.1 illustrates the four generations and timeline evolution of maintenance.

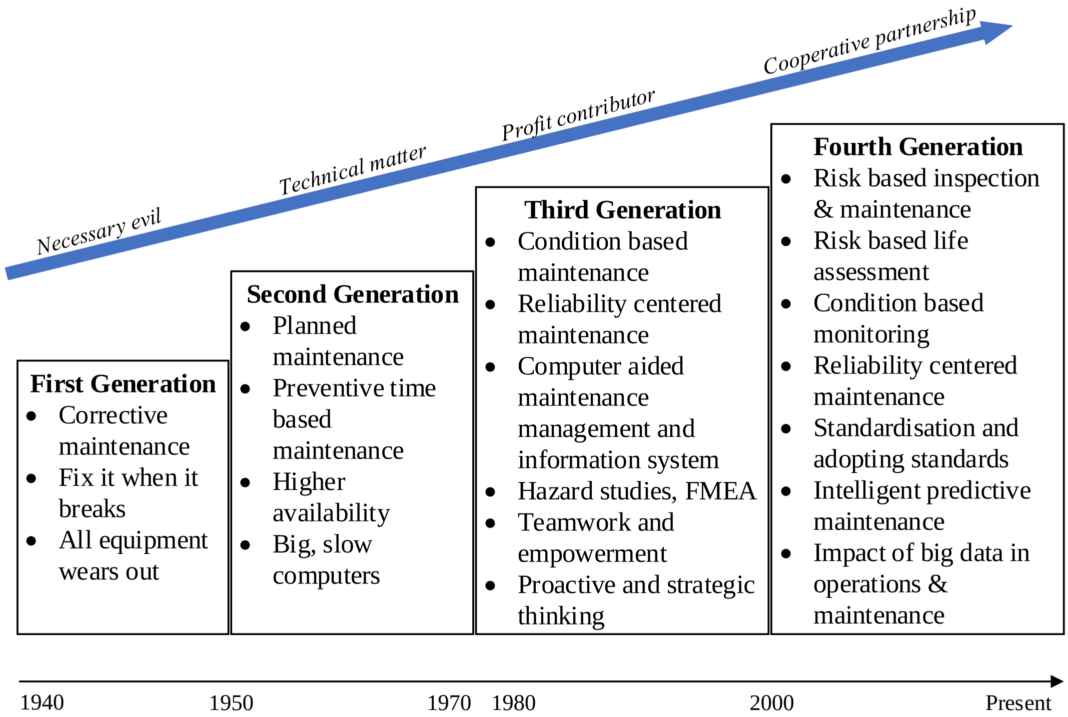



Figure 3.1 Generations and evolution of maintenance

It can be concluded from the timeline of maintenance evolution, that at first maintenance was nothing more than an inevitable part of production, consequently it was considered as a necessary evil. Repairs and replacement were tackled only when necessary with no optimisation taking place. Later, maintenance was considered as a technical matter. This included optimising technical maintenance solutions and attention was focused from the organisation to the maintenance work.

Further on, maintenance management became a complex function, encompassing technical and management skills, recognising that implementing a well thought out maintenance strategy could have a significant risk, safety, environmental and financial impact. Nowadays, this has led to treating maintenance as a mature partner in business strategy development (Pintelon and Parodi-Herz, 2008). The various types of maintenance are analysed in the next section in order to identify and comprehend the different approaches available and the key features that characterise them.

## 3.3 Maintenance classification & types

Various authors have investigated several maintenance concepts and classify maintenance differently. Wang (2002) classified maintenance policies into two major classes: corrective and preventive. Garg and Deshmukh (2006) classified the existing maintenance literature into six areas; maintenance optimisation models, maintenance techniques, maintenance scheduling, maintenance performance measurement, maintenance information systems and maintenance policies.

Classification of maintenance can be achieved based on type of maintenance, degree of maintenance and type of system to be maintained as illustrated in Figure 3.2. As far as the degree of maintenance is concerned, perfect maintenance restores the system to its initial operating condition or renders it as good as new. Minimal repair returns the system to the condition it was in immediately prior to failing, or as bad as old. In between these degrees lies imperfect maintenance, which returns the system to a condition in between as good as new and as bad as old (Marais and Saleh, 2009).

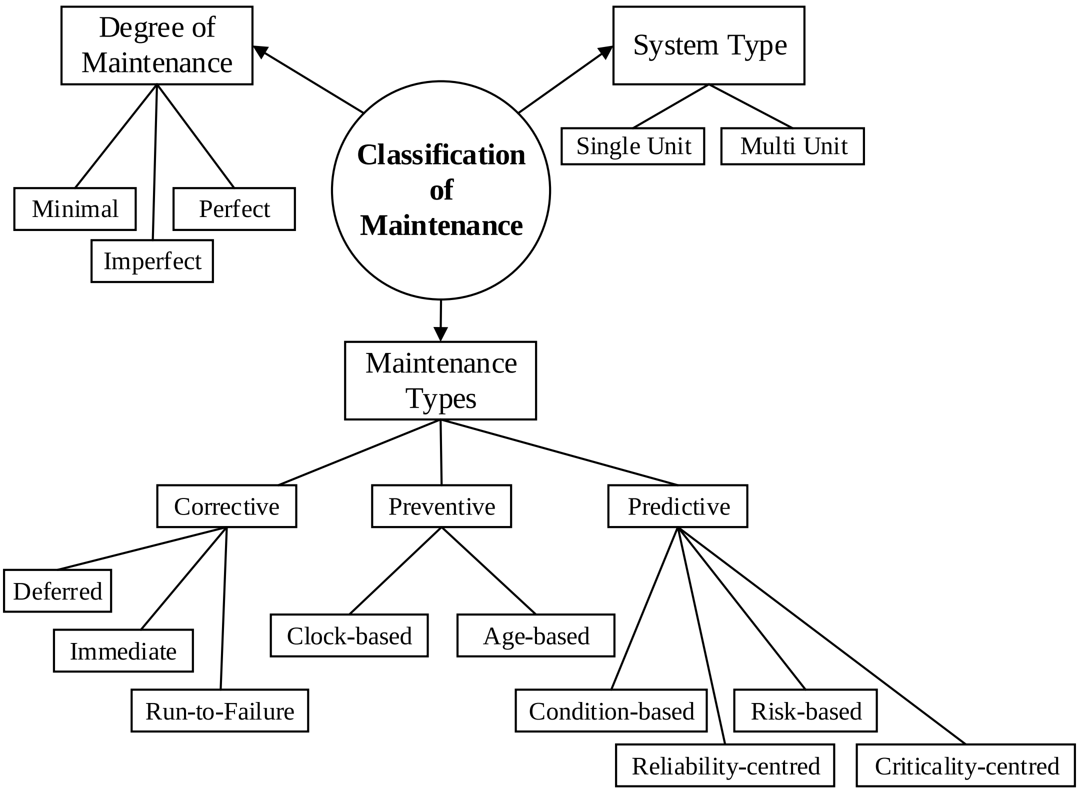



Figure 3.2 Classification of maintenance

Maintenance types can be classified into three main categories namely corrective, preventive and predictive maintenance. Corrective maintenance or unscheduled maintenance returns items/equipment to a defined state. Preventive maintenance is all actions carried out on a planned, periodic and specific schedule to keep an item/equipment in stated working condition through the process of checking and reconditioning. Predictive maintenance is the use of modern measurement and signal processing methods to accurately predict and diagnose items during operation (Sharma et al., 2011). The following sections explain and expand on these types of maintenance.

### *3.3.1 Corrective maintenance*

Also known as breakdown, run-to-failure, reactive, unplanned maintenance, corrective maintenance is the maintenance that occurs when a system fails and means all actions performed as a result of failure, to restore an item to a specified condition (Wang, 2002). It is the maintenance in which no actions or efforts are taken to maintain the equipment. Thus, corrective maintenance is reactive in nature, as the maintenance is triggered by the unscheduled event of an equipment failure and takes place only after failure occurs (Tsang, 1995). This type of maintenance is executed by firstly detecting the fault which can be achieved by a physical inspection of a system. It is important to determine the source of failure to select appropriate actions ensuring that further damage can be prevented. The next step is to isolate and eliminate the fault. The maintenance work could constitute repair, restoration or replacement of components in order to restore the system to its original state as it was in new condition (Prajapati et al., 2012). The final step is ensuring that the presented fault has been repaired and operation is running as normal.

Corrective maintenance can offer some advantages compared to other maintenance types. If a maintenance program is purely reactive, then less manpower and capital cost is expended. Also, the main advantage is that machinery parts are used to their full life or until they break. However, this type of maintenance program shortens the life of the equipment resulting in more frequent replacement. The effects of corrective maintenance contribute to high costs (unexpected failure costs), hence preventive maintenance strategy is preferable (Ahmad and Kamaruddin, 2012). Costs are usually high due to the penalty associated with the lost output and safety and health hazards inflicted by the failure. Moreover, efforts tend to be less efficient when people have to work under crisis situations (Tsang et al., 2006). Additionally, it is often more expensive since worn equipment or components can damage other parts and cause additional multiple damage. Corrective maintenance can in some cases be in fact the result of an insufficient and unsuccessfully designed preventive maintenance plan. In general, this type of maintenance is carried out when the consequences of failure or wearing out are not significant and for non-critical, inexpensive and easily replaced components whose replacement will not affect the efficiency of a plant’s operation (Fedele, 2011).

### *3.3.2 Preventive maintenance*

A series of tasks performed at a frequency dictated by predefined time intervals or system operating running hours that either extend the life of an asset or detect that an asset had critical wear and is going to fail or break down constitute preventive maintenance (Garg and Deshmukh, 2006). This maintenance concept has been derived from a level of repair analysis to determine the maintenance allocation for a given system or subsystem (Prajapati et al., 2012). Preventive maintenance can be defined as the actions performed on a time or machine-run based schedule that detect, preclude or mitigate degradation of a system or component aiming at sustaining or extending its useful life through controlling degradation to an acceptable level. Preventive maintenance can be subdivided into clock-based and age-based maintenance. It includes all actions performed in an attempt to retain an item in specified condition by providing systematic inspections, overhauls, detection and prevention of incipient failures (Wang, 2002). Thus, by conducting maintenance activities intended by the equipment manufacturer, equipment lifetime is extended and reliability is increased.

According to Ahmad and Kamaruddin (2012), from an industrial perspective, preventive maintenance is conducted through experience, Original Equipment Manufacturer (OEM) recommendations and based on scientific approach. Through experience, preventive maintenance is typically performed at similar time intervals and there are no standard procedures to be followed. The knowledge of experienced technicians and engineers becomes a corporate valuable asset. Their experience provides the knowledge of understanding what types of machinery malfunctions occur, how to diagnose problems, and how to repair them.

However, preventive maintenance through experience becomes problematic when the experienced person leaves the company. Moreover, these individuals are not available for 24 hours a day to solve maintenance problems. The application of preventive maintenance through OEM recommendation is also conducted at a fixed time interval. However this practice is not applicable usually in minimising operational costs and maximising machine performance; as according to Labib (2004), machinery equipment such as those operating onboard ships, differ as they work in different environments, and would therefore need a different preventive maintenance approach. The maintenance is carried out irrespective of the condition of the machinery and parts have to be replaced even if they can still be used.

Moreover, machinery designers do not have the same experience in machines as those who operate and repair them. Also, OEM companies may have the hidden agenda of maximising spare parts replacements through frequent preventive maintenance. On the other hand, the application of this maintenance type through scientific approaches involves processes and principles that employ various analytical techniques such as statistics, mathematical programming and artificial intelligence. The main advantage is that decisions are based on facts through real data analysis.

While preventive maintenance might not be the optimum maintenance program, it has several advantages over that of a purely corrective maintenance program. Preventive maintenance strategy has gradually replaced reactive strategy, giving way to the birth of maintenance research. Preventive maintenance is more effective than corrective maintenance because it always keeps a system in an available condition so that the large loss caused by unpredictable failures can be avoided (Tsai et al., 2004).

### *3.3.3 Predictive maintenance*

Predictive maintenance attempts to detect the onset of a degradation mechanism with the goal of correcting that degradation prior to significant deterioration in the component or equipment (Sullivan et al., 2010). It focuses on failure prediction, occurring through systematic follow-ups on parameters and equipment condition. This type of maintenance did not emerge as a replacement for corrective and preventive maintenance, but as an additional tool, which seeks to minimise, through the monitoring of specific parameters, maintenance costs and losses in equipment (de Faria Jr et al., 2015). The main function in predictive maintenance is to collect data which goes through a diagnosis and trend analysis, identifying potential problems through historical analysis of similar equipment and knowledge acquired over time.

Predictive maintenance differs from preventive maintenance by concentrating maintenance on the actual condition of the machinery rather on some predefined schedule (Niu, 2017). It uses modern measurement and signal processing methods to accurately predict and diagnose system and component condition during operation (Sharma et al., 2011). Although predictive maintenance requires an investment in order to effectively implement, operate and maintain systems, the actual cost is substantially lower than the lost production resulting from failure.

It does not normally involve an intrusion into the equipment, and the actual preventative action is taken only when it is believed that an incipient fault has been detected. Proper application and training is of critical importance in predictive maintenance technologies as they have become extremely sophisticated and technology driven. Moreover, diagnostic capabilities of predictive maintenance technologies have increased in recent years with advances made in sensor technologies.

### *3.3.4 Maintenance types summary*

Overall a maintenance strategy should be a mix of predictive, preventive and reactive methods, depending on the desired goal, operating aspects and business requirements. In applications such as ship machinery, where the criticality of the equipment and the impact of unplanned downtime and quality are high, a maintenance strategy characterised by preventive or predictive mechanisms offers numerous advantages. Independent studies indicate that preventive maintenance has a 5:1 cost advantage over reactive maintenance (Niu, 2017). Additionally, Niu (2017) states that the following industrial savings based on the initiation of a functional predictive maintenance program can be obtained: 10% Return on Investment (ROI), 25-30% reduction in maintenance costs, 70-75% eliminations of breakdown, 35-45% reduction in downtime and 20-25% increase in production.

Table 3.1 summarises the advantages and disadvantages of the different maintenance types described in the previous sections. The next section focuses on the identification and description of the various developed maintenance concepts.

Table 3.1 Strengths and weaknesses of different maintenance types

| Maintenance Types | Advantages | Disadvantages |
|---|---|---|
| **Corrective**<br>*"Run-to-failure maintenance"* | • Possibly suitable for non-critical, inexpensive and easily replaced components<br>• If a maintenance program is purely reactive, then less manpower and capital cost is expended.<br>• Useful if system is reaching end of its life cycle<br>• Machinery parts are used to their full life<br>• Lower start-up cost (CapEx)<br>• No condition monitoring related costs | • Necessary parts, supplies, personnel, and tools required for maintenance may not be adequately placed<br>• Unexpected failure costs and high repair/ replacement costs due to sudden failure of equipment<br>• Possible extensive damage to other equipment<br>• Compromises safety, performance and reliability<br>• Reduced income and asset availability<br>• Increased cost due to downtime<br>• Increased labour cost in case of overtime |
| **Preventive**<br>*"Fix it before it breaks"* | • Increased component lifecycle<br>• Reduced equipment failure and breakdown<br>• Reduces costly downtime<br>• Decreased cost of replacement<br>• Flexibility can allow for adjustment of schedule to accommodate other work (opportunistic maintenance)<br>• Maintenance performed in controlled manner<br>• Suitable for safe-life designed components<br>• Cost savings over reactive maintenance | • Includes performance of unnecessary maintenance<br>• Maintenance actions prior to occurrence of a failure<br>• Experience personnel not always available<br>• Reduction in operational capability<br>• The useful remaining-life is based on the fleet's statistical usage or manufacturers' recommendations and not on an individual engine's operational exposure or experience<br>• OEM recommendation not applicable in maximising machinery performance and minimising operational costs<br>• Potential damage to components in performing unrequired maintenance |
| **Predictive**<br>*"If it is not broke, do not fix it"* | • Increased component operational life and availability<br>• Allows pre-emptive corrective actions on non-critical items<br>• Decrease in equipment downtime and unexpected breakdown<br>• Allows for money to be budgeted for repairs and spares<br>• Lowers need for expensive parts inventory<br>• Reduction in unnecessary maintenance costs<br>• RCM can be effective to meet long-term maintenance and supportability goals<br>• CBM concentrates maintenance on actual condition of equipment<br>• CBM does not usually involve intrusion into equipment and preventive action is only taken when a failure is thought to be detected | • Increased investment in condition monitoring equipment<br>• Initial costs of deployment can be expensive (CapEx)<br>• Additional skills and training required for analysing monitored data<br>• Technologies are extremely sophisticated and technology driven<br>• Savings not readily visible without a baseline/history<br>• Proper infrastructure required for functional predictive strategy<br>• Smaller companies do not have enough assets to make an impact with such maintenance efforts |

## 3.4 Maintenance concepts

In this section, various maintenance concepts are analysed. A comparison of the different concepts is undertaken alongside their core advantages and disadvantages. In general, there are several maintenance concepts and they differentiate from each other in terms of their framework referring to a generic management and commercial approach or to a more technical oriented context.

### *3.4.1 Condition Based Maintenance (CBM)*

The concept of Condition Based Maintenance (CBM) was first introduced by the Rio Grande Railway Company in the late 1940s and initially was called predictive maintenance (Prajapati et al., 2012). There are various definitions of the concept of CBM. Bengtsson (2004) described it as preventive maintenance based on performance and/or parameter monitoring and the subsequent actions. Butcher (2000) defined CBM as a set of maintenance actions based on real time or near real-time assessment of equipment condition, which is obtained from embedded sensors and/or external tests and measurements taken by portable equipment. The above are in line with the definition provided by British Standard (2012), defining CBM as the maintenance policy carried out in response to a significant deterioration in a machine as indicated by a change in a monitored parameter of the machine condition. Thus, CBM works on the basis that equipment failures are preceded by certain signs, conditions or indications (Ahmad and Kamaruddin, 2012).

Hence, unlike breakdown maintenance and preventive maintenance, CBM focuses on not only fault detection and diagnostics of components but also degradation monitoring and failure prediction. The underlying maintenance process eventually triggers a business process (supply or maintenance action) to mitigate downtime at the optimal time. As a result, it provides the ability for the system to continue operating as long as it performs within predefined performance limits. However, not all subsystems are fit to be monitored in order to detect impending system failures. In order to develop a CBM strategy it is essential to understand equipment failure behavior (Prajapati et al., 2012).

The heart of CBM is condition monitoring which aims in collecting data regarding equipment conditions. Condition monitoring technologies are applied through various tools by recording and evaluating different measurable parameters. Data can include vibration, acoustic, temperature, oil and lubricant and current signal measurements. Such measurements are obtained through vibration monitoring, acoustic ultrasound, infrared thermography, oil analysis and tribology, combustion performance monitoring and electrical signature analysis. Sullivan et al. (2010) and Pascual (2015) describe such condition monitoring technologies and techniques in depth.

Condition monitoring has a number of important benefits. Unexpected failures can be avoided through the possession of quality information relating to the online condition of the system and the consequent ability to identify faults or problems while still in the incipient phases of development. Maintenance programs can be condition-based rather than periodically-based and the plant may be utilised more optimally using information relating to its real-time condition and/or performance. Condition monitoring can be carried out either online or offline and can be performed continuously or periodically. Raptodimos et al. (2016) presented a framework for the acquisition of measurements pertinent to condition monitoring and ship maintenance, identifying key data collection sources.

Jardine et al. (2006) identified two main limitations of continuous monitoring. Expensive and continuous data gathering increases amount of noise leading to possible inaccurate information. On the other hand, periodic monitoring is performed at regular or fixed intervals with the aid of manual practices or portable indicators such as hand-held devices, acoustic emission units, and vibration pens. The main limitation of periodic monitoring is the possibility of missing some important information on equipment failure between monitoring intervals.

In some industries, CBM has proven to reduce overall maintenance costs by up to 30% and eliminate breakdowns by up to 70% (Logan, 2015). CBM applications have been reported in the literature. Oke (2011) discussed the common understanding of CBM research and explored its application in various novel engineering disciplines such as mechanical, electrical, highway, transportation, and industrial, among others. Jardine et al. (2006) summarised and reviewed CBM research and development up to 2005, with emphasis on models, algorithms, and technologies for data processing and maintenance decision-making. Kothamasu et al. (2006) provided an overview of the philosophies and techniques that focus on improving reliability and reducing unscheduled downtime by monitoring and predicting machine health. Heng et al. (2009) presented a broad overview of the challenges and opportunities of CBM by focusing on rotating machinery cases.

### *3.4.2 Reliability Centred Maintenance (RCM)*

Reliability Centred Maintenance (RCM) was initially developed by the aviation industry delivering satisfying results in the 1970s from the US Department of Defence in order to improve the reliability of the Boeing 747 (ten Wolde and Ghobbar, 2013). This encouraged other industries to use it to improve their maintenance practices. The idea behind this approach is to make the maintenance program reliability centric. The maintenance program is focused on reliability of the system functions rather than the condition of components. This provides the option of ignoring failures that do not have any impact on the reliability of a system. Therefore, RCM focuses the maintenance resources only on those items that affect the system. It is a structured methodology for determining the maintenance requirement of any physical asset in its operating context and is a well-established analysis method for preventive maintenance planning (Manzini et al., 2009). Also, RCM allows maintenance programs to be evaluated and applied in a rational manner that provides the most value to an operator.

The main objective of RCM is to reduce maintenance costs and simultaneously increase reliability and safety. According to Takata et al. (2004), a two-step procedure is adopted, which initially considers an analysis of the potential Failure Modes, Effects and Criticality Analysis (FMECA) to determine critical components of the system. Then suitable preventive maintenance tasks are assigned to each of the maintenance significant items based on their reliability data. Secondly, logical decision diagrams are applied to specify suitable categories of maintenance. When the maintenance tasks are specified, the following procedure is to assess their intervals which can be tough, as some are complicated to apply in practice as they might require use of advanced mathematics or the input of data of limited availability and failure rate functions that are hard to determine (Selvik and Aven, 2011).

Since RCM relies on statistical estimation of the total operation life expectation, it can reduce unscheduled or unnecessary maintenance if the system is static and the failure modes are well studied. However, RCM is still prone to large deviation of the system dynamic and it lacks significant insight into the actual system performance (Mokashi et al., 2002a). For example, the same pump working on a ship or in a system may have different functions, operating conditions or failure detection probabilities somewhere else. Hence, the RCM analysis has to be carried out individually for each ship and system. Also, ships operate in different and changing environments making it difficult to use failure data from one ship to another.

The RCM framework combines various maintenance strategies including time-directed preventive maintenance, CBM, run-to-failure, and proactive maintenance techniques in an integrated manner to increase the probability that a system or component will function in the required manner in its operating context over its design life-cycle. One should be careful that the initial simplistic appeal of the methodology should not make a user unsighted to the real application issues and challenges. Availability of experienced personnel and on-site plant staff with the present work load are some of the issues to handle for successful RCM implementation. Scheduling considerations also play a key role in RCM success and management's direct support, commitment and involvement are always crucial. With a learning curve required to grasp fully the RCM philosophy, initial investments on training also serves well (Ben-Daya and Knezevic, 2009).

### 3.4.3 Total Productive Maintenance (TPM)

Total Productive Maintenance (TPM) is a unique Japanese philosophy, introduced by Toyota Motor Company in the 1970's, defined by Nakajima (1988), which employs a strategy for maintaining plant and equipment to its optimum level of operational effectiveness; by eliminating the six big losses such as downtime, set-up and adjustment, speed, reduced speed, defect losses and reduced yield. TPM seeks to improve the Overall Equipment Effectiveness (OEE), which is an important indicator, used to measure success of TPM in an organisation (Ahuja and Khamba, 2008). Ahula and Khamba (2008) conduct a comprehensive review of the literature on TPM and present an overview of its implementation practices adopted by the manufacturing industry. TPM is used to modify the preventive maintenance on the basis of the results obtained in the field rather than from the manufacturer (Prabhakar and Jagathy, 2014). It relies upon the fact that the deterioration of machines is accelerated by abusive operation and lack of primary care, such as greasing, spannering and cleaning, all of which can be alleviated by the operator (Sherwin, 2000).

Maintenance is divided into three levels. Independent maintenance is carried out by the operator, second level is carried out by the maintenance staff and the third level by the manufacturer. Lycke (2003) points out that TPM is a highly structured approach and careful, thorough planning and preparation are keys to successful company-wide implementation of TPM and so is senior management's understanding and belief in the concept. Additionally, Total Quality Management (TQM), Just-in-Time (JIT) and Total Employee Involvement (TEI) programs have often been referred to as components of "World Class Manufacturing" (Ben-Daya and Knezevic, 2009).

The TPM initiative is targeted to enhance competitiveness of organisations and it encompasses a powerful structured approach to change the mind-set of employees thereby making a visible change in the work culture of an organisation. Some of the issues regarding TPM implementation include partial implementation of TPM, overly optimistic expectations, lack of a well-defined routine for attaining the objectives of implementation, lack of training and organisational communication.

While RCM advocates the use of condition-based maintenance, TPM tries to expose abnormalities, clarify operating conditions, abolish environments causing accelerated deterioration, establish daily checks and introduce extensive visual control. Therefore, TPM can be a good facilitator for implementing RCM (Mokashi et al., 2002b). Additionally, RCM can be considered as a maintenance improvement strategy, while TPM is implemented holistically, without assessing technical aspects in terms of reliability improvement.

### *3.4.4 Business Centered Maintenance (BCM)*

Business Centered Maintenance (BCM) is a concept and process of continuous improvement in maintenance and maintenance processes, equipment condition and performance to improve OEE, operations efficiency, output quality and worker safety. BCM roots from TPM and takes TPM one step further and actively ensures that the goal of focused improvement activities is to increase productivity by minimising input and maximising output (Fedele, 2011). BCM was initiated by Kelly (2006) and it can be categorised as an approach that includes maintenance optimisation as part of the outcomes of the overall business strategy. Thus, BCM can be described as the opposite of Integrated Logistics Support (ILS)/Logistic Support Analysis (LSA) (Ren et al., 2017) and its main drawback is that it can easily become a complex and extensive procedure, especially in the case of complex systems.

Additionally, Houghton and Lea (2009) suggest that BCM is best suited for an organisation with broader business objectives. Waeyenbergh and Pintelon (2002), describe BCM as a profitability contributor compared to RCM. Moreover, BCM can consider both the technical aspects of the system and additional factors such as operational profile and customer requirements. For example, this is the case for the UK Ministry of Defence (MoD) and Royal Navy projects, as naval warships require high levels of reliability and availability in order to have the capability to operate under different survivability scenarios.

### *3.4.5 Asset Management (AM)*

The Publicly Available Specification (PAS) standard 55 (BSI, 2008) defines Asset Management (AM) as "systematic and coordinated activities and practices through which an organisation optimally manages its physical assets and their associated performance, risks and expenditures over their lifecycles for the purpose of achieving its organisational strategic plan". PAS 55 highlights the need for performance-accountable asset/business focus, with enabler activities closely mapped onto the asset needs. AM is also defined as the process of maximising the ROI of equipment over its entire life cycle, by maximising performance and minimising CapEx (Capital Expenditures) and OpEx (Operational Expenditures) (Khuntia et al., 2016). It is a concept designed in order to examine assets over their full life cycle and aims through better awareness of the assets value, reviewing the assets in a more satisfactorily way and perform the best possible service and standards to increase profitability (Schneider et al., 2006). AM can, if broaden, be seen as asset care and asset exploitation. Hence, AM resembles BCM and must be seen in a time perspective and over the whole life cycle, thus including original investment, maintaining, disposal and modification (Woodhouse, 2006).

### *3.4.6 Risk Based Maintenance (RBM)*

Risk Based Maintenance (RBM) is a maintenance strategy that attempts to meet the dual objectives of minimisation of hazards caused by unexpected failures of equipment and a cost-effective strategy. Risk Based Inspection (RBI) is commonly used in planning of inspections for static mechanical equipment and is commonly used within the chemical, petrochemical, oil and gas and refinery industries. The inspections are prioritised based on risk, expressed as expected values, integrating the likelihood and consequences of failures. The methodology for RBI is based on a mix of qualitative, semi-quantitative and quantitative tools and elements (Selvik et al., 2011). RBI is commonly used in the offshore industry and ship structures. While RCM selects the maintenance strategy based on qualitative evaluation of failures, RBI/RBM use risk for prioritising potential failures. Risk is defined as the product of a failure probability for each item and its respective consequence (Takata et al., 2004). Hence, the basic concept of RBI/RBM is to focus inspection and/or maintenance efforts on items with higher risks.

### *3.4.7 Terotechnology*

The concept of terotechnology was developed in the 1970's from UK government work and is defined by its characteristic of calling for feedback of information at several points in the maintained system's life cycle (Sherwin, 2000). However, all the feedback goes to the designers, and so, one does not immediately appreciate that any actual changes, to either the design or the maintenance policy, are contemplated between successive generations of machinery. Thus, practice of terotechnology is a continuous cycle that begins with the design and the selection of the required item, follows through with its installation, commissioning, operation and maintenance until the item's removal and disposal and then restarts with its replacement.

Although a very interesting concept, it has not been taken up on a large scale in industry. This lack of response was primarily due to the fact that there was no support from practical methods and techniques (Pintelon and Gelders, 1992). The development in terotechnology from Life Cycle Cost (LCC)-based to Life Cycle Planning (LCP)-based may seem minor, but is in fact profound because it allows the maintenance function to be seen as contributing to profits, rather than just spending money (Sherwin, 2000). It can be concluded that terotechnology considers maintenance within the overall administrative framework of an organisation. Other management concepts that also contain maintenance activities as part of their framework are Integrated Logistic Support (ILS) and Logistic Support Analysis (LSA) (Shukla et al., 2014, Waeyenbergh and Pintelon, 2002, Blanchard, 1981).

### 3.4.8 Summary of maintenance concepts

The salient features on the key maintenance concepts are summarised and tabulated in Table 3.2. Based on the criteria stated in the table, a qualitative comparison of the strategies is executed alongside their core advantages and disadvantages.

Table 3.2 Comparison table of maintenance concepts

| **Criteria** | **Maintenance Concepts** | | | |
|---|---|---|---|---|
| | **CBM** | **RCM** | **TPM** | **BCM** |
| *Core Intent* | Failure detection | Failure prevention | Cultural change | Continuous improvement |
| *Focus of implementation* | Monitoring | Coverage of all possible failure modes | Planning for different conditions | Maintenance optimisation |
| *Initiation* | Selection of parameters | Team assembly and training | Top management announcement, training initiation | Top management business objectives |
| *Correlation to maintenance activities* | Initiator of maintenance jobs | Generation of maintenance plan based on RCM outcome | Autonomous maintenance by operators | Autonomous maintenance by operators |
| *Measure of effectiveness* | Number of failures | MTBF | OEE | OEE |
| *Objective* | Breakdown prevention | Reliability improvement | Complexity | Maximise profitability |
| *Personnel participation* | Limited to personnel focusing on CBM core | Core analyst group involved | Organisation high participation | Organisation high participation |
| *Skill requirements* | High skill for detection and analysis | High skill for proper FMEA and RCM analysts | Low skill implementers | Low skill implementers |
| *Approach* | System driven Technically detailed approach | System driven Technically detailed approach | Individual driven Managerial framework approach | Individual driven Business oriented approach |
| *Advantages* | Increased availability | System reliability improvement | Productivity and quality improvement | Integrated auditing possibility |
| | Indication of system condition | Rationalisation, description of system and components | Powerful structured approach | Accuracy, focused improvement activities |
| *Disadvantages* | Potential high capital cost | Reliability-centred, cost implications if too detailed | Not really a maintenance concept | Complexity and extensive procedure for complex systems |
| | Extensive need for data for analysis and correct diagnostics | Extensive need for data and resources for analysis | No decision rules for basic maintenance policies | Extensive use of resources, time consuming |

## 3.5 Maintenance in the maritime industry

Effective maintenance planning of a ship aims at minimising failures, equipment downtime, spare parts inventory, maintenance costs and emergency maintenance simultaneously while satisfying regulations and meeting voyage scheduled with a limited crew capability and under budget constraints. The following sections provide an overview of the maintenance elements that shape and govern maintenance activities in the shipping sector.

### *3.5.1 Ship maintenance regulatory & supervisory elements*

Examining Figure 3.1 and associating it with maintenance in the shipping industry, ship maintenance was initially treated as a procedure that could be accomplished in a random day by day operation based on crew knowledge of equipment. However, in the last years this attitude has changed as maintenance started to be regarded as a strategic issue in the organisation. Factors such as environmental concerns, safety issues, liability, regulatory matters and cost reduction factors have contributed towards this change. Furthermore, shipowners and operators are interested in promoting a good image outwards which is crucial in today's world of competitiveness and public awareness (Lazakis et al., 2010).

Additionally, optimisation of maintenance is challenging due to highly restrictive and harsh operating conditions of ships. The optimisation is even more complicated due to the high level of uncertainty accompanied by these operating conditions. In the meantime, there is a delicate trade-off between the cost of over maintenance and the cost of avoided maintenance. Therefore, maintenance in the marine industry has conflicting multiple objectives, such as maximisation of reliability and safety and minimising costs simultaneously (Inozu and Karabakal, 1992).

With the progress of innovating technology and shipping, consulting bodies and international standards promote the safe operation of ships for environmental and safety issues. The importance of maintenance is demonstrated by the fact that it is the only shipboard activity to have one whole element assigned to it in the ISM code (IMO, 1997). ISM Code element 10 focuses on maintenance of ship and equipment stating that "*The company should establish procedures in its SMS (Safety Management System) to identify equipment and technical systems the sudden operational failure of which may result in hazardous situations*". In chapter 10 of this code, the procedures, requirements and obligations that a shipping company must follow are mentioned so as to ensure the company's compliance with the international regulations. Accordingly, shipping companies follow the international regulations and Classification Society's rules in order to develop the safety management manual which organises inspections at defined intervals, takes appropriate corrective actions if necessary and keeps records with all necessary steps followed in the maintenance procedures. BS/ISO 13613 (2011) provides shipboard personnel and other parties information concerning maintenance and testing for critical ship propulsion systems.

Moreover, IACS recommendation 74 (IACS, 2001), mentions that in order to conduct corrective maintenance tasks, certain steps have to be followed such as identification of the existing failure, establishment of the failure cause and finally suggestion and implementation of a corrective measure. Furthermore, Tanker Management Self-Assessment (TMSA) has been introduced (OCIMF, 2008) since 2004 in the oil shipping market including in element 4, a maintenance parameter which demonstrates the best practices ship operators or owners should adopt by identifying critical ship components and arranging the procedures for controlling maintenance. In addition, TMSA2 was introduced in 2008 incorporating operators experience and industry feedback and adjustment of Key Performance Indicators (KPIs). The latest addition, TMSA3 (OCIMF, 2017) has been updated to make the self-assessment conduction easier and to promote continuous improvement and is fully integrated within OCIMF's Ship Inspection Report Programme (SIRE), providing a single area to maintain data related to ship inspections, crew reports and incidents.

In order to simplify and make the safety management manual more efficient, the Planned Maintenance System (PMS) was introduced, which keeps track of the maintenance actions and tasks (Lazakis and Ölçer, 2015). The PMS is a paper or software-based system that allows ship operators to carry out maintenance in intervals suggested by machinery manufacturers based upon running hours or calendar time scheduling and the requirements of the Classification Society. The PMS is a type of preventive maintenance and the maintenance activities are carried out irrespective of the condition of the machinery and parts must be replaced if it is written in the PMS even if they can still be used. Moreover, the equipment is maintained before breakdown occurs in an attempt to avoid failures, which can also lead to over-maintenance, speeding aging due to excess dismantling and re-assembly, and increasing the risks of damage through human error.

Dhillon and Liu (2006) present the impact of human errors in maintenance and attempted to develop a systematic model for incorporating human error in optimisation of CBM system by integrating human reliability model into the cost optimisation of CBM. Computerised Maintenance Management System (CMMS) is also a type of maintenance software that performs functions in support of management and tracking of operations and maintenance activities. However, there are some common pitfalls of CMMS such as inadequate training of personnel, lack of commitment to properly implement the CMMS and lack of commitment to persist in CMMS use and integration.

### *3.5.2 Application of reliability tools in ship maintenance*

An innovative ship maintenance strategy is presented by Turan et al. (2011) based on criticality and reliability assessment while utilising Fault Trees with time-dependent dynamic gates in order to accurately present the interrelation of the components for a diving support vessel. The above paper utilises the Fault Tree (FT) capabilities by using quantitative methods of analysis and data such as Failure Rates (FR) and Mean Time Between Failures (MTBF). Laskowski (2015) applied the Fault Tree Analysis (FTA) and Reliability Block Diagram (RBD) as tools for modelling the reliability structure of a marine main engine by conducting qualitative means of analysis using the minimal cut sets method. Moreover, Guan et al. (2016) presented a FT model considering fires and explosion in a dual fuel engine room as the top event. The primary factors that affect these kinds of accidents are determined through minimum cut sets and based on the results; suggested measures are proposed to improve safety and reliability. Furthermore, Ananthraraman et al. (2014) created a FT for a two stroke main engine lubrication oil system in order to examine the reliability of the overall system and identify critical components and demonstrated that with the use of additional components in the system, component reliability could be increased which contributed to the overall reliability of the main engine lubrication system.

The American Bureau of Shipping has released guidance notes (ABS, 2015a) related to FMEA requiring the development and submission of FMEAs as part of Classification requirements for certain systems such as dynamic positioning systems, drilling systems, dual fuel diesel engines etc. Moreover, the International Association of Classification Societies (IACS) (2014) published recommendations for the FMEA process for diesel engines and reporting the FMEA process. To contribute and improve the ongoing efforts of Classification Societies and operators, Cicek and Celik (2013) examined the application of FMEA in order to prevent and reduce the occurrence of crankcase explosion failure to improve machinery system reliability and enhance operational safety on board ships.

In addition, FMEA can favourably be combined with FTA as both tools complement each other. Specifically, Souza and Alvares (2008) applied FMEA in conjunction with FTA as a risk assessment tool for the application of RCM. The methodology was used to study and analyse the failure mode of a hydraulic Kaplan turbine and showed that these two tools can complement each other for the execution of an effective predictive maintenance plan, on the basis that the FMEA provided the information required for the FTA basic events. Moreover, Hidalgo et al. (2011) carried out the failure analysis of steering systems for LNG carriers. FTA was developed in order to identify the most critical components for the steering gear system and then the application of FMEA was conducted for each critical component in order to identify the failure modes and provide appropriate maintenance policies based on RCM philosophy. Furthermore, Gao and Kang (2016) applied the FMEA method for the reliability analysis of the main failure events and their interrelations regarding the offloading systems of an FPSO. The main failure events were then demonstrated using a FT.

Hence, a combined analysis can be performed as both tools can complement each other for the execution of an effective predictive maintenance plan, on the basis that the FMEA provides information required for the FTA basic event. They are two traditional safety analysis methods (BS, 2007, BS, 2006), both of which can provide a complementary way of identifying errors and tracking their possible influences. FTA will identify combinations of conditions and component failures which will lead to a single defined adverse effect. FMEA on the other hand considers all single component failures in turn and identifies the range of their effects on the system. Logical relationship between top events and basic events of the FT can also be verified based on FMEA and results. Whilst FTA focuses on a defined adverse effect, FMEA implicitly considers all adverse effects that may occur as a result of any single failure.

### *3.5.3 Industrial marine maintenance software*

Maintenance software and products are available for the shipping industry, developed by regulatory bodies, manufacturers, ship operators and bodies from other industries. Most of these products focus on asset management, maintenance planning, data collection, prognosis and diagnosis for predictive maintenance purposes as presented in the following paragraphs.

ABB Asset Health Center integrates existing monitoring infrastructure and systems with business intelligence that transforms operational data into actionable information such as strategic repair/replace decisions and tasks, managing parts inventory and scheduling maintenance activities (ABB, 2015). Kongsberg (2014) have developed a monitoring system, approved by major engine designers, for the bearings on an engine. It consists of bearing wear and bearing temperature monitoring of crank-train bearings, water in oil, cylinder liner temperature and shaft power monitoring, aiming at improved operations and optimised monitoring of engines.

Moreover, MAN (2012) have developed a service concept, named engine management concept for LNG ships in order to support their operation and maintenance. The tool aims in optimising plant operations and ensuring reliable operation of machinery using monitoring and diagnostic systems. Wartsila (2012) also provides a propulsion condition monitoring service for ship propulsion systems. In addition, Rolls-Royce (2016) approach SATAA (Sense, Acquire, Transfer, Analyse and Act) provides asset optimisation solutions in terms of health management, optimisation, decision support and remote and autonomous operation by utilising data analytics.

Lloyds Register published a report (2013) regarding machinery planned maintenance and condition monitoring called ShipRight which was revised in order to add machinery condition based maintenance procedures and describe how a machinery planned maintenance scheme can be accepted as an integral part of the continuous survey machinery cycle. DNV-GL (2014) also published a report regarding condition monitoring in the shipping industry, reviewing existing condition monitoring technologies and methods for implementing such technologies.

Class NK introduced the concept of PrimeShip-Total Ship Care (2013) which has been designed to prevent pollution of the marine environment and ensure safety of ships at every stage of a ship's life including maintenance. The product contributes to improved reliability and increased efficiency of hull structure analysis, machinery shaft alignment and torsional vibrations and maintenance management amongst others. Furthermore, ABS (2015b) NS5 Entreprise aims to handle the primary functions of operational management and maintenance amongst other.

DANAOS shipping company has developed for its own fleet a performance system WAVES (2016), utilising big data analytics for statistical processing of past observations, anomaly detection and forecasting applications assisting in CBM activities. LAROS (2013) by Prisma Electronics, is another platform that enables remote monitoring and analysis of vessel operational parameters by collecting, processing and transmitting real-time data through a wireless network of smart sensors in order to provide diagnosis and prognosis.

BASSnet Maintenance is another software which enables users to plan and execute the maintenance of their fleet and manage their global stock of spare parts more efficiently alongside reminders and alerts for key maintenance issues (BASSnet, 2013). Additionally, Teledata Marine Solutions have developed ShipManager 7.0 (Teledata Marine Solutions, 2009) which provides a platform for predictive analysis and decision support; and addresses the operational requirements of commercial, technical managers and ship staff. Other maintenance products related to the marine industry are available such as Consultas from AD TEK, a hull stress monitoring system from HULLMOS (2012), AMOS by SpecTec, Teromarine Maintenance (2005), Ulysses Systems Task Assistant and Vector Maintenance Manager (2007).

### *3.5.4 Relevant research projects*

In the last few years the industry has collaborated with academic institutes to conduct research projects related to the topic of maritime maintenance. Some of the most important research projects are briefly described below.

The EC MINOAS (Marine Inspection Robotic Assistant System) project focused on automated structural inspection by developing robotic platforms for inspection of difficult to access areas (Caccia et al., 2010). Image processing and pattern recognition techniques for defect detection in metallic surfaces were developed alongside toolboxes enabling online processing of harvested data and operating as a decision support system in the aid of the inspector.

Additionally, Inspection Capabilities for Enhanced Ship Safety (INCASS) is an EU FP7 project related to the integration of monitoring, inspection, structural and machinery databases, risk analysis and decision support for ship structures and machinery equipment (INCASS, 2015d). In terms of the machinery and equipment condition monitoring, advanced reliability and criticality-based tools and methodologies utilising Bayesian Belief Networks (BBN) with Markov chains were exploited for CBM assessment in order to provide decision support actions.

The MUNIN (Maritime Unmanned Navigation through Intelligence in Networks) research project developed a technical concept for the operation of an unmanned merchant ship and assessed its technical, economic and legal feasibility (Burmeister et al., 2014). Specifically, one work package focused on an autonomous engine and monitoring control system, enriching the engine room and propulsion automation systems providing advanced condition monitoring functionalities for preventing breakdowns, planning maintenance and diagnostics.

ISEMMS (Integrated Ship Energy & Maintenance Management System) project aims at the development of an integrated energy and maintenance management system to optimise the energy efficiency and minimise the maintenance cost of ship machinery systems by monitoring condition parameters (Gkerekos et al., 2017). A number of advanced technologies such as statistical and artificial intelligence algorithms are applied to provide decision support and advisory generation for optimal operation and the most effective maintenance scheduling.

### *3.5.5 Remarks*

Classification Societies encourage condition monitoring techniques onboard ships, offer guidelines but do not oblige ship operators or owners to implement such techniques in their operation and maintenance. However, most shipping companies still follow the PMS based on ISM code (IMO, 1993). This can also be observed in a study by Lazakis and Olcer (2015) who introduced a reliability and criticality-based maintenance strategy by utilising a fuzzy multiple attributive group decision-making technique, which is further enhanced with the employment of Analytical Hierarchy Process (AHP). The outcome of this study indicated that preventive maintenance is still the preferred maintenance approach by ship operators, closely followed by predictive maintenance; hence, avoiding the ship corrective maintenance framework and increasing overall ship reliability and availability.

Additionally, the slow advancements of maintenance in this sector are also illustrated by the fact that maintenance concepts such as RCM and CBM have not been successfully implemented on ships due to reasons such as lack and portability of failure data, equipment condition cannot be taken for granted, training and overburden of shipboard personnel, lack of adequate redundancy and purview of regulatory bodies are some of the many reasons as discussed by Mokashi et al. (2002b).

RCM has gained recognition by the armed navies. The UK MoD has published Defence Standard 02-45 (Ministry of Defence, 2000). However, it seems that this approach is too resource demanding as far as an unorganised industry, as the maritime industry is concerned. Also, Formal Safety Assessment (FSA) of ships has a very similar approach compared to RCM with the difference identified in that FSA looks at all kinds of hazards, while RCM is primarily concerned with those that relate to functional failures (IMO, 2006).

Nowlan & Heap (1978) analysed failures of equipment onboard aircrafts and discovered that 89% of the proportion of failures were not age-related and could not be addressed therefore by the traditional preventive maintenance techniques. This proportion is similar for marine vessels, where according to the MSP study in 1982 by the US Navy the respective proportion was 77% while another study in 2001 from Submarine Maintenance Engineering, Planning and Procurement (SUBMEPP) showed that the proportion was equal to 71% on US Navy submarines (Allen, 2001).

In support of this fact, Amari et al. (2006) highlighted that several independent studies across various industries reveal that only 15% to 20% of equipment failures are age-related. The rest of equipment failures are based on the effects of random events that occur. The failure patterns where dominated by random failures which can be addressed by detecting them before they occur using a predictive maintenance strategy.

Technological advances and high cost of ownership have resulted in considerable interest in advanced maintenance techniques. The most recent research projects between academia and industry indicate the current research trend and exploration of advanced maintenance techniques. These techniques focus on machinery condition monitoring applications onboard, through the utilisation of artificial intelligence, reliability and data-driven methods to provide CBM functionalities and decision support. Moreover, Zaman et al (2017) presented the challenges and opportunities of big data analytics in the shipping sector and potential functionalities with regards to ship safety, energy management and performance monitoring amongst other. Raza and Liyanage (2009) also stated that there has been an increasing demand for testing and implementing intelligent techniques as a subsidiary to existing condition monitoring programs and that artificial neural networks have emerged as one of the most promising techniques in this regard, which are explained in the following section.

## 3.6 Artificial Neural Networks (ANNs)

According to Haykin (1998), a neural network can be defined as a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain within two respects; knowledge is acquired by the network from its environment through a learning process and interneuron connection strengths, known as synaptic weights are used to store the acquired knowledge. A more pragmatic definition that emphasises the key features of this technology can be given after Principe et al. (1999) as: "*ANNs are distributed, adaptive, generally nonlinear learning machines built from many different processing elements that receive connections from other processing elements and/or itself.*" Figure 3.3 displays a simple structure of a typical ANN with input, hidden and output layers.

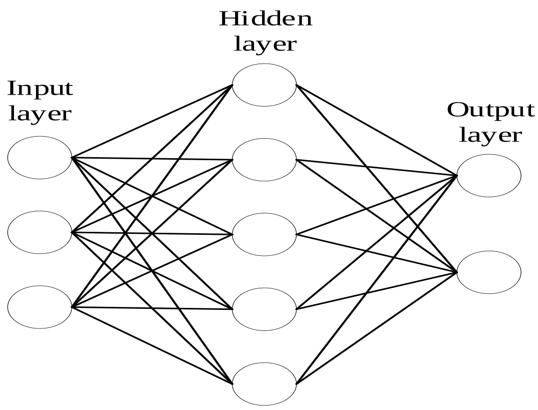



Figure 3.3 Artificial neural network

They are powerful tools for modelling, especially when the underlying data relationship is unknown. ANNs do not require a prerequisite establishment of rules and reasoning which govern relationships between a desired output and its significant effective variables. One desirable feature of ANNs is that they are readily updated as more historical data becomes available. Thus, they are referred as adaptive systems. The application fields of neural networks can be categorised with respect to different criteria, such as industrial application, type of reliability problem, life cycle phase in which the algorithms are predominantly applicable and the type of learning problem.

ANNs have been shown to be robust and reliable tools in many industrial applications. Applications of ANN can be found in condition monitoring, fault diagnosis, sensor validation, modelling, simulation and control (Yang et al., 2002b). Furthermore, ANNs can solve a variety of problems in optimisation, pattern recognition, clustering, function approximation, time series analysis, prediction and validation (Asgari et al., 2011). They learn from the data obtained from a system instead of learning from a specific program.

### *3.6.1 Artificial Neuron*

ANNs attempt to simulate the functioning of the human brain. According to a simplified description, the latter consists of about ten billion neurons, each connected, on average, to several thousand others. By means of these connections, neurons both forward and get messages, in the form of varying quantities of energy. A substantial aspect to be underlined relies in that the neurons do not react immediately to the reception of a signal. Instead, they sum all received inputs and transmit their own messages only when this sum has reached a certain critical threshold. Globally, the brain learns by adjusting the number and the strength of the above-mentioned connections (Bevilacqua et al., 2005).

The building block of a neural network is a neuron (Barad et al., 2012). From the biological description above, in a mathematical form, a neuron could be represented with a threshold logic unit. This consists of an object which accepts an array of weighted quantities (incoming from a set of synapses), sums them and whether the sum overcomes a certain bound (usually called threshold), outputs a value, generally known as the activation level. A transfer function takes this value and produces the output of the current artificial neuron, outgoing towards the neighbouring neurons by means of an axon.

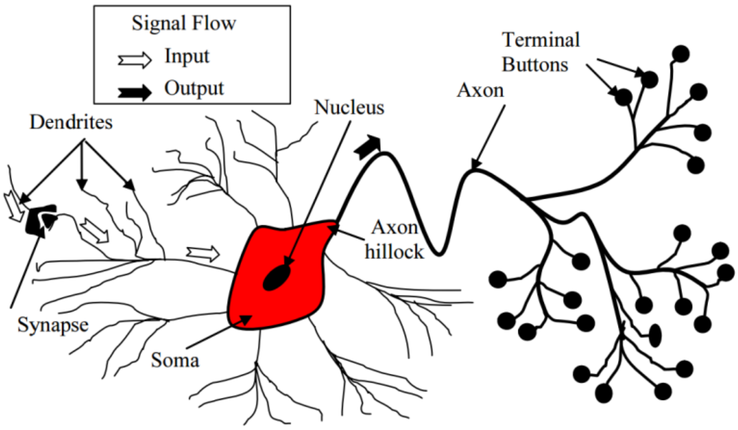



Figure 3.4 Representation of biological neuron (Bocaniala et al., 2006)

A neuron has several inputs $a_n$, each of these inputs are multiplied by weights $w_{ij}$ and then added up. Weights are basically adaptive coefficients within the network that determine the intensity of the input signal (Nasr et al., 2012). Often a bias is added $b_j$, which is the node's internal threshold. The result is the neuron activation $z$ as shown in Equation 1.

$$z = \sum_{i=1}^{n} a_i w_{ij} + b_j \qquad (1)$$

Once the neuron's activation $z$ is obtained, it is fed into the activation function $f(z)$. Common activation functions are the sigmoid and linear functions as described later. The output of this activation is then the output $O_j$ of the neuron as shown in Figure 3.5 which displays a single node of a neural network.

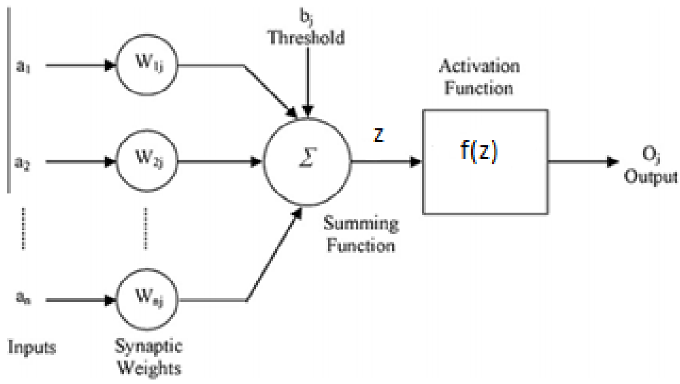



Figure 3.5 Artificial neuron model (Fausett, 1994)

### *3.6.2 ANN learning*

Neural networks can be classified according to the type of training. If the training algorithm uses different input and output patterns, then the network is trained using supervised learning. If the training algorithm has to extract information only from the input patterns, then the learning is named unsupervised (Ogaji et al., 2002). In supervised learning, the network is first trained using a set of actual data referred to as the training set. In supervised training, the data is divided into three categories: the training, validation and testing sets. A heuristic states that the number of the training set data should be at least a factor of ten times the number of network weights to adequately classify test data (Levin et al., 1991). The actual outputs for each input signal are made available to the network during the training. Processing of the input and result comparisons are then done by the network to get errors which are then back propagated, causing the system to adjust the weights which control the network (Hertz et al., 1991).

On the other hand, in unsupervised learning, only the inputs are provided without any outputs, meaning that the results of the learning process cannot be determined. This training is considered complete when the neural network reaches a user defined performance level. Such networks internally monitor their performance by looking for regularities or trends in the input signals and make adaptations according to the function of the network. This information is built into the network topology and learning rules (Levin et al., 1991).

### 3.6.3 *Neural network training*

ANN learn the relation between inputs and outputs of the system through an iterative process called training (Asgari et al., 2011). Neural networks are trained for input data and the output is computed. The error obtained by comparing outputs with a desired response is used to modify the weights with a specific training algorithm. This procedure is performed using the training dataset until a convergence criterion is met. ANNs are nonparametric as they automatically extract the parameters from input data and desired response by means of a training algorithm (Haykin, 1998). Moreover, neural networks have different learning algorithms to train these networks. The choice of a particular learning algorithm is influenced by the learning tasks a neural network has to perform.

The objective of training is to establish weights that minimise errors as the output neurons first give a set of values that differ from the correct results, while the objective of the validation and testing is to learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to learn. The training set is used for computing the gradient and updating the network weights and biases. The validation data are used to stop training early if further training on the primary data will hurt generalisation to the validation data. Test dataset can be used to measure how well the network generalises beyond training and validation data.

During training, both the inputs and outputs are presented to the network for a number of iterations. At the end of each iteration, the network evaluates the error between the actual and desired output. The error is used to modify the weights accordingly. Figure 3.6 illustrates the training structure of a neural network.

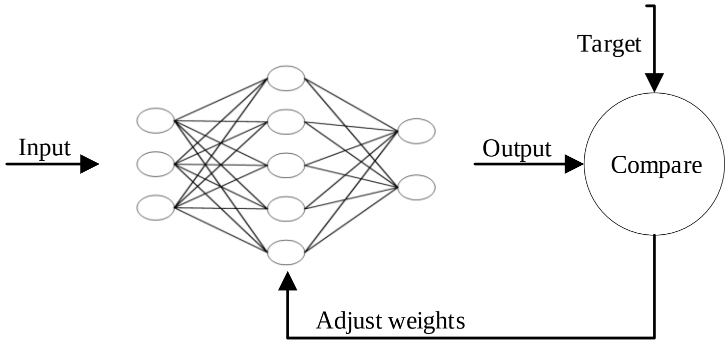



Figure 3.6 ANN training process

A performance function is defined based on the difference between target and actual output in order to examine the performance of the trained network. Furthermore, the backpropagation algorithm is the workhorse of learning in neural networks (Rojas, 2013) and is used to modify weights accordingly based on the error between actual and target output. The backpropagation algorithm is described in the following section.

### *3.6.4 Backpropagation algorithm*

Backpropagation is a systematic method to train multi-layered feedforward neural networks. The backpropagation algorithm can be used to calculate the sensitivity of a cost function with respect to the internal states and weights of a network. The term backpropagation infers a backward pass of error to each internal node within the network, which is then used to calculate weight gradients for that node (Adjallah et al., 2007). The greatest strength of backpropagation neural network is in the nonlinear solutions to ill-defined problems.

The backpropagation algorithm is based on the gradient descent method to minimise the output error with respect to the connection weights in the network. The delta rule is based on continuously modifying the strengths of the input connections to reduce the difference between the desired output value and the actual output of a processing element. At the initial stages of the backpropagation process, a set of input factors are presented to the ANN as well as their desired outputs. Then a training stage starts by arbitrary selecting a set of connection weights for each layer.

Each neuron calculates its summation function value and accordingly computes its transfer function value which represents its output. This process is a feed-forward process. A set of computed outputs is delivered to the output layer. For each processing element in the output layer an error is calculated, each representing a deviation of the computed output from the desired output. Using a learning rule, the errors are back propagated through the hidden layer of the network and the connection weights are adjusted and updated accordingly. A feed-forward process starts all over again with the new adjusted weights and new output values are calculated until a desired set of requirements are achieved as shown in Figure 3.7 (Oduyemi et al., 2015).

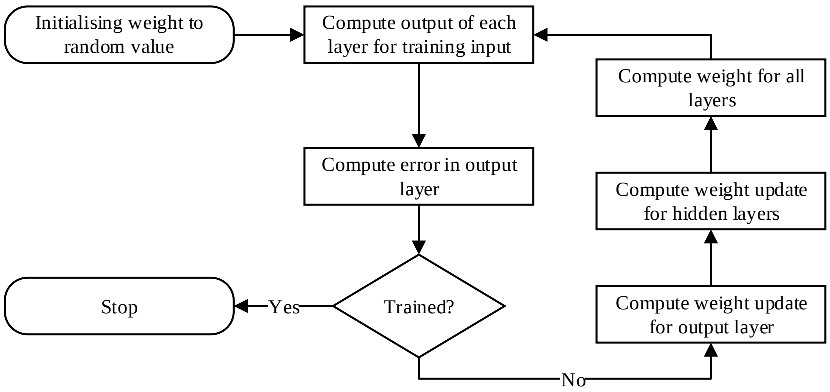



Figure 3.7 Backpropagation training algorithm

The standard backpropagation training is a gradient descent algorithm, in which the weights are moved along the negative of the gradient of the performance function. The gradient of the performance function is updated and backpropagated to the previous layer(s) until the input layer is reached. Such traditional gradient-based training algorithms do not necessarily produce fast converges, although the performance function decreases most rapidly along the steepest descent direction. Modification of the traditional backpropagation algorithm are the Levenberg-Marquardt algorithm, Bayesian regularization, conjugate gradient algorithms and the BFGS quasi-Newton method (Wu et al., 2007). The mathematical description of the backpropagation algorithm is provided in Appendix A.

### 3.6.5 *Neural network architecture*

An ANN consists of interconnections of neurons usually assembled in layers (Barad et al., 2012), as displayed in Figure 3.3. Each layer has a number of simple, neuron processing elements called nodes or neurons that interact with each other by using numerically weighted connections (Peng et al., 2010). Each layer consists of a number of neurons or nodes, and each node is connected to another node in another layer by weights (Fausett, 1994). Generally, a neural network consists of *n* layers of neurons of which two are input and output layers, respectively. The former is the first and the only layer which receives and transmits external signals while the latter is the last and the one that sends out the results of the computations. The remaining layers are called hidden layers which extract, in relays, relevant features or patterns from received signals. Those features considered important are then directed to the output layer. Sophisticated neural networks may have several hidden layers, feedback loops, and time-delay elements. Specific types of neural networks are described in Section 3.6.6.

The interconnectivity defines the topology of the ANN (Raza and Liyanage, 2009). The network topology describes the arrangement of the neural network. There are feed-forward, back-propagation and feedback types of network depending on the manner of neuron connections. The first allows only neuron connections between two different layers; the second has not only feed-forward but also ‘error feedback’ connections from each of the neurons above it. The last one shares the same features as the first, but with feedback connections, that permit more training or learning iterations before results can be generated.

A crucial step in the building of a neural network model is the determination of the number of processing elements and hidden layers in the network. A large number of processing elements can give the network the possibility of fitting very complex discriminating functions. However, it has been observed that too many weights produce poor generalisations. On the other hand, a very small number of processing elements reduces the discriminating power of a network. Since no theoretical basis exists to guide the selection, in practice the number of hidden nodes is often chosen through experimentation or by trial-and-error.

In determining the number of hidden layers to be used, there are two methods in the selection of network sizes: one can begin with a small network and then increase its size (growing method); the other method is to begin with a complex network and then reduce its size by removing not so important components (pruning method) (Oladokin et al., 2006). The determination of the number of hidden layers and nodes are crucial since if there are too many hidden layers, the neural network will not learn the underlying pattern, while with too few the neural network will not pick up the full details of the underlying patterns in the data (Oduyemi et al., 2015).

Hence, the best structure is the one which can predict behaviour of the system as accurately as possible (Asgari et al., 2011). It is observed that there is no specific rule in determining the number of hidden layers and the number of neurons in each hidden layer. Shtub and Versano (1999) suggested a few rules than can assist in determining the optimum number of neurons in a network. These include that a network with $n$ input and $m$ output units requires a hidden layer with at most $2n+1$ units. Moreover, the number of hidden nodes should be between the average and the sum of nodes on the input and output layers or should be 75% of the input nodes. Zhang et al. (1998) summarised unique characteristics of ANN, including network architecture, nodes and algorithms that affect the performance of ANNs. The performance of neural nets is affected by many factors, including the network structure, the training parameters and the nature of the data series (Barad et al., 2012).

### *3.6.6 Types of neural networks*

There are several types of neural networks, showing different characteristics and performances. Based on the network topology, ANNs can be classified into feedforward and recurrent networks using supervised or unsupervised learning algorithms (Figure 3.8). Examples of feedforward nets are the Feed-Forward Neural Network (FFNN), Multilayer Perceptron (MLP) and Radial Basis Function (RBF) network. Variants of Recurrent Neural Network (RNN) models are the Nonlinear Autoregressive (NAR), Nonlinear Autoregressive with Exogenous Input (NARX) and Long-Short Term Memory (LSTM), Adaptive Resonance Theory (ART) networks amongst others.

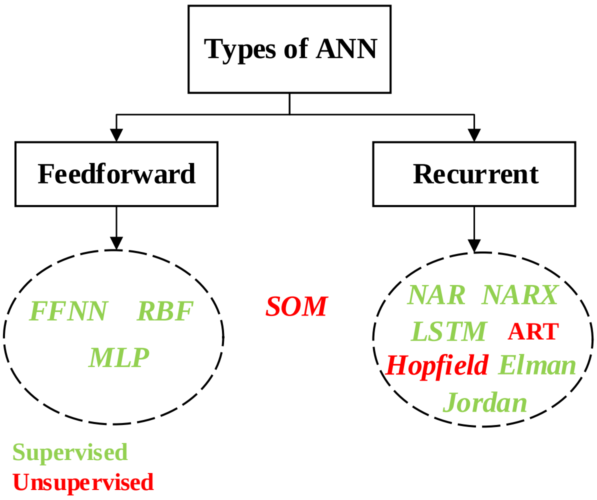



Figure 3.8 ANN classification

While it is typical to consider the Self-Organising Map (SOM) structure as related to feedforward networks, their architecture is fundamentally different in arrangement and motivation as they use competitive learning as opposed to error-correction learning techniques (Kurd and Kelly, 2007).

### *3.6.6.1 Feed-Forward Neural Network (FFNN)*

In a FFNN, the neurons are organised in the form of layers. The neurons in a layer get input from the previous layer and feed their output to the next layer. In this kind of network, connections to the neurons in the same or previous layers are not permitted. The last layer of neurons is called the output layer and the layers between the input and output layers are called the hidden layers. The input layer is made up of special input neurons, transmitting only the applied external input to their outputs. In a network if there is only the layer of input nodes and a single layer of neurons constituting the output layer then they are called single layer network. If there are one or more hidden layers, such networks are called multilayer networks. A feed-forward neural net with a single hidden layer can serve as a universal approximator to any continuous function (Hornik et al., 1990, Funahashi, 1989).

### *3.6.6.2 Multilayer Perceptron (MLP)*

Multilayer Perceptron (MLP) is the most popular type of ANN and belong to a general class of structures called feedforward neural networks. In the MLP structure, the neurons are grouped into layers. Typically, an MLP neural network consists of an input layer, one or more hidden layers and an output layer. An MLP usually is composed of several input, hidden and output nodes. The training data is fed forward from the input to the output through the hidden layers and use the backpropagation supervised learning algorithm. These networks have found their way into countless applications requiring pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map (Oladokin et al., 2006). The key disadvantages are that they train slowly, and require lots of training data, typically three times more training samples than network weights (Du and Swamy, 2014).

### *3.6.6.3 Radial Basis Function(RBF) network*

Feedforward neural networks with a single hidden layer that use radial basis activation functions for hidden neurons are called Radial Basis Function (RBF) networks. It consists of an input layer, a radial basis hidden layer and an output layer and are usually used for pattern recognition (Heger, 2012).Common used radial basis functions are Gaussian and multiquadratic. RBF networks have the disadvantage of requiring good coverage of the input space by radial basis functions. RBF centres are determined with reference to the distribution of the input data, but without reference to the prediction task. As a result, representational resources may be wasted on areas of the input space that are irrelevant to the learning task.

The hidden neuron activation functions in MLP and RBF behave differently. The activation function of each hidden neuron in an MLP processes the inner product of the input vector and the synaptic weight vector of that neuron. On the other hand, the activation function of each hidden neuron in an RBF network processes the Euclidean norm between the input vector and the centre of that neuron. MLP networks construct global approximators to nonlinear input-output mapping, while RBF use exponentially decaying nonlinearities to construct local approximations.

#### *3.6.6.4 Recurrent Neural Network (RNN)*

Contrary to feedforward networks, Recurrent Neural Networks (RNNs) are models with bi-directional data flow. While a FFNN propagates data linearly from input to output, RNNs also propagate data from later processing stages to earlier stages. It allows time-domain behaviours of a dynamic system to be modelled. The outputs of a dynamic system depend not only on the present inputs, but also on the history of the system states and inputs (Hu et al., 2007).

A FFNN having one or more hidden layers with at least one feedback loop is known as a recurrent network. The output of a neuron is fed back to its own input. Feedback loops involve the use of unit delay elements, which results in nonlinear dynamic behaviour assuming the network contains nonlinear units. RNNs may have multiple types of feedback loops. The two that can be employed are the input delays and the feedback delays. Each type of delay effectively increases the number of input nodes by providing the network with delayed information along with current information.

In the case of input delays, multiple consecutive time steps of the input features are presented to the network simultaneously. For feedback delays, the output of the model is provided to input nodes, along with previous data. This can either be done with *"open"* loops, where the known output is provided as an input, or with *"closed"* loops, which connects the network output to the input directly. RNNs can store sequential information in the form of historical data and can be used in forecasting. Elman and Jordan networks are known as simple recurrent networks (Du and Swamy, 2014). Nonlinear Autoregressive (NAR) (Ahmed and Khalid, 2017), Nonlinear Autoregressive with Exogenous Input (NARX) (Asgari et al., 2016) and Long Short-Term Memory (LSTM) networks (Wielgosz et al., 2017) are recurrent dynamic networks. A special type of recurrent neural network is the Hopfield network (Rojas, 2013). It is a simple single layer recurrent network typically used for pattern recognition and is trained via an algorithm that teaches it to learn to recognise patterns, by indicating that the pattern is recognised by echoing it back.

#### *3.6.6.5 Self-Organising Map (SOM)*

Self-Organising Map (SOM) is a class of ANN with neurons arranged in a one or two dimensional structure and trained by an iterative unsupervised or self-organising procedure (Yan, 2015). They find clusters in the data by evaluating neighbourhood measures and employing competitive learning strategies. The output neurons of the network compete among themselves to be activated or fired, with the results that only one output neuron, or one neuron per group is on at any one time. An output neuron that wins the competition is called a winner-takes-all neuron or winning neuron. Every data item is mapped into one point (node) in the map and the distances of the items in the map reflect similarities between the items (Kohonen, 1998) .

The SOM is a flexible, unsupervised neural network for data analysis and clustering (Hagenauer and Helbich, 2013). It maps input data to neurons in such a way that the distance relationships between input signals are mostly preserved (Kohonen, 2013). SOM projects input space on prototypes of a low-dimensional regular grid that can be effectively utilised to visualise and explore the properties of the data (Vesanto and Alhoniemi, 2000).

### *3.6.7 Neural networks in the context of CBM*

According to Nasr et al. (2012) ANNs provide an effective analysing and diagnosing tool to understand and simulate the nonlinear behaviour of complex systems and can be used as a valuable performance assessment tool for operators and decision makers. As more data describing the system condition and its influencing parameters become available, data-based methods are being increasingly applied to predict system behaviour (An et al., 2015) and the reliability of a system (Yam et al., 2001). Several distinguishing features of ANNs make them attractive for the development of intelligent techniques relative to condition monitoring programs (Peng et al., 2010, Zhang et al., 1998).

First of all, opposed to the traditional model-based methods, ANNs are data-driven and self-adaptive methods, meaning that there are few a priori assumptions about the models under study. They learn from past examples and capture subtle functional relationships among the data even if the underlying relationships are hard to describe or unknown. ANNs do not rely on a priori principles or statistical models and can significantly simplify the model synthesised process. They can readily address modelling problems that are analytically difficult and for which conventional approaches are not practical, including complex physical processes having nonlinear, high-order and time-varying dynamics and those for which analytical models do not yet exist.

Secondly, ANNs have good generalisation capabilities. After learning the data presented to them, ANNs can only correctly infer the unseen part of a population even if the sample data contain noisy information. Thirdly, ANNs are universal functional approximators and have more general and flexible functional forms than the traditional analytical and/or statistical methods can effectively deal with. Fourth, they are nonlinear. Real word failure models are generally non-linear. However, these models are still limited in that they are based on a little knowledge of underlying law.

Moreover, they can increase fault tolerance through adaptation and can be self-modifying over the lifecycle of a system. With the increased availability of monitoring data on the condition of a specific system, neural networks are also increasingly applied in the field of fault detection (Tan et al., 2012), fault diagnostics (Tamilselvan and Wang, 2013) and for predicting the residual useful life (Tian et al., 2010). They have been applied among others for applications in nuclear power plants (Molina et al., 2000, Reifman, 1997), mining (Sottile and Holloway, 1994), for different industrial applications of motor bearings (Li et al., 2000, Marichal et al., 2011, Yang et al., 2002a), electric machines (Tallam et al., 2002), cutting tools (Choudhury et al., 1999, Das et al., 1997) and gas turbines (Fast et al., 2008).

Although ANNs have recently gained importance in time series applications (Aizenberg et al., 2016, Szoplik, 2015, Liu et al., 2015, Laboissiere et al., 2015) , some methodological shortcomings still continue to exist, such as proper network selection, architecture and learning algorithms. Aizenberg et al. (2016) performed time series analysis using multilayer neural network for forecasting oil production in the Gulf of Mexico. They concluded that the choice of embedding dimensions from time series data is a challenging and ongoing task requiring additional research effort. Adjallah et al. (2007) applied ANN for classifying bearing faults based on condition monitoring of bearing acceleration signals in order to ease the burden of decision making on system and equipment integrity.

In addition, Zhu (2009) utilised ANN to diagnose faults of a six cylinder marine diesel engine, specifically variations in valve clearance and differences in engine cylinder loads. Their research indicated that ANN has a high degree of accuracy when predicting ship main engine faults and can improve the reliability of the engine overall. Furthermore, Zhou and Xu (2010) applied neural networks for the fault diagnosis of a marine engine cooling system by using failure modes as input to the network and failure causes as output based on simulated data.

Oladokin et al (2006) demonstrated the usefulness of ANN in maintenance planning and management by creating an ANN for predicting the expected downtime resulting from a breakdown or maintenance activity. Naffisah et al. (2014) applied neural networks to estimate the duration of dry docking maintenance activities using volume and dry docking type of activity as input to their model. Their results indicated an average error value of under six days between the actual and forecasted duration results.

Basurko and Uriondo (2015) applied ANNs for CBM of medium speed diesel engines in operation assessed for the case study of a fishing vessel. The developed ANN analyses actual monitored data to generate an engine performance model and determines four engine fault conditions. Moreover, Noor et al. (2016) applied ANN modelling on a marine diesel engine in order to predict its performance in terms of output torque, brake power, brake specific fuel consumption and exhaust gas temperature using as input data various engine speeds and loads. The network was based on a standard back-propagation Levenberg-Marquardt training algorithm and results were compared with those of a mathematical model. Results showed that the prediction error of the ANN model was lower than the mathematical model.

Moreover, Cipollini et al. (2018) investigated data-driven models for performing CBM on a ship propulsion system. The results confirmed the possibility to implement regression techniques for CBM and that amongst the machine learning models tested, ANN models generally showed the best performance. Based on the aforementioned, Table 3.3 presents a summary of the advantages and disadvantages of neural networks.

Table 3.3 Advantages and disadvantages of ANNs

| **Strengths** | **Weaknesses** |
|---|---|
| Can handle nonlinear relationships, which are characteristics of ship machinery parameter interrelationships | Rules for selecting the amount and type of data for training as to improve quality of network are minimal |
| Tolerant to measurement non-repeatability problems or noise | Criteria for the validation of a network is not well defined |
| Can operate satisfactorily even in the presence of limited information | Optimal network structure is generally unknown |
| Learning capabilities, does not have to be re-programmed | Convergence of training algorithms is not guaranteed |
| Flexibility in classification, clustering and regression related applications | Data representing faults can be difficult to obtain in some actual situations |

### 3.6.8 *Remarks*

By examining the literature, it can be observed that it is usually a tough problem for system designers to fit domain knowledge to ANN in practical applications. This is mainly due to lack of proper data for ANN training and testing. As observed, research articles applying ANN with actual monitored data are limited. CBM relies on data to determine the need for maintenance. Neural network models are fast and memory efficient, enabling them to be used for real-time condition monitoring onboard ships. They are tolerant of noisy or incomplete input data and are able to statistically quantify uncertainty and to learn classification tasks from sample training data. Furthermore, as companies are preparing the ground to adopt data-driven strategies to utilise their condition monitoring data for enhanced operation and maintenance, their approach must deploy a clear integrated strategy for how to select and analyse data with the desired business impact. The strategy should be driven by the business not by the technology that services the business.

Although various authors suggest methods and recommendations in achieving an optimum neural network architecture, it is evident through the literature that there is no standard and accepted method to automatically select the optimum ANN architecture. There are some rules of thumb for the network size which often fail drastically since they ignore both the complexity of the task and the redundancy in the training data. The optimal network size is usually not known in advance. As ANN grows in size, training can become a complicated issue. For example, how many hidden layers should be included, and what is the number of processing nodes that should be used for each layer are vague questions for model developers (Brotherton et al., 2000).

Due to the lack of manpower and information resources, the diagnosis and repair on failed equipment usually cannot be performed immediately, hence lead to long down time and unavailability. Advanced techniques such as artificial intelligence techniques have been applied for equipment degradation assessment, intelligent diagnosis and prognosis. The application of AI techniques can make the maintenance process intelligent. Different types of neural networks can be designed and implemented for various applications such as clustering, classification, regression, time series forecasting and dynamic system modelling and control. In the context of condition monitoring and CBM, they can be applied for predictive maintenance strategies that can assist decision makers in selecting appropriate maintenance actions for critical ship machinery.

## 3.7 Identified gaps

The gaps identified through the literature and critical review are defined and described below:

- Maintenance on ships is still seen as a cost item instead of a way to ensure safety and efficient vessel performance and operation.
- Maintenance and technical managers need to investigate the selection of the most appropriate techniques to deal effectively with each type of failure, implement the maintenance measures in the most cost-effective way and enhance the efficient collaboration of all personnel involved, from the crew of the ship to top management.
- Additionally, maintenance is not always fully understood or treated with the correct level of priority at board or senior management level. This is often the case until an incident occurs. Moreover, maintenance lacks a business culture as strategies can be highly technically focused with minimal business content or linkage to strategic goals. This illustrates that maintenance is isolated with little integration with other departments and is often only seen as an engineering function with little or no inputs from operators, supply chain or wider business.
- Classification Societies encourage condition monitoring techniques onboard ships, offer guidelines but do not oblige ship operators or owners to implement such techniques in their operation and maintenance, despite the benefits proven by adopting such techniques in various industries.
- Most shipping companies still follow the Planned Maintenance System (PMS) based on ISM code (IMO, 1993), comprising of preventive maintenance, either

calendar based or based on operating hours of equipment. This creates the problem of *"over-maintaining"* equipment since maintenance activities are carried out irrespective of the condition of the machinery and parts must be replaced if it is written in the PMS even if they can still be used.

- Various studies have shown that a high percentage of failures are not age related and could not therefore be addressed by traditional preventive maintenance techniques. The failure patterns where dominated by random failures which can be addressed by detecting them before they occur using a predictive maintenance strategy.
- Maintenance in the marine industry may have conflicting multiple objectives, such as maximisation of reliability and safety and minimising costs simultaneously in conjunction with the challenging operating conditions. In applications such as ship machinery, where the criticality of the equipment and the impact of unplanned downtime and quality are high, a maintenance strategy characterised by preventive and/or predictive mechanisms offers numerous advantages, including the regulatory and safety aspects.
- Technological advances and high cost of ownership have resulted in considerable interest in advanced maintenance techniques. Latest research and commercial products are aligned with the most recently established predictive maintenance and data analytics strategies. The most recent research projects between academia and industry indicate the current research trend and exploration of advanced maintenance techniques. These techniques focus on machinery condition monitoring applications onboard, through the utilisation of artificial intelligence, reliability and data-driven methods to provide CBM functionalities and decision support. Moreover, recent marine maintenance products focus on predictive maintenance and asset management through condition monitoring and data analysis of real-time operational vessel data.
- Neural networks can readily address modelling problems that are analytically difficult and for which conventional approaches are not practical, including complex physical processes having nonlinear, high-order and time-varying dynamics and those for which analytical models do not yet exist. Therefore, they

can be applied for predictive maintenance strategies that can assist decision makers in selecting appropriate maintenance actions for critical ship machinery.

- In the existing literature, neural networks developed for fault diagnostics cover a relative small number of faults focusing on a specific component or system. Their value in diagnostics of larger systems and faults, such as those related to ship systems should be investigated. Moreover, in terms of time series analysis and forecasting, there is a gap in the literature regarding such ANN applications in the marine industry which could assist in reporting future health status of systems and components and provide users with the earliest warning of potential faults.
- Data collection and processing problems exist and there is a gap between theory and practice. OEMs share limited information with operators, making it hard to develop data-driven models that can be trained using data representing faults and from which correct classification of different failure patterns can be achieved.
- Furthermore, the availability of data to train and validate such models is generally problematic. Neural network models are fast and memory efficient, enabling them to be used for real-time condition monitoring onboard ships. By examining the literature, application of ANNs models with actual monitored data are limited. Most models are trained through simulated mock data, which although can prove the accuracy and performance of data-driven models, highly demonstrates the existing gaps between theory and practice.
- Shipping companies also face challenges in analysing collected data from their vessels. The main problem in this case is how to use the collected data efficiently to maximise the benefit stemming from them. It is not unusual for shipping companies to possess large databases of stored operational data with no specific functionality or usefulness, with high percentages of data not usable in some cases. It is therefore important that the recorded data is utilised in an efficient and robust condition monitoring framework that can provide concise and clear information regarding the current and future condition of the various systems and components.
- Data for ship systems is not collected in a standardised way so that it can lead to more informed and effective decision making. The question of how much data, which data, and how often this should be collected and how has also risen; as

shipowners and operators pursue to adopt an efficient and reliable condition monitoring scheme.

- There is a need for an overall condition monitoring and predictive maintenance framework that will assist in creating a condition monitoring tool tailored to the requirements and needs of a shipping company/operator if they are unsure of which systems to monitor, or if the economics of the situation may limit the number of components that can be monitored.
- A condition monitoring framework employing a hybrid approach to identify critical ship machinery systems and components and subsequently monitor their condition through the employment of data-driven methods such as ANNs should be investigated. This flexible and innovative framework should identify critical systems through a systematic organised method. This could be accomplished through a combination of reliability tools such as FTA and FMEA. Moreover, it should aim for forecasting accurate failure warnings (alarms/threshold) before an incipient fault occurs, detect potential failures and provide appropriate maintenance actions to repair/maintain systems and components only when required. This novel framework will be demonstrated in the next chapter.

## 3.8 Chapter summary

In this chapter, the review of the existing literature was presented. Initially, the evolution of maintenance was presented alongside the various maintenance types and concepts. Additionally, the current status of maintenance practices and research trends within the maritime industry was described, concluding towards an interest in advanced maintenance techniques. Following this conclusion, the background of ANN was provided followed by their application in maritime CBM, demonstrating their prospect to be used as valuable tools for ship condition monitoring. Finally, by summarising and identifying the gaps in the existing literature, the thesis methodology is proposed and presented in the following chapter.

# 4 Methodology and Modelling

## 4.1 Chapter outline

Following the gaps identified in the previous chapter through the literature and critical review, this chapter aims to present and describe analytically the development of the overall methodology framework oriented towards predictive ship machinery condition monitoring. Initially, an overview of the key elements encompassing the suggested methodology framework is presented in Section 4.2, followed by an analytical description of the tools and methods applied for the development of the methodology framework in Section 4.3. As a conclusion, the summary of this chapter is presented in Section 4.4.

## 4.2 Overview of methodology framework

This section presents the overall hybrid condition monitoring framework strategy applicable for the maritime sector. The framework is oriented towards ship machinery systems condition monitoring with predictive characteristics through the development of a hybrid approach, utilising both reliability tools and ANN data-driven methods. The methodology initially provides a systematic approach for identifying critical ship machinery systems and components and subsequently analyses and monitors their related key performance parameters. The critical system's components and their relevant performance parameters are identified though the combination of Fault Tree Analysis (FTA) and Failure Mode and Effects Analysis (FMEA), therefore contributing to the development of a generic model capable of identifying critical subsystems and components of the main system under investigation. Subsequently, models based on dynamic ANNs are developed, using the performance parameters of the FTA-FMEA identified critical items as input for data clustering, time series forecasting and diagnostic analysis and health assessment using RBDs, leading to the recommendation of appropriate maintenance actions. Figure 4.1 presents the overall framework of the proposed methodology as applicable to the maritime sector.

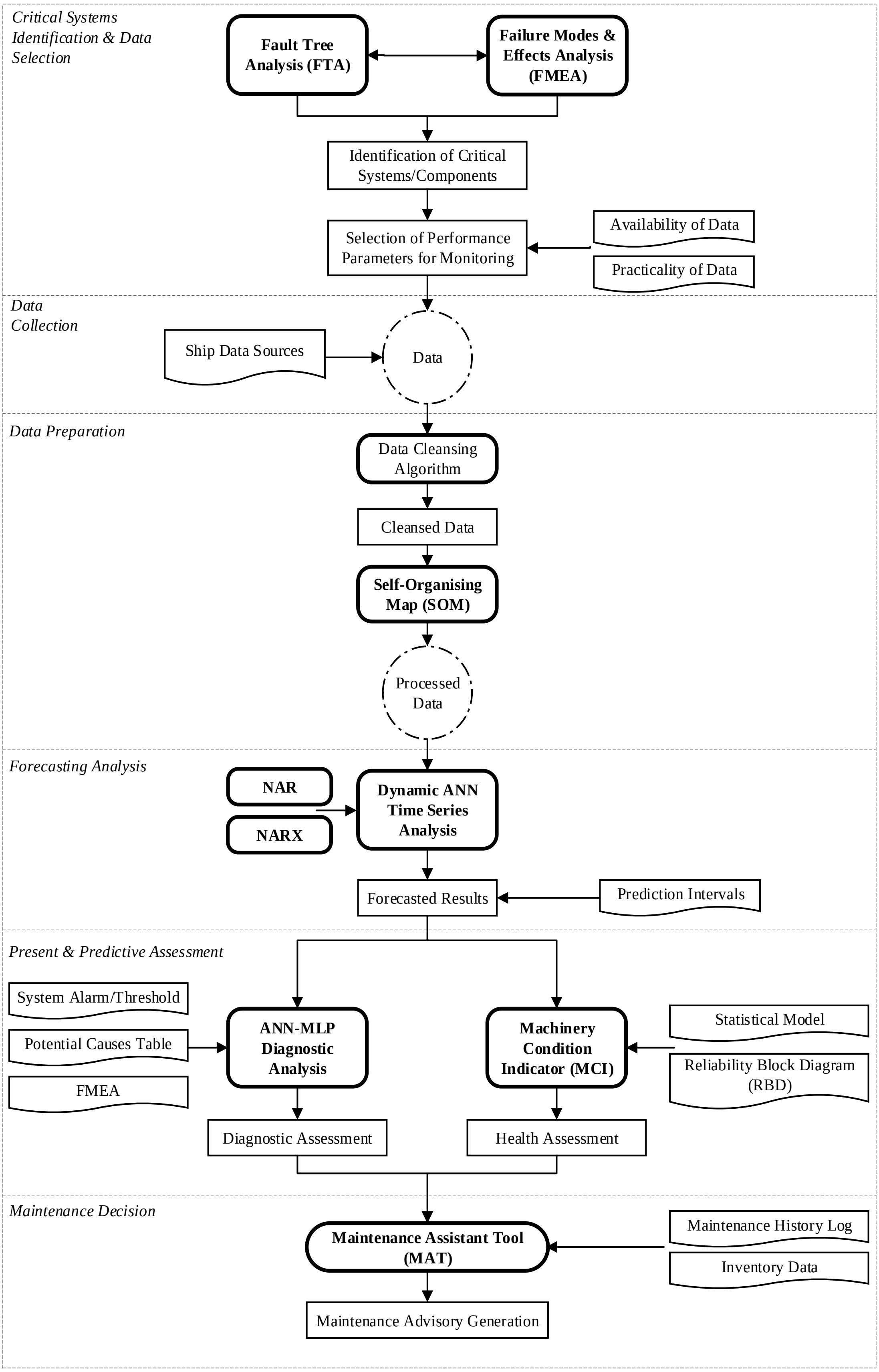



Figure 4.1 Overall hybrid methodology framework

As illustrated in Figure 4.1, the overall methodology framework consists of six major segments. More specifically:

*1) Critical systems identification & data selection*

The first part of the hybrid condition monitoring framework refers to the identification of the critical systems and the selection of data that assist in assessing the condition of the identified critical systems and relevant components. The combination of the FTA and FMEA assists in identifying critical systems and components and moreover provides significant information regarding possible faults, symptoms, causes and their effects not only in component, but also in subsystem level, which affects the overall performance and reliability of the main system under investigation. Therefore, the FTA-FMEA approach assist in focusing monitoring activities and resources on the most critical systems. Furthermore, the referred combination also provides important information regarding potential parameters affecting the performance of components as fluctuations in these performance parameters could indicate the presence or occurrence of faults leading to system failure. Therefore, based on the FTA-FMEA results, parameters that can express the condition of the system are selected which can be monitored to evaluate the system status. In this stage, it is important to mention that selection of parameters also depends on the availability and practicality of data.

Specifically, availability of data refers to the shipping company/operator possessing a database with available information and data from their ship systems or onboard sensors that can detect and transfer measurements related to the selected parameters. Additionally, the practicality of the data must be considered. For example, this could be the case in which the required parameters of the identified critical systems do not express the condition of the system to derive useful and practical conclusions regarding the system condition. Moreover, monitoring from the crew or technicians and if permanent sensors or portable equipment will be used alongside the associated costs of installing sensors for collecting the data should also be considered based on the requirements and demands of a ship operator or shipping company (Raptodimos et al., 2016)

*2) Data collection*

The second stage of the methodology is related to data collection based on the results and outcomes of stage 1. Data gathering from various sources such as historical data, machinery databases, internet cloud services, ship sensors, portable handheld devices and onboard measurement campaigns can be performed depending on the availability of resources. In this stage, the selected input data for the critical systems identified from the FTA-FMEA analysis is collected and is ready for further analysis in the following stage.

*3) Data preparation*

The data preparation stage consists of two parts. The first part consists of a developed data cleansing algorithm for detecting incorrect, inaccurate or irrelevant elements and values within a dataset. Once these have been detected, they can then be either replaced, modified or removed from the dataset. Inconsistencies detected or removed are assumed to originate from either error in the data acquisition system or human error during the data recording and collection process. The second part incorporates an innovative data clustering tool for processing the data and extracting useful information by grouping unlabeled data into clusters. The SOM clustering process is based upon unsupervised learning in order to model the underlying structure or distribution in the data in order to learn more about the data.

Opposed to classification algorithms, clustering relies on unsupervised learning and does not require large amounts of data for training thus offers simplicity and flexibility for information extraction out of limited data sources. Additionally, obtaining clusters according to the format and characteristics of the input data at this early stage of the proposed methodology makes clustering a valuable tool to be employed. Unwanted clusters representing excessive values that could possibly have a bad effect in the performance of the next stages of the condition monitoring analysis can be removed. The output of the clustering tool is the processed data which is used as input in the dynamic neural networks in the forecasting analysis stage.

In addition to the application of the clustering tool in the data preparation stage, in the case where a shipping company/operator provides a dataset, the clustering tool can also act as an early diagnostic tool providing warning of potential present faults. This is achieved by identifying clusters in the dataset representing abnormal operation and detecting clusters exceeding OEM thresholds. Thus, in this early stage of the proposed methodology, an initial analysis and feedback to the shipping company/operator can be provided prior to any further analysis and evaluation in the condition monitoring of the examined system.

*4) Forecasting analysis*

The processed data from the previous stage is used as input in the NAR and NARX dynamic neural networks for time series analysis and forecasting, constructing a predictive element to the maintenance and condition monitoring process. The time series analysis predicts the upcoming future parameter values related to the identified critical systems based on past observations in order to assess the performance of the system. In addition, prediction intervals are calculated for the various parameter observations for the forecasting model to predict with confidence faults in the critical systems and issue warnings and actions when necessary in the later stages of the proposed framework.

*5) Present and predictive assessment*

The current status of the system and the outputs from the forecasting analysis are used as input in this stage in order to assess and evaluate the system condition. The assessment is conducted using two approaches. The first approach exploits an ANN-MLP classifier for modelling and identifying faults and combination of faults. Alarm levels and thresholds are set as condition indicators. They are based on values that classify the input data as acceptable or abnormal in order to set acceptable operational levels. They can be based either on user-defined limits, OEM recommendations or parameter deviations from an established baseline. A table containing potential causes of listed faults related to all examined systems, subsystems and components is constructed as a source of diagnostic intelligence, based on OEM resources, technical manuals, maintenance history logbooks and ship operators input and knowledge. Moreover, faults and their possible causes are also connected to the relevant FMEA table for providing additional information for each respective system. In this case, the FMEA functions as a knowledge acquisition system for fault-symptom association.

The second approach employs a statistical model in combination with the Reliability Block Diagram (RBD) tool, used as a Machinery Condition Indicator (MCI) for component, subsystem and system level. This approach provides warning regarding reductions in the condition indicators during operation based on a continuous process of change. The predictive capabilities of the developed condition monitoring strategy enable the detection of possible failures and their causes prior to their occurrence, enabling the crew onboard the ship and the onshore personnel to prepare accordingly and proactively.

*6) Maintenance decision*

The last stage of the methodology develops an overall maintenance advisory generation model based on substantive and corroborated prognostic and diagnostic information. It receives as input the outputs of the previous stage and recommends predictive maintenance actions and suggestions based on the present and future status of the system. Outputs from the diagnostic and health assessment stage are presented alongside remedies assisting in rectifying identified faults. Moreover, the model produces the recommended maintenance actions based on an in-house developed code that considers user input, creating an interactive platform for maintenance decision-making. In this aspect, managerial evaluation is also considered based on resource allocation, safety and economic factors. Furthermore, the model also contains maintenance history logs and inventory data such as pictures, videos, OEM guidelines, Classification Society guidance notes and rules and service manuals assisting the crew and technical staff of the company in preparing maintenance intervals and scheduling. The following section presents the development of the methodology framework through the description of the methods and tools applied in more detail.

## 4.3 Methodology framework development

Each stage shown in Figure 4.1 is implemented through the deployment of various tools and methods presented in detail in the next sections. Critical systems are identified through the combination of FTA and FMEA tools. Their combination is initially demonstrated in Section 4.3.1 to show how these tools complement each other, followed by their individual detailed description. Data preparation consisting of a data cleansing algorithm and the SOM clustering tool for processing data is presented in Section 4.3.2. Section 4.3.3 describes the time series analysis and forecasting process for short-term and long-term predictions through the implementation of two dynamic neural networks, the NAR and NARX models. Moreover, Section 4.3.4 presents the development of the ANN-MLP classifier network for diagnostic assessment of the system. The Machinery Condition Indicator (MCI) method based on the analysis of a statistical model and RBD for obtaining MCIs of subsystem and system levels applied as a health monitoring tool is also described in this section. Finally, Section 4.3.5 analyses the development of the Maintenance Assistant Tool (MAT) which is the final tool encompassing the overall condition monitoring strategy.

### *4.3.1 Critical systems identification*

The combination of the FTA and FMEA tools is applied to identify critical systems and components and to assist in focusing monitoring activities and resources on the most critical systems. Therefore, based on the FTA-FMEA results, parameters that can express the condition of the system are selected, which can be monitored to evaluate the system condition. FMEA is an inductive "*bottom-up*" technique which examines the failure modes of the components within a system (i.e. the failure symptoms) and traces forward the potential effects of each component failure mode on system performance. Thus, it is a cause-effect model. On the other hand, FTA is the reverse of FMEA in that it is concerned with the identification and analysis of conditions, including component failures, that lead to the occurrence of a defined effect. In contrast with FMEA it is therefore a deductive "*top-down*" technique and is an effect-cause model.

The connection and combination of these two tools is graphically demonstrated in Figure 4.2.

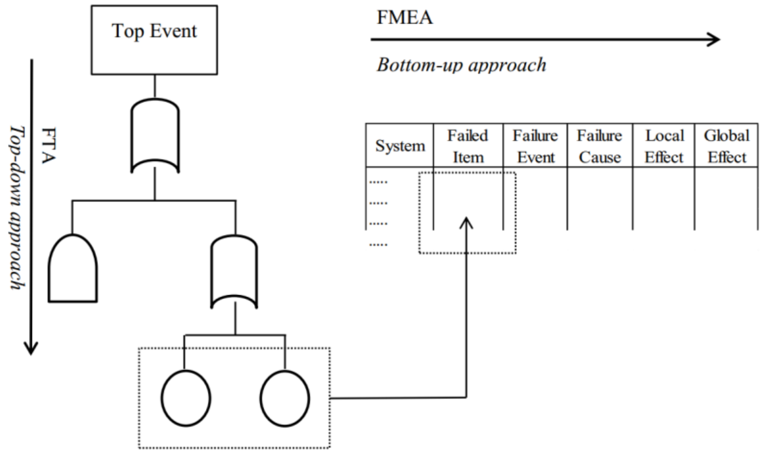



Figure 4.2 Combination of FTA-FMEA tools

In the FTA the main system (top event) is divided into its subsystems and they are consequently analysed to their components, which is the last level of the FT (basic events). As shown in Figure 4.2, the basic events of the FT are used as input in the FMEA. The FT basic events are the failed items of the FMEA worksheet while the subsystems of the FT system are included in the FMEA system column. The FMEA provides details on how to identify failures and their causes, mapping overall failure events of a system. For each failed item, all possible failure events and failure causes are considered alongside their effect in a local and global scale for the subsystems and top event respectively. Through this approach, the range of parameters which indicate the presence or occurrence of such conditions can be obtained. The FTA and FMEA methods are described in more detail in the next sections.

#### *4.3.1.1 Fault Tree Analysis (FTA)*

FTA is a systematic technique used for acquiring information on a system and finding out how the system or its components could contribute to a failure and can assist decision-making process developed by safety and maintenance engineers who plan and organise maintenance and monitoring activities (Manzini et al., 2009). It is a failure-oriented approach that considers an undesirable event associated with the system as the top event. The various possible combinations of fault events leading to the top event are represented with logic gates. Therefore, the FT provides useful information on the various cases of undesired top events (Verma et al., 2010). The graphical representation is done through FT diagrams which are a graphical design technique following a top-down approach. It uses a graphic model of the pathways within a system that can lead to a projected undesirable event or failure (Rausand and Arnljot, 2004). The pathways interconnect contributory events and conditions, using standard logic symbols and the basic constructs in a FT diagram are gates and events. The FT analysis module is based on sets of rules and logic symbols from probability theory and Boolean algebra.

Gates representing logic operators that link the various branches of the FT together, can be either static or dynamic and determine whether the top event can occur or not. The gates show the relationship of events needed for the occurrence of a higher event and serve to permit or inhibit the fault logic up the tree. Basic events can be defined as the lower level events in each FT branch. A static gate indicates that the order of the inputs of a gate do not matter, therefore are not sequence-dependent as in dynamic gates. On the other hand, in dynamic gates, the order of the occurrence of input events is vital for determining the output. If dynamic gates are used, then the FT becomes a dynamic FT. The most common static gates include the AND, OR and Voting gates (VOT) while dynamic gates include the Sequence Enforcing-gate (SEQ), Priority AND-gate (PAND), Spare-gate (SP) and Functional Dependency-gate (FD) amongst other (PTC, 2015). A thorough description of advanced FT symbols can be found in NASA (2002) and from the U.S. Nuclear Regulatory commission NUREG (1981). A summary description of them is provided in Appendix B.1.

Additionally, the top gate should be clearly defined as if a top event is not concisely defined then the FT can possibly become too large and complex, resulting in an unfocused system analysis (Longhi et al., 2015). The following steps are performed for the construction of a FT (NASA, 2002): 1) definition of the FTA scope, 2) identification of the top event, 3) identification of the first level events, 4) connection of the first level events with the top event by means of gates, 5) identification of the second level events, 6) connection of the second level events with first level by using gates, 7) repetition of the above steps for all subsequent event levels.

The FTA can be conducted in a qualitative or quantitative manner, depending on the type of data available. FTA uses Failure Rates (FR), Mean Time Between Failures (MTBF) and minimal cut sets to evaluate the reliability and availability of the system. Ultimately, FR are derived from well-substantiated historical data, including MTBF of components, units and subsystems (Pascual, 2015). If no data is available, a FT can be analysed qualitatively by using the minimal cut sets method (Ruilin and Lowndes, 2010). Finding minimum cut sets provides insight into weak points of complex systems. By using qualitative analysis, the combinations of events that cause the top event to occur can be identified. A cut set is a set of basic events, which if they all occur, will result in the top event of the FT occurring.

A minimal cut set is a combination (intersection) of primary events sufficient for the top event occurring. The combination is a *minimal* combination in that all the failures are required for the top event to occur; if one of the failures in the cut set does not occur, then the top event will not occur. To determine the minimal cut sets of a FT, the tree is first translated to its equivalent Boolean equations. These equations can be used to determine the associated minimal cut sets. The minimal cut set expression for the top event can be written in the general form according to equation 2 as:

$$T = M_1 + M_2 + \dots + M_k \tag{2}$$

where $T$ is the top event and $M_i$ are the minimal cut sets, each of them consisting of a combination of specific component failures. The general $n$-component minimal cut can be expressed as:

$$M_i = X_1 \bullet X_2 \bullet \dots \bullet Xn \tag{3}$$

where $X_1$, $X_2$, …, $X_n$ are basic component failures. In the case where data suitable for FTA exists, then the FT can be analysed quantitatively by applying various calculation methods such as the cut set summation, cross product, Esary Proschan and exact calculation method. These calculation methods are described in Appendix B.2. Once the FT has been analysed based on one of the calculation methods, reliability importance measures can be employed to identify which systems and components are the most critical for the function of the main system. The Birnbaum, Criticality and Fussell-Vesely reliability importance measures are described next (Relex, 2009).

A Birnbaum importance measure is the rate of change in the top gate probability with respect to the change in the unavailability of a basic event. Therefore, the ranking of events obtained using the Birnbaum importance measures is helpful when selecting the event to improve when the actual efforts for improvement is the same for all events and is defined as:

$$I_B(A) = P\{X|A\} - P\{X|{\sim}A\} \tag{4}$$

where *A* indicates the event whose importance is being measured, ~*A* indicates that this event did not occur, *X* indicates the top event.

The Criticality importance measure of event *A* is the probability that component *A* is critical for the system and has occurred given that the top event has occurred. The Criticality importance measure modifies the Birnbaum importance measure by adjusting for the relative probability of basic event *A* to reflect how likely the event is to occur and how feasible it is to improve the event. The Criticality importance measure is defined as:

$$I_i^{cr}(A) = (P\{X|A\} - P\{X|{\sim}A\}) * \frac{P\{A\}}{P\{X\}} \tag{5}$$

where $I_i^{cr}(A)$is the criticality importance measure for event *A*, *A* is the event whose importance is being measured, ~*A* indicates the event did not occur, *X* is the top event.

In cases where event $A$ contributes to the top event but is not necessarily critical, the Fussell-Vesely importance measure can be used. The Fussell-Vesely importance measure shows the ratio of the probability of occurrence of any cut set containing event A and the probability of the top event. The Fussell-Vesely importance measure is defined by the following equation:

$$I_i^{FV}(A) = \frac{1 - \bigcap_{j=1}^{m}[1 - P\{M_{ij}(t)\}]}{1 - R_s[r(t)]} \tag{6}$$

where $I_i^{FV}(A)$is the Fussell-Vesely importance measure, $M_i$ is the number of minimal cut sets containing $I$, $\bigcap_{j=1}^{m}$ is the minimal cut set, $M_{ij}(t)$is the j$^{th}$ minimal cut set among those containing $I$ verified at time $t$, $R_s$ is the system reliability, $r(t)$ is the end event occurring at time $t$.

#### *4.3.1.2 Failure Mode and Effects Analysis (FMEA)*

FMEA provides a systematic method for organising the study of a particular system or process in terms of failure analysis. The aim of FMEA is to review the system in order to provide details on how to identify failures and their causes as well as determine the end results of the failures occurring. It involves reviewing as many components, assemblies and subsystems as possible. Thus, FMEA is a formalised method to consider all components, their functions, failure modes and system failures (Isermann, 2006). FMEA can be applied in a bottom-up approach which assists in mapping the overall failure potential of the system. This technique is most suited for the risk assessment of mechanical and electrical systems and the approach can be either quantitative or qualitative. According to Ben-Daya and Knezevic (2009), FMEA performs three functions. These are initially the identification and recognition of potential failures including their causes and effects, the evaluation and prioritisation of identified failure modes and the identification and suggestion of actions to either eliminate or reduce the chance of the potential failures from occurring. The FMEA is constructed by integrating information and knowledge sourced from OEM manuals, Classification Societies, ship operators and marine consultancy companies.

Additionally, as mentioned in Chapter 3, guidelines from Classification Societies and IACS have also been utilised for the development of the FMEA.

#### *4.3.1.3 Data selection*

Once the critical systems of the main system have been identified through the FTA-FMEA process, data related to the identified systems are selected that express the condition of these systems in order to proceed with the hybrid condition monitoring strategy. However, if no measurable parameters exist expressing the system condition or if the shipping company/operator do not have suitable resources (sensors, portable equipment etc.) for collecting such condition monitoring data, then alternative maintenance strategies may have to be applied (Figure 4.3).

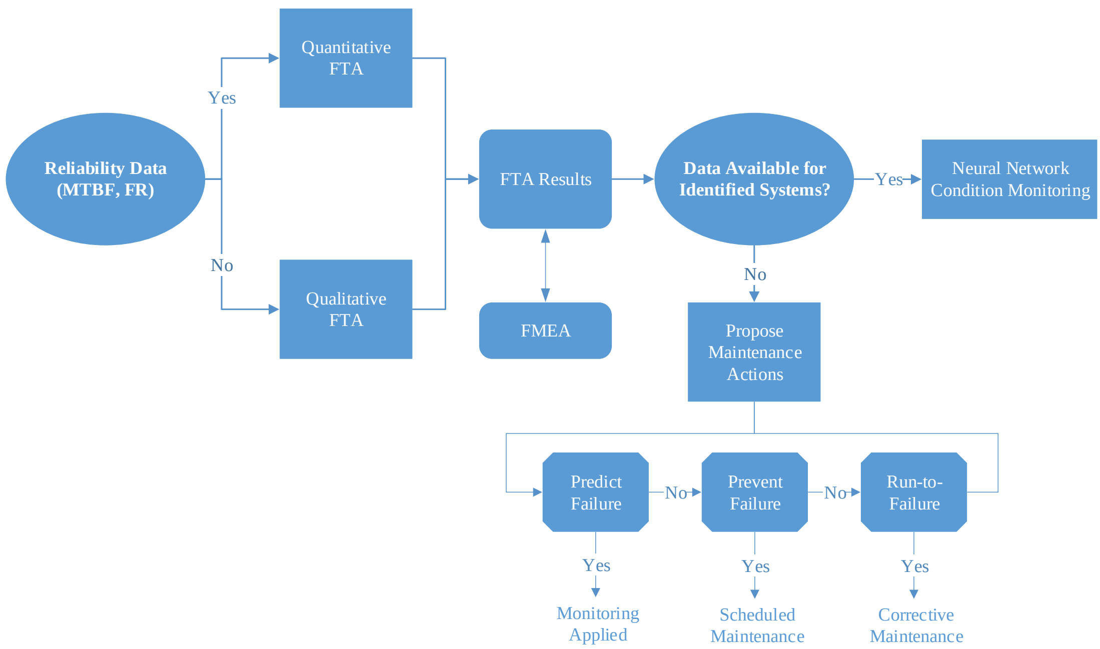



Figure 4.3 FTA-FMEA and data selection process

FTA results are obtained either qualitatively or quantitatively depending on the availability of reliability data (FR, MTBF) for the main system analysed. Once the FTA-FMEA results have been obtained then as previously mentioned, the economics of the situation may limit the number of components that can be monitored. In addition, there will also be a number of components and/or machinery for which condition monitoring is not particularly appropriate. In such a case, maintenance actions for these systems can be proposed. If predicting failures relevant to these systems is applicable, then such an outcome may lead to updating the maintenance procedures and practices with the objective of bringing maintenance practices in line with possible monitoring options to proceed with the hybrid condition monitoring strategy. If this is not an option, then preventing failures through preventive-scheduled maintenance can be undertaken or else run-to-failure and corrective maintenance actions should be taken as the least preferable option.

### *4.3.2 Data collection*

The second stage of the methodology is related to data collection based on the FTA-FMEA results. Data gathering from various sources such as raw data from ship sensors, historical data, machinery databases, internet cloud services, onboard measurement campaigns can be performed depending on the availability of resources.

### *4.3.3 Data preparation*

The data preparation stage consists of two parts. The first part consists of a developed data cleansing algorithm whilst the second part consists of a data clustering tool for clustering data and extracting useful information. Overall, the objective of this part of the methodology is to cleanse data and remove unwanted clusters so that the processed data can then be used for proper neural network training and results, as bad data observations in the ANN training set can affect network performance and invalidate the model.

#### *4.3.3.1 Data cleansing algorithm*

Data entry and acquisition is inherently prone to errors. Varieties of different reasons result in the introduction of incompleteness in datasets. Examples include manual data entry procedures, incorrect measurements, equipment errors, and many others. The existence of errors, and in particular missing values, makes it often difficult to generate useful knowledge from investigated data (BS, 2015b). Data cleansing is regarded as a first step or a preprocessing step, however no precise definition and perspective over the data cleansing process is provided (Maimon and Rokach, 2005). Overall, there is no commonly agreed formal definition of data cleansing and various definitions exist. Maletic and Marcus (2000) define data cleansing as the process implementing computerised methods of examining databases, detecting missing and incorrect data and correcting errors. Galhardas et al. (2001) describe data cleansing as the process of eliminating errors and the inconsistencies in data and solving the object identity problem.

Solid theoretical foundations to support different data cleansing approaches does not exist. Furthermore, it is an interactive approach, as different sets of data have different rules determining the validity of data. In addition to this, much of the real data cleansing work is done in a customised, in-house manner resulting in the use of undocumented and ad hoc methods. Thus, there is no best, universal method of handling missing attribute values. If there are missing attribute values within the dataset, sequential methods can be applied, which include techniques based on deleting cases with missing attribute values, replacing a missing value by the most common value of that attribute, assigning all possible values to the missing attribute value, replacing a missing value by the mean for numerical attributes or replacing it by a new value computed from a new dataset.

The developed data cleansing algorithm aims at detecting errors in datasets, removing them and replacing them when required. Error in the data acquisition system or human error during the data recording and collection process are assumed to be the prime sources for dataset inconsistencies. The flowchart of the data cleansing algorithm is demonstrated in Figure 4.4. For every attribute in the dataset, each attribute value in the dataset is compared against the defined criteria. The criteria define if an attribute value is missing (empty cell), if a value is negative when it should be positive etc. The criteria are evaluated by creating Boolean variables that tests if the conditions are satisfied or not.

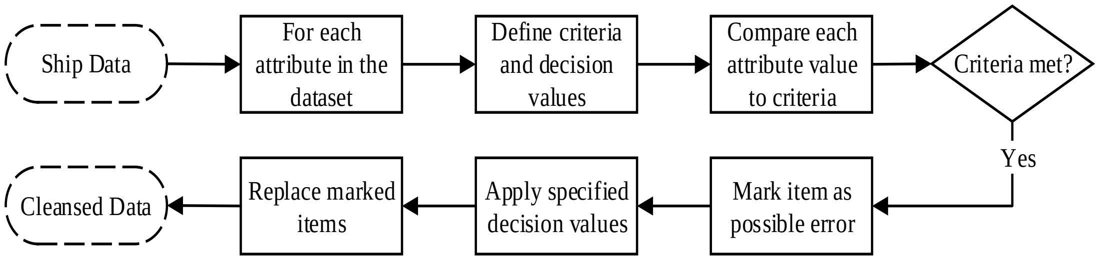



Figure 4.4 Data cleansing algorithm flowchart

If the conditions are not met, then no data cleansing is required for the dataset. On the other hand, if the conditions are satisfied for the defined criteria, then the attribute values are marked as possible errors and are then populated with the decision values specified for replacing them. Data from ship transient phases are very irregular, hence data referred to these modes are excluded for the training of the neural networks used in time series analysis. As such, transient data are deleted from the dataset and a new dataset table is created as a result. As the datasets used in this thesis contain numerical attributes, replacing missing attribute values by the attribute mean is applied. In this method, every missing attribute value for a numerical attribute is replaced by the arithmetic mean of known attribute values.

#### *4.3.3.2 Self-Organising Map (SOM) clustering*

The goal of clustering is to identify structure in an unlabelled sample or unordered data by objectively organising data into homogeneous groups (Yan, 2015). Given a set of data objects, the objective of clustering is to partition them into a certain number of clusters to explore the underlying structure and provide useful insight for further analysis. However, there exists no universally agreed-upon and precise definition of the term cluster, partially due to the inherent subjectivity of clustering, which precludes an absolute judgment as to the relative efficacy of all clustering techniques. Data clustering definitions differ among researchers as these are dependent on the desired goal and the data properties.

In this respect, Xu and Wunsch (2010) offer various interpretations of data clustering definitions such as: (1) A cluster is a set of data objects that are similar to each other, while data objects in different clusters are different from one another; (2) a cluster is a set of data objects such that the distance between an object in a cluster and the centroid of the cluster is less than the distance between this object and the centroids of any other clusters; (3) a cluster is a set of data objects such that the distance between any two objects in the cluster is less than the distance between any object in the cluster and any object not in it; (4) a cluster is a continuous region of data objects with a relatively high density, which is separated from other such dense regions by low-density regions.

Namratha and Prajwala (2012) provided an overview of clustering techniques and compared the disadvantages and advantages of each technique. They concluded that each clustering technique depends on the scope of its application and that to overcome the disadvantages, optimisation techniques can be used for better performance when required. One of the most popular and simple clustering algorithms, k-means is still widely used today although it was first published over 50 years ago. This illustrates the difficulty in designing a general purpose clustering algorithm and the ill-posed problem of clustering (Jain, 2010). Ultsch et al. (1995) demonstrated the capability of the SOM to classify a difficult artificially generated dataset using unsupervised learning, over other well-known statistical clustering methods such as k-means algorithm and hierarchical clustering requiring previous information on the dataset.

The SOM is a flexible unsupervised neural network for data analysis and clustering and does not require previous information on the dataset or a predefined number of clusters compared to k-means (Hagenauer and Helbich, 2013). It consists of a grid of interconnected nodes, where each node is an N-dimensional vector of weights. In general, given a vector as input to the SOM, the node closest to it is found, and then its weights and weights of neighbouring nodes are updated so that they can approach that of the input vector. A SOM network identifies a winning neuron using the same procedure as employed by a competitive layer. However, instead of updating only the winning neuron, all neurons within a certain neighbourhood of the winning neuron are updated, using the Kohonen rule as described in Curry and Morgan (2004).

The neurons in the SOM are arranged in physical positions originally, according to a topology function, arranging the neurons either in a grid, hexagonal or random topology. The network is trained using the batch unsupervised weight/bias training algorithm (Du and Swamy, 2014). Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes are applied to the weights and biases of the network after presentation of each individual input vector. A key advantage of batch training is that it offers no dependence upon the order in which the input records are presented, hence eliminating concerns that input records encountered later in the training sequence may overly influence the final results (Gan et al., 2007).

During training, the SOM forms an elastic net that folds towards the space formed by the input data. Data points lying near each other in the input space are mapped onto nearby map units. Thus, the SOM can be interpreted as a topology for preserving mapping from input space onto the two-dimensional grid of the map. The SOM is trained iteratively until no noticeable changes in the feature map are observed. At each training step, a sample vector *x* is randomly chosen from the input dataset. There are three basic steps involved in the application of the algorithm after the initialisation stage: sampling, similarity matching and updating Haykin (1998). These three steps are repeated until formation of the feature map has been completed based on the input dataset. The algorithm is summarised as follows:

(1) Initialisation: Choose random values for the initial weights $w_j$.

(2) Sampling: Draw a sample *x* from the input space with a certain probability; the vector *x* represents the activation pattern that is applied to the lattice. The dimension of vector *x* is equal to *m*.

(3) Similarity Matching: find the best matching (winning) neuron *i(x)* at time step *n* by using the minimum Euclidean distance criterion:

$$\mathrm{i(x)} = \mathrm{argmin}\left\|\mathrm{x(n)} - \mathrm{w_j}\right\|, \mathrm{j} = 1, 2, \ldots, l \tag{7}$$

where, the operator *argmin* returns values of the winning neuron *i(x)* that minimises the Euclidean distance criterion, *l* is the total number of neurons and $\|\cdot\|$ indicates the Euclidean norm.

(4) Updating: adjust the synaptic weight vectors of all neurons by using the update formula:

$$w_j(n+1) = w_j(n) + ή(n)h_{j,i(x)}(n)(x(n) - w_j(n)) \quad (8)$$

where $ή(n)$is the learning rate parameter and $h_{j,i(x)}(n)$ is the neighborhoood function centered around the winning neuron *i(x)*; both $ή(n)$ and $h_{j,i(x)}(n)$ are varied dynamically during learning rate to obtain the best results.

(5) Continuation: Continue step 2 until no noticeable changes in the feature map are observed.

As in the case with other ANNs, the SOM operates in two modes. The first mode is the training phase in which the map is defined and shaped based on the input data, while the second phase automatically classifies new inputs into the clusters defined in the training stage (mapping). The SOM consists of an input and output layer. Inputs in the SOM are the input vector (one-dimensional data) or vectors (multidimensional data) containing vessel data measurements of performance parameters. The output of the algorithm is the number of neurons the input data has been assigned to.

As shown in the methodology flowchart for the data clustering process in Figure 4.5, the data clustering phase comprises of a two-stage procedure. Initially, the input data is clustered in the SOM to produce the clusters. Subsequently, the clusters obtained from the SOM analysis are inspected for the existence of data similarities between them and can be further distinguished into groups by applying the Euclidean distance metric amongst the centres of the SOM clusters. Clusters can be categorised under the same group based on their *“closeness”*.

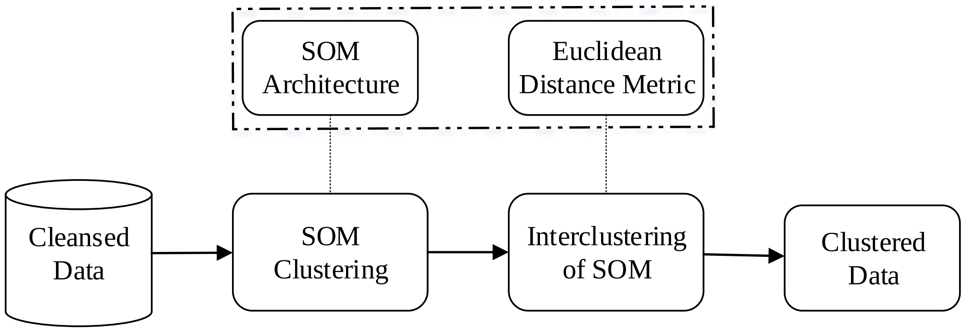



Figure 4.5 ANN-SOM clustering methodology flowchart

Clustering strategies generally follow two fundamentally different strategies namely hierarchical or agglomerative clustering and point assignment clustering respectively. In hierarchical or agglomerative clustering, clusters can be combined based on their "*closeness*", using a distance measure/metric (Vesanto and Alhoniemi, 2000). As such, after obtaining the initial clusters from the SOM, the SOM clusters are *interclustered* based on the Euclidean distance metric to divide them into groups providing useful insight and information regarding the initial clustered data. The centre of each SOM cluster is calculated, and based on the hierarchical clustering principle, can be used in a Euclidean space for finding similar clusters.

A Euclidean space allows the representation of a cluster by its centroid or average of the points in the cluster. *Interclustering* distances are defined by calculating the Euclidean distance between the SOM cluster centres and selecting the clusters with the shortest distance. Cluster centres with small Euclidean distances between them could possibly contain similar data and thus can be contained under one cluster group. Stopping can be achieved by considering the number of clusters that should be in the data or when the best combination of existing clusters produces a cluster that is inadequate, pre-defined by the user or when the Euclidean distances exceed a threshold (Jung et al., 2003).

The Euclidean distance between two points $p$ and $q$ is the length of the line segment connecting them. In Cartesian coordinates, if $p=(p_1,p_2,\ldots,p_n)$ and $q=(q_1,q_2,\ldots,q_n)$ are two points in Euclidean $n$-space, then the distance $d$ from $p$ to $q$ or vice versa is given by the Pythagorean formula (Pascual, 2015) as shown in Equation 9. Figure 4.6 demonstrates the Euclidean distance $d_{pq}$ between two points $p$ and $q$.

$$d(p,q) = d(q,p) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2} = \sqrt{\sum_{j=1}^{n}(q_i - p_i)^2} \qquad (9)$$

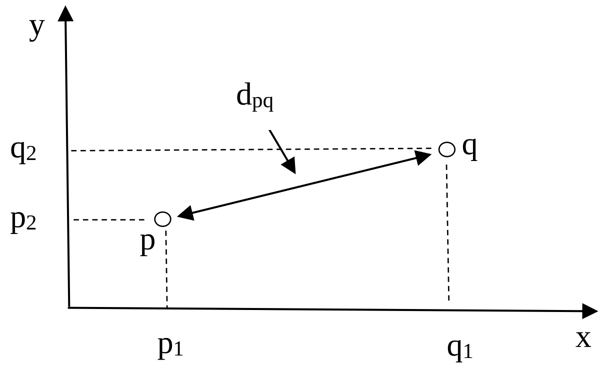



Figure 4.6 Euclidean distance $d_{pq}$ of two points $p$ & $q$

The Euclidean distances of the SOM cluster centres are imported into a developed algorithm utilising a combination of logical operators and conditional statements and expressions in order to compare cluster distances and search for clusters that have the shortest distance between them. The algorithm searches for clusters containing similar data, starting from cluster centres that have the closest distance towards larger ones, by increasing the initial distance criteria by 50% increments. The algorithm stops searching for nearby clusters if the distance is larger than 0.50, as in this case the cluster distances are large and usually no similarities exist in their contained data. However as previously mentioned, the maximum distance criteria can be defined by the user. Table 4.1 displays the criteria used for the *interclustering* purposes.

Table 4.1 Criteria for interclustering of SOM clusters

| **Neighbour cluster** | **Criteria** |
|---|---|
| 1st Possible neighbour cluster | Distance smaller or equal to 0.10 |
| 2nd Possible neighbour cluster | Distance smaller or equal to 0.15 |
| 3rd Possible neighbour cluster | Distance smaller or equal to 0.20 |
| 4th Possible neighbour cluster | Distance smaller or equal to 0.25 |
| 5th Possible neighbour cluster | Distance smaller or equal to 0.30 |

As seen in Table 4.1, if the distance between two clusters in smaller or equal to 0.1, then these clusters are very close to each other, compared to clusters with larger distances. If no clusters have a Euclidean distance smaller or equal to 0.1, then the algorithm searches for clusters with Euclidean distances smaller or equal to 0.15 and forth.

The unsupervised learning nature of the SOM provides a fast and efficient method to cluster data and model the underlying structure or distribution in the data. Moreover, through the Euclidean distance metric, clusters sharing data similarities can be identified and contained under the same group. The SOM provides a mechanism for processing ship data which is used in the following stage of the proposed condition monitoring strategy. Unwanted clusters that could have undesired effects in the performance of the next stages of the condition monitoring analysis can be removed. These are described as clusters containing irrational data values that are excessive. In addition to the application of the clustering tool in the data preparation stage, the SOM can identify clusters in the dataset representing abnormal operation and exceeding OEM thresholds.

### *4.3.4 Forecasting analysis*

#### *4.3.4.1 ANN time series analysis*

The processed data of the previous stage is used as input in the dynamic neural networks for time series analysis in the forecasting analysis stage. Time series forecasting permits to improve safety, schedule maintenance and reduce maintenance costs and downtime by predicting machinery condition. The main aim of time series modelling is to carefully collect and rigorously study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This model is then used to generate future values for the series. The procedure of fitting a time series to a proper model is termed as time series analysis, while time series forecasting can be termed as the act of predicting the future by understanding the past (Hipel and McLeod, 1994). The forecasting methodology includes the following steps:

1) Selection of type of ANN for forecasting
2) Data preparation for ANN forecasting
3) Determination of ANN architecture
4) Design of ANN training strategy
5) Evaluation of ANN forecasting results

*1) Selection of type of ANN for forecasting*

A time series is a sequential set of data points, measured typically over successive points in time spaced at uniform time intervals. It is mathematically defined as a set of vectors $y(t)$, $t = 0, 1, 2, \ldots, d$ where $t$ represents the time elapsed with a set of discrete values $y_1$, $y_2$, $y_3$, *..., etc.* The variable $y(t)$ is treated as a random variable and the measurements taken during an event in a time series are arranged in a proper chronological order. The developed forecasting analysis comprises of both short-term and long-term forecasting in order to provide information regarding the future system condition. This is achieved by developing two dynamic neural networks applicable for time series analysis and predictions. The NAR model is used for multiple-step-ahead predictions to provide the operator with the earliest possible warning for commencing corrective actions, while the NARX model is used for one-step-ahead predictions as it requires input data from the exogenous input for additional predictions.

In the NAR model, the future values of a time series $y(t)$ are predicted only from the past values of that series. This form of prediction is called nonlinear autoregressive and can be written as:

$$y(t) = f(y(t-1), \ldots, y(t-d)) \tag{10}$$

where $y(t)$ is the observation at time $t$ and $d$ is the dimension of the input vector or number of past observations used to predict the future; and $f$ is a non-linear function.

In the NARX model, future values of a time series *y(t)* are predicted from past values of *y(t)* and another external series *x(t)*. Therefore, compared to the NAR model, NARX can consider external (exogenous) input for predicting the time series *y(t)* and detecting changes in model parameters due to external conditions.

$$y(t)=f(x(t-1),\ \ldots,\ x(t-d),\ y(t-1),\ \ldots,\ y(t-d)) \tag{11}$$

where *x(t)* is the observation of the exogenous input at time *t*

Although the NARX network is applied for short-term forecasting, multi-step-ahead predictions can be acquired if knowledge of the future exogenous inputs is known. This is done by using the output of a one-step ahead prediction as the input for the subsequent prediction in an iterative process as described below and presented in Figure 4.7. In order to predict a target time series $d$ at moment $t_1$, $N-1$ points before $t_1$ of the time series $d_{t_1-N+1}$, $d_{t_1-N+2}$,…, $d_{t_1-1}$ are used as inputs of the prediction model and the output $\hat{d}_{t_1}$ is the predicted indicator value. In step 2, the inputs are updated by removing the first value $d_{t_1-N+1}$ and adding the new value $\hat{d}_{t_1}$ as the last data. The output in this step is $\hat{d}_{t_1+1}$. Then, following the same updating procedure, a series of multi-step-ahead predicted data can be obtained.

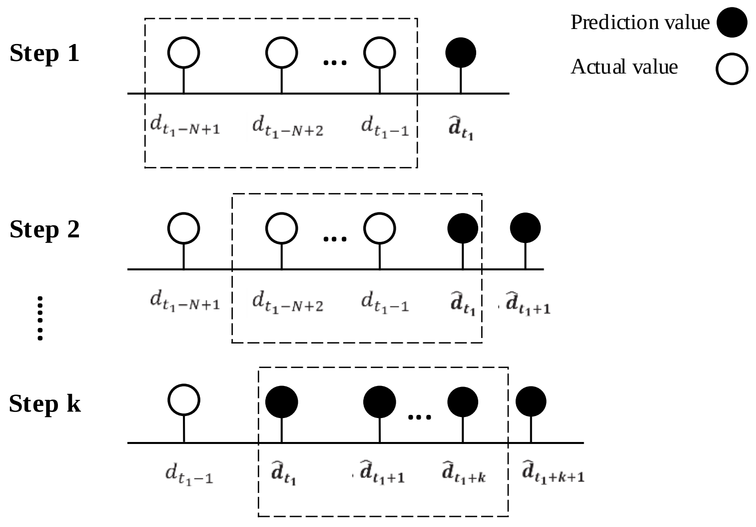



Figure 4.7 Procedure for multi-step-ahead NARX predictions

*2) Data preparation for ANN forecasting*

Data are normalised for direct use in network training by transforming them to the network's operating range, shaped to meet the requirements of the network input layer and are adapted to the nonlinearities of the neurons, so that their outputs should not cross the saturation limits (Maier and Dandy, 2000). The data is pre-processed in the ANN models by mapping data to a matrix row with minimum and maximum values from -1 to 1 for conducting proper analysis and improving efficiency of the network training. Additionally, the time series data is prepared by shifting time by the minimum amount to fill input states and layer states for network open loop and closed loop feedback modes. This allows the original time series data to remain unchanged, easily customising it for networks with different numbers of delays. Tapped delay lines are used to store previous values of the $x(t)$ and $y(t)$ sequences. Moreover, delays allow the network to model complex dynamic systems, such as the case in ship machinery systems.

Finally, data is divided into two subsets in the network for training and testing. The training set is used for computing the gradient and updating the network weights and biases and the test data is used to measure the network generalisation capabilities. The training set is used to train the network while the test set is used to test its forecasting capability. Both datasets are built from the collected data, however no specific guidance is available in the literature so far for splitting the prepared data into the training and testing sets. Recommendations in the literature range from a 90% to 10% up to a 50% to 50% ratio. Thus experimental runs might be considered for splitting the data to obtain satisfactory network training and performance (Palit and Popovic, 2005). Regardless of the ratio selected, attention should be paid to ensure that the training dataset is large enough to cover all dominant characteristic features required for reliable network training as a forecaster. The remaining dataset can be used for testing the trained ANN on the data samples never used in the training. Moreover, the ANN architecture must be established to design a network capable of analysing and forecasting time series data.

*3) ANN architecture*

A crucial step in the building of a neural network model is the determination of the number of processing elements in the network. Hidden nodes are used to capture the nonlinear structures in a time series. Since no theoretical basis exists to guide the selection, in practice the number of hidden nodes is often chosen through trial and error experimentation. The transfer function or activation function of a node defines the output of that node given an input or set of inputs. The transfer function for neural networks must be differential and therefore continuous to enable correcting error (Beale, 2011). The most commonly used transfer functions and their equations are presented in Table 4.2.

Table 4.2 Description of ANN activation functions

| | | |
|---|---|---|
| *Sigmoid activation function:* | $f(x) = \frac{1}{1+e^{-x}}$ | (12) |
| *Hardlim activation function:* | $f(x) = 1 \ if \ x \geq 0 \ else \ f(x) = 0$ | (13) |
| *Purelin activation function:* | $f(x) = x$ | (14) |
| *Hyberbolic tangent function:* | $f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$ | (15) |

A hyperbolic tangent transfer function in the hidden layer and linear transfer function in the output layer of the models are employed, capable of approximating any function with a finite number of discontinuities. The training algorithm is selected next for the NAR and NARX models in order to proceed with the prediction results.

*4) Design of ANN training strategy*

The NAR and NARX models are initially designed as feedforward backpropagation networks. During training, the network weights and biases are updated after all the inputs and target values have been presented to the network. The networks are autoregressive as the only inputs are lagged target values and lagged external input values in the case of the NARX model. The Bayesian regularisation backpropagation algorithm is primary used for training the NAR and NARX networks. This algorithm can provide better solutions for smaller datasets compared to the Levenberg-Marquardt training algorithm, which can also be applied depending on the amount of data available for training (Kayri, 2016).

When the data set is small, Bayesian regularisation provides better generalisation performance than early stopping. This is because it does not require that a validation dataset be separate from the training dataset. However, the Bayesian regularisation method takes longer to converge than early stopping (Demuth and Beale, 2002). This algorithm updates the weight and bias values according to Levenberg-Marquardt optimisation. It minimises a combination of squared errors and weights and then determines the correct combination to produce a network which generalises well. Therefore, a slower iterative algorithm with a small learning rate is used to avoid overtraining.

The performance of the network is evaluated using the Mean Square Error (*MSE*) average sum of square errors and Correlation Coefficient (*R*) given by the following equations respectively:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(d_{ij} - y_{ij}\right)^2}{NP} \tag{16}$$

where $P$ is the number of output processing elements; $N$ is the number of exemplars in the data set; $y_{ij}$ is the network output for exemplars $i$ at processing element $j$; and $d_{ij}$ is the desired output for exemplars $i$ at processing element $j$.

$$R = \frac{\dfrac{\sum\left(x_i - x_{mean}\right)\left(d_i - d_{mean}\right)}{N}}{\left[\left(\dfrac{\sum\left(d_i - d_{mean}\right)^2}{N}\right)\left(\dfrac{\sum\left(x_i - x_{mean}\right)^2}{N}\right)\right]^{0.5}} \tag{17}$$

where $x_i$ is the network output for exemplar $i$, $d_i$ is the desired output for exemplar $i$ and $N$ is the number of exemplars in the dataset.

According to Shine et al. (2018), Correlation Coefficient R values greater that 0.90 suggest the strength of agreement between actual and predicted values is excellent, values between 0.80 and 0.90 is considered substantial, while values between 0.65 and 0.80 are considered moderate and poor if lower than 0.65. The ANN is then trained based on the above parameters in open loop, as a feedforward network. The trained ANN can then be converted to closed loop mode and the data is reformatted to simulate the network's closed loop response in order to carry out multi-step-ahead predictions. The output $y(t)$ is fed back to the input of the network. The trained ANN is converted to closed loop by replacing the feedback input and creating a feedback connection from the network output to the network input, thus making the network a Recurrent Neural Network (RNN).

RNNs can store sequential information in the form of historical data and can be used in forecasting. The input nodes of the RNN network are used as the value of the current condition $X_t$ and values of the previous time series condition ($X_{t-1}$, $X_{t-2}$, $X_{t-3}$, …, $X_{t-d}$ and $X_n$). The value of the output $X_{t+1}$ can provide a one-step-ahead prediction of a time-series condition, which is a function of the current value $X_t$ and time-lagged values of the previous condition ($X_{t-1}$, $X_{t-2}$, $X_{t-3}$, …, $X_{t-d}$ and $X_n$). The predicted value $X_{t+1}$ of a time series, one-step-ahead in the future is given by the following equation:

$$X_{t+1} = F\left(X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-l}, \ldots, X_n\right) \tag{18}$$

where, $l$ is the time lag, $X_{t+1}$ is the predicted value, $X_t$ is the current value or condition and $X_{t-d}$ is the values of previous condition lagged by time $d$.

*5) Evaluation of ANN forecasting results*

The network architecture and training parameters are selected to minimise prediction errors. Furthermore, the forecasting results obtained are evaluated through defined performance measures (Aladag, 2017). The Absolute Percentage Error (APE) and Mean Absolute Percentage Error (MAPE) are used as the evaluation criteria. The accuracy of each forecast is expressed as the APE which is calculated as follows:

$$APE = \left|\frac{(y(t) - \hat{y}(t))}{y(t)}\right| \times 100\% \tag{19}$$

MAPE represents the percentage of average absolute error of forecasted values from original ones, showing the magnitude of overall error occurring due to forecasting and it is calculated as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} APE \tag{20}$$

where *y(t)* is the actual observation, $\hat{y}(t)$ is the forecasted observation for the same time interval *t* and *N* in the number of data points.

This part of the methodology develops an overall prediction model based on time series analysis. Two dynamic neural networks, the NAR and NARX networks are exploited for long-term and short-term horizon predictions. The prediction model contributes towards a predictive indication of system condition and potential failures.

#### *4.3.4.2 Measurement uncertainty-calculation of prediction intervals*

An important task when forecasting a value of *y* from one or more predictor variables is to obtain an estimate of the likely amount of error inherent in the forecast (Chatfield, 1995). A prediction interval is an assessment of this forecast error and is a range that is probable to contain the response value of a single new observation and allows assessment of future uncertainty (Chatfield, 1993). The ability of the network to provide trustworthy results depends on the accuracy of measurements available. Sensor measurements are often distorted by noise and bias, thereby masking the true condition of the system which can lead to incorrect estimation results (Bocaniala et al., 2006). The prediction intervals are defined as:

$$Prediction\ Intervals = \widehat{y_{pred}} \pm t_{1-\frac{a}{2},n-2} \times SE_{\widehat{y_{pred}}} \tag{21}$$

where $\widehat{y_{pred}}$ is the predicted point, $t$ is the value of the two tailed *"$t$"* distribution for a probability equal to $a$, $n$ is the number of samples in the data and $SE_{\widehat{y_{pred}}}$ is the standard error of the prediction (standard deviation of the sampled population). Given a dataset $x$, the standard error of the prediction is calculated through equation 22:

$$SE_{\widehat{y_{pred}}} = s\sqrt{1 + \frac{1}{n} + \frac{(x - \bar{x})^2}{{S_x}^2(n-1)}} \tag{22}$$

where $s$ is the standard error, $S_x$ is the standard deviation of $x$ and $\bar{x}$ is the sample average of $x$.

Therefore, a prediction interval forecast consists of an upper and lower limit between which a future value is expected to lie with a prescribed probability. Furthermore, it is important to mention that no generally accepted method of calculating prediction intervals exist (Chatfield, 2000). Moreover, it is significant to define that the term confidence intervals is usually applied to estimates of fixed but unknown parameter values while a prediction interval is an estimate of an unknown future value of a random variable, therefore estimates the outcome of future samples. The assessment of the system condition is described in the following section.

### *4.3.5 Present and predictive assessment*

Unwanted failures result in economic impact in the form of higher maintenance costs and lower machinery reliability and availability. Input from the time series neural networks transform the ANN classifier into a predictive diagnostic tool, enabling the necessary precautions to be taken at an early stage to prevent the further development of faults leading to system failure. In addition to the developed ANN classifier, a second method is applied at this stage as a health monitoring tool combining the development of a statistical-based model with RBDs for acquiring Machinery Condition Indicators (MCIs). These approaches are described in the following sections.

#### *4.3.5.1 ANN-MLP classifier*

A supervised MLP feedforward backpropagation neural network is developed for the detection and classification of system faults and their causes through monitoring system parameters at regular intervals. Compared to knowledge-based diagnostic approaches, data-driven methods have the advantage of not requiring in-depth knowledge of the system to be diagnosed (Vachtsevanos et al., 2006). However, they require training the algorithm using a large set of baseline and observed fault data. Baseline data are data measured when the machinery operation is known to be acceptable and stable. The ANN-MLP classifier is trained with a large dataset as its input, covering baseline data and data representing symptoms of possible faults. Such information may be obtained by expert opinion and historical legacy fault data. Through the optimal network architecture and training, the network provides accurate results for classifying different system faults and can predict faults in new sets of data not seen before by the network. Figure 4.8 displays the ANN diagnostic framework.

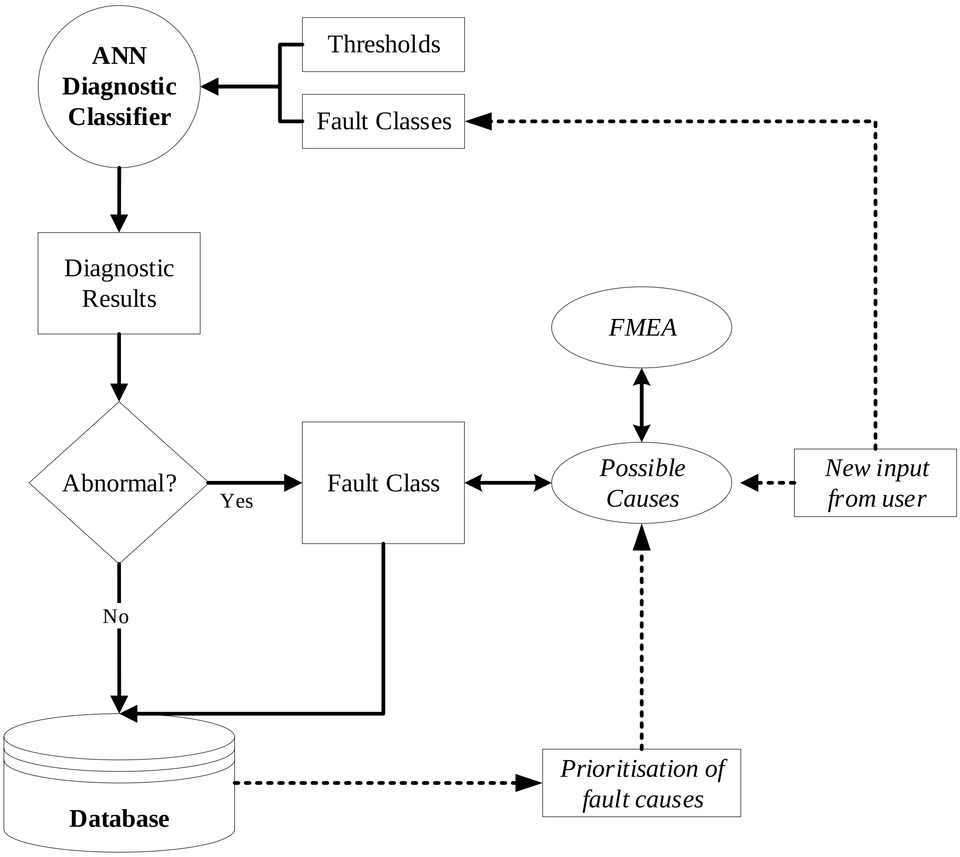



Figure 4.8 ANN-MLP diagnostic classifier framework

The system condition is determined in terms of depended or measurable parameters and faults are characterised by a shift in the measurable parameters under and/or over defined thresholds. The input variables are composed into a set of vectors and each possible feature pattern belongs to exactly one out of *n* output classes. Prior to training the network, the outputs of the ANN-MLP classifier have to be determined. The outputs are the number of fault classes which represent the various system faults. It is assumed that a system fault exists once the corresponding threshold limit has been exceeded. Once the network's inputs and outputs have been defined, the ANN architecture can be developed as discussed in Section 4.3.4.

For the ANN-MLP, the input data is separated into the training, testing and validation set. The validation set is applied to validate the performance of the network to correctly classify data not included in training. Network training is stopped when network output error has reached its minimal value, also known as early stopping. If training is continued beyond this point, then the result could be the network overtraining or overfitting the data. If the training of the network is deemed to provide inaccurate results, the network can be re-trained using a different number of layers, nodes or training function in order to provide improved results. After training, the developed network is ready for predictions on new datasets.

As observed in Figure 4.8 ,for each fault class a table is created containing information regarding potential fault causes. In addition, the fault classes and causes are also connected with relevant FMEA information providing further insight into the diagnosis of the system. Furthermore, compared to unsupervised learning, the ANN-MLP classifier enables through its supervised learning a structured method for classifying faults and adding new fault classes and causes if required. The existence of new fault data representing faults not covered by the network can form the basis to update the ANN-MLP classifier by training it with the inclusion of the new fault class as depicted in Figure 4.8.

Finally, the identified causes of restored faults are stored in a database which prioritises them from highest to lowest based on their frequency over time. Repetitive faults can reduce system reliability and increase operating cost. By identifying the root cause of the fault, the maintenance action can be reviewed and optimised to avoid or reduce the impact of the faults. Therefore, if the same fault occurs in the future, the database can assist the ship crew and onshore technical department to primarily concentrate their focus in the most frequent fault causes which have been historically reported for the vessel and fleet.

#### *4.3.5.2 Machinery Condition Indicator (MCI)*

The Machinery Condition Indicator (MCI) performs as a health assessment monitoring tool complementing the overall condition monitoring strategy, providing information regarding the current and future health of the machinery system. As stated in BS ISO 13374-1 (2003) *"It is important that the data be converted to a form that clearly represents the information necessary to make corrective-action decisions. This may be done in a written format, numerically in order to demonstrate magnitudes, graphically in order to show trends, or a combination of all three"*. Moreover, management needs to be kept informed of abnormal equipment condition situations and should be provided with information clearly representing the overall status. Therefore, the MCI is applied as an effective indicator that is easy to understand from non-experts, assisting management's understanding of potential impacts of no action, which is important for approval of recommended actions.

The MCI approach is based on the development of a statistical model describing the condition of the system and its components at any instant of time as suggested and presented in Knezevic (1987), Saranga and Knezevic (2000) and (2001) and Saranga (2002) applicable to all engineering systems. A condition parameter is required that is directly or indirectly connected to an item and its performance and describes the condition of the item during operation. The numerical value of the condition parameter describes and quantifies the condition of the system at every instant of operating time. Such a parameter is called a Relevant Condition Parameter (RCP). RCP can be values of pressure, temperature of components/systems, level of vibration and oil levels amongst others. A key characteristic of this method is that it is based on the actual condition of the item and on a continuous process of change rather than the time-to-failure approach which is only based on the moments of transition to a state of failure.

According to this method, changes in the condition parameter have a completely random nature which can be described in a probabilistic way. An item is in a functioning state as long as the RCP lies between limits at time *t*, which are defined by its initial value $RCP_{in}$ and limiting value $RCP_{lim}$. As long as the value of the RCP lies within the tolerance range, it is assumed that the item can perform its intended function successfully or there is no functional degradation. When the MCI reaches a minimum required level, it is assumed that the item has reached a critical state and the required maintenance activities should be carried out.

$$RCP_{in} < RCP(t) < RCP_{lim} \tag{23}$$

At every instant of operating time the RCP is a random variable and can be expressed through its probability density function. The probability density function of the RCP at a stated time *t* is denoted by $f_{RCP}(c,t)$. For calculation purposes it is assumed that $f_{RCP}(c,t)$ belongs to one family of probability distribution. According to this method, the probability of the value of the condition parameter being within the tolerance range for the stated time *t* is also the probability of the reliable operation of the whole item.

$$MCI(t) = P(RCP_{in} < RCP, t < RCP_{lim}) \tag{24}$$

Thus, it is important to state that the approach applies probability theory to define system reliable operation as the ability of the system to perform required functions under stated conditions for a stated period of time. Moreover, the probability that RCP at an instant *t* will have a value not exceeding the limiting value is defined as:

$$P(RCP_{in} < RCP(t) < RCP_{lim}) = \int_{RCP_{in}}^{RCP_{lim}} f_{RCP}(c,t)dc \tag{25}$$

Substituting equation 25 with equation 24 provides the calculation for the MCI function taking into account the mechanism of change in the condition of the system, as shown in equation 26.

$$MCI(t) = \int_{RCP_{in}}^{RCP_{lim}} f_{RCP}(c,t)dc \tag{26}$$

The integral on the right of the equation represents the difference between cumulative distribution functions of RCP as shown in equation 27.

$$MCI(t) = F(c,t)\Big|_{RCP_{in}}^{RCP_{lim}} = F(RCPlim, t) \tag{27}$$

The cumulative probability function represents the probability that the random variable will be equal to or less than a particular value. The MCI methodology flowchart is presented in Figure 4.9.

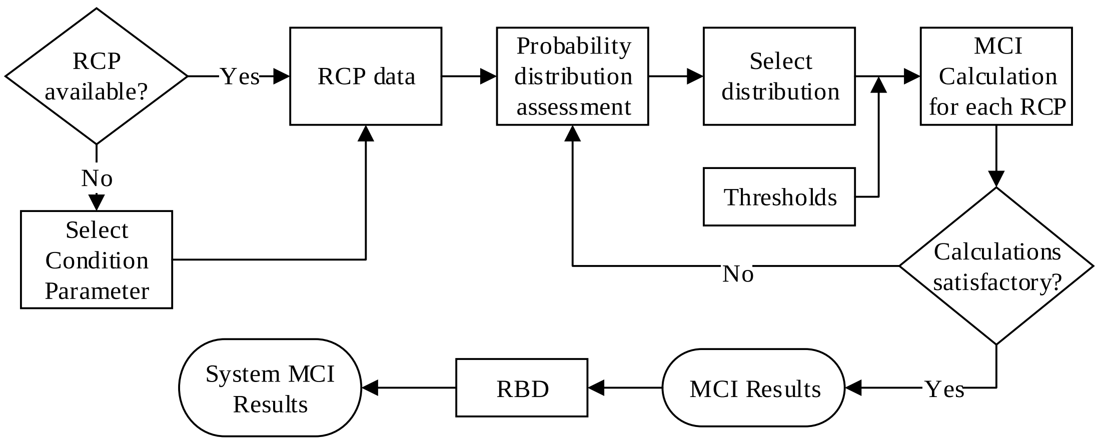



Figure 4.9 Machinery Condition Indicator (MCI) methodology

In order to proceed with the MCI calculations as previously presented, data are fitted into continuous probability distribution functions. In order to find the best fit for the data, an in-house algorithm is developed which fits the data to the most commonly used distribution functions and finds the best distribution that fits the data through a set of information criteria. Information criteria are likelihood-based measures of model fit that include a penalty for complexity (the number of parameters) which penalise distributions with greater number of parameters and help to avoid the overfitting issues (Kuha, 2004). A likelihood function gives the probability of observing the data given a certain set of model parameters.

These criteria include the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC) and the Akaike Information Criterion with a Correction for finite sample sizes (AICc). BIC is a criterion for model selection among a finite set of models, based on the likelihood function and the distribution with the lowest BIC is preferred. The AIC is an estimator of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection. If the sample size is small, AIC might overfit the data in the models and in order to address this issue AICc is applied. Remarks related to these criteria are provided in Burnham and Anderson (2002) and (2004).

Notably, the MCI approach offers flexibility in defining and altering the system thresholds in the case where the ship operator wishes to endorse additional emphasis on system safety in addition to other thresholds, such as those specified by the OEM or other technical authorities. Therefore, the MCI thresholds can be customised by the operator for the system and various subsystems, or for any particular subsystem of specific interest.

The MCI for each system item is calculated based on the existence of one or more relevant condition parameters. Based on the calculations performed for each individual MCI, a '*bottom-up*' approach is suitable for obtaining MCIs for subsystem and system level. In order to analyse the MCI in system and subsystem level, the concept and principle of Reliability Block Diagram (RBD) is utilised. RBD is a pictorial representation of a system's successful functioning, illustrating the logical connection of components (shown as blocks) required for successful system operation (BS, 2016). directly to calculate condition indicators of series and parallel configurations. Moreover, BBN was also considered for MCI analysis. However, the conditional probabilities of such a network cannot be determined without historical data or expert knowledge to identify the node state (Kobbacy and Murthy, 2008) (Mkrtchyan et al., 2016). Additionally, the principal numerical equations behind RBD configurations are well-suited for this application since individual MCIs range from 0 to 1 and can be used. The relationship between components is determined by the effect that the failure of each one has on the functionality of the entire system. If all blocks are required for the system function, then the blocks are connected in series and the system MCI can be calculated from the following equation:

$$MCI_s = \prod_{i=1}^{n} MCI_i \tag{28}$$

where $MCI_s$ is the system machinery condition indicator for a series configuration, $n$ is the number of components in the system and $MCI_i$ is the machinery condition indicator of each block. If only one system component is required for the system success, then the MCI calculation equation based on the RBD principle for a parallel system configuration is:

$$MCI_p = 1 - \prod_{i=1}^{n} (1 - MCI_i) \tag{29}$$

Additionally, if the system success definition is that $k$ or more out of $n$ identical items connected in parallel are required for mission success then the calculation equation for the system MCI is as shown in equation 30.

$$MCI_{system}(k, n, MCI) = \sum_{r=k}^{n} \binom{n}{r} MCI^r \, n - r \tag{30}$$

where $n$ is the total number of components in parallel, $k$ is the minimum number of components required for system success and MCI is the condition indicator of each unit. For $k$ out of $n$ non-identical items the event space method can be used which considers all possible operational combinations to obtain the system's MCI

(Handbook, 1998). In the event space method, all mutually exclusive events are determined, and those which result in system success are considered.

Through a combination of series, parallel and k out of n configurations, the RBD for the main system under investigation can be developed in order to obtain the system MCI based on the MCIs calculated for every individual system component. Equations for the RBD calculations are coded in MATLAB and the obtained results are also assessed and verified by using a well-known commercial software Reliasoft BlockSim which provides a platform for RBD analysis.

### *4.3.6 Maintenance Assistant Tool (MAT)*

The Maintenance Assistant Tool (MAT) is an overall maintenance advisory generation model, recommending predictive maintenance actions and suggestions based on substantive and corroborated prognostic and diagnostic information provided from the previous condition monitoring layers. The framework of MAT has been based on BS ISO 13374-4 (BS, 2015a) which provides the basic requirements for communicating and displaying condition monitoring and diagnostic information of machinery. The results of the NAR and NARX forecasting models in combination with the ANN diagnostic and MCI health assessment outputs are transformed into actionable information for the operator, resulting in advisory generation.

Moreover, MAT produces the recommended maintenance actions based on an in-house developed code that considers user input, creating a user-friendly interactive decision-making process, through which the user selects certain criteria for MAT to assemble maintenance options. The criteria-input are based on and include the criticality of the piece of equipment, maintenance costs, availability of spare parts and the PMS. The recommendations can range from *"continue routine monitoring"* to *"corrective maintenance"*. Figure 4.10 presents the maintenance decision flowchart through the criteria leading to the maintenance suggested actions.

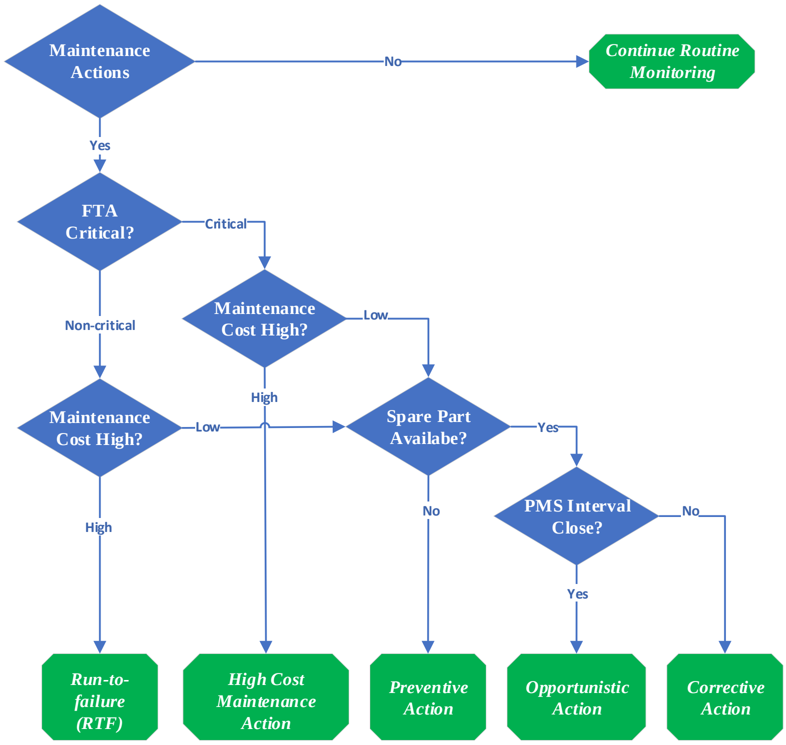



Figure 4.10 Maintenance predictive action decision flowchart

As observed, RTF, corrective, preventive and opportunistic maintenance actions are presented based on the item criticality, maintenance costs, availability of spare parts and the PMS. For equipment with low criticality and high maintenance cost, RTF action can be performed, otherwise MAT will inform the user of the non-critical items and provide opportunistic, preventive and corrective suggested actions for the non-critical equipment with low maintenance costs for future reference, following the same procedure for critical and low maintenance cost items. In the case of critical and high maintenance cost items, MAT will provide high cost maintenance actions related to overall preventive and corrective actions and activities. In such a case, onshore personnel should liaise with the crew regarding the best maintenance action to follow.

If no spare parts are available for the crew to proceed with repairs, preventive actions such as check, inspect and service the item are recommended. If spare parts are available then corrective actions such as replace, repair or overhaul can be achieved. In the case where spares are available and the PMS of the item is eminent, then opportunistic actions could be considered. These actions are in the form of preventive maintenance based upon replacement of components by taking advantage of the shutdown of a system, based that suitable maintenance resources are on the vessel or in arrival ports. Thus, opportunistic actions can extend the PMS. Appendix C provides a list of the maintenance actions produced by MAT. In practice, a combination of the actions and activities exist but the provided list is an initial well-defined set of maintenance actions to guide ship operators and decision makers.

Consequently, MAT provides the suggested maintenance actions alongside technical data related to the identified system faults. Possible faults and their causes obtained from the diagnostic assessment output are presented alongside their specified remedies, assisting in rectifying identified faults in combination with the diagnostic database which provides failure related data. The diagnostic database presents the most frequent fault causes historically reported. MCIs are also presented displaying the health status of system, subsystems and components. The MCIs can also act as a prioritisation mechanism for maintenance planning in the case of dealing with multiple faults. If confidence in the forecasting results is high, then maintenance or corrective actions can be initiated immediately upon declaration of a fault.

Furthermore, MAT contains and provides to the user upon request, maintenance and repair logs and inventory data. MAT contains a maintenance and repair history log that provides a platform for forming historical records of maintenance actions assisting in future diagnosis and maintenance organisation. The date, time, staff and maintenance actions carried out alongside spare parts used is contained in this log. Moreover, inventory data such as documents related to safety, inspection and survey, technical descriptions of equipment and spare parts list and drawings including guidelines for specific repairs and maintenance procedures assisting and guiding the crew and technical staff are included in MAT. Furthermore, based on hardware capacity, pictures and videos of previous inspections can also be included in the MAT platform.

IACS recommendations and guidelines, Classification Society guidance notes, rules and regulations, ship condition survey report and PMS, OEM guides related to system safety checks and tests, operation, maintenance and service manuals are amongst inventory data that can be extracted from MAT. Information related to available spare parts and their associated cost are also provided. In the case where spare parts are not available but the item repeats in the maintenance history log or in the diagnostic database, then spare part planning can be executed accordingly from the operator.

## 4.4 Chapter summary

The novel hybrid condition monitoring framework oriented towards ship machinery was presented in this chapter. An overview of the novel condition monitoring strategy was presented introducing the major elements comprising the overall framework. The methods and tools applied for the various stages were analysed and demonstrated. FTA assists in identifying critical systems while the FMEA expands on these systems and provides an auditing platform for producing information for system faults, causes and effects establishing information regarding the range of parameters to be measured which indicate the presence or occurrence of such conditions. The data cleansing and SOM clustering algorithm process the data so that it can be further analysed, as bad data observations in the ANN training set can affect and invalidate the model. Moreover, the SOM can also act as an early diagnostic tool by identifying clusters containing potential system faults or abnormal operation. The dynamic NAR and NARX networks are exploited for long-term and short-term horizon predictions. The developed prediction model contributes towards a predictive indication of failures. Consequently, the forecasting results are used for assessing the future system condition. The assessment in conducted using two approaches. The first approach exploits an ANN-MLP classifier for modelling and identifying faults and combination of faults, further connected with relevant FMEA information providing further insight. The MCI approach is applied as a health assessment monitoring tool complementing the overall condition monitoring strategy. By applying RBD, MCIs for subsystem and top system level can be obtained. Finally, MAT acts as a portal for the outputs of the previous stages providing important technical information through presenting data and extracting files through its database for suggesting suitable maintenance actions to the user through its interactive decision-making process. In the following chapter, the case studies carried out for demonstrating the application of the hybrid condition monitoring strategy are presented.

# 5 Case Study

## 5.1 Chapter outline

This chapter presents the application of the hybrid condition monitoring strategy described in the previous chapter. The case study related to the main engine of a Panamax container ship is applied for the development and analysis of the methodology tools and models. A description of the case study followed by the acquisition and description of the input data is provided in Section 5.2. Subsequently, the development of the FTA-FMEA tool, data cleansing algorithm, ANN models, MCI tool and MAT are analytically described in Section 5.3. Finally, the chapter summary is provided at the end providing remarks on the work performed in this chapter.

## 5.2 Case study description and input data acquisition

The methodology is applied on a two-stroke, eight cylinder marine diesel engine of a Panamax container ship. The main particulars of the Panamax ship are demonstrated in Table 5.1 below.

Table 5.1 Case study main characteristics

| **Principal characteristics** | |
|---|---|
| Year built | 2009 |
| Ship type | Cellular container |
| DWT (summer) | 50829 *tons* |
| Length overall | 260.00 *m* |
| Beam | 32.00 *m* |
| Depth moulded | 19.30 *m* |
| Draft (summer) | 12.60 *m* |
| **Engine Particulars** | |
| Main engine | HSD MAN B&W 8K90MC-C |
| Maximum Continuous Rating (MCR) | 49680 *BHP* @ 104 *RPM* |
| Number of cylinders | 8 |
| Bore | 900 *mm* |
| Stroke | 2300 *mm* |

The successful development of the case study requires input data to feed and test the suggested methodology. The accessibility of data in the marine industry is limited as issues such as confidentiality and reluctance of ship operators and OEM companies to share their data exist. Moreover, scarce current studies exist utilising raw data or data representing faulty conditions. In an effort to collect relevant input data for developing the condition monitoring strategy, a measurement campaign was conducted onboard the Panamax container ship. The onboard measurement campaign took place on the container ship sailing from Tarragona, Spain to the port of Livorno, Italy in November 2015 (Figure 5.1). Data was collected by utilising existing sensors installed in the various systems and components of the main engine. The measurements for the various main engine performance parameters were manually recorded in Microsoft Excel spreadsheets per hourly intervals from the engine control room, which provides real time sensor readings for the system. Hence, input data observations are acquired in uniform time step intervals, ensuring consistency in the predictions of the developed neural network models described in the next sections of this chapter.


Figure 5.1 First onboard measurement campaign departure: Tarragona, Spain arrival: Livorno, Italy

Overall, the main engine rpm together with 39 performance parameters and 35 corresponding hourly measurements for each parameter were collected related to the various main engine subsystems and components, presented in Table 5.2. The various parameter measurements are mostly related to temperature and pressure and are used as input data in the various ANNs, establishing the foundations for the construction of the case study analysis and results.

Table 5.2 Case study input data

| Main engine performance parameters | Units |
|---|---|
| Scavenging air temperature (per cylinder 1-8) | °C |
| Exhaust gas outlet temperature (per cylinder 1-8) | °C |
| Jacket cooling fresh water outlet temperature (per cylinder 1-8) | °C |
| Piston cooling lubrication oil inlet pressure | $kg/cm^2$ |
| Piston cooling oil outlet temperature (per cylinder1-8) | °C |
| Fuel oil inlet temperature | °C |
| Fuel oil inlet pressure | $kg/cm^2$ |
| Air cooler cooling water inlet pressure | $kg/cm^2$ |
| Main lubrication oil inlet pressure | $kg/cm^2$ |
| Main lubrication oil inlet temperature | °C |
| Thrust bearing lubrication oil outlet temperature | °C |

It is imperative to mention that no faults or alarms occurred during the onboard measurement campaign. Furthermore, the main engine was in good running condition, upon discussions with the ship's chief and second engineer and examining the up-to-date voyage and repair reports. Additionally, the vessel was operating at speeds of 12-14 knots with an engine speed of 60 rpm sailing in slow steaming conditions. These conditions further emphasise the importance of condition monitoring, as due to current fuel costs and reduced operational revenue, ship operators use slow steaming to reduce their fuel consumption levels, despite the negative impacts it has on engine operation and although manufacturers advise that extended periods of low-load operation should be avoided to ensure reliability and efficiency. Due to the potential slow steaming issues, conducting maintenance following the traditional time-based strategy may expose ship operators to higher risk of equipment failures and downtime. Thus, this risk can be mitigated by transitioning to condition monitoring.

In addition to the first measurement campaign, another larger dataset compared to the measurement campaign was provided from the ship operator upon discussion for analysis purposes. Finally, a second onboard measurement campaign was undertaken in March 2017 from Piraeus, Greece to Livorno, Italy. The data from this campaign is used as a dataset for simulation purposes in the trained ANN models in order to validate their performance. Table 5.3 presents the overview of the three datasets used for the case study development and analysis.

Table 5.3 Overview of input data acquisition and purpose

| Dataset reference | Input data | Purpose | Number of measurements per parameter |
|---|---|---|---|
| 1 | 1st measurement campaign | ANN model training | 35 |
| 2 | Data acquired from operator | ANN model training | 986 |
| 3 | 2nd measurement campaign | ANN model simulation | 47 |

Summarising the information presented in Table 5.3, the 1st measurement campaign and the acquired data from the vessel operator are used for developing and training the ANN models. Moreover, these datasets will be referred to in the following sections and chapters as dataset 1 and dataset 2. Finally, data from the 2nd measurement campaign are used for simulating the ANNs and is referred to as dataset 3. Dataset 1 and 3 can be found in Appendix F.2.4 and I respectively. Due to confidentiality agreements with the shipping company, dataset 2 is not fully presented in this thesis.

## 5.3 Development of case study models

This section presents the development of all case study models, starting from the development of the main engine FT and FMEA to the various ANNs, through to the main engine MCIs and MAT.

### *5.3.1 Development of FT and FMEA for the main engine system*

#### *5.3.1.1 FTA for the main engine system*

Prior to constructing the FT for the ship main engine system, the boundaries of the system have to be defined. The main engine system is defined as the top event of the FT and is divided into six subsystems which form the boundary conditions of the system as illustrated in Figure 5.2. It is noteworthy mentioning that the selected system set-up was derived after examining several varying structures and upon technical expertise feedback and suggestions. Also, due to unavailability of FR or MTBF data for the case study FT analysis, the minimal cut sets method is used for the identification of critical main engine systems and components.

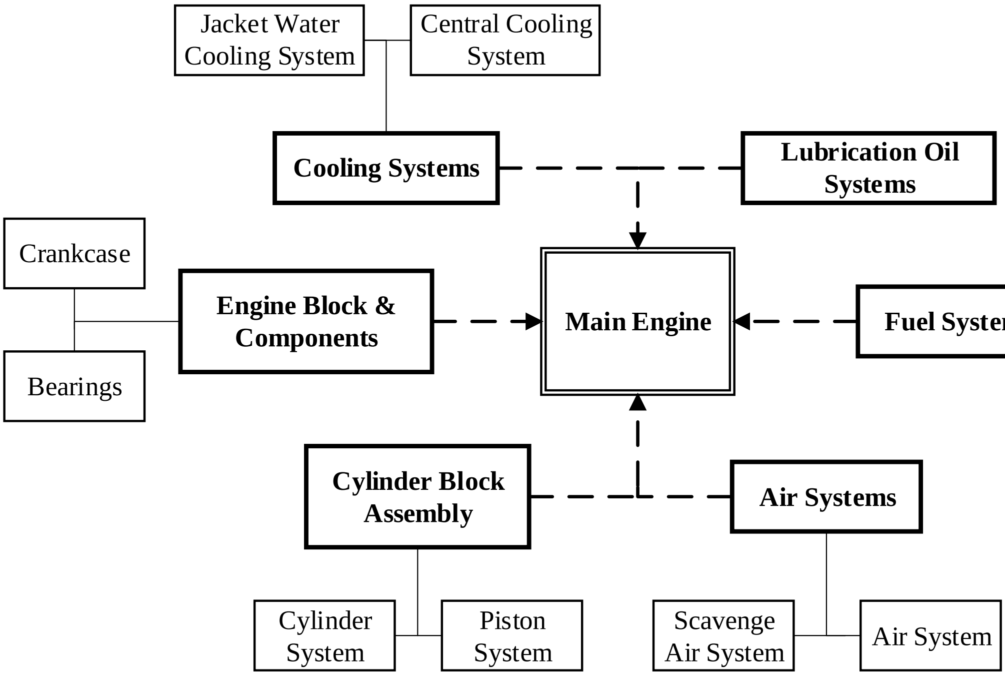



Figure 5.2 Boundary conditions for main engine system

As observed in Figure 5.2, the main engine system is divided into the cooling, lubrication oil, fuel, air, cylinder block assembly and engine block and components subsystem. Regarding the cooling system, it is divided into the jacket water cooling and central cooling system. The lubrication oil and fuel systems consist of their relevant components modelled as basic events in the FT. The air system is further separated into the main air system and scavenging air system. In the cylinder block assembly system, the system has been separated into the cylinder system and the piston assembly system. Finally, the engine block and components group contain components of the main engine such as the crankcase and various engine bearings. All these systems are explained in detail in the following pages. In total, 42 basic events were modelled in the main engine FT representing the components of the various main engine subsystems as demonstrated in Table 5.4.

Table 5.4 Basic events for main engine FT

| | | | |
|---|---|---|---|
| JFW Cooling Pump | Fuel Pumps | Air Filter | Piston Rod Stuffing Box |
| Jacket Water Cooler | Fuel Valves | Camshaft Bearing | Piston Connecting Rod |
| Sea Chest Strainer | Fuel Injector | Thrust Bearing | Scavenge Air Port |
| Seawater Pipes | Main Air Compressor | Main Bearings | Scavenge Air Receiver |
| Central Cooler | Air Distributor | Cylinder Head | Crosshead Bearings |
| Lube Oil Filter | Air Starting Valves | Cylinder Liner | Crankshaft |
| Main Lube Oil Pump | Air Filter | Cylinder Jacket | Crankcase |
| Lube System Valves | Auxiliary Blower | Piston Crown | Camshaft |
| Lube Oil Cooler | Air Receiver | Piston Ring | Exhaust Manifold |
| Fuel Piping System | Air Cooler Piping | Piston Skirt | |
| Fuel Oil Filter | Air Cooler | Exhaust Valves | |

A four level FT for the case study main engine is constructed including 14 gates and the 42 basic events defined in Table 5.4. Figure 5.3 displays the overall FT for the main engine top event. The FT is modelled with time-dependent dynamic gates in order to represent the interrelation of the main engine system and components in an accurate and realistic manner. Furthermore, dynamic logic gate is applied for improving veracity of the FT.

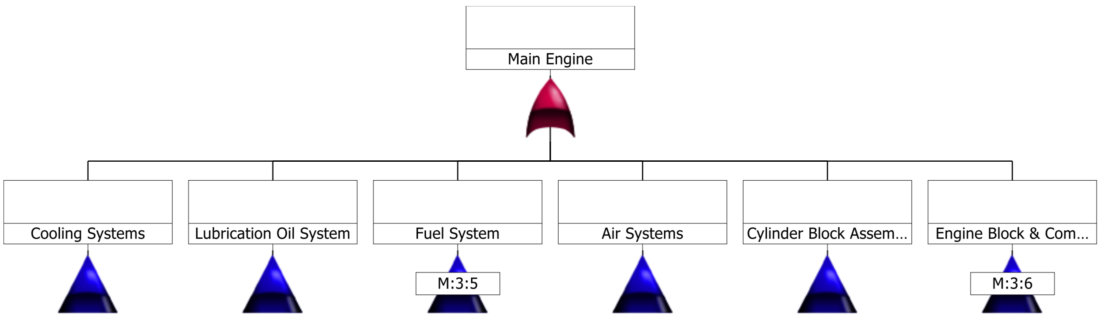



Figure 5.3 Main engine Fault Tree diagram

As shown in Figure 5.3, the main engine system is interconnected with its subsystems with an *'OR'* gate, meaning that the failure of the main engine occurs if any one of the lower level systems occur, as all of the subsystems are important for the operation of the main engine. Moreover, *'TRANSFER'* gates are applied for enhancing the graphical representation of the FT. All subsystems are modelled through the employment of static and dynamic gates. The FT structure of the cooling system is represented below in Figure 5.4.

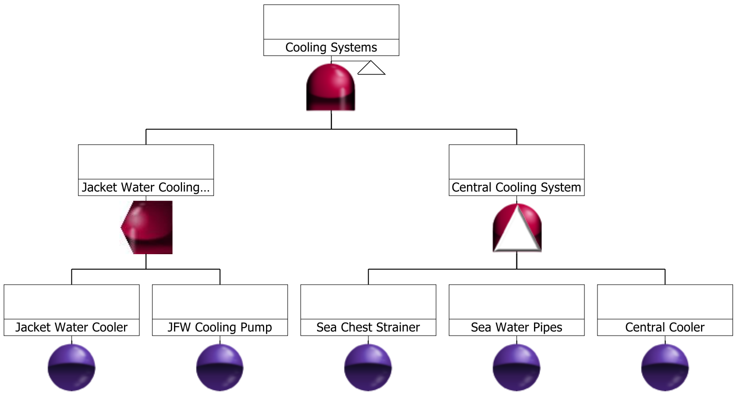



Figure 5.4 FT structure of the cooling systems

The cooling system is modelled using an '*AND*' gate assuming both the jacket water cooling and central cooling system must fail in order for the cooling system to fail. The jacket water cooling system consists of the jacket fresh water cooling pump and jacket water cooling and has been modelled with a '*SEQ*' gate. The basic events here are positioned from left to right based on the fact that failure of the jacket water cooler will influence the operation of the Jacket Fresh Water (JFW) cooling pump. Moreover, the central cooling system consists of the sea chest strainer, seawater pipes and central cooler and has been modelled with a *Priority-AND* (*PAND*) gate, prioritising components from left to right order.

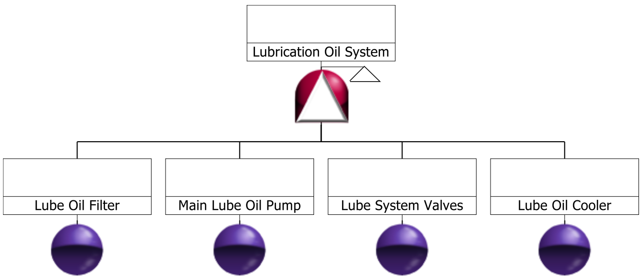



Figure 5.5 FT structure of the lubrication oil system

The lubrication oil system FT structure as shown in Figure 5.5, has been modelled using a *PAND* gate assuming that the lube oil filter failure has to occur prior to the pump, valves and then lube oil cooler failing. This assumption is made on the basis that a failure in the lube oil filter will have a knock back effect on the lube oil pump, system valves and then on the cooler. Hence, the presented configuration consents measuring the impact of a component failure on another system component, the so-called domino effect.

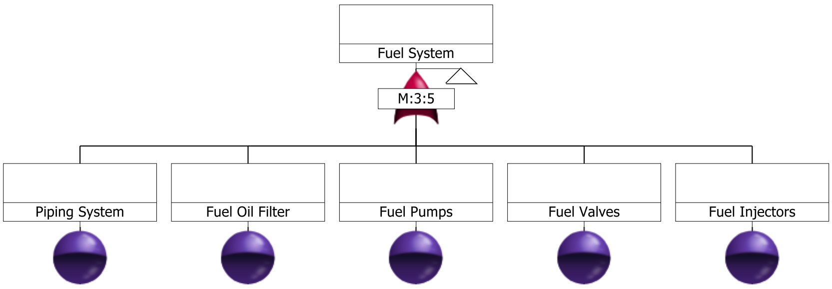



Figure 5.6 FT structure of the fuel oil system

The fuel system consists of the piping system, fuel oil filter, fuel pumps, fuel valves and fuel injectors and has been modelled using a '*Voting*' gate of 3 out of 5 systems assuming that any three of the five components of the fuel system have to fail in order for the fuel system to fail as presented in Figure 5.6.

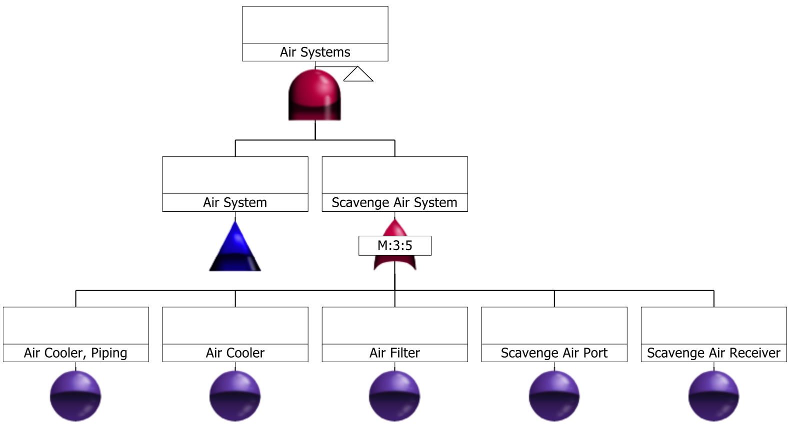



Figure 5.7 FT structure of the air systems

The air system displayed in Figure 5.7 has been modelled as an *AND* gate assuming that both its subsystems, the main air system and scavenge air system respectively have to fail in order for the air system to fail. The scavenge air system gate consists of the air cooler piping, air cooler, air filter, scavenge air ports and scavenge air receiver. The scavenge air system has been modelled using a '*Voting*' gate of 3 out of 5 systems assuming that any three of the five components of the scavenge air system have to fail in order for it to fail. Figure 5.8 displays the FT structure for the air subsystem.

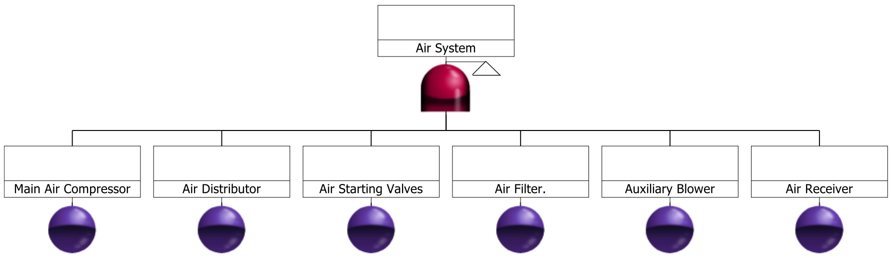



Figure 5.8 FT structure of the air system

The air system comprises of the main air compressor, air distributor, air starting valves, air filter, auxiliary blower and air receiver. The air subsystem is described using an '*AND*' gate meaning that all components in this subsystem must fail for the air system to fail.

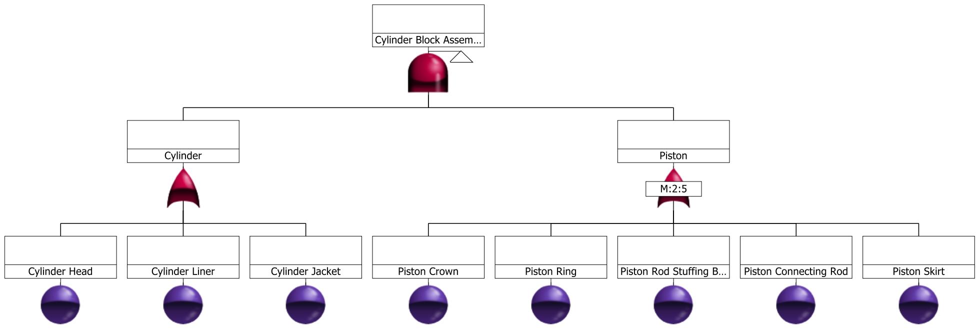



Figure 5.9 FT structure of the cylinder block assembly

The cylinder block assembly gate has been modelled with an '*AND'* gate consisting of the cylinder system containing the cylinder head, liner and jacket as basic events and the piston system modelled with a '*Voting'* gate of 2 out of 5 components as seen in Figure 5.9. The piston subsystem consists of the piston crown, piston rings, piston rod stuffing box, piston connecting rod and skirt.

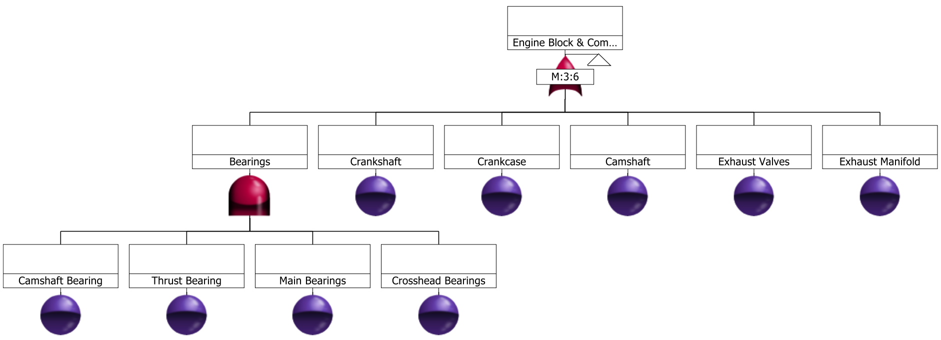



Figure 5.10 FT structure of the engine block and components system

Finally, the engine block and components gate is composed of a '*Voting*' gate assuming that any three of the bearings, crankshaft, crankcase, camshaft, exhaust valves or exhaust manifold components have to occur as seen in Figure 5.10. The bearings consist of the camshaft bearings, thrust bearing, main bearings and crosshead bearings and are composed using an '*AND*' gate as each one of the components must fail for the bearing system overall to fail.

#### *5.3.1.2 FMEA for the main engine system*

The FMEA for the case study was set up by using the basic events of the main engine FT as input in the '*Failed Item*' column of the FMEA spreadsheet. The basic events of the FT correspond to various components of the main engine itself. Additionally, the '*System*' tab in the FMEA table corresponds to the various gates of the FT, which are essentially the subsystems of the main engine. Afterwards, for each failed item, a list of potential failure events and failure causes is developed alongside their respective local and global effect on the FT top gate which is the main engine. The main engine FMEA worksheet is developed by following the structure illustrated in Table 5.5.

Table 5.5 FMEA worksheet structure

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| *FT gates (Main engine subsystems)* | *FT basic events (Main engine components)* | .... | .... | .... | .... | .... |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

In the '*Failure Event*' column, for each component all potential failure modes are identified and recorded. In the '*Failure Cause*' column, the possible failure mechanisms (corrosion, erosion, fatigue, etc.) that may produce the identified failure events are recorded. The '*Local Effect*' and '*Global Effect*' columns consist of all the main effects the identified failure modes have on other components of the subsystem and top system respectively. Finally, in the '*Detection method*' tab, the various methods for detecting the identified failure modes are noted and may involve different high/low temperature or pressure alarms and visual inspection amongst other.

Information collected for the formation of the main engine FMEA is based on Cicek and Celik (2013), Turan et al. (2011), Mokashi et al. (2002b), Emovon (2016), INCASS EU funded project deliverables (INCASS, 2014b, INCASS, 2014a) and experts opinion. As part of the FMEA process, various technical meetings were organised in order to collect useful information. In this respect, information was collected from three Classification Societies, two ship operators and two consultancy companies. Specifically, experts included IACS Classification Societies surveyors and researchers with many years of onsite experience. Moreover, experts from ship operators and marine consultancy companies included technical managers, superintended engineers, and chief engineers sailing onboard the mentioned vessel.

### *5.3.2 Development of data preparation for main engine analysis*

#### *5.3.2.1 Data cleansing*

As the initial stage of the data preparation, the data cleansing algorithm has been developed in MATLAB. Prior to any data cleansing actions, a back-up of the raw dataset is stored in the system in order to have a copy of the data intact. Data representing vessel speeds of 4 knots or less, or engine speeds of 15 rpm or less are removed from the dataset, as in such cases the ship operating profile contains parameter fluctuations that can affect ANN training. In the case of empty cells within the dataset, these are replaced with null values and then are replaced with the average value of the particular attribute. Additionally, measurements corresponding to zero values follow the same data cleansing process as in the case of empty cells. A table containing empty cell and zero value incidents is also created to keep records of such occurrences as this could assist in identifying faulty sensor instrument readings. Finally, through the data cleansing stages, the cleansed data is obtained which is used for analysis and training in the developed neural network models which include the SOM, NAR, NARX and ANN-MLP classifier.

### *5.3.2.2 SOM for the main engine*

The SOM developed for clustering the multidimensional input data consists of a 10-by-10 two-dimensional map of 100 neurons. Several SOM topologies were analysed, however this configuration was adapted as it provided sufficient clusters for processing the data based on the training input data. The SOM topology prior to training the input data is shown in Figure 5.11.

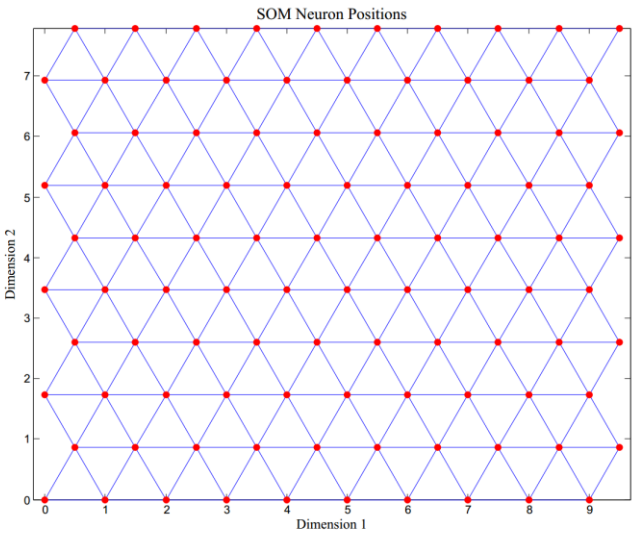



Figure 5.11 ANN SOM 10x10 topology

The red dots represent the SOM neurons and the blue lines are the connections between the neurons. The SOM is trained for a maximum of 1000 epochs (iterations). As the input data is measured in different scales of temperatures and pressures, the collected monitored data are normalised according to equation 31 in order to standardise the range of independent variables of data in the range [0,1].

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{31}$$

where $z_i$ is the $i^{th}$ normalised data point, $x_i$ is the $i^{th}$ data point of vector $x$.

The objectives of the SOM process it to cluster the data into healthy and faulty. Healthy data represents performance parameter measurements within the OEM thresholds for the main engine. In the case of faulty data, these are distinguished between data exceeding the OEM thresholds and data representing excessive measurements typically 75% above the OEM defined values (e.g. cylinder exhaust gas outlet temperature of 700 °C). In order to successfully model the healthy and faulty data distinctions, in addition to the data from the onboard measurement campaign and ship operator, additional artificial data is used for training the SOM. The artificial data correspond to faulty data, as no faulty data exist in the datasets as previously mentioned in Section 5.2. Thus, real data in combination with artificial data is used in order to enhance the capabilities of the SOM and preserve the original dataset characteristics. The SOM is trained using 144 hourly measurements for each parameter presented in Table 5.2.

The artificial data was produced by generating random values for the performance parameters within their normal operating conditions and above their thresholds. Therefore, the artificial data is developed to meet certain conditions that cannot be obtained from the original, real data. However, it provides realistic data for the development and achievement of the SOM scope.

The SOM is modelled to cluster data for the main engine subsystem and component level. Specifically, the trained SOM is used for clustering data related to each cylinder of the main engine, as amongst the input data of Table 5.2, the only parameters that correspond individually to the cylinders are namely the cylinder scavenging air temperature, exhaust gas outlet temperature, jacket fresh water cooling outlet temperature and piston cooling oil outlet temperature. This reduces the total number of input dimensions for effective SOM training and the clustering process can be focused primarily on the main engine subsystems and components, and thus on the main engine system overall without increasing the dimensions in the data that would implicate the data analysis and interpretation process.

During training, the SOM is defined and shaped based on the input data while the second phase automatically classifies new inputs into the clusters defined in the training stage. Once training is complete, the multidimensional input data vectors have been assigned into clusters. By identifying the cluster centre positions, a distance metric between the clusters can be implemented in order to examine if any clusters can be *interclustered* based on the concept that clusters with the shortest distances between them share possible similarities in the data. The SOM clustering and *interclustering* process is highlighted in Figure 5.12.

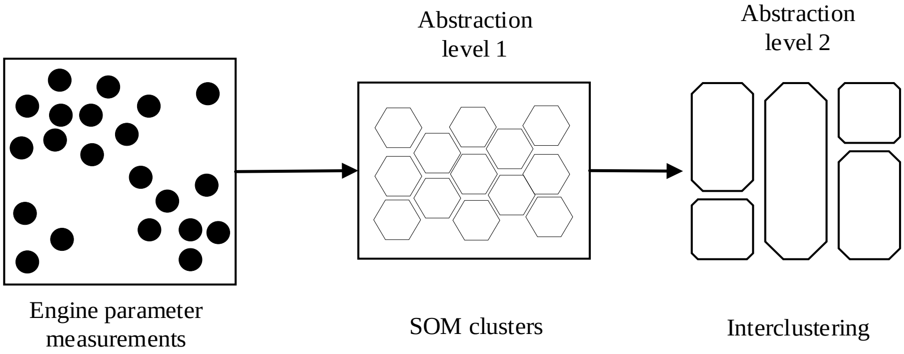



Figure 5.12 SOM clustering and interclustering process

The engine data is clustered in the SOM as a first abstraction level. In the second abstraction level, by applying the Euclidean distance metric to the clusters created by the SOM training process, similar clusters can be allocated in the same group. In terms of interclustering the SOM clusters, the Euclidean distance metric is applied. Moreover, other metrics such as the Manhattan distance (Rohlf, 2013) were applied, providing the same results. This outcome is rational and reasonable since the values in the dataset have been normalised in order to avoid discrepancies in the dataset that can distort the calculations. Moreover, the Manhattan distance may be more appropriate if different dimensions are not comparable (Guttag, 2016).

Furthermore, an additional case study is presented in Section 6.3.2 regarding the application of the SOM network to monitor the main engine condition by identifying clusters containing data which are diverse compared to data representing normal engine operating conditions. This SOM case study is applied for performance parameters of the most critical systems identified in the FTA-FMEA process.

### 5.3.3 *Development of NAR and NARX models*

In this section the selected network structure and training parameters are presented for the NAR and NARX models for both input datasets 1 and 2 respectively. A network with enough elements can model dynamic systems with arbitrary accuracy and are well suited for addressing non-linear dynamic problems, comparable to those attained in a ship main engine system. Table 5.6 presents the training parameters applied for training the NAR and NARX models for all case study performance parameters. In total 39 NAR models are developed for the performance parameters of dataset 1, and a further 39 NAR and 39 NARX models are developed for dataset 2.

Table 5.6 NAR & NARX training parameters

| **Training conditions** | **Value** | **Description** |
|---|---|---|
| net.trainParam.epochs | 1000 | Maximum number of epochs |
| net.trainParam.goal | 0 | Performance goal |
| net.trainParam.lr | 0.01 | Learning rate |
| net.trainParam.max_fail | 6 | Maximum validation failures |
| net.trainParam.min_grad | 1E-05 | Minimum performance gradient |
| net.trainParam.time | inf | Maximum time to train (seconds) |
| net.trainFcn | trainbr | Training algorithm |
| net.performFcn | mse | Performance function |
| net.divideFcn | divideblock | Dataset division |
| net.divideParam | 70%-0%-30% | Training, validation, test set ratio |

Training stops when any of the following conditions are met; The maximum number of epochs (iterations) for training is reached, performance is minimised to the goal, the maximum amount of time is exceeded, the validation performance has increased more than the maximum number of validation failures since the last time it decreased. In terms of the training algorithm, the Bayesian regularisation backpropagation algorithm (trainbr) was selected for network training that uses Jacobian derivatives as it updates the weight and bias values according to Levenberg-Marquardt optimisation.

This algorithm minimises a combination of squared errors and weights in the network and then determines the correct combination to produce a network which generalises well (Okut, 2016). This algorithm was selected as it provided more accurate network training and performance compared to training several other network models with training algorithms such as the Levenberg-Marquardt algorithm and scaled conjugate gradient algorithm.

Moreover, this training algorithm includes the validation data in the training set, hence the dataset is split 70% for training and 30% for testing. Furthermore, as the aim is to develop models for time series analysis and forecasting, the data is divided into blocks in the training and testing set, meaning that the first 70% hourly measurements of the dataset is used for training while the next remaining 30% hourly measurements in the time series is used for the test set as a completely independent test of network generalisation. This is done compared to splitting the dataset randomly in order to preserve the correlation relationships of the time series data.

As mentioned previously in Section 4.3.4, NAR and NARX neural networks use feedback delays in their topology in order to dynamically forecast one-step ahead or multi-step-ahead predictions of the time series data. The number of delays is set experimentally. Experimental runs with different number of network feedback delays were performed to obtain an accurate prediction model that performs well.

#### *5.3.3.1 NAR and NARX models for dataset 1*

Regarding dataset 1, from the 35 measurements, 30 are used for network training while the remaining 5 measurements are isolated for comparison purposes against the forecasting results obtained from the trained network. Figure 5.13 displays the selected topology for the NAR model in open loop mode.

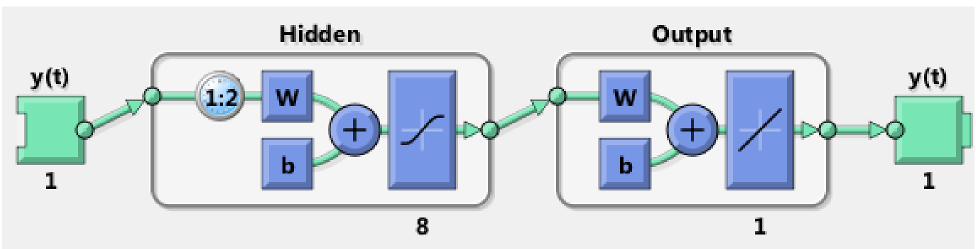



Figure 5.13 NAR model open loop mode

As presented in Figure 5.13, the NAR model has one hidden layer with 8 neurons, with a hyberbolic tangent function in the hidden layer and a linear transfer function in the output layer. Moreover, 2 feedback delays are used to store previous values of the univariate time series data. The network is trained in open loop form to match the input data with the target data, hence the targets are used as feedback. Once training is complete, the network is converted into closed loop form and as observed in Figure 5.14 below, its own predictions in the output layer become the feedback inputs for carrying out multi-step-ahead predictions.

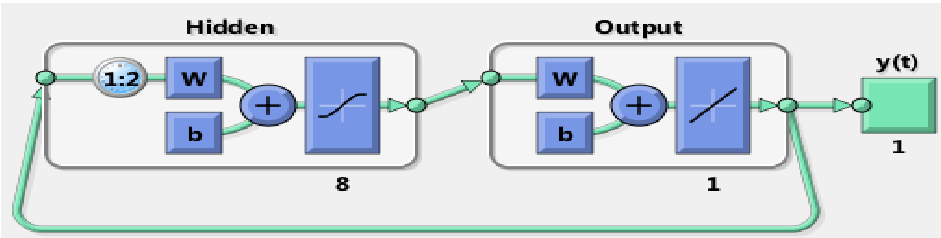



Figure 5.14 NAR model closed loop mode

NARX models for dataset 1 are not developed due to the fact that sufficient and proper training of a NARX model is not achievable since the dataset size is relatively small. Research concretely conducted in the early stages of the investigation of NARX models for this specific dataset indicated that the delays associated with each tapped delay line limited the selection of an optimal network structure and therefore satisfactory network training and performance could not be achieved.

### *5.3.3.2 NAR and NARX models for dataset 2*

For the NAR models related to dataset 2, the same principle is followed as described in the previous section for dataset 1. However, due to the larger dataset applied here, the number of nodes in the hidden layer is increased to 18 and 40 feedback delays are used. In many real applications, there is an important correlation between the modelled time series and additional external data.

For the main engine, the performance parameters largely depend on the main engine rpm. Thus, the integration of knowledge or data related to the engine rpm speed is applied as exogenous input in the NARX models. Figure 5.15 displays the selected topology for the NARX model in open loop form

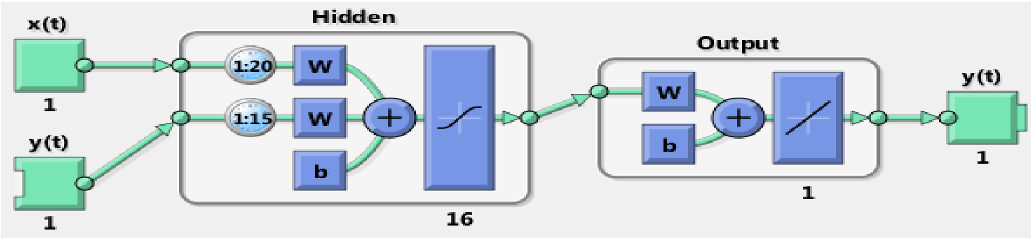



Figure 5.15 NARX model open loop mode

As demonstrated, the NARX model consists of 16 neurons in the hidden layer and uses a hyberbolic tangent function in the hidden layer and a linear transfer function in the output layer. Moreover, 15 feedback delays of the target time series *y(t)* and 20 input delays of the external input *x(t)* which is the main engine rpm are applied.

Once training is complete, the network is converted into closed loop form and as observed in Figure 5.16 below, its own predictions *y(t)* in the output layer become the feedback inputs for carrying out one-step-ahead or multi-step-ahead predictions alongside the external input *x(t)* time series.

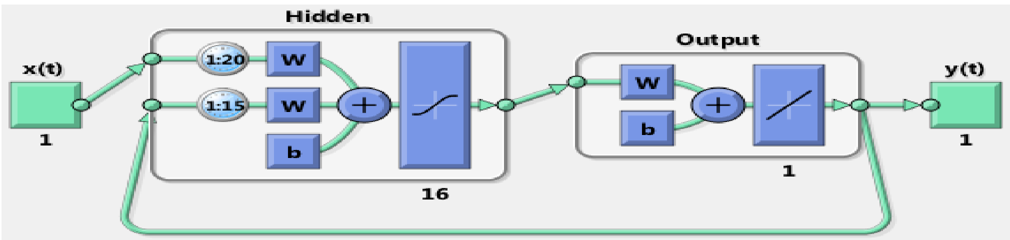



Figure 5.16 NARX model closed loop mode

The forecasted results for the main engine performance parameters can then be evaluated in the main engine diagnostic ANN-MLP classifier and MCI health assessment tool in order to provide the current and predictive evaluation of the condition of the main engine and its subsystems.

### 5.3.4 *Development of main engine diagnostic ANN-MLP and MCI*

#### *5.3.4.1 ANN-MLP engine diagnostic classifier*

Main engine faults are classified through the development of an ANN-MLP classifier network that takes as input the performance parameters of the engine and yields the corresponding fault class as its output. The classification neural network is trained with a large database consisting of actual data from the onboard campaigns and artificial data in order to simulate various engine faults. The artificial data is generated using the same process described in Section 5.3.2.2. The principles underlying the engine diagnostic analysis are illustrated in Figure 5.17. The data consisting the simulated engine faults are characterised by a shift in the measurable parameters below and/or above defined thresholds. Thus, the artificial data is generated for implanting engine faults in the input dataset.

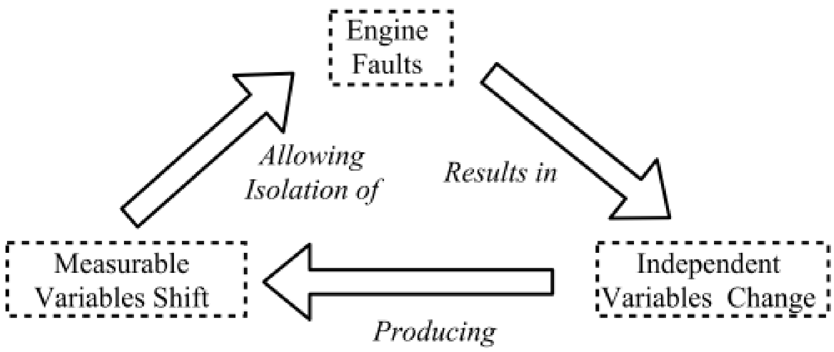



Figure 5.17 Engine diagnostic principle

The defined thresholds established for the analysis of the engine diagnostics are based on the engine OEM guidelines and through recommendations of both the crew onboard the vessel and staff of the shipping company such as marine engineers and technical superintendents. The thresholds applied are presented in Table 5.7.

Table 5.7 Main engine case study thresholds

| Main engine performance parameter | Value | Unit |
|---|---|---|
| Scavenging air temperature (cyl. 1-8) high | 80 | °C |
| Exhaust gas outlet temperature (cyl. 1-8) low | 200 | °C |
| Exhaust gas outlet temperature (cyl. 1-8) high | 430 | °C |
| Jacket fresh water cooling outlet temperature (cyl. 1-8) high | 90 | °C |
| Piston cooling lubrication oil inlet pressure low | 1.4 | $kg/cm^2$ |
| Piston cooling oil outlet temperature (cyl. 1-8) high | 70 | °C |
| Fuel oil inlet temperature low | 115 | °C |
| Fuel oil inlet temperature high | 165 | °C |
| Fuel oil inlet pressure low | 6.5 | $kg/cm^2$ |
| Air cooler cooling water inlet pressure low | 2 | $kg/cm^2$ |
| Main lubrication oil inlet pressure low | 1.4 | $kg/cm^2$ |
| Main lubrication oil inlet temperature low | 40 | °C |
| Main lubrication oil inlet temperature high | 55 | °C |
| Thrust bearing lubrication oil outlet temperature high | 70 | °C |

The input dataset consists of 6016 measurements for all 39 engine performance parameters, while 16 network target vectors are created and indicate the fault classes to which the input vectors have been assigned to. Therefore, the network outputs correspond to the fault classes the input vectors are assigned to. The network is trained to classify engine faults and multi-faults.

Faults owing to fluctuations in the performance parameters monitored are modelled in the network. Moreover, multi-faults such as increase of exhaust gas temperature in all cylinders, decrease of exhaust gas temperature in all cylinders and engine inlet air and exhaust temperature excessive are also modelled in the developed network, based on industry practice and OEM guidelines. The engine faults modelled in the network are presented in Table 5.8.

Each possible input feature pattern belongs exactly to one of 16 output classes. The neural network has 16 outputs, corresponding to each of the 16 fault classes. During training, 1 is applied for the correct class designator while 0 is applied to the other output classes as demonstrated in Table 5.9. While testing the network when a new input is presented, an output of 1 or near 1 indicated the membership in that class.

Table 5.8 Main engine faults modelled in network

| Fault Number | Fault Code | Fault Description |
|---|---|---|
| 1 | F0 | No Fault |
| 2 | F1 | Exhaust gas temperature increase in one cylinder |
| 3 | F2 | Exhaust gas temperature increase in all cylinders |
| 4 | F3 | Exhaust gas temperature decrease in one cylinder |
| 5 | F4 | Exhaust gas temperature decrease in all cylinders |
| 6 | F5 | Fuel oil inlet temperature low or high |
| 7 | F6 | Fuel oil inlet pressure low |
| 8 | F7 | Main lubrication oil inlet pressure low |
| 9 | F8 | Main lubrication oil inlet temperature high |
| 10 | F9 | Thrust bearing lubrication oil outlet temperature high |
| 11 | F10 | Piston cooling lubrication oil inlet pressure low |
| 12 | F11 | Air cooler cooling water inlet pressure low |
| 13 | F12 | Cylinder scavenging air temperature high |
| 14 | F13 | Jacket fresh water cooling outlet temperature high |
| 15 | F14 | Piston cooling oil outlet temperature high |
| 16 | F15 | Inlet air temperature & exhaust temperature excessive |

Table 5.9 Defining inputs with corresponding outputs-ANN MLP classifier

| Input Data | Fault Classes | | | |
|---|---|---|---|---|
| | $F_0$ | $F_1$ | $F_2$ | $F_{15}$ |
| 1 | 1 | 0 | 0 | 0 |
| 2 | 0 | 1 | 0 | 0 |
| 3 | 0 | 0 | 1 | 0 |
| n | 0 | 0 | 0 | 1 |

As observed in Table 5.9, the input datasets contain all data used as input in the network. The faults are classified into various faults $F_0$-$F_{15}$ with the first fault class $F_0$ assigned as a no-fault condition representing healthy engine performance. If input set 2 corresponds to fault $F_1$ as seen in the table, then 1 is applied to the output vector for class $F_1$ and 0 for all other fault classes for defining the designated class.

The network training characteristics are shown in Table 5.10. As observed, data is split randomly with 70% of the data used as the network training set, while 15% is used for validation set and the other 15% for the testing set. The network is trained using a training function that updates weights and bias values according to the scaled conjugate gradient backpropagation method (trainscg). The network is trained for 1000 epochs and the performance function used is the Cross-Entropy performance function. This performance function calculates network performance given targets, outputs, performance weights and parameters with a measure that heavily penalises outputs which are extremely inaccurate and with very little penalty for fairly correct classifications (Bishop, 2006). Minimising cross-entropy leads to good classifiers. A hyberbolic tangent and softmax transfer function are applied in the hidden and output layer.

Table 5.10 ANN-MLP training parameters

| **Training conditions** | **Value** | **Description** |
|---|---|---|
| net.trainParam.epochs | 1000 | Maximum number of epochs |
| net.trainParam.goal | 0 | Performance goal |
| net.trainParam.lr | 0.01 | Learning rate |
| net.trainParam.max_fail | 6 | Maximum validation failures |
| net.trainParam.min_grad | 1E-06 | Minimum performance gradient |
| net.trainParam.time | inf | Maximum time to train (seconds) |
| net.trainFcn | trainscg | Training algorithm |
| net.performFcn | Cross entropy | Performance function |
| net.divideFcn | dividerand | Dataset division |
| net.divideParam | 70%-15%-15% | Training, validation, test set ratio |

Another method that is used for improving generalisation of the network is the early stopping method. The validation data are used to stop training early if further training on the primary data will hurt generalisation to the validation data. Specifically, the error on the validation set is monitored during the training process. The validation error decreases during the initial phase of training alongside the training set error. If the network starts to overfit the data, then the error in the validation set begins to rise. When the validation error increases for the specified number of validation failures specified in Table 5.10, network training is stopped and the weights and biases at the minimum of the validation error are returned.

The number of neurons in the hidden layers was found to be the optimal after testing a variety of network architectures under different initial training conditions. A network topology from 1 up to 50 hidden neurons in the hidden layer were examined in order to obtain a network with optimal classification accuracy. For the numerous iterations, the average percentage of classification error is plotted for each network topology as demonstrated in Figure 5.18.

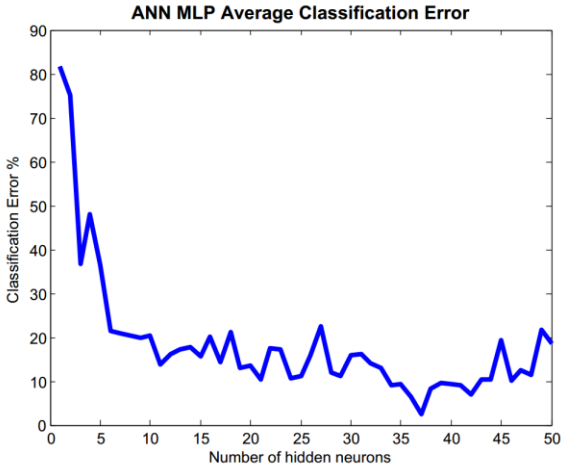



Figure 5.18 ANN-MLP average classification error for different number of hidden neurons

Figure 5.18 demonstrates that the lowest classification error was obtained for the 37 hidden neurons network configuration. Based on the obtained analysis results, 37 hidden neurons were selected for training the ANN-MLP classifier. Each time the ANN MLP classifier is trained with different initial weights and biases and with a different random split of the dataset into training, validation and test sets. Due to this, the selected network topology was trained several times to ensure that a network with good generalisation capabilities is obtained. Specifically, the selected network was trained for 1000 repetitions to sufficiently examine its overall accuracy due to the different initial weight, biases and dataset conditions each time the network is trained. Figure 5.19 displays the results obtained for the overall network classification accuracy, including training, validation and testing data accuracy.

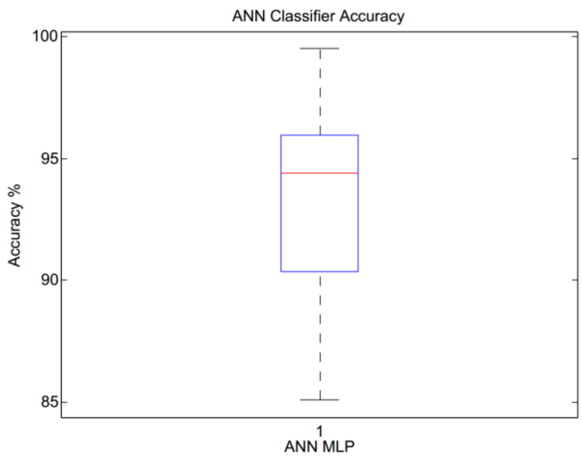



Figure 5.19 ANN MLP accuracy for different initial training conditions

As observed from Figure 5.19, the selected network topology has good generalisation capabilities and robust network performance can be verified. The minimum obtained network accuracy is equal to 85.1% while the maximum network accuracy is 99.64%. from the boxplot of the various network training iterations. Moreover, the 25$^{th}$ percentile is equal to 90.35% accuracy while the 75$^{th}$ percentile is equal to 95.95%. Furthermore, the median represented by the red horizontal line in the boxplot, is equal to 94.4% accuracy which verifies the selected network's generalisation capabilities and robust performance. The number of iterations is chosen as it is statistically adequate for considering extreme values in the analysis (Yang, 2011).

For each fault class modelled in the network, a table containing information regarding potential fault causes is developed. In addition, the fault classes are also connected with relevant FMEA information of the main engine, providing further insight into the diagnosis of the system. Table 5.11 presents a sample of the table created alongside potential remedies for fault codes *'F2- Exhaust gas temperature increase in all cylinders'* and *'F1-Exhaust gas temperature increase in one cylinder'*.

Reference points are created for ease of access and reference and for also updating the diagnostic database after a fault occurs. The remedies of the potential fault causes are presented in MAT to the user. In total, 87 potential fault causes and their respective remedies are constructed in the table for all the monitored performance parameters of the main engine. Information regarding the fault causes and remedies are obtained from engine guides and manuals, maritime industry personnel such as senior and technical engineers and ship operators, Classification Societies, plus maritime consultants and academia (INCASS, 2015b, INCASS, 2015a). The complete diagnostic table is presented in Appendix D.1.

Table 5.11 Diagnostic table and remedies (sample table)

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| ***Cylinder exhaust gas outlet temperature*** | | | |
| *F2-Temperature increase in all engine cylinders* | 1 | Increased scavenge air temperature owing to inadequate air cooler function | Inspect, overhaul and clean air side of air cooler |
| | 2 | Fouled air and gas passages | Clean turbine by means of dry cleaning/water washing<br>Clean blowers and air coolers<br>Check the back pressure in the exhaust gas system just after the T/C turbine side |
| | 3 | Inadequate fuel oil cleaning and/or altered combustion characteristics of fuel | Check fuel quality and fuel treatment |
| | 4 | Wrong position of camshaft | Check pmax<br>Check camshaft with pin gauge<br>Check chain tension |
| *F1-Temperature increase in one cylinder* | 5 | Defective fuel valves | Overhaul fuel valves and replace |
| | 6 | Fuel valve leakage/dripping | Replace or overhaul valve |

Therefore, through the optimal network architecture and training, the network provides accurate results for faults and multi-combination of faults as will be presented in Chapter 6. Moreover, the network is capable of predicting faults in new sets of data not seen before by the network.

### *5.3.4.2 Main engine MCI*

The main engine MCI is obtained through the process described in Section 4.3.5.2, by calculating initially the MCI of each Relevant Condition Parameter (RCP) and subsequently obtaining the main engine subsystems and top system MCIs through the concept of RBD. The performance parameter measurements are fitted into continuous probability distribution functions to obtain the distribution parameters in order to proceed with the MCI calculations. In order to select the best fit for the data of each performance parameter, an algorithm is developed which fits the data for the main engine performance parameters to various distribution functions in order to search for the most suitable distribution function that fits the data. The quality of the fits is ranked depending on the BIC, AIC and the AICc results.

The developed algorithm attempts to fit the data into continuous distributions such as the Birnbaum-Saunders, gamma, exponential, logistic, lognormal, normal, t-location scale and Weibull distribution function amongst other. Overall, after analysing the measurements in dataset 1 for the performance parameters of the case study in order to obtain the best distribution fit to the various data, it was observed that the best fits for the data were primarily the Weibull distribution followed in some cases by the Normal distribution. Figure 5.20 presents a sample demonstration for the distribution fitting related to measurements from dataset 1 for the exhaust gas temperature outlet parameter. The top three best fits among all the distributions are shown in the figure alongside the representation of the empirical values for the data. As it can be observed, the best fit for the data is the Weibull distribution which is the green line in the figure, while extreme value and the normal distribution also provide good alternative fits to the data.

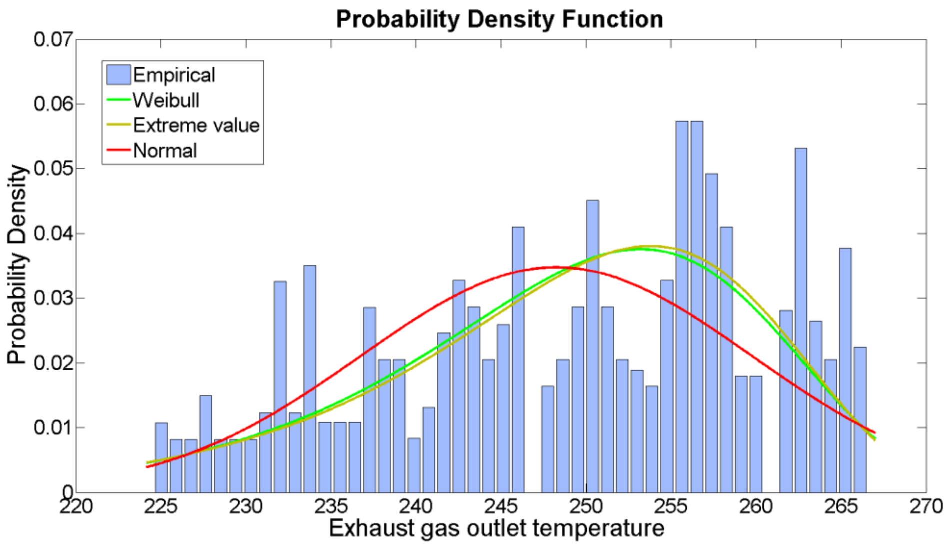



Figure 5.20 Exhaust gas outlet temperature distributions

In the case of the Weibull distribution and based on equation 27, representing the cumulative distribution function, the following equation is applied for calculating the MCI based on the Weibull distribution parameters.

$$MCI(t) = 1 - \exp\left[-\left(\frac{RCP_{lim} - C}{A(t) - C}\right)^{B(t)}\right] \tag{32}$$

where $RCP_{lim}$ is the limit threshold of the relevant condition parameter, A is the Weibull scale parameter, B is the Weibull shape parameter and C is the Weibull location parameter.

The Weibull parameters are obtained from fitting the performance parameter measurements to the distribution. The Weibull location parameter C is equal to the initial threshold $RCP_{in}$ of the relevant condition parameter. The scale parameter A defines the location of the distribution on the horizontal scale while the shape parameter B controls the shape of the distribution curves. Moreover, the Weibull parameters are computed using the maximum likelihood estimate method (Millar, 2011). Overall, it is a versatile distribution that can take on the characteristics of other types of distributions (Rausand and Arnljot, 2004, Ebeling, 2004), based on the value of the shape parameter B and is used for the majority of the case study data.

In the case of utilising the normal distribution, the following equation is applied for calculating the MCI:

$$MCI(t) = \Phi\left[\frac{RCP_{lim} - A(t)}{B(t)}\right] \tag{33}$$

Where $\Phi$ is the normal cumulative distribution function evaluated at the values obtained within the bracket, A is the scale parameter and B is the shape parameter of the normal distribution.

The RCP thresholds for cylinder 1 are defined in Table 5.12, while the remaining table for all other parameters is contained in Appendix D.2. The MCI thresholds are flexible and can be altered based on custom values defined by the ship operator or technical department. Moreover, the thresholds can be altered for various engine operational loads. This implies that the MCI can be a tailored made tool to fit any shipping company requirements per ship or fleet.

Table 5.12 Main engine MCI thresholds for cylinder 1

| **Main engine RCP** | **$RCP_{in}$** | **$RCP_{lim}$** | **Unit** |
|---|---|---|---|
| Scavenging air temperature (cylinder 1) | 30 | 48 | °C |
| Exhaust gas outlet temperature (cylinder 1) | 100 | 263 | °C |
| JCFW cooling outlet temperature (cylinder 1) | 50 | 84 | °C |
| Piston cooling lubrication oil inlet pressure | 2.6 | 2.8 | $kg/cm^2$ |
| Piston cooling oil outlet temperature (cylinder 1) | 30 | 49 | °C |
| Fuel oil inlet temperature | 130 | 140 | °C |
| Fuel oil inlet pressure | 8.05 | 8.4 | $kg/cm^2$ |
| Air cooler cooling water inlet pressure | 2.9 | 3.12 | $kg/cm^2$ |
| Main lubrication oil inlet pressure | 2.7 | 2.9 | $kg/cm^2$ |
| Main lubrication oil inlet temperature | 40 | 50 | °C |
| Thrust bearing lubrication oil outlet temperature high | 42 | 50 | °C |

Through a combination of series, parallel and k out of n configurations, the RBD for the main engine system is developed to obtain the overall system MCI based on the MCIs calculated for every main engine subsystem and component. Following the structure developed for the main engine FT, the main engine RBD consists of the lubrication oil, fuel oil, air, cylinder block and engine block and components subsystems. The cooling system has not been modelled due to lack of parameters expressing the system condition. Additionally, the jacket cooling fresh water outlet temperature per cylinder has been incorporated into the cylinder block system RBD.

Thus, the main engine RBD construction is based initially on the FT structure developed, expert judgement feedback and moreover on the performance parameters available to model each relevant RBD system. The air system and engine block and components system comprise of the air cooler cooling water inlet pressure MCI and thrust bearing lubrication oil outlet temperature respectively. Figure 5.21 displays the overall RBD for the top system under consideration which is the ship main engine.

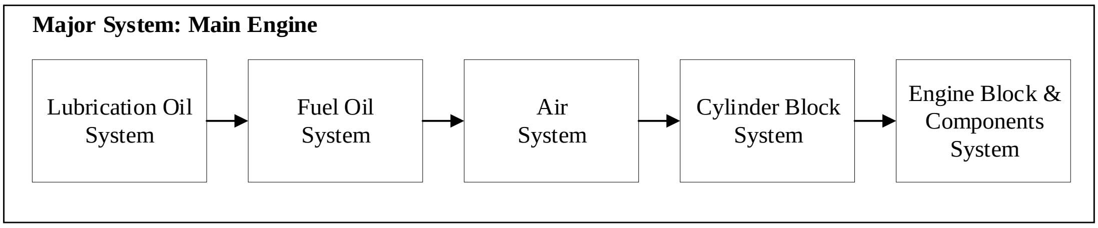



Figure 5.21 Main engine RBD and consisting subsystems

The main engine RBD consists of the aforementioned subsystems and is modelled as a series configuration so that the degradation of any of the subsystem MCIs directly affects the main engine condition indicator. Figure 5.22 presents the RBD developed for the lubrication oil system and fuel oil system. The lubrication oil system is modelled as a parallel configuration consisting of the main lubrication oil inlet pressure and main lubrication oil inlet temperature MCIs. The fuel oil system is modelled in an analogous manner, based on expert judgment and available parameters for modelling.

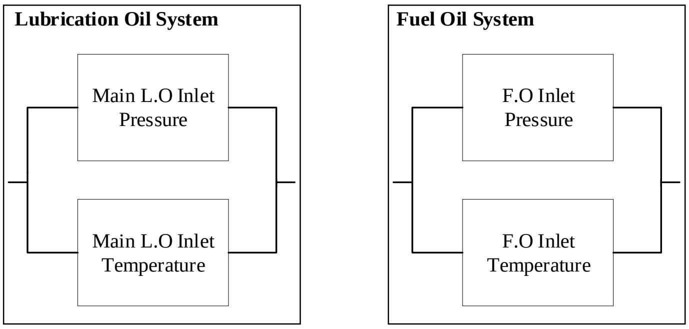



Figure 5.22 Lubrication oil system RBD & fuel oil system RBD

The cylinder block system level RBD is shown below in Figure 5.23 and comprises of a combination of series and parallel configuration. This system consists of the piston cooling lubrication oil inlet pressure MCI connected in series with the RBDs of the eight main engine cylinders. The eight cylinder RBDs are connected as a k out of n configuration and a 5 out of 8 configuration is selected, meaning that at least 5 cylinders are required to function for the cylinder block system to function. This configuration is selected assuming that a degradation of the MCIs in less than 5 cylinders will not affect the performance of the main engine.

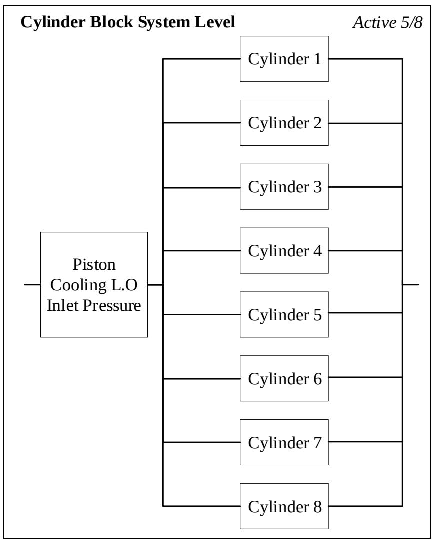



Figure 5.23 Cylinder block system RBD

Moreover, each cylinder block shown in Figure 5.23 is further expanded into its subsystem level as shown in Figure 5.24 for cylinder 1. The blocks for all other cylinders are modelled in a similar manner.

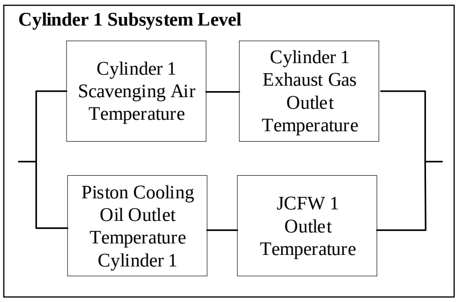



Figure 5.24 Cylinder 1 RBD subsystem level

The cylinder 1 RBD consists of a combined parallel and series configuration. The cylinder scavenging air temperature and exhaust gas outlet temperature MCIs are modelled in a series configuration. The practicality of this option is that these parameters affect immediately one another, as an increase in scavenging air temperature will also create an increase in the exhaust gas temperature. Moreover, the piston cooling oil outlet temperature and jacket cooling fresh water outlet temperature

MCIs are similarly modelled. Through the overall process presented, the calculation of the subsystem MCIs and overall engine system MCI through the application of the reliability block diagrams can be achieved.

### 5.3.5 *Development of MAT*

The framework of the Maintenance Assistant Tool (MAT) is developed and coded in MATLAB. The system utilises data originating from the outputs of the ANN-MLP diagnostic classifier of the main engine and the condition indicators (MCIs) of the main engine and its subsystems, based on the forecasting future results of the time series forecasting analysis tools. Therefore, the main aim of MAT is to display potential upcoming faults and the impending health status of the main engine and relevant systems, while providing the operator with additional information for producing relevant maintenance actions and activities as seen in Figure 5.25.

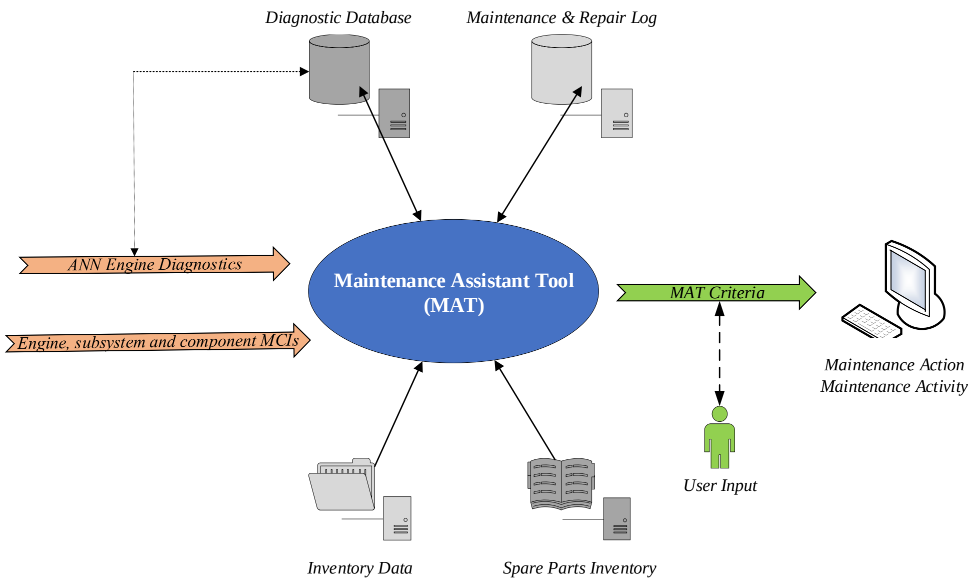



Figure 5.25 MAT flowchart for main engine

As seen in Figure 5.25, MAT provides to the operator (upon request), inventory data including the engine OEM manual, vessel PMS and IACS guidelines for managing maintenance in accordance with ISM code requirements amongst other. Furthermore, the spare parts inventory presents to the user spare part drawings, spare part costs that assist the user in deciding if the costs associated with a maintenance action is high or low alongside the availability of the spare parts onboard. Figure 5.26, displays a sample of the spare parts inventory table extracted from MAT for display to the user.

```
Display available spare parts and costs? 1 for [Yes] and 0 for [No] 1
Spare parts cost:
           Spare_Part                Cost_Unit_Price_USD    Available
    ___________________________    ___________________    _________

    'Cylinder Gasket'                   35                  'Yes'
    'Cylinder Liner'                 11620                  'No'
    'Cylinder Cover'                 18272                  'Yes'
    'Cooling Jacket Cyl. Liner'       3725                  'No'
```

Figure 5.26 Sample of spare parts inventory table

As observed, the program prompts the user to select to display the spare parts and their costs. The spare parts, their cost in USD ($) and their availability onboard are then displayed after the user has requested for MAT to display them. The spare part costs originate upon examination of provided quotation lists from marine suppliers and further discussion with marine engineers, technical managers, academia. The maintenance and repair log contain past maintenance actions carried out for the system.

The diagnostic database with the prioritised fault causes for the system is also presented to the user once a potential upcoming fault has been identified. Additionally, the diagnostic database interacts with MAT and the operator by providing the prioritised fault causes sorted in the database and subsequently prompting the user to enter the fault code that rectified an occurring fault in the main engine system as demonstrated in Figure 5.27. Then, the diagnostic database is updated accordingly based on the new user input. In the case of a new fault cause not contained in the database, MAT will update the database accordingly based on the new information.

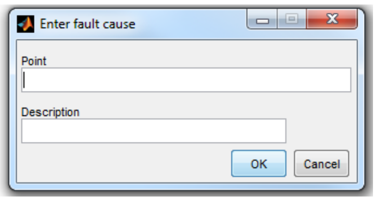



Figure 5.27 Input dialog for entering rectified fault cause and description

The overall programming steps and structure for coding MAT are presented in the Table 5.13 below.

Table 5.13 MAT coding structure and steps

```
start
  load files
  run neural network diagnostics
  display faults identified
    prompt user to enter fault code for further info
      display fault causes and remedies
        prompt user for further info
          extract relevant system FMEA info
            display highest recorded fault causes
  run MAT criteria for maintenance decision making
    display spare parts cost and availability to user
      display vessel PMS
        produce suggested maintenance action/activity
  extract spare part drawings
  extract relevant inventory data upon user request
  prompt user to update diagnostic database
    update database and save
end
```

Once the data of MAT have been presented to the operator, the MAT criteria (presented in Section 4.3.6, Figure 4.10) are presented to the user to produce the corresponding appropriate maintenance action and activities such as replace, repair, check, service etc. of components amongst other. Figure 5.28 presents a sample output produced by MAT for a corrective maintenance action and activity.

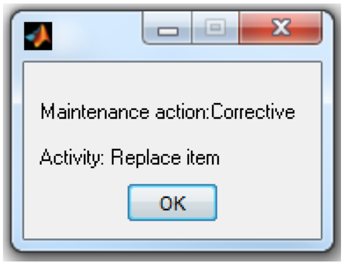



Figure 5.28 Maintenance action produced by MAT

## 5.4 Chapter summary

This chapter presented the description of the case study related to the main engine of a Panamax container ship which is applied for the development and analysis of the specified methodology tools and models. The input data utilised for the case study analysis was also presented. Two datasets of different sizes are used for training and analysing the developed networks, while a third dataset is used for validating the ANN models based on real vessel data. The main engine FT consists of four levels, 14 static and dynamic gates and 42 basic events representing the components of the various main engine systems. The main engine FMEA was set up by using the basic events of the main engine FT as input in order to investigate potential failure modes, causes, effects and detection methods. Moreover, data representing vessel speeds of 4 knots or less, or engine speeds of 15 rpm or less are removed from the dataset, as in such cases the parameters contain fluctuations that can affect ANN training. The SOM developed for clustering the multidimensional input data consists of a 10-by-10 two-dimensional map of 100 neurons. Afterwards, the selected network structure and training parameters were presented for the NAR and NARX models for both input datasets 1 and 2 respectively. In terms of the developed engine diagnostic ANN-MLP, the network is trained with a large database consisting of actual data from the onboard campaigns and artificial data in order to simulate various engine faults. Faults owing to fluctuations in the performance parameters monitored are modelled in the network. The input dataset consists of 6016 measurements for all 39 engine performance parameters, while 16 network target vectors are created and indicate the fault classes to which the input vectors have been assigned to. The main engine MCI was presented and the process of fitting the performance data to the most suitable distribution fitting was described. Additionally, the MCIs are obtained through the concept of RBD and the MCI thresholds are flexible and can be altered based on custom values or different engine operating loads to monitor the main engine health condition. Finally, the MAT flowchart for the main engine system alongside coding structure and steps of MAT were also demonstrated. Following the above, the next chapter presents the case study results based on the analysis of the developed tools and defined parameters presented in this chapter.

# 6 Case Study Results

## 6.1 Chapter outline

In this chapter, the results of the hybrid condition monitoring strategy for the described main engine case study are described. Initially, the results of the main engine FT are presented. Specifically, the main engine FT minimal cut sets are demonstrated followed by the presentation of the main engine FMEA, leading to the selection of the main engine performance parameters based on the results of the above. Subsequently, the data cleansing and SOM results comprising of the data preparation stage of the hybrid condition monitoring strategy are presented for the selected performance parameters. Furthermore, the results of the dynamic neural networks NAR and NARX respectively are presented for both dataset 1 and dataset 2. Subsequently, the ANN-MLP classifier, engine MCIs and MAT results are demonstrated. Finally, Section 6.7 contains the discussion of the obtained results followed by the chapter summary.

## 6.2 FTA and FMEA results

This section presents the results obtained for the main engine FTA and constructed FMEA worksheet. Firstly, the minimal cut sets of the FT results are presented followed by the main engine FMEA table containing components of the main engine, modelled as basic events in the FT.

### *6.2.1 FTA results*

The cut set results assist in identifying the potential ways that a failure of the top event can occur. The top ranked cut sets lead to the identification of the minimal cut sets which are the combination of primary events sufficient for the fault occurrence of the top event. Thus, cut sets are employed in the developed main engine FT in order to obtain the most critical components and subsystems. Table 6.1 displays the top 10 minimal cut sets obtained from the main engine FTA.

Table 6.1 Main engine FT top 10 minimal cut sets

| # | Cut set events | Order |
|---|---|---|
| 1 | Cylinder head, piston crown, piston ring | 3 |
| 2 | Cylinder head, piston crown, piston rod stuffing box | 3 |
| 3 | Cylinder head, piston crown, piston connecting rod | 3 |
| 4 | Cylinder head, piston crown, piston skirt | 3 |
| 5 | Cylinder head, piston ring, piston rod stuffing box | 3 |
| 6 | Cylinder head, piston ring, piston connecting rod | 3 |
| 7 | Cylinder head, piston ring, piston skirt | 3 |
| 8 | Cylinder head, piston rod stuffing box, piston connecting rod | 3 |
| 9 | Cylinder head, piston rod stuffing box, piston skirt | 3 |
| 10 | Cylinder head, piston connecting rod, piston skirt | 3 |

The minimal cut sets are thus obtained providing insight into the components of the complex main engine system. By examining Table 6.1, it can be observed that the first 10 minimal cut sets are third order cut sets and that the most influential set of events are components related to the cylinder block assembly subsystem of the main engine FT top event. Specifically, the FT results indicate that components such as the cylinder head, piston rings, piston skirt and piston crown are the furthermost identified critical main engine components.

The importance of the identified critical components of the FT results can also be confirmed from a practical viewpoint. The piston crown is subjected to tremendous forces and heat during normal engine operation and is thus subject to fatigue, wear and tear while the cylinder head secures the top of the combustion chamber and provides mechanical support for two other engine components, namely the exhaust valves and fuel injectors. Moreover, the piston rings prevent the compressed charge of fuel-air mixture from leaking to the other side of the piston as it creates a gas tight fit of the piston when moving from Top Dead Centre (TDC) to Bottom Dead Centre (BDC) in the cylinder.

Due to the size of the complete main engine cut sets, a summarised table of various minimal cut sets, specifically 3$^{rd}$ order FT cut sets and 4$^{th}$ order for the main engine system are shown in Table 6.2. Overall, the FT results produce 72 cut sets for the main engine system ranging from 3rd order to 10th order cut sets. Appendix E.1 contains the complete table for the main engine cut sets. It is worth mentioning that the top 30 minimal cut sets are related to the cylinder and piston system components.

Table 6.2 Summary of 3rd order and 4th order main engine FT cut sets

| Cut set events | Order |
|---|---|
| Cylinder head, piston crown, piston ring | 3 |
| Cylinder liner, piston crown, piston skirt | 3 |
| Piston crown, piston ring, cylinder jacket | 3 |
| Piston connecting rod, piston skirt, cylinder jacket | 3 |
| Crankcase, crankshaft, exhaust valves | 3 |
| Crankcase, exhaust valves, exhaust manifold | 3 |
| Crankshaft, camshaft, exhaust valves | 3 |
| Fuel piping system, fuel oil filter, fuel pumps | 3 |
| Fuel oil filter, fuel valves, fuel injector | 3 |
| Main lube oil pump, lube system valves, lube oil filter, lube oil cooler | 4 |

Alongside the relative cylinder and piston items, other 3rd order cut sets involve components from the engine block and components subsystem such as the crankcase, crankshaft and camshaft. These are also important engine components as crankcase failures can lead to explosions due to the likelihood of cylinder liner and piston skirt wear allowing air into the crankcase, thus endangering lives onboard. In addition, the camshaft is one of the most critical engine parts as it ensures timing of exhaust valves opening/closure and fuel injection. Furthermore, the other 3rd order minimal cut sets involve components and items of the engine fuel system and include the fuel piping system, fuel oil filter, fuel valves, fuel pumps and fuel injectors. Finally, the 4th order engine minimal cut set is related to components of the lubrication oil system which are critical for correct engine operation as they assist in providing a slippery film between moving parts that reduces wear, dissipate and remove heat resulting from friction and also remove contaminants, debris and residues of combustion.

Through the FT results, the engine critical items are identified which if properly monitored and maintained, enhance safety and engine condition and performance. Moreover, in combination with the FMEA results presented in the next section, the identified items are further analysed in terms of their specific failure modes and associated causes, which collectively assist in identifying key performance parameters of the main engine critical items for monitoring the engine condition.

### *6.2.2 FMEA results*

The FT minimal cut sets method was employed to obtain the critical components and subsystems of the top gate of the FT, which is the main engine system. Table 6.3 presents a sample of the FMEA table created for the main engine. As observed from the FMEA failure events and causes and by examining the local and global effects and detection methods; the possible performance parameters to be monitored can be identified. The entire main engine FMEA table containing more than 50 failure modes for the main engine components is included in Appendix E.2.

Table 6.3 FMEA sample for main engine FTA critical items

| **Failed Item** | **Failure Mode** | **Failure Cause** | **Local Effect** | **Global Effect** | **Detection Method** |
|---|---|---|---|---|---|
| Cylinder Head | *Cracked* | Overheating, fatigue | Compression loss, cylinder damage | Possible engine stop | Temperature, pressure alarm |
| | *Overheating* | Cracks, faulty exhaust valves | High temperature alarm, smoke, cylinder damage | Possible engine stop, engine damage | High temperature alarm |
| Cylinder Liner | *Wear* | Fatigue, lubrication oil quality | Compression loss, increased lubrication consumption | Engine performance reduction | Increment of exhaust temperature in cylinder |
| Piston Rings | *Scuffing* | Insufficient lubrication | Scuffing mark on liner surface, oil smoke from exhaust | Engine performance reduction | Visual inspection |
| Fuel Pumps | *Low supply pressure* | Suction valve early or late operation | Erratic engine operation | Engine stop, engine performance reduction | Low pressure alarm |
| Lube Oil Cooler | *Temperature abnormal* | Fouling | Insufficient lubrication oil cooling temperature | Engine overheating, Engine stop | High temperature alarm |
| Jacket Fresh Water Cooling Pump | *Higher temperature of fresh water* | Clogged, faulty impeller, thermostat not operating fully | Cylinder overheating | Engine damage, engine slow down | High temperature alarm |

The sample table presents the FMEA conducted for the identified critical FTA components related to the cylinder and piston, fuel and lubrication system. As observed and described in Section 4.3.1, the basic events of the identified minimal cut sets of the FT are used as the failed item in the FMEA spreadsheet column. The main engine FMEA table indicates that failure modes related to the cylinder head such as cracked and overheating can be detected through high temperature and pressure alarms and that the effects of such failures would relate to cylinder damage and engine damage, locally and globally respectively. In the case of the cylinder liner wear or piston ring scuffing, insufficient lubrication could be a possible failure cause. Low supply pressure of the fuel pumps can be caused by early or late operation of a suction valve and can trigger erratic engine operation. An appropriate relevant performance parameter for such a case would be the fuel oil inlet pressure.

In terms of the lube oil cooler, abnormal temperature caused by fouling will have a local effect of insufficient lubrication oil cooling temperature, a global effect of engine overheating which can be detected from high engine temperature alarms. Monitoring parameters such as the main lubrication oil inlet temperature can assist in monitoring the system condition and detecting potential failures. Furthermore, high temperature of fresh water of the jacket fresh water cooling pump can result in cylinder overheating and engine damage. Cracking of cylinder liners and cylinder heads can occur due to poor cooling causing thermal fatigue if cooling water is not heated sufficiently prior to circulation around the combustion space. All these provide an indication in terms of which parameters to monitor. Thus, an engine overheating can be identified by the cylinder jacket cooling fresh water outlet temperature and also the cylinder exhaust gas outlet temperature.

### *6.2.3 Selection of main engine performance parameters*

Through the FTA-FMEA process, parameters applicable for monitoring the engine condition and assisting in detection of the described failure modes for each system and component can be identified. Therefore, as described in the previous section, performance parameters related to the FT cylinder block assembly system, specifically related to the cylinder subsystem such as the exhaust gas outlet temperature is selected. Specifically, the exhaust gas temperature is directly emitted from the engine cylinders and therefore will indicate the operation and condition of the engine and its combustion process. Additionally, the jacket cooling fresh water outlet temperature per cylinder parameter of the jacket water cooling subsystem can also assist in monitoring the status of the cylinders and main engine overall. Referring to the piston subsystem, relevant performance parameters are the piston cooling lubrication oil outlet temperature per engine cylinder and the piston cooling lubrication oil inlet pressure. Monitoring of the fuel pumps and FT fuel system overall based on the FMEA failure modes can be achieved through examining the fuel oil inlet pressure. Finally, in terms of the FT lubrication oil system, the main lubrication oil inlet temperature can assist in monitoring the system condition and detecting potential failures.

These parameters can be selected as a first step for the presentation of the novel condition monitoring strategy of this research. However, to further enhance the research analysis of the thesis, additional parameters available from the data collection process during the onboard measurement campaign are also included as presented in Table 5.2 of Section 5.2. These include the scavenging air temperature of each cylinder for the cylinder system, the fuel oil inlet temperature for the fuel system, the main lubrication oil inlet pressure for the lubrication oil system, the air cooler cooling water inlet pressure for the air system and the thrust bearing lubrication oil outlet temperature for the engine block and components system, based on the main engine FT structure. The following section presents the data preparation results regarding the collected case study datasets.

## 6.3 Data preparation results

This section presents the results obtained regarding the application of the data cleansing algorithm on the case study datasets and the results obtained from the SOM clustering tool. Also, an additional case study applying the SOM for main engine condition monitoring applications is also presented.

### *6.3.1 Data cleansing*

In terms of the datasets utilised for analysis as described in Table 5.3, dataset 2 required cleaning for further data processing in the next steps. Initially, prior to data cleansing taking place, a duplication of the original intact dataset is created for back-up purposes. Secondly, the main engine rpm is used for cleansing the data. Thus, data related to an engine speed of 15 rpm or lower are removed from the dataset as such data measurements were invalid and could not be used for further analysis. Furthermore, in most of these cases, no data was recorded for any of the main engine parameters. In the next step, the data cleansing algorithm searches for empty cells within the dataset. Null values are initially assigned to the empty cells and then are replaced with the average value of the corresponding attribute. Overall 66 such conditions were identified in the dataset. Prior to cleansing, the original size of the dataset consists of 986 hourly measurements for each parameter; while the dataset size was reduced to 920 hourly measurements after cleansing. Figure 6.1 illustrates a sample of the data cleansing process for a missing attribute value in the exhaust gas temperature outlet of main engine cylinder no.3 (units are in degrees Celsius $^{o}$C).

**Raw dataset**

| | *13:00* | *14:00* | *15:00* | *16:00* | *17:00* | *18:00* |
|---|---|---|---|---|---|---|
| Texh Cyl.1 | 294.4 | 294.3 | 303.1 | 298.3 | 295.8 | 300.8 |
| Texh Cyl.2 | 282.8 | 282.9 | 296.8 | 293.2 | 288.9 | 291.2 |
| Texh Cyl.3 | 312.8 | 313.7 | | 316.1 | 316.9 | 316.2 |
| Texh Cyl.4 | 315.4 | 312.7 | 324.2 | 325.7 | 323.7 | 321.2 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

**Boolean table**

| | *13:00* | *14:00* | *15:00* | *16:00* | *17:00* | *18:00* |
|---|---|---|---|---|---|---|
| Texh Cyl.1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Texh Cyl.2 | 0 | 0 | 0 | 0 | 0 | 0 |
| Texh Cyl.3 | 0 | 0 | 1 | 0 | 0 | 0 |
| Texh Cyl.4 | 0 | 0 | 0 | 0 | 0 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

**Cleansed dataset**

| | *13:00* | *14:00* | *15:00* | *16:00* | *17:00* | *18:00* |
|---|---|---|---|---|---|---|
| Texh Cyl.1 | 294.4 | 294.3 | 303.1 | 298.3 | 295.8 | 300.8 |
| Texh Cyl.2 | 282.8 | 282.9 | 296.8 | 293.2 | 288.9 | 291.2 |
| Texh Cyl.3 | 312.8 | 313.7 | 301.49 | 316.1 | 316.9 | 316.2 |
| Texh Cyl.4 | 315.4 | 312.7 | 324.2 | 325.7 | 323.7 | 321.2 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

Figure 6.1 Data cleansing sample for missing attribute in cylinder 3

Figure 6.1 presents a sample of the dataset for the hourly exhaust gas temperature outlet ($T_{exh}$) measurements of cylinders 1-4. The attributes in the raw dataset are compared against the criteria defined in the cleansing algorithm. The Boolean table presents the results from the criteria evaluation showing if the conditions are satisfied and identifies the location of an empty value attribute. A value of 0 represents that the criteria is not met while a result of 1 means that the criteria have been satisfied. Finally, the empty cell is replaced by the arithmetic mean of the known attribute values for the attributes where the criteria have been satisfied. Through the data cleansing process, the cleansed data is obtained ready for analysis in the next stages.

### *6.3.2 SOM results*

This section presents the results obtained from training the developed SOM after the data cleansing process. Once training of the SOM is complete, the multidimensional input data vectors representing the main engine performance parameters have been assigned into clusters. The initialisation of the SOM training spreads the initial SOM weights across the input space. The SOM topology after training is presented in Figure 6.2, in which the green dots represent the input training data vectors for the cylinder main engine parameters and the red dots represent the SOM neurons-clusters assigned to the data points, while the blue lines connect each node of the map.

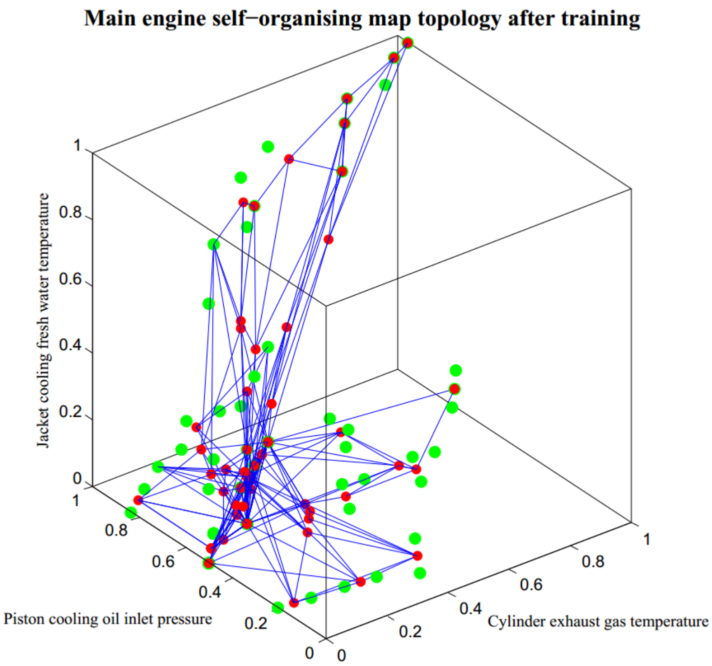



Figure 6.2 Main engine SOM topology after training

The final SOM topology is presented after training has occurred with all input data according to the batch unsupervised weight/bias training algorithm. For visualisation purposes, the SOM is plotted in three-dimensions illustrating in each dimensional axis the normalised measurement values of 3 out the 11 main engine cylinder parameters. The SOM clusters obtained alongside the data they contain are presented in Table 6.4.

Table 6.4 Main engine SOM clusters and description

| Description | SOM Cluster |
|---|---|
| All monitored parameters in normal operating conditions | 49, 77, 87, 99 |
| Cylinder Scavenging Air Temperature above OEM threshold | 51, 62, 92 |
| Cylinder Scavenging Air Temperature excessive | 61, 71, 81, 91 |
| Cylinder Exhaust Gas Outlet Temperature above OEM threshold | 80, 89 |
| Cylinder Exhaust Gas Outlet Temperature excessive | 79, 100 |
| Cylinder Jacket Cooling Fresh Water Outlet Temperature above OEM threshold | 26, 27, 86, 95 |
| Cylinder Jacket Cooling Fresh Water Outlet Temperature excessive | 5, 6, 16 |
| Piston Cooling Lubrication Oil Inlet Pressure above OEM threshold | 34, 35, 45 |
| Piston Cooling Lubrication Oil Inlet Pressure excessive | 28, 67, 96 |
| Piston Cooling Oil Outlet Temperature above OEM threshold | 59, 66, 75, 76 |
| Piston Cooling Oil Outlet Temperature excessive | 50, 55, 60, 65 |
| Fuel Oil Inlet Temperature above OEM threshold | 74, 82 |
| Fuel Oil Inlet Temperature excessive | 30, 40, 72, 73 |
| Fuel Oil Inlet Pressure above OEM threshold | 68, 69, 78 |
| Fuel Oil Inlet Pressure excessive | 10, 93, 94 |
| Air Cooler Cooling Water Inlet Pressure above OEM threshold | 29, 84, 97 |
| Air Cooler Cooling Water Inlet Pressure excessive | 20, 36, 37, 47 |
| Main Lubrication Oil Inlet Pressure above OEM threshold | 8, 9, 18 |
| Main Lubrication Oil Inlet Pressure excessive | 58, 85 |
| Main Lubrication Oil Inlet Temperature above OEM threshold | 19, 25, 52, 53 |
| Main Lubrication Oil Inlet Temperature excessive | 32, 33, 43 |
| Thrust Bearing Lubrication Oil Outlet Temperature above OEM threshold | 39, 88, 98 |
| Thrust Bearing Lubrication Oil Outlet Temperature excessive | 21, 31, 38, 41 |
| All data excessive | 1, 2, 3, 12, 13 |

In more detail, data representing normal engine operating conditions are assigned into the SOM clusters 49, 77, 87 and 99 respectively. Moreover, if all parameters in the dataset are excessive, then they are represented by clusters 1, 2, 3. 12 and 13. Data corresponding to the fuel oil inlet temperature being above the OEM threshold is clustered into cluster 74 and 82 while clusters 30, 40, 72 and 73 indicate that in the dataset the fuel oil inlet temperature is excessive. Thus, as presented in Table 6.4, the SOM network has successfully clustered the main engine cylinder data into various clusters representing particular characteristics within the dataset. Moreover, it can be noticed from Table 6.4 and Figure 6.2 that not all 100 neurons of the SOM have been assigned to the input data, thus remaining inactive, meaning that no input vectors from the training dataset has been assigned to such clusters. However, the SOM algorithm treats all the neurons on the map as active and does learning accordingly.

The main reason of occurrence of inactive clusters is due to the nature of the data used for the SOM training and the competitive training process, as data with similar characteristics will be assigned to the same cluster or neighbouring clusters of the map. Also, during the competitive training process, clusters and neighbouring clusters are shifted towards areas of the map with higher data density. Therefore, if input vectors occur with varying frequency throughout the input space, the feature map layer tends to allocate neurons to an area in proportion to the frequency of input vectors there. Neurons close to the winning neuron for each input vector are updated along with the winning neuron.

After the network training phase, the trained SOM network is saved in order to carry out additional simulations using new data as input. To validate the network performance in clustering data successfully, new input data is used to simulate the SOM model. The input dataset represents actual engine data operating under normal operating conditions extracted from dataset 3 for cylinder 1.

The data consisting of raw performance parameters measurements are normalised prior to input in the trained SOM network. After simulating the data in the trained SOM, the SOM has clustered the actual engine data for all eight cylinders into clusters 49, 77 and 57. As observed, the data have been clustered successfully in cluster 49 and 77 which represent parameters operating in normal conditions as represented in Table 6.4. Moreover, it can be noticed that a fraction of the dataset has been clustered in the SOM cluster 57, which has previously remained inactive in reference to the SOM training results. By using the Euclidean distance metric and the custom developed algorithm for identifying similar clusters, the clusters with the shortest distance related to cluster 57 can be identified and are displayed in Table 6.5 in order to identify potential neighbouring clusters containing similar data.

Table 6.5 Similar clusters to cluster 57 based on Euclidean distance criteria

| **Euclidean Distance** | *<0.1* | *<0.15* | *<0.2* | *<0.25* | *<0.3* | *<0.35* |
|---|---|---|---|---|---|---|
| **Similar Clusters** | No | No | 48, 56 | No | No | 42, 46, 77 |

The results of Table 6.5 indicate that the identified neighbouring clusters to cluster 57 are inactive apart from cluster 77 which represents healthy engine performance data. Therefore, it can be concluded that cluster 57 also represents healthy engine data based on the fact that the Euclidean distance criteria between these clusters is satisfied. Thus, the input monitored data representing healthy data has been successfully clustered in the SOM in combination with the custom algorithm identifying clusters that have the shortest distance between them containing similar data. Table 6.6 presents the Euclidean distances for cluster 57 with respect to the identified neighbouring clusters.

Table 6.6 Euclidean distances of identified clusters to cluster 57

| **Cluster** | **Status** | **Distance** |
|---|---|---|
| 48 | Inactive | 0.157 |
| 56 | Inactive | 0.158 |
| 77 | Healthy data | 0.336 |
| 42 | Inactive | 0.342 |
| 46 | Inactive | 0.349 |

#### *6.3.2.1 SOM case study for condition monitoring applications*

This case study demonstrates the capability of the SOM to monitor the main engine condition by identifying clusters containing data which are diverse compared to data representing normal engine operating conditions. The SOM is applied for performance parameters of the most critical systems identified in the FTA-FMEA process. These parameters refer to the exhaust gas temperature outlet of cylinder 8, piston cooling oil temperature outlet of cylinder 8 and piston cooling oil inlet pressure of the main engine.

Data related to these parameters are extracted from dataset 1 and correspond to a constant vessel speed of 14 knots as the main engine operates at 60 rpm. Specifically, 57 measurements per parameter were used as input for the training of the SOM. With the main engine operating at 60 rpm, the cylinder exhaust gas temperature ranged from 250 to 260 °C, the piston cooling oil outlet temperature between 48 and 51 °C and the piston cooling oil inlet pressure readings were constant at 2.7-2.8 kg/cm$^2$. However, additional artificial data is used for the analysis which correspond to unusual measurements of the monitored parameters, representing abnormal engine behaviour affecting the performance of the main engine. These measurements are compared to those related to the engine speed and rpm which represent the normal engine operating condition. As an additional functionality, data exceeding OEM alarm threshold levels are also used for the analysis as these thresholds fulfil the requirements of the engine manufacturer and ensure the safe operation of the main engine.

Table 6.7 displays the thresholds utilised to determine abnormal engine operation both for the scenario of the apparently vague parameter measurements and measurements exceeding the engine guide recommended thresholds. The abnormal state thresholds for the monitored parameters were defined based on discussions with experts such as senior and technical marine engineers, two ship operators and three Classification Societies senior personnel with ship systems experience and expertise, interviewed as part of the INCASS project.

Table 6.7 Alarm thresholds for the main engine monitored parameters

| **Measurable engine parameter** | **Normal range** | **Abnormal state** | **OEM alarm threshold** |
|---|---|---|---|
| Cylinder exhaust gas temperature outlet °C | 250-260 | Lower than 200, Greater than 300 | Greater than 450 |
| Cylinder piston cooling oil temperature outlet °C | 48-51 | Greater than 65 | Greater than 70 |
| Piston cooling oil pressure inlet kg/cm$^2$ | 2.7-2.8 | Lower than 1.8 | Lower than 1.4 |

The SOM created for clustering the multidimensional input vectors consists of a 4-by-4 two-dimensional map of 16 neurons. Once training is complete, the multidimensional input data vectors have been assigned into clusters. The SOM topology after training is shown in Figure 6.3.

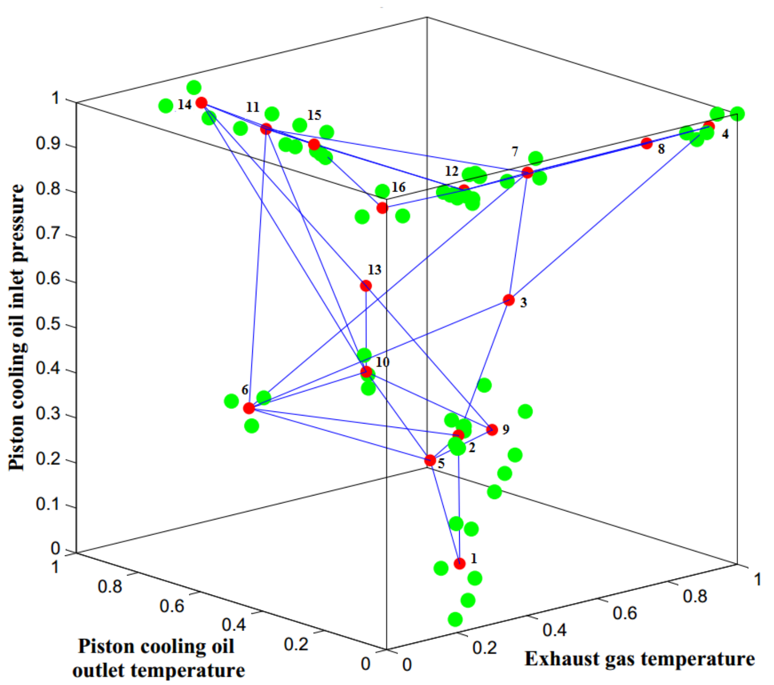



Figure 6.3 SOM main engine clusters after training

As observed in Figure 6.3, cluster 15 represents data in which the cylinder piston cooling oil outlet temperature operates in an abnormal state while the piston cooling oil inlet pressure and cylinder exhaust gas temperature are operating normally. The data has been clustered into twelve clusters as observed in Table 6.8. Each cluster the data has been assigned to has been labelled to provide informative insight regarding the condition of the monitored parameters and the main engine.

Table 6.8 Description of clusters

| Cluster | Cluster Description |
|---|---|
| 12 | No faults- normal operating parameter values |
| 16 | Cylinder exhaust gas temperature outlet abnormal state, lower than 200 ºC |
| 7 | Cylinder exhaust gas temperature outlet abnormal state, greater than 300 ºC |
| 4 | Cylinder exhaust gas temperature outlet exceeding OEM alarm level |
| 15 | Piston cooling oil outlet temperature abnormal state |
| 11 & 14 | Piston cooling oil outlet temperature exceeding OEM alarm level |
| 2 | Piston cooling oil inlet pressure abnormal state |
| 1 | Piston cooling oil inlet pressure OEM alarm level |
| 6 & 10 | All monitored parameters operating in abnormal state |
| 9 | All monitored parameters exceeding OEM alarm levels |

As observed in Table 6.8, the clusters produced by the SOM have clustered the multidimensional data related to the cylinder of the main engine and have been interpreted accordingly to provide useful data insight. Specifically, the data have been classified into 10 categories. Cluster 12 represents no faults, in which the monitored parameters are operating under normal conditions. On the other hand, clusters 16 and 7 represent abnormal data indicating decreased or increased cylinder exhaust gas temperature respectively compared to the normal engine operating values at 60 rpm, while the cylinder piston cooling oil outlet temperature and inlet pressure are operating normally. Cluster 4 contains data related to the exhaust gas temperature exceeding the OEM alarm level.

Additionally, data representing all parameters operating simultaneously in abnormal state have been clustered into cluster 6 and 10 and have been assigned under one group based on the interclustering approach. During the SOM training process no data has been assigned to cluster 5 and 13. This is due to the reasons mentioned in the previous section. After the network training phase, the network is saved to carry out additional simulations using new data as input. In order to validate the network performance in clustering data successfully, new input data is used to simulate the SOM model. The parameters are normalised for the simulation and the input data and the resulting cluster numbers are shown in Table 6.9.

Table 6.9 New input data and assigned clusters

| **Parameters** | **Healthy state** | | | **Exhaust gas increased (abnormal state)** | | | **All parameters abnormal state** | | |
|---|---|---|---|---|---|---|---|---|---|
| Exhaust gas temperature outlet | 251 | 253 | 255 | 304 | 310 | 312 | 301 | 305 | 310 |
| Piston cooling oil outlet temperature | 49 | 48.5 | 50 | 50 | 48 | 49 | 65 | 66 | 67 |
| Piston cooling oil inlet pressure | 2.7 | 2.8 | 2.7 | 2.7 | 2.7 | 2.7 | 1.8 | 1.7 | 1.7 |
| *ANN-SOM cluster results* | ***12*** | ***12*** | ***12*** | ***7*** | ***7*** | ***7*** | ***10*** | ***10*** | ***10*** |

The results of the clustering process in the table above successfully demonstrate the ability of the trained SOM to cluster the input data with abnormal parameter values. As observed, the first three sets of data represent actual data extracted from dataset 3 and are assigned to the SOM cluster 12 which represents healthy data. The next three input vectors represent data for abnormal increased exhaust gas outlet temperature and this has been clustered accordingly in cluster 7. The data representing the abnormal engine operating conditions have been created using artificial data. Finally, the last three input data display data in abnormal state compared to the normal engine operating condition for all three monitored parameters and the SOM has classified this data in cluster 10 effectively.

## 6.4 NAR and NARX results

This section presents the results regarding the developed NAR and NARX network models for the main engine performance parameters. The results are presented for the modelled main engine systems for both dataset 1 and dataset 2.

### *6.4.1 NAR results for dataset 1*

This section presents the results obtained for the main engine performance parameters related to dataset 1. A set of 39 parallel neural networks are created in order to forecast the upcoming 5 hourly values of each parameter. Due to the large number of networks developed, for ease of reading, this section presents and describes the results obtained for the exhaust gas temperature outlet of cylinder 8 based on the developed NAR network training results. A summary table of results for parameters related to the main engine FT subsystems is also provided. Appendix F.1 contains the results of all trained NAR networks for the remaining 38 main engine parameters. The regression plots of the correlation coefficient *R* for the training and testing data set as shown in Figure 6.4.

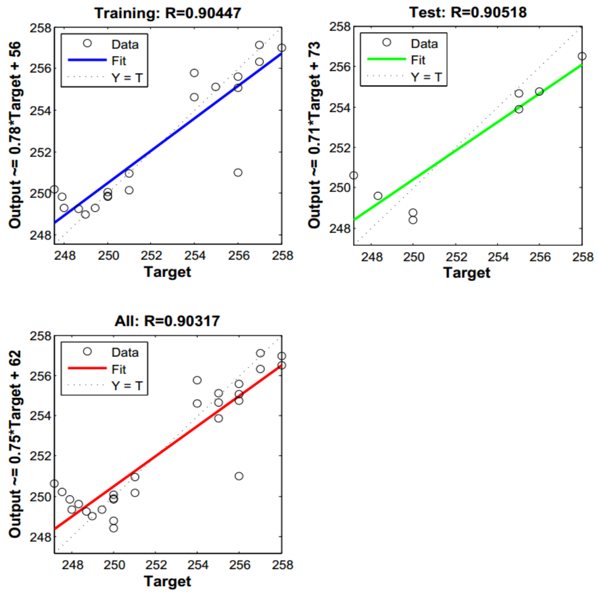



Figure 6.4 NAR regression results for cylinder 8 exhaust gas outlet temperature

The regression plot showing the correlation coefficient *R* is a good measure of how well the NAR network has fitted the data and displays the network outputs with respect to targets for training and test sets. The regression plot shows the actual network outputs on the *y* axis plotted in terms of the associated target values presented in the *x* axis of the plot. Regression values measure the correlation between outputs and targets. A correlation coefficient *R* value of 1 implies a perfect fit of outputs exactly equal to targets. It should be reminded at this point, that the Bayesian regularisation training algorithm does not use a validation set but includes this in the training set. The plot results indicate a good network fit to the input data for the exhaust gas temperature outlet of cylinder 8. Specifically, the training data indicate a good fit as does the test data results, showing values of *R* equal to 90% in both sets.

Besides the correlation coefficient, the error autocorrelation function is used to validate the NAR network performance. This function describes how the prediction errors are related in time. For a faultless prediction network model, there should be only one non-zero value of the autocorrelation function occurring at zero lag implying that the forecast errors are entirely uncorrelated with each other. Figure 6.5 presents the error autocorrelation function results for exhaust gas outlet temperature of cylinder no.8. The remaining are shown in Appendix F.1.3.

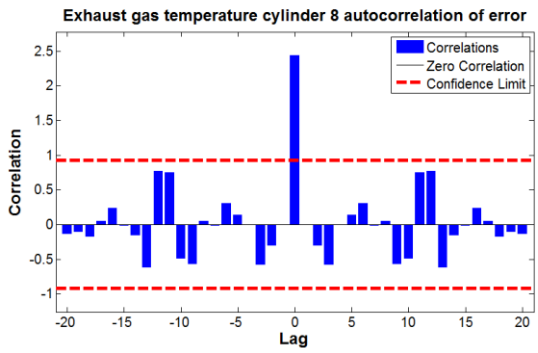



Figure 6.5 Autocorrelation of error for cylinder 8 exhaust gas outlet temperature

Satisfactory network training has been achieved as the forecast errors are completely uncorrelated with each other and fall within the 95% confidence limits around zero which are calculated based on the sample size of the time series data generated from the MATLAB autocorrelation function. This implies that the prediction errors are completely uncorrelated with each other. Figure 6.6 presents the forecasted results with their 95% prediction intervals for cylinder 8 exhaust gas outlet temperature.

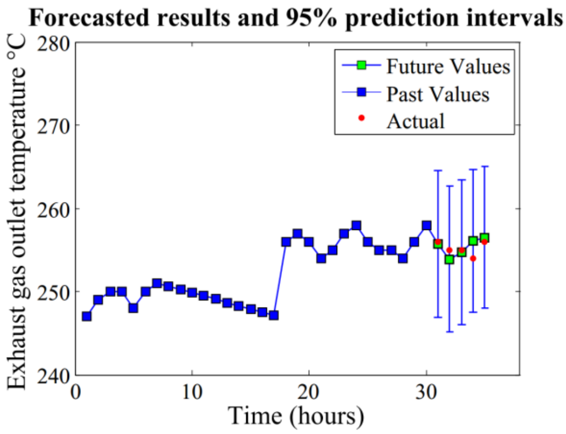



Figure 6.6 NAR forecast results for exhaust gas outlet temperature of cylinder 8

The first 30 hourly measurements are the recorded values from the dataset, while the last 5 hourly data points, from 31 hours until 35 hours are the ones forecasted from the NAR model, which lie within the expected prediction intervals. The recorded temperatures for the cylinder are within the range of 245 $^{o}$C to 260 $^{o}$C and such variations could be the result of the specific state and condition of the individual cylinder. Specifically, an increase of approximately 10 $^{o}$C after 17-18 hours of operation is observed which is negligible but can be tracked due to an increase in the engine fuel load. This is due to the engine governor regulating the engine speed, as the vessel was sailing at a constant speed of 10 knots. Moreover, localised weather conditions such as current, waves and wind direction could be contributing factors. Similar patterns are observed in all other cylinders as shown in Appendix F.1.4.

For ease of reading, Table 6.10 presents a sample of the various NAR models developed for performance parameters of the main engine modelled systems. The remaining results are contained in Appendix F.1.2. The forecasted results are compared with the actual onboard measurements using the APE and MAPE criteria for validation purposes.

Table 6.10 NAR multi-step-ahead forecast results for dataset 1 (sample)

| **Parameter** | **Results** | **t+1** | **t+2** | **t+3** | **t+4** | **t+5** | **MAPE** |
|---|---|---|---|---|---|---|---|
| Cylinder Exhaust Gas Outlet Temperature no.1 | Actual | 263 | 260 | 262 | 262 | 263 | |
| | ANN Prediction | 262.2 | 262.4 | 262.4 | 262.4 | 262.4 | |
| | APE | 0.30% | 0.92% | 0.15% | 0.15% | 0.23% | **0.35%** |
| Thrust Bearing LO Outlet Temperature | Actual | 46.8 | 46.8 | 46.7 | 46.8 | 46.8 | |
| | ANN Prediction | 46.8 | 46.8 | 46.8 | 46.8 | 46.8 | |
| | APE | 0.01% | 0.01% | 0.20% | 0.02% | 0.02% | **0.05%** |
| Fuel Oil Inlet Temperature | Actual | 136 | 137 | 137 | 137 | 137 | |
| | ANN Prediction | 137.2 | 137.2 | 137.3 | 137.3 | 137.3 | |
| | APE | 0.88% | 0.18% | 0.22% | 0.24% | 0.25% | **0.35%** |
| Main Lubrication Oil Inlet Pressure | Actual | 2.8 | 2.8 | 2.8 | 2.8 | 2.8 | |
| | ANN Prediction | 2.8 | 2.8 | 2.8 | 2.8 | 2.8 | |
| | APE | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | **0.00%** |
| Cylinder JCFW Outlet Temperature no.1 | Actual | 83 | 83 | 83 | 83 | 83 | |
| | ANN Prediction | 83.4 | 83.3 | 83 | 83.1 | 83 | |
| | APE | 0.48% | 0.36% | 0.00% | 0.12% | 0.00% | **0.19%** |
| Air Cooler Cooling Water Inlet Pressure | Actual | 3.1 | 3.2 | 3.1 | 3.1 | 3.1 | |
| | ANN Prediction | 3.1 | 3.1 | 3.1 | 3.1 | 3.1 | |
| | APE | 0.00% | 2.82% | 0.00% | 0.00% | 0.00% | **0.56%** |

As observed from Table 6.10, the actual and NAR network forecasted results for the engine parameters are provided for five step-ahead predictions from the present timestep *t*. The maximum APE between the actual and predicted values is 2.82% for the air cooler cooling water inlet pressure. Moreover, by examining the overall table of results (provided in Appendix F.1.2), the maximum MAPE model is equal to 1.02% for the exhaust gas outlet temperature of main engine cylinder 7. As such, the performance and accuracy of the 39 trained NAR neural networks are verified, indicating satisfactory predictive time series capabilities.

### *6.4.2 NAR and NARX results for dataset 2*

#### *6.4.2.1 NAR results*

This section presents the results obtained for the NAR models related to each main engine performance parameter regarding dataset 2. In total, 39 NAR dynamic neural network models are developed to forecast the upcoming 20 hourly measurements of each parameter. As mentioned in Section 6.3.1 for dataset 2, the original dataset size of 986 hourly measurements per parameter was reduced to 920 after the data cleansing and preparation process.

In terms of training the networks, 900 measurements are used while the last 20 hourly measurements of the dataset are used in order to compare the forecasted network results with the actual recorded results. Relevant results for all developed NAR models are contained in Appendix F.2.

The regression plots of the correlation coefficient R for the training, test and all data regarding the piston cooling oil outlet temperature of cylinder 5 is presented in Figure 6.7 below. Regression results for all models can be found in Appendix F.2.1.

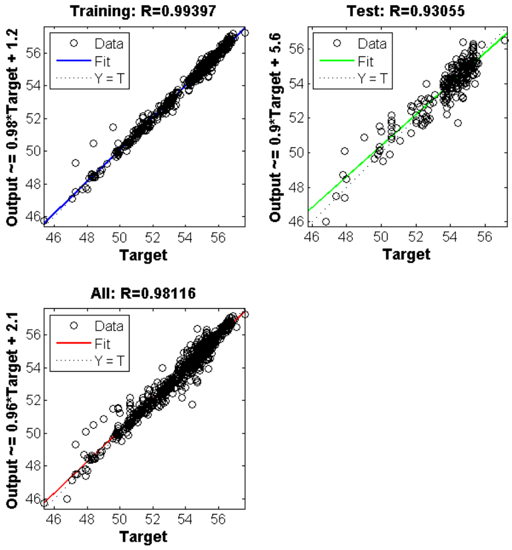



Figure 6.7 NAR regression results for cylinder 5 piston cooling oil outlet temperature

The regression plot displays a good network fit to the input data. Specifically, for the training data the results indicate a correlation coefficient value of 99.39% while 93.05% is achieved for the test data. Figure 6.8 presents the forecasted results with the 95% calculated prediction intervals for the piston cooling oil outlet temperature of cylinder 5.

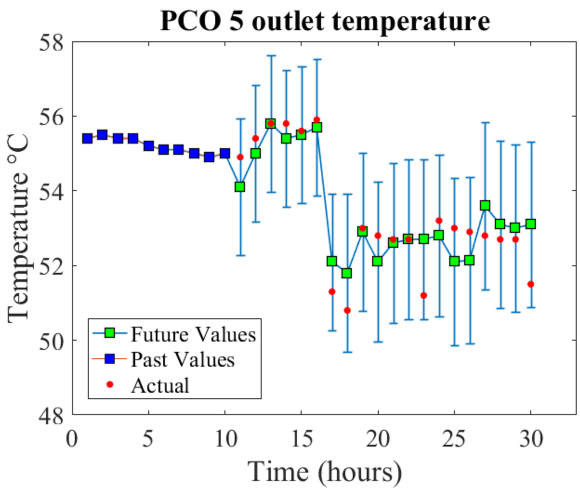



Figure 6.8 NAR forecast results for cylinder 5 piston cooling oil outlet temperature

For ease of reading and presenting, the last 10 hourly measurements of the actual dataset are plotted in blue, while the 20 forecasted measurements, from timestep 11 to

30, are plotted in green and the corresponding red dots represent the actual monitored values. The piston cooling oil outlet temperature ranges from 51 °C to 56 °C. Overall, the NAR model is capable of predicting the future values of the time series as all values lie within the prediction intervals. The model has a MAPE value of 1.07% for the total 20 forecasted points, demonstrating satisfactory forecasting capabilities overall. Moreover, the APE for each forecasted value is small but there are however some instances where particular APE values are significantly larger than other observations. Due to its large size, the table of APE and MAPE results for each NAR model is presented in Appendix F.2.2. Specifically, at timestep 17 and 18 it can be observed that the oil temperature decreased approximately by 4 °C from 56 °C to 52 °C and the APE values are equal to 1.56% and 1.97% respectively. A similar situation can be observed in timesteps 23 and 30 where the actual values are smaller than the forecasted ones and their APE values are equal to 2.93% and 3.11% respectively.

Nevertheless, the NAR model is able to successfully forecast the majority of the future piston cooling oil temperature values, with all values falling within the 95% prediction intervals and maintain a low overall MAPE value which is due to the its capability of capturing the general parameter trendline as observed in Figure 6.8. However, this is not the case for all parameters modelled with the NAR models, as observed in Figure 6.9 presenting the results for the exhaust gas outlet temperature of cylinder 5.

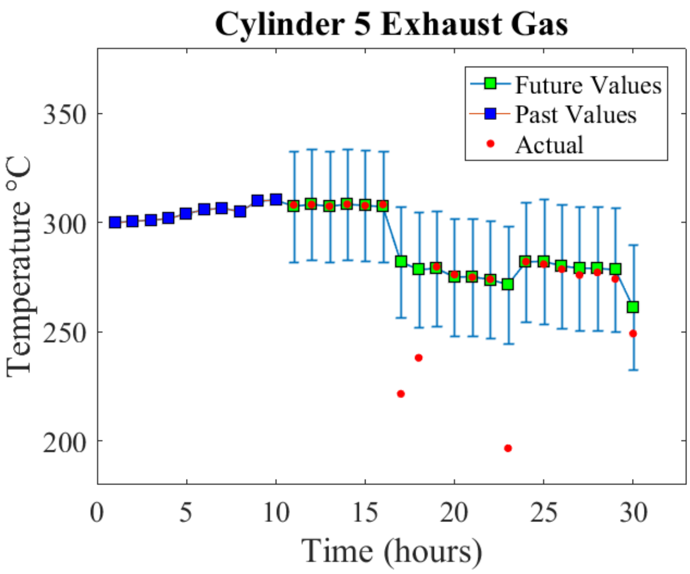



Figure 6.9 NAR forecast results for exhaust gas outlet temperature of cylinder 5

As observed, although the NAR model for the cylinder exhaust gas forecasts most values successfully, the results obtained have significant errors in timesteps 17, 18 and 23 specifically, owing mostly in the alteration of the main engine's rpm. Specifically, from timestep 1-15 the engine speed is equal to 61-63 rpm while at timestep 17 it is reduced to 40 rpm and is then increased to 51 rpm, thus explaining the shift in the parameters and the reasonable hiatus of the NAR model to capture this change. Moreover, the next section presents the results for the NARX models which aims to resolve this issue by introducing the main engine's rpm as exogenous input to the time series models.

For ease of reading, Table 6.11 presents a sample of the various NAR forecast results related to the various the main engine performance parameters. The remaining results are contained in Appendix F.2.2 and F.2.4. As observed in Table 6.11, the actual and NAR network forecasted results for the engine parameters are provided for the twenty step-ahead predictions from the present timestep t.

Overall, the trained models can predict the future values of the time series as all future values lie within the prediction intervals and are close to the actual recorded values, hence verifying good network accuracy and performance. However, high APE results are observed in the main engine cylinder exhaust gas outlet temperature models, in the timesteps in which alteration in the main engine rpm occurs. Moreover, the maximum MAPE model is equal to 5.88% for the total 20 forecasted points of cylinder 4 exhaust gas outlet temperature model. The next section presents the results obtained for the developed main engine NARX models, which consider the main engine rpm as exogenous input in the time series analysis and forecasting process.

Table 6.11 NAR multi-step-ahead forecast results for dataset 2 (sample)

| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder Exhaust Gas Temperature no.4 | Actual | 317.10 | 316.90 | 314.50 | 314.10 | 315.50 | 319.30 | 248.80 | 234.10 | 276.60 | 274.20 | 271.10 | 270.70 | 188.50 | 278.50 | 273.40 | 272.60 | 271.60 | 271.50 | 272.20 | 242.20 | |
| | ANN Prediction | 316.89 | 315.01 | 316.41 | 312.94 | 314.92 | 317.61 | 294.80 | 284.13 | 281.76 | 271.90 | 273.86 | 267.23 | 252.50 | 293.67 | 286.24 | 283.91 | 283.80 | 281.00 | 281.50 | 268.20 | |
| | APE | **0.07%** | **0.60%** | **0.61%** | **0.37%** | **0.18%** | **0.53%** | **18.49%** | **21.37%** | **1.87%** | **0.84%** | **1.02%** | **1.28%** | **33.95%** | **5.45%** | **4.70%** | **4.15%** | **4.49%** | **3.50%** | **3.42%** | **10.73%** | **5.88%** |
| Cylinder Exhaust Gas Temperature no.5 | Actual | 308.10 | 308.30 | 307.50 | 308.40 | 307.80 | 308.30 | 221.60 | 238.10 | 279.80 | 276.20 | 275.00 | 274.10 | 196.70 | 282.10 | 281.00 | 278.70 | 276.00 | 277.20 | 274.20 | 249.20 | |
| | ANN Prediction | 307.50 | 308.30 | 307.50 | 308.40 | 307.80 | 307.30 | 282.00 | 278.50 | 279.00 | 275.10 | 275.20 | 273.90 | 271.65 | 282.00 | 282.30 | 280.13 | 279.13 | 279.04 | 278.41 | 261.32 | |
| | APE | **0.19%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.32%** | **27.26%** | **16.97%** | **0.29%** | **0.40%** | **0.07%** | **0.07%** | **38.10%** | **0.04%** | **0.46%** | **0.51%** | **1.13%** | **0.66%** | **1.54%** | **4.86%** | **4.64%** |
| Thrust Bearing Temperature | Actual | 50.30 | 50.50 | 50.70 | 50.70 | 50.60 | 50.90 | 48.40 | 47.40 | 49.00 | 48.80 | 48.70 | 48.70 | 47.50 | 49.40 | 49.20 | 49.20 | 49.10 | 49.10 | 49.10 | 48.30 | |
| | ANN Prediction | 50.10 | 50.35 | 50.60 | 50.70 | 50.60 | 50.60 | 48.00 | 47.30 | 48.91 | 48.70 | 48.60 | 48.69 | 47.39 | 49.00 | 49.20 | 49.10 | 49.20 | 49.11 | 49.10 | 49.00 | |
| | APE | **0.40%** | **0.30%** | **0.20%** | **0.00%** | **0.00%** | **0.59%** | **0.83%** | **0.21%** | **0.18%** | **0.20%** | **0.21%** | **0.02%** | **0.23%** | **0.81%** | **0.00%** | **0.20%** | **0.20%** | **0.02%** | **0.00%** | **1.45%** | **0.30%** |
| Fuel Oil Inlet Pressure | Actual | 7.45 | 7.43 | 7.40 | 7.41 | 7.42 | 7.37 | 7.70 | 7.74 | 7.66 | 7.72 | 7.71 | 7.65 | 7.72 | 7.61 | 7.62 | 7.61 | 7.60 | 7.59 | 7.59 | 7.70 | |
| | ANN Prediction | 7.45 | 7.50 | 7.52 | 7.52 | 7.52 | 7.46 | 7.59 | 7.61 | 7.57 | 7.56 | 7.57 | 7.57 | 7.61 | 7.55 | 7.57 | 7.55 | 7.56 | 7.56 | 7.56 | 7.59 | |
| | APE | **0.12%** | **0.94%** | **1.69%** | **1.56%** | **1.43%** | **1.16%** | **1.44%** | **1.65%** | **1.19%** | **2.03%** | **1.80%** | **1.05%** | **1.44%** | **0.78%** | **0.66%** | **0.74%** | **0.58%** | **0.42%** | **0.38%** | **1.44%** | **1.12%** |
| Main Lube Oil Temperature | Actual | 45.20 | 45.30 | 45.30 | 45.30 | 45.40 | 45.30 | 45.30 | 45.10 | 45.20 | 45.30 | 45.10 | 45.30 | 45.20 | 45.30 | 45.30 | 45.30 | 45.10 | 45.10 | 45.20 | 45.20 | |
| | ANN Prediction | 45.25 | 45.27 | 45.27 | 45.28 | 45.26 | 45.25 | 45.27 | 45.26 | 45.27 | 45.25 | 45.25 | 45.25 | 45.24 | 45.25 | 45.23 | 45.25 | 45.25 | 45.25 | 45.25 | 45.25 | |
| | APE | **0.10%** | **0.07%** | **0.06%** | **0.04%** | **0.30%** | **0.11%** | **0.07%** | **0.35%** | **0.16%** | **0.10%** | **0.33%** | **0.11%** | **0.08%** | **0.12%** | **0.14%** | **0.12%** | **0.33%** | **0.34%** | **0.10%** | **0.11%** | **0.16%** |
| Air Cooler Cooling Water Inlet Pressure | Actual | 3.89 | 4.04 | 4.22 | 4.24 | 4.24 | 4.25 | 4.19 | 3.87 | 4.24 | 3.86 | 3.80 | 3.86 | 3.86 | 3.81 | 3.83 | 3.74 | 3.75 | 3.74 | 3.73 | 3.75 | |
| | ANN Prediction | 3.93 | 3.95 | 4.18 | 4.18 | 4.20 | 4.24 | 4.20 | 4.15 | 4.16 | 3.81 | 3.79 | 3.84 | 3.84 | 3.70 | 3.71 | 3.64 | 3.66 | 3.71 | 3.71 | 3.71 | |
| | APE | **1.06%** | **2.21%** | **1.01%** | **1.49%** | **1.02%** | **0.32%** | **0.19%** | **7.35%** | **1.96%** | **1.18%** | **0.38%** | **0.40%** | **0.40%** | **2.95%** | **2.90%** | **2.76%** | **2.49%** | **0.89%** | **0.73%** | **1.16%** | **1.64%** |
| Cylinder CFW Outlet Temperature no.4 | Actual | 84.80 | 85.00 | 85.40 | 85.30 | 85.40 | 86.20 | 86.20 | 86.10 | 85.80 | 85.50 | 85.50 | 85.40 | 84.70 | 85.70 | 85.50 | 85.70 | 85.40 | 85.70 | 85.40 | 85.40 | |
| | ANN Prediction | 85.24 | 85.38 | 85.31 | 85.20 | 85.45 | 85.51 | 85.52 | 85.55 | 85.44 | 85.68 | 85.82 | 85.68 | 85.67 | 85.76 | 85.78 | 85.97 | 85.90 | 85.74 | 85.64 | 85.86 | |
| | APE | **0.52%** | **0.44%** | **0.11%** | **0.12%** | **0.06%** | **0.80%** | **0.78%** | **0.63%** | **0.42%** | **0.21%** | **0.38%** | **0.33%** | **1.15%** | **0.06%** | **0.33%** | **0.31%** | **0.59%** | **0.05%** | **0.28%** | **0.54%** | **0.41%** |
| Cylinder PCO Outlet Temperature no.5 | Actual | 54.90 | 55.40 | 55.80 | 55.80 | 55.60 | 55.90 | 51.30 | 50.80 | 53.00 | 52.80 | 52.70 | 52.70 | 51.20 | 53.20 | 53.00 | 52.90 | 52.80 | 52.70 | 52.70 | 51.50 | |
| | ANN Prediction | 54.10 | 55.00 | 55.80 | 55.40 | 55.50 | 55.70 | 52.10 | 51.80 | 52.90 | 52.10 | 52.60 | 52.70 | 52.70 | 52.80 | 52.10 | 52.14 | 53.60 | 53.10 | 53.00 | 53.10 | |
| | APE | **1.46%** | **0.72%** | **0.00%** | **0.72%** | **0.18%** | **0.36%** | **1.56%** | **1.97%** | **0.19%** | **1.33%** | **0.19%** | **0.00%** | **2.93%** | **0.75%** | **1.70%** | **1.44%** | **1.52%** | **0.76%** | **0.57%** | **3.11%** | **1.07%** |

### *6.4.2.2 NARX results*

This section presents the results obtained for the NARX models related to the main engine performance parameters. In total, 39 NARX dynamic neural network models are developed which utilise the main engine rpm as the exogenous input time series. For multi-step-ahead predictions in the NARX model, data for the exogenous input is required. The NARX models are developed to forecast a one-step-ahead prediction which requires past values of both the exogenous input and target time series.

Moreover, by following the steps presented in Figure 4.7, the trained NARX models can be utilised to simulate further forecast predictions based on the obtained one-step-ahead prediction results. The results are presented in the next pages for the main engine subsystems. All relevant results for all developed NARX models are contained in Appendix F.3.

The upcoming 20 hourly measurements of cylinder 5 exhaust gas outlet temperature are presented in Figure 6.10 below to demonstrate and compare the results obtained against the results of the respective NAR case study presented in Figure 6.9.

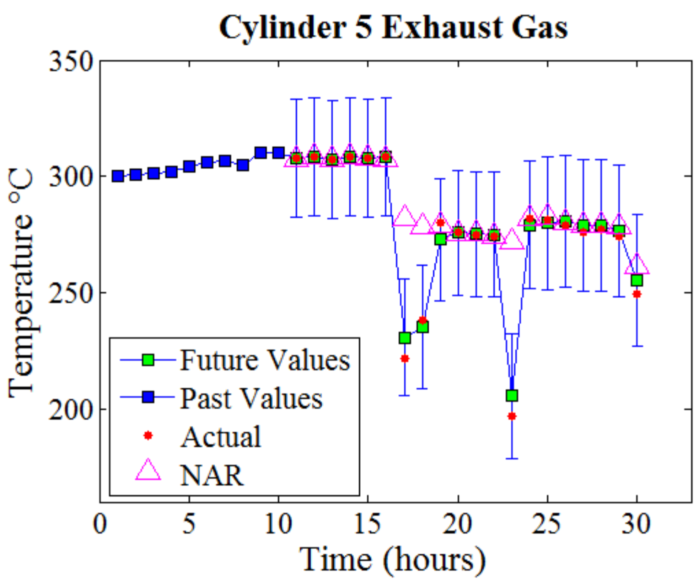



Figure 6.10 NARX forecast results for exhaust gas outlet temperature of cylinder 5 and comparison with NAR results

The forecasted NARX results are plotted in green for timesteps 11-30 hours while the actual values are plotted as red dots on the graph. Moreover, the magenta triangles represent the associated NAR results of Figure 6.9 for cylinder 5. As observed by examining the graph, compared to the NAR model, the trained NARX model is capable of identifying the fluctuations in the modelled parameter through the addition of the main engine rpm as the exogenous input to the time series model and analysis. Specifically, in the 17$^{th}$, 18$^{th}$ and 23$^{rd}$ hour mark the exhaust gas temperature forecasted values fall close to the actual monitored values compared to the NAR results.

In the 17$^{th}$ hour interval, for the NAR model the APE value between the forecasted and actual exhaust gas outlet temperature value is equal to 27.26%, while the results for the NARX model indicate a major reduction in the APE of 23.12% magnitude, resulting in an APE value for the NARX model of 4.14%. Furthermore, in the 18$^{th}$ hourly mark the APE is reduced from 16.97% to 1.20% and at 23 hours it is reduced from 38.10% obtained in the NAR model to 4.52% by applying the NARX model. Moreover, the overall model MAPE value is reduced from 4.64% down to 1.02%.

Table 6.12 presents a summary of the NARX APE and MAPE results for the main engine parameters in which the most significant changes in APE results were obtained compared to the corresponding NAR results. Specifically, significant changes were observed in the exhaust gas outlet temperature and scavenging air temperature, particularly related to the 17$^{th}$, 18$^{th}$ and 23$^{rd}$ hourly timesteps, in which significant shifts in the monitored parameters exist due to the alteration of the main engine's rpm. By examining Table 6.12, it can be noticed that for the specific timesteps presented, the APE values have been significantly reduced by comparing the NARX and NAR results for the main engine parameters. Moreover, this results in an important reduction in the overall MAPE of the models for the total 20 hourly forecasted values of each parameter, thus improving the forecasting accuracy by introducing the main engine rpm as the exogenous input in the NARX models. Appendix F.3.2 contains the complete NARX APE and MAPE results for the main engine parameters and Appendix F.3.3 includes all graphs and 95% prediction intervals.

Table 6.12 Comparison of APE-MAPE for NAR and NARX models

| **Main Engine Parameter** | **ANN Model** | **Timestep & APE** | | | **Model MAPE** |
|---|---|---|---|---|---|
| | | **17** | **18** | **23** | |
| Cylinder exhaust gas outlet temperature no.1 | NAR | 5.63% | 24.71% | 25.48% | 3.25% |
| | NARX | *2.64%* | *2.58%* | *2.49%* | *0.61%* |
| Cylinder exhaust gas outlet temperature no.2 | NAR | 6.87% | 19.78% | 26.04% | 4.65% |
| | NARX | *1.46%* | *2.13%* | *4.62%* | *0.84%* |
| Cylinder exhaust gas outlet temperature no.3 | NAR | 14.02% | 8.93% | 29.66% | 3.72% |
| | NARX | *3.10%* | *2.26%* | *5.19%* | *0.83%* |
| Cylinder exhaust gas outlet temperature no.4 | NAR | 18.49% | 21.37% | 33.95% | 5.88% |
| | NARX | *2.87%* | *4.00%* | *7.92%* | *1.19%* |
| Cylinder exhaust gas outlet temperature no.5 | NAR | 27.26% | 16.97% | 38.10% | 4.64% |
| | NARX | *4.14%* | *1.20%* | *4.52%* | *1.02%* |
| Cylinder exhaust gas outlet temperature no.6 | NAR | 0.94% | 13.75% | 33.45% | 3.65% |
| | NARX | *0.54%* | *1.76%* | *8.43%* | *0.87%* |
| Cylinder exhaust gas outlet temperature no.7 | NAR | 11.45% | 26.03% | 42.13% | 4.80% |
| | NARX | *1.48%* | *4.30%* | *7.56%* | *0.93%* |
| Cylinder exhaust gas outlet temperature no.8 | NAR | 8.48% | 24.84% | 43.41% | 4.86% |
| | NARX | *2.28%* | *0.91%* | *5.35%* | *1.63%* |
| Cylinder scavenging air temperature no.1 | NAR | 12.92% | 8.03% | 0.97% | 2.10% |
| | NARX | *2.15%* | *1.61%* | *0.97%* | *0.52%* |
| Cylinder scavenging air temperature no.2 | NAR | 12.29% | 10.68% | 2.00% | 2.30% |
| | NARX | *2.51%* | *1.23%* | *1.00%* | *0.64%* |
| Cylinder scavenging air temperature no.3 | NAR | 15.52% | 11.80% | 1.14% | 3.73% |
| | NARX | *2.11%* | *0.98%* | *0.76%* | *0.55%* |
| Cylinder scavenging air temperature no.4 | NAR | 13.52% | 15.49% | 0.78% | 3.23% |
| | NARX | *1.59%* | *0.20%* | *0.19%* | *0.41%* |
| Cylinder scavenging air temperature no.5 | NAR | 13.76% | 15.51% | 5.77% | 3.61% |
| | NARX | *0.19%* | *0.60%* | *0.96%* | *0.52%* |
| Cylinder scavenging air temperature no.6 | NAR | 13.79% | 10.61% | 2.09% | 3.10% |
| | NARX | *0.57%* | *0.39%* | *0.19%* | *0.51%* |
| Cylinder scavenging air temperature no.7 | NAR | 13.48% | 13.22% | 0.82% | 3.55% |
| | NARX | *2.21%* | *0.83%* | *0.10%* | *0.69%* |
| Cylinder scavenging air temperature no.8 | NAR | 16.35% | 11.24% | 4.58% | 4.07% |
| | NARX | *1.58%* | *0.59%* | *0.23%* | *0.71%* |

## 6.5 Present and predictive assessment results

### *6.5.1 ANN-MLP results*

The overall results of the trained ANN-MLP classifier, described in Section 5.3.4, are presented in Table 6.13, showing the total percentage of correctly classified and misclassified cases for the training, validation, test dataset and all three sets combined.

Table 6.13 ANN MLP response results

| **Data** | **Accuracy %** | **Error %** |
|---|---|---|
| Training set | 100.00% | 0.00% |
| Validation set | 98.70% | 1.30% |
| Test set | 98.70% | 1.30% |
| All data | 99.60% | 0.40% |

The results for all three datasets show excellent network response and classification accuracy by checking the high percentage of correct responses and the low percentage of incorrect responses. Furthermore, another measure of the quality of the network is examining how well the neural network has fitted data is the Receiver Operating Characteristic (ROC) plot shown in Figure 6.11 for all datasets.

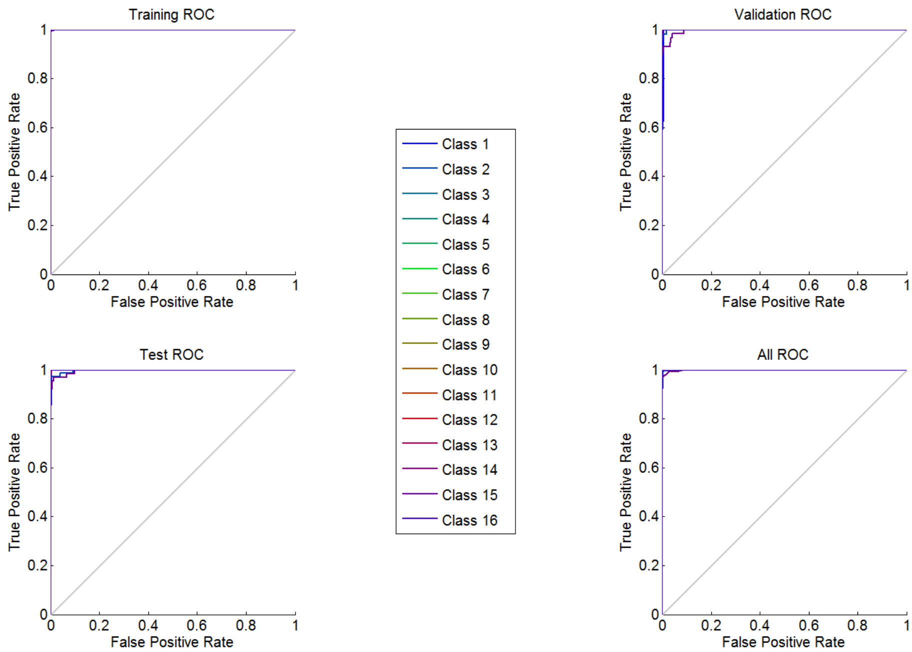



Figure 6.11 Receiver Operating Characteristics for all network 16 fault classes

This shows how the false positive and true positive rates relate as the thresholding of outputs is varied from 0 to 1. The farther left and up the line is, the fewer false positives need to be accepted in order to get a high true positive rate. The best classifiers will have a line going from the bottom left corner, to the top left corner, to the top right corner, or close to that. As observed, the network performs almost perfectly as most points and fault classes are in the upper left corner of the ROC plots. Figure 6.12 presents the detailed confusion matrix for the network test dataset for all 16 main engine fault classes. The rows correspond to the output classes of the network and the columns show the true class (target class). Appendix G.1 contains the detailed confusion matrices for the training, validation and complete dataset.

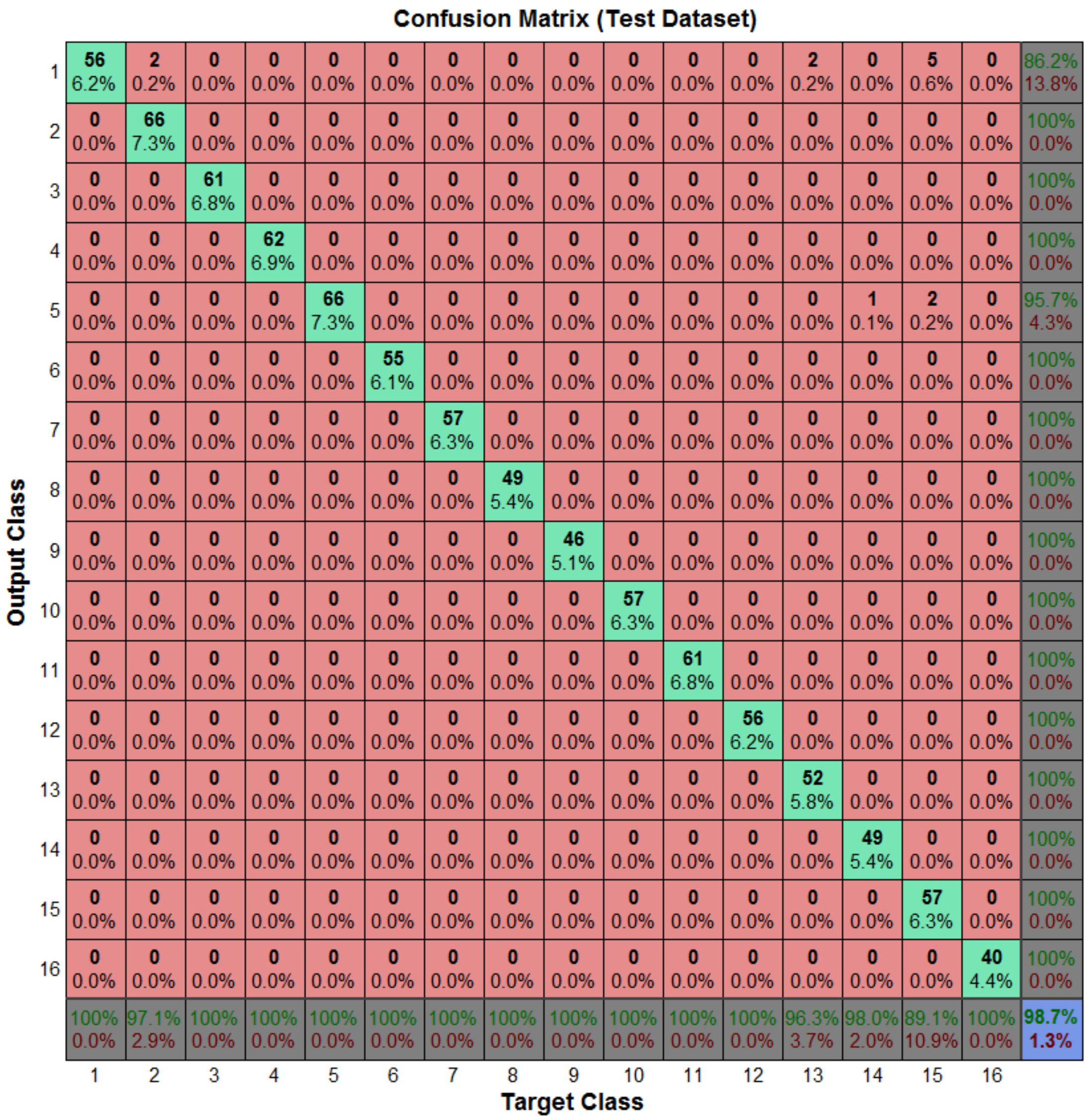



Figure 6.12 Test dataset confusion matrix for all 16 main engine fault classes

The diagonal green cells show for how many and what percentage of the data the trained network has correctly estimated the classes of the observations, while the red cells show the misclassified cases. Thus, it shows which percentage of the true and predicted classes match. Overall the results for all the modelled main engine fault classes show excellent network response and 98.7% classification accuracy overall has been achieved. As a reminder, network output classes are connected and referenced with engine fault codes ($F_0$-$F_{15}$) as defined in Table 5.8 in Chapter 5. Specifically, most of the fault classes have been perfectly classified while some other fault classes, class 1 ($F_0$) and 5 ($F_4$), have high classification accuracies and minor misclassifications. Specifically, the first class of the network representing healthy engine data ($F_0$) has an overall accuracy of 86.2% while the fifth class representing exhaust gas temperature decrease in all cylinders ($F_4$) has an overall 95.7% classification accuracy. It is unfeasible to obtain a perfect classifier model with several faults and multi-faults as besides overfitting issues that would occur, the nature of the input data may contain some features that do not have sufficient differences to provide a clear line for classification.

### *6.5.2 MCI results*

This section presents the results for the main engine MCI, subsystem and individual MCIs based on the data contained in dataset 1 alongside the forecasted multi-step-ahead results. Although the data represents normal operating conditions, this particular case study and defined thresholds presented in Table 5.12 and Appendix D.2 are selected in order to demonstrate the capabilities of the developed MCI tool. Therefore, the MCIs of various Relevant Condition Parameters (RCPs) are presented initially followed by the MCIs obtained for the main engine and its subsystems through the RBD calculations. Figure 6.13 presents the monitored measurements and calculated individual MCI for cylinder 6 piston cooling oil outlet temperature parameter.

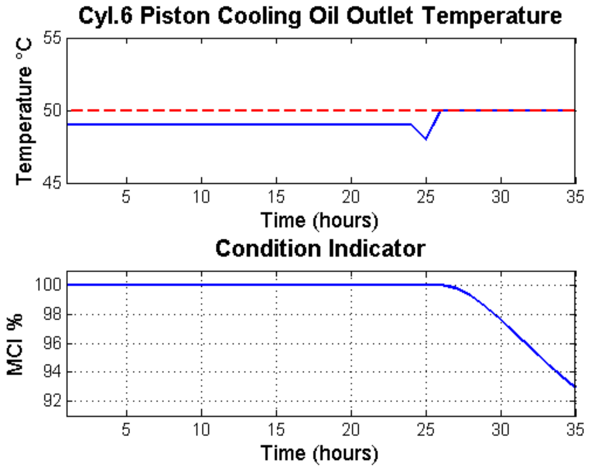



Figure 6.13 MCI for cylinder 6 piston cooling oil outlet temperature

As observed, the upper graph presents the piston cooling oil outlet temperature measurements represented with a blue continuous line while the red dashed line represents the defined $RCP_{lim}$ equal to 50°C for this particular parameter. The lower graph presents the corresponding hourly MCI. During the first 25 hours, the parameter measurements are within the defined thresholds and therefore the associated MCI is equal to 100%. However, from the 26$^{th}$ until the 35$^{th}$ hour, the piston cooling oil temperature is increased from 49 °C to 50°C reaching the defined $RCP_{lim}$. Therefore, the MCI identifies this condition and starts to degrade accordingly to a final 92.89% condition indicator.

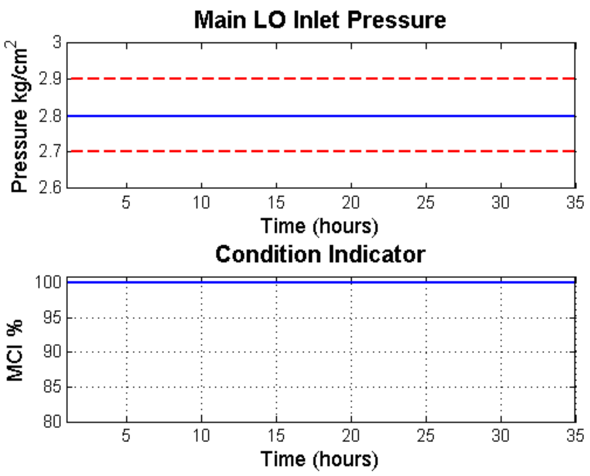



Figure 6.14 MCI for main lubrication oil inlet pressure

In Figure 6.14, the $RCP_{in}$ and $RCP_{lim}$ for the main lubrication oil inlet pressure are equal to 2.7 and 2.9 kg/cm$^2$ respectively, while the parameter measurements are constantly equal to 2.8 kg/cm$^2$. Therefore, the MCI in this case is equal to 100% throughout the data. Figure 6.15 presents the MCI for cylinder 3 JCFW outlet temperature.

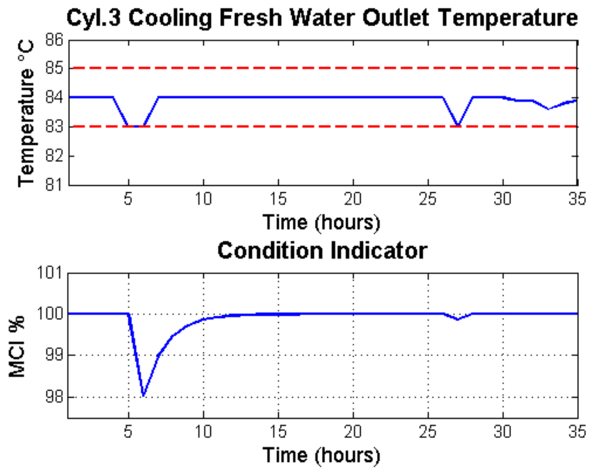



Figure 6.15 MCI for cylinder 3 jacket cooling fresh water outlet temperature

In this case, the $RCP_{in}$ and $RCP_{lim}$ are equal to 83 $^{o}$C and 85 $^{o}$C respectively, while the parameter measurements are equal to 84 $^{o}$C with some particular timesteps moving to the $RCP_{in}$ limit. Specifically, at timestep 6 and 7 the MCI is equal to 98.01% as the parameter temperature is equal to $RCP_{in}$. Then after the 7$^{th}$ hourly interval, the MCI trendline increases as the parameter is restored within the defined limits and is progressively restored to 100%. Finally, there is a single point in the 27$^{th}$ hour mark reaching $RCP_{in}$, causing a relatively small change in the MCI equal to 99.75% which is immediately restored as the following measurements are contained within the limits. The remaining MCI graphs for all other main engine RCPs are contained in Appendix G.2.

Once all the individual MCIs have been obtained for the main engine RCPs, the MCIs related to the main engine and subsystems are calculated through the RBD model described in Section 5.3.4. Figure 6.16 presents the MCIs obtained for all eight main engine cylinders.

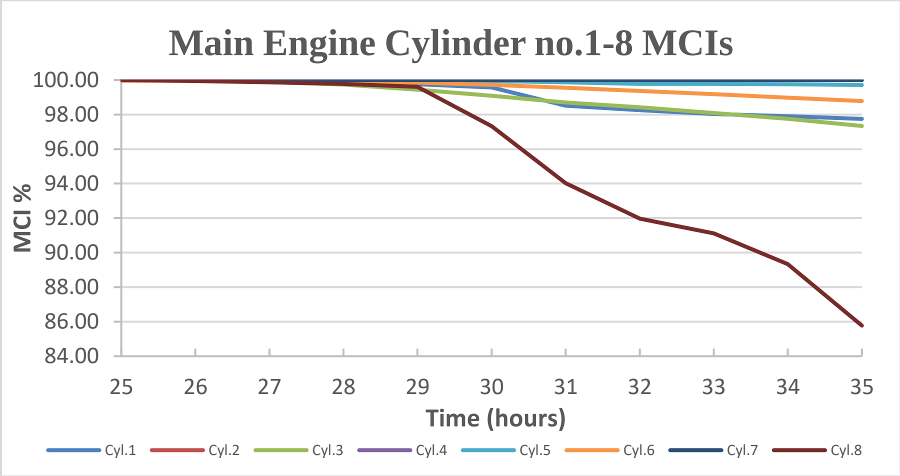



Figure 6.16 MCIs for cylinders no.1-8

The graph demonstrates the obtained condition indicators for all eight individual cylinders of the main engine. For illustration purposes, the graph starts at the 25th hour mark as at this point it can be observed that most cylinders have decreased MCIs because the individual MCIs regarding the RCPs in each cylinder have exceeded their defined thresholds. It is observed that cylinder 8 has the lowest MCI reaching a value of 85%. This is because the individual MCIs of the RCPs comprising the cylinder 8 RBD consisting of the exhaust gas outlet, scavenging air, PCO outlet and JCFW outlet temperature have lower condition indicator values that the other cylinders. Figure 6.17 displays the results for all modelled main engine subsystems.

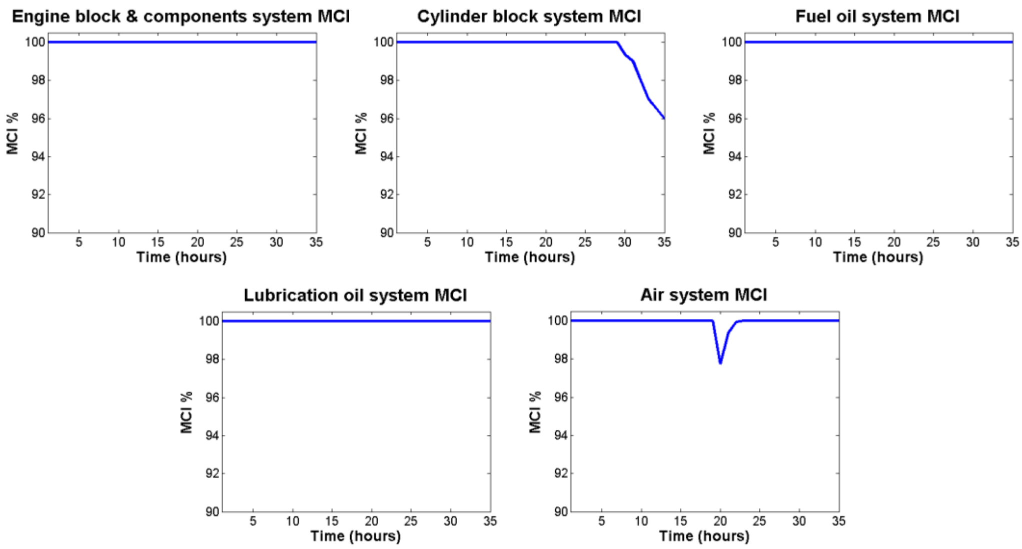



Figure 6.17 MCIs for main engine subsystems

The MCIs for the engine subsystems are presented and include the MCI for the lubrication oil, fuel oil, air, engine block and cylinder system, compiling the overall main engine RBD model. As observed from the graphs, the lubrication oil, fuel oil and engine block and components system maintain 100% MCI throughout, thus the parameters lie within the defined thresholds. Moreover, the air system MCI decreases to a value of 97.74% at the 20 hour mark and is then gradually restored. On the other hand, the cylinder system MCI starts degrading at 30 hours reaching 95.98% MCI at the 35 hour mark. Figure 6.18 presents the calculated system MCI for the overall main engine system.

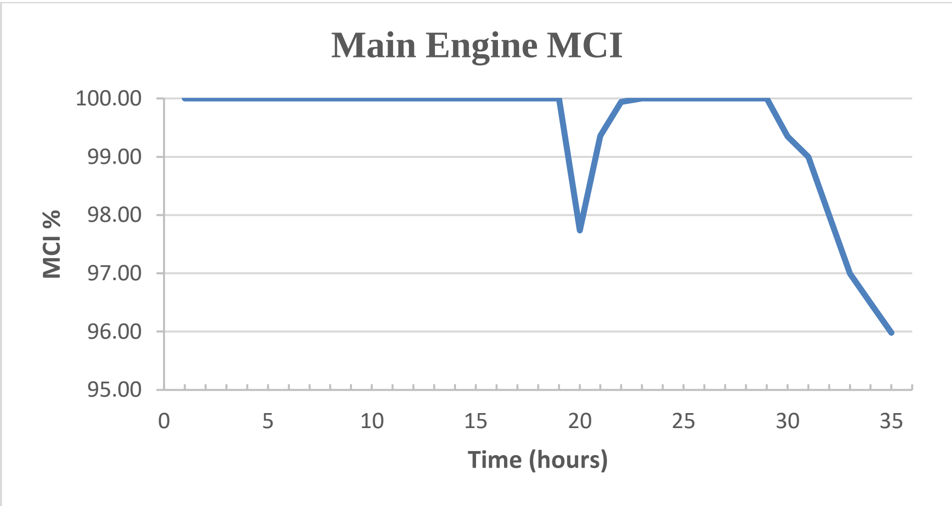



Figure 6.18 Main engine MCI

The main engine RBD consists of its subsystems connected in series. Thus, any degradation in the condition indicators for the subsystems directly have an effect on the main engine MCI. As presented in Figure 6.18 the main engine MCI is equal to 100% and after 20 hours is decreased to just below 98% owing solely to the degradation of the air system MCI as presented in Figure 6.17. Furthermore, the MCI is increased as at 21 hours and 22 hours it is equal to 99.36% and 99.94% respectively and is then decreased again at 30 hours until the 35$^{th}$ hour due to the decrease observed in the cylinder system, reaching 95.98% overall.

Alternatively, the MCIs for the engine and its various systems can be represented in MAT as bar plots to the user for each time interval. Figure 6.19 presents the main engine, cylinder 8 and respective piston cooling oil outlet temperature MCI for timestep 32.

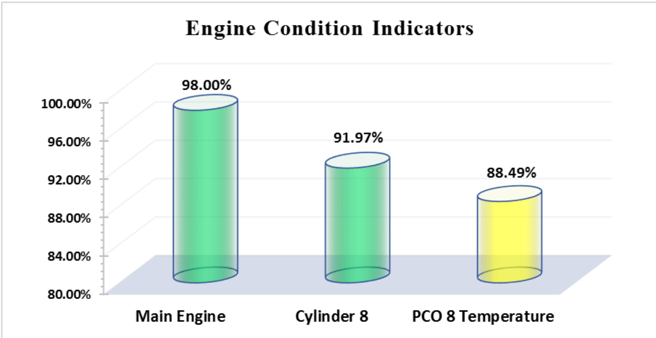



Figure 6.19 Main engine, subsystem and component MCI at hourly timestep 32

## 6.6 MAT results

Based on the results obtained from both datasets in the case study, the datasets are used as input in MAT to provide the suggested maintenance action, in the event of any faults present. As the data represent healthy operating engine operation with no faults occurring based on the results of the ANN-MLP, '*$F_0$-No Fault: Continue Routine Monitoring*' was the suggested maintenance action produced by MAT as also demonstrated in Figure 6.20.

```
F0-No Fault : Continue Routine Monitoring
Please press enter to continue for additional information:
```

Figure 6.20 Produced maintenance action by MAT

Therefore, the action is valid based on the input data and the assessment output of the ANN-MLP classifier for the main engine diagnostics. However, as demonstrated in the second line of the MAT output, upon user input additional information can be displayed such as the health status of the main engine system, in the format presented in Figure 6.19 or other historical records. Moreover, it should be mentioned that the MATLAB code of MAT has been fully developed to provide information and maintenance actions for all main engine faults and inputs prompted by the user. The following page demonstrates fundamental aspects of MAT for a simulated fault regarding exhaust gas temperature increase in one cylinder.

```
Symptom: Exhaust gas temperature increase in one cylinder
```

| Point | PotentialCauses | Remedy |
|---|---|---|
| 5 | 'Defective fuel valves ' | 'Overhaul fuel valves and replace' |
| 6 | 'Fuel valve leakage/dripping' | 'Replace or overhaul valve' |
| 7 | 'Fuel injection nozzles worn' | 'Replace nozzles' |
| 8 | 'Wrongly adjusted/slipped fuel cam' | 'Check fuel pump lead' |
| 9 | 'Blow-by in combustion chamber' | 'Reduce engine speed, inspect and if required replace piston rings and cylinder liner surface' |
| 10 | 'Exhaust valve burned/leakage' | 'Replace or overhaul valve, grind the valve seat and head' |
| 11 | 'Improper scavenging' | 'Clean and overhaul scavenging air receiver air flaps' |
| 12 | 'Scavenge air port fouling' | 'Clean scavenge air ports' |
| 13 | 'Cylinder liner wear' | 'Check cylinder liner surface' |
| 14 | 'Exhaust thermometer defective' | 'Replace the exhaust thermometer' |

```
Display more information? Please enter 1 for [Yes] and 0 for [No]:
```

Figure 6.21 Fault causes and remedies for simulated main engine fault

As displayed in Figure 6.21, MAT presents the identified symptom which is the exhaust gas temperature outlet increase in one main engine cylinder. Subsequently, the developed tool presents the full list of potential fault causes and associated remedies. Moreover, the user is asked if additional information is required regarding the identified fault. This is achieved by providing the relevant FMEA table information to the user regarding the potentially affected system and components. A sample of this is presented in Figure 6.22.

```
Display more information? Please enter 1 for [Yes] and 0 for [No]:1
```

| System_Item | FailedItem | FailureEvent | FailureCause | LocalEffect |
|---|---|---|---|---|
| 'Cylinder' | 'Cylinder Head' | 'Cracked' | 'Overheating, fatigue' | 'Compession loss, cylinder damage, engine misfire' |
| '' | '' | 'Overheating' | 'cracks, faulty exhaust valves' | 'high temperature alarm, smoke, cylinder damage' |
| '' | 'Cylinder Liner' | 'Leakage' | 'Overheating ' | 'Compession loss, cooling water in cylinder' |
| '' | '' | 'Wear ' | 'Fatigue, lubrication oil quality' | 'Compession loss, increased lubrication consumption' |

Figure 6.22 Sample of FMEA table presented by MAT

Thus, MAT provides initial diagnostic information extracted from the developed diagnostic fault causes and FMEA table alongside remedies. Moreover, through the diagnostic database, the highest fault causes prioritised based on their historically recorded frequency are presented to assist the crew and operator as shown in Figure 6.23

```
Highest_causes =

    'Cause Point'    'Frequency'
    [         11]    [       21]
    [          7]    [       20]
    [         10]    [        8]
    [         13]    [        4]

Display condition indicators:
```

Figure 6.23 Presentation of most recorded fault causes

After this point, MAT provides to the user additional information regarding the MCI for system, subsystem and component level, followed by the defined criteria and relevant information, in order to provide the most appropriate maintenance action and activity based on the user's input decision.

```
Is the component critical? 1 for [Yes] and 0 for [No]: 1
Display available spare parts and costs? 1 for [Yes] and 0 for [No] 0
Is the maintenance cost high? 1 for [Yes] and 0 for [No]: 0
Spare parts available? 1 for [Yes] and 0 for [No]: 0
Display vessel PMS? 1 for [Yes] and 0 for [No] 0
Is the PMS interval eminent? 1 for [Yes] and 0 for [No]: 0
```

Figure 6.24 Presentation of MAT criteria and user input

As seen in Figure 6.24, MAT initiates the progress of the appropriate maintenance action and activity by prompting the user to define if the component is critical. Afterwards, availability of spare parts onboard and costs are displayed to decide if the maintenance cost is high and if spare parts are available. After this, the vessel's PMS is also displayed to investigate if the PMS interval for the component/system is imminent, which could lead to opportunistic maintenance activities. Based on the input fed to MAT, the component has been deemed critical, while maintenance cost has been selected to be low and no spare parts exists onboard. Moreover, the PMS interval is not imminent. Hence, preventive maintenance action with activities such as check regularly and replace when possible are suggested as seen in Figure 6.25.

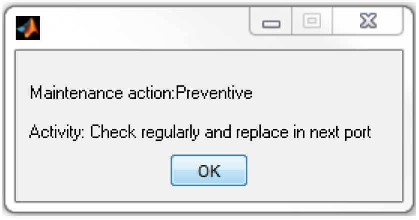



Figure 6.25 Suggested maintenance action and activity by MAT

Finally, as also described in Section 5.3.5, additional information such as spare part drawings, OEM and IACS guidelines, maintenance and repair logs are also provided to assist the maintenance process. Moreover, at the end of the process, the user is prompted to enter the root cause of the fault alongside any additional information which is used to update the diagnostic database and update historical records.

## 6.7 Discussion of case study results

This section aims to summarise and discuss the main outcomes of the case study presented in this chapter. The case study examined the overall suggested hybrid condition monitoring methodology strategy by utilising collected actual input data regarding the main engine of the Panamax container ship. The case study results are presented for various subsystems of the main engine such as the fuel, lubrication, air, engine block and components, and cylinder block assembly system.

The FTA of the main engine provided invaluable information on prioritisation of components for monitoring activities, while the FMEA provides a platform audit for producing information and selecting performance parameters for commencing monitoring. Through the FT results, the engine critical items are identified which if properly monitored and maintained, enhance safety and engine condition and performance. Overall, the FT results produce 72 cut sets for the main engine system ranging from 3$^{rd}$ order to 9$^{th}$ order cut sets. The minimum cut sets of the FT provided good insight into the systems critical systems and components. The results obtained were realistic, in the sense that the identified components are important components for normal engine operation which are subject to various failure modes and their failure can lead to costly ship downtime and unavailability and even more to potential hazardous situations such as explosions, endangering lives onboard.

In addition, through the FMEA results, the FTA cut sets were further analysed in terms of their specific failure modes and associated causes. Therefore, through the FTA-FMEA process, parameters applicable for monitoring the engine condition and assisting in detection of the described failure modes for each system and component can be identified. In the case where data is not available for a component in the minimal cut sets such as the fuel oil filter, then actions such as overhauling, checking that the filtering material is intact and that no foreign bodies are found can be suggested.

The identification of the parameters acts as a first step regarding the development and analysis of the novel condition monitoring strategy for monitoring the overall main engine condition. Key parameters in performance observations of the main engine are selected based on the FTA-FMEA analysis and include the exhaust gas outlet and jacket fresh water cooling outlet temperature per engine cylinder, the piston cooling lubrication oil outlet temperature per engine cylinder, the piston cooling lubrication oil inlet, fuel oil inlet pressure and the main lubrication oil inlet temperature. However, the availability of additional parameters accessible from the case study datasets were also included for developing the ANN models, further enhancing the research investigation and outcome of the thesis.

The addition of bad data points in a neural network training set can invalidate a model. The data cleansing algorithm was applied to cleanse the datasets from invalid measurements (irrational measurement readings, negative values etc.). Overall regarding dataset 2, 66 conditions were found containing invalid data or no data at all, demonstrating the faults that can occur in the data acquisition system. Moreover, the arithmetic mean was selected for replacing empty cell attributes. The arithmetic mean provided satisfactory data cleansing properties which did not affect the training or performance of the neural networks. Moreover, using the arithmetic mean was adequate since there was a small number of missing data elements. In other cases, the arithmetic median or regression techniques could also be selected for replacing empty cells.

The two SOM case studies illustrated the capability and flexibility of the SOM algorithm both for clustering main engine data as a processing tool in the overall condition monitoring framework and as a tool for monitoring the engine condition. In the first case study, the developed SOM successfully clusters the main engine data into clusters representing normal engine operating conditions and clusters containing data exceeding OEM thresholds and excessive data. The SOM results were validated through using actual main engine operational data from dataset 3 as input, which contains data not seen before by the SOM. The second case study indicated that the SOM is also capable of identifying the engine condition through abnormal state thresholds in addition to the OEM thresholds. The unsupervised learning nature of the SOM provides a fast and efficient method to cluster data and model the underlying structure or distribution in the data. Moreover, through the Euclidean distance metric, data assigned in previously inactive SOM clusters, can be identified and labelled with near clusters sharing data similarities.

The NAR and NARX models were developed for both datasets, demonstrating the impact of data size on the training accuracy. In total, 39 NAR models were developed for dataset 1 and an additional 39 NAR and 39 NARX models were developed for dataset 2, representing the selected performance parameters of the main engine case study. The forecasted results are demonstrated in two segments of time including the actual data and the forecasted future data. Overall, good network fits to the input data was achieved. Moreover, the results obtained for the error autocorrelation function demonstrate the uncorrelation of errors with each other, thus ensuring satisfactory network performance and confidence in the forecasting analysis. In terms of dataset 1, the MAPE for all models is very low, indicating good forecasting capabilities, as the highest MAPE is equal to 1.02% for the exhaust gas outlet temperature of main engine cylinder 7. Moreover, the forecasted results fall within the expected 95% prediction intervals, further enhancing the confidence in the network results and is important in testing whether or not a specification has been met (alarm/threshold) as there could be situations where a result may fall clearly inside or outside a specified limit, but the uncertainty may overlap the limit.

The increased amount of data in dataset 2 provided better results regarding the regression plots of the correlation coefficient $R$ for the training and testing data set for all main engine parameters. The NAR models were capable of forecasting with relative small APE values most of the multi-step ahead predictions. In most instances, the APE error is increased towards the end of the 20 multi-step-ahead predictions and thus further forecasting beyond this point increased the error in forecasting. This is due to the accumulation of network errors during the multi-step-ahead analysis of the NAR network in the closed loop mode. Furthermore, in parameters such as the cylinder exhaust gas outlet temperature, the NAR models were unable to detect the shift in parameter measurements due to the alteration in the main engine rpm. In order to resolve this issue, NARX models were also developed by introducing the main engine's rpm as exogenous input to the time series models. The introduction of the main engine rpm as the external time series data indicated that the NARX models are capable of identifying the fluctuations in the modelled parameters and thus reduced significantly the APE and MAPE of the models compared to the results obtained from the respective NAR models.

The ANN-MLP diagnostic classifier results demonstrate excellent classification accuracy for the trained network regarding the 16 modelled main engine fault classes, including the modelling of several faults and multi-faults. Most of the fault classes have been perfectly classified while some other fault classes, class 1 ($F_0$) and 5 ($F_4$), have high classification accuracies and minor misclassifications. The collected and forecasted data from dataset 1 and 2 are within the acceptable operating limits as predefined by the OEM thresholds.

The main engine MCI case study successfully demonstrates the capabilities of the method for parameters exceeding upper and lower thresholds, which are custom and can be defined accordingly in a tailored-made fashion according to ship operators. Furthermore, the individual condition indicator results for the main engine parameters are obtained through the statistical parameters of the selected probability distribution family. Therefore, based on the distribution of data and the statistical parameters of the selected distribution, the condition indicator results are calculated for each RCP.

The machinery condition indicators are presented on system, subsystem and component level for the main engine. The results obtained for the main engine and subsystem MCIs are based on the selected RBD architecture. The constructed RBD is a combination of series, parallel and k-out-of-n configurations in an attempt to model a complex system such as the ship's main engine. The case study illustrated that a series configuration directly affects the top system in contrast to a parallel or k-out-of-n configuration which provide a level of redundancy to the system. Thus, different configurations would provide different results. Regardless, the scope of this case study was to provide a health assessment mechanism for the system by demonstrating that the main engine MCI and subsystem MCIs can be obtained and start to degrade as a result of the individual MCIs exceeding their defined thresholds.

Finally, MAT has been developed mainly as a fundamental platform for collecting the information outputs from the forecasted NAR and NARX results which are assessed in the ANN-MLP diagnostic classifier and main engine MCI in order to present these data to the user and suggest appropriate predictive maintenance actions. MAT successfully suggests the user to continue routine monitoring and presents the fault code $F_0$ as the case study data from datasets 1 and 2 represent normal (healthy) engine operation. In addition, a simulated case study was presented representing increase of exhaust gas temperature outlet in one cylinder. This case study demonstrated the capabilities of the developed tool.

## 6.8 Chapter summary

In this chapter, the results of the hybrid condition monitoring strategy for the described main engine case study were described in Sections 6.2-6.6. Initially, the FTA-FMEA results were presented followed by the selection of the main engine parameters. Furthermore, the data preparation consisting of the data cleansing algorithm and SOM clustering tool were presented. Moreover, a case study demonstrating the ability of the SOM for monitoring the condition of the main engine for some of the identified critical FTA components was conducted. The NAR and NARX models were developed for all 39 main engine performance parameters for both dataset 1 and dataset 2. Also, the results of the ANN-MLP classifier and main engine MCI were displayed followed by the recommended maintenance action produced by MAT based on the assessment of the forecasted data for both dataset 1 and 2. Finally, the discussion of the attained case study results was presented in Section 6.7. Supplementary information and data regarding the results obtained in this chapter are attached in Appendices E to G. These appendices incorporate information related to the FTA minimal cut sets, the developed main engine FMEA and the results for all 39 main engine performance parameters for the NAR, NARX, ANN-MLP networks and MCIs.

# 7 Sensitivity Analysis

## 7.1 Chapter outline

In the previous chapters, the Panamax container ship case study and results were presented in order to demonstrate the overall hybrid condition monitoring methodology. In this chapter, a partition of the ANN models of the case study is selected and tested through the utilisation of a sensitivity analysis to examine the robustness of the trained models and the level of change in the one-step-ahead forecasted predictions by altering the input data. Section 7.2 provides the description of the sensitivity analysis carried out while Section 7.3 presents the results of the sensitivity analysis for the different scenarios conducted, followed by the chapter summary in Section 7.4.

## 7.2 Sensitivity analysis description

In this section, sensitivity analysis scenarios are conducted in order to assess the forecasted results obtained from the NARX neural network models developed for the main engine performance parameters regarding the case study presented in the previous chapter. Saltelli et al. (2008) defines sensitivity analysis as the field examining how uncertainty in model outputs can be apportioned, qualitatively or quantitatively, to different sources of uncertainty in the model input. Therefore, sensitivity generally refers to the variation in output of a model with respect to changes in the values of the model's input (Chu-Agor et al., 2011). Moreover, a sensitivity analysis attempts to provide a ranking of the model's input assumptions with respect to their contribution to mode output variability or uncertainty (Uusitalo et al., 2015). In a broader sense, sensitivity can refer to how conclusions may change if models, data, or assessment assumptions are altered.

The implementation of the sensitivity analysis on the NARX neural network model was selected as it is part of the time series analysis and forecasting stage of the overall hybrid condition monitoring strategy, from which the predicted main engine system diagnostic and health assessment can be obtained alongside predictive maintenance actions. Moreover, compared to the NAR networks, the NARX model output is dependent on both the input time series data and the exogenous input data. The input parameters of the NARX neural network are examined individually and also in a combinatorial approach as parameter combinations may include nonlinear interactions, hence performing both local and global sensitivity analysis (Baroni and Tarantola, 2014). The objectives of the sensitivity analysis are listed below:

- Examine the ability of the NARX model to simulate data and perform predictions that differ from the original data.
- Investigate and determine the contribution of the uncertainty of the input parameters on the NARX model output results for the one-step-ahead prediction forecast.
- Investigate unreliable data states by simulating unhealthy input data in the model.

The Monte Carlo method is used as a comprehensive approach for accomplishing the sensitivity analysis (Wei et al., 2013). In the context of Monte Carlo simulation, this is described as the process of approximating the model output through repetitive random application of the model’s algorithm. Monte Carlo sensitivity analysis is performed with Latin hypercube sampling which is a sampling scheme designed to ensure that the upper and lower ends of the data used in the sensitivity analysis are well included in the analysis (Firestone et al., 1997). Furthermore, this sampling method is generally recommended over simple random sampling and is one of the most widely used random sampling methods for Monte Carlo based analysis (Shields and Zhang, 2016).

As 39 NARX models were developed for the components and subsystems of the main engine, the implementation of the sensitivity analysis is performed on a particular developed NARX model for one of the main engine subsystems and components. Hence, the analysis is presented for the NARX network related to the main engine cylinder system, specifically for the cylinder 5 exhaust gas outlet temperature parameter. This parameter was selected as the results of the NARX models developed for the cylinder exhaust gas outlet temperature parameters vary significantly for different main engine rpm speeds compared to the other main engine modelled parameters. Moreover, the exhaust gas temperature is directly emitted from the engine cylinders and therefore will indicate the operation and condition of the engine and its combustion process and is a valuable source of diagnostic information regarding the technical condition of elements such as the cylinder and piston, scavenging air, fuel supply system amongst other (Taylor, 1996); as also presented in the main engine FMEA and diagnostic table developed for the case study. Figure 7.1 provides a graphical outline of the sensitivity analysis regarding the inputs and output for the one-step-ahead prediction of the NARX model.

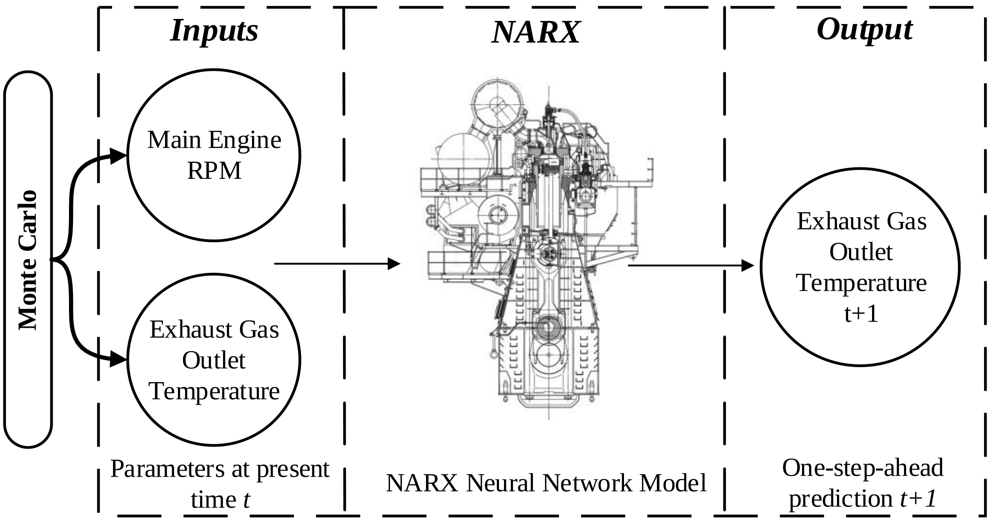



Figure 7.1 Graphical outline of NARX model inputs and output for sensitivity analysis

As presented in Figure 7.1, the sensitivity analysis is conducted through Monte Carlo simulation by varying the inputs of the NARX model, the main engine rpm and/or cylinder exhaust gas outlet temperature at timestep *t* representing the present time, used for producing the subsequent one-step-ahead prediction *t+1* output. Based on the above, three sensitivity scenarios are created to examine the output of the NARX neural network model and are presented in the following section. Sensitivity scenario 1 investigates the effects on the model output by varying the exogenous input data-main engine rpm at present time *t* while the exhaust gas outlet temperature parameter remains constant. On the other hand, in the second scenario, the main engine rpm parameter at time *t* remains the same while the exhaust gas outlet temperature is altered. Finally, in sensitivity scenario 3, both the main engine rpm and exhaust gas outlet temperature parameters are varied to examine the output of the NARX model.

## 7.3 Sensitivity analysis results

### *7.3.1 Sensitivity scenario 1*

In this sensitivity scenario, the main engine rpm is shifted progressively in ranges from its original baseline value of 61.9 rpm at current time *t* to examine the NARX output regarding the one-step-ahead forecast. The investigated rpm parameter ranges are presented in Table 7.1. In total, 14 test cases are conducted to systematically examine the NARX outputs. These are referenced as Test-1 to Test-7 for decreasing the rpm from the baseline, initially by increments of 2% until Test-5 and then by 10% in Test-6 and Test-7 cases until a percentage difference of 30% from the baseline point is obtained for including extreme values in the analysis. The same procedure is followed for increasing the main engine rpm from the baseline for test cases Test+1 to Test+7.

Table 7.1 Main engine rpm parameter range from baseline (rpm=61.9)

| **Test Case** | **% difference from baseline** | **Engine rpm values** |
|---|---|---|
| *Test -1* | [0% -2%] | 61.9-60.6 |
| *Test -2* | [-2% -4%] | 60.6-59.4 |
| *Test -3* | [-4% -6%] | 59.4-58.2 |
| *Test -4* | [-6% -8%] | 58.2-56.9 |
| *Test -5* | [-8% -10%] | 56.9-55.7 |
| *Test -6* | [-10% -20%] | 55.7-49.5 |
| *Test -7* | [-20% -30%] | 49.5-43.3 |
| *Test +1* | [0% +2%] | 61.9-63.1 |
| *Test +2* | [+2% +4%] | 63.1-64.4 |
| *Test +3* | [+4% +6%] | 64.4-65.6 |
| *Test +4* | [+6% +8%] | 65.6-66.8 |
| *Test +5* | [+8% +10%] | 66.8-68.0 |
| *Test +6* | [+10% +20%] | 68-74.3 |
| *Test +7* | [+20% +30%] | 74.3-80.5 |

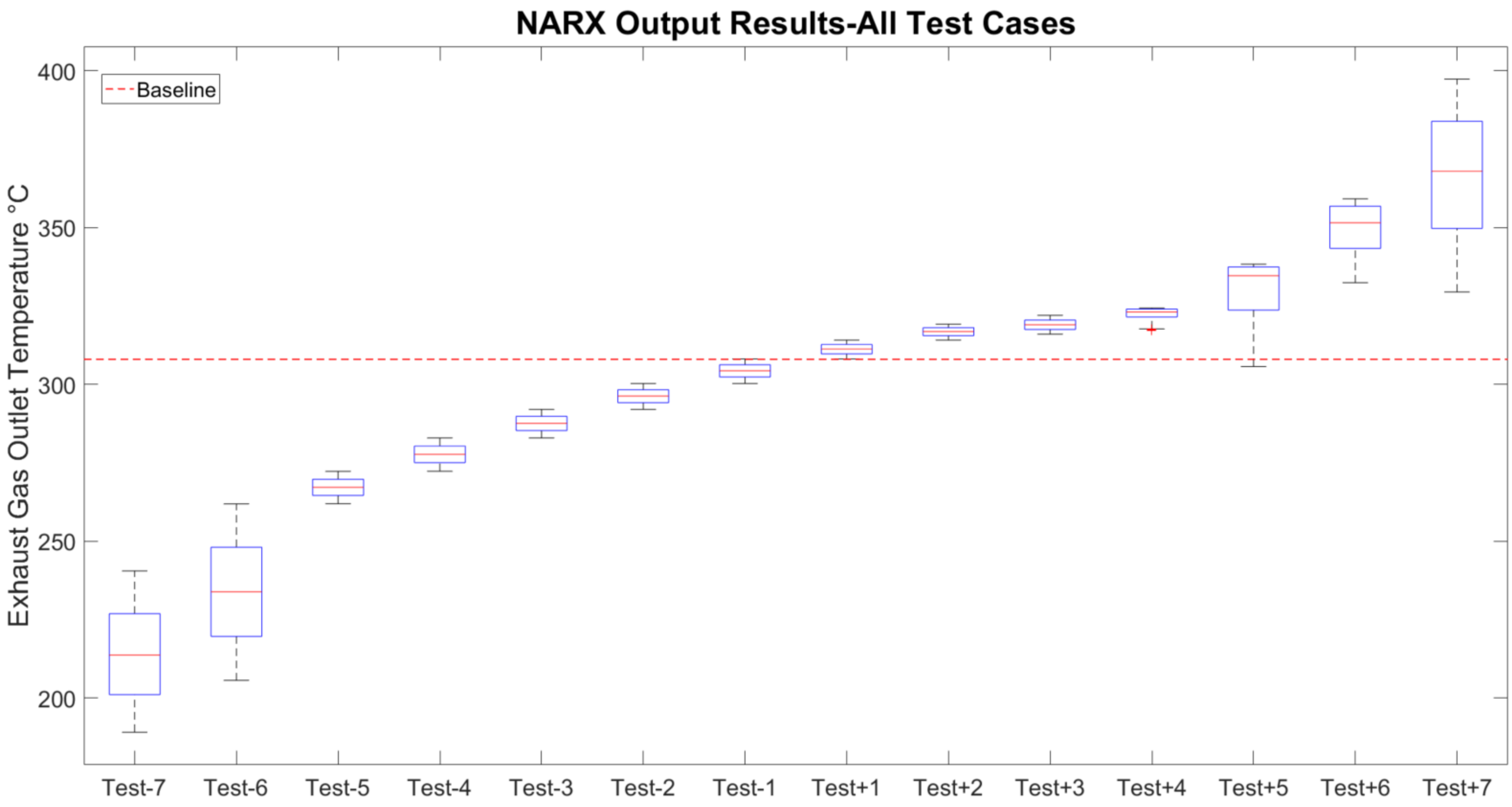


Figure 7.2 NARX sensitivity analysis results for test cases (Scenario 1)

Figure 7.2 presents the results for the described 14 test cases. A Monte Carlo simulation of 1000 iterations is applied for each test case. The number of iterations is chosen as it is statistically adequate for considering extreme values in the analysis (Yang, 2011). Moreover, the simulation time of the NARX model is also taken into account, as larger number of iterations are profoundly time consuming.

The results of the Monte Carlo analysis for each test case are presented and the forecasting result for the one-step-ahead prediction (308$^{o}$C), obtained from the NARX model as presented in Section 6.4.2, is used as the baseline reference for comparing the sensitivity analysis results. By initially examining the cases for Test-1 to Test-7, it is observed that the obtained results for the one-step-ahead prediction move further away from the baseline as the percentage difference from the baseline is increased. For Test-1, the obtained results are within close range of the baseline, demonstrating that a decrease of main engine rpm parameter values of up to 2% from the baseline marginally changes the NARX output and provides satisfactory outputs.

Furthermore, the exhaust gas outlet temperature output in Test-2 to Test-5 is gradually shifted further away from the baseline due to the additional alteration in the main engine rpm ranges. However, this is a reasonable and expected outcome demonstrating that the NARX model effectively simulates the change in the exogenous input data. Moreover, for the additional extreme cases of Test-6 and Test-7 it is noticed that the variance of the Monte Carlo results increases due to the larger parameter range modelled, illustrating that the NARX produces outputs that are further away from the median and each other.

For the cases of Test+1 to Test+7 where the main engine rpm parameter is gradually increased, the same pattern as the other test cases can be observed. In Test+1, the obtained results are within close range of the baseline, demonstrating that a reasonable increase of main engine rpm parameter values up to 2% from the baseline slightly changes the NARX output, providing satisfactory outputs. Reasonable results are also obtained for Test+2 and Test+3. The exhaust gas outlet temperature outputs are increased in the other case tests and an increase in the variance of the Monte Carlo results and instability in the NARX model is noticed when the rpm parameter ranges are significantly different from the baseline. The sensitivity analysis overall demonstrates the good performance and generalisation of the NARX model as it successfully takes into account the different values of the exogenous input data for conducting the one-step-ahead output for lower and higher main engine rpm values from the baseline. On that note, it is essential to mention that the sensitivity analysis results are based on the input dataset used to train the neural network.

Thus, the analysis is conducted on the trained model which produces forecasts based on what is has learned in the past from the dataset. For example, although the network has not been trained with data containing main engine rpm values in the range of 70-80 rpm, the proper training of the model demonstrates its generalisation capabilities especially in the input data of Test+6 and Test+7 where the ANN NARX model provides appropriate reasonable outputs for data it has not seen before. Hence, the results obtained are based on the input dataset applied for training of the NARX model representing certain engine operational profiles and should not be compared with results acquired in shop trials or sea trials. Figure 7.3 presents the error results from the baseline for the average forecasted results *t+1* of Monte Carlo analysis for each test case.

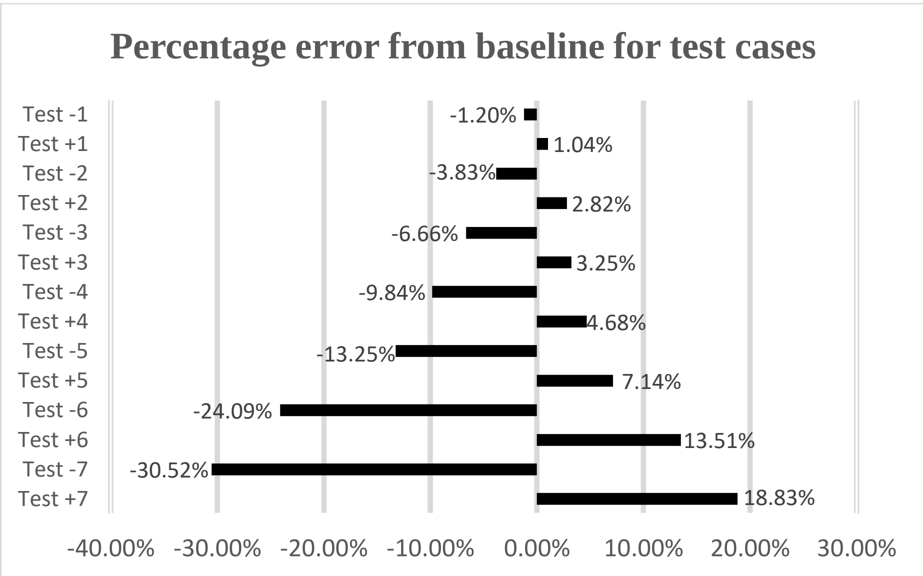



Figure 7.3 Error results from baseline for each test case (Scenario 1)

From Figure 7.2 and Figure 7.3 it can be concluded that for the test cases 1-3 (both decreasing and increasing rpm), where there are small differences in the rpm values from the baseline, the NARX *t+1* output value does not change significantly and thus the output is robust to reasonable changes in parameter values within the model. Moreover, the main engine is fitted with various sensors that could malfunction or provide inaccurate data due to factors such as vibration, high temperature, humidity and dust. Therefore, the sensitivity analysis also demonstrates the practical implication aspect of the results.

Hence the uncertainty about the value is relatively small since the differences in values in these test cases do not cause large differences in the outcome. For the remaining test cases where the main engine rpm range and increment from baseline is significant, the output of the variable and error from baseline changes markedly. However, these test cases are not within the reasonable range required to obtain an accurate output and as previously mentioned, these test cases demonstrate the correct training of the NARX model. The next section presents the results for the second sensitivity scenario.

### *7.3.2 Sensitivity scenario 2*

In this sensitivity scenario, the exhaust gas temperature outlet parameter is shifted progressively in ranges from its original baseline value of 310.3 $^{o}$C at present time t in order to examine the output of the NARX model regarding the one-step-ahead forecast result at time t+1. The investigated exhaust gas parameter ranges are presented in Table 7.2 and follow the same procedure introduced in sensitivity scenario 1. Hence, 14 test cases are conducted in total and are referenced as Test-1 to Test-7 for decreasing the exhaust gas from the baseline, initially by increments of 2% for Test-1 until Test-5 and then by 10% in Test-6 and Test-7 cases until a percentage difference of 30% from the baseline point in order to include extreme values in the analysis. Accordingly, the same procedure is undertaken for increasing the exhaust gas from the baseline for test cases Test+1 to Test+7.

No additional analysis is necessary beyond the 30% mark as the objectives of the sensitivity analysis are achieved within the presented test cases. Moreover, it should be highlighted that test cases were also carried out by smaller increments which provided small variations of the results and for this reason are considered insignificant and are not presented.

Table 7.2 Main engine exhaust gas parameter range from baseline (=310.3 $^{o}$C)

| **Reference** | **% difference from baseline** | **Exhaust gas values $^{o}$C** |
|---|---|---|
| *Test -1* | [0% -2%] | 310.3-304.1 |
| *Test -2* | [-2% -4%] | 304.1-297.9 |
| *Test -3* | [-4% -6%] | 297.9-291.7 |
| *Test -4* | [-6% -8%] | 291.7-285.5 |
| *Test -5* | [-8% -10%] | 285.5-279.3 |
| *Test -6* | [-10% -20%] | 279.3-248.2 |
| *Test -7* | [-20% -30%] | 248.2-217.2 |
| *Test +1* | [0% +2%] | 310.3-316.5 |
| *Test +2* | [+2% +4%] | 316.5-322.7 |
| *Test +3* | [+4% +6%] | 322.7-328.9 |
| *Test +4* | [+6% +8%] | 328.9-335.1 |
| *Test +5* | [+8% +10%] | 335.1-341.3 |
| *Test +6* | [+10% +20%] | 341.3-372.4 |
| *Test +7* | [+20% +30%] | 372.4-403.4 |

As observed, reasonable exhaust gas temperature parameter values close to the baseline are examined in the first test cases and the ranges are then further expanded in test cases Test+6, Test+7, Test-6 and Test-7 respectively. The minimum value examined in Test-7 is equal to 217.2 $^{o}$C while the maximum value modelled is 403.4 $^{o}$C in Test+7. Thus, large deviations from the baseline are also taken into account in the sensitivity analysis.

Figure 7.4 in the following page presents the results for the described 14 test cases regarding the NARX t+1 Monte Carlo results. As in sensitivity scenario 1, the Monte Carlo simulation is performed for 1000 iterations in each test case. The results of the Monte Carlo analysis for each test case is presented and the forecasting result for the one-step-ahead prediction (308$^{o}$C) is presented as the baseline reference for comparing the sensitivity analysis results.

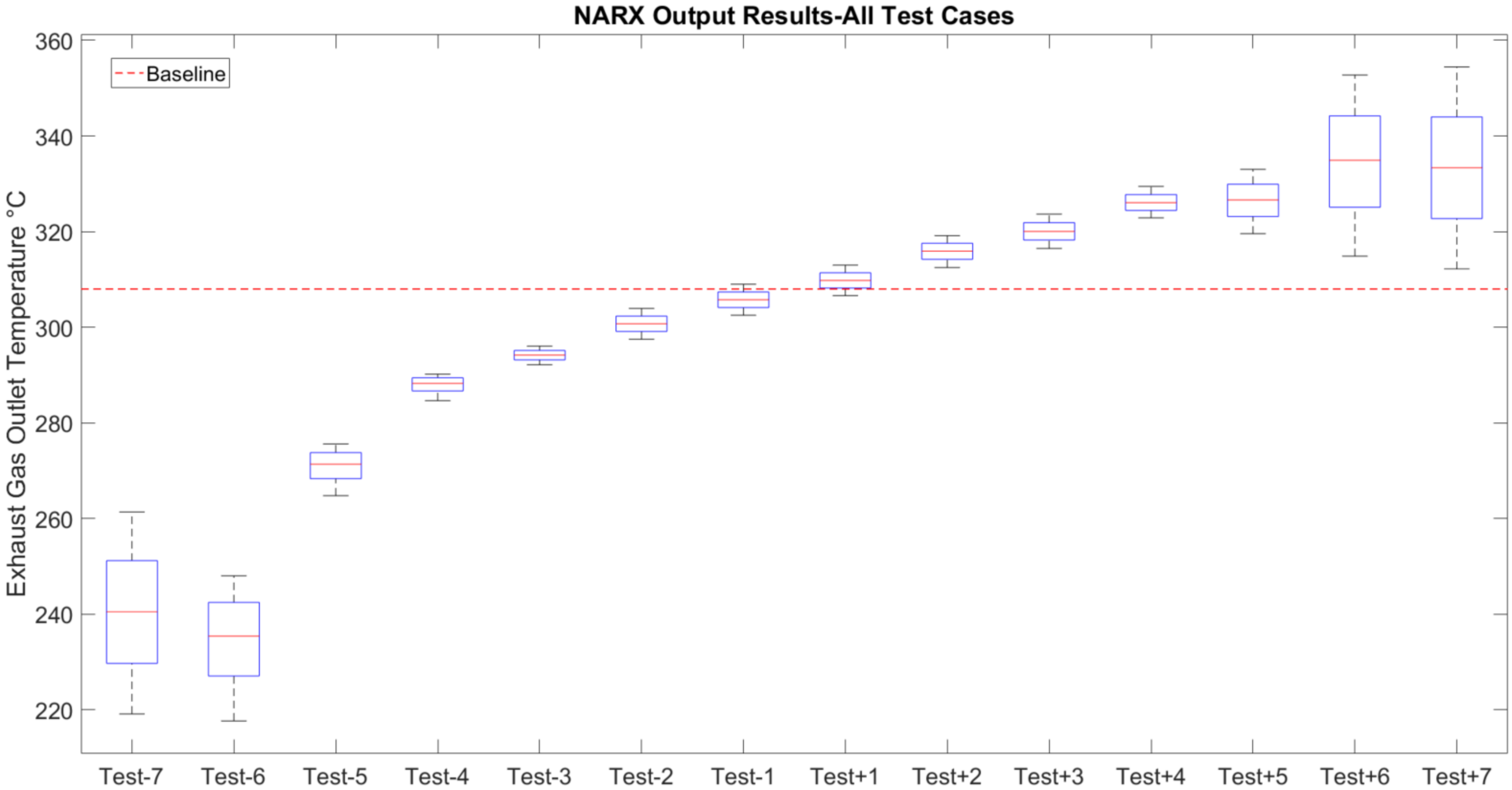



Figure 7.4 NARX sensitivity analysis results for test cases (Scenario 2)

In Figure 7.4 it is observed that the obtained results for Test-1 and Test-2 for the one-step-ahead prediction *t+1* are close to the baseline and decrease in a reasonable manner. Moreover, these test cases demonstrate reliable performance of the NARX model for the reasonable changes in the exhaust gas outlet temperature parameter as the error from the baseline is small. Moreover, the Monte Carlo results demonstrate good network output stability for the 1000 simulations, as the outputs are spread near the median and the variance is minor. Therefore, decreasing the exhaust gas outlet temperature up to 4% from the baseline provides satisfactory outputs.

Furthermore, from Test-3 to Test-7 the exhaust gas outlet temperature output is gradually shifted further away from the baseline and the error increases due to the increase in exhaust gas parameter ranges from the baseline. In Test-3 to Test-5 the model provides sensible reduced results due to the decrease in exhaust gas parameter values and as such the error from the baseline is increased. Specifically, in Test-5 the variance of the outputs starts to increase indicating that an 8% to 10% deviation from the baseline starts to have an effect on the NARX outputs. This is further extended in Test-6 and Test-7 where the error is significantly increased compared to the previous test cases. As observed, in Test-7 the average output of the simulations is larger than Test-6 as is the variance of the results; concluding that the model produces unsteady results in these test cases.

The sensitivity analysis provides satisfactory results regarding Test+1 and Test+2 demonstrating that the NARX responds well to input alterations in the range of +4% for the exhaust gas outlet temperature. Moreover, reasonable results are obtained for Test+3, in which the increase in input parameter results in a reasonable increase in the outputs. Furthermore, for Test+4 and Test+5 it is observed that although the outputs are expectedly increased from the baseline, the median for both test cases remains constant, thus providing equivalent results.

It is reminded that the NARX model predicts the step-ahead-prediction from the past, thus based on the training dataset and the exogenous input correlated values it has seen in the past for the corresponding exhaust gas temperature time series data. Moreover, the larger deviation of the input parameters in Test+6 and Test+7 produce unsteady outputs as in some cases the outputs are closer to the baseline; concluding that the exogenous input strongly influences the output in this sensitivity scenario. Figure 7.5 presents the error results from the baseline for the average forecasted results *t+1* of Monte Carlo analysis for each test case.

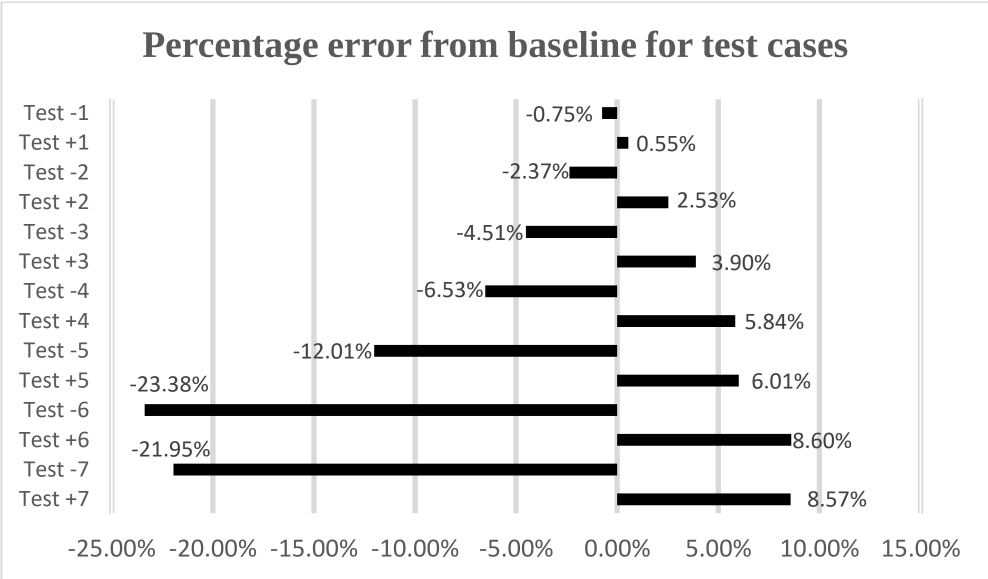



Figure 7.5 Error results from baseline for each test case (Scenario 2)

It can be observed that the errors are relatively small for Test-1, Test-2, Test-3, Test+1, Test+2 and Test+3 where reasonable changes in the input parameters are executed. Hence the model is considered robust and the differences in values in these test cases do not cause large changes in the outcome. On the other hand, for the remaining test cases the output of the variable and error from baseline increases. The differences in error magnitudes in Test cases -5 to -7 and +5 to +7 are caused by the extent of data the network has seen during its training phase. Specifically, the training dataset did not contain data covering the parameter ranges presented in Test+4 and forward.

This sensitivity analysis demonstrated satisfactory outputs of the NARX model for the various values of the exhaust gas time series input data for conducting the one-step-ahead output while keeping the exogenous input constant. Moreover, by comparing the results with those of scenario 1, it can be observed that the exogenous input strongly influences the output in this sensitivity scenario. The next section presents the results for the third sensitivity scenario.

### *7.3.3 Sensitivity scenario 3*

In this sensitivity scenario, both the main engine rpm and the exhaust gas temperature input values are altered progressively from their original value at present time *t* in order to examine the output of the NARX model regarding the one-step-ahead forecast result at time *t+1*. Table 7.3 presents the different tests conducted for the various input values.

Table 7.3 Input parameter ranges from their baseline (rpm=61.9, exhaust gas=310.3 $^{o}$C)

| **Reference** | **% difference from baseline** | **Engine rpm values** | **Exhaust gas values oC** |
|---|---|---|---|
| *Test -1* | [0% -2%] | 61.9-60.6 | 310.3-304.1 |
| *Test -2* | [-2% -4%] | 60.6-59.4 | 304.1-297.9 |
| *Test -3* | [-4% -6%] | 59.4-58.2 | 297.9-291.7 |
| *Test -4* | [-6% -8%] | 58.2-56.9 | 291.7-285.5 |
| *Test -5* | [-8% -10%] | 56.9-55.7 | 285.5-279.3 |
| *Test -6* | [-10% -20%] | 55.7-49.5 | 279.3-248.2 |
| *Test -7* | [-20% -30%] | 49.5-43.3 | 248.2-217.2 |
| *Test +1* | [0% +2%] | 61.9-63.1 | 310.3-316.5 |
| *Test +2* | [+2% +4%] | 63.1-64.4 | 316.5-322.7 |
| *Test +3* | [+4% +6%] | 64.4-65.6 | 322.7-328.9 |
| *Test +4* | [+6% +8%] | 65.6-66.8 | 328.9-335.1 |
| *Test +5* | [+8% +10%] | 66.8-68.0 | 335.1-341.3 |
| *Test +6* | [+10% +20%] | 68-74.3 | 341.3-372.4 |
| *Test +7* | [+20% +30%] | 74.3-80.5 | 372.4-403.4 |

Figure 7.6 in the following page presents the results for the described 14 test cases regarding the NARX t+1 Monte Carlo results. The results of the Monte Carlo analysis for each test case is presented and the forecasting result for the exhaust gas temperature one-step-ahead prediction (308$^{o}$C) is presented as the baseline reference for comparing the sensitivity analysis outputs.

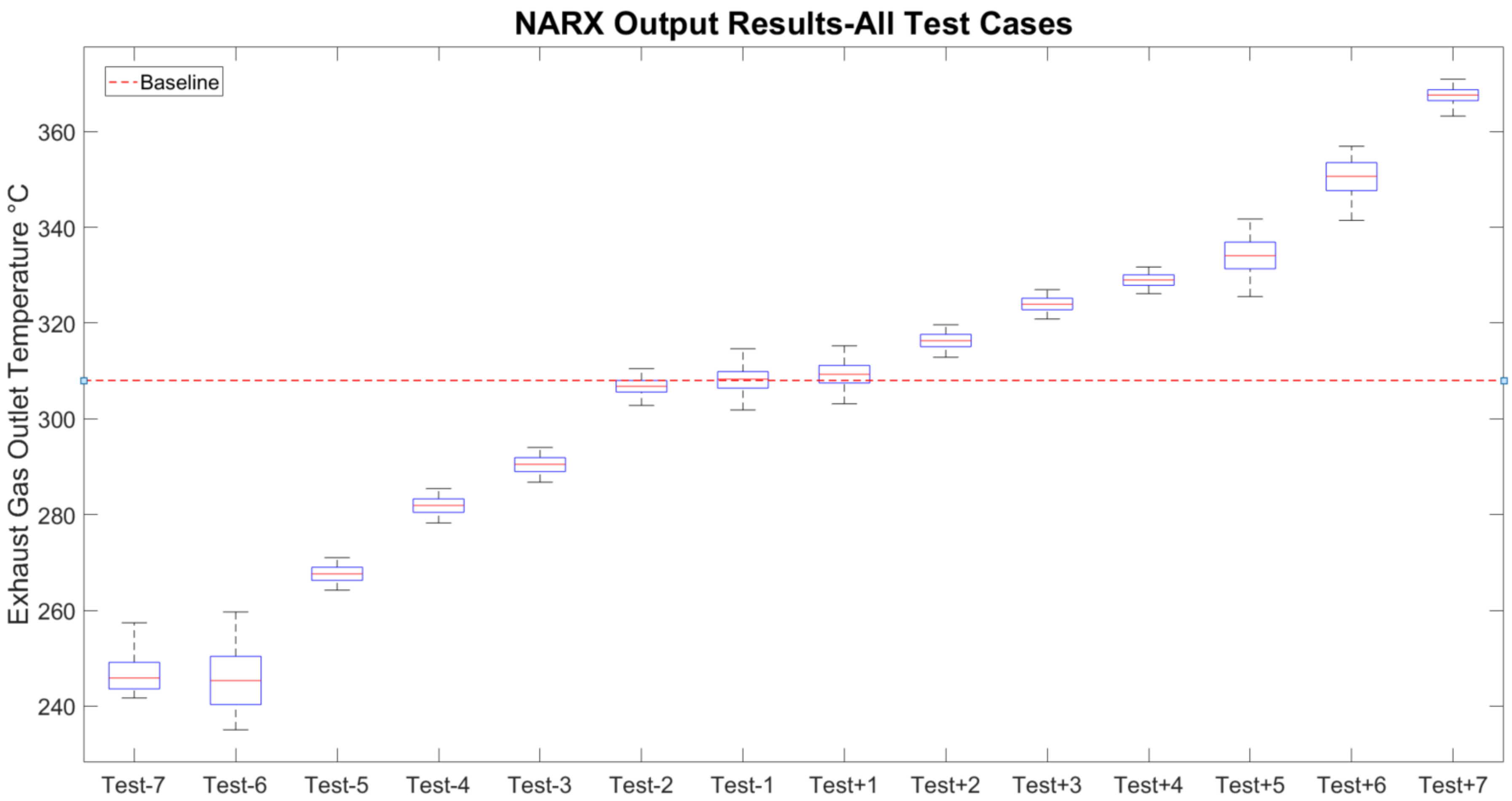



Figure 7.6 NARX sensitivity analysis results for test cases (Scenario 3)

As observed in Figure 7.6, the results obtained in this sensitivity analysis are in line with the previous two sensitivity scenarios presented. For Test-2 to Test+2 the results indicate satisfactory network output for rational reductions and increments of the input parameters around the baseline value. Moreover, in the remaining test cases the error is increased from the baseline as both the exogenous NARX input and exhaust gas input time series data are reduced and increased respectively to protracted ranges. Concurrently, the response of the NARX model to these input parameters also demonstrates its generalisation capabilities and that overfitting manifestations have been avoided. Figure 7.7 presents the error results obtained from the baseline for the average forecasted results *t+1* of Monte Carlo analysis for each test case.

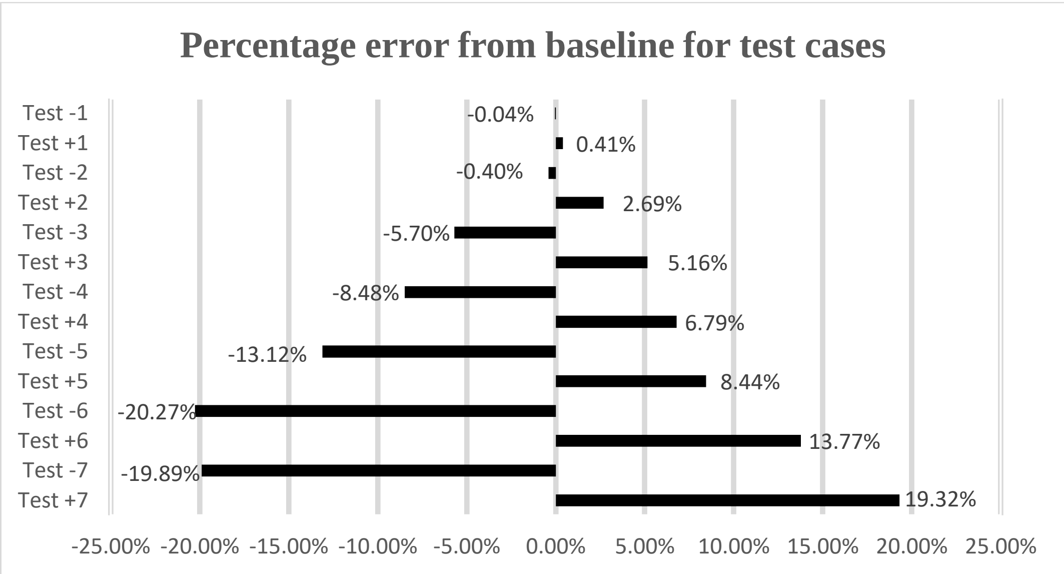



Figure 7.7 Error results from baseline for each test case (Scenario 3)

It can be observed that the errors are insignificant for the test cases Test-1, Test+1, Test-2 and Test+2 where reasonable changes in the input parameters were executed. Hence the model is considered robust and the differences in values in these test cases do not cause any significant effects in the outcome. On the other hand, for the remaining test cases the output of the variable and error from baseline increases as the input parameters take on acute values.

### *7.3.4 Remarks*

The sensitivity analysis was carried out for three scenarios. These scenarios examined the sensitivity of the NARX model output to changes in the input parameters. Initially, scenario 1 examined the analysis by changing only the main engine rpm, which represents the exogenous input data of the model. Secondly, the second scenario followed the same procedure as the first and results were examined for changing the exhaust gas temperature values while the exogenous input data remained constant. Finally, scenario 3 studied the change in model output for shifts in both input data.

Overall, the sensitivity analysis demonstrated reliable performance of the NARX model output and that it is tolerable to reasonable changes in the input parameters in all three scenarios. Therefore, the output is robust to reasonable changes in parameter values within the model. For the extreme test case scenarios, the error from the baseline is increased as expected for the exhaust gas outlet temperature. Moreover, these test cases also illustrated the satisfactory response of the NARX neural network model to variations in the input values of the main engine rpm and exhaust gas outlet temperature, implicating that network generalisation has also been achieved.

## 7.4 Chapter summary

This chapter presented a detailed sensitivity analysis for the developed NARX model of the condition monitoring strategy for different sensitivity scenarios and configurations. A description of the overall sensitivity analysis was provided followed by the presentation of the results and concluding remarks. The next chapter presents the cost benefit analysis performed for the condition monitoring strategy.

# 8 Cost-Benefit Analysis

## 8.1 Chapter outline

This chapter describes and presents the Cost-Benefit Analysis (CBA) conducted to assess the value of the developed hybrid condition monitoring framework compared to a traditional preventive maintenance scheme for a variety of scenarios and charter rates. The analysis is executed for the ship main engine and is described in Section 8.2 and the obtained results and concluding remarks are presented in Section 8.3. The final section provides a recap of the work performed in this chapter.

## 8.2 Cost-Benefit Analysis (CBA) description

### *8.2.1 Description*

Cost-Benefit Analysis (CBA) is a decision-making procedure for comparing costs and benefits of activities such as projects and policies (Stenström et al., 2016). The objective of CBA is to support decision-making and make it more rational providing more efficient allocation of resources (Boardman et al., 2013). Common decision rules for assessing case studies of CBA include calculation of net benefits, benefit-cost (B/C) ratios and Return on Investment (ROI).

The CBA is performed for the developed condition monitoring framework. The main aim of the analysis is to examine and demonstrate the benefits associated with applying the developed condition monitoring tools compared to an existing preventive maintenance scheme for the case study of a main engine. The parameters examined are related to costs included in a traditional PMS scheme against the costs and both direct and indirect savings associated with employing the developed condition monitoring methodology. The following assumptions have been considered in order to carry out the cost-benefit analysis:

- The CBA is carried out over a vessel life cycle span equivalent to 25 years.
- Overhauling of the main engine occurs approximately every 3750 operating hours by the vessel crew and 7500 hours by technicians, carrying out preventive maintenance tasks. The selected hours are based upon examination of several ship machinery PMS and discussion with industry and academia experts.
- Vessel drydocking occurs every 15000 hours corresponding to 2.5 years which is the typical interval according to Classification Societies. In such instances the spare part and labour costs are adjusted accordingly compared to the costs used in the 3750 and 7500-hour maintenance intervals.
- The ship main engine operates approximately 6000 hours yearly which is equivalent to 250 days (Christensen, 2010, Corbett and Koehler, 2003).
- There is a loss of income due to preventive maintenance activities and downtime every 7500 hours intervals.
- Escalation rates of 8% for labour cost, 4% for loss of income, 3% for drydocking costs and 2% for oil renewal, spare parts and condition monitoring operating costs are applied in the analysis.
- The Net Present Value (NPV) is calculated based on a 5% discount rate (INCASS, 2017).

As a CBM policy would reduce the number of required shutdowns for conducting maintenance activities, four scenarios have been developed to analyse and calculate the financial benefits of the developed monitoring framework, starting from the least optimal to most optimal scenarios. By applying the condition monitoring tools onboard, mean time between intervals for the main engine inspection and maintenance tasks could be extended up to:

1. Scenario 1: PMS+25%
2. Scenario 2: PMS+50%
3. Scenario 3: PMS+75%
4. Scenario 4: PMS+100%

Calculations for the CBA are executed by applying the Net Present Value (NPV) formula for expressing all benefits and costs in discounted present values as defined in equation 34 below:

$$NPV = \sum_{i=0}^{N} \frac{C_i}{(1+r)^i} \tag{34}$$

where $i$ is the time of the cash flow, $C_i$ is the net cash flow at time $i$, $r$ is the applied discount rate and N is the total years

Moreover, the formula for calculating the escalated cost with the relevant escalation rate is defined as:

$$C_e = C_t\,(1+e)^n \tag{35}$$

where $C_t$ is the present cost and $e$ is the escalation rate

### *8.2.2 Determination and calculation of preventive maintenance costs*

Every aforementioned scenario is considered separately in the analysis and then a comparison between them is made. In terms of the preventive maintenance costs, these include spare parts costs per cylinder (e.g. oil rings, piston rings, bolts, sealing rings etc.), labour costs (superintendent, technicians etc.) and oil renewal costs upon discussion with experts from shipping companies and Class surveyors. The vessel drydock costs have also been included in the preventive maintenance costs which include amongst others, drydock cost per day and dock services charge. Moreover, the cost values for the preventive maintenance activities are based on cost evaluation from reports, marine supplier quotations for engine repair kits, ship operators and manufacturers. The values used for the calculations are contained in Appendix H.1. The overall equation for calculating the total preventive maintenance cost is presented below:

$$Cost_{PM} = Cost_{Sp} + Cost_{La} + Cost_{oil} + Cost_{drydock} + Cost_{downtime} \quad (36)$$

where $Cost_{Sp}$ is the total cost of the spare parts for the main engine, $Cost_{La}$ is the total labour costs for undertaking the various inspection and overhauling activities, $Cost_{oil}$ is the cost associated with the main engine oil renewal, $Cost_{drydock}$ is the costs associated with vessel drydocking activities and $Cost_{downtime}$ is the monetary cost associated with loss of income due to downtime owing to preventive maintenance shutdown.

The equation from which the total cost of the spare parts $Cost_{Sp}$ is calculated is provided below:

$$Cost_{Sp} = \sum_{i=0}^{m} (n_{cyl} C_{Sp_{cyl}} + C_{Sp_{misc}} + n_{cyl} C_{Sp_{cyl^*}} + C_{Sp_{misc^*}}) \quad (37)$$

Where *i* is the number of intervals for inspection, m is the total number of inspections, $n_{cyl}$ is the number of main engine cylinders, $C_{Sp_{cyl}}$ is the spare parts cost for each cylinder, $C_{Sp_{misc}}$ is the spare parts cost relevant to miscellaneous engine parts (filters, bearings etc.), $C_{Sp_{cyl^*}}$ is the spare part cost associated with the overhauling of the main engine from the vessel crew and $C_{Sp_{misc^*}}$ is the spare parts cost for miscellaneous engine parts regarding engine overhauling from the crew.

The total labour cost $Cost_{La}$ is equal to the number of persons, days, hours and cost rate required for conducting the main engine inspection and repairs every 7500 hours from technicians as stated in the assumptions and is equal to:

$$Cost_{La} = \sum_{i=0}^{m} n_d n_h n_p L_h \quad (38)$$

where $n_d$ is the number of days, $n_h$ is the number of hours, $n_p$ is the number of technicians and $L_h$ is the hourly charge rate for each technician

In terms of drydocking, the cost of labour also includes the number and hourly rates of superintendent engineers, senior service engineers and technicians as defined below:

$$Cost_{La_{drydock}} = \sum_{i=0}^{m} n_d n_h (n_{SS} L_{SS} + n_{SE} L_{SE} + n_T L_T) \tag{39}$$

where $n_d$ is the number of days, $n_h$ is the number of hours, $n_{SS}$ is the number of superintendent engineers, $L_{SS}$ is the superintendent's hourly rate in USD, $n_{SE}$ is the number of senior service engineers, $L_{SE}$ is the senior service engineer's hourly rate, $n_T$ is the number of technicians and $L_T$ is the technician's hourly rate.

The oil renewal cost $Cost_{oil}$ is calculated by the amount of oil renewal obtained from the engine guide and the cost per litre of oil.

$$Cost_{oil} = \sum_{i=0}^{m} l C_l \tag{40}$$

where $l$ is the amount of oil renewal in litres and $C_l$ is the cost per litre of oil.

Finally, the drydocking costs $Cost_{drydock}$ are calculated by obtaining the days the vessel is in drydock, the drydock charge per day, provided drydock services and associated spare parts and labour costs.

$$Cost_{drydocking} = \sum_{i=0}^{m} n_d c_d c_s + Cost_{Sp_{drydock}} + Cost_{La_{drydock}} + Cost_{oil} \tag{41}$$

Where $n_d$ is the number of days the vessel is in drydock, $c_d$ is the drydocking cost per day and $c_s$ is the cost of drydocking services. An average price for drydocking services $c_s$ is used which is based on quotations for general drydocking services such as mooring/unmooring, fire watchman, fire line, shore power, earth connection, cooling water, compressed air garbage, gangway, ballast water, cranes, tailshaft withdrawal etc. Also, $Cost_{Sp_{drydock}}$ follows the same calculation process as equation 37.

### 8.2.3 *Determination of condition monitoring costs and benefits*

The costs considered for condition monitoring are related to capital costs, analysis costs and software maintenance costs amongst other, as presented in Table 8.1. Capital costs include a certain amount of tailoring of the monitoring strategy to fit the business objectives. This includes the purchase and installation cost of the condition monitoring application and the cost of implementing a data acquisition system for collecting data on a regular basis and required sensors that might not be installed onboard. The installation can be done by an existing offshore team or by external personnel. Moreover, a monetary cost associated with a Classification certificate for the condition monitoring tools is considered. Analysis costs are related to associated cost for trained/certified personnel to provide reports regarding the data analysis and hence the machinery condition on regular intervals. The software will have to be updated from time to time to consider new input data or vessel operating profiles and as such an annual software maintenance cost is assigned and considered in the analysis.

Table 8.1 Capital and operating costs for applying the condition monitoring strategy

| Cost description | Cost ($) |
|---|---|
| *Capital costs* | |
| Installation cost | 10,000 |
| Data acquisition system | 10,000 |
| Sensors | 4,800 |
| Class certificate | 10,000 |
| Total cost | 34,800 |
| *Operating costs* | |
| Data analysis and reporting | 4,000 |
| Software maintenance | 1,000 |
| Calibration for sensors | 800 |
| Miscellaneous cost | 1,000 |
| Total cost | 6,800 |

The above provides a summary table of the cost for implementing the condition monitoring approach. The sensor costs are calculated considering an average of 8 sensors are required priced at an individual monetary cost equal to $600. Moreover, the data analysis and reporting value is calculated considering that two trained personnel are required for two days at an hourly rate of $125. Additionally, miscellaneous cost considers costs such as transportation, accommodation etc. of the personnel involved. The values are selected after discussion with INCASS project partners, operating in the field of installing and utilising sensors for monitoring in engineering applications and ship operations.

Benefits from the application of the condition monitoring strategy include higher charter rates. A vessel equipped with condition monitoring tools has a much better probability of reliability of main engine that a vessel that does not. As such, there will be a reduction of risk of the vessel failing whilst on voyage and hence can reduce the possibility of intervention by a coastal state for example on the progress of a voyage. Therefore, the cost-benefit procedure considers various charter rates and increased premium rates for the analysis.

If the vessel has an approved condition monitoring strategy onboard, then indirect savings such as discount rates on Classification Society annual surveys are considered in the CBA. For analysis purposes, the cost of a Classification Society annual survey is considered to be equal to $114,000 and a 20% discount rate is applied. These values are selected upon discussion and advise from Classification Societies surveyors and vessel technical fleet managers.

In addition, the enhanced monitoring of machinery that can be achieved through the employment of the condition monitoring framework results in a mitigation of risk that the plant will fail and as such can attract a reduction in premium for insurance. The CBA focuses on hull and machinery insurance premium and as the premium depends on many factors, an average value of $100,000 is used in the analysis of the cost-benefit based on information provided by a shipping company.

Figure 8.1 provides an overview of the various elements utilised for the completion of the cost-benefit analysis regarding the condition monitoring strategy.

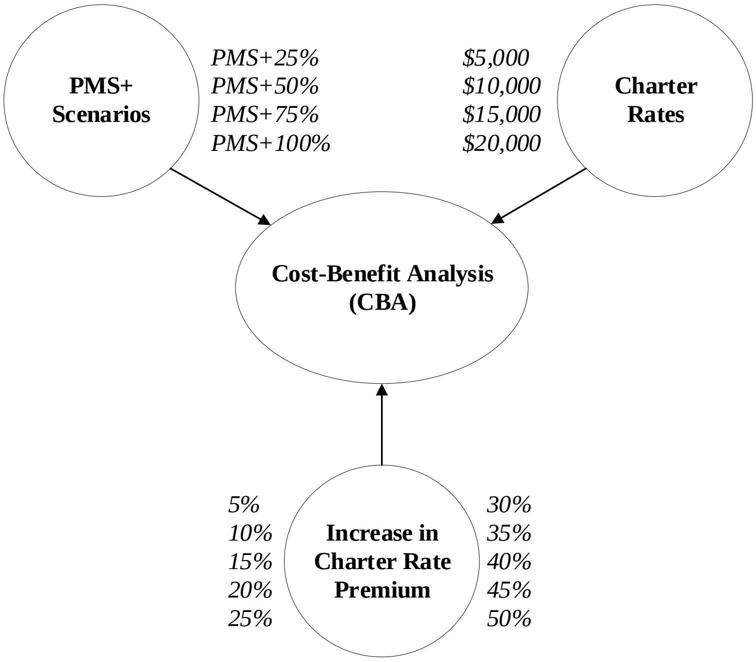



Figure 8.1 CBA overview

For each of the four extended PMS scenarios, various charter rates are considered in the analysis. The charter rates are selected based on the latest recorded charter rates regarding the container ship charter market according to BRS group (2018). In addition, for each PMS scenario and charter rate, the financial benefits related to potential increases of charter rate premiums are modelled from a minimum of 5% to a maximum of 50%, in 5% increments.

The results regarding the CBA for the aforementioned four scenarios in which mean time between intervals for the engine inspection and maintenance are extended up to 25%, 50%, 75% and 100% respectively are presented in the following section.

## 8.3 CBA results

This section presents the CBA results obtained for the aforementioned four scenarios in which mean time between intervals for the engine inspection and maintenance are extended up to 25%, 50%, 75% and 100% respectively. Appendices H.2-H.5 contain the CBA results for all four scenarios.

### *8.3.1 Scenario 1 PMS+25%*

This section presents the results for the various charter rates and return of charter rate premium for the PMS+25% scenario. Figure 8.2 displays the cost analysis for a charter rate of $5,000 with a 5% increase in premium, based on a worst-case scenario of poor business environment.

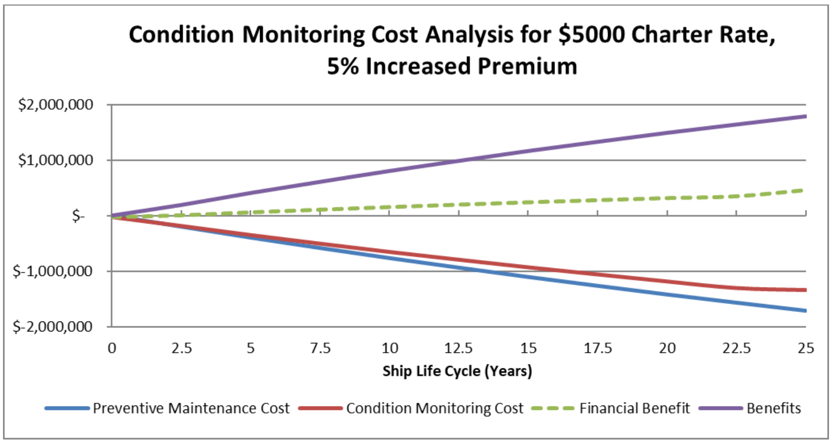



Figure 8.2 Cost analysis PMS+25% for $5000 charter rate-5% premium increase

As it can be seen from the graph, the negative costs correspond to the calculated maintenance costs. Specifically, the blue line is the cost associated with the existing ship preventive maintenance scheme for the main engine for the life cycle analysis of 25 years. It can be seen from the graph that the condition monitoring cost (red line) is less than the total cost of the preventive maintenance plan for the PMS+25% scenario. Moreover, the purple line displays the total calculated benefits obtained for the condition monitoring application, while the financial benefits (green dashed line) of the application of the condition monitoring framework are increased through the lifecycle of the ship and is equal to the difference between the condition monitoring costs and associated cost-benefits. Furthermore, Figure 8.3 presents the results obtained regarding the sensitivity analysis carried out for the financial benefits related to the potential increase of charter rate premium from 5% to 50% in 5% increments.

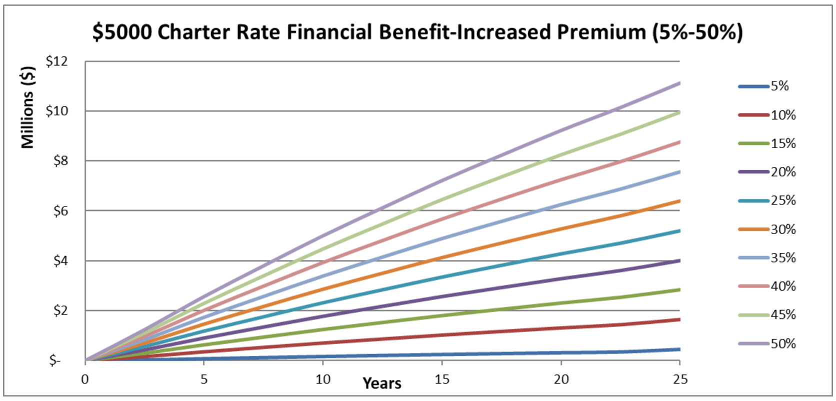



Figure 8.3 Financial benefits for 5%-50% premium increase-$5000 charter rate

By examining Figure 8.3, it can be noticed that for the selected $5,000 charter rate, the financial benefits by utilising the condition monitoring approach increase throughout the lifecycle of the vessel and for increased premium rates. Specifically, the minimum financial benefit is equal to approximately half a million USD for a 5% increase in charter premium while for 10% increase it is equal to approximately 2 million USD for the 25 year period. The maximum financial benefit is equal to 11 million USD for 50% at the end of the vessel's lifespan. Appendix H.2 contains the results for the remaining charter rates. The following section presents the CBA for the PMS+50% scenario.

### *8.3.2 Scenario 2 PMS+50%*

This section presents the cost-benefit results for the PMS+50% scenario for the different charter rates and premium returned. Figure 8.4 presents the obtained financial benefits for considering various increased premiums in the $5,000 charter rate region. As observed from the figure, the financial benefits reach a total amount of $560,000 for a small charter rate of just $5,000 with the minimum 5% increase in charter rate premium due to implementing the condition monitoring framework.

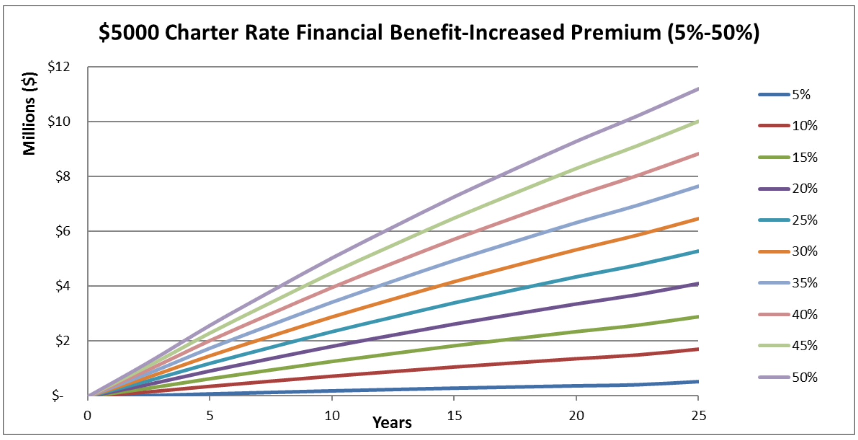



Figure 8.4 Financial benefits for 5%-50% premium increase-$5000 charter rate

The financial benefits significantly increase when considering increased vessel charter rate premiums for the specified charter rate ranging from a minimum financial benefit of $560,000 for the 5% increased premium to a maximum 11.2 million USD for 50% increased premium. Hence, the financial benefits can be clearly interpreted. Appendix H.3 contains the results for the remaining charter rates. The following section presents the CBA for the PMS+75% scenario.

### *8.3.3 Scenario 3 PMS+75%*

This section presents the cost-benefit results for the PMS+75% scenario for the different charter rates and premium returned. Figure 8.5 displays the obtained financial benefits for considering various increased premiums in the $5,000 charter rate region for the PMS+75% scenario.

The financial benefits significantly increase when considering increased vessel charter rate premiums and vary from a minimum financial benefit of $570,000 for the 5% increased premium to a maximum 11.4 million USD for 50% increased premium.

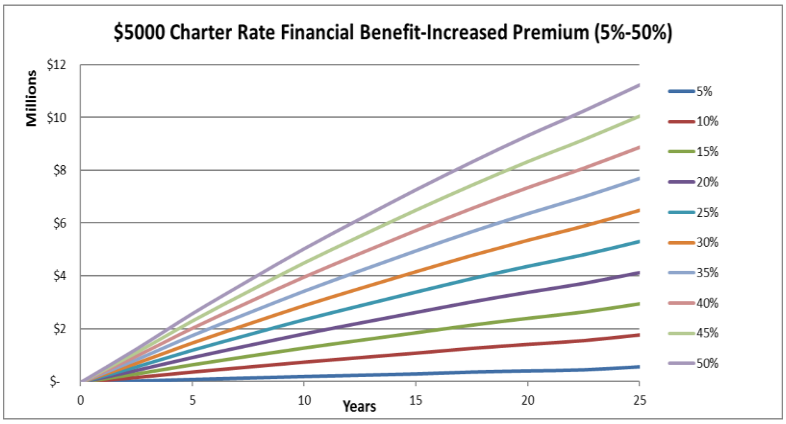



Figure 8.5 Financial benefits for 5%-50% premium increase-$5000 charter rate

Appendix H.4 contains the results for the remaining charter rates. The following section presents the CBA for the PMS+100% scenario.

### *8.3.4 Scenario 4 PMS+100%*

This section presents the cost-benefit results for the PMS+100% scenario for the different charter rates and premium returned. Figure 8.6 displays the obtained financial benefits for considering various increased premiums in the $5,000 charter rate region.

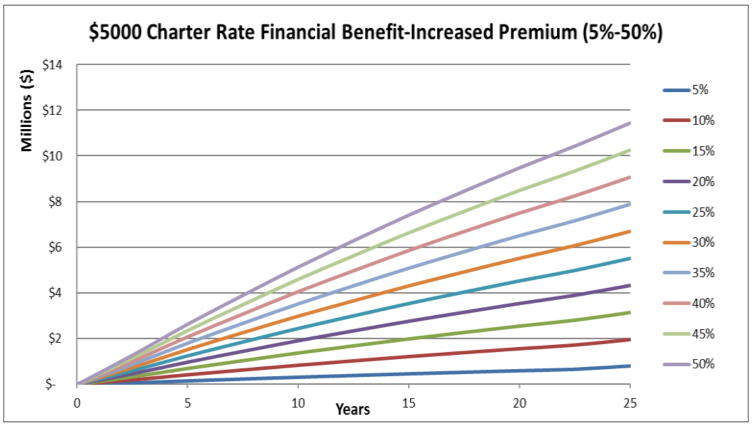



Figure 8.6 Financial benefits for 5%-50% premium increase-$5000 charter rate

The financial benefits significantly increase when considering increased vessel charter rate premiums for the specified charter rate ranging from a minimum financial benefit of $771,000 for the 5% increased premium to a maximum 11.6 million USD for 50% increased premium. In addition, for the most optimistic scenario analysed

(PMS+100%, $20,000 charter rate, 50% increased premium), the financial benefits are equal to 47 million USD, as presented in Appendix H.5.

### *8.3.5 Remarks*

The CBA investigated the benefits obtained from capitalising the condition monitoring framework over a traditional vessel PMS scheme by considering both direct and indirect savings. Moreover, the CBA was executed considering various market fluctuations and augmented levels of charter premium, with all case studies demonstrating a solid realisation of the potential financial benefits obtained from implementing the condition monitoring framework. Figure 8.7 presents the B/C ratio for all four scenarios for the $5,000 charter rate, 5%-20% increased premium studies.


Figure 8.7 B/C ratio for $5000 charter rate, 5%-20% premium increase

As observed from Figure 8.7, there is a zero B/C ratio in year 0, due to the capital costs and start of the ship's lifecycle and the benefits exceed the condition monitoring costs before 2.5 years for all scenarios and premiums. It is also observed that by comparing the B/C ratios for the four scenarios, the B/C increases as the mean time between inspections are increased for the main engine from the PMS+25% to the PMS+100% scenario. In particular, it can be noticed that the B/C ratio is reasonably the highest between the four scenarios for the PMS+100% scenario. Furthermore, at the end of the vessel lifecycle for the PMS+25% scenario, the B/C ratio is equal to 1.34 for the 5% increased premium while for the 10% it is 2.23, 3.12 for the 15% and 4.0 for the 20% premium increase; highlighting the impact the increased charter rate premium can have on the investment and benefits of the condition monitoring framework.

Therefore, by considering the lowest case study conducted (PMS+25%, $5000 charter rate, 5% increased premium), the ROI is equal to 2.2 years, while for 10% increase in premium the ROI is dropped down to roughly 6 months and for 15% and 20% increase in charter rate premium, the ROI occurs below 3 months. As the lowest case study has been described and presented, the ROI and overall benefits can be perspicuously realised for all other PMS+ scenarios, higher charter rates and higher premiums where the financial benefits are further increased. Moreover, Table 8.2 presents the summary of the CBA results, obtained for all PMS scenarios and various charter rates related to the 5% increase in charter rate premium study.

Table 8.2 Summary of CBA results ($) for 5% charter rate premium increase

| **PMS Scenario** | **Charter Rate ($)** | **Ship Lifecycle (Years)** | | | | |
|---|---|---|---|---|---|---|
| | | **5** | **10** | **15** | **20** | **25** |
| **PMS+25%** | *5,000* | 60,320 | 154,965 | 239,849 | 314,550 | 457,058 |
| | *10,000* | 337,220 | 692,782 | 1,014,662 | 1,304,633 | 1,642,675 |
| | *15,000* | 614,120 | 1,230,599 | 1,789,476 | 2,294,715 | 2,828,291 |
| | *20,000* | 891,020 | 1,768,416 | 2,564,289 | 3,284,798 | 4,013,907 |
| **PMS+50%** | *5,000* | 78,673 | 189,434 | 288,052 | 374,634 | 527,685 |
| | *10,000* | 355,572 | 727,251 | 1,062,865 | 1,364,717 | 1,713,301 |
| | *15,000* | 632,472 | 1,265,068 | 1,837,679 | 2,354,800 | 2,898,917 |
| | *20,000* | 909,372 | 1,802,885 | 2,612,493 | 3,344,882 | 4,084,534 |
| **PMS+75%** | *5,000* | 86,177 | 197,186 | 296,248 | 410,364 | 566,686 |
| | *10,000* | 363,077 | 735,002 | 1,071,062 | 1,400,446 | 1,752,302 |
| | *15,000* | 639,976 | 1,272,819 | 1,845,875 | 2,390,529 | 2,937,918 |
| | *20,000* | 916,876 | 1,810,636 | 2,620,689 | 3,380,612 | 4,123,534 |
| **PMS+100%** | *5,000* | 128,368 | 287,730 | 433,632 | 567,151 | 770,969 |
| | *10,000* | 405,268 | 825,547 | 1,208,445 | 1,557,234 | 1,956,585 |
| | *15,000* | 682,168 | 1,363,364 | 1,983,259 | 2,547,316 | 3,142,202 |
| | *20,000* | 959,068 | 1,901,181 | 2,758,072 | 3,537,399 | 4,327,818 |

The CBA focused on direct and indirect savings subject to reasonable comparison between the costs of preventive maintenance and the costs and benefits of the condition monitoring strategy. However, there are other intangible benefits that can be considered by utilising the condition monitoring strategy such as value of avoiding loss of reputation, value of avoiding environmental damage and value of avoiding death or injury. A vessel capitalising on the described condition monitoring framework can also consider the possibility of an increased life span by proven records of good maintenance practices and machinery condition. Overall, the CBA demonstrated the financial benefits that can be obtained considering one ship. Hence, the financial benefits can be immensely prolonged when considering a vessel fleet.

## 8.4 Chapter summary

This chapter presented the cost-benefit analysis conducted for implementing the developed condition monitoring framework compared to an existing preventive maintenance scheme regarding a ship main engine. The CBA investigates both direct and indirect savings and considers various charter rates and increase in charter rate premium due to utilising condition monitoring. The results were presented for 4 scenarios in which mean time between intervals for maintenance and inspection activities for the main engine were extended up to 25%, 50%, 75% and 100% respectively. Moreover, the longest ROI was equal to 2.2 years for the least beneficial case study, while the shortest were below 3 months for other case studies. The following chapter presents the overall discussion topics of the thesis.

# 9 Discussion and Conclusions

## 9.1 Chapter outline

This chapter presents the discussion and concluding remarks related to the developed hybrid condition monitoring framework. The accomplishment of the research aim and objectives are analysed, followed by the novelty of the presented research. Moreover, concluding statements regarding the performed research study are presented followed by recommendations for future research.

## 9.2 Accomplishment of research aim and objectives

The purpose of this research is to contribute theoretically and empirically to ship machinery condition monitoring in the maritime maintenance field. This was achieved by tackling the defined main aim regarding the development of a predictive condition monitoring framework for application on ship machinery systems through the proposed innovative hybrid condition monitoring framework. In this regard, the main aim was realised through the thesis objectives defined in Chapter 2 and are individually addressed and discussed in this section.

*Objective 1:* *Identify the gaps in the literature and issues in maritime maintenance and condition monitoring by conducting a detailed literature and critical review pertinent to the research topic.*

This objective has been achieved by identifying and examining generic maintenance types and concepts, maritime maintenance and condition monitoring features and ANN applications in Chapter 3. Salient features, advantages and drawbacks have been investigated setting the foundation for further research and development towards the establishment of a novel and adaptive maintenance strategy for the maritime industry. Maintenance practices within the maritime sector and recent state-of-the-art commercial software and academic projects highlighted the rigidity of the maritime industry on preventive maintenance tasks and demonstrated the emergent of advanced maintenance frameworks based on CBM functionalities. In this respect, the application of ANNs in the context of CBM was investigated revealing the literature paucity regarding their application in the maritime sector despite their recognised advantages and applications in other fields.

*Objective 2:* *Focus the identified research gaps to propose an innovative condition monitoring framework methodology for the maritime industry and demonstrate the various elements that is consists of in full depth.*

This has been achieved by the establishment and analytical description of the proposed hybrid condition monitoring framework in Chapter 4. The developed framework consists of reliability tools such as FTA, FMEA and RBD, a data cleansing algorithm and clustering, ANN time series analysis and forecasting, ANN diagnostics, health assessment and maintenance advisory generation stages. The developed framework can be utilised to identify critical items, improve the data selection and collection process and monitor the present and future condition of the system, leading to fundamental recommended maintenance actions and activities. All these stages are combined to create the comprehensive hybrid condition monitoring strategy which have never been examined under a single framework in the maritime maintenance sector before. The flexibility and adaptability of the methods and tools in the framework enable further research and application in the maritime and other industries.

*Objective 3:* *Collect data for analysis through ship onboard measurement campaigns to demonstrate the proposed methodology.*

This objective was achieved by acquiring three datasets for analysis upon discussion with one of the INCASS project partner's vessel fleet manager and personnel. The first dataset was collected through an onboard measurement campaign in the Mediterranean Sea while the second dataset was provided by a shipping company. These two datasets were utilised for training the ANN models. Finally, a third dataset was obtained from another onboard measurement campaign in the Mediterranean Sea on the same vessel and was applied for simulating and verifying the ANN models. In terms of reliability data (FR, MTBF) for the Fault Tree analysis, this was not feasible and thus the minimal cut-set method was employed to identify critical systems and components. Moreover, the inspection intervals of a vessel's PMS were attempted to quantitatively analyse the Fault Tree. Unrealistic results were obtained due to mostly assuming the intervals as MTBF, and thus were excluded from the study.

*Objective 4: Demonstrate the applicability of the developed methodology for the main engine system of a container ship.*

This objective was achieved by employing the proposed methodology for the case study of a Panamax container ship main engine described in Chapter 5 and presenting the results in Chapter 6. The FTA and FMEA was conducted for various main engine subsystems such as the cylinder, piston, air, cooling, fuel, lubrication and engine block systems. The minimal cut sets of the FT main engine were calculated identifying the cylinder, piston, engine block and fuel system as the most critical main engine components and subsystems. The combination with the FMEA provided insight for the selection of important monitoring parameters. Hence, in combination with the acquired datasets, 40 main engine performance parameters were utilised such as main engine rpm, temperatures and pressures for the multiple main engine systems.

Input data were pre-processed through data cleansing, while the SOM clustering tool was developed using real and simulated data for identifying parameters exceeding OEM thresholds or representing abnormal engine operation. The work performed regarding the SOM networks is considered original and novel since its application for monitoring the condition of machinery systems has not been investigated before. Moreover, the SOM case studies demonstrated its flexibility in addressing the issue of finding the correct number of clusters which does not have a finite solution.

The processed data from both input datasets are used in the dynamic NAR and NARX neural network models for multi-step-ahead forecasting. The larger size of dataset 2 provided more accurate network training for both models. Moreover, all models presented accurate forecasting capabilities with NAR MAPE values ranging from

0.05% to 1% for dataset 1 and 0.12% to 5.88% for dataset 2 respectively. Furthermore, the introduction of the exogenous input in the NARX models reduced APE values by up to 35% compared to the NAR results especially when significant shifts in the main engine rpm occurred; thus, improving the overall forecasting accuracy. These dynamic time series neural network models have not been addressed before in the context of the maritime industry for forecasting data of performance parameters.

The ANN-MLP classifier achieved overall 98.7% classification accuracy in the testing dataset for simulating various main engine faults. The health assessment method utilised custom thresholds to calculate MCIs and illustrated system degradation when parameters exceeded the thresholds. Based on the acquired present and forecasted diagnostic and health assessment results, maintenance suggestions are generated through MAT while also providing additional information to the user.

*Objective 5: Validate key aspects of the methodology and demonstrate the performance of the methodology under different circumstances through a sensitivity analysis*

This objective has been addressed in Chapter 7 by defining three sensitivity scenarios for examining and testing the level of change in the NARX model output for various input data alterations. The sensitivity analysis was performed by utilising Monte Carlo analysis with the Latin hypercube sampling method. For all three sensitivity scenarios, satisfactory model performance was achieved for different alterations in the input data. Moreover, the results of the sensitivity analyses also ensured and demonstrated correct network training and generalisation capabilities.

*Objective 6: Perform a cost-benefit analysis to investigate and assess the value associated with implementing the developed condition monitoring framework*

This objective was achieved by conducting a Cost-Benefit Analysis (CBA) in Chapter 8 by investigating the benefits obtained from capitalising the condition monitoring framework over a traditional vessel PMS scheme. The CBA considered both direct and indirect savings and was presented for 4 scenarios in which mean time between intervals for main engine maintenance and inspection were extended. In addition, the CBA was executed considering various charter rates and augmented levels of charter rate premium. All case studies demonstrated a solid realisation of the potential financial benefits obtained from implementing the condition monitoring framework. Moreover, the longest ROI was equal to 2.2 years for the least beneficial case study, while the shortest were below 3 months for other case studies. The CBA results were validated by executing and presenting a similar CBA in the EU FP7 INCASS project, for a bulk carrier, tanker and container vessel.

## 9.3 Novelty of presented research

The novelty of the undertaken research is derived from the combination of reliability tools with data-driven AI methods incorporated within a hybrid framework and the application of the various artificial neural network models to monitor the condition of a system. Due to their data-driven nature, these methods and tools can be applied to a plethora of industrial systems. The developed hybrid condition monitoring framework introduces novelties in the context of condition-based maintenance and condition monitoring in the maritime industry. The main benefits stem from utilising available onboard sensors to collect real-time data which can be stored and adopted for developing AI data-driven models for condition monitoring applications, without requiring any a priori knowledge of the underlining physical phenomena.

One of the novel features of the research, is the application of the SOM algorithm for clustering data and simultaneously identifying data exceeding thresholds or representing abnormal engine behaviour, thus being implemented as a tool for directly monitoring system condition and performance. Additionally, the NAR and NARX models have been introduced for dynamic time series analysis and forecasting, utilising performance parameter data for predicting the future system state, thus enhancing the monitoring framework with predictive capabilities. This leads to the present and future diagnostic and health assessment on system, subsystem and component level. Moreover, all the stages of the hybrid approach can be utilised both independently and dependently of each other and are adaptable and flexible in considering new input data representing new ship operating profiles or previously unmodelled faults and failures.

In terms of the research practicality of the developed innovative framework, it can assist shipping industry stakeholders such as ship owners, operators, crew and regulatory bodies. The overall framework methodology and modular nature allows the tools to be updated with new input data and can be applied to different ship types and is suitable for real-life implementation onboard. Decision makers frequently face questions such as which maintenance strategy should be introduced for specific machinery and equipment and how to justify their decision. Furthermore, some shipping companies have started to collect vast amounts of data without having a strategy on exploring and analysing the data effectively. The FTA-FMEA combination can assist practitioners in producing tailor-made CBM strategies, starting from a pilot project on the identified critical items, failures and causes; while simultaneously assisting on targeting and harvesting the correct data to reduce costs and enhance operation and maintenance.

The AI tools can provide ship operators with early warnings of upcoming faults to mitigate potential issues in advance through the NAR and NARX models, which helps reduce unplanned downtime and increased availability by enabling the crew onboard the ship and the onshore personnel to prepare accordingly and proactively. The unsupervised learning nature of the SOM provides a fast and efficient method to cluster data and model the underlying structure or distribution in the data providing an initial analysis and feedback to the shipping company/operator. Moreover, the interclustering approach can assist in grouping similar data or distinguishing data that could represent possible fault conditions or abnormal system operation.

The ANN-MLP classifier enables an adaptive structured method for updating the model with the inclusion of new fault classes without requiring in-depth knowledge of the system to be diagnosed, enhancing future fault detection and diagnosis. Moreover, the diagnostic database can assist ship operators to concentrate efforts in the most frequently reported fault causes in the long term, compare defects per sister vessel, correlate this to maintenance performance and forecast maintenance costs. The MCI method offers flexibility in defining custom thresholds for monitoring the health of various systems and can act as a prioritisation mechanism for maintenance planning in the case of dealing with multiple faults. Moreover, assuming the same thresholds are defined, a regulatory body can investigate the appointment of a tolerable health index value and correlate historical health index trends and values to specific faults and conditions.

Through its interactive process, MAT can assist operators select appropriate maintenance actions based on available data and their own judgment of specified criteria. Moreover, appropriate information can be reported to different users according to their needs under one platform, assisting in the decision-making process. As such, onboard personnel require key conditions or constraints, imminent system problems alongside short-term prognosis, current operation characteristics, diagnostics with enhanced details while the onshore personnel could require additional information such as historical records and costs.

## 9.4 Conclusions

The concluding remarks of this research study are presented in the following statements:

- The presentation of the hybrid condition monitoring framework has been enabled through examining the current literature, industry practices and research trends regarding maintenance in a generic and specific context targeting the maritime sector. The need for an overall CBM strategy and investigation of data-driven methods such as ANN for condition monitoring has facilitated the introduction of the hybrid condition monitoring framework.
- In this respect, the proposed hybrid framework has addressed condition monitoring and assessment of ship machinery systems by extracting the

benefits of reliability tools and AI in a combinatory strategy. This creates a dynamic framework consisting of robust tools and stages that can operate as a unified entity under the framework or be self-sufficient.

- The hybrid framework is initially implemented through the application of FTA-FMEA. These tools complement each other and assist in identifying critical items and suitable parameters for initiating a pilot condition monitoring project.
- The case studies demonstrated the capabilities of the various neural networks with respect to condition monitoring applications. The SOM and interclustering approach addressed the issue of finding the correct number of clusters. Moreover, the SOM can be used for directly monitoring the system condition by applying unsupervised learning algorithms.
- Furthermore, high forecasting accuracy was achieved by employing the NAR and NARX models. These ANN models predict the future by learning from past data. Hence, adequate datasets should be provided to accurately forecast different conditions and take seasonality factors into account. The case studies demonstrated that up to 35% increased forecasting accuracy can be achieved by introducing the main engine rpm as the exogenous input in the NARX models compared to the accuracy of the NAR models. For example, in the NAR model of cylinder 5 exhaust gas outlet temperature related to dataset 2, the APE value between the 23$^{rd}$ hour forecasted and actual exhaust gas outlet temperature value is equal to 38.10%, while the results for the NARX model indicate a major reduction in the APE of 33.58% magnitude, resulting in an APE value for the NARX model of 4.52%. Moreover, the overall model MAPE value is reduced from 4.64% down to 1.02%.
- The ANN-MLP classifier can be trained to predict system faults subject to sufficient training data, without requiring any a priori knowledge. An overall accuracy of 99.6% was achieved for the 16 modelled main engine faults $F_0$-$F_{15}$. Most of the fault classes have been perfectly classified while some other fault classes, $F_0$, $F_1$, $F_3$ and $F_4$, have high classification accuracies and minor misclassifications over the training, validation and test sets. The diagnostic assessment is further enhanced by introducing the FMEA as an additional

source of diagnostic intellect, connecting system faults with failure modes, causes and effects locally and globally.

- The lack of systematic approaches to ANN modelling is the primary cause of inconsistency findings in reports. ANN modelling depends strongly on the characteristics of input data and application scope.
- The cost-benefit analysis demonstrated direct and indirect saving obtained from implementing the proposed framework. These include extension of PMS maintenance intervals, increased reliability and charter rate premium, Classification Society annual survey discounts and reduced insurance premiums. Financial benefits range from $560,000 for the worst-case scenario modelled to 47 million USD for the most optimistic scenario over the ship's lifecycle, while ROI is equal to 2.2 years for the least beneficial case study, 6 months for a $5,000 charter rate with 10% increase in charter premium and below 3 months for the other cost-benefit scenarios.
- The proposed methodology can be applied to other machinery systems such as diesel generators, boilers, turbochargers etc. and can also be extended beyond machinery systems, as it has the flexibility and capability factors to adapt accordingly due to its data-driven nature.
- The hybrid condition monitoring framework can be further enhanced by using MAT as the platform to connect the overall framework with in-depth decision-making attributes. Benefits can be further enhanced by combining the overall framework with automatic data acquisition from sensors, cloud-based services, enabling real-time monitoring and decision support actions. This will also enable further validation of the framework performance and investigate any required calibration of network models to capture new information.
- *'Absolute and lasting optimisation of the maintenance of any working system is not possible, the optimum is never achieved because it is a moving target and because the data for its estimation are never quite complete or up to date and seldom sufficient in number',* Sherwin (2000). The importance of data quality and availability must be highlighted once more, for researching, developing and improving the constituents of maintenance in the maritime industry.

## 9.5 Recommendations for future research

Through the research and development of the hybrid condition monitoring framework, future research areas were identified that can extent the research scope and thesis impact. The following statements summarise these areas:

- The employment of additional data points and measurements should be considered. As observed in the case study, the dataset population size affects the training accuracy of the trained neural networks. Larger datasets could require alteration in the network training algorithms such as the Levenberg-Marquardt optimisation algorithm. Moreover, the impact of measurement time intervals between measurements can affect outputs and the overall model uncertainty.
- Data availability is limited as data is not easily accessible, especially data representing fault conditions. Moreover, even in the existence of data, they might not represent faults and/or no history log accompanies them in order to know if the data is healthy or if alarms or system shutdowns occurred. Thus, these factors make it hard to interpret the data and understand it. Hence, future studies should elaborate on the importance of reliable data and data quality. In addition, it is important to consider the legal implications and how the new technology fits within the existing contractual and legal framework.
- In addition, depending on the level of data available for analysis, ANN models can be trained and correlated for different engine performance profiles, developing an in-depth condition monitoring tool. Moreover, if data such as engine load, fuel consumption and weather conditions are available, performance monitoring can be achieved by developing AI and machine learning regression models to predict the performance of the main engine and ship overall.
- In addition, further examination of the condition monitoring framework should be researched by applying other data-driven state-of-the-art models such as support vector machines. Integration of various data-driven methods can potentially lead to enhanced accuracy and performance.
- The development of autonomous and unmanned vessels will create a necessity for improved maintenance, supported by intelligent, autonomous and predictive

characteristics. The developed framework can contribute towards this by investigating automated means of creating a fully adaptable and self-updated mechanism for the AI methods.

- AI and machine learning techniques are considered as black box techniques. A key challenge for shipowners is measuring a baseline level of performance against which the output from any newly introduced system can be assessed and evaluated. Benchmarking of AI and machine learning techniques could be researched to validate their performance and increase their confidence level in the shipping industry.
- The identification of critical systems was achieved through the FTA and FMEA tools. The selection of critical systems can be further enhanced by adding other factors such as spare part and repair costs and Failure Reporting, Analysis, and Corrective Action System (FRACAS). Additionally, the FMEA can be converted to a quantitative FMECA although the subjective evaluation of it should be carefully considered.
- The impact of data cleansing methods on the training process of the neural networks could be investigated to ensure adequate network training and performance.
- As more data becomes available, the NAR and NARX models should be trained again to fully take advantage of the new information so that the models can capture the developing trend of the monitored system more accurately. When and how to implement such an update should be further examined.
- The Maintenance Assistant Tool (MAT) was developed to provide a fundamental advisory generation model regarding maintenance actions and to demonstrate the potential of such a platform for recording and extracting maintenance data. Another recommendation would be to further develop this model with sophisticated decision-making tools and optimisation models (AHP, analytic network process, fuzzy set theory, genetic algorithms) in order to calculate optimal maintenance intervals and costs. Additionally, a decision support mechanism that considers costs, reliability, risk and safety factors in a multi attribute environment could be considered and be beneficial for the industry.

## 9.6 Chapter summary

In this chapter key discussion topics and conclusions regarding the hybrid condition monitoring framework were presented. A description of the accomplishment of the research aim and objectives was provided followed by the presentation of the research novelty. Moreover, concluding remarks regarding the research study were described and recommendations for future research were presented. List of references and appendices are provided next supplementing the presented thesis work.

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# Appendices

# Appendix A: Backpropagation algorithm mathematical description

Figure 1 demonstrates a multilayer feedforward network with all inputs, outputs and hidden elements. The following pages explain and illustrate mathematically the concept of the backpropagation algorithm.

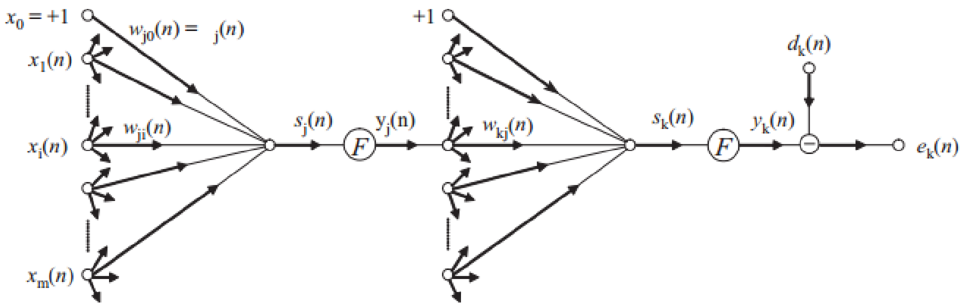


Figure 1-Signal flow through a multilayer feedforward network

MLP has besides an input and output layer also one or more hidden layers. The neurons in the hidden layer(s) of the multi-layer FFNN possess activation functions. The figure displays how an arbitrarily input signal xi propagates through the MLFNN (Zhang and Yi, 2011). The input Sj(n) is expressed by Equation 1:

$$s_j(n) = \sum_{i=0}^{m} w_{ji}(n) x_i(n) \tag{1}$$

The input is then entered into the activation function in order to provide the output of the neuron yj(n):

$$y_j(n) = F(s_j(n)) \tag{2}$$

The output of the neuron of this layer together with the output from the other neurons is then the input to the next layer. Thus, all outputs are summed up to produce the effective output sk(n) of the neuron in the next layer.

$$s_k(n) = \sum_{i=0}^{h} w_{kj}(n) y_j(n) \tag{3}$$

Similarly, the input is fed into an activation function to produce the output of the neuron yk(n)

$$y_k(n) = F(s_k(n)) \tag{4}$$

An arbitrary output yk can then be calculated from equation 5:

$$y_k = F_0 \left\{ \sum_{j=0}^{h} [w_{kj}(n) F_h( \sum_{i=0}^{m} w_{ji}(n) x_i(n))] \right\} \tag{5}$$

Once the output of the final layer has been calculated, it is then compared with the desired output, dk(n) in order to find the error between the calculated and the measured value as seen in equation 6:

$$e_k(n) = d_k(n) - y(n) \tag{6}$$

This error is minimised by updating the weights through a learning algorithm, the backpropagation algorithm. When using backpropagation for training the network, the activation functions have to be differentiable due to the fact that the backpropagation algorithm utilises the delta rule.

The error is propagated back through the entire network, utilising the gradient descent method. The instantaneous value of the cost/error function based on the error signal is shown in equation 7 and describes the value that has to be minimised. N equals to the number of patterns used for training the network:

$$E_{av} = \frac{1}{2N}\sum_{n=1}^{N}\sum_{k} e_k{}^2(n) \tag{7}$$

The updating of the weights are assumed to be proportional to the gradient descent of the error function, which are used in the backpropagation, is defined in the following two equations. The learning rate is defined by n.

$$\Delta w_{kj} = -n\frac{dE}{dw_{kj}} \tag{8}$$

$$\Delta w_{ji} = -n\frac{dE}{dw_{ji}} \tag{9}$$

The differentiation of the cost function becomes:

$$\frac{dE}{dw_{kj}} = \frac{d}{dw_{kj}}\left\{\frac{1}{2N}\sum_{n=1}^{N}\sum_{k}(d_k(n) - F_k(s_k(n)))^2\right\} \tag{10}$$

When calculating the weight update of the connections between the input and hidden layers, the chain rule has to be applied to equation 9 giving the following equation:

$$\frac{dE}{dw_{ji}} = \frac{dE}{dy_k}\frac{dy_k}{dy_j}\frac{dy_j}{dw_{ji}} \tag{11}$$

Once these derivatives have been calculated, the local gradients, δ, are stated in equation z for the matrix between the output and the hidden layer and in equation f for the matrix between the hidden and the input layer.

Weight correction of the weight matrix between the output and the hidden layers

$$\Delta w_{kj} = n\frac{1}{N}\sum_{n} \delta_k(n)y_j(n) \tag{12}$$

$$\delta_k(n) = e_k(n)F'_k(s_k(n)) \tag{13}$$

Weight correction of the weight matrix between the hidden and the input layers

$$\Delta w_{ji} = n\frac{1}{N}\sum_n \delta_j(n)x_i(n) \tag{14}$$

$$\delta_j(n) = F'_j(s_j(n))\sum_k \delta_k(n)w_{kj}(n) \tag{15}$$

The above updating equations are valid for batch training, meaning that all patterns (input-output) are introduced to the network prior to any weight updating taking place. This introduction of all patterns is also called one epoch or one iteration. If sequential updating is selected, the weights are updated after each pattern is introduced to the network, the equations then become:

$$\Delta w_{kj}(n) = n\delta_k(n)y_j(n) \tag{16}$$

$$\Delta w_{ji}(n) = n\delta_j(n)x_i(n) \tag{17}$$

Once the weight updates have been calculated, the connections are updated according to equations:

$$w_{kj}(n+1) = w_{kj}(n) + \Delta w_{kj}(n) \tag{18}$$

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) \tag{19}$$

# Appendix B: Fault tree gates and calculation methods

## *B.1 Fault tree gates*

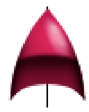
The following pages provide a brief explanation of the gates (static & dynamic) and events usually used in the modeling of a Fault Tree.

<u>Static Gates</u>

A static gate indicates a gate where the order of the inputs does not matter. This means that the underlying occurrence of events is not sequence-dependent and only the occurrence of the input event is considered. For all static gates, the output can be the top event or any intermediate event. The input events can be basic events, intermediate events (outputs of other gates), or combinations of both. A brief explanation of all static gates used in this project is provided below.

- *OR*

  The OR gate is used to indicate that the output occurs if and only if at least one of the input events occur. In order to use an OR gate there must be at least two inputs.

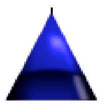
- *AND*

  The AND gate is used to indicate that the output will occur if and only if all the input events occur.

- *TRANSFER*

  This type of gate is basically used to simplify the view of the fault tree in order to represent its logic more reasonably.

- *VOT*

  The Voting (VOT) gate points out that the output occurs if and only if at least m out of the n input events occurs. For example, if

a gate is compiled from 5 events, then the user can define a failure of 3 out of 5 events in order to obtain an output from the gate.

<u>Dynamic Gates</u>

A dynamic gate considers the temporal order of the occurrence of input events. This means that the order of the occurrence of input events is important to determining the output. Thus, a fault tree becomes a dynamic fault tree whenever a dynamic gate is present. There are four types of dynamic gates that can be inserted in a fault tree to make it a dynamic fault tree.

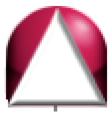
- *SEQ*

  Sequence Enforcing (SEQ) is a dynamic gate that forces events to occur in a particular order from left-to-right. Thus for an input event to occur, the event next to it on the left has to occur first. SEQ gate follows a sequential order as an event connected to this gate will be initiated immediately after occurrence of its immediate left event.

- *PAND*

  The Priority AND (PAND) gate is another dynamic gate which is similar to the SEQ gate but the events are examined in a particular order whereas the SEQ gate allows events to occur only in the specified order.

- *SPARE*

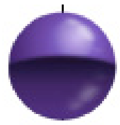
  Spare gates are used to indicate that the output occurs if and only if all spare events occur. Spare events are a special event type used to model spare usage. A spare gate consists of the combination of a primary event (left-most event) and spare events (next to primary event).

Events

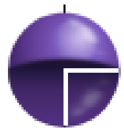
- *Basic Event*

  Basic event are the lowest level of the fault tree structure or branch and define the end of the analytical structure. Their input can include failure rates or MTBF in order to carry out the reliability calculations of the fault tree.

- *Spare Event*

  Spare events are only used with spare gates and are characterized by a dormancy factor. The primary event is initially active while the spare events are on stand-by mode and are only activated when the primary input is subjected to failure. Thus the reliability of the system can be increased by using spare events.

## B.2 *Fault tree calculation methods*

- **Cut-Set Summation**

Cut sets are a series of events that can possibly lead to the failure of the top or intermediate gate/system under consideration. When the Cut Set Summation method is selected, the gate probability is calculated as the summation of cut set probabilities (of the cut sets of that gate). This approximation is acceptable for small failure probabilities. However, it may give gross results for fault trees with higher cut set probabilities. (Cut set probabilities may result in a sum greater than 1.0.) The probability of each cut set is calculated as the product of event probabilities. The frequency of occurrence is calculated by assuming the frequency of occurrences of the cut sets of that gate.

$$P\{TE\} = P\{C_1 U C_2 \ldots U C_m\} = P\{\cup_{i=1}^{m} C_i\} \tag{1}$$

Where P{TE} is the probability of occurrence of the top event, (Ci…i=1, 2,…, m) the cumulative summation of the minimal cut-sets.

- **Cross Product**

When the Cross Product method is chosen, probabilities and frequencies are calculated using the summation and product terms of the cut set probabilities and frequencies using Poincare's formula. It is equivalent to the product of all basic events that are present in those cut sets. Each basic event is considered only once (Relex, 2009). The unavailability at a gate is calculated by using:

$$Q(t) = \sum_{i1=1}^{n} \Pr(C_{i1}) - \sum_{i1=1}^{n} \sum_{i2=2}^{n} \Pr(C_{i1} \bigcap C_{i2}) + \cdots + (-1)^{r-1} \bullet \sum_{1 \le i1 < i2 < \cdots < ir \le n} \Pr(\bigcap_{j=1}^{r} Ci_j) + \cdots + (-1)^{n-1} \bullet Ci_1{}^{*} \bigcap Ci_2{}^{*} \quad (2)$$

Where n is the order of product terms and its maximum value is equivalent to the total number of cut sets of the gate. When n=1 this is the same as the cut set summation method.

- **Esary Proschan**

With the Esary Proschan method the upper bound of the gate probability is calculated as:

$$Q(t) = Q_c(t)\{1 - \prod_i (1 - Q_i(t)^{*})\} \quad (3)$$

Where $Q_c(t)$ is the product of the probabilities of events that are common to cut sets of that gate.

- **Exact Calculation**

The exact calculation method uses the gate logic and not cut set information in order to calculate the unreliability/unavailability of the top/intermediate gate.

## Appendix C: MAT Maintenance actions and activities

| Activity | Description | Maintenance action |
|---|---|---|
| Replace | *Replacement of the item by a new or refurbished item* | Corrective, Preventive |
| Repair | *Manual maintenance action performed to restore an item to its original state* | Corrective |
| Modify | *Replace, renew or change the item or part of it with an item/part of different type, make, material, design* | Corrective, Preventive |
| Adjust | *Bringing any out of tolerance condition into tolerance e.g align or calibrate* | Corrective, Preventive |
| Refit | *Minot repair/servicing activity to bring back an item to an acceptable appearance e.g clean, lube oil change* | Corrective, Preventive |
| Check | *Investigate cause of failure e.g noise, smoke, leakage etc.* | Corrective, Preventive |
| Service | *Periodic service tasks: usually no dismantling of the item e.g cleaning* | Preventive |
| Test | *Periodic test of function or performance* | Preventive |
| Inspection | *Periodic inspection/check: careful scrutiny of an item carried out with or without dismantling* | Preventive |
| Overhaul | *Major overhaul* | Corrective, Preventive |
| Shut down | *Shut down of equipment due to major fault* | Corrective emergency |
| Combination | *Several of the above activities included together* | Corrective, Preventive |
| Other | *Maintenance activity other than specified above* | Corrective, Preventive |

# Appendix D: Main engine diagnostic table and MCI thresholds

## *D.1 Main engine diagnostic table and remedies*

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| ***Cylinder exhaust gas outlet temperature*** | | | |
| ***a) F2-Temperature increase in all engine cylinders*** | 1 | Increased scavenge air temperature owing to inadequate air cooler function | Inspect, overhaul and clean air side of air cooler |
| | 2 | Fouled air and gas passages | Clean turbine by means of dry cleaning/water washing<br>Clean blowers and air coolers<br>Check the back pressure in the exhaust gas system just after the T/C turbine side |
| | 3 | Inadequate fuel oil cleaning and/or altered combustion characteristics of fuel | Check fuel quality and fuel treatment |
| | 4 | Wrong position of camshaft | Check pmax<br>Check camshaft with pin gauge<br>Check chain tension |
| ***b) F1-Temperature increase in one cylinder*** | 5 | Defective fuel valves | Overhaul fuel valves and replace |
| | 6 | Fuel valve leakage/dripping | Replace or overhaul valve |
| | 7 | Fuel injection nozzles worn | Replace nozzles |
| | 8 | Wrongly adjusted/slipped fuel cam | Check fuel pump lead |
| | 9 | Blow-by in combustion chamber | Reduce engine speed<br>Inspect and if required replace piston rings and cylinder liner surface |
| | 10 | Exhaust valve burned/leakage | Replace or overhaul valve<br>Grind the valve seat and head |
| | 11 | Improper scavenging | Clean and overhaul scavenging air receiver air flaps |
| | 12 | Scavenge air port fouling | Clean scavenge air ports |

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| | 13 | Cylinder liner wear | Check cylinder liner surface |
| | 14 | Exhaust thermometer defective | Replace the exhaust thermometer |
| ***c) F4-Temperature decreases in all cylinders*** | 15 | Falling scavenge air temperature | Check seawater system thermostat valve is functioning correctly |
| | 16 | Air/gas/steam in fuel system | Check the fuel oil supply and circulating pump pressures<br>Check the function of the de-aerating valve<br>Check the suction side of the supply pumps for air leakages<br>Check the fuel oil preheater for steam leakages |
| ***d) F3-Temperature decreases in one cylinder*** | 17 | Defective fuel pump suction valve | Repair the suction valve |
| | 18 | Fuel pump plunger or puncture valve sticking/leaking | Replace the fuel pump or the puncture valve |
| | 19 | The injection nozzles are in unsatisfactory condition, nozzle tip broken, the flow limiter valve cannot move | Replace nozzle tip or flow limiter valve |
| | 20 | Reversible roller guide in wrong position | Check roller guide mechanism for seized bearing, roller guide, roughened rollers or cam<br>In case of seizure being observed, check cam shaft lubrication oil filter and by-pass filter for possible damage |
| | 21 | Exhaust valve sticking in open position | Replace exhaust valve |
| ***F10-Piston cooling lubrication oil inlet pressure low*** | | | |

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| | 22 | Inadequate circulation of cooling media | Check all parts of cooling system |
| | 23 | L.O filter chocked | Clean and/or change L.O filter |
| | 24 | L.O pump operating at degraded head | Check L.O pump discharge & suction pressure |
| | 25 | L.O pump defective | Repair or replace L.O pump |
| | 26 | Pressure lines leakage | Check tubing and connections<br>Repair or replace as required |
| | 27 | Low oil level | Adjust oil level |
| | 28 | Defect in oil pressure gauge | Install new gauge |
| ***F14-Piston cooling oil outlet temperature high*** | | | |
| | 29 | Insufficient piston cooling | Check piston condition<br>Check lubrication oil quality |
| | 30 | Gas flows through defective or worn piston rings | Cut out injection of related cylinder for short time |
| | 31 | Cylinder liner surface scratches due to cylinder lubricating oil decrease | Increase feed rate of cylinder lubricating oil<br>Replace piston, piston skirt and cylinder liner |
| | 32 | Faulty temperature sensor | Replace sensor |
| ***F5-Fuel oil inlet temperature low or high*** | | | |
| | 33 | Unsatisfactory fuel oil treatment | Adjust fuel oil treatment accordingly and check HFO separators and HFO heat exhanger |
| | 34 | Fuel oil heater defective | Inspect and overhaul fuel oil heater |
| | 35 | Viscosity regulator incorrect | Adjust viscosity regulator or replace |
| | 36 | Faulty instrumentation reading | Install new sensor |
| | | | |

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| ***F6-Fuel oil inlet pressure low*** | | | |
| | 37 | F.O filter blocked or dirty | Remove, clean and/or change F.O filter |
| | 38 | F.O booster pump pressure insufficient or faulty | Repair or replace F.O pump |
| | 39 | Fuel pump plunger leakage or worn | Unscrew the limit screw of the fuel pump control rack<br>Increase the fuel capacity<br>Replace a new plunger and barrel assembly |
| | 40 | Air/Water in fuel system | Check fuel system at fuel prefilter<br>Drain fuel prefilter<br>Check and carry out air bleeding<br>Check and carry out water drainage |
| | 41 | Suction valve early or late operation | Adjust valve spring<br>Replace suction valve |
| | 42 | Fuel pressure regulating valve defective | Check and clean<br>Adjust and replace |
| | 43 | Fuel viscosity is low | Check HFO properties<br>Check viscosity regulator settings |
| | 44 | Fuel pipe is blocked | Check and clean or blow free the fuel pipe |
| | 45 | Faulty instrumentation reading | Install new sensor |
| ***F8-Main Lubrication oil inlet temperature high*** | | | |
| | 46 | Lubrication oil cooler fouling | Clean tube and shell side of cooler |
| | 47 | Thermostat malfunction | Repair thermostast or replace |
| ***F7-Main Lubrication oil inlet pressure low*** | | | |
| | 48 | Pressure adjusting valve spring fractured | Replace spring |
| | 49 | Loose pipe joints and oil leakage in oil line | Check and tighten |

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| | 50 | Air in oil pipeline | Check oil pipeline and bleed lubricating system |
| | 51 | Poor lubrication oil quality | Select proper lubrication oil according to relevant specifications |
| | 52 | Oil pressure in oil sump tank too low or oil pump suction height excessive | Add oil or reinstall the oil pump and oil tank |
| | 53 | Clearance between connecting rod bearing and main bearing too large | Check and replace |
| | 54 | Lubrication oil pump failure<br>Operates at degraded head | Repair pump or replace |
| | 55 | Filter dirty or clogged | Remove, clean and/or change L.O filter |
| | 56 | Lubrication oil cooler leakage | Inspect for leakages and overhaul to repair |
| | 57 | Fuel leakage into lubrication oil | Repair leaks and/or install new parts where needed |
| | 58 | Faulty instrumentation reading | Install new sensor |
| ***F13-Jacket fresh water cooling outlet temperature high*** | | | |
| | 59 | Water temperature regulator | Check water temperature regulator for correct operation<br>Install new parts when necessary |
| | 60 | Water inlet temperature too high | Reduce the water inlet temperature |
| | 61 | Shut-off valves in pipes of related cylinder defective | Replace shut-off valves |
| | 62 | Pressure in cooling spaces not sufficiently released | Release the pressure |
| | 63 | The piston is too hot | Stop engine and let piston temperature decrease |
| | 64 | Cooling water piping system blocked<br>Insufficient water flow | Treatment of cooling system for removal of grease and sediments |

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| | 65 | Exhaust gases in cooling water due to crack in cylinder liner, cylinder cover, valve cage | Replace defective cylinder cover or cylinder liner<br>Close valves to the cooling water inlet and outlet of related cylinder and lock exhaust valve in open position |
| | 66 | Heat exchanger malfunction<br>Insufficient cooling | Check all cylinder cooling water temperatures |
| | 67 | JCFW pump failure/defect | Overhaul or replace |
| | 68 | Temperature gauge defect | Check temperature gauge operation<br>Install new sensor |
| ***F12-Cylinder scavenging air temperature high*** | | | |
| | 69 | Air filter clogged | Remove and clean |
| | 70 | Air supply insufficient due to air cooler contaminated or defective | Reduce engine speed<br>Clean and overhaul air cooler |
| | 71 | Scavenge air port fouling | Clean scavenge ports |
| | 72 | Scavenge air receiver contamination | Clean, overhaul or replace scavenging air receiver air flaps |
| | 73 | Faulty temperature sensor | Replace with new sensor |
| ***F11-Air cooler cooling water inlet pressure low*** | | | |
| | 74 | Air cooler fouling | Overhaul and clean |
| | 75 | Cooling water piping system blocked<br>Insufficient water flow | Check and repair |
| | 76 | Cooling water piping system leakage<br>Insufficient water flow | Inspect piping system for leakages |
| | 77 | Cooling water pump defective | Overhaul or replace |
| | 78 | Defective gauge | Replace with new gauge |
| ***F9-Thrust bearing lubrication oil outlet temperature high*** | | | |
| | 79 | Improper bearing lubrication | Overhaul lubrication system and clean it |

| Fault | Point | Potential Causes | Remedy |
|---|---|---|---|
| | 80 | Thrust bearing too hot | Overhaul lubrication system and clean it |
| | 81 | Excessive thrust bearing lubrication | Check lubrication oil flow rate |
| | 82 | Lubrication oil cooler outlet temperature too high | Inspect and repair lubrication oil cooling system |
| | 83 | Lubricant is being lost through the seal | Replace seal |
| | 84 | Bearing has inadequate internal clearance for conditions where external heat is conducted through the shaft. | Check bearing clearance according to original design specification |
| | 85 | Contact seals are dried out or have excessive spring tension. | Replace contact seals with seals having correct spring tension |
| | 86 | Rotating seals or flingers are rubbing against stationary parts | Check the running clearance of the rotating seal or flinger to eliminate rubbing Correct the alignment. |
| | 87 | Defective gauge | Replace with new gauge |

## *D.2 Main engine MCI thresholds*

| Main engine RCP | $RCP_{in}$ | $RCP_{lim}$ | Unit |
|---|---|---|---|
| Exhaust gas outlet temperature cylinder 1 | 100 | 263 | °C |
| Exhaust gas outlet temperature cylinder 2 | 100 | 240 | °C |
| Exhaust gas outlet temperature cylinder 3 | 100 | 263 | °C |
| Exhaust gas outlet temperature cylinder 4 | 100 | 260 | °C |
| Exhaust gas outlet temperature cylinder 5 | 100 | 250 | °C |
| Exhaust gas outlet temperature cylinder 6 | 100 | 250 | °C |
| Exhaust gas outlet temperature cylinder 7 | 100 | 270 | °C |
| Exhaust gas outlet temperature cylinder 8 | 100 | 252 | °C |
| Fuel oil inlet temperature | 130 | 140 | °C |
| Fuel oil inlet pressure | 8.05 | 8.4 | $kg/cm^2$ |
| Main lubrication oil inlet pressure | 2.7 | 2 | $kg/cm^2$ |
| Main lubrication oil inlet temperature | 40 | 50 | °C |
| Thrust bearing lubrication oil outlet temperature | 42 | 50 | °C |
| Piston cooling lubrication oil inlet pressure | 2.6 | 2.8 | $kg/cm^2$ |
| Air cooler cooling water inlet pressure | 2.9 | 3.12 | $kg/cm^2$ |
| Scavenging air temperature cylinder 1 | 30 | 48 | °C |
| Scavenging air temperature cylinder 2 | 30 | 49 | °C |
| Scavenging air temperature cylinder 3 | 30 | 47 | °C |
| Scavenging air temperature cylinder 4 | 30 | 49 | °C |
| Scavenging air temperature cylinder 5 | 30 | 53 | °C |
| Scavenging air temperature cylinder 6 | 30 | 52 | °C |
| Scavenging air temperature cylinder 7 | 30 | 53 | °C |
| Scavenging air temperature cylinder 8 | 30 | 54 | °C |
| JCFW cooling outlet temperature cylinder 1 | 50 | 84 | °C |
| JCFW cooling outlet temperature cylinder 2 | 50 | 84 | °C |
| JCFW cooling outlet temperature cylinder 3 | 83 | 85 | °C |
| JCFW cooling outlet temperature cylinder 4 | 50 | 87 | °C |
| JCFW cooling outlet temperature cylinder 5 | 50 | 85 | °C |
| JCFW cooling outlet temperature cylinder 6 | 50 | 84 | °C |
| JCFW cooling outlet temperature cylinder 7 | 50 | 86 | °C |
| JCFW cooling outlet temperature cylinder 8 | 50 | 77 | °C |
| Piston cooling oil outlet temperature cylinder 1 | 0 | 49 | °C |
| Piston cooling oil outlet temperature cylinder 2 | 0 | 50 | °C |
| Piston cooling oil outlet temperature cylinder 3 | 0 | 49 | °C |
| Piston cooling oil outlet temperature cylinder 4 | 0 | 49 | °C |
| Piston cooling oil outlet temperature cylinder 5 | 0 | 50 | °C |
| Piston cooling oil outlet temperature cylinder 6 | 0 | 50 | °C |
| Piston cooling oil outlet temperature cylinder 7 | 0 | 51 | °C |
| Piston cooling oil outlet temperature cylinder 8 | 0 | 50 | °C |

# Appendix E: Main engine FTA and FMEA results

## *E.1 Main engine FTA minimal cut sets results*

| # | Cut set events | | | Order |
|---|---|---|---|---|
| **1** | Cylinder Head | Piston Crown | Piston Ring | **3** |
| **2** | Cylinder Head | Piston Crown | Piston Rod Stuffing Box | **3** |
| **3** | Cylinder Head | Piston Crown | Piston Connecting Rod | **3** |
| **4** | Cylinder Head | Piston Crown | Piston Skirt | **3** |
| **5** | Cylinder Head | Piston Ring | Piston Rod Stuffing Box | **3** |
| **6** | Cylinder Head | Piston Ring | Piston Connecting Rod | **3** |
| **7** | Cylinder Head | Piston Ring | Piston Skirt | **3** |
| **8** | Cylinder Head | Piston Rod Stuffing Box | Piston Connecting Rod | **3** |

| # | Cut set events | | | Order |
|---|---|---|---|---|
| **9** | Cylinder Head | Piston Rod Stuffing Box | Piston Skirt | **3** |
| **10** | Cylinder Head | Piston Connecting Rod | Piston Skirt | **3** |
| **11** | Cylinder Liner | Piston Crown | Piston Ring | **3** |
| **12** | Cylinder Liner | Piston Crown | Piston Rod Stuffing Box | **3** |
| **13** | Cylinder Liner | Piston Crown | Piston Connecting Rod | **3** |
| **14** | Cylinder Liner | Piston Crown | Piston Skirt | **3** |
| **15** | Cylinder Liner | Piston Ring | Piston Rod Stuffing Box | **3** |
| **16** | Cylinder Liner | Piston Ring | Piston Connecting Rod | **3** |
| **17** | Cylinder Liner | Piston Ring | Piston Skirt | **3** |
| **18** | Cylinder Liner | Piston Rod Stuffing Box | Piston Connecting Rod | **3** |

| # | Cut set events | | | Order |
|---|---|---|---|---|
| **19** | Cylinder Liner | Piston Rod Stuffing Box | Piston Skirt | **3** |
| **20** | Cylinder Liner | Piston Connecting Rod | Piston Skirt | **3** |
| **21** | Piston Crown | Piston Ring | Cylinder Jacket | **3** |
| **22** | Piston Crown | Piston Rod Stuffing Box | Cylinder Jacket | **3** |
| **23** | Piston Crown | Piston Connecting Rod | Cylinder Jacket | **3** |
| **24** | Piston Crown | Piston Skirt | Cylinder Jacket | **3** |
| **25** | Piston Ring | Piston Rod Stuffing Box | Cylinder Jacket | **3** |
| **26** | Piston Ring | Piston Connecting Rod | Cylinder Jacket | **3** |
| **27** | Piston Ring | Piston Skirt | Cylinder Jacket | **3** |

| # | Cut set events | | | Order |
|---|---|---|---|---|
| **28** | Piston Rod Stuffing Box | Piston Connecting Rod | Cylinder Jacket | **3** |
| **29** | Piston Rod Stuffing Box | Piston Skirt | Cylinder Jacket | **3** |
| **30** | Piston Connect. Rod | Piston Skirt | Cylinder Jacket | **3** |
| **31** | Crankcase | Crankshaft | Camshaft | **3** |
| **32** | Crankcase | Crankshaft | Exhaust Valves | **3** |
| **33** | Crankcase | Crankshaft | Exhaust Manifold | **3** |
| **34** | Crankcase | Camshaft | Exhaust Valves | **3** |
| **35** | Crankcase | Camshaft | Exhaust Manifold | **3** |
| **36** | Crankcase | Exhaust Valves | Exhaust Manifold | **3** |
| **37** | Crankshaft | Camshaft | Exhaust Valves | **3** |
| **38** | Crankshaft | Camshaft | Exhaust Manifold | **3** |
| **39** | Crankshaft | Exhaust Valves | Exhaust Manifold | **3** |

| # | Cut set events | | | | Order |
|---|---|---|---|---|---|
| **40** | Camshaft | Exhaust Valves | Exhaust Manifold | | **3** |
| **41** | Piping System | Fuel Oil Filter | Fuel Pumps | | **3** |
| **42** | Piping System | Fuel Oil Filter | Fuel Valves | | **3** |
| **43** | Piping System | Fuel Oil Filter | Fuel Injector | | **3** |
| **44** | Piping System | Fuel Pumps | Fuel Valves | | **3** |
| **45** | Piping System | Fuel Pumps | Fuel Injector | | **3** |
| **46** | Piping System | Fuel Valves | Fuel Injector | | **3** |
| **47** | Fuel Oil Filter | Fuel Pumps | Fuel Valves | | **3** |
| **48** | Fuel Oil Filter | Fuel Pumps | Fuel Injector | | **3** |
| **49** | Fuel Oil Filter | Fuel Valves | Fuel Injector | | **3** |
| **50** | Fuel Pumps | Fuel Valves | Fuel Injector | | **3** |
| **51** | Main Lube Oil Pump | Lube System Valves | Lube Oil Filter | Lube Oil Cooler | **4** |

| # | Cut set events | | | | | | Order |
|---|---|---|---|---|---|---|---|
| **52** | Sea Water Pipes | Central Cooler | Sea Chest Strainer | JCFW Cooling Pump | Jacket Water Cooler | | **5** |
| **53** | Crankcase | Crankshaft | Camshaft Bearing | Thrust Bearing | Main Bearings | Crosshead Bearings | **6** |
| **54** | Crankcase | Camshaft Bearing | Thrust Bearing | Main Bearings | Camshaft | Crosshead Bearings | **6** |
| **55** | Crankcase | Camshaft Bearing | Thrust Bearing | Main Bearings | Exhaust Valves | Crosshead Bearings | **6** |
| **56** | Crankcase | Camshaft Bearing | Thrust Bearing | Main Bearings | Exhaust Manifold | Crosshead Bearings | **6** |
| **57** | Crankshaft | Camshaft Bearing | Thrust Bearing | Main Bearings | Camshaft | Crosshead Bearings | **6** |
| **58** | Crankshaft | Camshaft Bearing | Thrust Bearing | Main Bearings | Exhaust Valves | Crosshead Bearings | **6** |
| **59** | Crankshaft | Camshaft Bearing | Thrust Bearing | Main Bearings | Exhaust Manifold | Crosshead Bearings | **6** |
| **60** | Camshaft Bearing | Thrust Bearing | Main Bearings | Camshaft | Exhaust Valves | Crosshead Bearings | **6** |
| **61** | Camshaft Bearing | Thrust Bearing | Main Bearings | Camshaft | Exhaust Manifold | Crosshead Bearings | **6** |
| **62** | Camshaft Bearing | Thrust Bearing | Main Bearings | Exhaust Valves | Exhaust Manifold | Crosshead Bearings | **6** |

| # | Cut set events | | | | | | | | | Order |
|---|---|---|---|---|---|---|---|---|---|---|
| **63** | Air Cooler, Piping | Air Cooler | Air Filter | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **64** | Air Cooler, Piping | Air Cooler | Scavenge Air Receiver | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **65** | Air Cooler, Piping | Air Cooler | Scavenge Air Manifold | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **66** | Air Cooler, Piping | Scavenge Air Port | Scavenge Air Receiver | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **67** | Air Cooler, Piping | Air Filter | Scavenge Air Port | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **68** | Air Cooler, Piping | Scavenge Air Port | Scavenge Air Receiver | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **69** | Air Cooler | Air Filter | Scavenge Air Port | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **70** | Air Cooler | Air Filter | Scavenge Air Port | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |

| # | Cut set events | | | | | | | | | Order |
|---|---|---|---|---|---|---|---|---|---|---|
| **71** | Air Cooler | Air Filter | Scavenge Air Receiver | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |
| **72** | Air Filter | Scavenge Air Port | Scavenge Air Receiver | Air Receiver | Main Air Compressor | Air Distributor | Air Starting Valves | Air Filter. | Auxiliary Blower | **9** |

## *E.2 Main engine FMEA*

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| Cylinder | Cylinder Head | *Cracked* | Overheating, fatigue | Compression loss, cylinder damage, engine misfire | Possible engine stop | Temperature, Pressure alarm |
| | | *Overheating* | Cracks, faulty exhaust valves | High temperature alarm, smoke, cylinder damage | Possible engine stop, engine damage | High temperature alarm |
| | Cylinder Liner | *Leakage* | Overheating | Compression loss, cooling water in cylinder | Engine performance reduction, engine damage | Pressure fluctuation cooling water |
| | | *Wear* | Fatigue, lubrication oil quality | Compression loss, increased lubrication consumption | Engine performance reduction | Increment of exhaust temperature in cylinder |
| | Cylinder Jacket | *Cracked* | Stress corrosion cracking, excessive rust and scale development, use of wrong bolts to secure jacket | Cylinder damage, loss of engine cooling water | Engine slow down, propulsion reduction | High temperature alarm |
| Piston | Piston Crown | *Hole in piston crown* | Dripping of fuel valve, erosion due to poor fuel injection | Escape of combustion gas into the crankcase | Engine performance reduction, possible engine stop, possible engine explosion | Alarm, visual inspection |
| | | *Cracked* | Thermal stressing due to carbon build up | Leakage to combustion space | Possible engine explosion | Alarm |
| | Piston Rings | *Scuffing* | Insufficient lubrication | Scuffing mark on liner surface, oil smoke from exhaust | Engine performance reduction | Visual inspection |
| | | *Cracked* | Excessive gap pressure, ring groove worn-out | Power loss, oil smoke from exhaust | Engine performance reduction | Visual inspection |

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| | | *Wear* | Insufficient lubrication, solid residue, Insufficient clearance | Power loss | Engine performance reduction | Visual inspection |
| | | *Blow-by* | Piston ring stuck, piston ring worn, piston rings broken, worn cylinder liner, incorrect operation of a lubricating quill, running surface of cylinder liners damaged | Power loss | Engine performance reduction | Visual inspection |
| | Piston Rod Stuffing Box | *Rings wear out* | Sealing lose | Spark | Engine performance reduction, engine damage, possibility of explosion | Visual inspection |
| | | *Malfunction* | Faulty oil scraper rings | Combustion gas in crankcase | Engine stop, possibility of explosion | Visual inspection |
| | Piston Connecting Rod | *Damage, break* | Fatigue, incorrect tightening of bolts, snap of piston pin | Power loss, damaged crankshaft | Engine stop, possibility of explosion, engine damage | Alarm |
| | Piston | *Stuck* | Connecting rod nut loose, insufficient lubrication | Cylinder power loss, connecting rod damage, piston pin cracked | Engine stop, possibility of explosion | Alarm, Visual inspection |
| Engine Block & Components | Camshaft Bearing | *Overheating* | Wear and tear, nuts slackness | Camshaft damage | Engine damage, engine failure | Alarm |
| | Thrust bearing | *Improper Lubrication* | Leakage | Thrust bearing damage | Unexpected stop of engine<br>Engine damage | Alarm |
| | | *Shaft rotation malfunctioning* | Wear | Thrust bearing damage | Engine slow down | Visual inspection |

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| | Main Bearing | *Lubrication failure* | Low oil pressure | Excessive heat, friction | Engine performance reduction, engine damage | Alarm |
| | Crankshaft | *Cracked* | Insufficient lubrication, bearing misalignment, lack of maintenance | Connecting rod damage, engine block damage | Engine damage, reduced engine output, possible engine stop | Visual inspection |
| | | *Journal damage* | Insufficient lubrication, bearing misalignment, propeller fouling | Connecting rod damage | Engine damage, reduced engine output, possible engine stop | Visual inspection |
| | Crankcase | *Relief valve not operating* | Not seated properly | Air escape into crankcase | Engine performance reduction, possibility of explosion | Visual inspection |
| | Camshaft | *Break* | Connecting rod loose, insufficient lubrication | Failure of inlet and exhaust valve | Engine damage, possible engine stop | Visual inspection |
| | Exhaust Valve | *Valve burned* | Valve spring weak | Leakage | Engine power reduction, misfire in cylinder | Differential Temperature of exhaust gas |
| Scavenge Air System | Air Cooler, Piping | *Blinded* | Sea water contamination | Excessive air temperature and exhaust temperature | Fuel consumption high, engine output low | High temperature alarm |
| | Air Cooler | *Water content in air* | Deterioration of casing, leakage of tubes | Improper cooling, insufficient cooling | Engine damage, engine failure, engine derating | Visual inspection |
| | | *No flow of water* | No flow inlet/outlet valve | Air cooler not operating | Engine stop, engine damage | High temperature alarm |
| | Air Filter | *Clogged* | Contamination | Reduced airflow, compressor not efficient | Increased fuel consumption, engine power reduction | Visual inspection |
| | Scavenge Air Port | *Fouling* | Contamination from exhaust gases | Insufficient air supply, smoke, improper combustion | Engine output reduction | High exhaust temperature alarm |

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| | Scavenge Air Receiver | *Improper scavenging* | Faulty timing, unburned fuel and carbon | Improper combustion | Result loss of engine power and high exhaust temperature at affected cylinders | High exhaust temperature alarm |
| | Scavenge Air Manifold | *Pressure of inlet air lower than expected* | Leakage, flow interruption | Improper combustion | Derating engine, engine damage, turbo damaged | Low pressure alarm |
| Air System | Main Air Compressor | *Operates at degraded head/flow performance* | Fatigue | Reduction in air pressure and air flow | Loss of service air, engine performance reduction | Alarm |
| | | *Fails to start* | Control system and valves faulty | Loss of engine start | Loss of engine start, no other significant effect | Low pressure shown on gauge |
| | Air Receivers | *Oil and water mixture in receiver* | Unsuccessful drainage of mixture | Air supply pipe contaminated by oil coating | Possibility of explosion | Service |
| | Air Distributor | *Leakage, stuck* | Fatigue, malfunction, insufficient maintenance | Loss of start air, starting air valves do not open | Loss of engine start | Pressure alarm, visual inspection |
| | Air Starting Valves | *Position stuck* | Faulty valves, control system, faulty air distributor | Loss of engine start | Loss of engine start, no other significant effect | Alarm |
| | Air Filter | *Plug* | Contamination, lack of maintenance | Air flow reduced | Inefficient compressor operation, low flow of air to engine | Alarm |
| | Auxiliary Blower | *Motor windings burnt out* | Zero motor insulation | Loss of minimum scavenge pressure | Insufficient combustion | Alarm |
| Fuel Oil System | Piping System | *Leakage, sludge* | Fuel oil quality poor, deposits | Fuel oil spill, hot spot creation | Engine stop, possibility of fire | Visual inspection |
| | Fuel Oil Filter | *Clogged* | Contaminants, lack of maintenance | Fuel flow and pressure low | Engine speed drop, engine stop, engine performance reduction | Differential pressure alarm |
| | | *Low supply pressure* | Suction valve early or late operation | Erratic engine operation | Engine stop, engine performance reduction | Low pressure alarm |

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| | Fuel Pumps (Circulating, Transfer, Supply, Booster) | *Abnormal sound* | Vibrations, bearing defective, shaft displacement | Electric motor overloading | Engine output reduction | Noise |
| | Fuel Valves | *Leakage* | Deposits, erosion | Excessive temperature | Engine output reduction | High exhaust temperature alarm |
| | | *Dripping* | Oversized injection mechanisms | Sticking of piston rings | Engine performance reduction, engine damage | High exhaust temperature alarm |
| | Fuel Injectors | *Nozzle obstructed* | Inadequate maintenance, contaminants, poor fuel quality | Poor combustion | Engine performance reduction, engine failure | High exhaust temperature alarm |
| | | *Incorrect atomization of fuel* | Spraying disabled, back flow interruption disabled, fuel temperature not correct | Fuel loss | Derating engine, differential exhaust gas temperature | Differential Temperature of exhaust gas |
| | | *Valve spindle seizure* | Control system failure | High exhaust temperature, smoke, excessive fuel injection | Engine performance reduction, environmental damage | High exhaust temperature alarm |
| Lubrication Oil System | Main Lube Oil Pump | *Rupture, Leakage* | Erosion, pump housing failure | Stan-by pump starts | No other significant effect | Standby pump starts functioning |
| | | *Operation failure* | Motor failure, motor coupling failure, motor seizing | Interruption of lube oil supply to engine, stand-by pump starts | No other significant effect | n/a |
| | | *Operates at degraded head* | Pump gears worn, housing leak | Lube oil pressure low, pump stand-by starts | No other significant effect | Pressure alarm |
| | Lubrication System Valves and Piping | *Leakage* | Contaminants, lack of maintenance | Oil leakage, oil pressure low, engine components wear | Engine stop, possibility of fire | Visual inspection |
| | Lube Oil Filter | *Clogged* | Contaminants, accumulation of carbon matter | Improper cleaning, oil pressure low | Engine stop, engine performance reduction | Differential pressure alarm |

| System | Failed Item | Failure Mode | Failure Cause | Local Effect | Global Effect | Detection Method |
|---|---|---|---|---|---|---|
| | Lube Oil Cooler | *Temperature abnormal* | Fouling | Insufficient lubrication oil cooling temperature | Engine overheating, Engine stop | High temperature alarm |
| Central Cooling System | Sea Water Pipes | *Leakage* | Fatigue, corrosion | Flow reduction, loss of cooling | Engine room flooding, | Bilge alarm |
| | Central Cooler | *Leakage* | Corrosion | Insufficient cooling | High engine temperature | High temperature alarm |
| | Sea Chest Strainer | *Obstruction* | Debris | None | None | High temperature of cooler |
| Jacket Water Cooling System | Jacket Fresh Water Cooling Pump | *No flow* | Seized bearing, shaft wear, sleeve wear, impeller clogged, leakage | Loss of redundancy | Engine damage, engine stop | High temperature alarm |
| | | *Higher temperature of fresh water* | Clogged, operation disabled, obstruction | Cylinder overheating | Engine damage, engine slow down | High temperature alarm |
| | Jacket Water Cooler | *Leakage* | Corrosion, seal ring leakage at cylinder liner | Insufficient cylinder cooling | Containment of fresh water, engine performance reduction | Alarm |
| | | *Insufficient Cooling* | Restricted passage, particles/dirt in cooling medium | Cylinder overheating, cylinder liner cracking | Engine performance reduction | Increment of cooling water temperature |

# Appendix F: NAR and NARX results

## F.1 NAR results dataset 1

### F.1.1 NAR regression results

| Parameter | Training | Test | All |
|---|---|---|---|
| Cylinder Exhaust Gas Temperature no.1 | 88.25% | 89.38% | 87.97% |
| Cylinder Exhaust Gas Temperature no.2 | 83.13% | 97.43% | 86.69% |
| Cylinder Exhaust Gas Temperature no.3 | 84.29% | 85.22% | 84.94% |
| Cylinder Exhaust Gas Temperature no.4 | 74.18% | 93.82% | 78.45% |
| Cylinder Exhaust Gas Temperature no.5 | 84.99% | 96.13% | 88.01% |
| Cylinder Exhaust Gas Temperature no.6 | 84.25% | 97.19% | 86.95% |
| Cylinder Exhaust Gas Temperature no.7 | 89.01% | 92.26% | 87.96% |
| Cylinder Exhaust Gas Temperature no.8 | 90.45% | 90.52% | 90.32% |
| Fuel Oil Inlet Temperature | 87.61% | 84.39% | 85.12% |
| Fuel Oil Inlet Pressure | 96.98% | 97.03% | 97.13% |
| Main Lube Oil Pressure | 93.23% | 95.57% | 94.41% |
| Main Lube Oil Temperature | 99.14% | 86.67% | 90.32% |
| Thrust Bearing Temperature | 96.18% | 86.63% | 89.10% |
| Piston Cooling Oil Inlet Pressure | 94.18% | 98.93% | 97.15% |
| Air Cooler Cooling Water Inlet Pressure | 83.13% | 79.19% | 80.78% |
| Cylinder Scavenging Air Temperature Inlet no.1 | 83.19% | 88.44% | 86.78% |
| Cylinder Scavenging Air Temperature Inlet no.2 | 85.15% | 94.35% | 87.31% |
| Cylinder Scavenging Air Temperature Inlet no.3 | 82.91% | 84.12% | 83.62% |
| Cylinder Scavenging Air Temperature Inlet no.4 | 77.21% | 86.12% | 79.75% |
| Cylinder Scavenging Air Temperature Inlet no.5 | 82.82% | 94.23% | 88.01% |
| Cylinder Scavenging Air Temperature Inlet no.6 | 84.25% | 97.19% | 85.45% |
| Cylinder Scavenging Air Temperature Inlet no.7 | 91.23% | 93.56% | 91.42% |
| Cylinder Scavenging Air Temperature Inlet no.8 | 89.13% | 92.71% | 88.79% |
| Cylinder CFW Outlet Temperature no.1 | 95.95% | 93.25% | 91.14% |
| Cylinder CFW Outlet Temperature no.2 | 91.16% | 89.57% | 90.89% |
| Cylinder CFW Outlet Temperature no.3 | 91.89% | 95.55% | 93.63% |
| Cylinder CFW Outlet Temperature no.4 | 94.07% | 93.13% | 93.89% |
| Cylinder CFW Outlet Temperature no.5 | 94.32% | 96.24% | 95.87% |
| Cylinder CFW Outlet Temperature no.6 | 94.46% | 90.06% | 92.32% |
| Cylinder CFW Outlet Temperature no.7 | 93.83% | 91.18% | 92.79% |
| Cylinder CFW Outlet Temperature no.8 | 97.32% | 91.57% | 95.07% |
| Cylinder PCO Outlet Temperature no.1 | 94.29% | 85.73% | 88.66% |
| Cylinder PCO Outlet Temperature no.2 | 92.45% | 90.91% | 92.14% |
| Cylinder PCO Outlet Temperature no.3 | 92.94% | 99.12% | 94.23% |

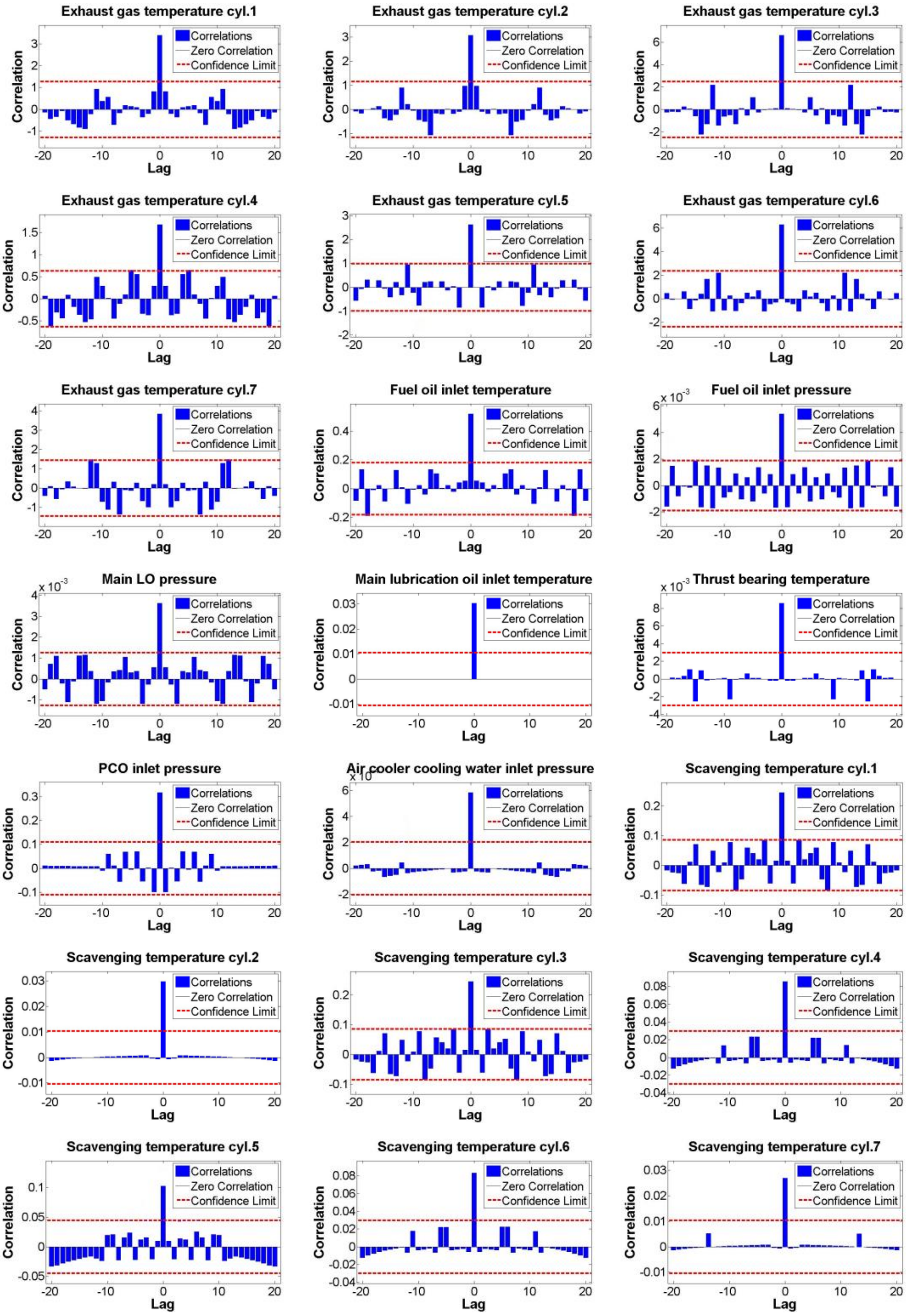
| Parameter | Training | Test | All |
|---|---|---|---|
| Cylinder PCO Outlet Temperature no.4 | 98.84% | 85.56% | 94.24% |
| Cylinder PCO Outlet Temperature no.5 | 97.29% | 89.78% | 94.88% |
| Cylinder PCO Outlet Temperature no.6 | 99.02% | 89.87% | 94.84% |
| Cylinder PCO Outlet Temperature no.7 | 88.69% | 89.60% | 88.88% |
| Cylinder PCO Outlet Temperature no.8 | 94.72% | 85.02% | 91.56% |

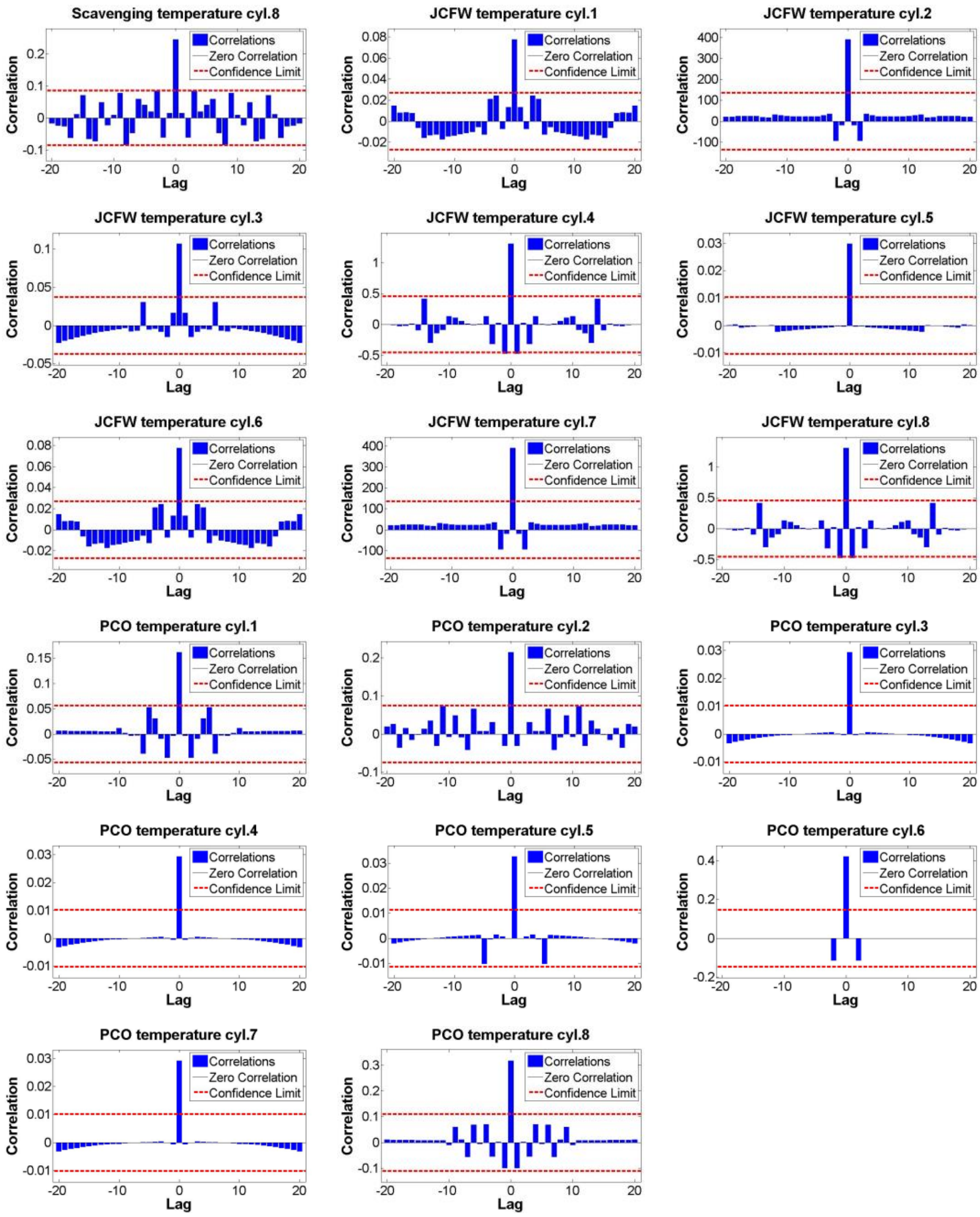
### *F.1.2 APE and MAPE forecast results for main engine parameters*

| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | MAPE |
|---|---|---|---|---|---|---|---|
| Cylinder Exhaust Gas | Actual | 263 | 260 | 262 | 262 | 263 | |
| Temperature no.1 | ANN Prediction | 262.2 | 262.4 | 262.4 | 262.4 | 262.4 | |
| | APE | **0.30%** | **0.92%** | **0.15%** | **0.15%** | **0.23%** | **0.35%** |
| Cylinder Exhaust Gas | Actual | 232 | 232 | 232 | 233 | 232 | |
| Temperature no.2 | ANN Prediction | 232.1 | 231.9 | 231.8 | 231.8 | 231.7 | |
| | APE | **0.04%** | **0.04%** | **0.09%** | **0.52%** | **0.13%** | **0.16%** |
| Cylinder Exhaust Gas | Actual | 265 | 264 | 264 | 265 | 262 | |
| Temperature no.3 | ANN Prediction | 264.4 | 264.7 | 264.5 | 264.5 | 264.5 | |
| | APE | **0.23%** | **0.27%** | **0.19%** | **0.19%** | **0.95%** | **0.36%** |
| Cylinder Exhaust Gas | Actual | 246 | 245 | 246 | 246 | 247 | |
| Temperature no.4 | ANN Prediction | 245.6 | 245.3 | 245.1 | 244.9 | 244.8 | |
| | APE | **0.16%** | **0.12%** | **0.37%** | **0.45%** | **0.89%** | **0.40%** |
| Cylinder Exhaust Gas | Actual | 237 | 237 | 235 | 236 | 238 | |
| Temperature no.5 | ANN Prediction | 238.3 | 238 | 237.8 | 237.7 | 237.7 | |
| | APE | **0.55%** | **0.42%** | **1.19%** | **0.72%** | **0.13%** | **0.60%** |
| Cylinder Exhaust Gas | Actual | 250 | 249 | 251 | 250 | 251 | |
| Temperature no.6 | ANN Prediction | 251.2 | 250.7 | 250.5 | 250.4 | 250.4 | |
| | APE | **0.48%** | **0.68%** | **0.20%** | **0.16%** | **0.24%** | **0.35%** |
| Main Lube Oil | Actual | 2.8 | 2.8 | 2.8 | 2.8 | 2.8 | |
| Pressure | ANN Prediction | 2.8 | 2.8 | 2.8 | 2.8 | 2.8 | |
| | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** |
| Main Lube Oil | Actual | 45 | 45 | 45 | 45 | 45 | |
| Temperature | ANN Prediction | 45 | 45 | 45 | 45 | 45 | |
| | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** |
| Thrust Bearing | Actual | 46.8 | 46.8 | 46.7 | 46.8 | 46.8 | |
| Temperature | ANN Prediction | 46.8 | 46.8 | 46.8 | 46.8 | 46.8 | |
| | APE | **0.01%** | **0.01%** | **0.20%** | **0.02%** | **0.02%** | **0.05%** |
| Piston Cooling Oil | Actual | 2.7 | 2.7 | 2.7 | 2.7 | 2.7 | |
| Inlet Pressure | ANN Prediction | 2.7 | 2.7 | 2.7 | 2.7 | 2.7 | |
| | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** |
| Air Cooler Cooling | Actual | 3.1 | 3.2 | 3.1 | 3.1 | 3.1 | |
| Water Inlet Pressure | ANN Prediction | 3.1 | 3.1 | 3.1 | 3.1 | 3.1 | |
| | APE | **0.00%** | **2.82%** | **0.00%** | **0.00%** | **0.00%** | **0.56%** |
| Cylinder Scavenging | Actual | 47 | 47 | 48 | 48 | 47 | |
| Air Temperature Inlet | ANN Prediction | 47.4 | 47.2 | 47.5 | 47.5 | 47.5 | |
| no.1 | APE | **0.77%** | **0.43%** | **1.11%** | **1.08%** | **1.02%** | **0.88%** |
| Cylinder Scavenging | Actual | 48 | 48 | 48 | 48 | 48 | |
| Air Temperature Inlet | ANN Prediction | 48.0 | 48.0 | 48.0 | 48.0 | 48.0 | |
| no.2 | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** |
| Cylinder Scavenging | Actual | 46 | 46 | 46 | 46 | 46 | |
| Air Temperature Inlet | ANN Prediction | 45.4 | 45.7 | 46 | 45.1 | 45.5 | |
| no.3 | APE | **1.30%** | **0.65%** | **0.00%** | **1.96%** | **1.09%** | **1.00%** |
| Cylinder Scavenging | Actual | 48 | 48 | 48 | 48 | 48 | |
| Air Temperature Inlet | ANN Prediction | 48.2 | 48.2 | 48 | 48.1 | 48 | |
| no.4 | APE | **0.42%** | **0.42%** | **0.00%** | **0.21%** | **0.00%** | **0.21%** |
| Cylinder Scavenging | Actual | 52 | 52 | 53 | 52 | 52 | |
| Air Temperature Inlet | ANN Prediction | 52.1 | 52.1 | 52.1 | 52.1 | 52.1 | |
| no.5 | APE | **0.26%** | **0.26%** | **1.64%** | **0.25%** | **0.25%** | **0.53%** |

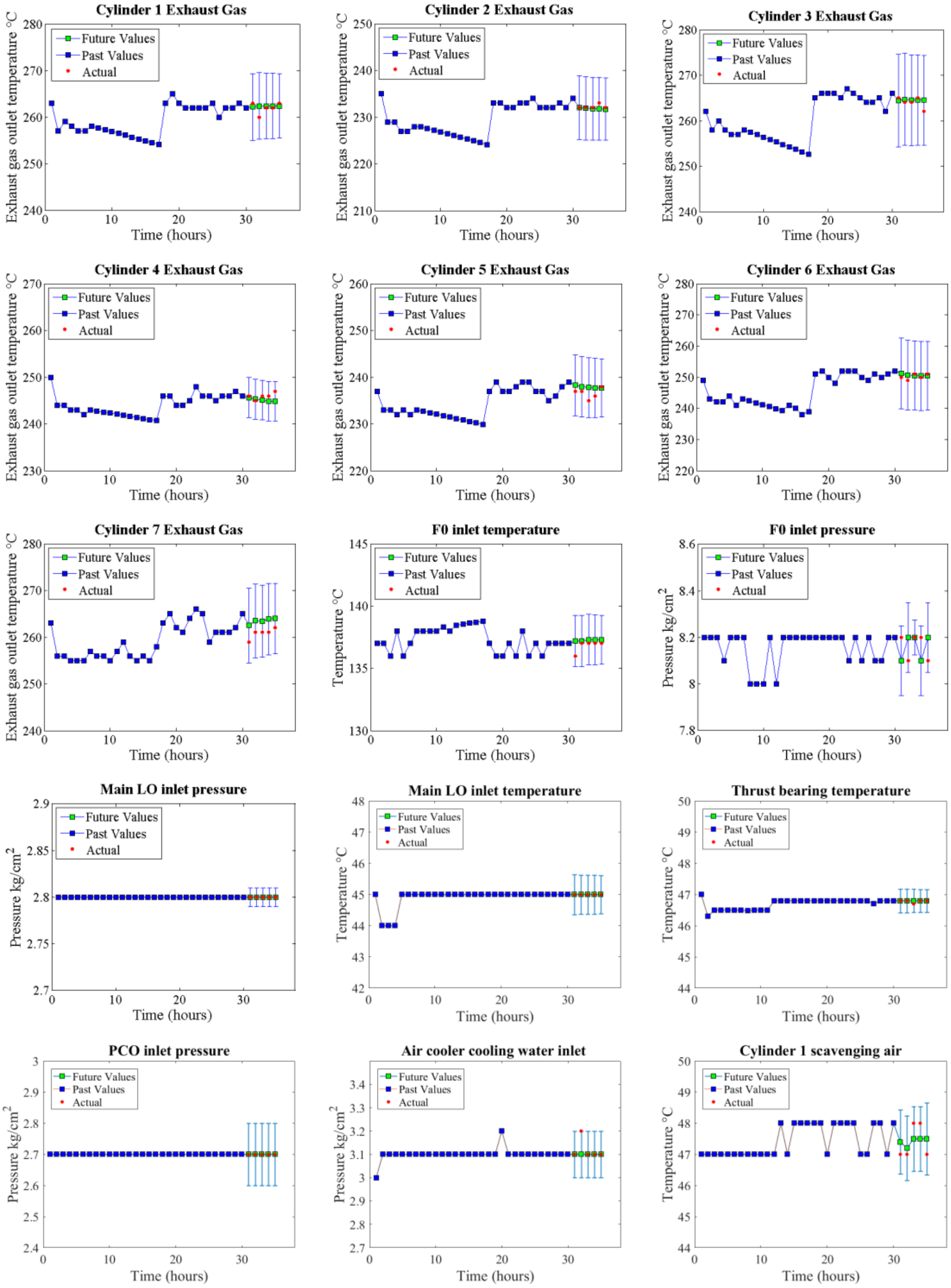
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | MAPE |
|---|---|---|---|---|---|---|---|
| Cylinder Scavenging | Actual | 51 | 51 | 51 | 52 | 51 | |
| Air Temperature Inlet | ANN Prediction | 51.1 | 51.1 | 51.1 | 51.7 | 51.4 | |
| no.6 | APE | **0.28%** | **0.28%** | **0.28%** | **0.58%** | **0.78%** | **0.44%** |
| Cylinder Scavenging | Actual | 52 | 52 | 52 | 52 | 52 | |
| Air Temperature Inlet | ANN Prediction | 52 | 51.7 | 52 | 52.1 | 52 | |
| no.7 | APE | **0.00%** | **0.58%** | **0.00%** | **0.19%** | **0.00%** | **0.15%** |
| Cylinder Scavenging | Actual | 53 | 53 | 53 | 53 | 53 | |
| Air Temperature Inlet | ANN Prediction | 52.5 | 52.9 | 53 | 52.9 | 53 | |
| no.8 | APE | **0.94%** | **0.19%** | **0.00%** | **0.19%** | **0.00%** | **0.26%** |
| Cylinder CFW Outlet | Actual | 83 | 83 | 83 | 83 | 83 | |
| Temperature no.1 | ANN Prediction | 83.4 | 83.3 | 83 | 83.1 | 83 | |
| | APE | **0.48%** | **0.36%** | **0.00%** | **0.12%** | **0.00%** | **0.19%** |
| Cylinder CFW Outlet | Actual | 84 | 83 | 83 | 84 | 83 | |
| Temperature no.2 | ANN Prediction | 83.4 | 83.3 | 83 | 83.7 | 83.2 | |
| | APE | **0.71%** | **0.36%** | **0.00%** | **0.40%** | **0.24%** | **0.34%** |
| Cylinder CFW Outlet | Actual | 84 | 84 | 83 | 84 | 84 | |
| Temperature no.3 | ANN Prediction | 83.9 | 83.9 | 83.6 | 83.8 | 83.9 | |
| | APE | **0.17%** | **0.17%** | **0.72%** | **0.24%** | **0.17%** | **0.29%** |
| Cylinder CFW Outlet | Actual | 83 | 83 | 83 | 83 | 83 | |
| Temperature no.4 | ANN Prediction | 83.1 | 83.2 | 83.3 | 83.2 | 83.0 | |
| | APE | **0.17%** | **0.28%** | **0.32%** | **0.24%** | **0.00%** | **0.20%** |
| Cylinder CFW Outlet | Actual | 83 | 83 | 83 | 83 | 83 | |
| Temperature no.5 | ANN Prediction | 83 | 83 | 83.2 | 83 | 82.9 | |
| | APE | **0.00%** | **0.00%** | **0.24%** | **0.00%** | **0.12%** | **0.07%** |
| Cylinder CFW Outlet | Actual | 83 | 83 | 83 | 83 | 83 | |
| Temperature no.6 | ANN Prediction | 83.1 | 83.2 | 83.2 | 83.1 | 83.1 | |
| | APE | **0.16%** | **0.19%** | **0.18%** | **0.18%** | **0.18%** | **0.18%** |
| Cylinder CFW Outlet | Actual | 84 | 84 | 84 | 84 | 84 | |
| Temperature no.7 | ANN Prediction | 83.7 | 84.2 | 84 | 84.1 | 84.1 | |
| | APE | **0.36%** | **0.24%** | **0.00%** | **0.12%** | **0.12%** | **0.17%** |
| Cylinder CFW Outlet | Actual | 75 | 75 | 75 | 75 | 75 | |
| Temperature no.8 | ANN Prediction | 75 | 75 | 75.1 | 74.8 | 75 | |
| | APE | **0.00%** | **0.00%** | **0.13%** | **0.27%** | **0.00%** | **0.08%** |
| Cylinder PCO Outlet | Actual | 50 | 49 | 49 | 49 | 49 | |
| Temperature no.1 | ANN Prediction | 49.7 | 49.2 | 49.2 | 49.0 | 49.1 | |
| | APE | **0.60%** | **0.34%** | **0.37%** | **0.00%** | **0.20%** | **0.30%** |
| Cylinder PCO Outlet | Actual | 50 | 50 | 50 | 49 | 50 | |
| Temperature no.2 | ANN Prediction | 50.3 | 50.1 | 49.8 | 49.2 | 49.9 | |
| | APE | **0.60%** | **0.20%** | **0.40%** | **0.41%** | **0.20%** | **0.36%** |
| Cylinder PCO Outlet | Actual | 49 | 49 | 49 | 49 | 49 | |
| Temperature no.3 | ANN Prediction | 49.00 | 48.99 | 48.99 | 48.99 | 48.98 | |
| | APE | **0.01%** | **0.01%** | **0.02%** | **0.03%** | **0.04%** | **0.02%** |
| Cylinder PCO Outlet | Actual | 49 | 49 | 49 | 49 | 49 | |
| Temperature no.4 | ANN Prediction | 49.0 | 49.0 | 49.0 | 49.0 | 49.0 | |
| | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** |
| Cylinder PCO Outlet | Actual | 51 | 51 | 51 | 51 | 51 | |
| Temperature no.5 | ANN Prediction | 51.0 | 51.0 | 51.0 | 51.0 | 51.0 | |
| | APE | **0.01%** | **0.01%** | **0.01%** | **0.01%** | **0.01%** | **0.01%** |
| Cylinder PCO Outlet | Actual | 50 | 50 | 50 | 50 | 50 | |
| Temperature no.6 | ANN Prediction | 50 | 50 | 50 | 50 | 50 | |
| | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** |
| Cylinder PCO Outlet | Actual | 51 | 51 | 51 | 51 | 51 | |
| Temperature no.7 | ANN Prediction | 51.04 | 51.04 | 51.04 | 51.04 | 51.04 | |
| | APE | **0.07%** | **0.07%** | **0.08%** | **0.08%** | **0.08%** | **0.08%** |
| Cylinder PCO Outlet | Actual | 51 | 51 | 50 | 50 | 51 | |
| Temperature no.8 | ANN Prediction | 50.95 | 50.56 | 50.06 | 50.39 | 50.85 | |
| | APE | **0.10%** | **0.86%** | **0.12%** | **0.78%** | **0.29%** | **0.43%** |

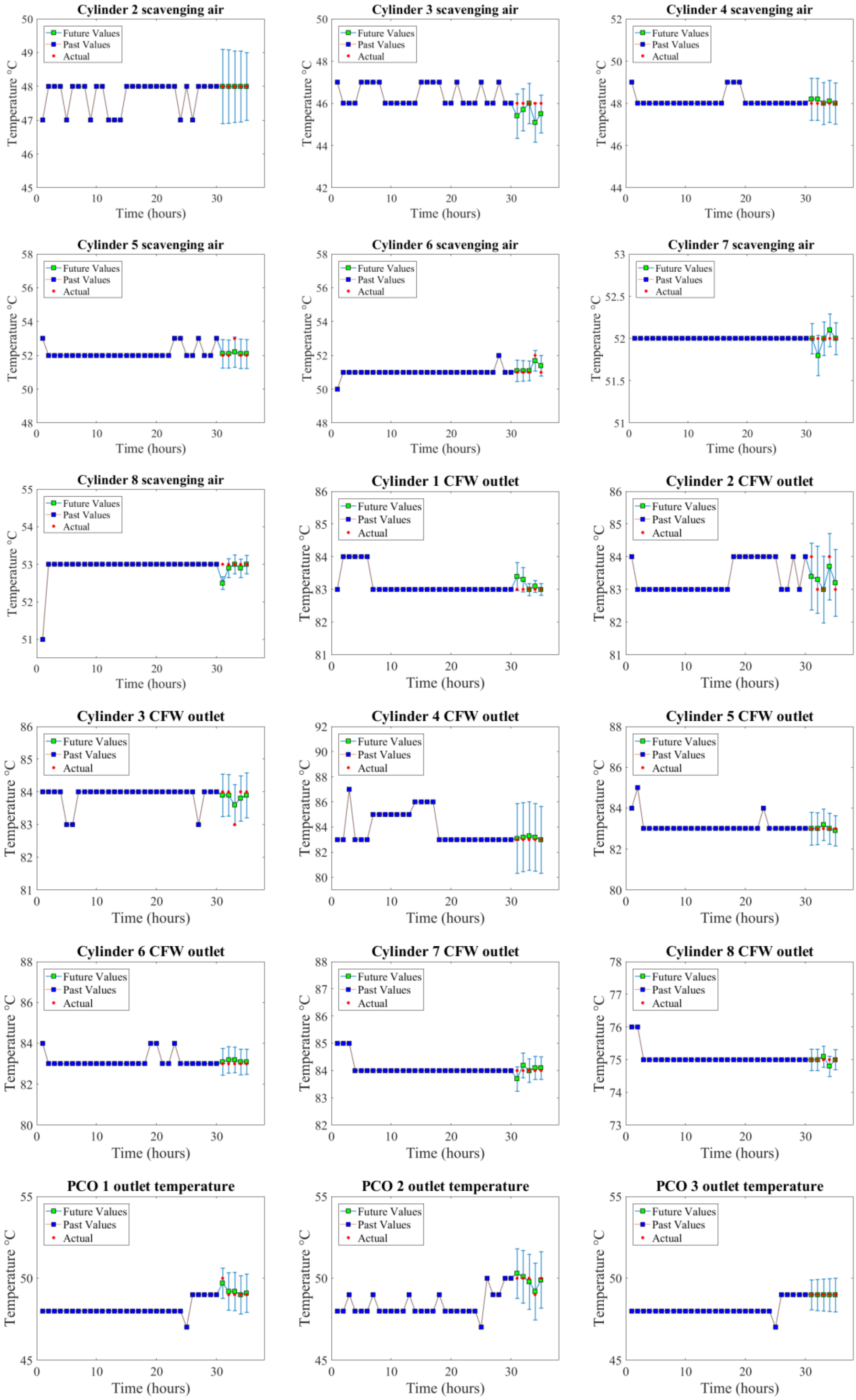
### *F.1.3 Main engine performance parameters autocorrelation graphs*

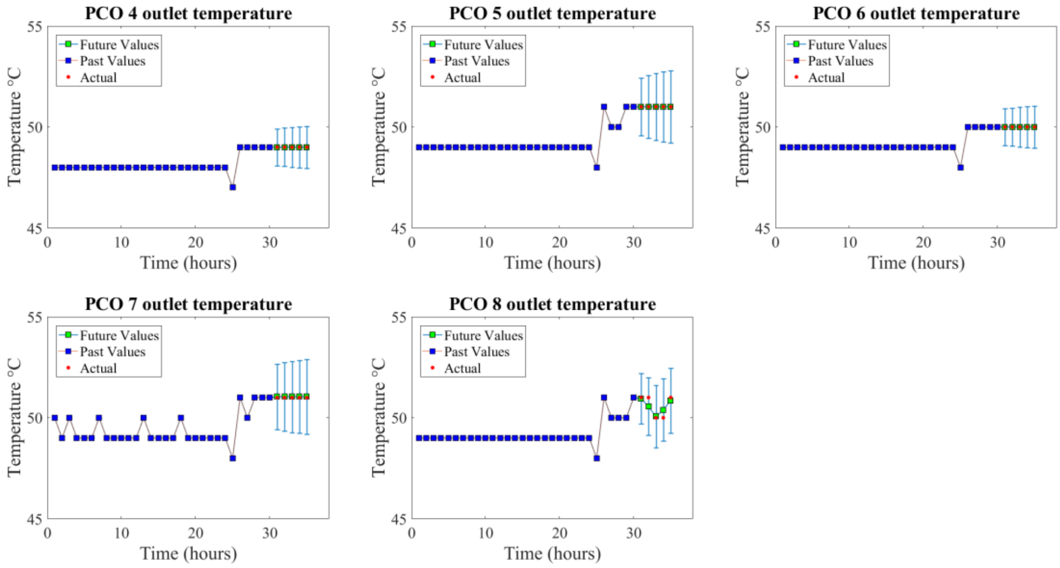



Scavenging temperature cyl.8
JCFW temperature cyl.1
JCFW temperature cyl.2
JCFW temperature cyl.3
JCFW temperature cyl.4
JCFW temperature cyl.5
JCFW temperature cyl.6
JCFW temperature cyl.7
JCFW temperature cyl.8
PCO temperature cyl.1
PCO temperature cyl.2
PCO temperature cyl.3
PCO temperature cyl.4
PCO temperature cyl.5
PCO temperature cyl.6
PCO temperature cyl.7
PCO temperature cyl.8
Correlations
Zero Correlation
Confidence Limit
Correlation
Lag

### *F.1.4: Forecasting results with 95% prediction intervals*




Cylinder 2 scavenging air
Cylinder 3 scavenging air
Cylinder 4 scavenging air
Cylinder 5 scavenging air
Cylinder 6 scavenging air
Cylinder 7 scavenging air
Cylinder 8 scavenging air
Cylinder 1 CFW outlet
Cylinder 2 CFW outlet
Cylinder 3 CFW outlet
Cylinder 4 CFW outlet
Cylinder 5 CFW outlet
Cylinder 6 CFW outlet
Cylinder 7 CFW outlet
Cylinder 8 CFW outlet
PCO 1 outlet temperature
PCO 2 outlet temperature
PCO 3 outlet temperature
Future Values
Past Values
Actual
Temperature °C
Time (hours)


PCO 4 outlet temperature
PCO 5 outlet temperature
PCO 6 outlet temperature
PCO 7 outlet temperature
PCO 8 outlet temperature
Future Values
Past Values
Actual
Temperature °C
Time (hours)
55
50
45
0
10
20
30

## F.2 NAR results dataset 2

### F.2.1 NAR regression results

| Parameter | Training | Test | All |
|---|---|---|---|
| Cylinder Exhaust Gas Temperature no.1 | 99.34% | 98.43% | 99.13% |
| Cylinder Exhaust Gas Temperature no.2 | 99.22% | 98.30% | 99.02% |
| Cylinder Exhaust Gas Temperature no.3 | 99.34% | 98.49% | 99.16% |
| Cylinder Exhaust Gas Temperature no.4 | 99.69% | 99.45% | 99.63% |
| Cylinder Exhaust Gas Temperature no.5 | 97.71% | 95.93% | 97.31% |
| Cylinder Exhaust Gas Temperature no.6 | 99.78% | 99.53% | 99.67% |
| Cylinder Exhaust Gas Temperature no.7 | 98.93% | 97.88% | 98.69% |
| Cylinder Exhaust Gas Temperature no.8 | 99.01% | 97.89% | 98.75% |
| Fuel Oil Inlet Temperature | 99.56% | 99.00% | 99.46% |
| Fuel Oil Inlet Pressure | 98.02% | 96.54% | 97.69% |
| Main Lube Oil Pressure | 98.89% | 98.45% | 98.77% |
| Main Lube Oil Temperature | 97.19% | 94.13% | 96.41% |
| Thrust Bearing Temperature | 95.79% | 92.55% | 95.18% |
| Piston Cooling Oil Inlet Pressure | 90.79% | 89.72% | 90.74% |
| Air Cooler Cooling Water Inlet Pressure | 96.40% | 92.29% | 95.37% |
| Cylinder Scavenging Air Temperature Inlet no.1 | 96.91% | 92.13% | 94.24% |
| Cylinder Scavenging Air Temperature Inlet no.2 | 98.42% | 91.98% | 96.92% |
| Cylinder Scavenging Air Temperature Inlet no.3 | 98.80% | 92.14% | 97.20% |
| Cylinder Scavenging Air Temperature Inlet no.4 | 97.81% | 89.98% | 95.11% |
| Cylinder Scavenging Air Temperature Inlet no.5 | 98.43% | 94.32% | 96.78% |
| Cylinder Scavenging Air Temperature Inlet no.6 | 95.87% | 89.44% | 93.38% |
| Cylinder Scavenging Air Temperature Inlet no.7 | 96.46% | 93.17% | 95.92% |
| Cylinder Scavenging Air Temperature Inlet no.8 | 98.16% | 92.04% | 96.97% |
| Cylinder CFW Outlet Temperature no.1 | 99.05% | 98.93% | 98.97% |
| Cylinder CFW Outlet Temperature no.2 | 98.10% | 93.91% | 97.67% |
| Cylinder CFW Outlet Temperature no.3 | 99.29% | 96.67% | 99.03% |
| Cylinder CFW Outlet Temperature no.4 | 88.17% | 87.00% | 87.94% |
| Cylinder CFW Outlet Temperature no.5 | 89.38% | 86.72% | 87.65% |
| Cylinder CFW Outlet Temperature no.6 | 98.85% | 97.50% | 98.31% |
| Cylinder CFW Outlet Temperature no.7 | 89.67% | 87.40% | 89.04% |
| Cylinder CFW Outlet Temperature no.8 | 98.38% | 92.71% | 97.90% |
| Cylinder PCO Outlet Temperature no.1 | 99.45% | 99.28% | 99.39% |
| Cylinder PCO Outlet Temperature no.2 | 97.65% | 95.33% | 97.20% |
| Cylinder PCO Outlet Temperature no.3 | 98.81% | 98.45% | 98.74% |
| Cylinder PCO Outlet Temperature no.4 | 98.78% | 96.83% | 98.38% |
| Cylinder PCO Outlet Temperature no.5 | 99.39% | 93.05% | 98.11% |
| Cylinder PCO Outlet Temperature no.6 | 97.63% | 94.73% | 96.98% |
| Cylinder PCO Outlet Temperature no.7 | 98.22% | 94.47% | 97.46% |
| Cylinder PCO Outlet Temperature no.8 | 98.91% | 95.27% | 98.18% |

## F.2.2 APE and MAPE forecast results for main engine parameters

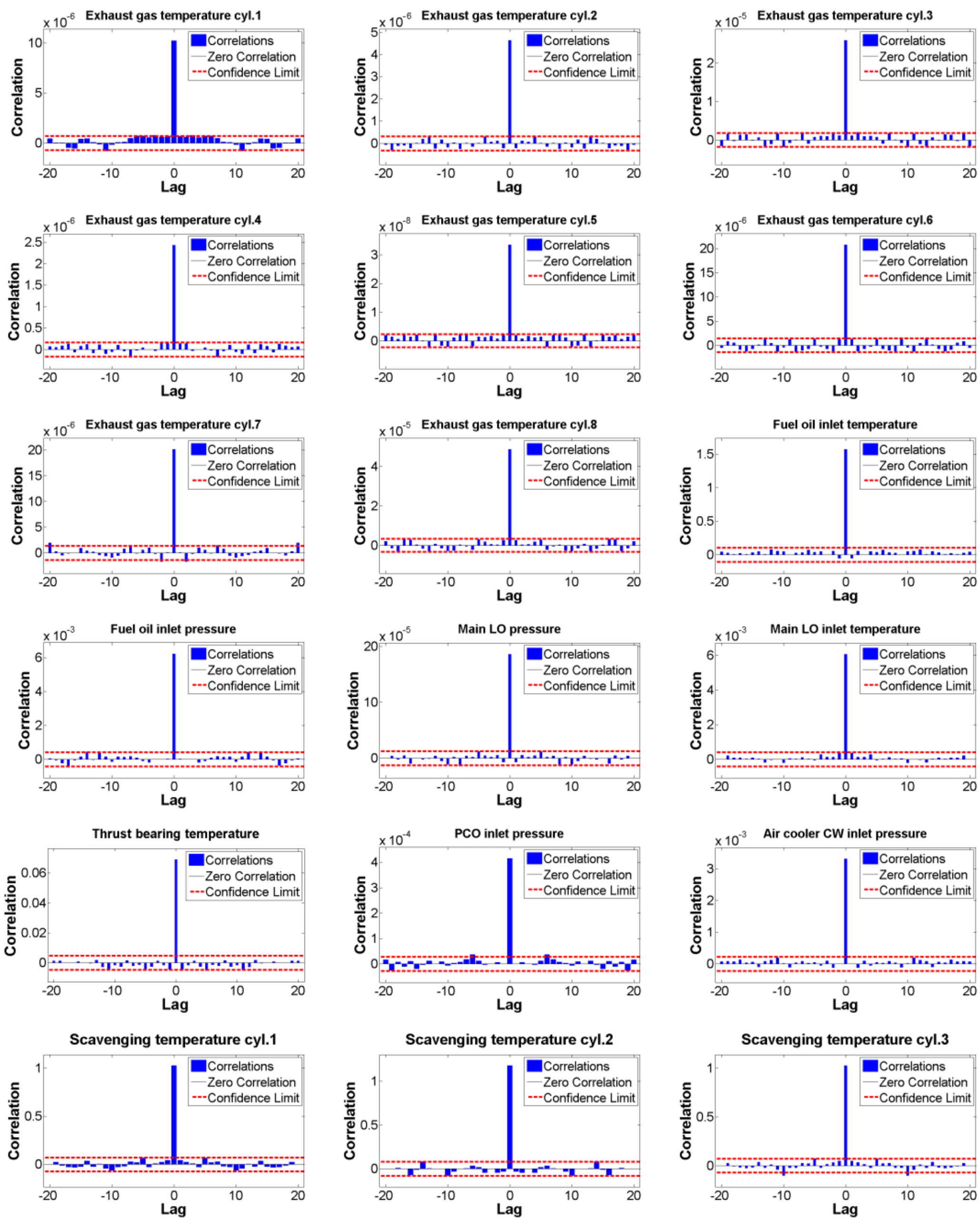
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder Exhaust Gas Temperature no.1 | Actual | 300.70 | 300.00 | 296.60 | 295.60 | 297.80 | 298.90 | 263.60 | 217.90 | 261.00 | 256.30 | 256.10 | 253.30 | 187.90 | 266.10 | 263.00 | 259.50 | 261.10 | 258.70 | 258.00 | 229.90 | |
| | ANN Prediction | 299.00 | 300.00 | 296.59 | 295.00 | 297.00 | 298.83 | 278.44 | 271.74 | 260.50 | 255.85 | 256.00 | 253.69 | 235.77 | 267.00 | 264.82 | 263.94 | 264.60 | 261.00 | 260.00 | 234.00 | |
| | APE | **0.57%** | **0.00%** | **0.00%** | **0.20%** | **0.27%** | **0.02%** | **5.63%** | **24.71%** | **0.19%** | **0.18%** | **0.04%** | **0.15%** | **25.48%** | **0.34%** | **0.69%** | **1.71%** | **1.34%** | **0.89%** | **0.78%** | **1.78%** | **3.25%** |
| Cylinder Exhaust Gas Temperature no.2 | Actual | 290.10 | 290.60 | 293.90 | 293.00 | 292.00 | 294.40 | 247.50 | 216.40 | 261.90 | 257.70 | 255.80 | 255.40 | 190.00 | 260.80 | 259.70 | 256.50 | 258.20 | 255.00 | 254.60 | 224.80 | |
| | ANN Prediction | 289.82 | 290.00 | 292.00 | 292.10 | 292.10 | 293.00 | 264.50 | 259.20 | 256.92 | 257.20 | 256.00 | 255.00 | 239.47 | 249.17 | 266.58 | 266.29 | 265.00 | 263.41 | 263.17 | 260.55 | |
| | APE | **0.10%** | **0.21%** | **0.65%** | **0.31%** | **0.03%** | **0.48%** | **6.87%** | **19.78%** | **1.90%** | **0.19%** | **0.08%** | **0.16%** | **26.04%** | **4.46%** | **2.65%** | **3.82%** | **2.63%** | **3.30%** | **3.37%** | **15.90%** | **4.65%** |
| Cylinder Exhaust Gas Temperature no.3 | Actual | 318.30 | 317.10 | 318.80 | 316.90 | 315.20 | 317.60 | 289.90 | 225.20 | 272.80 | 269.50 | 264.40 | 265.40 | 192.80 | 269.10 | 268.20 | 264.30 | 264.00 | 265.80 | 263.90 | 238.10 | |
| | ANN Prediction | 318.00 | 317.00 | 317.00 | 316.00 | 315.30 | 317.79 | 249.26 | 245.30 | 272.89 | 269.29 | 264.16 | 265.98 | 249.98 | 266.95 | 265.99 | 258.08 | 256.91 | 252.15 | 254.43 | 249.75 | |
| | APE | **0.09%** | **0.03%** | **0.56%** | **0.28%** | **0.03%** | **0.06%** | **14.02%** | **8.93%** | **0.03%** | **0.08%** | **0.09%** | **0.22%** | **29.66%** | **0.80%** | **0.82%** | **2.36%** | **2.69%** | **5.14%** | **3.59%** | **4.89%** | **3.72%** |
| Cylinder Exhaust Gas Temperature no.4 | Actual | 317.10 | 316.90 | 314.50 | 314.10 | 315.50 | 319.30 | 248.80 | 234.10 | 276.60 | 274.20 | 271.10 | 270.70 | 188.50 | 278.50 | 273.40 | 272.60 | 271.60 | 271.50 | 272.20 | 242.20 | |
| | ANN Prediction | 316.89 | 315.01 | 316.41 | 312.94 | 314.92 | 317.61 | 294.80 | 284.13 | 281.76 | 271.90 | 273.86 | 267.23 | 252.50 | 293.67 | 286.24 | 283.91 | 283.80 | 281.00 | 281.50 | 268.20 | |
| | APE | **0.07%** | **0.60%** | **0.61%** | **0.37%** | **0.18%** | **0.53%** | **18.49%** | **21.37%** | **1.87%** | **0.84%** | **1.02%** | **1.28%** | **33.95%** | **5.45%** | **4.70%** | **4.15%** | **4.49%** | **3.50%** | **3.42%** | **10.73%** | **5.88%** |
| Cylinder Exhaust Gas Temperature no.5 | Actual | 308.10 | 308.30 | 307.50 | 308.40 | 307.80 | 308.30 | 221.60 | 238.10 | 279.80 | 276.20 | 275.00 | 274.10 | 196.70 | 282.10 | 281.00 | 278.70 | 276.00 | 277.20 | 274.20 | 249.20 | |
| | ANN Prediction | 307.50 | 308.30 | 307.50 | 308.40 | 307.80 | 307.30 | 282.00 | 278.50 | 279.00 | 275.10 | 275.20 | 273.90 | 271.65 | 282.00 | 282.30 | 280.13 | 279.13 | 279.04 | 278.41 | 261.32 | |
| | APE | **0.19%** | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.32%** | **27.26%** | **16.97%** | **0.29%** | **0.40%** | **0.07%** | **0.07%** | **38.10%** | **0.04%** | **0.46%** | **0.51%** | **1.13%** | **0.66%** | **1.54%** | **4.86%** | **4.64%** |
| Cylinder Exhaust Gas Temperature no.6 | Actual | 269.80 | 271.00 | 268.80 | 268.90 | 271.20 | 271.80 | 256.50 | 214.20 | 251.80 | 246.60 | 246.00 | 245.40 | 177.60 | 251.00 | 251.00 | 248.80 | 248.60 | 247.80 | 247.10 | 222.80 | |
| | ANN Prediction | 270.27 | 268.35 | 268.41 | 268.00 | 270.32 | 269.94 | 258.91 | 243.65 | 249.94 | 246.20 | 244.55 | 244.80 | 237.01 | 239.00 | 241.14 | 249.24 | 242.57 | 243.25 | 244.28 | 236.52 | |
| | APE | **0.17%** | **0.98%** | **0.15%** | **0.33%** | **0.32%** | **0.68%** | **0.94%** | **13.75%** | **0.74%** | **0.16%** | **0.59%** | **0.24%** | **33.45%** | **4.78%** | **3.93%** | **0.18%** | **2.43%** | **1.84%** | **1.14%** | **6.16%** | **3.65%** |
| Cylinder Exhaust Gas Temperature no.7 | Actual | 317.20 | 320.60 | 308.80 | 306.00 | 313.30 | 311.70 | 264.70 | 227.10 | 277.30 | 271.70 | 269.10 | 268.50 | 188.10 | 277.10 | 274.20 | 271.50 | 274.30 | 274.60 | 273.50 | 237.70 | |
| | ANN Prediction | 316.78 | 320.10 | 308.60 | 306.00 | 313.00 | 310.00 | 295.00 | 286.22 | 276.00 | 270.30 | 267.10 | 268.10 | 267.34 | 272.87 | 271.13 | 271.00 | 272.13 | 276.04 | 274.96 | 258.74 | |
| | APE | **0.13%** | **0.16%** | **0.06%** | **0.00%** | **0.10%** | **0.55%** | **11.45%** | **26.03%** | **0.47%** | **0.52%** | **0.74%** | **0.15%** | **42.13%** | **1.53%** | **1.12%** | **0.18%** | **0.79%** | **0.52%** | **0.53%** | **8.85%** | **4.80%** |
| Cylinder Exhaust Gas Temperature no.8 | Actual | 301.10 | 304.70 | 299.90 | 299.00 | 300.60 | 301.10 | 271.30 | 225.50 | 273.30 | 271.30 | 271.80 | 274.10 | 187.10 | 273.50 | 272.20 | 266.60 | 270.20 | 268.50 | 266.90 | 243.50 | |
| | ANN Prediction | 300.00 | 304.60 | 299.50 | 299.00 | 300.00 | 301.00 | 294.30 | 281.51 | 276.10 | 273.00 | 272.34 | 272.50 | 268.13 | 267.52 | 270.22 | 271.69 | 270.53 | 269.99 | 270.95 | 268.59 | |
| | APE | **0.37%** | **0.03%** | **0.13%** | **0.00%** | **0.20%** | **0.03%** | **8.48%** | **24.84%** | **1.02%** | **0.63%** | **0.20%** | **0.58%** | **43.31%** | **2.19%** | **0.73%** | **1.91%** | **0.12%** | **0.56%** | **1.52%** | **10.30%** | **4.86%** |
| Fuel Oil Inlet Temperature | Actual | 136.50 | 137.60 | 138.00 | 138.20 | 136.90 | 138.80 | 137.60 | 137.30 | 137.20 | 137.50 | 137.50 | 137.80 | 137.60 | 139.40 | 139.10 | 138.90 | 138.00 | 137.70 | 136.70 | 137.60 | |
| | ANN Prediction | 137.31 | 137.25 | 137.34 | 137.02 | 137.24 | 137.62 | 137.32 | 137.31 | 137.42 | 137.72 | 137.76 | 137.76 | 137.60 | 137.43 | 137.61 | 137.67 | 137.74 | 137.74 | 137.63 | 137.60 | |
| | APE | **0.59%** | **0.26%** | **0.48%** | **0.85%** | **0.25%** | **0.85%** | **0.21%** | **0.01%** | **0.16%** | **0.16%** | **0.19%** | **0.03%** | **0.00%** | **1.41%** | **1.07%** | **0.88%** | **0.19%** | **0.03%** | **0.68%** | **0.00%** | **0.41%** |
| Fuel Oil Inlet Pressure | Actual | 7.45 | 7.43 | 7.40 | 7.41 | 7.42 | 7.37 | 7.70 | 7.74 | 7.66 | 7.72 | 7.71 | 7.65 | 7.72 | 7.61 | 7.62 | 7.61 | 7.60 | 7.59 | 7.59 | 7.70 | |
| | ANN Prediction | 7.45 | 7.50 | 7.52 | 7.52 | 7.52 | 7.46 | 7.59 | 7.61 | 7.57 | 7.56 | 7.57 | 7.57 | 7.61 | 7.55 | 7.57 | 7.55 | 7.56 | 7.56 | 7.56 | 7.59 | |
| | APE | **0.12%** | **0.94%** | **1.69%** | **1.56%** | **1.43%** | **1.16%** | **1.44%** | **1.65%** | **1.19%** | **2.03%** | **1.80%** | **1.05%** | **1.44%** | **0.78%** | **0.66%** | **0.74%** | **0.58%** | **0.42%** | **0.38%** | **1.44%** | **1.12%** |
| Main Lube Oil Pressure | Actual | 2.51 | 2.50 | 2.49 | 2.49 | 2.50 | 2.48 | 2.52 | 2.56 | 2.52 | 2.55 | 2.56 | 2.56 | 2.59 | 2.54 | 2.56 | 2.60 | 2.59 | 2.59 | 2.60 | 2.60 | |
| | ANN Prediction | 2.51 | 2.50 | 2.49 | 2.49 | 2.50 | 2.48 | 2.52 | 2.56 | 2.52 | 2.55 | 2.55 | 2.56 | 2.59 | 2.53 | 2.55 | 2.59 | 2.58 | 2.60 | 2.59 | 2.60 | |
| | APE | **0.10%** | **0.09%** | **0.14%** | **0.11%** | **0.17%** | **0.07%** | **0.00%** | **0.16%** | **0.07%** | **0.11%** | **0.29%** | **0.06%** | **0.00%** | **0.23%** | **0.40%** | **0.42%** | **0.42%** | **0.36%** | **0.42%** | **0.14%** | **0.19%** |

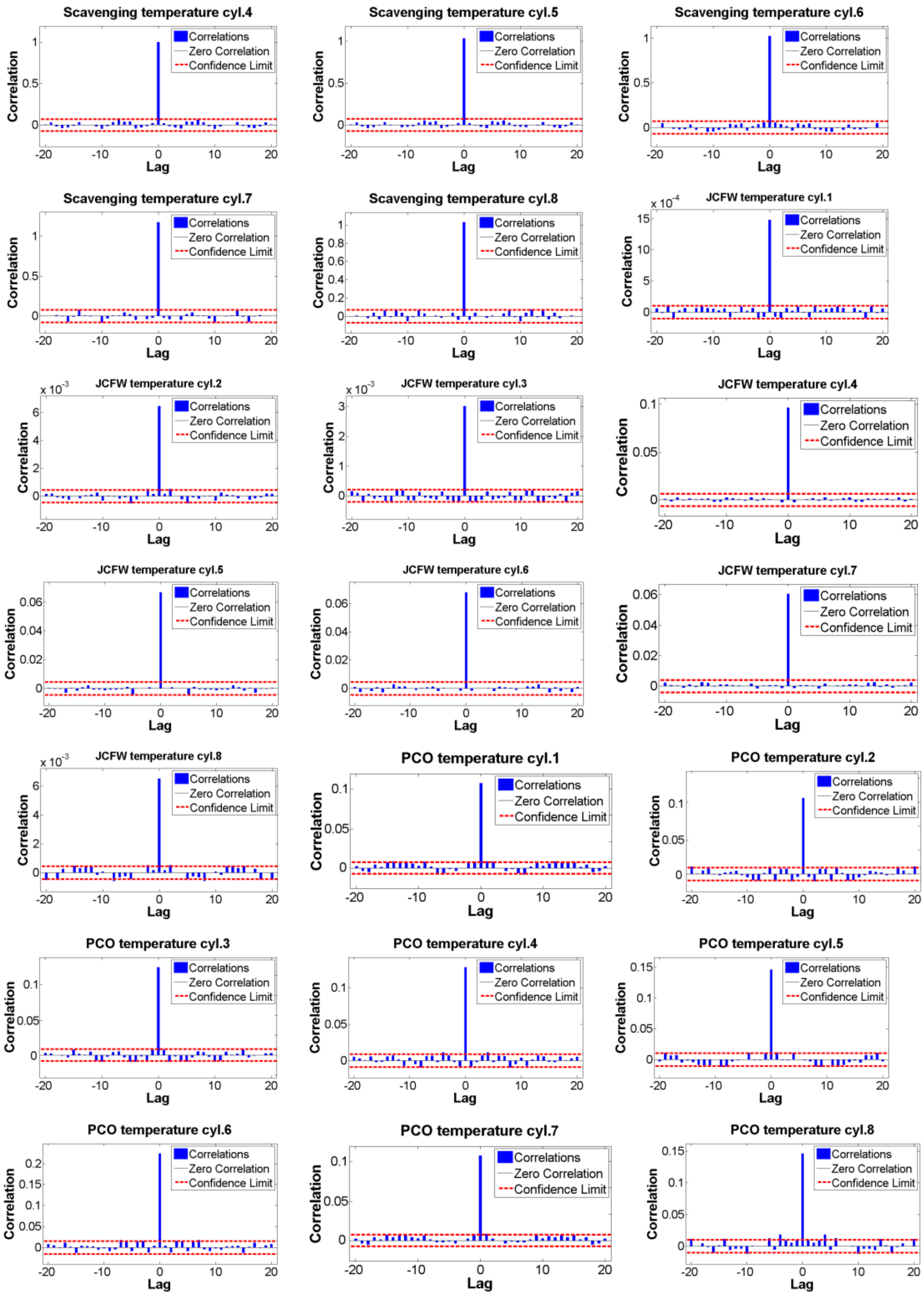
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Main Lube Oil Temperature | Actual | 45.20 | 45.30 | 45.30 | 45.30 | 45.40 | 45.30 | 45.30 | 45.10 | 45.20 | 45.30 | 45.10 | 45.30 | 45.20 | 45.30 | 45.30 | 45.30 | 45.10 | 45.10 | 45.20 | 45.20 | |
| | ANN Prediction | 45.25 | 45.27 | 45.27 | 45.28 | 45.26 | 45.25 | 45.27 | 45.26 | 45.27 | 45.25 | 45.25 | 45.25 | 45.24 | 45.25 | 45.23 | 45.25 | 45.25 | 45.25 | 45.25 | 45.25 | |
| | APE | **0.10%** | **0.07%** | **0.06%** | **0.04%** | **0.30%** | **0.11%** | **0.07%** | **0.35%** | **0.16%** | **0.10%** | **0.33%** | **0.11%** | **0.08%** | **0.12%** | **0.14%** | **0.12%** | **0.33%** | **0.34%** | **0.10%** | **0.11%** | **0.16%** |
| Thrust Bearing Temperature | Actual | 50.30 | 50.50 | 50.70 | 50.70 | 50.60 | 50.90 | 48.40 | 47.40 | 49.00 | 48.80 | 48.70 | 48.70 | 47.50 | 49.40 | 49.20 | 49.20 | 49.10 | 49.10 | 49.10 | 48.30 | |
| | ANN Prediction | 50.10 | 50.35 | 50.60 | 50.70 | 50.60 | 50.60 | 48.00 | 47.30 | 48.91 | 48.70 | 48.60 | 48.69 | 47.39 | 49.00 | 49.20 | 49.10 | 49.20 | 49.11 | 49.10 | 49.00 | |
| | APE | **0.40%** | **0.30%** | **0.20%** | **0.00%** | **0.00%** | **0.59%** | **0.83%** | **0.21%** | **0.18%** | **0.20%** | **0.21%** | **0.02%** | **0.23%** | **0.81%** | **0.00%** | **0.20%** | **0.20%** | **0.02%** | **0.00%** | **1.45%** | **0.30%** |
| Piston Cooling Oil Inlet Pressure | Actual | 2.48 | 2.47 | 2.46 | 2.46 | 2.46 | 2.45 | 2.49 | 2.54 | 2.48 | 2.52 | 2.53 | 2.52 | 2.55 | 2.51 | 2.52 | 2.56 | 2.55 | 2.58 | 2.58 | 2.57 | |
| | ANN Prediction | 2.46 | 2.46 | 2.46 | 2.45 | 2.45 | 2.44 | 2.48 | 2.54 | 2.48 | 2.51 | 2.53 | 2.52 | 2.55 | 2.51 | 2.51 | 2.56 | 2.55 | 2.58 | 2.59 | 2.58 | |
| | APE | **0.75%** | **0.34%** | **0.07%** | **0.33%** | **0.33%** | **0.33%** | **0.35%** | **0.01%** | **0.06%** | **0.37%** | **0.02%** | **0.02%** | **0.00%** | **0.03%** | **0.37%** | **0.01%** | **0.00%** | **0.00%** | **0.36%** | **0.37%** | **0.21%** |
| Air Cooler Cooling Water Inlet Pressure | Actual | 3.89 | 4.04 | 4.22 | 4.24 | 4.24 | 4.25 | 4.19 | 3.87 | 4.24 | 3.86 | 3.80 | 3.86 | 3.86 | 3.81 | 3.83 | 3.74 | 3.75 | 3.74 | 3.73 | 3.75 | |
| | ANN Prediction | 3.93 | 3.95 | 4.18 | 4.18 | 4.20 | 4.24 | 4.20 | 4.15 | 4.16 | 3.81 | 3.79 | 3.84 | 3.84 | 3.70 | 3.71 | 3.64 | 3.66 | 3.71 | 3.71 | 3.71 | |
| | APE | **1.06%** | **2.21%** | **1.01%** | **1.49%** | **1.02%** | **0.32%** | **0.19%** | **7.35%** | **1.96%** | **1.18%** | **0.38%** | **0.40%** | **0.40%** | **2.95%** | **2.90%** | **2.76%** | **2.49%** | **0.89%** | **0.73%** | **1.16%** | **1.64%** |
| Cylinder Scavenging Air Temperature Inlet n0.1 | Actual | 42.10 | 42.40 | 42.60 | 42.80 | 42.30 | 43.50 | 51.10 | 49.80 | 51.00 | 51.50 | 52.00 | 52.00 | 51.50 | 50.30 | 51.00 | 50.30 | 49.90 | 50.10 | 50.10 | 51.40 | |
| | ANN Prediction | 42.10 | 42.40 | 42.60 | 42.80 | 42.50 | 43.10 | 44.50 | 45.80 | 48.80 | 50.20 | 50.00 | 51.00 | 51.00 | 51.00 | 51.00 | 51.10 | 50.10 | 50.10 | 50.10 | 50.05 | |
| | APE | **0.00%** | **0.00%** | **0.00%** | **0.00%** | **0.47%** | **0.92%** | **12.92%** | **8.03%** | **4.31%** | **2.52%** | **3.85%** | **1.92%** | **0.97%** | **1.39%** | **0.00%** | **1.59%** | **0.40%** | **0.00%** | **0.00%** | **2.63%** | **2.10%** |
| Cylinder Scavenging Air Temperature Inlet n0.2 | Actual | 41.00 | 41.50 | 41.70 | 41.80 | 41.00 | 42.40 | 49.00 | 48.70 | 50.00 | 50.00 | 51.00 | 51.00 | 50.00 | 49.60 | 51.00 | 49.50 | 49.00 | 49.10 | 49.50 | 50.10 | |
| | ANN Prediction | 41.10 | 41.30 | 41.70 | 41.50 | 41.50 | 42.40 | 42.98 | 43.50 | 47.80 | 50.10 | 49.00 | 50.00 | 51.00 | 50.00 | 50.00 | 49.50 | 50.00 | 50.00 | 50.10 | 50.10 | |
| | APE | **0.24%** | **0.48%** | **0.00%** | **0.72%** | **1.22%** | **0.00%** | **12.29%** | **10.68%** | **4.40%** | **0.20%** | **3.92%** | **1.96%** | **2.00%** | **0.81%** | **1.96%** | **0.00%** | **2.04%** | **1.83%** | **1.21%** | **0.00%** | **2.30%** |
| Cylinder Scavenging Air Temperature Inlet n0.3 | Actual | 43.22 | 43.50 | 43.74 | 43.92 | 43.00 | 44.10 | 52.50 | 51.00 | 52.12 | 52.61 | 53.00 | 53.50 | 52.60 | 51.50 | 52.12 | 51.30 | 51.02 | 51.16 | 52.00 | 52.50 | |
| | ANN Prediction | 43.20 | 43.50 | 43.70 | 43.50 | 42.90 | 44.00 | 44.35 | 44.98 | 44.90 | 48.00 | 48.00 | 51.24 | 52.00 | 51.00 | 51.00 | 50.70 | 50.94 | 51.10 | 51.00 | 51.59 | |
| | APE | **0.05%** | **0.00%** | **0.09%** | **0.96%** | **0.23%** | **0.23%** | **15.52%** | **11.80%** | **13.85%** | **8.76%** | **9.43%** | **4.22%** | **1.14%** | **0.97%** | **2.15%** | **1.17%** | **0.16%** | **0.12%** | **1.92%** | **1.73%** | **3.73%** |
| Cylinder Scavenging Air Temperature Inlet n0.4 | Actual | 43.00 | 42.50 | 42.70 | 42.90 | 42.00 | 43.50 | 50.30 | 49.90 | 51.10 | 51.60 | 51.90 | 52.30 | 51.60 | 50.10 | 51.00 | 50.50 | 50.00 | 50.60 | 51.00 | 51.50 | |
| | ANN Prediction | 43.00 | 43.00 | 43.10 | 43.01 | 42.00 | 43.00 | 43.50 | 42.17 | 45.65 | 51.50 | 46.76 | 49.50 | 52.00 | 50.60 | 51.00 | 51.00 | 50.50 | 50.50 | 51.00 | 50.50 | |
| | APE | **0.00%** | **1.18%** | **0.94%** | **0.26%** | **0.00%** | **1.15%** | **13.52%** | **15.49%** | **10.67%** | **0.19%** | **9.90%** | **5.35%** | **0.78%** | **1.00%** | **0.00%** | **0.99%** | **1.00%** | **0.20%** | **0.00%** | **1.94%** | **3.23%** |
| Cylinder Scavenging Air Temperature Inlet n0.5 | Actual | 42.60 | 42.90 | 43.10 | 43.30 | 42.80 | 44.00 | 51.60 | 50.30 | 51.50 | 52.00 | 52.50 | 52.50 | 52.00 | 50.80 | 51.50 | 50.80 | 50.40 | 50.60 | 50.60 | 51.90 | |
| | ANN Prediction | 42.30 | 42.50 | 43.00 | 43.10 | 42.50 | 44.00 | 44.50 | 42.50 | 46.50 | 49.90 | 51.50 | 49.45 | 49.00 | 51.00 | 51.00 | 51.00 | 50.90 | 49.00 | 49.00 | 50.00 | |
| | APE | **0.70%** | **0.93%** | **0.23%** | **0.46%** | **0.70%** | **0.00%** | **13.76%** | **15.51%** | **9.71%** | **4.04%** | **1.90%** | **5.81%** | **5.77%** | **0.39%** | **0.97%** | **0.39%** | **0.99%** | **3.16%** | **3.16%** | **3.66%** | **3.61%** |
| Cylinder Scavenging Air Temperature Inlet n0.6 | Actual | 43.20 | 43.50 | 43.70 | 43.90 | 43.40 | 44.60 | 52.20 | 50.90 | 52.10 | 52.60 | 53.10 | 53.10 | 52.60 | 51.40 | 52.10 | 51.40 | 51.00 | 51.20 | 51.20 | 52.50 | |
| | ANN Prediction | 43.00 | 43.50 | 43.60 | 44.00 | 44.10 | 44.60 | 45.00 | 45.50 | 50.00 | 47.50 | 49.15 | 51.00 | 51.50 | 52.00 | 52.40 | 52.00 | 51.50 | 52.00 | 51.50 | 51.50 | |
| | APE | **0.46%** | **0.00%** | **0.23%** | **0.23%** | **1.61%** | **0.00%** | **13.79%** | **10.61%** | **4.03%** | **9.70%** | **7.44%** | **3.95%** | **2.09%** | **1.17%** | **0.58%** | **1.17%** | **0.98%** | **1.56%** | **0.59%** | **1.90%** | **3.10%** |
| Cylinder Scavenging Air Temperature Inlet n0.7 | Actual | 40.70 | 41.00 | 41.20 | 41.40 | 40.90 | 42.10 | 49.70 | 48.40 | 49.60 | 50.10 | 50.60 | 50.60 | 50.10 | 48.90 | 49.60 | 48.90 | 48.50 | 48.70 | 48.70 | 50.00 | |
| | ANN Prediction | 40.23 | 40.99 | 41.60 | 41.44 | 40.92 | 42.60 | 43.00 | 42.00 | 44.90 | 50.50 | 51.00 | 50.82 | 50.51 | 51.00 | 52.00 | 52.25 | 51.00 | 51.00 | 50.00 | 50.00 | |
| | APE | **1.15%** | **0.02%** | **0.97%** | **0.10%** | **0.05%** | **1.19%** | **13.48%** | **13.22%** | **9.48%** | **0.80%** | **0.79%** | **0.43%** | **0.82%** | **4.29%** | **4.84%** | **6.85%** | **5.15%** | **4.72%** | **2.67%** | **0.00%** | **3.55%** |
| Cylinder Scavenging Air Temperature Inlet n0.8 | Actual | 43.00 | 43.30 | 43.50 | 43.70 | 43.20 | 44.40 | 52.00 | 50.70 | 51.90 | 52.40 | 52.90 | 52.90 | 52.40 | 51.20 | 51.90 | 51.20 | 50.80 | 51.00 | 51.00 | 52.30 | |
| | ANN Prediction | 42.89 | 43.00 | 43.50 | 43.69 | 43.15 | 44.00 | 43.50 | 45.00 | 44.50 | 46.00 | 49.60 | 52.00 | 50.00 | 50.50 | 50.00 | 50.00 | 50.00 | 50.00 | 50.76 | 51.50 | |
| | APE | **0.26%** | **0.69%** | **0.00%** | **0.02%** | **0.12%** | **0.90%** | **16.35%** | **11.24%** | **14.26%** | **12.21%** | **6.24%** | **1.70%** | **4.58%** | **1.37%** | **3.66%** | **2.34%** | **1.57%** | **1.96%** | **0.47%** | **1.53%** | **4.07%** |

| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder CFW Outlet Temperature no.1 | Actual | 86.00 | 86.10 | 86.00 | 85.90 | 86.10 | 86.70 | 86.60 | 86.40 | 86.30 | 85.90 | 85.90 | 85.80 | 85.40 | 86.10 | 85.90 | 86.10 | 85.80 | 86.10 | 85.90 | 85.60 | |
| | ANN Prediction | 86.02 | 85.96 | 85.97 | 86.00 | 86.10 | 86.52 | 86.56 | 86.32 | 86.19 | 85.92 | 85.99 | 85.95 | 85.55 | 86.07 | 85.70 | 86.00 | 86.04 | 86.10 | 85.60 | 85.50 | |
| | APE | **0.02%** | **0.16%** | **0.04%** | **0.11%** | **0.00%** | **0.21%** | **0.04%** | **0.09%** | **0.12%** | **0.03%** | **0.11%** | **0.18%** | **0.18%** | **0.04%** | **0.23%** | **0.12%** | **0.28%** | **0.00%** | **0.35%** | **0.12%** | **0.12%** |
| Cylinder CFW Outlet Temperature no.2 | Actual | 86.30 | 86.40 | 86.40 | 86.40 | 86.50 | 87.00 | 87.00 | 86.80 | 86.60 | 86.30 | 86.30 | 86.30 | 86.00 | 86.50 | 86.40 | 86.50 | 86.20 | 86.40 | 86.20 | 86.00 | |
| | ANN Prediction | 86.38 | 86.50 | 86.44 | 86.46 | 86.38 | 86.73 | 86.60 | 86.52 | 86.57 | 86.33 | 86.27 | 86.52 | 86.33 | 86.31 | 86.46 | 86.46 | 86.43 | 86.46 | 86.32 | 86.32 | |
| | APE | **0.10%** | **0.11%** | **0.05%** | **0.07%** | **0.14%** | **0.31%** | **0.46%** | **0.32%** | **0.03%** | **0.04%** | **0.03%** | **0.25%** | **0.39%** | **0.22%** | **0.07%** | **0.04%** | **0.26%** | **0.07%** | **0.14%** | **0.37%** | **0.17%** |
| Cylinder CFW Outlet Temperature no.3 | Actual | 85.80 | 85.90 | 85.90 | 85.90 | 86.10 | 86.50 | 86.30 | 86.30 | 86.10 | 85.70 | 85.70 | 85.70 | 85.40 | 85.80 | 85.60 | 85.80 | 85.50 | 85.80 | 85.60 | 85.40 | |
| | ANN Prediction | 85.90 | 85.99 | 85.95 | 85.92 | 86.00 | 86.30 | 86.20 | 86.14 | 86.07 | 85.98 | 86.01 | 86.12 | 85.98 | 86.07 | 86.00 | 85.81 | 86.04 | 85.91 | 85.80 | 85.90 | |
| | APE | **0.12%** | **0.11%** | **0.05%** | **0.03%** | **0.11%** | **0.23%** | **0.11%** | **0.19%** | **0.04%** | **0.33%** | **0.37%** | **0.49%** | **0.67%** | **0.31%** | **0.47%** | **0.01%** | **0.63%** | **0.13%** | **0.24%** | **0.58%** | **0.26%** |
| Cylinder CFW Outlet Temperature no.4 | Actual | 84.80 | 85.00 | 85.40 | 85.30 | 85.40 | 86.20 | 86.20 | 86.10 | 85.80 | 85.50 | 85.50 | 85.40 | 84.70 | 85.70 | 85.50 | 85.70 | 85.40 | 85.70 | 85.40 | 85.40 | |
| | ANN Prediction | 85.24 | 85.38 | 85.31 | 85.20 | 85.45 | 85.51 | 85.52 | 85.55 | 85.44 | 85.68 | 85.82 | 85.68 | 85.67 | 85.76 | 85.78 | 85.97 | 85.90 | 85.74 | 85.64 | 85.86 | |
| | APE | **0.52%** | **0.44%** | **0.11%** | **0.12%** | **0.06%** | **0.80%** | **0.78%** | **0.63%** | **0.42%** | **0.21%** | **0.38%** | **0.33%** | **1.15%** | **0.06%** | **0.33%** | **0.31%** | **0.59%** | **0.05%** | **0.28%** | **0.54%** | **0.41%** |
| Cylinder CFW Outlet Temperature no.5 | Actual | 86.50 | 86.60 | 86.60 | 86.50 | 86.70 | 87.20 | 87.30 | 87.20 | 86.90 | 86.60 | 86.50 | 86.50 | 86.00 | 86.70 | 86.50 | 86.60 | 86.40 | 86.70 | 86.40 | 86.40 | |
| | ANN Prediction | 86.56 | 86.56 | 86.59 | 86.55 | 86.57 | 86.58 | 86.51 | 86.54 | 86.56 | 86.55 | 86.57 | 86.60 | 86.54 | 86.54 | 86.57 | 86.54 | 86.52 | 86.56 | 86.52 | 86.53 | |
| | APE | **0.07%** | **0.05%** | **0.01%** | **0.06%** | **0.15%** | **0.71%** | **0.90%** | **0.75%** | **0.40%** | **0.05%** | **0.08%** | **0.11%** | **0.63%** | **0.19%** | **0.08%** | **0.07%** | **0.14%** | **0.16%** | **0.14%** | **0.15%** | **0.25%** |
| Cylinder CFW Outlet Temperature no.6 | Actual | 87.50 | 87.50 | 87.50 | 87.40 | 87.60 | 88.10 | 88.30 | 88.30 | 88.00 | 87.60 | 87.60 | 87.60 | 87.10 | 87.70 | 87.50 | 87.70 | 87.40 | 87.60 | 87.40 | 87.40 | |
| | ANN Prediction | 87.57 | 87.58 | 87.61 | 87.56 | 87.56 | 87.67 | 87.61 | 87.60 | 87.59 | 87.59 | 87.65 | 87.66 | 87.58 | 87.58 | 87.62 | 87.63 | 87.59 | 87.64 | 87.60 | 87.61 | |
| | APE | **0.08%** | **0.09%** | **0.13%** | **0.19%** | **0.04%** | **0.48%** | **0.78%** | **0.79%** | **0.46%** | **0.02%** | **0.06%** | **0.06%** | **0.56%** | **0.14%** | **0.14%** | **0.08%** | **0.21%** | **0.04%** | **0.22%** | **0.25%** | **0.24%** |
| Cylinder CFW Outlet Temperature no.7 | Actual | 88.30 | 88.30 | 88.30 | 88.30 | 88.40 | 88.50 | 88.70 | 88.60 | 88.50 | 88.10 | 88.10 | 88.00 | 87.60 | 88.20 | 88.10 | 88.20 | 88.00 | 88.30 | 88.00 | 87.70 | |
| | ANN Prediction | 88.27 | 88.27 | 88.20 | 88.11 | 88.16 | 88.21 | 88.18 | 88.20 | 88.17 | 88.16 | 88.18 | 88.20 | 88.17 | 88.13 | 88.18 | 88.13 | 88.16 | 88.15 | 88.07 | 88.07 | |
| | APE | **0.03%** | **0.04%** | **0.11%** | **0.21%** | **0.27%** | **0.33%** | **0.59%** | **0.46%** | **0.37%** | **0.07%** | **0.09%** | **0.23%** | **0.65%** | **0.08%** | **0.09%** | **0.08%** | **0.18%** | **0.17%** | **0.08%** | **0.43%** | **0.23%** |
| Cylinder CFW Outlet Temperature no.8 | Actual | 86.10 | 86.20 | 86.10 | 86.00 | 86.30 | 86.70 | 86.80 | 86.50 | 86.30 | 86.00 | 85.90 | 86.00 | 85.40 | 86.00 | 85.90 | 86.00 | 85.80 | 86.20 | 85.90 | 85.70 | |
| | ANN Prediction | 86.11 | 86.11 | 86.17 | 86.00 | 86.31 | 86.35 | 86.36 | 86.35 | 86.36 | 86.17 | 86.33 | 86.41 | 86.10 | 85.95 | 86.10 | 85.92 | 85.83 | 85.98 | 85.71 | 85.98 | |
| | APE | **0.01%** | **0.10%** | **0.08%** | **0.01%** | **0.02%** | **0.40%** | **0.51%** | **0.17%** | **0.07%** | **0.20%** | **0.50%** | **0.48%** | **0.82%** | **0.06%** | **0.24%** | **0.09%** | **0.04%** | **0.26%** | **0.22%** | **0.33%** | **0.23%** |

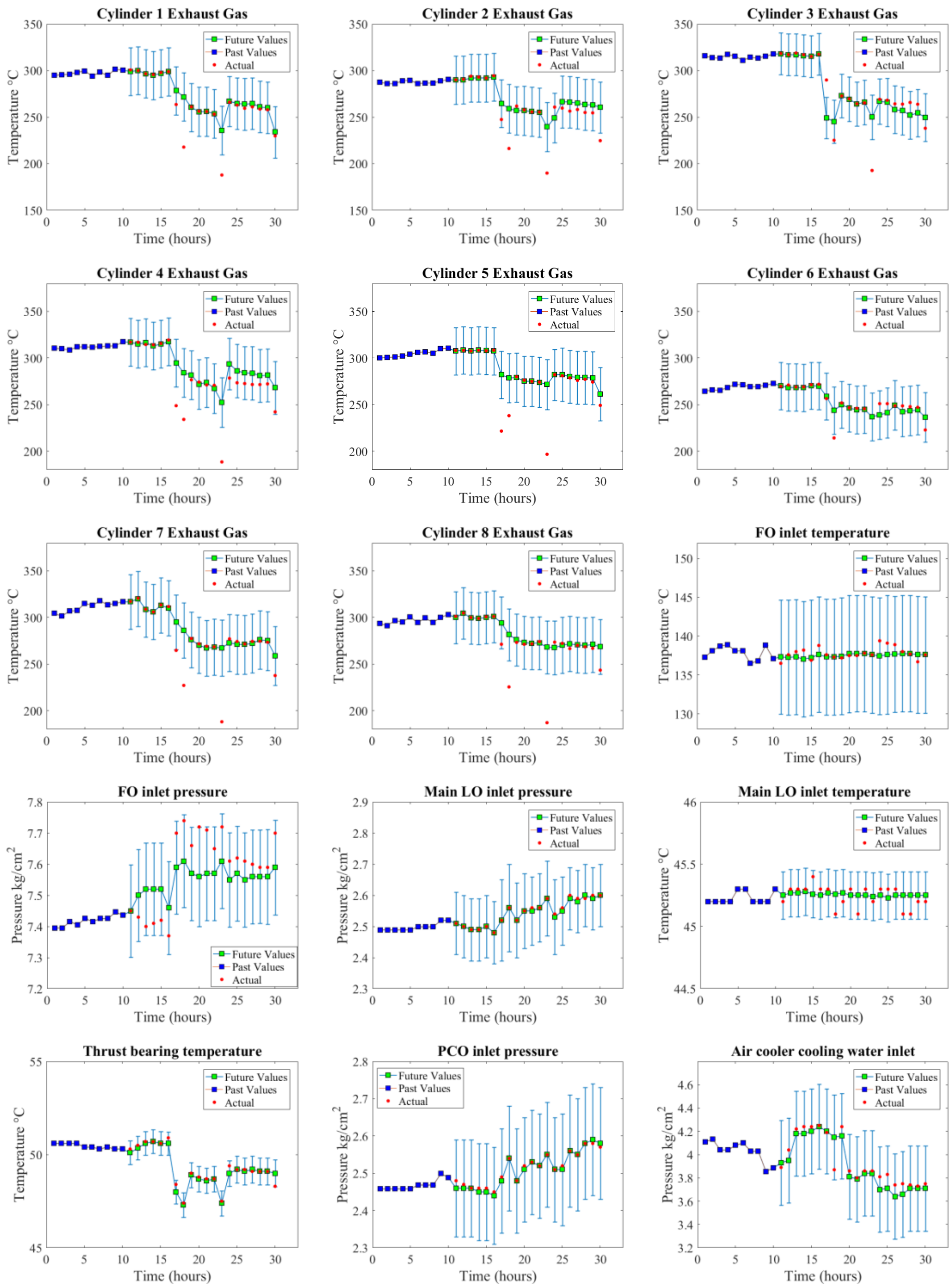
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder PCO Outlet Temperature no.1 | Actual | 54.50 | 54.80 | 55.10 | 55.20 | 54.90 | 55.30 | 52.00 | 50.40 | 52.70 | 52.30 | 52.20 | 52.20 | 49.80 | 52.90 | 52.80 | 52.60 | 52.50 | 52.50 | 52.50 | 51.10 | |
| | ANN Prediction | 54.50 | 54.82 | 55.12 | 55.25 | 54.96 | 55.37 | 53.40 | 51.15 | 52.73 | 52.56 | 52.39 | 52.42 | 50.95 | 52.79 | 52.50 | 52.02 | 52.33 | 51.67 | 51.99 | 51.00 | |
| | APE | **0.00%** | **0.04%** | **0.04%** | **0.10%** | **0.12%** | **0.14%** | **2.69%** | **1.49%** | **0.06%** | **0.49%** | **0.37%** | **0.42%** | **2.31%** | **0.22%** | **0.56%** | **1.10%** | **0.33%** | **1.58%** | **0.97%** | **0.20%** | **0.66%** |
| Cylinder PCO Outlet Temperature no.2 | Actual | 54.60 | 54.90 | 55.30 | 55.30 | 55.10 | 55.40 | 52.20 | 50.60 | 52.80 | 52.40 | 52.30 | 52.30 | 49.10 | 52.90 | 52.80 | 52.70 | 52.50 | 52.60 | 52.50 | 51.20 | |
| | ANN Prediction | 54.25 | 54.40 | 55.00 | 55.10 | 54.50 | 55.00 | 53.10 | 51.30 | 51.90 | 52.20 | 52.10 | 52.30 | 51.10 | 52.14 | 52.10 | 51.90 | 52.00 | 52.30 | 52.00 | 51.58 | |
| | APE | **0.65%** | **0.91%** | **0.54%** | **0.36%** | **1.09%** | **0.72%** | **1.72%** | **1.38%** | **1.70%** | **0.38%** | **0.38%** | **0.00%** | **4.07%** | **1.44%** | **1.33%** | **1.52%** | **0.95%** | **0.57%** | **0.95%** | **0.74%** | **1.07%** |
| Cylinder PCO Outlet Temperature no.3 | Actual | 54.40 | 54.80 | 55.20 | 55.20 | 54.90 | 55.30 | 51.60 | 50.00 | 52.30 | 52.00 | 51.90 | 51.90 | 48.70 | 52.60 | 52.30 | 52.30 | 52.20 | 52.10 | 52.10 | 50.80 | |
| | ANN Prediction | 54.10 | 54.80 | 55.00 | 55.10 | 54.50 | 55.20 | 53.25 | 51.24 | 52.75 | 51.90 | 51.90 | 51.89 | 49.70 | 51.18 | 51.10 | 51.50 | 52.00 | 52.00 | 52.10 | 52.00 | |
| | APE | **0.55%** | **0.00%** | **0.36%** | **0.18%** | **0.73%** | **0.18%** | **3.20%** | **2.48%** | **0.86%** | **0.19%** | **0.00%** | **0.02%** | **2.05%** | **2.70%** | **2.29%** | **1.53%** | **0.38%** | **0.19%** | **0.00%** | **2.36%** | **1.01%** |
| Cylinder PCO Outlet Temperature no.4 | Actual | 54.40 | 54.80 | 55.30 | 55.20 | 54.90 | 55.30 | 52.00 | 50.90 | 52.60 | 52.40 | 52.20 | 52.20 | 49.60 | 52.80 | 52.60 | 52.60 | 52.40 | 52.40 | 52.30 | 51.10 | |
| | ANN Prediction | 54.12 | 53.93 | 54.50 | 55.00 | 55.10 | 55.30 | 51.10 | 51.30 | 52.10 | 52.10 | 52.20 | 52.20 | 50.10 | 52.38 | 51.58 | 52.15 | 52.26 | 52.30 | 52.80 | 50.21 | |
| | APE | **0.51%** | **1.60%** | **1.45%** | **0.36%** | **0.36%** | **0.00%** | **1.73%** | **0.79%** | **0.95%** | **0.57%** | **0.00%** | **0.00%** | **1.01%** | **0.80%** | **1.94%** | **0.86%** | **0.26%** | **0.19%** | **0.96%** | **1.74%** | **0.80%** |
| Cylinder PCO Outlet Temperature no.5 | Actual | 54.90 | 55.40 | 55.80 | 55.80 | 55.60 | 55.90 | 51.30 | 50.80 | 53.00 | 52.80 | 52.70 | 52.70 | 51.20 | 53.20 | 53.00 | 52.90 | 52.80 | 52.70 | 52.70 | 51.50 | |
| | ANN Prediction | 54.10 | 55.00 | 55.80 | 55.40 | 55.50 | 55.70 | 52.10 | 51.80 | 52.90 | 52.10 | 52.60 | 52.70 | 52.70 | 52.80 | 52.10 | 52.14 | 53.60 | 53.10 | 53.00 | 53.10 | |
| | APE | **1.46%** | **0.72%** | **0.00%** | **0.72%** | **0.18%** | **0.36%** | **1.56%** | **1.97%** | **0.19%** | **1.33%** | **0.19%** | **0.00%** | **2.93%** | **0.75%** | **1.70%** | **1.44%** | **1.52%** | **0.76%** | **0.57%** | **3.11%** | **1.07%** |
| Cylinder PCO Outlet Temperature no.6 | Actual | 54.40 | 54.70 | 55.00 | 55.20 | 54.90 | 55.20 | 52.10 | 51.40 | 52.70 | 52.30 | 52.10 | 52.20 | 51.00 | 52.90 | 52.70 | 52.60 | 52.60 | 52.50 | 52.40 | 51.20 | |
| | ANN Prediction | 54.46 | 54.70 | 54.98 | 54.90 | 54.90 | 55.00 | 53.90 | 53.50 | 52.64 | 52.60 | 52.30 | 52.30 | 51.90 | 53.36 | 52.26 | 52.35 | 52.00 | 52.15 | 52.69 | 52.34 | |
| | APE | **0.11%** | **0.00%** | **0.04%** | **0.54%** | **0.00%** | **0.36%** | **3.45%** | **4.09%** | **0.11%** | **0.57%** | **0.38%** | **0.19%** | **1.76%** | **0.88%** | **0.83%** | **0.48%** | **1.14%** | **0.67%** | **0.55%** | **2.23%** | **0.92%** |
| Cylinder PCO Outlet Temperature no.7 | Actual | 55.00 | 55.40 | 56.00 | 56.10 | 55.70 | 56.10 | 52.40 | 50.80 | 53.00 | 52.70 | 52.60 | 52.40 | 50.10 | 53.40 | 53.00 | 53.00 | 53.00 | 52.90 | 52.70 | 51.30 | |
| | ANN Prediction | 55.31 | 55.30 | 55.70 | 56.40 | 55.84 | 56.05 | 53.00 | 52.10 | 52.90 | 52.50 | 52.60 | 52.40 | 51.15 | 52.98 | 53.00 | 53.00 | 53.00 | 53.00 | 53.00 | 52.76 | |
| | APE | **0.56%** | **0.18%** | **0.54%** | **0.53%** | **0.25%** | **0.08%** | **1.15%** | **2.56%** | **0.19%** | **0.38%** | **0.00%** | **0.00%** | **2.10%** | **0.79%** | **0.00%** | **0.00%** | **0.00%** | **0.19%** | **0.57%** | **2.85%** | **0.65%** |
| Cylinder PCO Outlet Temperature no.8 | Actual | 55.10 | 55.30 | 55.90 | 55.90 | 55.60 | 56.10 | 52.40 | 50.80 | 52.90 | 52.60 | 52.50 | 52.40 | 50.30 | 53.20 | 53.00 | 53.00 | 52.80 | 52.70 | 52.70 | 51.40 | |
| | ANN Prediction | 54.63 | 55.56 | 56.26 | 56.15 | 55.97 | 57.01 | 53.12 | 52.94 | 52.96 | 52.28 | 52.40 | 52.40 | 52.60 | 53.00 | 53.00 | 52.00 | 52.50 | 52.50 | 53.00 | 52.45 | |
| | APE | **0.85%** | **0.46%** | **0.64%** | **0.44%** | **0.66%** | **1.63%** | **1.37%** | **4.21%** | **0.11%** | **0.61%** | **0.19%** | **0.00%** | **4.57%** | **0.38%** | **0.00%** | **1.89%** | **0.57%** | **0.38%** | **0.57%** | **2.04%** | **1.08%** |

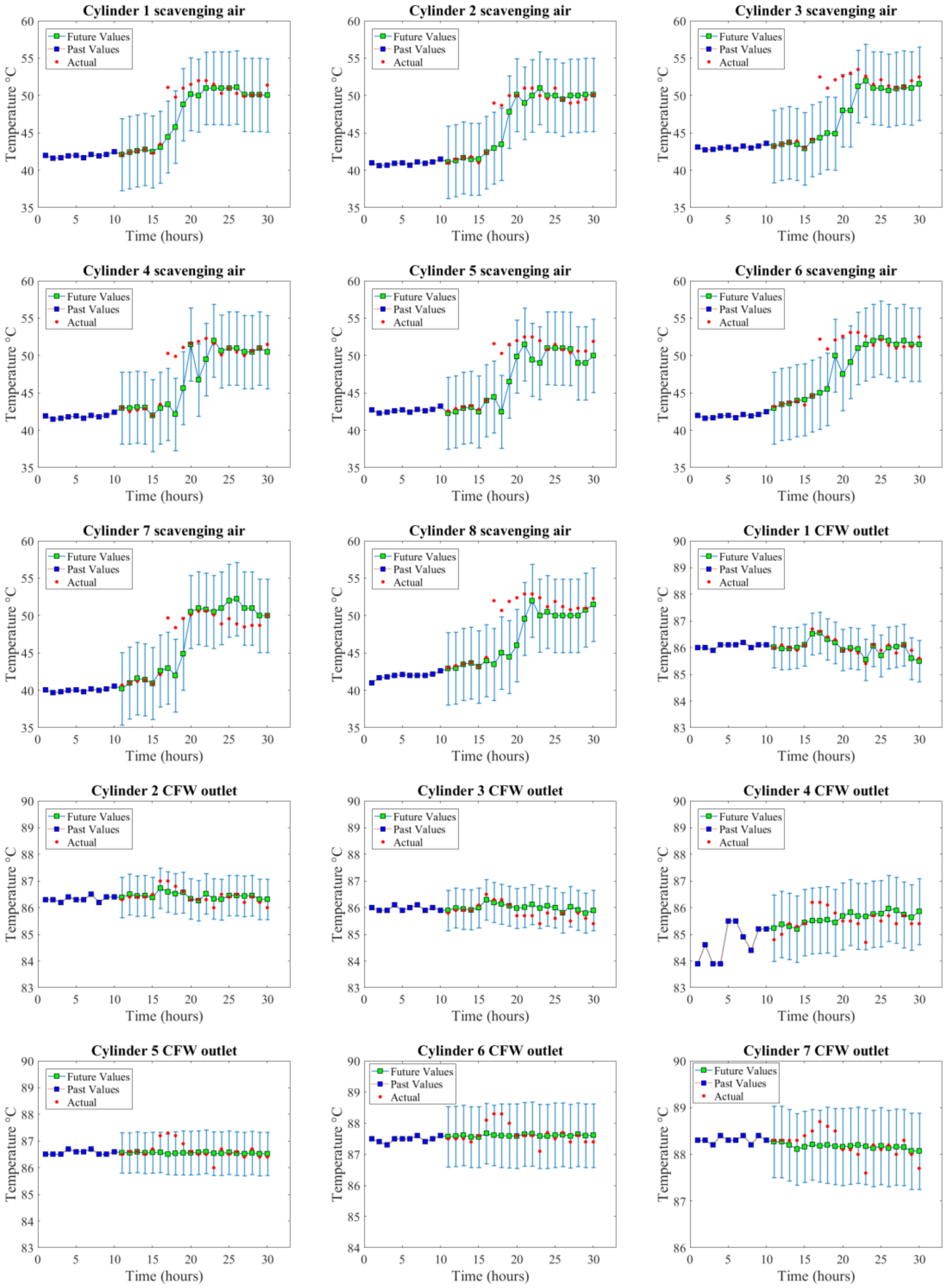
### *F.2.3 Main engine performance parameters autocorrelation graphs*

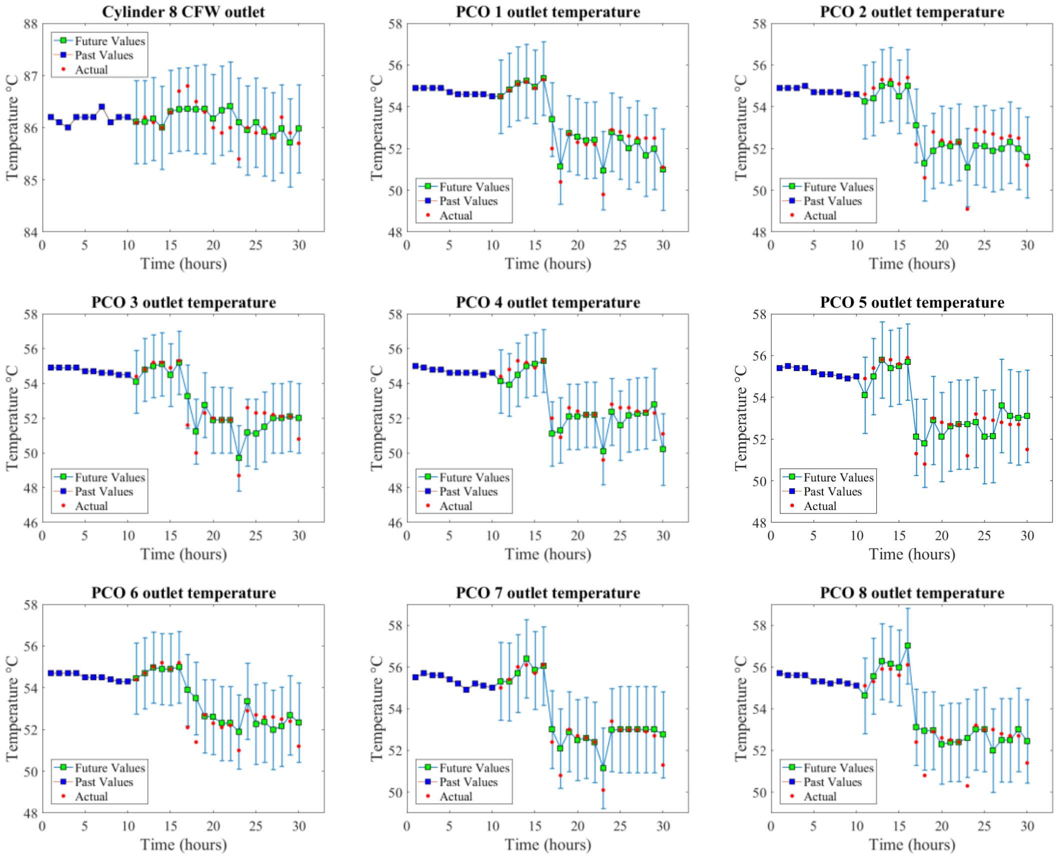



Scavenging temperature cyl.4
Scavenging temperature cyl.5
Scavenging temperature cyl.6
Scavenging temperature cyl.7
Scavenging temperature cyl.8
JCFW temperature cyl.1
JCFW temperature cyl.2
JCFW temperature cyl.3
JCFW temperature cyl.4
JCFW temperature cyl.5
JCFW temperature cyl.6
JCFW temperature cyl.7
JCFW temperature cyl.8
PCO temperature cyl.1
PCO temperature cyl.2
PCO temperature cyl.3
PCO temperature cyl.4
PCO temperature cyl.5
PCO temperature cyl.6
PCO temperature cyl.7
PCO temperature cyl.8
Correlations
Zero Correlation
Confidence Limit
Correlation
Lag

### F.2.4 Forecasting results with 95% prediction intervals




Cylinder 1 scavenging air
Cylinder 2 scavenging air
Cylinder 3 scavenging air
Cylinder 4 scavenging air
Cylinder 5 scavenging air
Cylinder 6 scavenging air
Cylinder 7 scavenging air
Cylinder 8 scavenging air
Cylinder 1 CFW outlet
Cylinder 2 CFW outlet
Cylinder 3 CFW outlet
Cylinder 4 CFW outlet
Cylinder 5 CFW outlet
Cylinder 6 CFW outlet
Cylinder 7 CFW outlet
Future Values
Past Values
Actual
Temperature °C
Time (hours)


Cylinder 8 CFW outlet
PCO 1 outlet temperature
PCO 2 outlet temperature
PCO 3 outlet temperature
PCO 4 outlet temperature
PCO 5 outlet temperature
PCO 6 outlet temperature
PCO 7 outlet temperature
PCO 8 outlet temperature
Temperature °C
Time (hours)
Future Values
Past Values
Actual

## F.3 NARX results dataset 2

### F.3.1 NARX regression results

| Parameter | Training | Test | All |
|---|---|---|---|
| Cylinder Exhaust Gas Temperature no.1 | 99.38% | 98.24% | 99.13% |
| Cylinder Exhaust Gas Temperature no.2 | 99.43% | 99.19% | 99.45% |
| Cylinder Exhaust Gas Temperature no.3 | 99.40% | 99.13% | 99.35% |
| Cylinder Exhaust Gas Temperature no.4 | 99.21% | 98.83% | 99.13% |
| Cylinder Exhaust Gas Temperature no.5 | 98.16% | 98.04% | 98.13% |
| Cylinder Exhaust Gas Temperature no.6 | 98.86% | 98.73% | 98.83% |
| Cylinder Exhaust Gas Temperature no.7 | 99.42% | 99.11% | 99.35% |
| Cylinder Exhaust Gas Temperature no.8 | 99.66% | 99.15% | 99.61% |
| Fuel Oil Inlet Temperature | 99.78% | 99.44% | 99.76% |
| Fuel Oil Inlet Pressure | 98.15% | 97.59% | 98.03% |
| Main Lube Oil Pressure | 98.87% | 97.99% | 98.14% |
| Main Lube Oil Temperature | 89.14% | 88.62% | 88.87% |
| Thrust Bearing Temperature | 98.79% | 97.76% | 98.60% |
| Piston Cooling Oil Inlet Pressure | 95.35% | 93.67% | 95.06% |
| Air Cooler Cooling Water Inlet Pressure | 98.13% | 97.55% | 98.04% |
| Cylinder Scavenging Air Temperature Inlet no.1 | 98.24% | 94.36% | 95.11% |
| Cylinder Scavenging Air Temperature Inlet no.2 | 98.35% | 92.24% | 97.07% |
| Cylinder Scavenging Air Temperature Inlet no.3 | 98.85% | 94.56% | 96.89% |
| Cylinder Scavenging Air Temperature Inlet no.4 | 98.10% | 94.78% | 96.95% |
| Cylinder Scavenging Air Temperature Inlet no.5 | 97.34% | 93.45% | 95.66% |
| Cylinder Scavenging Air Temperature Inlet no.6 | 96.53% | 92.88% | 93.83% |
| Cylinder Scavenging Air Temperature Inlet no.7 | 97.24% | 94.05% | 96.13% |
| Cylinder Scavenging Air Temperature Inlet no.8 | 98.45% | 92.13% | 97.11% |
| Cylinder CFW Outlet Temperature no.1 | 99.48% | 97.36% | 99.28% |
| Cylinder CFW Outlet Temperature no.2 | 99.63% | 98.95% | 99.34% |
| Cylinder CFW Outlet Temperature no.3 | 98.40% | 93.36% | 97.91% |
| Cylinder CFW Outlet Temperature no.4 | 96.76% | 95.29% | 96.38% |
| Cylinder CFW Outlet Temperature no.5 | 92.95% | 88.65% | 90.99% |
| Cylinder CFW Outlet Temperature no.6 | 99.14% | 96.90% | 98.81% |
| Cylinder CFW Outlet Temperature no.7 | 96.84% | 93.55% | 95.84% |
| Cylinder CFW Outlet Temperature no.8 | 98.29% | 92.28% | 97.78% |
| Cylinder PCO Outlet Temperature no.1 | 99.32% | 98.84% | 99.22% |
| Cylinder PCO Outlet Temperature no.2 | 99.27% | 98.52% | 99.13% |
| Cylinder PCO Outlet Temperature no.3 | 98.89% | 98.09% | 98.74% |
| Cylinder PCO Outlet Temperature no.4 | 98.63% | 96.35% | 98.18% |
| Cylinder PCO Outlet Temperature no.5 | 99.25% | 97.08% | 98.78% |
| Cylinder PCO Outlet Temperature no.6 | 98.85% | 96.03% | 98.25% |
| Cylinder PCO Outlet Temperature no.7 | 98.61% | 94.69% | 97.76% |
| Cylinder PCO Outlet Temperature no.8 | 99.08% | 95.86% | 98.36% |

### *F.3.2 APE and MAPE forecast results for main engine parameters*

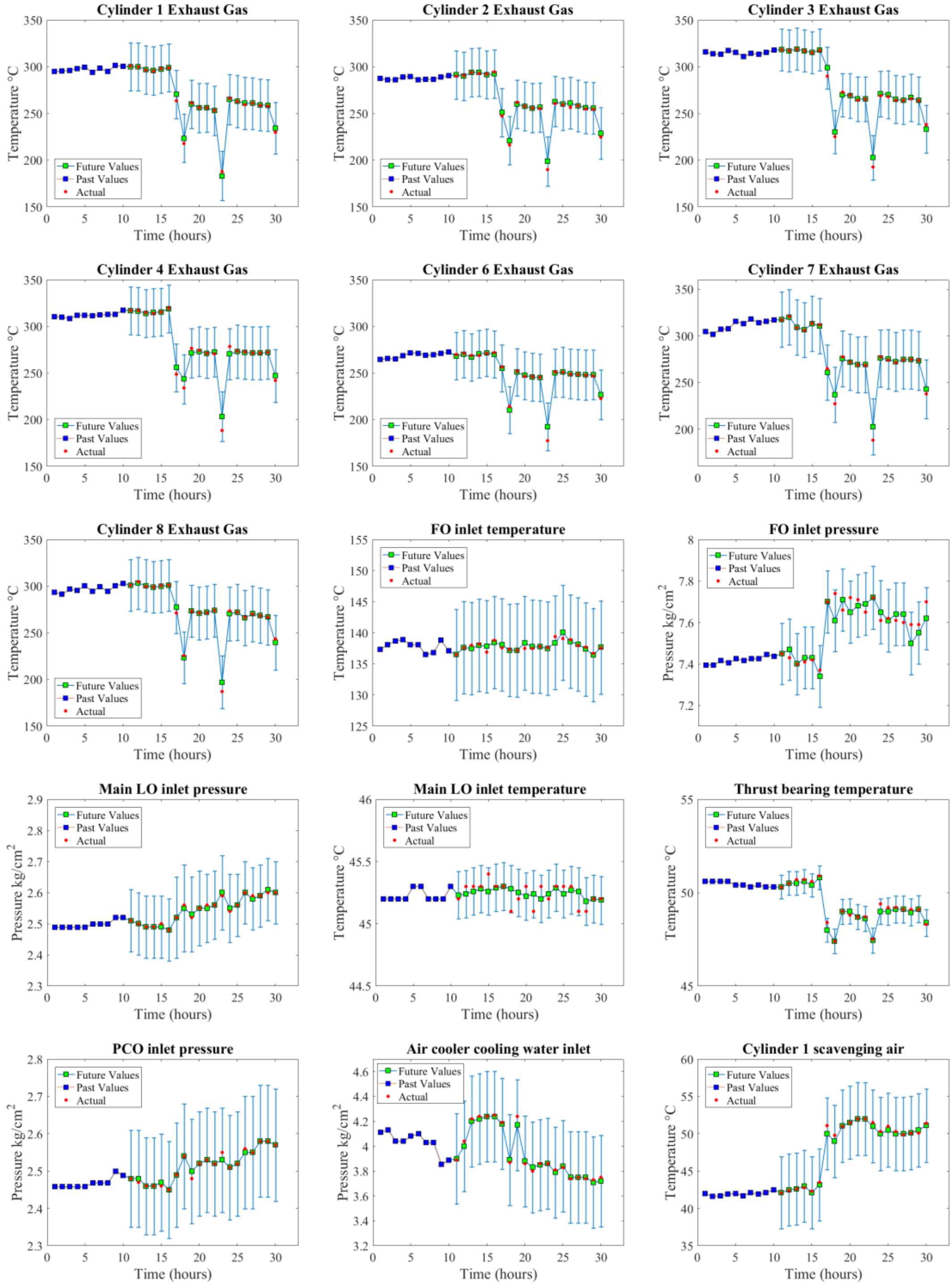
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder Exhaust Gas Temperature no.1 | Actual | 300.70 | 300.00 | 296.60 | 295.60 | 297.80 | 298.90 | 263.60 | 217.90 | 261.00 | 256.30 | 256.10 | 253.30 | 187.90 | 266.10 | 263.00 | 259.50 | 261.10 | 258.70 | 258.00 | 229.90 | |
| | ANN Prediction | 300.00 | 300.00 | 297.00 | 296.00 | 297.50 | 299.00 | 270.55 | 223.53 | 259.97 | 256.00 | 256.16 | 253.00 | 183.23 | 265.00 | 263.00 | 261.00 | 260.87 | 259.15 | 258.50 | 234.15 | |
| | APE | **0.23%** | **0.00%** | **0.13%** | **0.14%** | **0.10%** | **0.03%** | **2.64%** | **2.58%** | **0.39%** | **0.12%** | **0.02%** | **0.12%** | **2.49%** | **0.41%** | **0.00%** | **0.58%** | **0.09%** | **0.17%** | **0.19%** | **1.85%** | **0.61%** |
| Cylinder Exhaust Gas Temperature no.2 | Actual | 290.10 | 290.60 | 293.90 | 293.00 | 292.00 | 294.40 | 247.50 | 216.40 | 261.90 | 257.70 | 255.80 | 255.40 | 190.00 | 260.80 | 259.70 | 256.50 | 258.20 | 255.00 | 254.60 | 224.80 | |
| | ANN Prediction | 291.39 | 289.92 | 293.84 | 294.10 | 291.57 | 292.33 | 251.12 | 221.00 | 259.93 | 257.66 | 255.86 | 256.46 | 198.78 | 262.79 | 260.00 | 261.23 | 258.28 | 256.03 | 255.62 | 229.00 | |
| | APE | **0.45%** | **0.23%** | **0.02%** | **0.38%** | **0.15%** | **0.70%** | **1.46%** | **2.13%** | **0.75%** | **0.02%** | **0.02%** | **0.42%** | **4.62%** | **0.76%** | **0.12%** | **1.84%** | **0.03%** | **0.40%** | **0.40%** | **1.87%** | **0.84%** |
| Cylinder Exhaust Gas Temperature no.3 | Actual | 318.30 | 317.10 | 318.80 | 316.90 | 315.20 | 317.60 | 289.90 | 225.20 | 272.80 | 269.50 | 264.40 | 265.40 | 192.80 | 269.10 | 268.20 | 264.30 | 264.00 | 265.80 | 263.90 | 238.10 | |
| | ANN Prediction | 318.35 | 317.00 | 318.99 | 316.99 | 315.15 | 318.00 | 298.89 | 230.28 | 269.82 | 269.00 | 265.45 | 265.39 | 202.80 | 271.09 | 270.16 | 265.00 | 264.00 | 266.84 | 263.95 | 233.23 | |
| | APE | **0.02%** | **0.03%** | **0.06%** | **0.03%** | **0.02%** | **0.13%** | **3.10%** | **2.26%** | **1.09%** | **0.19%** | **0.40%** | **0.00%** | **5.19%** | **0.74%** | **0.73%** | **0.26%** | **0.00%** | **0.39%** | **0.02%** | **2.05%** | **0.83%** |
| Cylinder Exhaust Gas Temperature no.4 | Actual | 317.10 | 316.90 | 314.50 | 314.10 | 315.50 | 319.30 | 248.80 | 234.10 | 276.60 | 274.20 | 271.10 | 270.70 | 188.50 | 278.50 | 273.40 | 272.60 | 271.60 | 271.50 | 272.20 | 242.20 | |
| | ANN Prediction | 317.00 | 316.42 | 314.06 | 314.94 | 315.49 | 319.00 | 255.93 | 243.47 | 271.50 | 273.24 | 271.00 | 272.64 | 203.42 | 270.49 | 273.00 | 272.00 | 271.50 | 271.50 | 272.00 | 247.12 | |
| | APE | **0.03%** | **0.15%** | **0.14%** | **0.27%** | **0.00%** | **0.09%** | **2.87%** | **4.00%** | **1.84%** | **0.35%** | **0.04%** | **0.72%** | **7.92%** | **2.88%** | **0.15%** | **0.22%** | **0.04%** | **0.00%** | **0.07%** | **2.03%** | **1.19%** |
| Cylinder Exhaust Gas Temperature no.5 | Actual | 308.10 | 308.30 | 307.50 | 308.40 | 307.80 | 308.30 | 221.60 | 238.10 | 279.80 | 276.20 | 275.00 | 274.10 | 196.70 | 282.10 | 281.00 | 278.70 | 276.00 | 277.20 | 274.20 | 249.20 | |
| | ANN Prediction | 308.00 | 308.30 | 307.13 | 308.35 | 307.86 | 308.42 | 230.78 | 235.25 | 272.75 | 275.84 | 275.20 | 274.90 | 205.60 | 279.05 | 280.02 | 280.67 | 279.06 | 279.04 | 276.65 | 255.32 | |
| | APE | **0.03%** | **0.00%** | **0.12%** | **0.02%** | **0.02%** | **0.04%** | **4.14%** | **1.20%** | **2.52%** | **0.13%** | **0.07%** | **0.29%** | **4.52%** | **1.08%** | **0.35%** | **0.71%** | **1.11%** | **0.66%** | **0.89%** | **2.46%** | **1.02%** |
| Cylinder Exhaust Gas Temperature no.6 | Actual | 269.80 | 271.00 | 268.80 | 268.90 | 271.20 | 271.80 | 256.50 | 214.20 | 251.80 | 246.60 | 246.00 | 245.40 | 177.60 | 251.00 | 251.00 | 248.80 | 248.60 | 247.80 | 247.10 | 222.80 | |
| | ANN Prediction | 268.30 | 270.27 | 266.91 | 270.39 | 271.78 | 270.22 | 255.11 | 210.44 | 250.95 | 247.44 | 245.92 | 245.00 | 192.58 | 250.00 | 251.09 | 249.33 | 248.50 | 248.00 | 248.12 | 226.82 | |
| | APE | **0.56%** | **0.27%** | **0.70%** | **0.56%** | **0.21%** | **0.58%** | **0.54%** | **1.76%** | **0.34%** | **0.34%** | **0.03%** | **0.16%** | **8.43%** | **0.40%** | **0.04%** | **0.21%** | **0.04%** | **0.08%** | **0.41%** | **1.80%** | **0.87%** |
| Cylinder Exhaust Gas Temperature no.7 | Actual | 317.20 | 320.60 | 308.80 | 306.00 | 313.30 | 311.70 | 264.70 | 227.10 | 277.30 | 271.70 | 269.10 | 268.50 | 188.10 | 277.10 | 274.20 | 271.50 | 274.30 | 274.60 | 273.50 | 237.70 | |
| | ANN Prediction | 317.47 | 319.92 | 309.09 | 306.26 | 313.00 | 310.58 | 260.77 | 236.87 | 275.42 | 271.55 | 269.00 | 269.00 | 202.32 | 275.84 | 275.00 | 272.03 | 274.50 | 274.55 | 273.13 | 242.83 | |
| | APE | **0.09%** | **0.21%** | **0.09%** | **0.08%** | **0.10%** | **0.36%** | **1.48%** | **4.30%** | **0.68%** | **0.05%** | **0.04%** | **0.19%** | **7.56%** | **0.45%** | **0.29%** | **0.20%** | **0.07%** | **0.02%** | **0.14%** | **2.16%** | **0.93%** |
| Cylinder Exhaust Gas Temperature no.8 | Actual | 301.10 | 304.70 | 299.90 | 299.00 | 300.60 | 301.10 | 271.30 | 225.50 | 273.30 | 271.30 | 271.80 | 274.10 | 187.10 | 273.50 | 272.20 | 266.60 | 270.20 | 268.50 | 266.90 | 243.50 | |
| | ANN Prediction | 301.00 | 303.38 | 300.64 | 299.00 | 299.82 | 301.00 | 277.49 | 223.44 | 273.48 | 270.80 | 271.83 | 273.91 | 197.11 | 270.35 | 272.20 | 266.13 | 270.42 | 268.50 | 266.85 | 239.53 | |
| | APE | **0.03%** | **0.43%** | **0.25%** | **0.00%** | **0.26%** | **0.03%** | **2.28%** | **0.91%** | **0.06%** | **0.19%** | **0.01%** | **0.07%** | **5.35%** | **1.15%** | **0.00%** | **0.18%** | **0.08%** | **0.00%** | **0.02%** | **1.63%** | **0.65%** |
| Fuel Oil Inlet Temperature | Actual | 136.50 | 137.60 | 138.00 | 138.20 | 136.90 | 138.80 | 137.60 | 137.30 | 137.20 | 137.50 | 137.50 | 137.80 | 137.60 | 139.40 | 139.10 | 138.90 | 138.00 | 137.70 | 136.70 | 137.60 | |
| | ANN Prediction | 136.50 | 137.65 | 137.49 | 138.00 | 137.83 | 138.47 | 138.09 | 137.20 | 137.20 | 138.36 | 137.79 | 137.77 | 137.50 | 138.41 | 140.06 | 138.60 | 138.19 | 137.38 | 136.45 | 137.68 | |
| | APE | **0.00%** | **0.04%** | **0.37%** | **0.14%** | **0.68%** | **0.24%** | **0.36%** | **0.07%** | **0.00%** | **0.63%** | **0.21%** | **0.02%** | **0.07%** | **0.71%** | **0.69%** | **0.21%** | **0.14%** | **0.23%** | **0.18%** | **0.06%** | **0.25%** |
| Fuel Oil Inlet Pressure | Actual | 7.45 | 7.43 | 7.40 | 7.41 | 7.42 | 7.37 | 7.70 | 7.74 | 7.66 | 7.72 | 7.71 | 7.65 | 7.72 | 7.61 | 7.62 | 7.61 | 7.60 | 7.59 | 7.59 | 7.70 | |
| | ANN Prediction | 7.45 | 7.47 | 7.40 | 7.43 | 7.43 | 7.34 | 7.70 | 7.61 | 7.71 | 7.65 | 7.68 | 7.69 | 7.72 | 7.65 | 7.61 | 7.64 | 7.64 | 7.50 | 7.55 | 7.62 | |
| | APE | **0.05%** | **0.65%** | **0.07%** | **0.30%** | **0.23%** | **0.47%** | **0.01%** | **1.70%** | **0.63%** | **0.97%** | **0.46%** | **0.50%** | **0.02%** | **0.54%** | **0.06%** | **0.39%** | **0.58%** | **1.23%** | **0.50%** | **1.05%** | **0.52%** |
| Main Lube Oil Pressure | Actual | 2.51 | 2.50 | 2.49 | 2.49 | 2.50 | 2.48 | 2.52 | 2.56 | 2.52 | 2.55 | 2.56 | 2.56 | 2.59 | 2.54 | 2.56 | 2.60 | 2.59 | 2.59 | 2.60 | 2.60 | |
| | ANN Prediction | 2.51 | 2.50 | 2.49 | 2.49 | 2.49 | 2.48 | 2.52 | 2.55 | 2.53 | 2.55 | 2.55 | 2.56 | 2.60 | 2.55 | 2.56 | 2.60 | 2.58 | 2.59 | 2.61 | 2.60 | |
| | APE | **0.03%** | **0.07%** | **0.05%** | **0.05%** | **0.36%** | **0.06%** | **0.02%** | **0.40%** | **0.37%** | **0.00%** | **0.41%** | **0.07%** | **0.23%** | **0.40%** | **0.12%** | **0.12%** | **0.29%** | **0.09%** | **0.21%** | **0.03%** | **0.17%** |

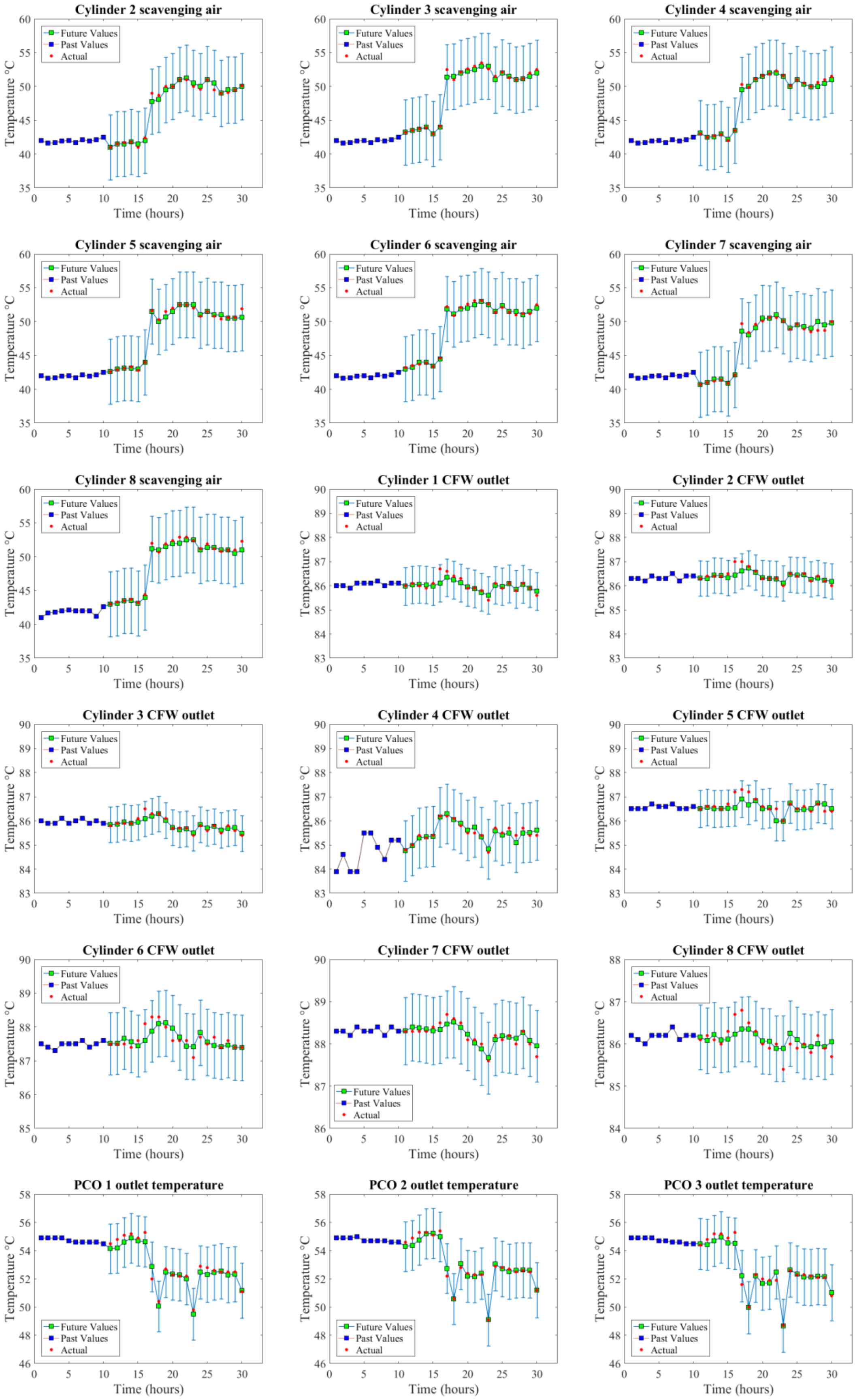
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Main Lube Oil Temperature | Actual | 45.20 | 45.30 | 45.30 | 45.30 | 45.40 | 45.30 | 45.30 | 45.10 | 45.20 | 45.30 | 45.10 | 45.30 | 45.20 | 45.30 | 45.30 | 45.30 | 45.10 | 45.10 | 45.20 | 45.20 | |
| | ANN Prediction | 45.23 | 45.24 | 45.26 | 45.28 | 45.26 | 45.29 | 45.30 | 45.28 | 45.25 | 45.22 | 45.24 | 45.20 | 45.24 | 45.29 | 45.24 | 45.27 | 45.26 | 45.18 | 45.20 | 45.19 | |
| | APE | **0.08%** | **0.14%** | **0.09%** | **0.03%** | **0.30%** | **0.03%** | **0.00%** | **0.41%** | **0.11%** | **0.17%** | **0.30%** | **0.22%** | **0.09%** | **0.03%** | **0.13%** | **0.06%** | **0.36%** | **0.18%** | **0.01%** | **0.03%** | **0.14%** |
| Thrust Bearing Temperature | Actual | 50.30 | 50.50 | 50.70 | 50.70 | 50.60 | 50.90 | 48.40 | 47.40 | 49.00 | 48.80 | 48.70 | 48.70 | 47.50 | 49.40 | 49.20 | 49.20 | 49.10 | 49.10 | 49.10 | 48.30 | |
| | ANN Prediction | 50.30 | 50.50 | 50.50 | 50.60 | 50.40 | 50.80 | 48.00 | 47.40 | 48.99 | 49.00 | 48.70 | 48.61 | 47.44 | 49.00 | 49.00 | 49.11 | 49.11 | 48.95 | 49.12 | 48.38 | |
| | APE | **0.00%** | **0.00%** | **0.39%** | **0.20%** | **0.40%** | **0.20%** | **0.83%** | **0.00%** | **0.02%** | **0.41%** | **0.00%** | **0.18%** | **0.12%** | **0.81%** | **0.41%** | **0.18%** | **0.02%** | **0.30%** | **0.04%** | **0.16%** | **0.23%** |
| Piston Cooling Oil Inlet Pressure | Actual | 2.48 | 2.47 | 2.46 | 2.46 | 2.46 | 2.45 | 2.49 | 2.54 | 2.48 | 2.52 | 2.53 | 2.52 | 2.55 | 2.51 | 2.52 | 2.56 | 2.55 | 2.58 | 2.58 | 2.57 | |
| | ANN Prediction | 2.48 | 2.48 | 2.46 | 2.46 | 2.47 | 2.45 | 2.49 | 2.54 | 2.50 | 2.52 | 2.53 | 2.52 | 2.53 | 2.51 | 2.52 | 2.55 | 2.55 | 2.58 | 2.58 | 2.57 | |
| | APE | **0.01%** | **0.47%** | **0.08%** | **0.05%** | **0.48%** | **0.04%** | **0.13%** | **0.00%** | **0.86%** | **0.03%** | **0.02%** | **0.03%** | **0.78%** | **0.01%** | **0.00%** | **0.40%** | **0.01%** | **0.05%** | **0.05%** | **0.01%** | **0.18%** |
| Air Cooler Cooling Water Inlet Pressure | Actual | 3.89 | 4.04 | 4.22 | 4.24 | 4.24 | 4.25 | 4.19 | 3.87 | 4.24 | 3.86 | 3.80 | 3.86 | 3.86 | 3.81 | 3.83 | 3.74 | 3.75 | 3.74 | 3.73 | 3.75 | |
| | ANN Prediction | 3.90 | 4.00 | 4.20 | 4.22 | 4.24 | 4.24 | 4.18 | 3.89 | 4.17 | 3.88 | 3.83 | 3.85 | 3.86 | 3.79 | 3.84 | 3.75 | 3.75 | 3.75 | 3.71 | 3.72 | |
| | APE | **0.36%** | **0.97%** | **0.54%** | **0.56%** | **0.02%** | **0.33%** | **0.24%** | **0.56%** | **1.82%** | **0.60%** | **0.79%** | **0.19%** | **0.17%** | **0.54%** | **0.26%** | **0.16%** | **0.16%** | **0.12%** | **0.60%** | **0.87%** | **0.49%** |
| Cylinder Scavenging Air Temperature Inlet no.1 | Actual | 42.10 | 42.40 | 42.60 | 42.80 | 42.30 | 43.50 | 51.10 | 49.80 | 51.00 | 51.50 | 52.00 | 52.00 | 51.50 | 50.30 | 51.00 | 50.30 | 49.90 | 50.10 | 50.10 | 51.40 | |
| | ANN Prediction | 42.10 | 42.50 | 42.60 | 43.00 | 42.10 | 43.19 | 50.00 | 49.00 | 51.05 | 51.50 | 52.00 | 52.00 | 51.00 | 50.00 | 50.50 | 50.00 | 50.00 | 50.10 | 50.50 | 51.10 | |
| | APE | **0.00%** | **0.24%** | **0.00%** | **0.47%** | **0.47%** | **0.71%** | **2.15%** | **1.61%** | **0.10%** | **0.00%** | **0.00%** | **0.00%** | **0.97%** | **0.60%** | **0.98%** | **0.60%** | **0.20%** | **0.00%** | **0.80%** | **0.58%** | **0.52%** |
| Cylinder Scavenging Air Temperature Inlet no.2 | Actual | 41.00 | 41.50 | 41.70 | 41.80 | 41.00 | 42.40 | 49.00 | 48.70 | 50.00 | 50.00 | 51.00 | 51.00 | 50.00 | 49.60 | 51.00 | 49.50 | 49.00 | 49.10 | 49.50 | 50.10 | |
| | ANN Prediction | 41.00 | 41.50 | 41.50 | 41.80 | 41.50 | 42.00 | 47.77 | 48.10 | 49.50 | 50.00 | 51.00 | 51.25 | 50.50 | 50.00 | 51.00 | 50.50 | 49.00 | 49.50 | 49.50 | 50.00 | |
| | APE | **0.00%** | **0.00%** | **0.48%** | **0.00%** | **1.22%** | **0.94%** | **2.51%** | **1.23%** | **1.00%** | **0.00%** | **0.00%** | **0.49%** | **1.00%** | **0.81%** | **0.00%** | **2.02%** | **0.00%** | **0.81%** | **0.00%** | **0.20%** | **0.64%** |
| Cylinder Scavenging Air Temperature Inlet no.3 | Actual | 43.22 | 43.50 | 43.74 | 43.92 | 43.00 | 44.10 | 52.50 | 51.00 | 52.12 | 52.61 | 53.00 | 53.50 | 52.60 | 51.50 | 52.12 | 51.30 | 51.02 | 51.16 | 52.00 | 52.50 | |
| | ANN Prediction | 43.20 | 43.50 | 43.65 | 44.00 | 43.00 | 44.00 | 51.39 | 51.50 | 52.00 | 52.25 | 52.50 | 53.00 | 53.00 | 51.00 | 52.00 | 51.50 | 51.00 | 51.10 | 51.50 | 52.00 | |
| | APE | **0.05%** | **0.00%** | **0.21%** | **0.18%** | **0.00%** | **0.23%** | **2.11%** | **0.98%** | **0.23%** | **0.68%** | **0.94%** | **0.93%** | **0.76%** | **0.97%** | **0.23%** | **0.39%** | **0.04%** | **0.12%** | **0.96%** | **0.95%** | **0.55%** |
| Cylinder Scavenging Air Temperature Inlet no.4 | Actual | 43.00 | 42.50 | 42.70 | 42.90 | 42.00 | 43.50 | 50.30 | 49.90 | 51.10 | 51.60 | 51.90 | 52.30 | 51.60 | 50.10 | 51.00 | 50.50 | 50.00 | 50.60 | 51.00 | 51.50 | |
| | ANN Prediction | 43.10 | 42.50 | 42.55 | 43.00 | 42.15 | 43.47 | 49.50 | 50.00 | 51.00 | 51.50 | 52.00 | 52.00 | 51.50 | 50.00 | 51.00 | 50.34 | 49.96 | 50.00 | 50.45 | 51.00 | |
| | APE | **0.23%** | **0.00%** | **0.35%** | **0.23%** | **0.36%** | **0.07%** | **1.59%** | **0.20%** | **0.20%** | **0.19%** | **0.19%** | **0.57%** | **0.19%** | **0.20%** | **0.00%** | **0.32%** | **0.08%** | **1.19%** | **1.08%** | **0.97%** | **0.41%** |
| Cylinder Scavenging Air Temperature Inlet no.5 | Actual | 42.60 | 42.90 | 43.10 | 43.30 | 42.80 | 44.00 | 51.60 | 50.30 | 51.50 | 52.00 | 52.50 | 52.50 | 52.00 | 50.80 | 51.50 | 50.80 | 50.40 | 50.60 | 50.60 | 51.90 | |
| | ANN Prediction | 42.60 | 43.00 | 43.11 | 43.10 | 43.00 | 43.98 | 51.50 | 50.00 | 50.67 | 51.50 | 52.50 | 52.50 | 52.50 | 51.00 | 51.50 | 51.00 | 51.00 | 50.50 | 50.50 | 50.60 | |
| | APE | **0.00%** | **0.23%** | **0.02%** | **0.46%** | **0.47%** | **0.05%** | **0.19%** | **0.60%** | **1.61%** | **0.96%** | **0.00%** | **0.00%** | **0.96%** | **0.39%** | **0.00%** | **0.39%** | **1.19%** | **0.20%** | **0.20%** | **2.50%** | **0.52%** |
| Cylinder Scavenging Air Temperature Inlet no.6 | Actual | 43.20 | 43.50 | 43.70 | 43.90 | 43.40 | 44.60 | 52.20 | 50.90 | 52.10 | 52.60 | 53.10 | 53.10 | 52.60 | 51.40 | 52.10 | 51.40 | 51.00 | 51.20 | 51.20 | 52.50 | |
| | ANN Prediction | 43.00 | 43.20 | 44.00 | 44.00 | 43.40 | 44.50 | 51.90 | 51.10 | 51.90 | 52.00 | 52.50 | 53.00 | 52.50 | 51.50 | 52.40 | 51.50 | 51.50 | 51.00 | 51.50 | 52.00 | |
| | APE | **0.46%** | **0.69%** | **0.69%** | **0.23%** | **0.00%** | **0.22%** | **0.57%** | **0.39%** | **0.38%** | **1.14%** | **1.13%** | **0.19%** | **0.19%** | **0.19%** | **0.58%** | **0.19%** | **0.98%** | **0.39%** | **0.59%** | **0.95%** | **0.51%** |
| Cylinder Scavenging Air Temperature Inlet no.7 | Actual | 40.70 | 41.00 | 41.20 | 41.40 | 40.90 | 42.10 | 49.70 | 48.40 | 49.60 | 50.10 | 50.60 | 50.60 | 50.10 | 48.90 | 49.60 | 48.90 | 48.50 | 48.70 | 48.70 | 50.00 | |
| | ANN Prediction | 40.70 | 41.00 | 41.50 | 41.50 | 40.85 | 42.10 | 48.60 | 48.00 | 49.10 | 50.50 | 50.50 | 51.00 | 50.15 | 49.00 | 49.50 | 49.25 | 49.00 | 50.00 | 49.50 | 49.80 | |
| | APE | **0.00%** | **0.00%** | **0.73%** | **0.24%** | **0.12%** | **0.00%** | **2.21%** | **0.83%** | **1.01%** | **0.80%** | **0.20%** | **0.79%** | **0.10%** | **0.20%** | **0.20%** | **0.72%** | **1.03%** | **2.67%** | **1.64%** | **0.40%** | **0.69%** |
| Cylinder Scavenging Air Temperature Inlet no.8 | Actual | 43.00 | 43.30 | 43.50 | 43.70 | 43.20 | 44.40 | 52.00 | 50.70 | 51.90 | 52.40 | 52.90 | 52.90 | 52.40 | 51.20 | 51.90 | 51.20 | 50.80 | 51.00 | 51.00 | 52.30 | |
| | ANN Prediction | 43.00 | 43.10 | 43.50 | 43.52 | 43.10 | 44.00 | 51.18 | 51.00 | 51.50 | 51.95 | 52.00 | 52.50 | 52.52 | 50.99 | 51.40 | 51.40 | 51.00 | 51.00 | 50.50 | 51.00 | |
| | APE | **0.00%** | **0.46%** | **0.00%** | **0.41%** | **0.23%** | **0.90%** | **1.58%** | **0.59%** | **0.77%** | **0.86%** | **1.70%** | **0.76%** | **0.23%** | **0.41%** | **0.96%** | **0.39%** | **0.39%** | **0.00%** | **0.98%** | **2.49%** | **0.71%** |

| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder CFW Outlet Temperature no.1 | Actual | 86.00 | 86.10 | 86.00 | 85.90 | 86.10 | 86.70 | 86.60 | 86.40 | 86.30 | 85.90 | 85.90 | 85.80 | 85.40 | 86.10 | 85.90 | 86.10 | 85.80 | 86.10 | 85.90 | 85.60 | |
| | ANN Prediction | 85.98 | 86.04 | 86.06 | 86.04 | 85.98 | 86.11 | 86.34 | 86.24 | 86.12 | 85.94 | 85.87 | 85.73 | 85.60 | 86.02 | 85.97 | 86.08 | 85.85 | 86.06 | 85.89 | 85.77 | |
| | APE | **0.03%** | **0.08%** | **0.06%** | **0.16%** | **0.14%** | **0.69%** | **0.30%** | **0.19%** | **0.21%** | **0.04%** | **0.04%** | **0.08%** | **0.24%** | **0.09%** | **0.08%** | **0.02%** | **0.06%** | **0.05%** | **0.02%** | **0.20%** | **0.14%** |
| Cylinder CFW Outlet Temperature no.2 | Actual | 86.30 | 86.40 | 86.40 | 86.40 | 86.50 | 87.00 | 87.00 | 86.80 | 86.60 | 86.30 | 86.30 | 86.30 | 86.00 | 86.50 | 86.40 | 86.50 | 86.20 | 86.40 | 86.20 | 86.00 | |
| | ANN Prediction | 86.31 | 86.30 | 86.43 | 86.42 | 86.33 | 86.44 | 86.61 | 86.73 | 86.55 | 86.33 | 86.30 | 86.28 | 86.10 | 86.47 | 86.44 | 86.45 | 86.27 | 86.32 | 86.23 | 86.18 | |
| | APE | **0.01%** | **0.12%** | **0.04%** | **0.02%** | **0.19%** | **0.64%** | **0.44%** | **0.08%** | **0.05%** | **0.03%** | **0.00%** | **0.02%** | **0.11%** | **0.03%** | **0.05%** | **0.06%** | **0.08%** | **0.09%** | **0.03%** | **0.21%** | **0.12%** |
| Cylinder CFW Outlet Temperature no.3 | Actual | 85.80 | 85.90 | 85.90 | 85.90 | 86.10 | 86.50 | 86.30 | 86.30 | 86.10 | 85.70 | 85.70 | 85.70 | 85.40 | 85.80 | 85.60 | 85.80 | 85.50 | 85.80 | 85.60 | 85.40 | |
| | ANN Prediction | 85.85 | 85.86 | 85.95 | 85.90 | 85.94 | 86.08 | 86.19 | 86.29 | 86.02 | 85.73 | 85.64 | 85.67 | 85.49 | 85.85 | 85.71 | 85.77 | 85.61 | 85.69 | 85.72 | 85.48 | |
| | APE | **0.06%** | **0.04%** | **0.06%** | **0.00%** | **0.19%** | **0.49%** | **0.13%** | **0.01%** | **0.09%** | **0.03%** | **0.07%** | **0.03%** | **0.11%** | **0.05%** | **0.13%** | **0.03%** | **0.13%** | **0.13%** | **0.14%** | **0.09%** | **0.10%** |
| Cylinder CFW Outlet Temperature no.4 | Actual | 84.80 | 85.00 | 85.40 | 85.30 | 85.40 | 86.20 | 86.20 | 86.10 | 85.80 | 85.50 | 85.50 | 85.40 | 84.70 | 85.70 | 85.50 | 85.70 | 85.40 | 85.70 | 85.40 | 85.40 | |
| | ANN Prediction | 84.76 | 84.98 | 85.29 | 85.34 | 85.36 | 86.15 | 86.29 | 86.06 | 85.90 | 85.61 | 85.74 | 85.33 | 84.83 | 85.59 | 85.41 | 85.50 | 85.10 | 85.50 | 85.52 | 85.61 | |
| | APE | **0.04%** | **0.03%** | **0.13%** | **0.04%** | **0.05%** | **0.06%** | **0.11%** | **0.04%** | **0.11%** | **0.12%** | **0.28%** | **0.09%** | **0.15%** | **0.12%** | **0.10%** | **0.23%** | **0.35%** | **0.23%** | **0.14%** | **0.25%** | **0.13%** |
| Cylinder CFW Outlet Temperature no.5 | Actual | 86.50 | 86.60 | 86.60 | 86.50 | 86.70 | 87.20 | 87.30 | 87.20 | 86.90 | 86.60 | 86.50 | 86.50 | 86.00 | 86.70 | 86.50 | 86.60 | 86.40 | 86.70 | 86.40 | 86.40 | |
| | ANN Prediction | 86.50 | 86.56 | 86.50 | 86.51 | 86.53 | 86.54 | 86.91 | 86.67 | 86.84 | 86.50 | 86.54 | 86.00 | 85.99 | 86.73 | 86.46 | 86.47 | 86.50 | 86.73 | 86.70 | 86.50 | |
| | APE | **0.00%** | **0.05%** | **0.12%** | **0.02%** | **0.19%** | **0.76%** | **0.45%** | **0.61%** | **0.07%** | **0.12%** | **0.05%** | **0.58%** | **0.01%** | **0.03%** | **0.04%** | **0.15%** | **0.12%** | **0.03%** | **0.35%** | **0.12%** | **0.19%** |
| Cylinder CFW Outlet Temperature no.6 | Actual | 87.50 | 87.50 | 87.50 | 87.40 | 87.60 | 88.10 | 88.30 | 88.30 | 88.00 | 87.60 | 87.60 | 87.60 | 87.10 | 87.70 | 87.50 | 87.70 | 87.40 | 87.60 | 87.40 | 87.40 | |
| | ANN Prediction | 87.51 | 87.52 | 87.67 | 87.57 | 87.44 | 87.60 | 87.88 | 88.10 | 88.12 | 87.97 | 87.70 | 87.43 | 87.42 | 87.84 | 87.55 | 87.46 | 87.42 | 87.47 | 87.40 | 87.39 | |
| | APE | **0.02%** | **0.03%** | **0.20%** | **0.20%** | **0.19%** | **0.56%** | **0.48%** | **0.23%** | **0.13%** | **0.42%** | **0.12%** | **0.19%** | **0.37%** | **0.16%** | **0.06%** | **0.28%** | **0.02%** | **0.15%** | **0.00%** | **0.01%** | **0.19%** |
| Cylinder CFW Outlet Temperature no.7 | Actual | 88.30 | 88.30 | 88.30 | 88.30 | 88.40 | 88.50 | 88.70 | 88.60 | 88.50 | 88.10 | 88.10 | 88.00 | 87.60 | 88.20 | 88.10 | 88.20 | 88.00 | 88.30 | 88.00 | 87.70 | |
| | ANN Prediction | 88.31 | 88.40 | 88.38 | 88.35 | 88.31 | 88.34 | 88.47 | 88.52 | 88.39 | 88.23 | 88.02 | 87.88 | 87.67 | 88.10 | 88.19 | 88.16 | 88.13 | 88.27 | 88.08 | 87.95 | |
| | APE | **0.01%** | **0.11%** | **0.09%** | **0.06%** | **0.11%** | **0.18%** | **0.26%** | **0.09%** | **0.13%** | **0.14%** | **0.09%** | **0.14%** | **0.08%** | **0.12%** | **0.10%** | **0.05%** | **0.15%** | **0.04%** | **0.09%** | **0.29%** | **0.12%** |
| Cylinder CFW Outlet Temperature no.8 | Actual | 86.10 | 86.20 | 86.10 | 86.00 | 86.30 | 86.70 | 86.80 | 86.50 | 86.30 | 86.00 | 85.90 | 86.00 | 85.40 | 86.00 | 85.90 | 86.00 | 85.80 | 86.20 | 85.90 | 85.70 | |
| | ANN Prediction | 86.16 | 86.08 | 86.22 | 86.09 | 86.11 | 86.23 | 86.35 | 86.35 | 86.24 | 86.07 | 86.06 | 85.89 | 85.89 | 86.25 | 86.10 | 85.95 | 85.93 | 86.00 | 85.93 | 86.05 | |
| | APE | **0.07%** | **0.13%** | **0.14%** | **0.11%** | **0.22%** | **0.54%** | **0.51%** | **0.18%** | **0.07%** | **0.08%** | **0.19%** | **0.13%** | **0.58%** | **0.30%** | **0.24%** | **0.06%** | **0.15%** | **0.23%** | **0.04%** | **0.41%** | **0.22%** |

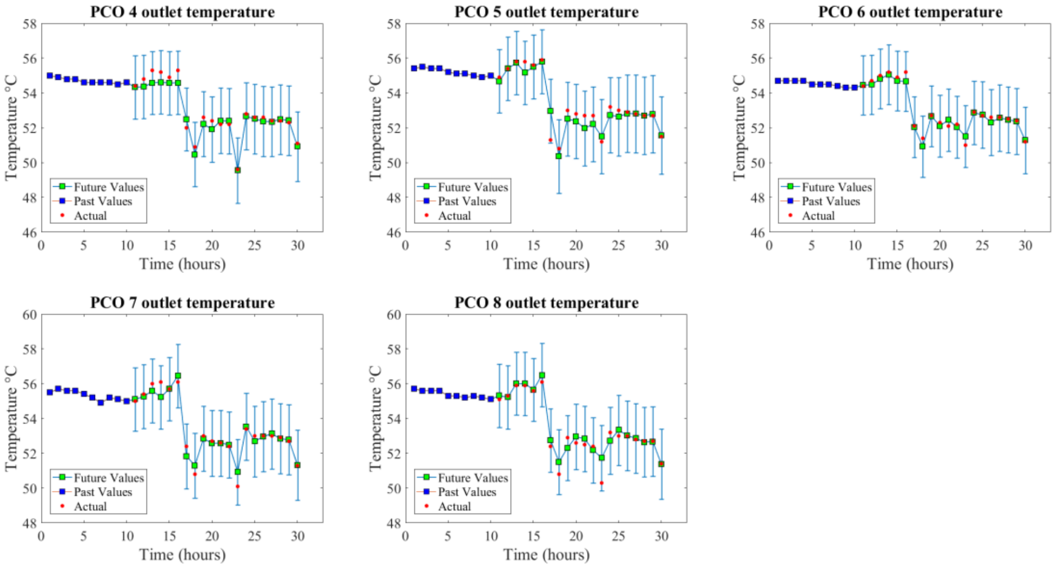
| Parameter | Results | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 | t+8 | t+9 | t+10 | t+11 | t+12 | t+13 | t+14 | t+15 | t+16 | t+17 | t+18 | t+19 | t+20 | MAPE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cylinder PCO Outlet Temperature no.1 | Actual | 54.50 | 54.80 | 55.10 | 55.20 | 54.90 | 55.30 | 52.00 | 50.40 | 52.70 | 52.30 | 52.20 | 52.20 | 49.80 | 52.90 | 52.80 | 52.60 | 52.50 | 52.50 | 52.50 | 51.10 | |
| | ANN Prediction | 54.15 | 54.19 | 54.60 | 54.89 | 54.70 | 54.64 | 52.86 | 50.06 | 52.49 | 52.35 | 52.29 | 52.00 | 49.50 | 52.48 | 52.31 | 52.45 | 52.54 | 52.29 | 52.35 | 51.18 | |
| | APE | **0.64%** | **1.11%** | **0.91%** | **0.55%** | **0.36%** | **1.20%** | **1.65%** | **0.67%** | **0.40%** | **0.10%** | **0.18%** | **0.39%** | **0.60%** | **0.80%** | **0.92%** | **0.29%** | **0.08%** | **0.40%** | **0.29%** | **0.16%** | **0.59%** |
| Cylinder PCO Outlet Temperature no.2 | Actual | 54.60 | 54.90 | 55.30 | 55.30 | 55.10 | 55.40 | 52.20 | 50.60 | 52.80 | 52.40 | 52.30 | 52.30 | 49.10 | 52.90 | 52.80 | 52.70 | 52.50 | 52.60 | 52.50 | 51.20 | |
| | ANN Prediction | 54.31 | 54.38 | 54.76 | 55.21 | 55.24 | 54.98 | 52.74 | 50.57 | 53.07 | 52.18 | 52.15 | 52.39 | 49.10 | 53.04 | 52.72 | 52.53 | 52.62 | 52.63 | 52.62 | 51.21 | |
| | APE | **0.53%** | **0.95%** | **0.97%** | **0.17%** | **0.26%** | **0.76%** | **1.03%** | **0.06%** | **0.51%** | **0.43%** | **0.29%** | **0.18%** | **0.00%** | **0.27%** | **0.16%** | **0.33%** | **0.22%** | **0.07%** | **0.23%** | **0.01%** | **0.37%** |
| Cylinder PCO Outlet Temperature no.3 | Actual | 54.40 | 54.80 | 55.20 | 55.20 | 54.90 | 55.30 | 51.60 | 50.00 | 52.30 | 52.00 | 51.90 | 51.90 | 48.70 | 52.60 | 52.30 | 52.30 | 52.20 | 52.10 | 52.10 | 50.80 | |
| | ANN Prediction | 54.50 | 54.44 | 54.70 | 54.95 | 54.56 | 54.51 | 52.21 | 49.98 | 52.23 | 51.68 | 51.72 | 52.49 | 48.68 | 52.65 | 52.34 | 52.14 | 52.13 | 52.19 | 52.16 | 51.03 | |
| | APE | **0.19%** | **0.66%** | **0.91%** | **0.45%** | **0.61%** | **1.43%** | **1.18%** | **0.04%** | **0.13%** | **0.62%** | **0.35%** | **1.13%** | **0.03%** | **0.09%** | **0.08%** | **0.32%** | **0.13%** | **0.18%** | **0.12%** | **0.46%** | **0.46%** |
| Cylinder PCO Outlet Temperature no.4 | Actual | 54.40 | 54.80 | 55.30 | 55.20 | 54.90 | 55.30 | 52.00 | 50.90 | 52.60 | 52.40 | 52.20 | 52.20 | 49.60 | 52.80 | 52.60 | 52.60 | 52.40 | 52.40 | 52.30 | 51.10 | |
| | ANN Prediction | 54.33 | 54.36 | 54.58 | 54.62 | 54.57 | 54.59 | 52.49 | 50.47 | 52.22 | 51.91 | 52.41 | 52.39 | 49.55 | 52.66 | 52.51 | 52.37 | 52.35 | 52.49 | 52.42 | 50.92 | |
| | APE | **0.13%** | **0.80%** | **1.30%** | **1.06%** | **0.61%** | **1.28%** | **0.94%** | **0.84%** | **0.72%** | **0.94%** | **0.40%** | **0.36%** | **0.10%** | **0.26%** | **0.17%** | **0.43%** | **0.09%** | **0.17%** | **0.22%** | **0.35%** | **0.56%** |
| Cylinder PCO Outlet Temperature no.5 | Actual | 54.90 | 55.40 | 55.80 | 55.80 | 55.60 | 55.90 | 51.30 | 50.80 | 53.00 | 52.80 | 52.70 | 52.70 | 51.20 | 53.20 | 53.00 | 52.90 | 52.80 | 52.70 | 52.70 | 51.50 | |
| | ANN Prediction | 54.68 | 55.40 | 55.73 | 55.17 | 55.50 | 55.80 | 52.97 | 50.36 | 52.51 | 52.38 | 51.97 | 52.21 | 51.50 | 52.73 | 52.64 | 52.82 | 52.81 | 52.70 | 52.80 | 51.56 | |
| | APE | **0.40%** | **0.00%** | **0.13%** | **1.13%** | **0.18%** | **0.18%** | **3.26%** | **0.87%** | **0.92%** | **0.79%** | **1.39%** | **0.93%** | **0.59%** | **0.89%** | **0.68%** | **0.15%** | **0.02%** | **0.01%** | **0.19%** | **0.12%** | **0.64%** |
| Cylinder PCO Outlet Temperature no.6 | Actual | 54.40 | 54.70 | 55.00 | 55.20 | 54.90 | 55.20 | 52.10 | 51.40 | 52.70 | 52.30 | 52.10 | 52.20 | 51.00 | 52.90 | 52.70 | 52.60 | 52.60 | 52.50 | 52.40 | 51.20 | |
| | ANN Prediction | 54.45 | 54.48 | 54.81 | 55.06 | 54.69 | 54.67 | 52.04 | 50.92 | 52.67 | 52.11 | 52.45 | 52.04 | 51.50 | 52.86 | 52.75 | 52.31 | 52.57 | 52.46 | 52.37 | 51.28 | |
| | APE | **0.09%** | **0.40%** | **0.34%** | **0.25%** | **0.38%** | **0.96%** | **0.11%** | **0.93%** | **0.06%** | **0.37%** | **0.67%** | **0.30%** | **0.98%** | **0.08%** | **0.10%** | **0.56%** | **0.06%** | **0.08%** | **0.06%** | **0.16%** | **0.35%** |
| Cylinder PCO Outlet Temperature no.7 | Actual | 55.00 | 55.40 | 56.00 | 56.10 | 55.70 | 56.10 | 52.40 | 50.80 | 53.00 | 52.70 | 52.60 | 52.40 | 50.10 | 53.40 | 53.00 | 53.00 | 53.00 | 52.90 | 52.70 | 51.30 | |
| | ANN Prediction | 55.10 | 55.27 | 55.60 | 55.23 | 55.70 | 56.45 | 51.84 | 51.30 | 52.85 | 52.58 | 52.59 | 52.50 | 50.93 | 53.54 | 52.69 | 52.96 | 53.13 | 52.84 | 52.78 | 51.33 | |
| | APE | **0.18%** | **0.23%** | **0.71%** | **1.55%** | **0.00%** | **0.62%** | **1.07%** | **0.99%** | **0.29%** | **0.24%** | **0.02%** | **0.19%** | **1.66%** | **0.26%** | **0.58%** | **0.08%** | **0.25%** | **0.11%** | **0.14%** | **0.07%** | **0.46%** |
| Cylinder PCO Outlet Temperature no.8 | Actual | 55.10 | 55.30 | 55.90 | 55.90 | 55.60 | 56.10 | 52.40 | 50.80 | 52.90 | 52.60 | 52.50 | 52.40 | 50.30 | 53.20 | 53.00 | 53.00 | 52.80 | 52.70 | 52.70 | 51.40 | |
| | ANN Prediction | 55.31 | 55.22 | 56.01 | 56.00 | 55.66 | 56.50 | 52.76 | 51.51 | 52.32 | 52.96 | 52.83 | 52.19 | 51.74 | 52.73 | 53.34 | 53.02 | 52.86 | 52.65 | 52.68 | 51.38 | |
| | APE | **0.38%** | **0.14%** | **0.20%** | **0.18%** | **0.11%** | **0.71%** | **0.69%** | **1.40%** | **1.10%** | **0.69%** | **0.63%** | **0.40%** | **2.86%** | **0.88%** | **0.65%** | **0.04%** | **0.11%** | **0.10%** | **0.04%** | **0.05%** | **0.57%** |

### *F.3.3 Forecasting results with 95% prediction intervals*





Cylinder 2 scavenging air
Cylinder 3 scavenging air
Cylinder 4 scavenging air
Cylinder 5 scavenging air
Cylinder 6 scavenging air
Cylinder 7 scavenging air
Cylinder 8 scavenging air
Cylinder 1 CFW outlet
Cylinder 2 CFW outlet
Cylinder 3 CFW outlet
Cylinder 4 CFW outlet
Cylinder 5 CFW outlet
Cylinder 6 CFW outlet
Cylinder 7 CFW outlet
Cylinder 8 CFW outlet
PCO 1 outlet temperature
PCO 2 outlet temperature
PCO 3 outlet temperature
Future Values
Past Values
Actual
Temperature °C
Time (hours)


PCO 4 outlet temperature
PCO 5 outlet temperature
PCO 6 outlet temperature
PCO 7 outlet temperature
PCO 8 outlet temperature
Temperature °C
Time (hours)
Future Values
Past Values
Actual

# Appendix G: Main engine ANN-MLP and MCI results

## G.1 ANN-MLP results (training, validation, all data)

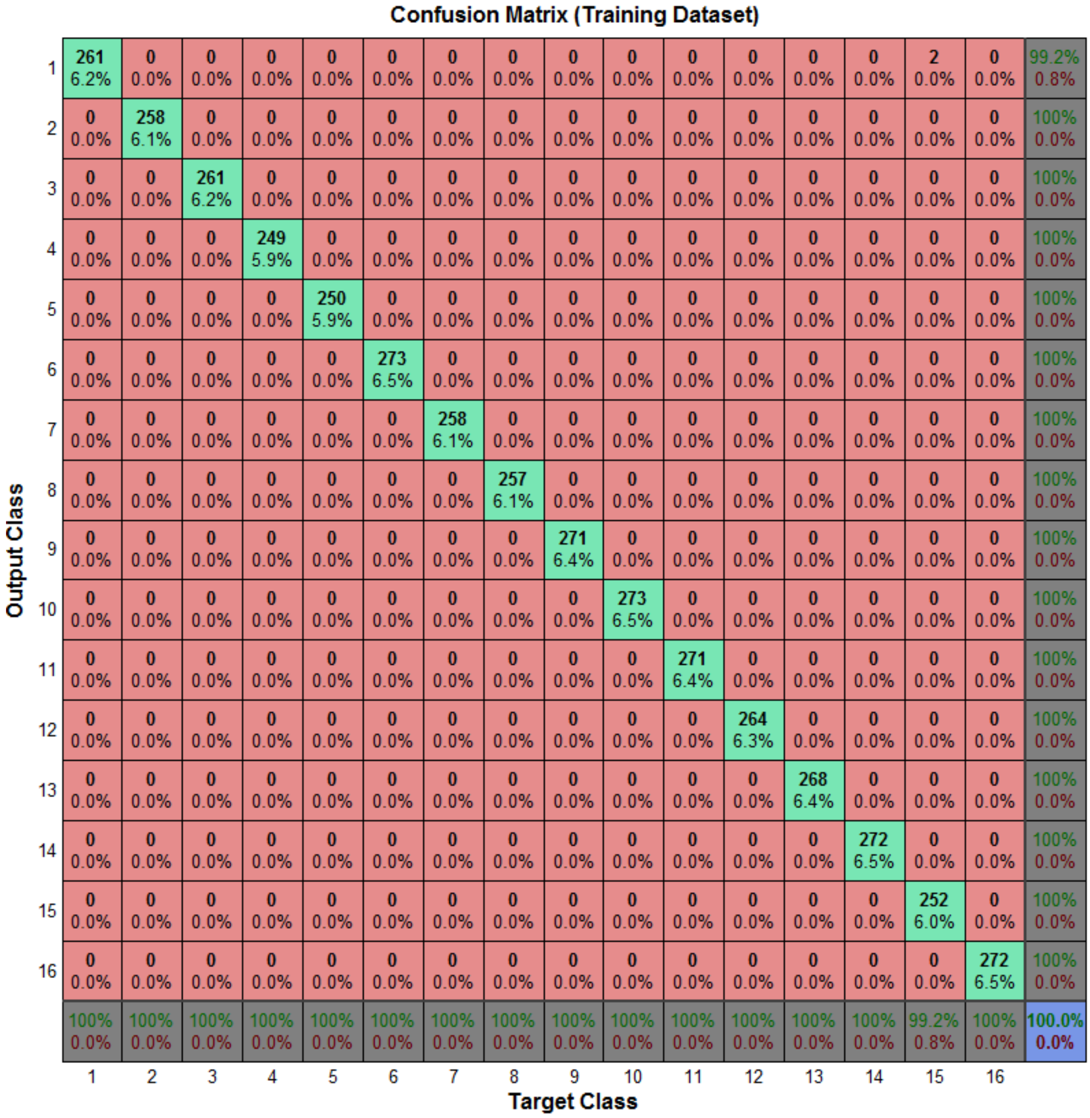



Figure 2 Training dataset confusion matrix for all 16 main engine fault classes

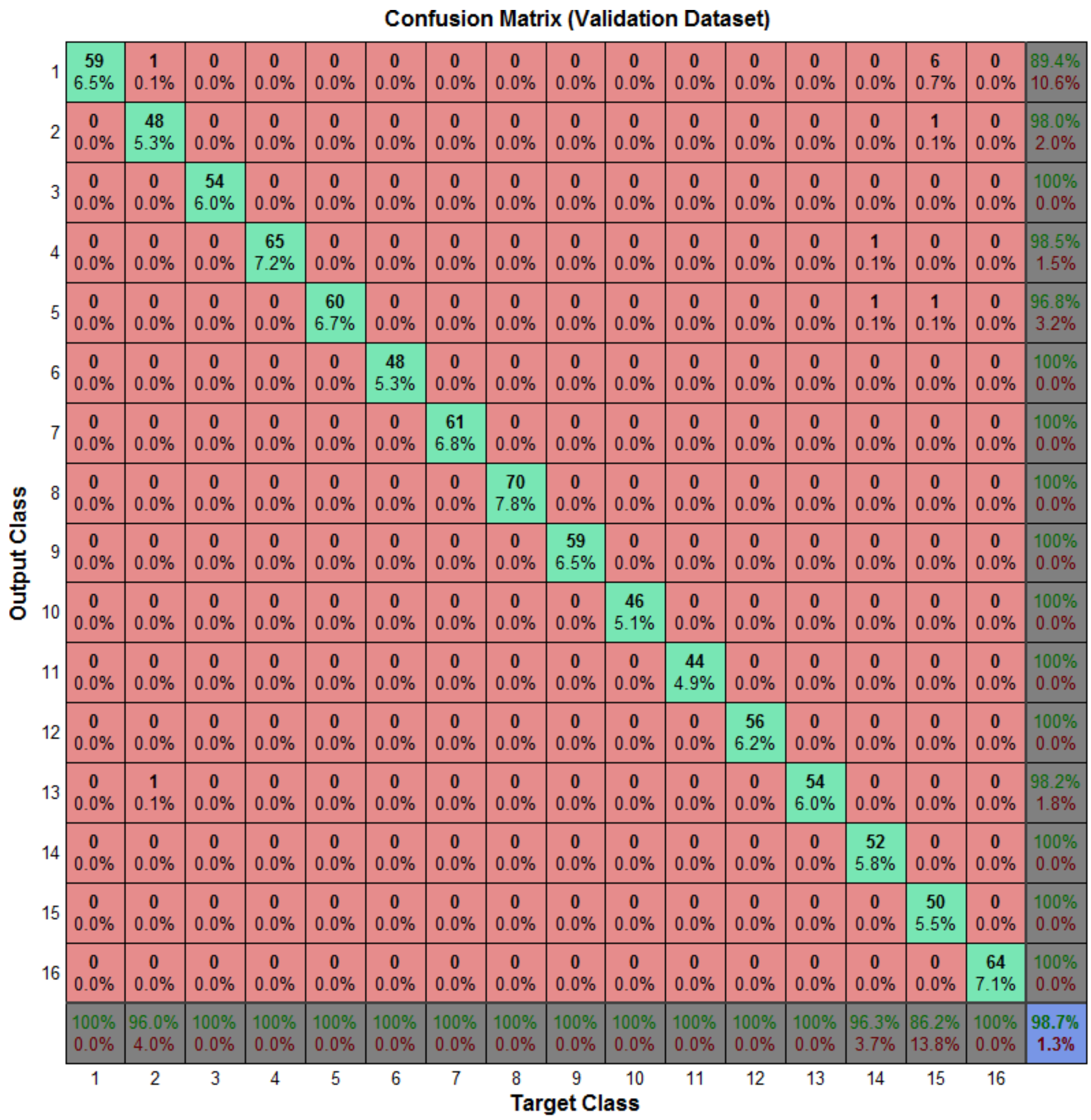



Figure 3 Validation dataset confusion matrix for all 16 main engine fault classes

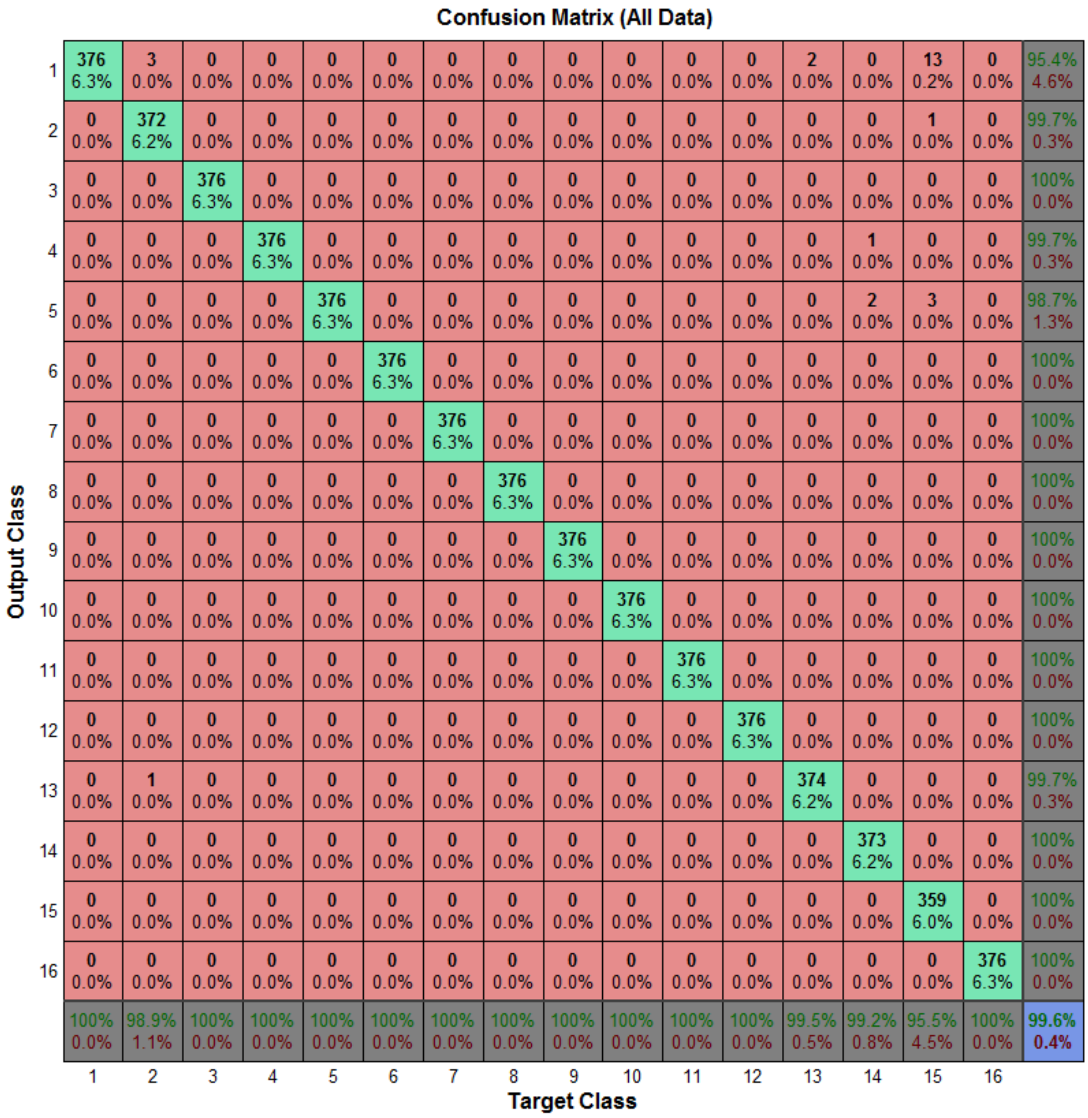
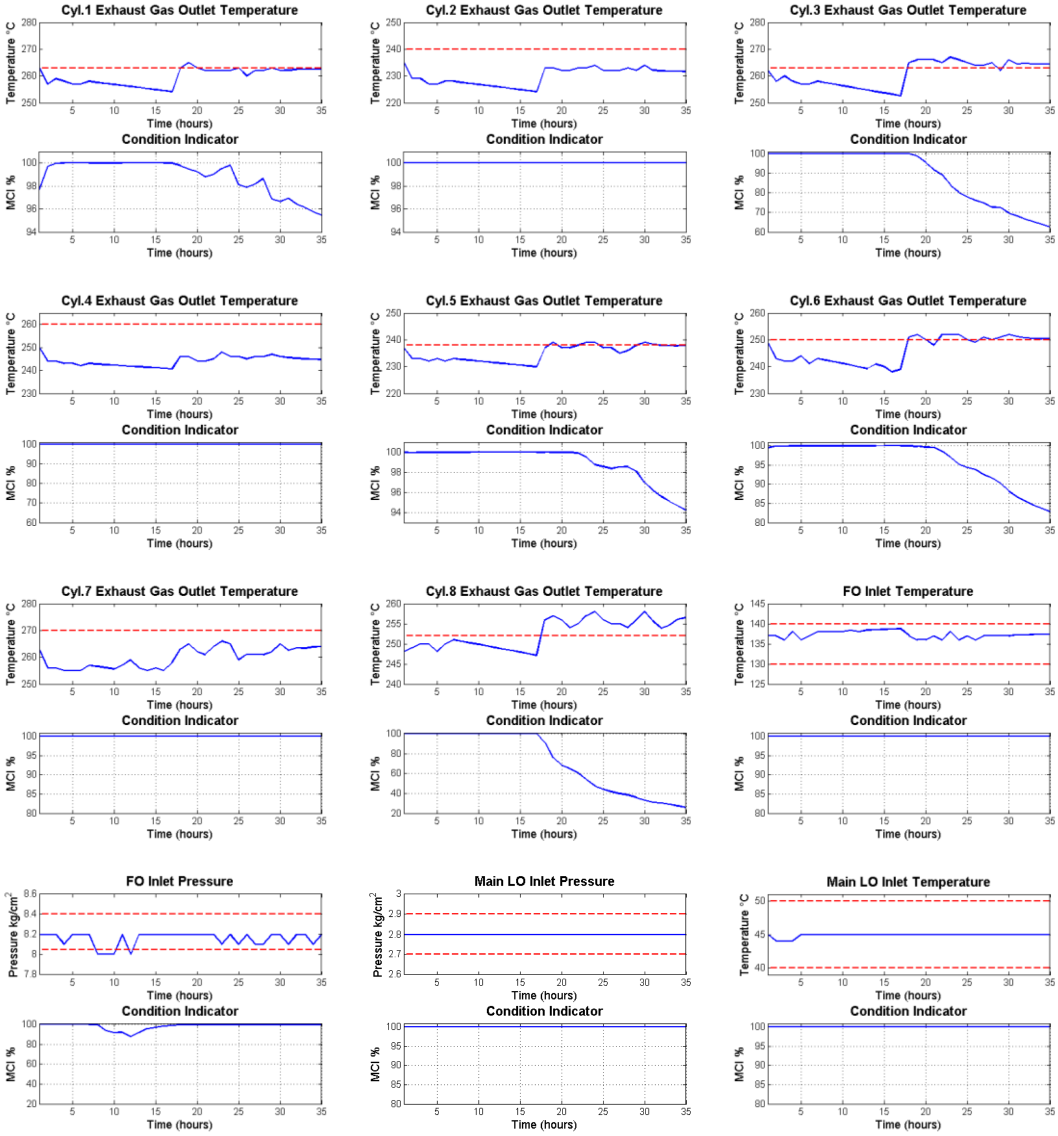
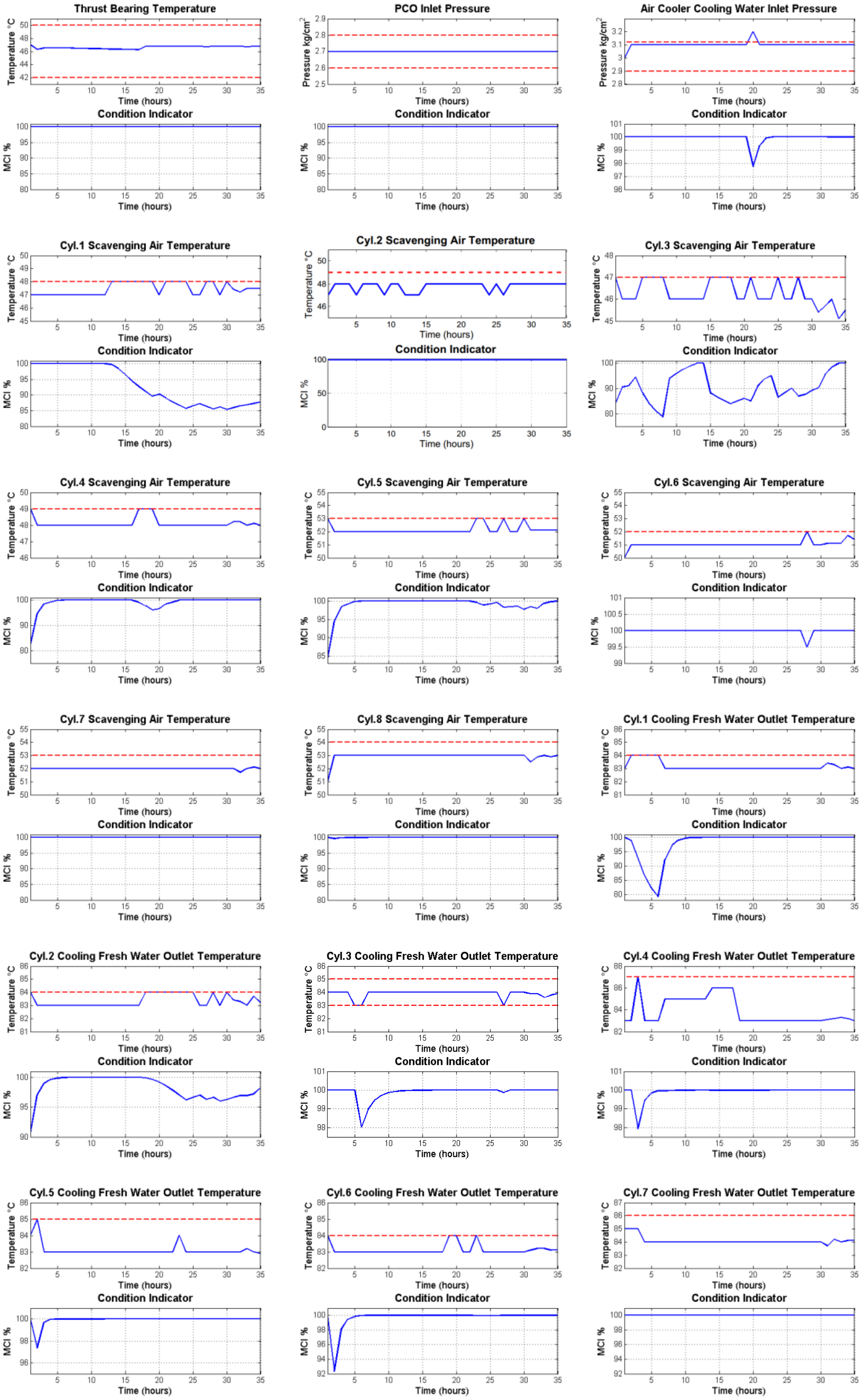
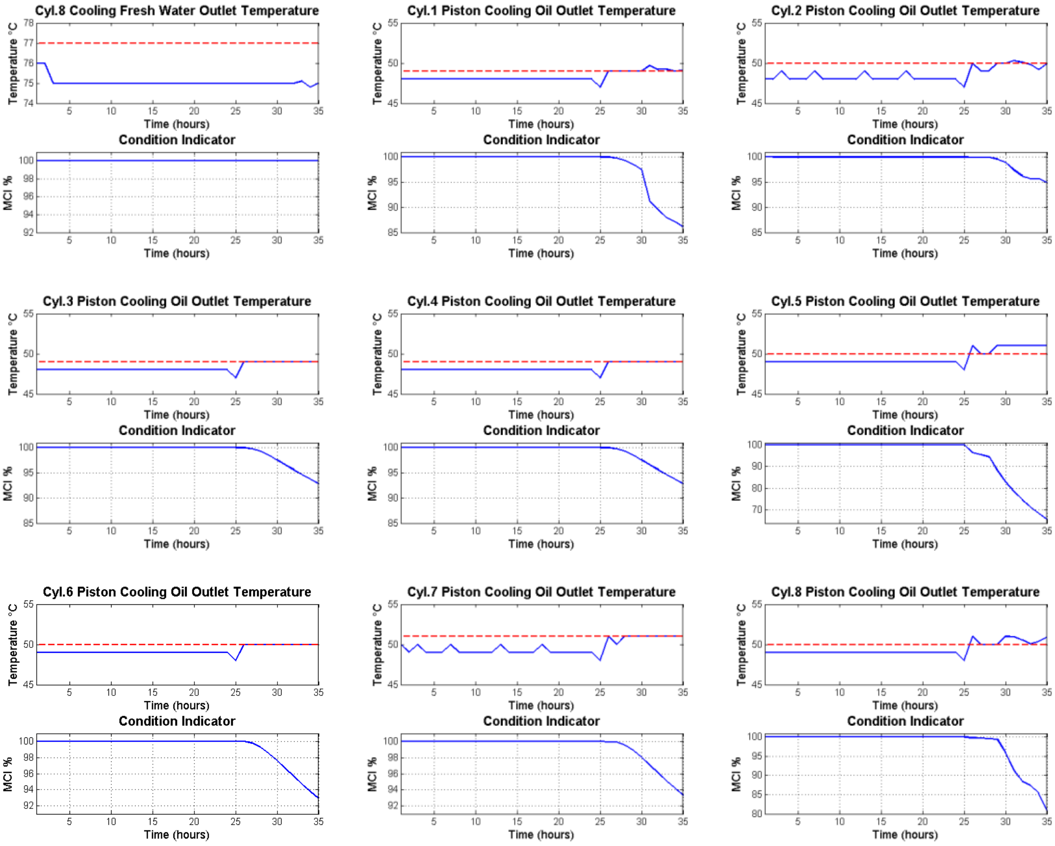



Figure 4 Complete dataset confusion matrix for all 16 main engine fault classes

## G.2 MCI results for main engine parameters




Thrust Bearing Temperature
Condition Indicator
PCO Inlet Pressure
Condition Indicator
Air Cooler Cooling Water Inlet Pressure
Condition Indicator
Cyl.1 Scavenging Air Temperature
Condition Indicator
Cyl.2 Scavenging Air Temperature
Condition Indicator
Cyl.3 Scavenging Air Temperature
Condition Indicator
Cyl.4 Scavenging Air Temperature
Condition Indicator
Cyl.5 Scavenging Air Temperature
Condition Indicator
Cyl.6 Scavenging Air Temperature
Condition Indicator
Cyl.7 Scavenging Air Temperature
Condition Indicator
Cyl.8 Scavenging Air Temperature
Condition Indicator
Cyl.1 Cooling Fresh Water Outlet Temperature
Condition Indicator
Cyl.2 Cooling Fresh Water Outlet Temperature
Condition Indicator
Cyl.3 Cooling Fresh Water Outlet Temperature
Condition Indicator
Cyl.4 Cooling Fresh Water Outlet Temperature
Condition Indicator
Cyl.5 Cooling Fresh Water Outlet Temperature
Condition Indicator
Cyl.6 Cooling Fresh Water Outlet Temperature
Condition Indicator
Cyl.7 Cooling Fresh Water Outlet Temperature
Condition Indicator
Time (hours)
Temperature °C
Pressure kg/cm²
MCI %


Cyl.8 Cooling Fresh Water Outlet Temperature
Cyl.1 Piston Cooling Oil Outlet Temperature
Cyl.2 Piston Cooling Oil Outlet Temperature
Cyl.3 Piston Cooling Oil Outlet Temperature
Cyl.4 Piston Cooling Oil Outlet Temperature
Cyl.5 Piston Cooling Oil Outlet Temperature
Cyl.6 Piston Cooling Oil Outlet Temperature
Cyl.7 Piston Cooling Oil Outlet Temperature
Cyl.8 Piston Cooling Oil Outlet Temperature
Condition Indicator
Temperature °C
MCI %
Time (hours)

# Appendix H: Cost-benefit analysis

## *H.1 CBA parameters*

*Table 1 Preventive maintenance cost table*

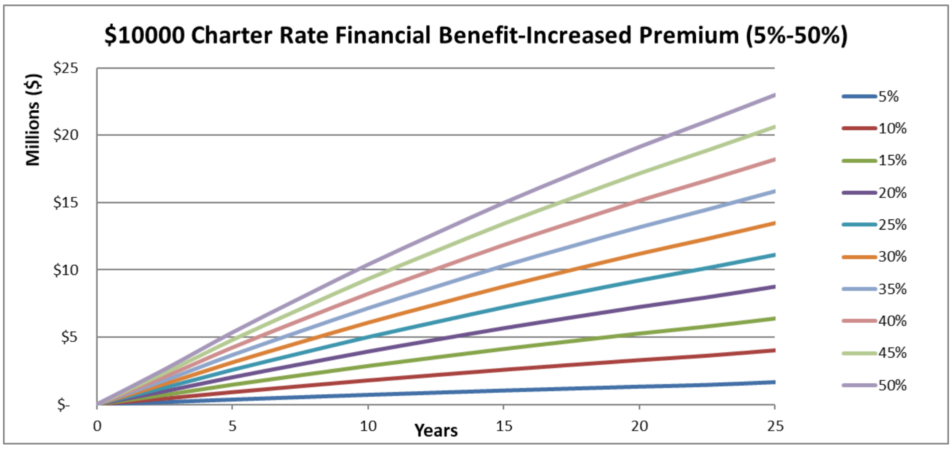
| Description of costs | Value |
|---|---|
| **Spare part costs (crew inspection)** | |
| Spare parts per cylinder | $ 350.00 |
| Number of cylinders | 8 |
| Spare parts costs (Total) | $ 2,800.00 |
| **Inspections by technicians (Labour cost)** | |
| Persons | 3 |
| Days | 2 |
| Hours | 8 |
| Cost per hour | $ 150.00 |
| Labour costs (Total) | $ 7,200.00 |
| **Loss of income** | |
| Loss per day | $ 10,000.00 |
| Days | 4 |
| Loss of income (Total) | 40000 |
| **Oil renewal costs** | |
| Oil (Litres) | 3000 |
| Oil cost per litre | $ 2.50 |
| Oil renewal cost (Total) | $ 7,500.00 |
| **Spare part costs (Technician inspection)** | |
| Spare parts per cylinder | $ 950.00 |
| Number of cylinders | 8 |
| Misceallaneous engine parts | $ 4,000.00 |
| Spare parts costs (Total) | $ 11,600.00 |
| **Drydocking cost per 2.5 years** | $ 126,660.00 |

*Table 2 Drydocking cost table*

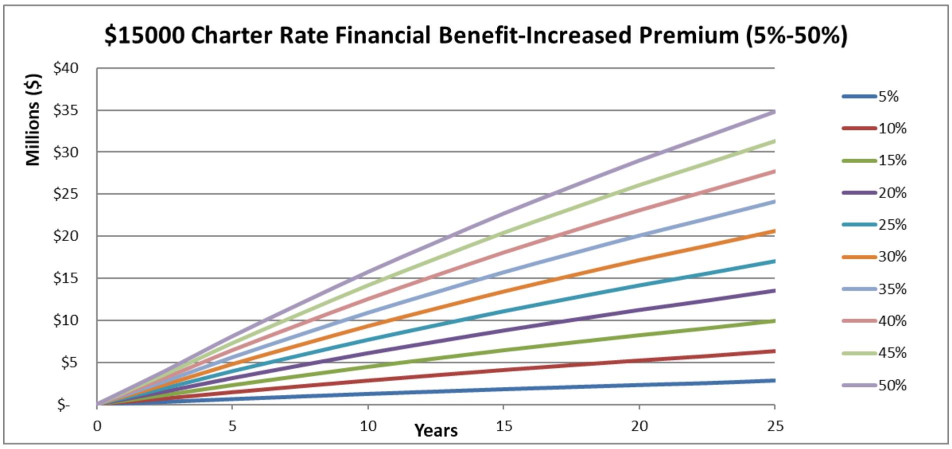
| Description of costs | Value | |
|---|---|---|
| Spare Parts per Cylinder | $ | 1,400 |
| Number of Cylinders | 8 | |
| Misc. Engine Parts | $ | 7,000 |
| **1)Spare Parts Costs (Total)** | **$** | **18,200** |
| Personnel (Total) | 6 | |
| Superintendent Engineer (S.E) | 1 | |
| Senior Service Engineer | 1 | |
| Service Engineer | 1 | |
| Technicians | 3 | |
| Days | 8 | |
| S.E Hourly Rate | $ | 150 |
| Hours/Day | 8 | |
| *S.E Costs* | $ | 9,600 |
| Senior Service Engineer Hourly Rate | $ | 125 |
| Hours/Day | 8 | |
| *Senior Service Engineer Costs* | $ | 8,000 |
| Service Engineer Hourly Rate | $ | 110 |
| Hours/Day | 8 | |
| *Service Engineer Costs* | $ | 7,040 |
| Technicians Hourly Rate | $ | 85 |
| Hours/Day | 8 | |
| *Technicians Costs* | $ | 16,320 |
| **2)Labour Costs (Total)** | **$** | **40,960** |
| Oil (Litres) | 3000 | |
| Oil Cost per Litre | $ | 2.50 |
| **3)Oil Renewal Cost (Total)** | **$** | **7,500.00** |
| Drydock Charge per day | $ | 4,000 |
| Days | 12 | |
| Services Misc. per day | $ | 1,000 |
| Services Costs | $ | 12,000 |
| **4)Drydock Costs** | **$** | **60,000** |
| | | |
| **TOTAL DRYDOCK COST (1+2+3+4)** | **$** | **126,660** |

## *H.2 PMS+25% results*

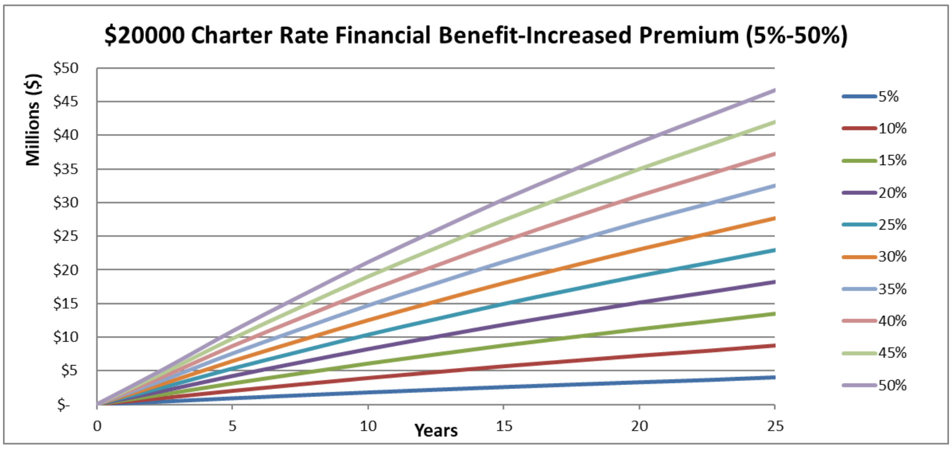
- $10,000 Charter Rate




- $15,000 Charter Rate

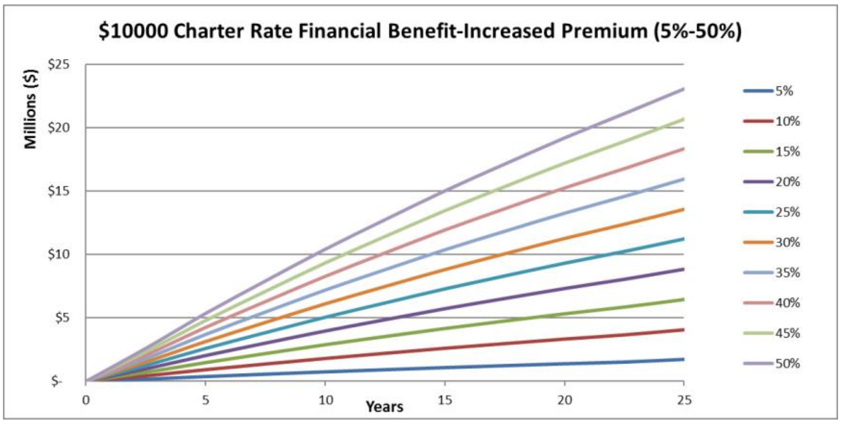



- $20,000 Charter Rate

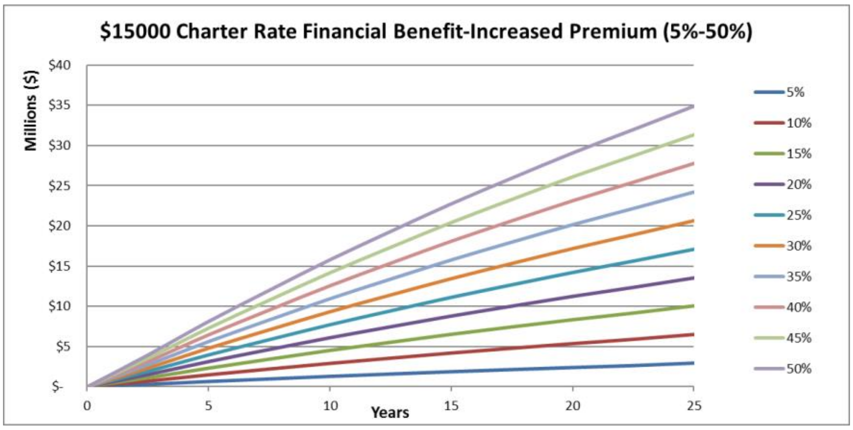


## *H.3 PMS+50% results*

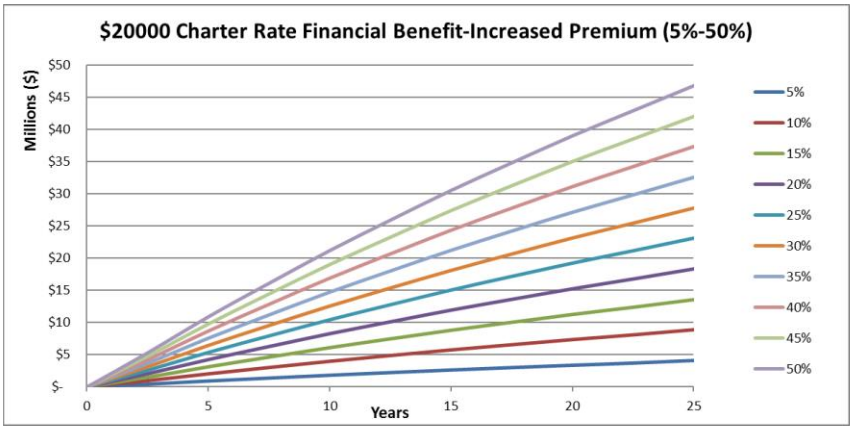
- $10,000 Charter Rate




- $15,000 Charter Rate

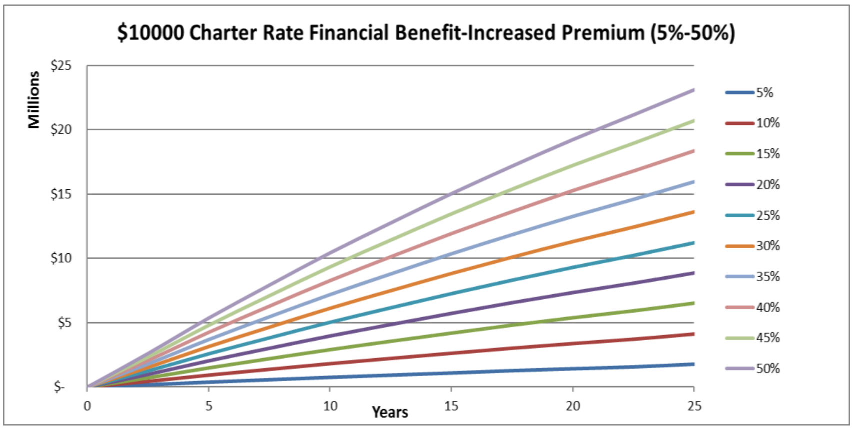



- $20,000 Charter Rate

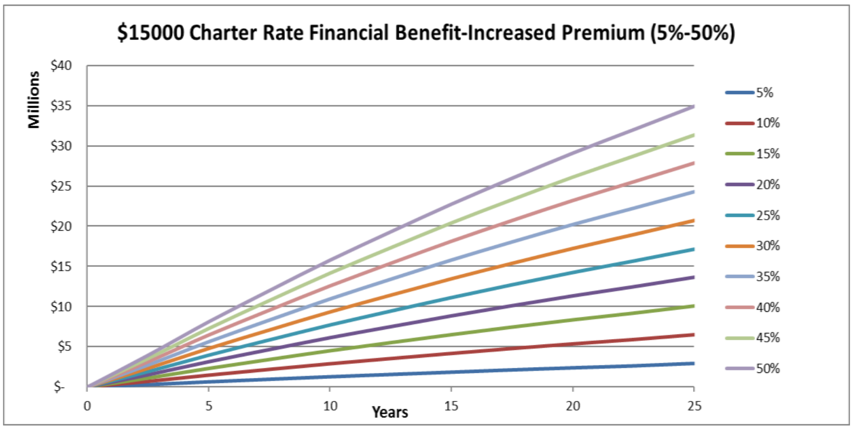


## H.4 PMS+75% results

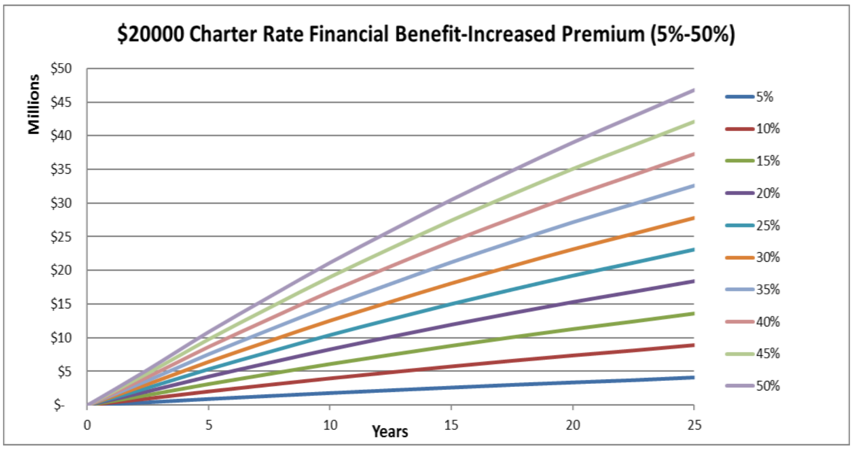
- $10,000 Charter Rate




- $15,000 Charter Rate

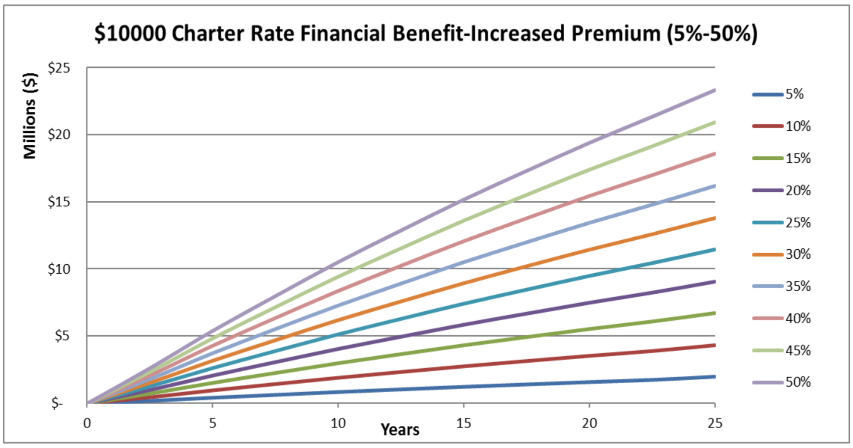



- $20,000 Charter Rate

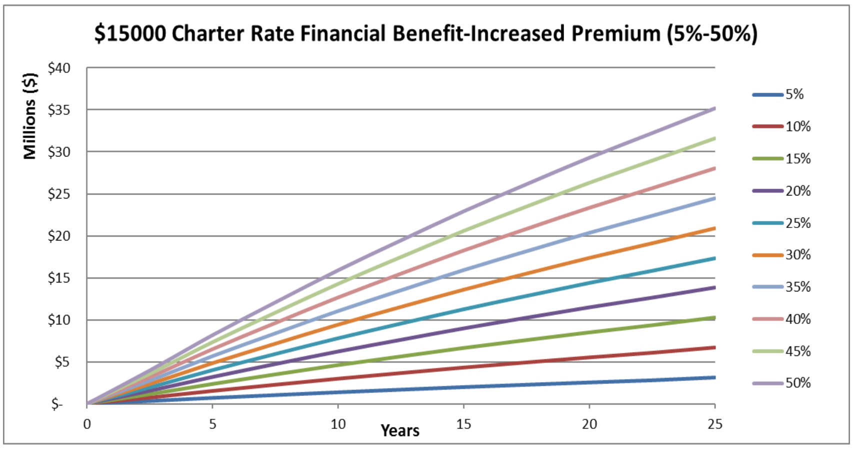


## H.5 PMS+100% results

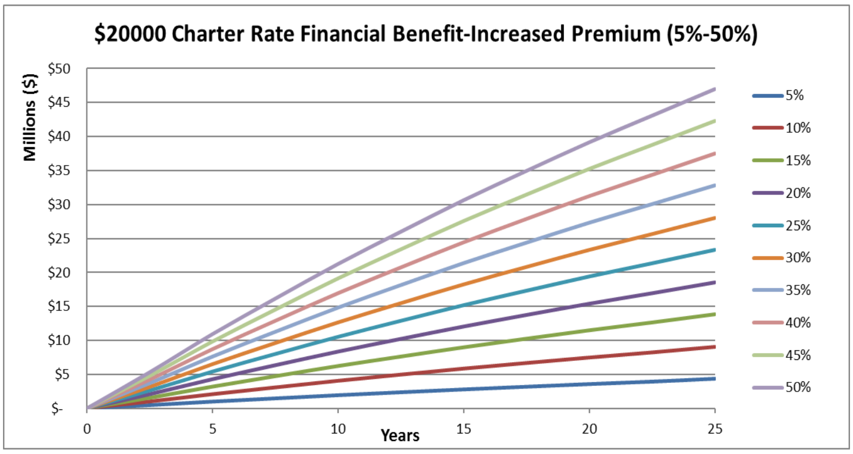
- <u>$10,000 Charter Rate</u>



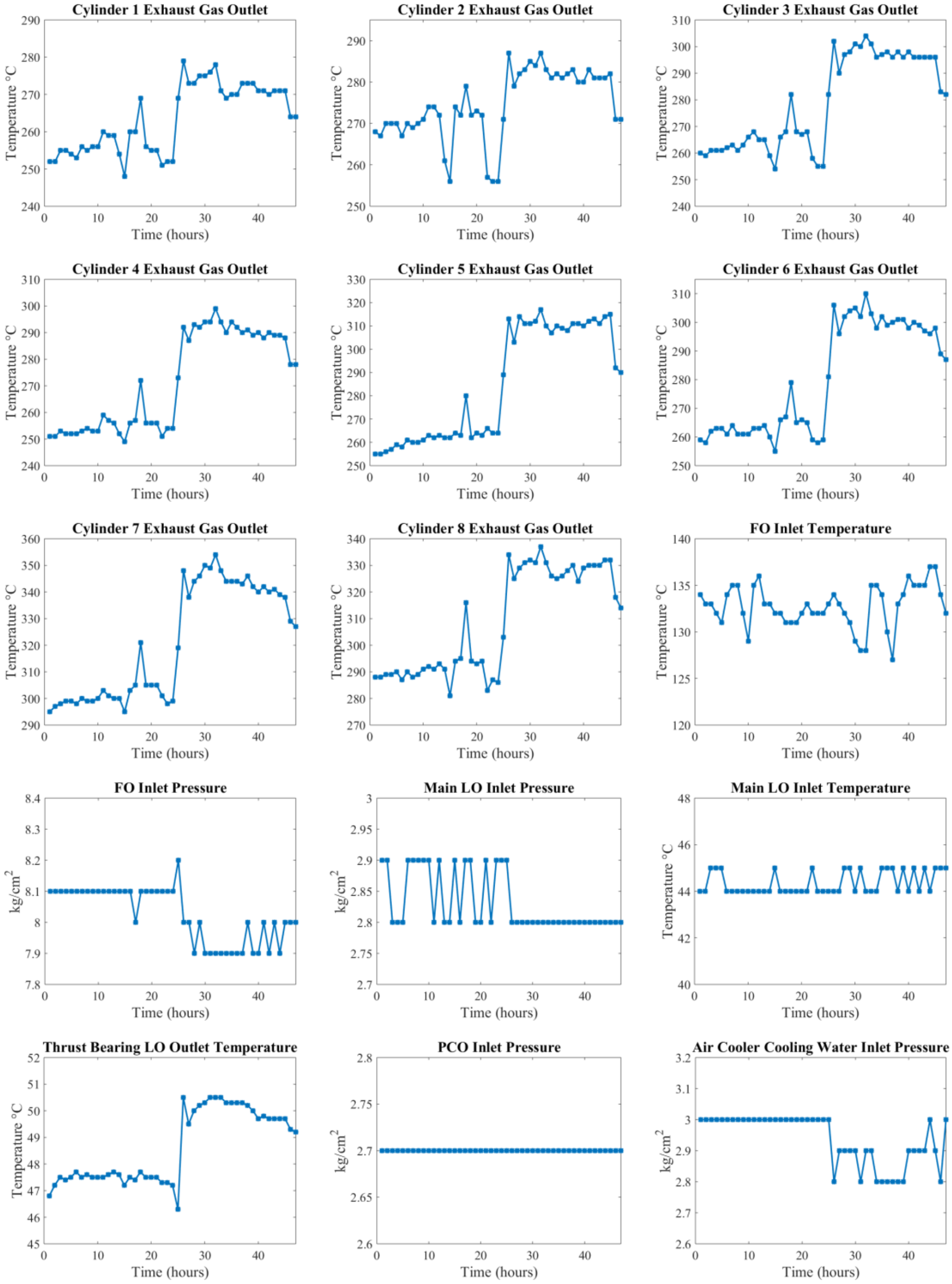

- <u>$15,000 Charter Rate</u>

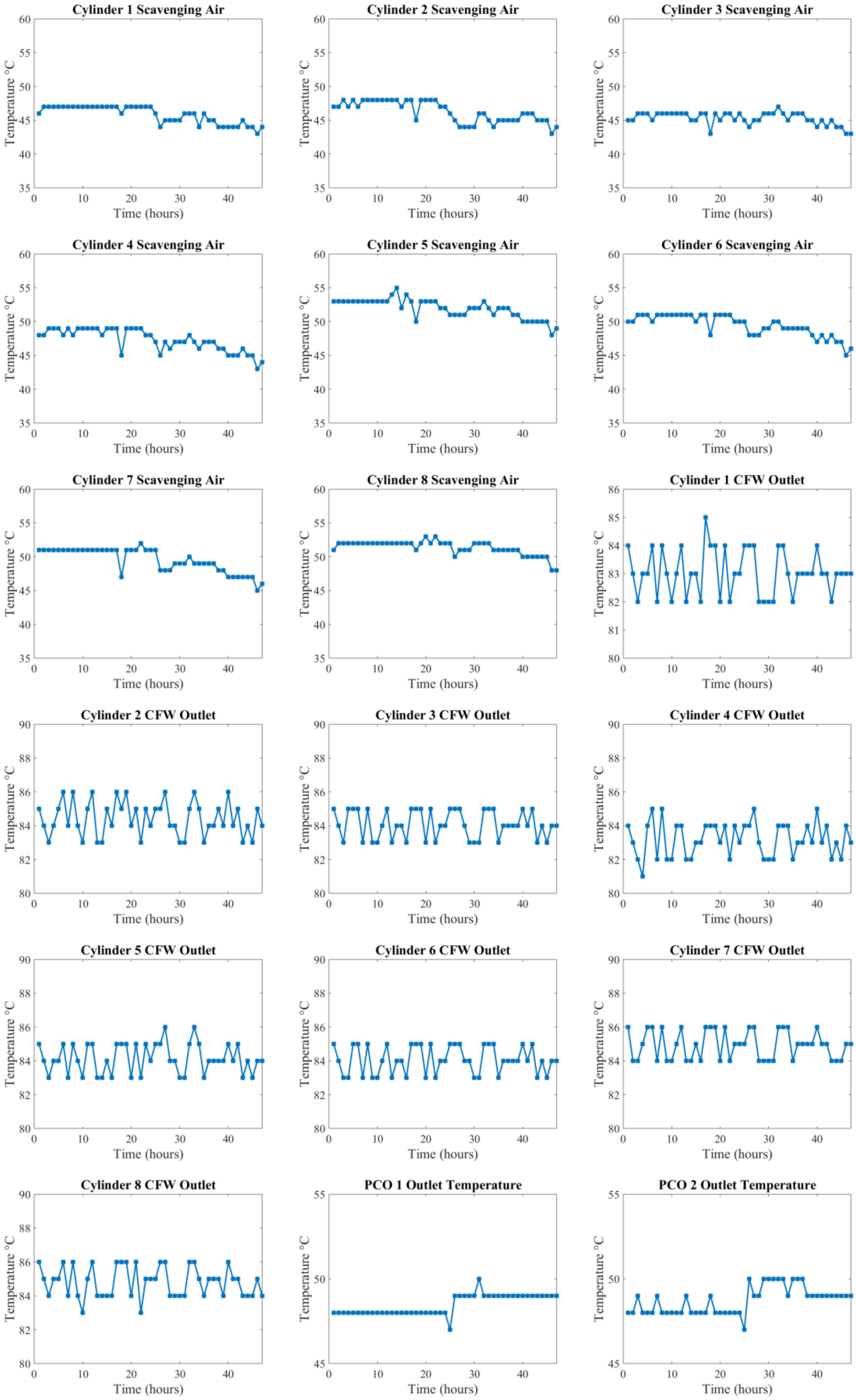


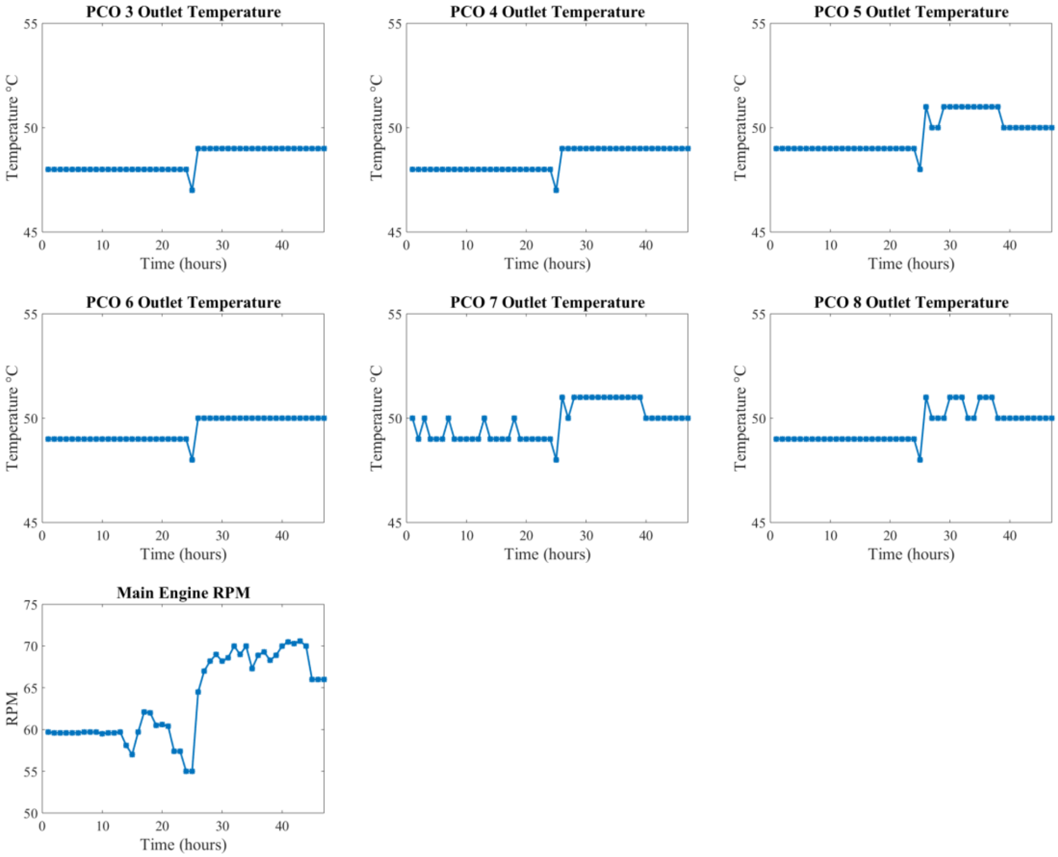

- <u>$20,000 Charter Rate</u>



# Appendix I: Dataset 3 measurements




Cylinder 1 Scavenging Air
Cylinder 2 Scavenging Air
Cylinder 3 Scavenging Air
Cylinder 4 Scavenging Air
Cylinder 5 Scavenging Air
Cylinder 6 Scavenging Air
Cylinder 7 Scavenging Air
Cylinder 8 Scavenging Air
Cylinder 1 CFW Outlet
Cylinder 2 CFW Outlet
Cylinder 3 CFW Outlet
Cylinder 4 CFW Outlet
Cylinder 5 CFW Outlet
Cylinder 6 CFW Outlet
Cylinder 7 CFW Outlet
Cylinder 8 CFW Outlet
PCO 1 Outlet Temperature
PCO 2 Outlet Temperature
Temperature °C
Time (hours)


PCO 3 Outlet Temperature
PCO 4 Outlet Temperature
PCO 5 Outlet Temperature
PCO 6 Outlet Temperature
PCO 7 Outlet Temperature
PCO 8 Outlet Temperature
Main Engine RPM
Temperature °C
RPM
Time (hours)