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Development of an Innovative Business-oriented Probability-based Maintenance (BOPM) Methodology for Ship Machinery Systems

By

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- Taheri, A., Lazakis, I. and Koch, T. 2015. An Innovative Machinery Data Management System for Ships using a Catalogue Data Model. International Maritime Association of Mediterranean (IMAM2015) conference. Pula, Croatia. (Taheri, et al., 2015)
- Taheri, A., Lazakis, I. and Koch, T. 2015. Catalogue Data Model Based Innovative Database System for Ship Structural and Machinery Condition Monitoring (MCM) Data Exchange Protocol. Ship in Changing Climate (SCC 2015). Glasgow, U.K. (Taheri, et al., 2015)
- Dikis, K., Lazakis, I., Taheri, A. and Theotokatos, G. 2015. Risk and Reliability Analysis Tool Development for Ship Machinery Maintenance. 5th International Symposium on Ship Operations, Management and Economics (SOME 2015), Athens, Greece. (Dikis, et al., 2015)
- Taheri, A., Lazakis, I. and Gohtbzadeh, J. 2016. Cost Based Dynamic Bayesian Network Reliability Analysis and Decision Making for Lub Oil System of a Suezmax Vessel. International Conference in Maritime Safety and Operations (MSO 2016) Conference, Glasgow, U.K. (Taheri, et al., 2016)

Abstract

Throughout the maritime industry, there has been relatively high number of shipping-related incidents. Therefore, numerous international, local and Classification Society based legislations have been developed in order to regulate shipping and reduce accidents. These policies not only dictate ship design methodologies but also inspection and maintenance activities of vessels. These policies on inspection and maintenance have generally increased the cost of shipping in the world. As a result, there has been substantial research on the risk and cost aspects of maintenance in the maritime industry. However, no research has put emphasised risk and technical aspects of maintenance with the business and cost related aspects of maintenance in one unified platform. Therefore, this PhD has developed an overall methodology in order to combine cost and business oriented aspects of a shipping company with their risk and technical aspects.

This methodology is called Business Oriented Probability-based Maintenance (BOPM). In this methodology, company business aspects and Maintenance Performance Indicators (MPIs) have been used to modify and personalise maintenance and repair cost values, risk factors (human risk, environmental risk, cost of failure and loss of operation), and component/sub-system performance reading limits. Performance limits from OEM reports modified by company specific inputs are then used to determine probabilistic performance values based on the monitored live values received from vessels. Subsequently, these probabilistic values are placed in a Probabilistic Analysis Unit (PAU) within the BOPM platform to predict the future performance values for each component/sub-system within the system. This PAU model uses an innovative Dynamic Bayesian Network (DBN) with first order Markov Chains to predict the future probabilistic pattern of each system monitored from the vessel.

Afterward, net cost analysis is performed using cost values modified by company MPIs inside utility and decision nodes added to the DBN model in order to provide cost-based decisions on the performance of each component and schedule specific maintenance or repair dates if required. In the other section of the BOPM risk values are combined with their probability of failure using a Fuzzy Set Theory (FST) in order to determine a final relevant risk value for each component/sub-system. Finally, obtained risk values are combined with decisions from the cost-based DBN Decision Analysis Unit (DAU) to prioritise tasks that are intervening with

each other. The overall methodology was approved and validated by both industrial experts and using results and conclusions made from the INCASS EU FP7 project that I was also involved in.

Three similar systems from three vessels have been used as the case studies in order to analyse the effectiveness of the BOPM platform and validate its results. These vessels are two chemical tanker sister ships and one general cargo vessel. Three similar system types from each vessel have been used namely the Lub-oil system, Fuel-oil system and Turbocharger. Having two sister ships operating in different environments has also created the possibility of evaluating the effects of environment on performance of each system.

Using the overall BOPM analysis platform, relative probabilistic performance and availability of all the sub-systems/components within the main observed systems were predicted for four future time slices. This was then compared with actual observed performance value and it was noted that the overall methodology has an accuracy of 97.8%. Subsequently, using the decision-making part of the methodology, future maintenance tasks were recommended. This was then compared with the maintenance logs of all three vessels and it was observed that they were not simply matching but also exceeding their recommendations and saving the company an extra $467. Finally, the results obtained also proved that the overall results and scope of the thesis have helped to meet and exceed the overall goals and targets of the company.

Keywords: Business-oriented Probability-based Maintenance (BOPM), Dynamic Bayesian Network (DBN), Markov Chain, Net cost analysis, Decision-making, Risk factors, Maintenance Performance Indicators (MPIs), Technical and business aspects

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Nomenclature

ACFM	Alternating Current field Measurement
ACM	Advanced Condition Monitoring
AHP	Analytic Hierarchy Process
ALARP	As Low As Reasonably Practicable
AM	Autonomous Maintenance
ANN	Analytical Neural Network
ANP	Analytic Network Process
AR	AutoRegressive
BAHRA	British Maritime Technology Hull Roughness Analyser
BBN	Bayesian Belief Network
BCM	Business centred Maintenance
BDMP	Boolean Driven Markov Process
BDR	Business Driven Reliability
BOPM	Business Oriented Probability-based Maintenance
BSC	Balanced ScorCard
BSI	British Standards Institution
CALS	Continuous Acquisition and Life-cycle Support
CAS	Condition Assessment Scheme
CBCM	Computer-Based Condition monitoring
CBFTA	Condition Based FTA
CBM	Condition Based Maintenance
CIBOCOF	Centrum voor Industrieel Beleid Onderhouds Concept Ontwikkeling Framework
CIM	Common Information Model
CIMOSA	Computer Integrated Manufacturing Open System Architecture
C-LCC	Comprehensive LCC
CMM	Condition Monitoring Maintenance
CMMS	Computerized Maintenance Management Systems
CMS	Computerized Maintenance systems
CoUR	Cost of Unreliability
CPD	Conditional Probability Distribution
CPT	Conditional Property Table
CSS	Critical Stress Strategies
CTQ	Critical To Quality
DAG	Directed Acyclic Graph

DAU	Decision Analysis Unit
DBBN	Dynamic BBN
DCM	Development Cycle Methodology
DES	Discrete Events Systems
DMG	Decision Making Grid
DTA	Dynamic Tree Analysis
DWT	Dead Weight Tonnage
EAI	Enterprise Application Integration
EAM	Enterprise Asset Management
EBRCM	Experience Based RCM
ECM	Effectiveness Centred Maintenance
ECSA	European Community Shipowners' Association
EDM	Express Data Management
EFNMS	European Federation of National Maintenance Societies
EM	Expectation-Maximisation
ERP	Enterprise Resource Planning
ESP	Enhanced Survey Program
FFT	Fast Fourier Transform
FI	Focus improvement
FME(C)A	Failure Mode Effect (Criticality) Analysis
FO	Fuel Oil
FORM	First Order Reliability Method
FPG	Failure Propagation Graph
FPM	Failure Propagation Model
FSO	Particle Swarm Optimization
FST	Fuzzy Set Theory
FTA	Fault Tree Analysis
FTSS	Fault Tree Support System
GMI	Giant Magneto Impedance
HAZID	Hazard Identification
HAZOP	Hazard and Operability
HIS	Information Handling Services
HMM	Hidden Markov Model
IACS	International Association of Classification Societies
IDMS	Inspection Data Management System
IET	Impulse Excitation Technique
IMO	International Maritime Organisation

ISI	In-service Inspection
IWSDB	Integrated Weapon System Database
KPI	Key Performance indicators
LCA	Life Cycle Analysis
LCC	Life Cycle Control
LO	Lube Oil
LTD	Long Term Data
MADM	Multiple-Attribute Decision Making
MARPOL	Marine Pollution
MCDA	Multi Criteria Decision Analysis
MCDM	Multi Criteria Decision Making
MCMC	Markov Chain Monte Carlo
MIMOSA	Machinery Information Management Open System Alliances
ML	Maximum Likelihood
MMT	Maintenance Management Tool
MPI	Maintenance Performance Indicators
MPI	Maintenance Performance Indicators
MPM	Maintenance Performance Measurements
MS	Mean Substitution
NDT	Non-Destructive Testing
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturer
OSE	Overall System Effectiveness
PAS	Publicly Available Specifications
PAU	Probability Analysis Unit
PCM	Profit centred Maintenance
PDCA	Plan Do Check Action
PdM	Predictive Maintenance
PEC	Pulsed Eddy Current
PHM	Proportional Hazard Modelling
PM	Preventive Maintenance
PMS	Preventive Maintenance System
QFD	Quality Function Deployment
RAMS	Reliability, Availability, Maintainability and Supportability
RBI	Risk Based Inspection
RBMI	Reliability Based Maintenance Inspection
RBOM	Risk Based Opportunistic Maintenance

RCBM	Reliability and criticality Based Maintenance
RCM	Reliability Centred Maintenance
RPN	Risk Priority Number
RRCM	Reliability and Risk Centred Maintenance
RST	Rough Set Theory
RTD	Real Time Data
SCADA	Supervisory Control and Data Acquisition
SEE	Spectral Emitted Energy
SLOFEC	Saturated Low Frequency Eddy Current
SOLAS	Safety Of Life At Sea
SORM	Second Order Reliability Method
SQL	Structured Query Language
SRCM	Stream-lined RCM
SWIFT	Structural What If Analysis
SWOT	Strengths, Weaknesses, Opportunities and Threats
TAM	Total Asset Management
TCI	Technical Condition Index
TF	Time Frequency
TFN	Triangular Fuzzy Number
TPM	Total Productive Maintenance
TQM	Total Quality Management
UNCTAD	United Nations Conference on Trade and Development
UTM	Ultrasonic Thickness Measurement
VDM	Value Driven Maintenance
WCM	World-Class Manufacturing

CHAPTER 1-INTRODUCTION

1.1 Chapter Introduction

This chapter contains introductory information and a general outline of the overall dissertation. The chapter will provide brief information on the content of other chapters of the thesis in order to clarify the overall flow of this dissertation.

1.2 General Background

Shipping is the most important type of transportation for goods in the world as approximately 90% of all goods are transported via the sea (ICS, 2015). A United Nations Conference on Trade and Development (UNCTAD) has estimated that shipping contributes to 5% of world trade at around US$380 billion. With the advancement of globalisation shipping trade has quadrupled in the past 40 years (from 8 thousand billion tonne-miles in 1968 to 32 thousand billion tonne-miles in 2008). This trend is still growing, as the graph on Figure 1 demonstrates (UNCTAD, 2014).

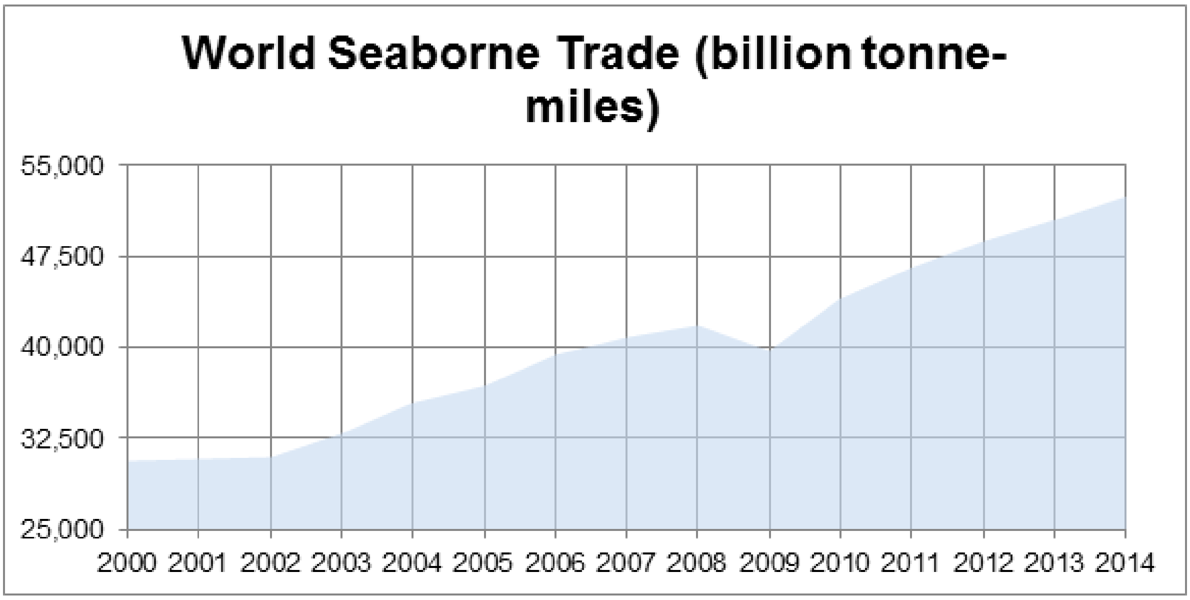

Figure 1 - World Seaborne Trade 2000-2014 (UNCTAD, 2014)

The Information Handling Services (IHS) insight company has also predicted an exponential increase in seaborne trade up to 2030 (Figure 2). This can drastically change the economy of some countries like Greece where they own beneficial dead weight tonnage of 258,484 (15.415% of total world dwt) for a population of approximately 11 million people (ICS, 2015).

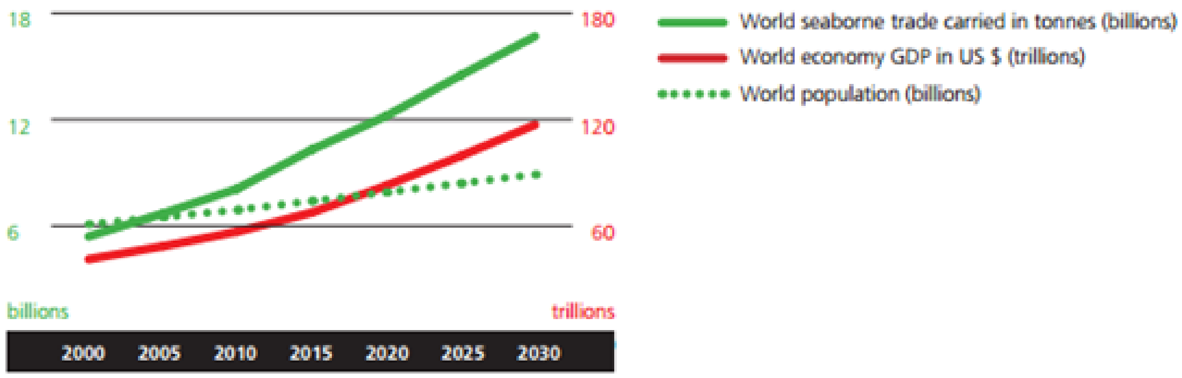

Figure 2 - Word Seaborne Trade Prediction up to 2030 (ICS, 2015)

General aspects of modern shipping and the maritime industry have been changing in the past decade. These changes have been mainly influenced by the public perception of global warming and pollution problems. This has also resulted in the introduction of tougher safety and environmental legislation to be adopted by the shipping industry. The European Community Shipowners' Association (ECSA) has introduced various reports on helping ship owners to adapt to the future of the shipping industry such as their 2013 CO_2 Emission Monitoring proposal (ECSA, 2013). The International Maritime Organisation (IMO), which is the main regulatory body for most of the shipping and maritime industry in the world, has introduced numerous rules and regulations (some mandatory and some optional) on the safe operation of sea-going vessels and other offshore structures. Such regulations will minimise accidents and lessen environmental impacts from hazardous and pollutant substances for the environment (ECSA, 2013).

These regulations can be characterised as operational, design, construction, decommissioning/recycling and maintenance areas. For example, well-known regulations and guidance have been introduced by the IMO including: the Guidance on Ship Recycling 2006, Pollution Prevention Equipment 2006, Ballast Water Management Convention 2004, Survey of Machinery Installation 2004, General Operators Certificate for GMDSS 2015, MSI (Maritime Safety Information) Manual 2015, Condition Assessment Scheme (CAS) and various MARPOL (Marine Pollution) protocols (IMO, 2016). The CAS scheme creates mandatory condition monitoring, assessment and renewal surveys of category 2 (20000dwt and above) and 3 (30000dwt and above) oil tankers of at least 15 years of age (ABS, 2016). MARPOL, or the International Convention for the Prevention of Pollution from Ships, first appeared as part of the IMO safe shipping protocol in 1973. This protocol now has six main annexes: Regulations for the Prevention of Pollution by Oil (1983), Regulations for the Control of Pollution by Noxious Liquid Substances in Bulk (1983), Prevention of Pollution by Harmful Substances Carried by Sea in Packaged Form (1992), Prevention of Pollution by Sewage from Ships (2003), Prevention of Pollution by Garbage from Ships (1988) and Prevention of Air Pollution from Ships (2005) (IMO, 2016).

All ship operators and owners of offshore structures should also follow guidance from at least one of the IACS (International Association of Classification Societies) members. This will allow the operators to insure their vessels and cargo in addition to enabling operation within different water regions and ports around the world. IACS provide more technical and detailed guidance on safe operation and maintenance of vessels. There are various generalised rules which all operators must follow including guidelines on risk assessment, coating surveys, hull condition monitoring, hull repairs and further guidelines on training and survey and condition monitoring techniques. General rules and guidelines from both regulatory bodies and classification societies prove the importance of maintaining a safe and environmentally friendly operational profile of sea-worthy vessels (IACS, 2017).

Further regulations on maritime pollution were agreed within Chapter 4 of Annexe VI from MARPOL, adopted in 2011 and enforced in 2013, that all new ships must improve their efficiency by 10% and reduce CO_2 emissions by 20% by 2020 (MARPOL, 2011). The efficiency values should also improve by 20% before the end of 2025 and by 30% by 2030 (ICS, 2015). Finally, CO_2 emissions should be reduced by half by 2050 throughout the entire shipping industry (ICS, 2015). This can be achieved both through better ship design and better maintenance programmes in order to maintain the overall performance and efficiency of the vessel during its lifecycle.

Another important regulation that proves the importance of safe operation and maintenance of the shipping industry is called SOLAS (International Convention for the Safety of Life at Sea, 1974). This regulation does not simply request for safe construction and implementation of safety equipment on vessels but also requires regular ship surveys and maintenance of vessels to meet with both IMO and relevant flag state compliances (IMO, 2016). This regulation has 14 chapters:

- General provisions
- Construction
- Subdivision and stability
- Machinery and electrical installations plus fire protection
- Fire detection and fire extinction
- Life-saving appliances and arrangements
- Radio-communications
- Safety of navigation
- Carriage of cargoes
- Carriage of dangerous goods
- Nuclear ships
- Management for the safe operation of ships
- Safety measures for high-speed craft
- Special measures to enhance maritime safety and security
- Additional safety measures for bulk carriers
- Verification of compliance
- Safety measures for ships operating in polar waters.

As Figure 4 demonstrates, these safety regulations aid overall improvement of the safety of maritime shipping significantly (Maritime-Executive, 2014).

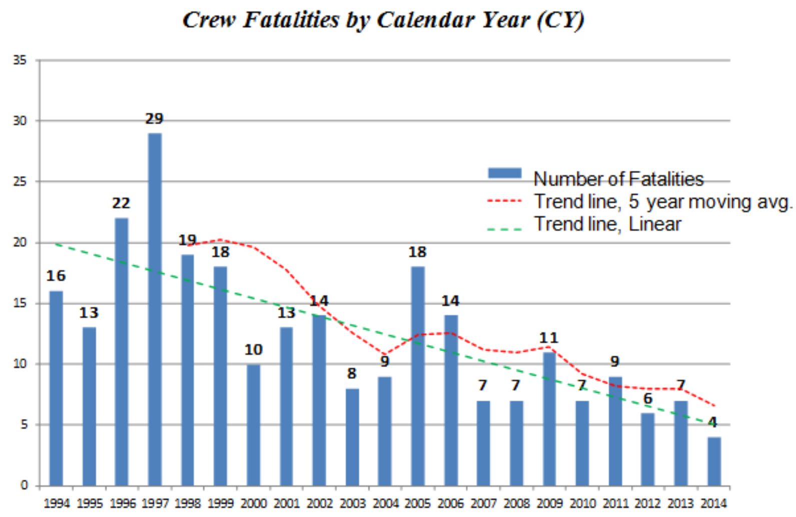

Figure 3 - Overall Maritime Crew Fatalities for the 1994-2014 Time-period (Maritime-Executive, 2014)

In brief, shipping is a large part of the world economy and plays a large role in transportation of goods, people and raw materials worldwide. Future trends in this industry illustrate a substantial growth in its marketplace. However, further regulations on ship safety, environmental impact and emissions creates some challenges for operators. This, in turn, heightens the operational costs of vessels. One of the best ways to enhance the safety of the vessel in operation and reduce unwanted costs is an effective maintenance programme. This is further emphasised with an increase in restrictions on periodic surveys by regulatory bodies and the IACS.

In general, the introduction of tougher regulations, mentioned previously, can increase the overall cost of shipping in the world. Therefore, it is crucial for companies to enhance their productivity and performance in order to sustain a profitable outcome. Three major types of production and asset performance metrics are used in industry including: Return on net assets (RoNA), Return on capital employed (RoCE) and economic value added (EVA). This shows the importance of efficient production processes and reliable equipment. However, long term production processes and environmental factors may significantly reduce their performance due to the appearance of wear, corrosion and fatigue. As a result, it is vital to have an appropriate maintenance and inspection strategy available to prevent any production losses. The European Federation of National Maintenance Societies (EFNMS) defines the term maintenance as (EFNMS, 2014): "*All actions, which have the objective of retaining or restoring an item in or to a state in which it can perform its required function. The actions* *include the combination of all technical and corresponding administrative, managerial, and supervision actions.*" This proves the importance of maintenance on sustainability of all engineering companies. Maintenance itself can be relatively expensive. Therefore, it is important to develop an optimum and cost-effective methodology for the maintenance of the plant in order to minimise its effect on the profitability of the company. In general, it is important to recognise maintenance as a profit-making factor of each company rather than an unwanted expenditure. Positioned in this theoretical and factual ground, and with particular focus on both the safety and profit-making aspects of maintenance in the maritime industry, this thesis will introduce an innovative approach of combining both technical (safety) aspects of maintenance with the business goals (profit) of the company in a unified maintenance methodology for the shipping industry.

1.3 Thesis Layout

The overall dissertation consists of eight distinctive chapters. These chapters start with a general overview of the maintenance and all different types of methodologies available in the industry. Subsequently, it introduces the reader to in-depth information on the main methodology created with its results based on the case studies obtained from three different ship types. Figure 4 illustrates the overall chapter flow of this thesis which starts with a statement of the research question, the aim and objectives; it has been designed to follow these objectives throughout its methodology development, case studies, results and discussion to help answer the research question.

Before the introduction of the methodology in response to the research question, an in-depth critical review of the present research in the area has been performed in the literature review chapter. This literature review starts with the presentation of different maintenance task types: Corrective, preventive, predictive, proactive and self-maintenance. It also explains which particular sectors and in which period of time each of the maintenance task types have been employed.

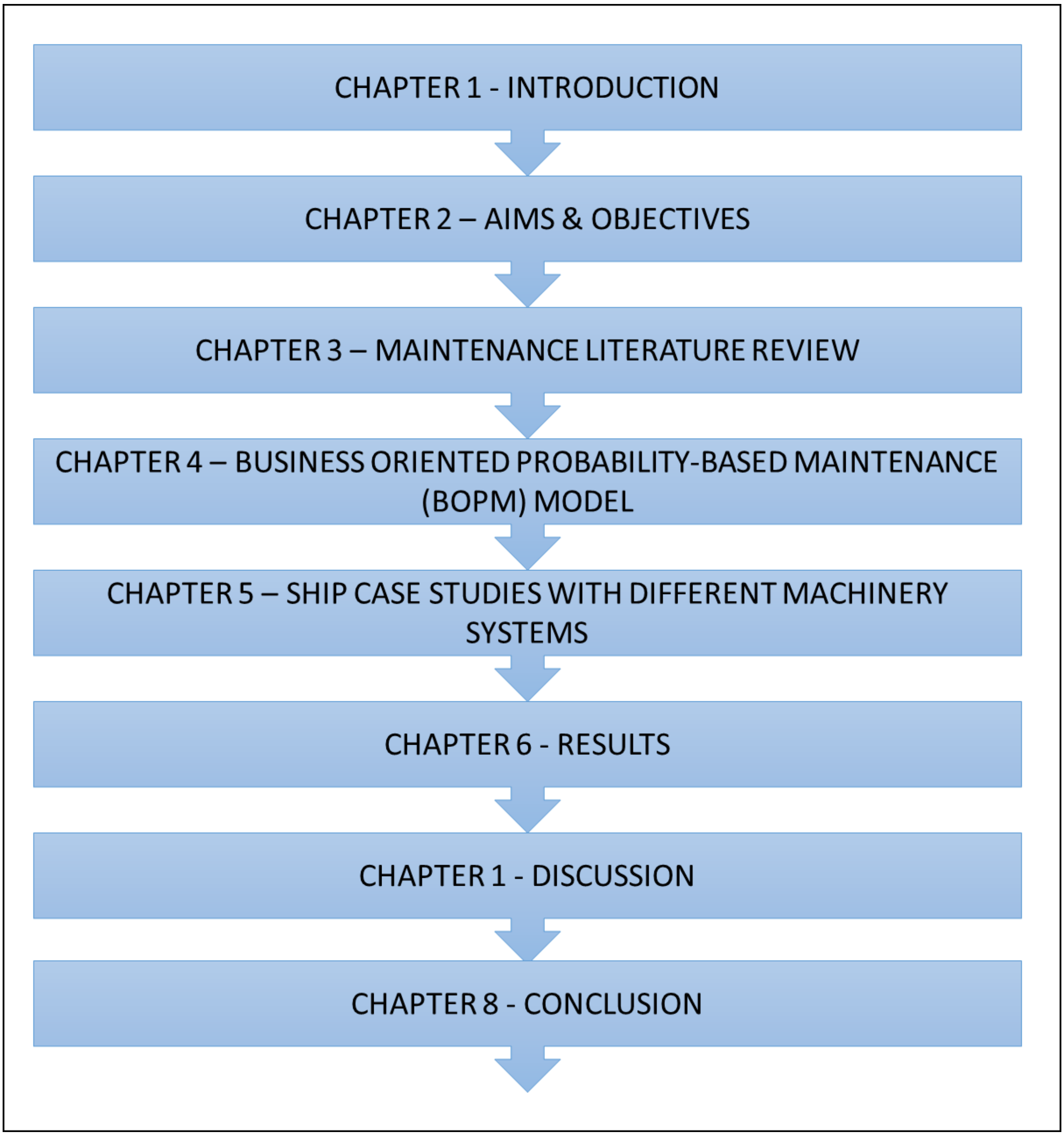

Figure 4 - Overall Dissertation Flowchart

The second section of the literature review starts with the introduction of the different maintenance strategies and concepts used throughout the industry. The first maintenance concept that is introduced is reliability-centred maintenance (RCM), which is becoming a norm in the maritime industry and other industrial sectors. Then, risk-based maintenance (RBM) is explained, especially from an offshore oil and gas industry perspective. Subsequently, condition-based maintenance (CBM) is discussed due to the introduction of the more advanced condition monitoring tools in the industry. Next, total productive maintenance (TPM) used in the manufacturing industry is described within its relevant industrial area. Finally, business-centred maintenance (BCM) has been studied to add a business view and an aspect on maintenance strategy compared with the other more risk- and reliability-based methods.

The third section of the literature review looks into various types of tools used within maintenance policies in order to help maintenance managers assess the performance and cost aspects of vessels and produce overall maintenance tasks and scheduling. This starts with an introduction of failure analysis, reliability assessment and probability analysis tools that help end users understand the current condition of the system and predict its future. The major tools and models are evaluated for failure analysis, reliability assessment and probability analysis include: FMECA (failure mode, effect and criticality analysis), fault tree analysis (FTA), Bayesian belief network (BBN), probability distribution function (PDF), neural networks, Markov chains and Monte Carlo simulations. Then, decision-making tools are researched from the available literature for maintenance in the industry. These tools help users to choose the best decision for a maintenance plan from various available choices. The major decision-making tools introduced in this literature review are: Fuzzy set theory (FST), analytical hierarchy process (AHP), analytical neural process (ANP), multi-criteria decision making (MCDM) and strengths, weaknesses, opportunities and threats (SWOT) analysis.

Subsequently, risk analysis tools are introduced from the literature in order to analyse and define the overall risk within systems and their failures. These risk analysis methods are: as low as reasonably practicable (ALARP), proportional hazard modelling (PHM), hazard identification (HAZID) and hazards and operability (HAZOP). Finally, condition monitoring tools developed in the industry are studied within the literature review section. These tools help scientists evaluate the overall condition of systems using condition monitoring systems and their data. The condition monitoring tools explained in the literature review are: Auto regressive (AR) model, Fourier transform, wavelets transform, time-frequency (TF) and Morlet wavelet filtering.

The next section of the literature review identifies the maintenance performance measurement techniques used in the industry. These techniques help users to determine the overall effectiveness of the developed maintenance programme and pinpoint its weak areas. The majority of maintenance performance measurement models explained in this literature review are: Maintenance key performance indicators (MPIs), overall equipment effectiveness (OEE), maintenance performance reporting, reliability, availability, maintainability and supportability

(RAMS), quality function deployment (QFD), balanced scorecard (BSC) and benchmarking. The final section of the literature review looks into different inspection, monitoring and data acquisition techniques used within the industry. These tools are categorised into four major areas of electromagnetic testing (alternating current field measurement (ACFM), time of flight and saturated low frequency eddy current (SLOFEC) and pulsed eddy current (PEC)), wave and vibration frequency monitoring (piezo-electric sensors, signal processing theory, and digital signal processors, acoustic emission monitoring, ultrasonic thickness measurements (UTM), impulse excitation technique (IET) and infrared cameras), structural surface and material property analysers (British Maritime Technology Hull Roughness Analyser (BAHRA), barnacle adhesion strength measurements and ellipsometry), and visual inspections.

Chapter four of the dissertation will represent the developed business-oriented probability-based maintenance (BOPM) model. This model has subsections of company goals, manufacturers performance limits, cost data, previous preventive maintenance (PM) reports, criticality classification of components, probabilistic analysis unit and decision-making unit. Criticality classification of the components and sub-systems are undertaken by creating risk matrices on three major risk areas of human risk, loss of operation and environmental risk. These risk values are then added together using the fuzzy logic technique created within the MATLAB environment. This will result in overall relative risk factor per component/sub-system, where they can be used in conjunction with probability and net cost analysis decision results to prioritise tasks that are intruding upon each other.

The probability analysis unit of the methodology starts by treating missing data areas from within data obtained from the ship operator partner. The Markov Chain Monte Carlo (MCMC) simulation model has been created within an SPSS environment to perform the missing data treatment task. Then, using manufacturers' limits and input from the operator on the limits these data are turned into probabilistic values to be used for overall performance analysis and as a future prediction model for the methodology using Bayesian tools.

Subsequently, these probabilistic values are analysed within a Dynamic Bayesian Network (DBN) with first order Markov chains to determine overall performance of the system at the moment and predict its future performance alterations. This model can also demonstrate the influence between each component or sub-system and the overall system. The result of this analysis is then further developed within the decision-making unit where utility and decision nodes are used to implement net cost analysis to produce maintenance task decisions. These decisions, obtained from the cost benefit analysis, are then combined with overall relative risk factors to prioritise maintenance tasks and produce final maintenance scheduling decisions.

The case study chapter of the thesis consists of three major systems: Lube-oil system, fuel oil system and turbochargers for three different ships. Two of these vessels are sister chemical tankers of 16500 dwt with seven-cylinder MAN B&W engines and one is a multi-purpose general cargo vessel of 9500 TDW with an eight-cylinder Wartsila engine. The overall structure of each major system with their performance limits and cost data are shown in chapter five. The general Bayesian network designs of each system with their utility and decision nodes are also illustrated in this chapter of the thesis.

The results chapter of the dissertation shows the main probabilistic analysis results of the DBN models illustrated in the case study chapter. Additionally, it will demonstrate the graphical representation of the cost benefit evaluation of the networks using utility and decision nodes. Finally, the component and sub-system criticality classification results for all the evaluated parts will be tabulated in order to be used for final decision-making.

The discussion chapter of the thesis will evaluate and generate final suggestions on the maintenance scheduling of the overall vessels using performance, net cost and criticality classification results. This section will also illustrate the comparison between different component and sub-system performance values of the two sister chemical tankers. This will give further insight into the effects different environmental conditions have on similar ship machinery and equipment used on both vessels. Finally, the overall benefits of using BOPM methodology in the maritime sector will be discussed with its benefits and weaknesses.

The conclusion chapter of the dissertation will state the overall flow and achievements of all previous chapters. It will also summarise the overall results and discussion of the case studies to give an overall view of the methodology implementation. At the end of this chapter, future recommendations and research on further strengthening the overall methodology will be discussed in order to take this work to the next level of appropriate implementation in shipping companies.

1.4 Chapter Summary

In summary, this chapter has given a comprehensive introduction to the importance of maintenance and development of an efficient maintenance methodology. This methodology is called BOPM. This chapter also described the overall flow of the dissertation in achieving this efficient maintenance model. The next chapter will highlight the overall research question with the aim and objective of answering the question through development of the methodology.

2 CHAPTER 2-AIMS & OBJECTIVES

2.1 Chapter Introduction

This chapter contains the research question as well as the main aim and objectives of the overall PhD thesis.

2.2 Research Question

The research question of this PhD thesis can be described as the following:

Is it possible to combine shipping company costs and general safety aspects with technical vessel aspects in order to achieve a more optimum maintenance programme that meets both business and technical goals of the company?

2.3 Aim & Objectives

The main aim of this dissertation is to answer the research question stated previously by introducing an innovative BOPM maintenance methodology which can be implemented on ship machinery systems. The objectives relevant to the mentioned aim can be formulated as:

1) A critical review and investigation of previous studies on business-oriented and reliability-based maintenance techniques and researching about company reliability and probability models, cost benefit analysis and other relevant tools implemented in the maritime industry and other relevant industries
2) Identification of the best tools and methodology and finding the overall gaps in the maintenance sector
3) Development of an overall innovative BOPM framework with an outline of the sub-sections
4) Development of reliability and probabilistic tools that can observe the overall condition of the system in order to predict its future condition

5) Introduction of a decision support system including a net cost analysis, which can produce maintenance scheduling for the observed system

6) Identification of component criticality classification to be used on task prioritisation for better maintenance

7) Check of the overall validity of sections of the methodology with progress of the INCASS FP7 EU project and compare outcomes

8) Implementation of the overall methodology with its tools on three main systems from three different ship case studies (two chemical tankers and one general purpose cargo vessel), discuss the results, compare with experts' opinions and recommend future research and improvements

2.4 Chapter Summary

This chapter represented the main research question that has been answered using the aims and objectives of the overall PhD thesis. The next chapter of the dissertation will demonstrate a comprehensive literature review, identifying the industry norm concerning maintenance in order to provide initial information concerning achieving the overall thesis aim.

3 CHAPTER 3-MAINTENANCE LITERATURE REVIEW

3.1 Chapter Introduction

This chapter represents a comprehensive literature review concerning maintenance in the industry. It includes maintenance task types, maintenance policies and methodologies, maintenance-related tools, maintenance performance measurements and inspection and data-gathering tools. This chapter also critically reviews all maintenance-related areas and gives an overall opinion of the gaps in the relevant literature.

Maintenance tasks are usually classified into three types: Corrective, preventive and predictive, all of which are mentioned in this section. However, having a general policy and maintenance system is important to gather these classification tasks to obtain maintenance schedules. These policies are mentioned in the next section of this chapter. Each of these policies would require further tools to obtain the data and make the final decisions on maintenance tasks. These tools are categorised into: probabilistic, reliability, risk analysis, condition monitoring and decision-making categories. Section 5 of this chapter explains different versions of these tools in more detail. Section 6 introduces performance measurement systems that are essential for evaluating the effectiveness of the maintenance policy used. Subsequently, data gathering and inspection systems crucial for obtaining information for maintenance tools are described in Section 7. Finally, Section 8 identifies the overall gaps in maintenance systems and suggests possible future research on each identified gap. Figure 6 illustrates the overall structure of the literature review in more detail.

It was from the mid-1990s that the introduction of more automated systems and much-restricted safety regulations provided a spark for progress in maintenance research. Preventive and predictive methodologies can be used as a beneficial option even on these small sized organisations. This proves insufficient research available concerning maintenance of slender-sized companies. Both preventive and predictive methodologies also require further development especially in the field of prognostics on predictive maintenance. The prognostic technique is a methodology of predicting the future pattern of failures based on diagnostic data. This method goes one step forward from predictive methodology as it not only predicts when a failure would occur, it also demonstrates the failure pattern of specific machinery. Additionally, no generic approach has been developed in the field of prognostic systems.

Most of the maintenance policies mentioned in this critical review do not link the business aspects fully into the tactical and the technical levels of their decision-making process. Research shows that any simplifications on RCM methodology can have devastating effects on performance of the maintenance system in a company. However, some organisations are still cutting corners in their RCM process to save money in the short-term. This proves that there are gaps between top management and the tactical team of organisations for maintenance. Value-driven maintenance (VDM) is a part of RCM that tries to consider the business aspects of a maintenance methodology but it requires good knowledge of burden to importance ratio (BIR). In condition monitoring systems, there are numerous ways of obtaining data using methodologies such as vibrational analysis which can be sent via ethernet or internet connections to the central servers and maintenance managers. However, these systems use various software languages.

This could have the effect of creating a problem concerning the overall picture of the whole system and waste time in the decision-making process. Condition monitoring and CBM would usually be more effective if it is combined with any other maintenance policy such as RBI. Therefore, the critical literature review has been divided into five major sections: maintenance classifications, maintenance management systems and policies, maintenance related analysis tools and systems, maintenance performance measurements, and inspection and monitoring tools and methodologies. Each section, at the end, has a discussion on overall points observed and possible gaps and improvements recommended. Finally, the overall major gaps and recommendations concerning the subject of maintenance are illustrated in the observation section of this chapter. Figure 5 demonstrates the overall section and sub-section layout of the critical literature review part of this thesis.

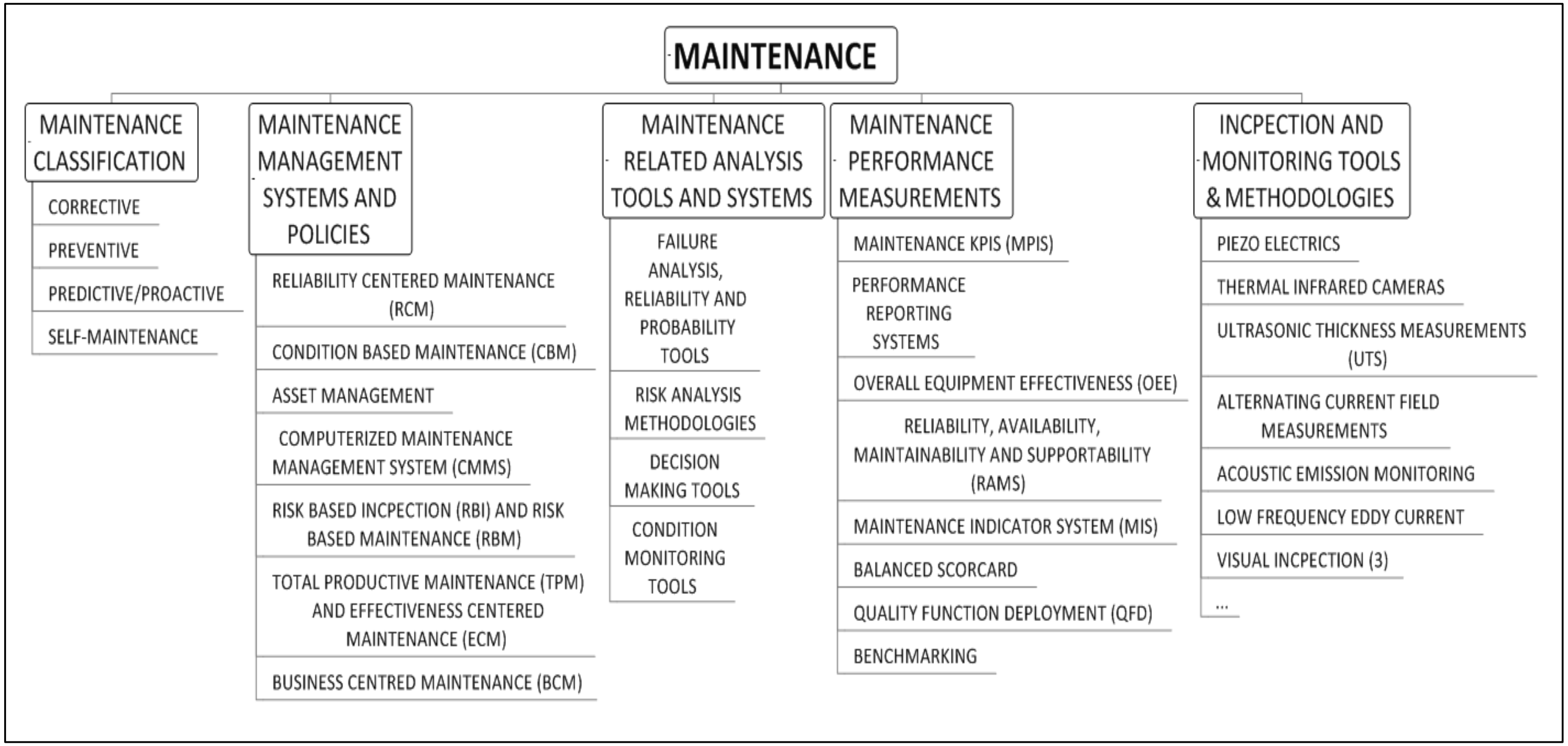

Figure 5 - Overall Maintenance Literature Review Flowchart

3.2 Maintenance Classification

Maintenance tasks are usually classified into three types: Corrective, preventive and predictive, each of which is mentioned in this section. There is a fourth, new, more advanced maintenance task classification that is developed and used on automated systems called self-maintenance but it is not fully developed and cannot be adopted in the majority of industrial sectors. It is important to have a general policy and maintenance system to organise these classification tasks to obtain maintenance schedules. These policies are mentioned further in the next section of this chapter. Each of these policies would require further tools to obtain the data and make the final decision on maintenance tasks. These tools are categorised into: probabilistic, reliability, risk analysis, condition monitoring and decision-making. Section 5 of this chapter explains different versions of these tools in more detail.

3.2.1 Corrective

Corrective maintenance, which is also known as reactive maintenance, works on a basis of a "fix it after it's broken" strategy (Pintelon & Herz, 2008). This first generation was mainly used until WWII as a quick and dirty way of repairing parts (Arunraj & Maiti, 2007). Corrective maintenance is usually carried out when the actual failure has occurred in order to bring the system back to its designed condition (Hameed, et al., 2010). Due to the severity of risks caused by component failures, it is important to use a combination of corrective and other maintenance procedures together (Crocker & Kumar, 2000). In general, corrective maintenance is less economical than other maintenance classifications (Pun, et al., 2002) and it can be expensive in the long run as failures are more expensive than frequent replacements (Tsang, et al., 2006). In more advanced versions of corrective methodologies, Wang, et al. (2014) have created more comprehensive corrective actions with more detail on the failures using failure propagation models (FPM) and failure propagation graphs (FPG).

3.2.2 Preventive

This second generation of maintenance technique has been used since around the 1970s (Arunraj & Maiti, 2007). Preventive maintenance activities are scheduled maintenance tasks designed to prevent failures in the system (Hameed, et al., 2010). There are two major types of preventive maintenance: scheduled maintenance and condition-based maintenance. The preventive technique has been created to prevent failures but the preventive maintenance task itself could initiate failures. Therefore, it is important to have preventive planning methodologies, e.g., RCM ready to prevent any of these maintenance failures and optimise preventive maintenance (Selvik & Aven, 2011). It is important to have a maintenance-planning concept unified inside the company in order to evaluate the cause of failures and take appropriate preventive action in a short time-period (Sharma, et al., 2006). Meller & Kim (1996) mention that periodic preventive maintenance can reduce overall operational costs in the long run. Having a preventive maintenance strategy rather than a corrective one can significantly enrich the company returns by preventing any unwanted failures occurring and creating devastating financial and reputational drawbacks.

In recent years, different reincarnations of the maintenance tasking techniques have been produced in the literature. Non-cyclical preventive planning and component replacement of multi-state systems have been developed by Fitouhi & Nourelfath (2013). Lynch, et al. (2013) also focus on the spare inventory sub-systems inside a preventive maintenance methodology. Different sectors have thorough research on this maintenance classification such as research on preventive scheduling issues of reusable rocket engines by Chen, et al., (2013). Percy, et al. (1997) developed a technique of preventive maintenance using limited data. Another maintenance technique that is usually used in conjunction with preventive tasking is opportunity-based maintenance (OBM). This technique can reduce maintenance costs by creating an opportunity to replace flawed parts during the maintenance of other critical and essential parts of a scheduled maintenance plan (Samhouri, 2009). One of the OBM techniques found in the literature is the method introduced by Jhang & Sheu (1999) called opportunity-based age replacement policy, which categorises failures into two different sub-categories: minor and severe. Another type of preventive maintenance methodology uses component values instead of simply pure cost factors to obtain an effective maintenance action plan (Liu, et al., 2014). This creates a more dynamic preventive methodology based on the reliability of the system components.

3.2.3 Predictive

Since the mid-1970s, due to the introduction of automation, more complete and complex predictive methodologies, condition monitoring and decision support systems have been developed and widely used (Sharma, et al., 2006). Maintenance procedures from this generation were focused on the practice of computer-based predictive and proactive maintenance methods (Hameed, et al., 2010). Sia & Ho (1997) developed a computerised proactive maintenance system using a prediction-based performance model. Predictive maintenance techniques can monitor damage initiations in order to predict the appropriate maintenance action for the near future (Al-Najjar, 2006). This maintenance classification can be cost-effective in the long run but it is crucial to justify the cost savings and investment advantages of its remote monitoring systems (Tetrault, 2012).

Numerous forms of predictive methodologies have been created in the industry in the past 20 years. One of the first automated predictive maintenance methodologies was introduced by Lewin (1995), which used the application of principal component analysis (PCA) on an automated predictive maintenance strategy. Another industrial application of predictive maintenance is illustrated in a study by Li, et al. (2014) which explores historical, correlated and continuous monitoring data in order to create a predictive maintenance action scheme for the rail network. Further literature for this maintenance classification is shown in the section for maintenance methodologies.

3.2.4 Self-maintenance

This new and futuristic maintenance technique is mainly developed on the basis of using robotic technology. Self-maintenance enabled systems can screen, detect and repair their own failures (Lee & Wang, 2008). Lee, et al. (2011), in their research, clarify the biological human immune system inspiration behind this methodology, where Prognostics and Health Management (PHM) is transformed into Engineering Immune Systems (EIS).

3.2.5 Major Observations on Maintenance Task Classification

In brief, corrective maintenance cannot be a feasible option on complex industrial systems created by the introduction of automation. Having a preventive or predictive policy instead of a corrective system may cost more at the beginning but it would be more cost-effective in the long run. Condition monitoring is one of the major aspects of more recent preventive and predictive maintenance methodologies. Predictive is generally better than preventive as it can optimise the maintenance scheduling depending on the actual demand and system behaviour rather than simply having a pre-scheduled maintenance plan from preventive techniques. Preventive maintenance task classification can predict the failure and schedule maintenance beforehand. This method can also delay any unwanted scheduled maintenance if not needed and save the company money. The next section will review literature on different maintenance policies that use the maintenance tasks discussed in this section.

3.3 Maintenance Management Systems and Methodologies

This section will review the literature on different maintenance policies such as RCM, CBM, Asset Management, RBI, TPM and (BCM introduced and improved over the past 20 years. The overall relationship with maintenance task classifications and maintenance policies can be seen in Figure 6. This shows the relationship between maintenance task classifications and industry-wide developed maintenance policies and strategies.

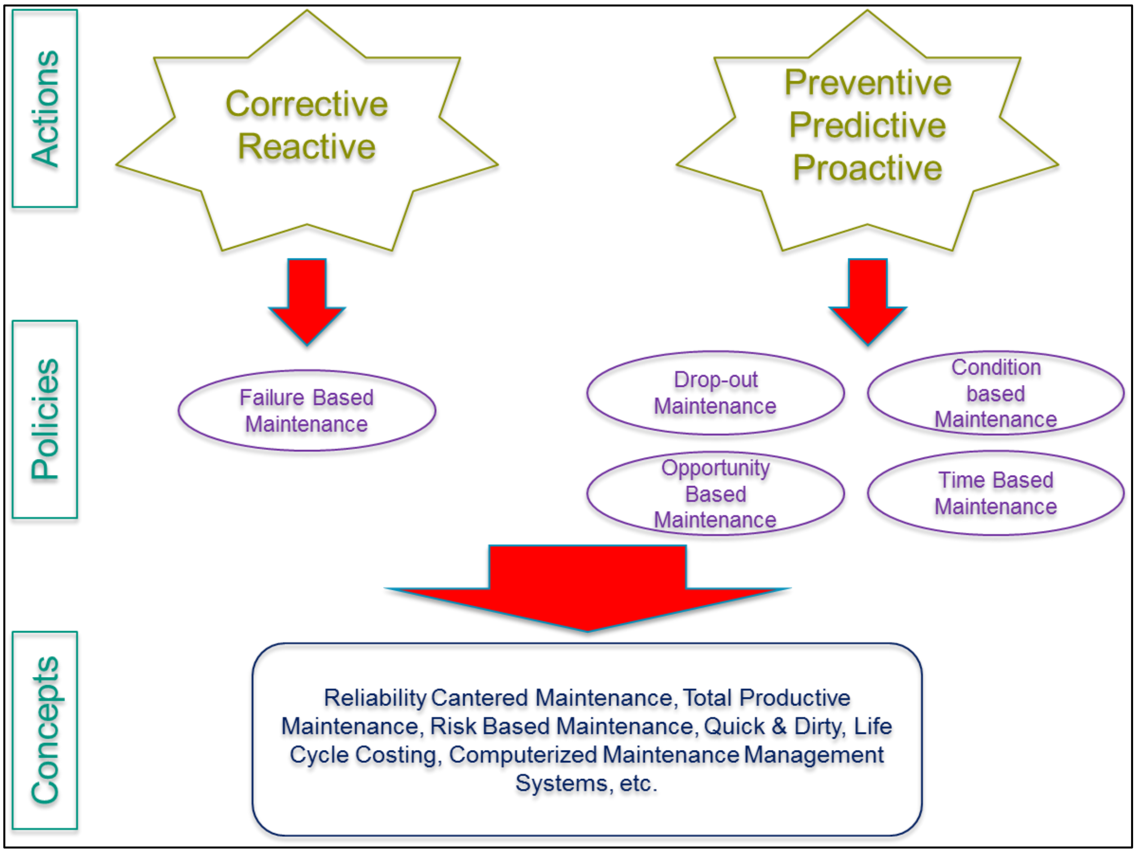

Figure 6 - Maintenance Task to Maintenance Policy/Concept Relationship

3.3.1 Reliability Centred Maintenance (RCM)

The Electric Power Research Institute (EPRI) states that Reliability Centred Maintenance (RCM) is: "*A systematic consideration of system functions, the way functions can fail, and a priority-based consideration of safety and economics that identifies applicable and effective PM tasks. The main focus of RCM is therefore on the system functions and not on the system hardware*" (EPRI, 1998). RCM can save costs by focussing upon important system functions and eliminating unnecessary actions. It can create a balance between reliability and cost. Sometimes, too many maintenance intervals could raise maintenance-induced failures. The main goal of RCM is to create an optimum preventive maintenance (PM) programme. To do so, the likelihood, severity and consequences of the failures must be known. The FAA airline industry was the first industry to introduce RCM in the 1950s. This methodology was introduced due to the fact that periodic maintenance on the items without dominant failure modes would be less effective on the overall reliability of the system (Kennedy, 2009).

Rausand (1998) states that a generic RCM methodology can be implemented in 12 steps: System selection and definition, functional failure analysis (FFA), critical item selection, data collection and analysis, failure mode, effect and criticality analysis (FMECA), selection of maintenance actions, determination of maintenance intervals, preventive maintenance comparison analysis, treatment of non-MSIs, implementation, and in-service data collection and updating the study preparation. On the other hand, Eisinger & Rakowsky (2001) cite that RCM methodology, in general, has four major steps: system preparation, system analysis, decision-making, and maintenance planning.

However, BS EN 60300-3-11:2009 declares five major steps for RCM methodology: 1) Initiation and planning (objective identification, analysis content development, knowledge and expertise determination, and clarification of the operational system of items); 2) Functional failure analysis (field data collection and analysis, functional system classification, and FMEA/FMECA); 3) Task selection (failure consequence analysis, policy selection, and task interval identification); 4) Implementation (task detail description, task prioritisation, task interval rationalisation, and preliminary age estimation); and 5) Continuous improvement (maintenance effectiveness evaluation, HSE monitoring, and age survey implementation) (BSI, 2009). Rausand 1998 defines a clearer path for the RCM methodology lacks the final step of overall continuous improvements recommended by the BSI. Therefore, BSI is a more up-to-date version of the RCM methodology but further clarification on each step and, maybe, more categorisations and in-depth steps, similar to Rausand's 1998 version, is recommended.

Anything about maintenance of a plant, especially on RCM, involves age and types of machinery, replacement cost and other health and safety costs. It is usually cheaper to replace components before they fail. Therefore, it is important to have a decent maintenance and replacement schedule. Thus, the machinery states (decreasing failure rate (DFR), constant failure rate (CFR) and increasing failure rate (IFR)) should be known (Abdul-Nour, et al., 1998). An effective RCM methodology has the main advantage of predicting failure (predictive maintenance) before it occurs. This can lower the expenditure as the cost of unwanted repairs is usually much higher than planned repairs and replacements (McGowin, 2006).

Reliability-based approaches are used in various industries and extensive research activities have been conducted on it over the past two decades. Sun & Soares (2006) looked into the implementation of RCM policy into a corroded structure of floating production storage and offloading (FPSO) hulls. Utne (2010) used RCM as a useful tool for the maintenance management of deep-sea wind farms. RCM provides information on asset structure and working patterns, failures that could occur, consequences and how to stop them by maintenance activities (Utne, 2010). Heo, et al. (2014) created an innovative method of particle swarm optimisation (PSO) for optimising RCM methodology used in electrical power transmission components. All of the above studies, in their own way, have tried highlight the importance of failure prediction of RCM methodology on different sectors. Abdul-Nour (1998) states the importance of determination machinery sets, i.e., DFR and CFR. However, in a proper failure classification and failure consequence determination as mentioned by Utne 2010, it would be useless as there should be a clear explanation of what each failure means before there can be more mathematical representaion of each machinery state on possible failures.

Onoufriou & Frangopol (2002) looked into the application of a reliability-based inspection approach on bridge structures. Due to the cost of implementation of RCM, Hipkin & De Cock (2000) looked into managers' points of view on RCM. Major issues of the RCM methodology adopted by numerous organisations have been identified by Gabbar, et al. (2003) to be threefold: It is time and resource consuming; not enough suitable information is available; and, there are many human and management factors. Reliability and maintainability analysis is the major part of a typical RCM methodology and that is why probabilistic risk assessment (PRA) is used within the RCM (Gabbar, et al., 2003). As a consequence Richet et al. (1995) discuss the implementation of RCM methodology in 15 different foundries. The approach of Gabbar (2003) only looks into the use of probabilistic risk assessment on fixing RCM shortcomings and does not mention a useful way for decreasing cost by different cost analysis methods and maintenance performance analysis techniques.

Numerous computerised additions have been developed for RCM. Fonseca & Knapp (2000) have created an innovative computerised RCM methodology that has a unique process design software (ASPEN Plus) that is connected to the RCM module. This model has an availability structure section to obtain information from the RCM and data analysis modules in order to perform dynamic maintenance scheduling, availability assessment and risk analysis. Pujadas & Chen (1996) have created specialised computerised RCM methodology for the US defence industry. In a recent study, Mkandawire, et al. (2015), looked into assessing the effectiveness of an RCM methodology used on electrical power transformers. They used the key performance indicators (KPIs) of the RCM methodology with a trending profile of the mean time to the first failure and average annual repair costs to analyse the performance of the RCM model used. This study further highlights the importance of updating the overall maintenance methodology with company KPI imputes. A similar case has also been made in a study by Tang, et al. (2017), where they analyse an innovative way of defining and incorporating the use of maintenance-significant items (MSIs) within an RCM platform. Both Mkanawire (2015) and Tang (2017) looked into importance of company KPIs and MPIs on improving the overall effectiveness of the RCM platform results. These methodologies, including, Fonseca and Knapp's (2000) model, use different software packages to determine their results. Each software package requires their own installations and may not work in different computer environments specifically in shipping where most people may use tablets. Therefore, Java based software packages can be more useful as they can be installed in different computer environments.

In the past, a quick and easy version of RCM methodology called streamlined RCM (SRCM) has been used in the industry. The retroactive SRCM process starts with current maintenance tasks rather than the first step of defining the functions of the system. This system does not focus on plant performance improvement and only considers PM tasks. Another type of SRCM methodology is the use of generic lists of failure modes. This is where an off-the-market system used in a similar type of organisation is bought and implemented. The final method of SRCM is the critical only method where only critical components are analysed. This method can be rather dangerous as it skips some important steps of true RCM methodology (Moubray, 2001).

Different reincarnations of RCM methodology have also developed in the industry. The RIMAP project has introduced an appropriate framework for enhancing the performance of the reliability-based maintenance inspection (RBMI) (Schroder & Kauer, 2004). RBMI is not simply a decision-making strategy for maintenance planning; it can also be used to determine the most critical components of the system. Stand-by safety systems should be inspected periodically as it is rather difficult to detect their failures (Khan, et al., 2004). The CIBOCOF (Centrum voor Industrieel Beleid Onderhouds Concept Ontwikkelings Framework, or in English, Centre for Industrial Management Maintenance Concept Development Framework) has been developed for the customisation of maintenance concepts (Waeyenbergh & Pintelon, 2006).

Value-driven maintenance (VDM) is another type of RCM methodology that uses performance goal-setting and measurement for plant management. The main principle of VDM methodology is called experience-based reliability-centred maintenance (EBRCM). EBRCM incorporates the integration of the feedback data, decision logic, fault modes, effects and criticality analysis (Rosqvist, et al., 2009). Selvik & Aven (2011) presented an updated version of RCM called reliability and risk centred maintenance (RRCM), which decreases the uncertainties. Turan et al. (2011) created an innovative new RCM technique based on criticality analysis called reliability- and criticality-based maintenance (RCBM). Lazakis (2011) added total productive maintenance (TPM) onto managerial aspects of the previous RCBM technique. RBMI and RRCM both use criticality classification to improve the technical results of the RCM, whereas VDM also adds company values and goals into the RCM methodology. However, Lazakis's (2011) RCBM update uses both criticality components and managerial aspects for the RCM. However, full integration of company MPIs and technical aspects are not developed within his methodology. The next section will discuss the condition monitoring systems and maintenance policies that can be used in conjunction with RCM.

3.3.2 Condition-based Maintenance (CBM)

A condition-based maintenance (CBM) strategy is developed in order to optimise maintenance activities by performing them when needed and also before the occurrence of the failure. CBM is based on the performance and monitored parameters of the system components, and is more effective in optimising maintenance activities (Tian, et al., 2011). A CBM strategy implemented in the manufacturing industry can use one of the three approaches of time domain, frequency domain and time-frequency domain (Bleakie & Djudjanovic, 2013). CBM schedules maintenance tasks according to data acquired by condition monitoring systems (Hameed, et al., 2010). This method can be more expensive than most preventive methodologies but is becoming more effective due to improvements in detection systems (cheaper systems) (Pintelon & Herz, 2008). Condition monitoring is part of CBM (Utne, 2010). Deterioration of machinery conditions could have external causes such as harsh operational conditions, bad raw materials, inefficient maintenance and external shocks. As a result, all of the above should be monitored. Product characteristics and the condition of the manufacturing process should also be taken into account (Al-Najjar, 2006). All of the above research represents the importance of data analysis techniques to be used in conjunction with condition monitoring systems in order to predict the future of each system. However, none of these techniques show how these conditional data can be used with cost analysis and company goals and in conjunction with other systems to develop effective maintenance scheduling.

Four major types of condition monitoring techniques are used for CBM in the industry: Vibration monitoring, thermal imaging, engine performance measurement and oil analysis (Tsang, et al., 2006). Multi-sensor and multi-parameter condition monitoring are two of the earliest stages of fault diagnosis for the manufacturing industry. The first stage of this technique is to detect important variables such as power, vibration and pressure of the machinery. Then, its diagnostic features are extracted from a maintenance action table (Zhou, et al., 2000). Preventive maintenance, in general, can be done either using statistical reliability data or using sensor-based monitoring systems (condition-based) (Pillay, et al., 2001). Current prognostic approaches of CBM are divided into three major groups: model-based, data-driven and hybrid (Lee & Wang, 2008). Williams & Hirani (1997) have created a multi-level condition based preventive maintenance strategy based on risk interval inspection. Williams 1997's technique adds more analysis on using the condition monitoring data to develop maintenance scheduling. However, his technique is only risk-based and it is preventive technique. Therefore, it does not include the cost elements and does not update schedules and predict their component future like more advanced predictive methods.

McGowin (2006) has created a report on condition based maintenance and condition monitoring techniques used in the wind farm industry. He has mentioned that unwanted failures can also cause consequential damage to other more expensive equipment inside the wind turbine. His technique mentions an important aspect of dependability and interconnectivity between the performance of different components within a system. Condition monitoring can provide data collection for the new designs implemented into the turbine machinery. Vibration analysis is one of the most common condition monitoring techniques, specifically for rotating machinery. In general, there are two types of condition monitoring equipment: portable and on-line. Periodic condition monitoring equipment is less expensive than continuous condition monitoring equipment (McGowin, 2006). Another piece of research on the implementation of CBM on wind turbines, carried out by Cross & Ma (2014), solved the non-linearity issue of the CBM process using an innovative parametric representation method. Lazakis, et al. (2016) have discussed an innovative DSS system to be used with online database, machinery analysis system and hull condition monitoring tools in order to minimise the risks of failure within commercial ships as part of the INCASS FP7 EU project. This study incorprates a dynamic Bayesian network (DBN) tool to implement its machinery condition analysis and future perfromance predictions.

Hontelez, et al. (1996) evaluated the relationship between condition-based inspection planning and deterioration processes on civil structures. Srinivasan & Parlikad (2013) discussed the benefits of using condition monitoring and CBM in the maintenance of civil structures. Hifi and Barltrop (2012) have developed an innovative method of combining RCM with condition monitoring for the maintenance and inspection of ship structures. They also created a central statistical database where subscribers can safely put their sensitive data. A further developed and improved version of the previous database and condition monitoring system was developed as part of the Inspection Capabilities for Enhanced Ship Safety (INCASS) EU FP7 project, where machinery probability analysis and a database system were added to the central database. The machinery database in this paper was developed using the combination of object-oriented and graph style databases within a catalogue data model using EXPRESS data schema (Taheri et.al., 2015). Another ship based condition-monitoring system, developed by Chen, et al.

(2014), explored the possibility of using condition monitoring on the planetary gearbox of communication antennas onboard ships.

Advanced condition monitoring (ACM) has been implemented by Tetrault (2012) for tackling large monitoring data of marine engines in order to use integrated algorithms to process critical data rapidly. Rao, et al. (2003) has looked into vibrational condition monitoring of the power station components. Rodseth, et al. (2007) have covered the idea of using computer-based condition monitoring (CBCM) maintenance methodologies. These intelligent systems continuously monitor the degradation of the system components. As a result, it has continuous and autonomous flow modification and system enhancement that results in almost zero downtime. A CBM methodology can do this by having a degradation analysis from online sensors in order to monitor the health of the system. Liu, et al. (2013) have used X control chart in conjunction with CBM methodology. Vibration and oil analysis are the two major sensors and analysis criteria used for this CBM methodology (Lee, et al., 2006).

3.3.3 Asset Management

Asset management is defined by the PAS standard as: "*Systematic and coordinated activities and practices through which an organisation optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organisational strategic plan."* (BSI, 2008). Key principles and attributes of asset management on achieving organisational goals are holistic, systematic, risk-based, optimal and sustainable advantages. The main and central types of assets are the physical assets that other asset types such as financial, human, information and intangible assets are integrated into. Concerning physical asset management, it is important to find the trade-off between short-term cost factors and long-term risk factors. Therefore, it would be beneficial to divide the whole asset management process into different levels of complex components, sites, networks, functional systems, portfolios, etc. (BSI, 2008). Muller (2012) has identified asset management tasks to be: 1) Entire lifecycle assets management by asset history, economic and technical data; 2) Maintenance governance of the asset; and 3) Information and data collection of the history and prognosis of asset health for decision-making. Holland, et al. (2005) have directed widespread research on the connection between BP and its suppliers through its asset management system. This study has been carried out at the business level only. Muller (2012) asset management system is more based on actual prognostics and technical information of assets, whereas Holland (2005) version based on the BP system is more business oriented. It would be more useful according to the BSI (2008) definition of asset management that both business and technical aspects to be considered with an equal importance.

Enterprise resource planning (ERP) is a type of asset management system and is becoming a norm on maintenance practices of most industries (Mathew, et al., 2006). ERP was first developed in the 1990s for integrating various functional (operations, marketing, finance) information systems with their business side across the company. This created a rationalised business to production systems across the organisation (Gupta & Kohli, 2006). Hoch & Dulebohn (2013), in their paper, focussed on the human resource management aspect of ERP, whereas Huin, et al. (2003) have developed a multi-flow small and medium-sized enterprise (M_SME) system using the combination of artificial intelligence and ERP. However, Aslan, et al. (2012) have questioned the implementation of off-the-shelf ERP systems. Yeh & Xu (2013) have created a critical success strategies (CSSs) system as a supplement for ERP. Reithofer & Naeger (1997) have introduced a bottom-up planning methodology for modelling ERP.

A maintenance strategy must have a smooth material flow from the suppliers to production lines to customers for high maintenance management performance. There should also be an effective information flow between maintenance process and management, life cycle cost, purchase, quality and production (Kans & Ingwald, 2008). Therefore, life cycle control (LCC) and life cycle analysis (LCA) are important approaches that should be used in medium to large asset management systems. Computerised versions of these two approaches are also created in the industry such as continuous acquisition and life cycle support (CALS) of the continuous analysis process of ship structures created by Kawamura & Sumi (2005). Ingwald & Al-Najjar (2006) have, additionally, studied the connection between the LCC and vibrational maintenance strategy whereas, Mitropoulou, et al. (2011) have performed LCA on the hazards of earthquake reinforced concrete structures. Ribeiro, et al. (2013) have introduced a comprehensive LCC (C-LCC) system for the injection moulding of plastic parts production. Generally, all of the above life-cycle assessment models create overall platforms in order to maintain the performance of the asset during its life cycle at the highest possible level. However, all of the above approaches would still need other types of maintenance methodologies to achieve their goals. Therefore, both LCC and LCA are considered more as management tools to help all the stakeholders achieve the best asset performance, but the actual procedures of achieving this can vary immensely.

3.3.4 Computerised Maintenance Management Systems (CMMS)

Any computerised maintenance programme has to have the following characteristics in order to be effective: High modularity, plug & play, open standards, ease of configuration, generic solution for module configuration, generic interfaces for modules/data, platform independence, modern software architecture, possible remote software updates, access and security, and be self-starting and stable. Software and hardware are the basis of all CMSs. Communication hardware for the CMS is categorised into two different areas: Networking (Ethernet networks with TCP/IP, and WLAN) and real time data (analogue and digital hardware signals). The main purposes of the software technologies for the CMS include data exchange and communication, database storage and data evaluation. Data exchange and evaluation itself can be categorised into two criteria: Real time data (RTD) and long-term data (LTD). Some well-known examples of CMS systems include: Gram & Juhl TCM System, Mita WP4000 System, DMT WindSafe System, B &KV's 3652 System, WT_U project based System, CONMOW project based System and SIEMENS' Monitoring and Safety System (Hameed, et al., 2010).

The main advantages of using CMMS include CBM support for failure evaluation**,** spare parts tracking**,** acceleration of the fault report**,** facilitation of intra-company communication**,** historical information access facility**,** more effective information types for maintenance managers**,** capital expenditure information, and asset healthcare status report (Labib, 2004). However, there are several drawbacks concerning CMMS systems used recently in the market. CMMS systems such as enterprise resource planning (ERP) usually acquire a large amount of data but do not provide enough output and results. They also lack any decision support system. Finally, most recent and advanced models of CMMS systems lack user friendliness (Labib, 2004).

Work orders and maintenance plans can be generated by CMMS. By interacting seamlessly, user intervention is minimised, and the process should have flexibility. Feedback from the CMMS should adjust parameters and settings. (Mathew, et al., 2006).

Leger, et al. (1999) illustrate the main framework of a CMMS with all its different domains and connections to each other through a unique system. For predictive and proactive maintenance strategies such as CBM it is crucial to have a CMMS system in place in order to make condition monitoring of data sharing possible (Kans & Ingwald, 2008). There are several IT integration tools available in the market for corporate data sharing and communication such as computer integrated manufacturing open system architecture (CIMOSA), the general reference architecture model (GERAM), the common information model (CIM) and the open system architecture for enterprise application integration (OSA-EAI). Kans & Ingwald, (2008) suggest the use of a common database at three levels: data integration, information system and business process. The IEC 62264, and MIMOSA's OSA-EAI and OSA-CBM are the major standards supporting this common database**.**

Integration of CMMS and enterprise asset management (EAM) can simplify the number of data requirements and collection methodologies (Moore & Starr, 2006). Mathew, et al. (2006) introduced an integration method between condition monitoring and maintenance management such as data acquisition, condition assessment, maintenance prediction, and work order notification. This framework exchanged data inside a standardised protocol called the machinery information management open systems alliance (MIMOSA). Moore & Starr (2006) describe the relationship between condition monitoring alarms and decision-makers as an arrangement of maintenance activities which are getting harder each time because of the complexity of modern organisational facilities and advancements in condition monitoring techniques. In CMMS systems, if a failure occurs by machinery exceeding a threshold, the alarm will be raised.

Sitton (2005) talks about the software packages used in risk based inspection programs that are called inspection data management systems (IDMS). Most well-known software packages created for this purpose include UltraPIPE by Berwanger, Inc., PCMS® by Conam Inspection, EMPRV by Shell and IDM by ExxonMobil. Loures, et al. (2006) looked into two different approaches of control monitoring maintenance (CMM) and development cycle methodology (DCM). Discrete events systems (DES) are usually solved in four sections of planning, real-time scheduling/supervision, co-ordination and local control. This model uses a hierarchical system of different levels, where it has a top-down approach and is a connection between lower and higher levels. Lee, et al. (2006) discuss another specified CMMS system called the integrated weapon system database (IWSDB) which integrates strategic, management and operational data for the defence industry. Labib (1998) mentions it is a world-class manufacturing (WCM) strategy that can use CMMS to implement its decision module. Kawamura & Sumi (2005) practiced the use of the STEP AP218 standard for data exchange model, graphical representation model and text files format for data exchanges on an express data management (EDM) tool.

Several information management systems have been developed by classification societies such as NK-SHIPS (from Class NKK), Nauticus (from DNV-GL), ABS SafeShip, ShipRight (from Lloyds' Register) and VeriStar (from Bureau Veritas) (Kawamura & Sumi, 2005). Hamada, et al. (2002) discuss the implementation of the ship inspection control, plan, do, check, action (PDCA) methodology for quality control of the inspections and CIM on integrated information systems developed for a ship inspection support system. Gabbar, et al. (2003) developed a CMMS to extract asset component and operational information, and send it to the RCM module. This paper introduces a dynamic integrated RCM-CMMS methodology in order to alter the maintenance tactics according to the plant condition.

The maintenance model used by Fernandez, et al. (2003) contains a three-dimensional structured query language (SQL) system. Decision making grid (DMG) is a visual tool used here for the decision support module of the maintenance framework, which monitors the downtime and failure frequency of system components for its analysis. Subsequently, DMG gives each component a boundary level and criteria for its ranking. BSI (2009) is also emphasised in the implementation of computerised systems such as supervisory control and data acquisition (SCADA) for the information system development of asset management systems. E-maintenance is part of the integration of e-business and e-manufacturing.

The PROTEUS European project has worked on creating a unique e-maintenance software platform. Maintenance implementation can face major problems due to lack of training, operator conception, resources, involvement of parties, long-term vision and momentum (Han & Yang, 2006). Finally, as part of the INCASS FP7 European project an overall platform of ship inspection, condition monitoring, maintenance scheduling, decision-making and central database with online data gathering function was created that covered both structural and machinery aspects of vessels used within the project. This intelligent CMS system allows the prediction of failures before occurring and makes best decisions based on the performance and overall condition of the system using real-time data gathered by its central database (Dikis et. al., 2016).

3.3.5 Risk-based Inspection (RBI)

Risk-based Inspection (RBI) is an inspection optimisation technique that uses risk as the basis of scheduling inspection and maintenance. RBI determines risk on high-risk components by multiplying the likelihood of failure to its consequences. It eliminates unnecessary inspections (Patel, 2005). RBI was first emphasised by the regulations presented by ASME and API. RBI can be implemented in three different ways: Qualitative, semi-quantitative and quantitative. Depending on the accuracy and time limit requirements, any of these methods can be used. RBI can be either implemented on plants with a run-to-failure inspection method where it can increase safety and reduce unwanted shutdowns or on facilities with traditional preventive maintenance systems where RBI can decrease inspection costs (Ablitt & Speck, 2005). RBI is the recommended method for the new generation of computer-aided maintenance procedures. RBI itself is categorised into two main phases: Risk assessment and maintenance planning. The most important phase is the risk assessment (Arunraj & Maiti, 2007). However, this can also mean that the risk will always be prioritised compared with the cost and other management factors of the maintenance.

The computational process required for RBI of offshore structures was quite high until the representation of the generic RBI approach (Straub, et al., 2006). RBI was first used on fixed offshore platforms to evaluate fatigue, especially on welded steel structures. Subsequently, it was adapted to the floating platforms, FPSOs, semi-submersibles, tankers and any structures subject to high corrosion (Swanson, 2001). Four main areas must be covered by RBI (Ablitt & Speck, 2005): 1) What components are more likely to fail; 2) Where should inspection be focused on; 3) Which types of non-destructive techniques (NDT) should be implemented; and 4) What time interval has to be used? However, this definition by Ablitt (2005) does not include another useful step of criticality analysis in order to prioritise most critical components and maintenance tasks. Dong & Frangopol (2015) have introduced a new probabilistic of assessing the risk of flexural failure based on corrosion and fatigue on hull structure of VLCC ships. Using this risk-based technique they can evaluate lifetime optimum inspection and repair planning for the vessel.

The main savings achieved from implementation of RBI are failure avoidance, production loss avoidance, early repair warnings, early detection, inspection interval optimisation, better design criteria for future projects, and less expensive inspection technique selection (Patel, 2005). Ku, et al. (2005) have implemented their RBI methodology on risk assessment and reliability analysis of offshore structures. Combining a reliability analysis aspect like RCM inside the RBI methodology introduced by Ku (2005) can also implement a better prediction element concerning avoidance of unwanted maintenance tasks when compared with only a risk-based approach, as used by Dong (2015). The first stage of any RBI planning for an offshore structure is collection of information on the following areas: Previous surveys and inspection reports, drawing documents, up-to-date weight reports, MeteOcean data, weld profile control, inspection philosophy, risk acceptance criteria, consequences, inspection techniques, and repair philosophy (Rouhan, et al., 2004).

Wu & Syau (1995) have introduced n-service inspection (ISI) for analysis of the probability of failure of structures. The RIMAP project has created an EU-wide RBI methodology for maintenance of different types of plants (Kauer, et al., 2004). Another specialised RBI methodology, developed by Hu & Zhang, (2014), is called risk-based opportunistic maintenance (RBOM). This technique uses the failure of one component as an opportunity to create a preventive system on other components using a global optimisation algorithm. This method also decreases cost and risk of failure based on the performance of the nearby components. However, none of the RBI methodologies introduced in this section include the cost factors and company goals concerning achieving the most optimum maintenance platform.

3.3.6 Total Productive Maintenance (TPM)

Total productive maintenance (TPM) was first introduced in Japan in the 1970s. This technique has various benefits such as helping to create a complete preventive maintenance system, increasing component effectiveness and employment of everyone working on the plant. This method unifies the operation and maintenance tasks of the company and everyone involved. This has numerous advantages such as everyone becoming multitasked, which improves the flexibility and skills of employees; enhancing feelings of pride in operators involved in maintenance; reduces delays; and promotion of team working skills (Ben-Daya, 2000). TPM is one of the most effective types of preventive maintenance methodologies, which helps companies to eradicate waste and interruptions, and achieve the best performance from their machinery. TPM identifies six major losses for organisations: Equipment failure, adjustments, minor stoppages, reduced speed, process errors and rework/scrap. TPM methodology implementation highly depends upon the structure and philosophy of the organisation.

Rodrigues & Hatakeyama (2006) have produced eight pillars for TPM: 1) Equipment and process improvement; 2) Autonomous maintenance (self-management and control); 3) Planned maintenance; 4) Education and training; 5) Early management of new equipment; 6) Process quality management; 7) Effective involvement of administration on TPM; and 8) Safety and environmental management. TPM uses autonomous maintenance (AM) and focus improvement (FI) to eliminate unwanted breakdowns. Typical failure modes in manufacturing systems include hydraulic failure, electronic failure, human failure, software failure and electrical failure. TPM has five general points: Equipment effectiveness enhancement, PM strategies for the whole system, various department involvement, full involvement of all personnel (from employee to the manager), and improvement on design and function of equipment. The word “total” in TPM has three meanings: Effectiveness, maintenance and participation. The ceneral steps and methodologies of TPM explained by Ben-Daya (200) and Rodrigues (2006) do not clearly indicate how each step can be implemented even though both studies represent similar outlines of TPM.

Total asset management (TAM) on TPM has seven steps (Sharma, et al., 2006): 1) Primary cleaning; 2) Mitigations for cause and effects; 3) Standards; 4) General inspection; 5) Autonomous inspection; 6) Organisation and tidiness; 7) Full implementation. TPM can be divided into two main areas. The first area is production equipment management; this method helps to improve asset utilisation and profitability of the plant. The second area is authorisation and enablement of employees, which can help to decrease the plant costs and maximise profitability by uniting the operators and mechanics and making them work towards the same goal (Ben-Daya, 2000). TPM enhances product quality by creating an appropriate connection between manufacturing and maintenance. Not all of the implementation steps mentioned by Sharma (2006) can be used in every type of industry as, in the marine industry, full autonomous inspection plus general organisation and tidiness will not be possible in all cases.

Overall equipment effectiveness (OEE) is used as a major measure of the effectiveness and machinery performance. TPM using OEE can help create an environment for assessing losses and prioritising maintenance schemes. TPM can improve six major losses: Breakdown, setup and adjustment, idling and minor stoppage, reduced speed, quality defects and rework, and start-up losses (Tsarouhas, 2007).

Puns, et al. (2002) discuss another TPM methodology called effectiveness-centred maintenance (ECM) which is useful for businesses of various natures as it uses an integrated approach. It identifies failure modes, prioritises the important ones and assesses their maintenance options using statistical and mathematical tools extensively. As a result, it uses RCM analysis with the concept of total quality management (TQM). This means that ECM is more comprehensive than other methodologies as it contains staff participation, quality improvement, performance measurement and maintenance strategy development. Integration of the TPM and TQM concept has been further investigated by Singh, et al. (2013) on CNC machinery. These last three research papers do indicate different methods for regulating each step of TPM in order to achieve the final results. However, these three methodologies have highlighted the importance of using other maintenance tools and methodologies in conjunction with TPM in order to achieve full maintenance methodology.

3.3.7 Business-Centred Maintenance (BCM)

Business-centred maintenance (BCM) and profit-centred maintenance (PCM) are other maintenance methods, which eliminate unnecessary practices to save money and expenditure on maintenance (Pun, et al., 2002). These business- and profit-oriented approaches actually originate from TPM (Hughes, 2001). Jones, et al. (2008) discuss an example of BCM through the application of business-driven reliability (BDR) using the cost of unreliability (CoUR) in refineries.

Albonico, et al., (2014) have also looked into the implementation of capital maintenance, which estimates the capital loss pattern due to maintenance scheduling. Peters (2015) identifies the benefits and drawbacks of using profit and customer-centred contract maintenance. He discusses the importance of using external maintenance expertise from contractors in addition to the in-house maintenance regime in order to increase the effectiveness of the maintenance plan and even make relative profit from maintenance scheduling. Using external expertise, as mentioned by Albonico (2014), could create irregularities as each expert can have a different opinion. In brief, BCM only takes the business side of maintenance into account and ignores more risk and technical aspects. Therefore, another maintenance approach has to be combined with BCM in order to broaden its appeal.

3.3.8 Major Observations on Maintenance Management Systems and Methodologies

Reliability-centred maintenance (RCM) methodology, mentioned in this section, uses system reliability and availability analysis in order to optimise the maintenance planning strategy of the asset. This method mainly uses a preventive strategy as its methodology; however, it can also contain predictive aspects. Other improved versions of RCM methodology have been created, such as VDM, in order to add different aspects and viewpoints to the strategy such as the business aspect. Criticality and risk analysis are other major aspects that are considered in the latest versions of RCM due to increasing concerns and costs of possible failures and disasters. This upsurge of safety concerns has reduced the viability of using shorter and quicker versions of RCM such as SRCM.

Another effective maintenance methodology, condition-based maintenance (CBM), uses different types of monitoring and analysis technologies such as vibration monitoring in order to predict and prevent unwanted breakdowns. CBM is usually implemented on machinery and internal parts but it could also be performed on structural sections using both online sensors and automated robotic systems. Due to the advancement in computer modelling systems more cutting-edge CBM techniques such as ACM and CBCM are being developed for the industry. Therefore, online monitoring systems are becoming more common-place on CBM. Prognostic approaches are also used within CBM concepts to predict the future failure patterns that are in development for more critical components in order to raise the competitiveness.

Asset management systems, discussed here, can use other maintenance strategies, combined with goals and business aspects of the organisation, in order to achieve predetermined goals by lowering both risk and cost elements. Risk and cost elements are two relatively contradicting elements so a trade-off between them should be defined. ERP and LCC are different types of asset management systems that, in conjunction with their computerised models, can create an effective connection between supply, marketing, spares, manufacturing, management and maintenance sections of a medium to large sized asset. A CMMS is important in the maintenance planning of more complex and modern systems as it can control and analyse both real-time and long-term data using both Ethernet networks and online systems. CMMS can be integrated into any other maintenance methodology. There are numerous off-the-shelf CMMS systems, developed by other companies, to be used by different types of industrial sectors but, still, some companies prefer to develop their own specialised CMMS model.

Risk-based maintenance (RBM) is another commonly used methodology that uses risk analysis techniques (qualitative, quantitative and semi-quantitative) to develop optimum inspection plans for maintenance of plant. Risk assessment on RBI would require results from previous surveys. Various standards are created in order to regulate the RBI methodologies used in different sectors such as offshore oil & gas. Total productive maintenance (TPM) is more focused on the effectiveness of management systems of assets especially in the product manufacturing industry. TPM believes in self-efficiency and automation of all quality control processes. This method can be integrated with other maintenance strategies such as RCM in order to increase their effectiveness. Overall equipment effectiveness (OEE) is the main measure of effectiveness that is being used to determine the progress of the TPM. BCM and PCM methodologies mostly focus on the cost elements of an asset which could be damaging in risk-oriented sectors such as nuclear power plants. All the policies mentioned in this section would require analysis methodologies in order to achieve their effectiveness. Therefore, the next section will talk about some of the most well-known analysis tools used in the maintenance sector.

3.4 Maintenance-related Analysis Tools and Systems

This section discusses different maintenance tools and systems used in maintenance policies. These tools are categorised into four major areas: Failure, reliability and probability analysis tools, decision-making systems, risk analysis tools, and condition analysis tools.

3.4.1 Failure Analysis, Reliability and Probability Tools

A criticality analysis such as FMECA would be useful to enable managers to prioritise tasks. FMECA can rank assets by determining the consequences, probabilities, and likelihood of asset failures. This method creates a risk priority number (RPN) in order to obtain factors for ranking asset failures. RPNs could be determined by converting qualitative data into quantitative values. However, it could create some uncertainties (Moore & Starr, 2006). Another important factor in machinery maintenance is component criticality. In order to analyse this factor, FMEA techniques should be used. The criticality of each component is analysed on four principles (Abdul-Nour, et al., 1998): 1) Effect of the machine downtime on the production process (EM); 2) Utilisation rate of the machine (UR); 3) Safety and environmental incidences (SEI) of machine failures; and 4) Technical complexity of the machine and requirements for external maintenance resources (MTC). Figure 8 demonstrates an example FMECA table used in industry. Various companies are able to develop FMECA models according to the IACS requirements for shipping companies, one of which has been developed by NPD Solutions, 2016, an example of which is illustrated in Figure 7. These steps for criticality assessment by Abdul-Nour (1998), themselves, can have further steps and different methodologies can be used to define them. This can create further uncertainties for defining the criticality of different components/sub-systems within the main system.

Potential Failure Mode and Effects Analysis (Design FMEA)

System	LTN2001 GPS SSU	**Revision**	B
Subsystem	Receiver Card	**Prepared By**	Robert Crow
Part Number	466230-100	**FMEA Date**	8/18/1992
Design Lead	J. Davies	**Revision Date**	

Item / Function	Potential Failure Mode(s)	Potential Effect(s) of Failure	Sev	Potential Cause(s)/ Mechanism(s) of Failure	Prob	Current Design Controls	Det	RPN	Recommended Action(s)	Responsibility & Target Completion Date	Action Results: Actions Taken	New Sev	New Occ	New Det	New RPN
Circuit Block 4.1.1	Output loss from pre-amp	Receiver & output data loss; track loss; GPS shut-down	5	C1 short	1	PR-20 & HV-5	2	10	QA Proc 20-6	R. Jones, 11/30/92	Added to control plan	2	1	1	2
			5	C88 short	2		2	20	QA Proc 20-6	R. Jones, 11/30/92	Added to control plan	2	1	1	2
			5	L1 open/short	3		2	30	QA Proc 20-3	R. Jones, 11/30/92	Added to control plan	2	2	1	4
			5	U21 function	4		2	40	Test 147	R. Jones, 11/30/92	Added to control plan	2	3	1	6
								0							0
Circuit Block 4.1.2	Undetected & insignificant component failure mode	No noticeable system effect	1	C1open/chg val.	2	None	8	16	None						0
			1	C88open/chg val	2		8	16	None						0
								0							0
Circuit Block 4.2.1	Loss of signal from 2nd RF amplifier & 1st down converter	Loss of position, velocity & time output data; track loss; GPS shut-down	4	C2 short	1	PR-20 & HV-5	2	8	QA Proc 20-6	B. Howell 10/15/92	Added to control plan				0
			4	C3 short	1	PR-20 & HV-5	2	8	QA Proc 20-6	B. Howell 10/15/92	Added to control plan	2	1	1	2
			4	C4 open/short	2	PR-20 & HV-5	2	16	QA Proc 20-6	B. Howell 10/15/92	Added to control plan	2	1	1	2
			4	C5 short	2	PR-20 & HV-5	2	16	QA Proc 20-6	B. Howell 10/15/92	Added to control plan	2	1	1	2
			4	C66 open/short	2	PR-20 & HV-5	2	16	QA Proc 20-6	B. Howell 10/15/92	Added to control plan	2	1	1	2
			4	C99 short	3	PR-20 & HV-5	2	24	QA Proc 20-6	B. Howell 10/15/92	Added to control plan	2	2	1	4
			4	FL1 short/open	5	None	2	40	100% Insp.	B. Howell 10/15/92	Added to control plan	2	2	2	8
			4	FL2 short/open	5	None	2	40	100% Insp.	B. Howell 10/15/92	Added to control plan	2	2	2	8
			4	R2open/chg val	2		2	16	None						0
			4	R18 open/chg val	2		2	16	None						0

Figure 7 - Example of FMECA (NPD-Solutions, 2017)

Defence Standard 00-45 also requires the FMECA to be implemented to identify all asset failure modes (New, 2012). Selvik & Aven (2011) use an RCM-adjusted FMECA worksheet and RCM logic diagram in their methodology. FMECA on the RCM process can indicate manufacturing process problems using appropriate field operational failure data and root cause analysis. Critical to quality (CTQ) failures can be identified easily if the data collection and FMECA document are described separately as it is quantitative rather than qualitative. The basics of FMECA include component identification of the system, data collection from the functional structural diagram of the system, failure modes generation, physical requirement description and criticality concept development (Igba, et al., 2013). Ahmad, et al. (2012) have practiced a methodology that uses the FMECA as the prior classification of data and for determination of external factors. Another issue highlighted by these two studies in this paragraph is the change of qualitative results into quantitative values for criticality which, on its own, creates further uncertainties and irregularities for the final outcomes.

Fault tree analysis (FTA) is one of the most commonly used system reliability tools for maintenance regimes. Top event (TE) is the starting point for the FTA and failure sequence follows the TE. Therefore, FTA is a top-down approach. Each basic failure event in FTA has a predetermined probability value assigned by statistical data (Shalev & Tiran, 2007). Numerous types of data inputs can be used on FTA such as non-repairable, repairable, test intervals, frequency and on-demand data. Non-repairable, repairable and test interval all have set durations whereas frequency is interval-free (Turan, et al., 2003). Therefore, it is important to define parameters that eliminate the interval element. FTA can have dynamic gates in order to analyse complex maintenance strategy elements (BSI, 2006). Lampis & Andrews (2008) illustrate that uncertainties can be an issue in fault tree constructions.

A study by Turan, et al. (2003) uses non-repairable and on-demand data input types for construction of fault tree of loss of life, collecting the data and assessment, and synthesising the possibility of loss of life. Contini (1995) has developed a hybrid fault tree system that can be analysed both top-down and bottom-up. Emmanouilidis, et al. (2006) use FTA to specify the component failures and their connections with the whole system. Trucco, et al. (2008) propose that FTA be integrated into human and organisational factors (HOF) within a risk analysis study. The directed acyclic graph (DAG), used in this study, consists of two parts, qualitative and quantitative evaluations. Liu & McDemid (1996) have developed a model-oriented FTA system called fault tree support system (FTSS). These different studies show the possible variations an FTA methodology can have and be used in different sectors. Therefore, it would be beneficial to have a study on determining the accuracy of each method relative to each other.

Shalev & Tiran (2007) introduced a condition-based fault tree analysis (CBFTA) to combine condition-based predictive maintenance data with FTA in order to modify and optimise the failure probability and system reliability results of FTA. This method is different than other types of FTA methodologies such as dynamic tree analysis (DTA) and real time FTA as it uses measured data. The major benefits of using this tool include achieving more reliable and safer systems, more precise data for critical components especially at the design stage, more accurate data for MBTF and MTTR, facilitation of a predictive maintenance strategy selection process and ease of evaluation for the design with most net cost outcomes. Another study, carried out by Manno et al., (2014), created Boolean-driven Markov processes (BDMPs) inside a MATLAB toolbox to solve repairability issues of ordinary DFTA tools. This is another, more effective way of creating dynamic gates within DFTA. Lazakis (2011), in his thesis, introduces an innovative way of mixing Dynamic FTA with criticality assessment in a more advanced criticality-based maintenance approach. An example of a DFTA model used in this thesis is shown in Figure 8. However, all types of FTA methodologies have one major drawback: their weakness on representing the interconnectivities between the function of different components within a system. Another possible shortcoming of FTA is its dependability on using outsourced cost benefit analysis tools, which can increase the error between the results achieved from DFTA and their adaption to the outsourced net cost analysis tool.

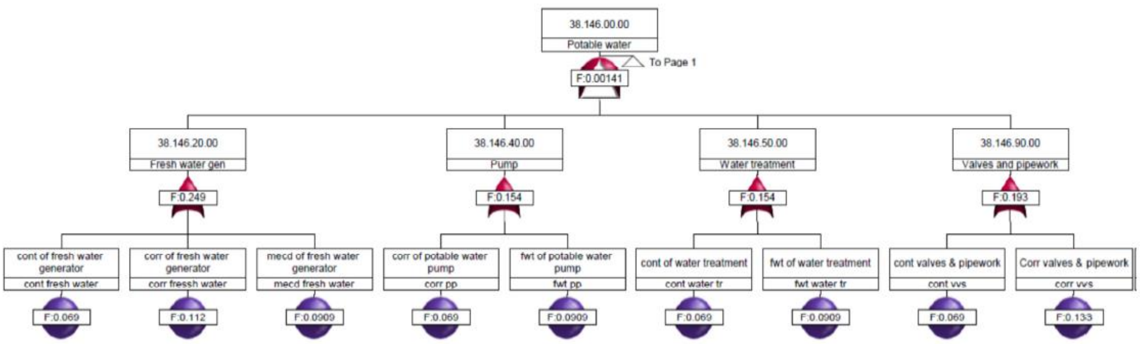

Figure 8 - FTA of the Water Sub-system of a Dive Support Vessel (Lazakis, 2011)

Bayesian networks do not always completely imply Bayesian statistics as conditional probability distribution (CPD) is often assessed using frequency calculations. Nevertheless, BBNs use Bayes' rules for interferences and hierarchical Bayesian models. The probability of events resulting in one child could end up having dependency even though they are marginally independent. This effect is called explaining away which, in statistics, is referred to as Berkson's paradox or selection bias. Bayesian networks can be viewed either from effect to cause (bottom-up) or from cause to effect (top-down) (Murphy, 2000). Weber et al. (2012) illustrate the increasing trend of BNN application on dependability structures and risk analysis.

The qualitative part of the study, as with Trucco et al. (2008), determines casual dependencies between different events and their quantitative part using the combination of FTA and BBN methodologies together. Cai, et al. (2013) have also created a methodology that converts dynamic fault tree gates into dynamic BBN automatically. Poropudas & Virtanen (2011) use dynamic BBN on the decision-making process of their methodology. There are numerous ways to solve DBN problems using statistical models. One of the most well-known models is the use of a mixture of Gaussian outputs to solve issues with DBN such as filling out the missing data (Zhang & Dong, 2014). In another study by Liang, et al. (2017), the overall reliability of warships is determined using a dynamic Bayesian network and multilevel synthetic method with numerical simulations. They conclude that the DBN is a very effective tool for determining a precise reliability and performance profile of complex structures and their maintenance planning. This is also the case in a study by Zhu & Collette (2015), where they used DBN to analyse complex and dynamic fatigue cracking using lifecycle and condition monitoring data. They also used Markov Chain Monte Carlo (MCM) stochastic sampling as an option for inference of large data from a Bayesian network. All previous studies so far demonstrate the fact that DBN can be used instead of DFTA in probability analysis and future prediction scenarios. They also demonstrate that DFTA can easily be turned into a DBN network. However, DBN can easily demonstrate interdependencies between different components; also, by adding cost and decision nodes, maintenance engineers can have net cost analysis integrated directly within the DBN platform.

For reliability indices, standard deviations of the distribution of the variables have been used. The dependence of reliability index is usually determined on three levels. The first and second levels are called the first order reliability method (FORM) and second order reliability method (SORM) respectively. Third level is the full probabilistic calculations using Monte Carlo simulation (MCS). FORM and SORM would give results quickly but would not have the accuracy of MCS (Vhanmane & Patra, 2010). Kolios, et al. (2010) use FORM and SORM to calculate structural reliability.

Weibull's distribution method can be used for data collection and end-of-life analysis on RCM (Rausand, 1998). Tsang, et al. (2006) implemented Weibull's distribution model as a foundation for their hazard rate function. Weibull's hazard function and time-dependent stochastic covariates have also been used by Jardine, et al. (1997) to simplify the reliability analysis of the large amount of data gathered from monitoring systems. Guo, et al. (2009) identify Weibull's model as the baseline of their reliability analysis system of the statistical field failure data for their wind turbine case study. Garbatov & Soares (2001) performed Weibull's distribution on the stress distribution measurement of lifecycle condition and typical sea states on floating structures. This method can cause irregularities especially if the overall distribution of the faults does not follow Weibull distribution but some other types of distributions.

The whole Markov technique can represent the reliability, maintainability, availability and safety behaviour of systems but state transition diagrams are used to graphically demonstrate Markov models (BSI, 2006). Hidden Markov models (HMMs) can represent the state of the interdependencies of the variables in dynamic BBNs (Murphy, 2000). In HMM, there is one discrete hidden node and one discrete or continuous observed node per section. Markov analysis has been used by Schea, et al. (2012) in order to realistically plot sea state time series for offshore wind farms as it can illustrate the persistence of the waves as well as their height distributions. Markov's decision process has been used by Tian, et al. (2011) for approximating degradation processes in their CBM methodology. The HMM technique on its own will not help analysis of probabilities and maintenance scenarios but it can be added to BBN and FTA in order to create dynamic future perdition of the reliability and probabilistic results.

Monte Carlo simulation helps to evaluate relevant system operational aspects using an analytical model. Monte Carlo simulation can be time-consuming but not when assessing the availability of predetermined maintenance strategies (Marquez & Iung, 2007). Weibull's distribution model on the methodology developed by Guo, et al., (2009) uses the Monte Carlo simulation in order to analyse its uncertainties. Distribution of probabilities and consequences of events on the LNG tankers' case study by Montewka, et al., (2012) have also been analysed using Monte Carlo simulations. In a similar fashion to HMM, Monte Carlo simulations have to be used in conjunction with other tools in order to analyse the data input of the other reliability and probabilistic methods.

3.4.2 Decision-making Tools

Fuzzy logic uses fuzzy rules and grades each of the parameters of the system (IAEA, 2008). Fuzzy mathematical formulation usually uses trapezoidal fuzzy coefficients to help the evaluation of the likelihood of the failure modes by investigating all participant factors, calculating likelihood factors and comparing the resulted factors (Fonseca & Knapp, 2000). The DuoFuzz and Quadro-Dou Fuzz classification systems are used in order to classify faults based on user-defined parameters. NovClass is the name of the software developed in a paper by Emmanouilidis, et al., (2006) that monitors, analyses and diagnoses the conditional data. The rough set approach is similar to fuzzy set approach but uses boundary regions instead of members. Additionally, rough set covers the differing areas of non-precision and uses discernment analysis and Boolean reasoning methods. The information system for rough sets consists of universe (U), attributes (Ω), domain (V) and information function (f) (Gento, 2004). The approach of this study would not fit with every scenario as availability of information may vary.

A study by Turan, et al. (2003) used Fuzzy Set Theory (FST) for analysing the loss of life on fishing vessels due to a variation in the design of the vessels. Rodseth, et al. (2007) used fuzzy reasoning on semi-quantitative analysis of human factors. Pan & Yun (1997) added fuzzy sets to FTA for system reliability analysis and Suresh, et al. (1996) discuss the application of fuzzy set theory on solving the uncertainties of FTA. Lihovd, et al. (1998) undertook fuzzy thresholding to perform calculations which assign a symptom strength (SS) factor for each diagnosis symptom on civil aircraft. Li & Nilkitsaranont (2009) solved the nonlinearity issue of the CBM methodology of a gas turbine by using fuzzy logic. Labib (2004) chose fuzzy logic for the decision making grid (DMG) of his Holonic Concept. In research undertaken by Khan, et al. (2004) fuzzy logic with triangular fuzzy numbers (TFNs) was used to connect qualitative results with numerical values. Heo, et al. (2012) implemented benefits, opportunities, costs and risks (BOCR) to fuzzy AHP to make decisions on the best hydrogen energy system infrastructure. These variations of applications of FST in different environments demonstrate its adaptiveness on different scenarios. However, an important fact has to be taken into account when turning qualitative results into quantitative values as it can create uncertainties. Therefore, this method should only be used in conjunction with other methods and it should also be implemented as a complementary result in order to validate results obtained from other techniques in more complex systems with the conditional data available.

An analytic hierarchy process (AHP) can solve the multi-criteria decision problem by pairwise comparison of each criterion by their weights using the two major approaches of eigenvector and geometric means solution. There are generally four major stages for AHP: 1) Decision matrix development; 2) comparison pairwise matrix construction; 3) relative weight identification from comparison matrix; and 4) computation of ranking based on the weights (Fernandez, et al., 2003). Ishizaka & Labib (2011) used weighting factors for both decision-makers and stakeholders in their AHP decision making strategy. Labib, et al. (1998) represented an AHP for the maintenance decision-making when analysing machinery faults and criticality as an important part of preventive maintenance due to the fact that use of only fault and criticality analysis may not be an effective option in most cases. Therefore, the multi-criteria decision analysis tool introduced in this paper works across three stages: 1) criteria identification for each piece of machinery; 2) prioritisation of each criterion by multiple-criteria evaluation method; and 3) criticality ranking of the machinery.

Labib (1998) used AHP to proper recording system results of previous maintenance actions as well as failure mode tree prioritisation for minimising the diagnostic phase of his model. AHP can also be used for value estimation of the value tree analysis (Hamalainen, 2002). Hauser & Tadikamalla (1996) used simulation on AHP in order to facilitate the judgment process. Liu, et al. (2012) introduced three different vulnerability levels into their AHP neural network analysis and decision-making. Magro and Pinceti (2009) used an AHP neural network for the demonstration of interdependencies within their analysis. The decision tree resulting from the AHP model of this study is shown in Figure 9. Finally, Paulson and Zahir (1995) created a methodology for solving uncertainty factors on AHP. The figure below contains an example of the AHP developed for intelligent pressure transmitter devices. Recent work by Lazakis and Olcer (2015) combined AHP with fuzzy multiple attributive group decision-making for improving overall maintenance decision-making on a ship diesel generator within previously developed reliability- and criticality-based maintenance. This AHP approach uses criticality values and general ranking which, in a similar way to the FMECA technique, can cause uncertainties due to turning qualitative expressions into quantitative results. The best way of implementing an AHP technique is to create a neural network in similar fashion to a BBN. Therefore, the AHP technique used by Magro (2009) can be more effective. However, other techniques such as those used by Paulson (1995) and Lazakis (2015) have to be added in order to enhance the effectiveness of AHP by decreasing the uncertainties.

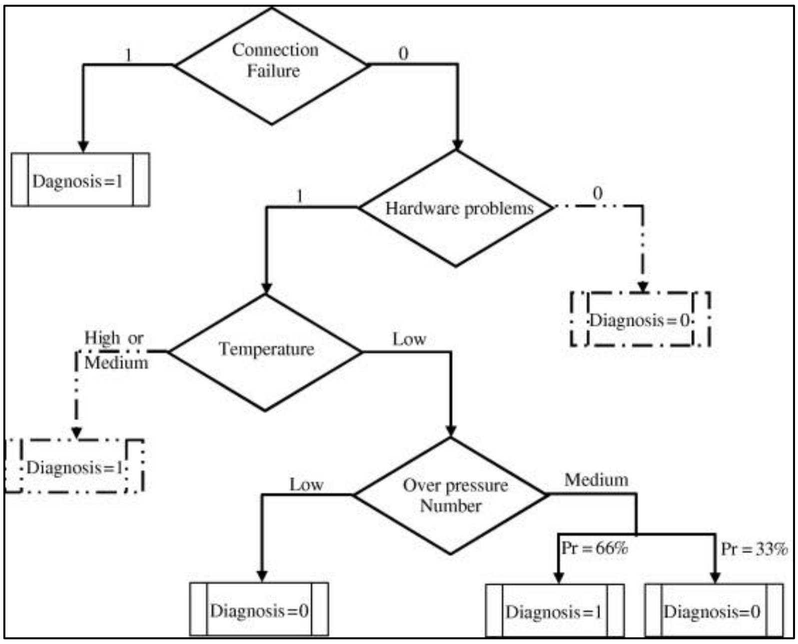

Figure 9 - Decision Tree resulted from Analytic Heirarchy Process (AHP) (Magro & Pinceti, 2009)

Rosqvist, et al. (2009) have introduced multiple criteria decision making (MCDM) for a decision logic system of VDM methodology. Moore & Starr (2006), in their paper, talk about the fuzzy version of MCDM evaluation methodology. Peres, et al. (2007) discuss a decision-support data system. Lee, et al., (2012), in their research, focus on the use of fuzzy group AHP and rough set theory (RST) for selecting and evaluating a new service concept (NSC) by modelling MCDM. Mazza, et al. (2014) have developed an automatic MCDM tool for solution ranking of network loss scenarios. Agrell (1997) discusses the importance of having a redundancy concept within MCDM for operational research. Baserba, et al. (2012) have created customised multi-criteria decision analysis (MCDA) for appropriate design criteria option selection. Dhouib (2014) selected MCDA for the waste tyre logistic selection process. In summary, an MCDM method needs to incorporate other decision-making tools in order to work properly. This would mean that it could inherit their disadvantages.

Strengths, weaknesses, opportunities and threats (SWOT) usually illustrate internal factors (strength and weaknesses) and external factors (opportunity and threats from the market) on a single framework (Gorener, et al., 2012). SWOT can create the foundation for MCDM (Gao & Peng, 2011). Yuksel & Dagdeviren (2007) have developed a quantitative SWOT analysis using analytic network process (ANP) algorithms. Seker & Ozgurler (2012) have looked into the implementation of SWOT with AHP in the Turkish electronics industry (Figure 10). Gorener, et al. (2012) have introduced a SWOT analysis system that uses both AHP and MCDM. Chang & Huang (2006) have created a quantified SWOT analytical method and multiple-attribute decision making (MADM) for the determination of competing for strength of container ports in East Asia. Mohammadpur & Tabriz (2012) have performed SWOT analysis for a Petro Karan factory in Iran. They also used fuzzy logic for analysis of uncertainties. SWOT analysis can produce high uncertainty as it uses the correlation between qualitative and quantitative results and also requires the use of other decision-making tools.

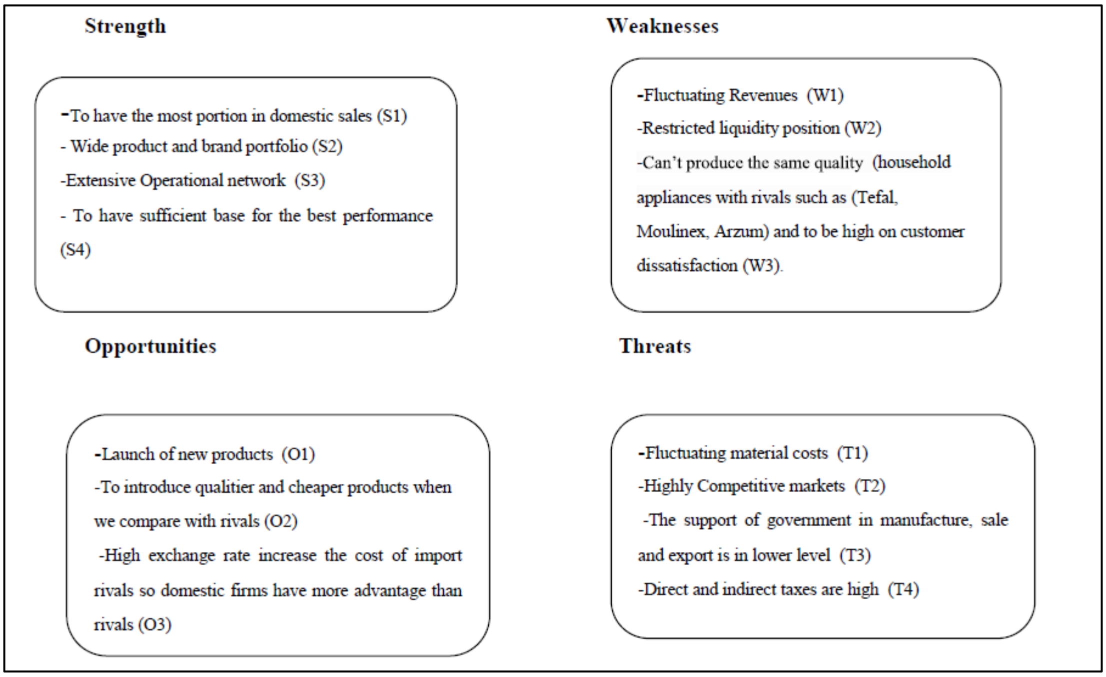

Figure 10 - Example of a SWOT Analysis in the Turkish Electronics Industry (Seker & Ozgurler, 2012)

3.4.3 Risk Analysis Methodologies

As low as reasonably practicable (ALARP) was introduced in the offshore industry in the UK following the Piper Alpha accident in 1988. ALARP considers that the likelihood of occurrence of failure affecting the reliability of safety protection should be less than 10^{-3} per platform year

(Wang, 2001) (Figure 11). The main aim of inspections on FPSOs and RBI methodology are ALARP principles for risk management and physical condition for maintenance in order to follow legislation and obtaining production availability (Goyet, et al., 2002). Net cost analysis concerning the cost of inspection analysis methodology used by Faber (2002) emphasises the importance of ALARP even further.

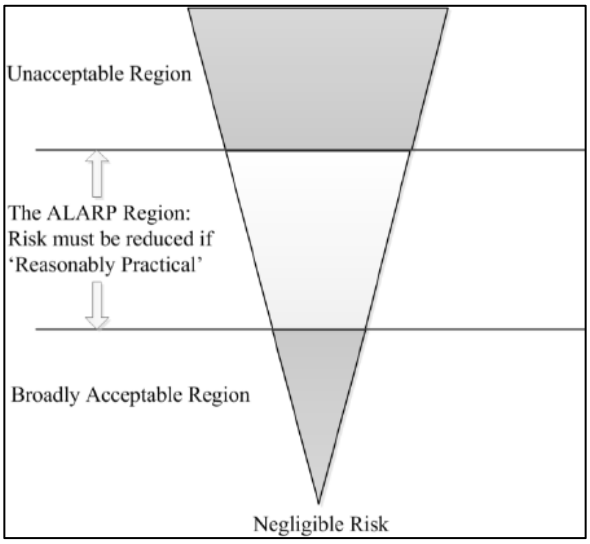

Figure 11 - Example of an ALARP Principle (Wang, 2011)

Proportional hazard modelling (PHM) is a technique of evaluating hazards of condition monitoring data (Tsang, et al., 2006). Jardine, et al. (1997) discuss the use of multiple regression types of analysis based on Cox's PHM for analysing the monitored data. The HAZard IDentification (HAZID) model can help in the early identification of hazards and warnings (Paltrinieri, et al., 2013). McCoy, et al. (2000) developed an innovative way of enhancing the performance of HAZID models using case studies and feedback. The figure below demonstrates a HAZID model from industry.

HAZard and OPerability (HAZOP) is a technique that has been used over the past 40 years for identification of hazards on complex manufacturing processes and systems (Marin & Toral, 2013). Hu, et al. (2009) have developed a computer aided HAZOP model using fuzzy systems. Mohammadfam, et al. (2012) have looked into safety problems in a Tehran water treatment plant using the HAZOP model. Marin & Toral (2013) performed a HAZOP study on the safety of the Mexican oil & gas industry. A descriptive example of the HAZOP structure they used is demonstrated in Figure 12. Cagno, et al. (2002) have created Human HAZOP and multilevel HAZOP systems for process plants. The structural what-if technique (SWIFT) is an expert brainstorming technique that asks the following questions: What if…?; Could someone…?; and, Has anyone ever…? (Maragakis, et al., 2009). It is more useful for high-level rather than smaller risk problems (DNV, 2001).

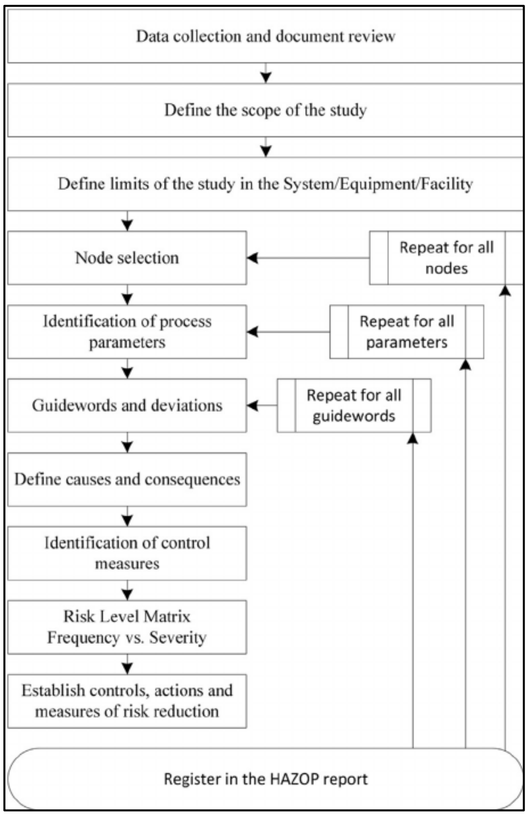

Figure 12 - Structure of a HAZOP Model used in Oil & Gas Industry (Marin & Toral, 2013)

3.4.4 Condition Analysis Tools

Signal processing and feature extraction tools (AutoRegressive (AR) model, Fourier transform, wavelets transform, time-frequency (TF) and Morlet wavelet filtering) use condition-monitoring modelling (Lee, et al., 2006). One of the most well-known time series models is called seasonal autoregressive integrated-moving average (SARIMA) (Liang, 2008).

Zhou, et al. (2000) has introduced the implementation of fast Fourier transformation (FFT) on the Spiewak project. FFT spectrum analysis can identify te low-frequency vibrations better than other techniques as it focusses on the surface wave running across the components on a sonic speed rather than the direct motion of the structural components (McGowin, 2006).

Empirical modelling is one of the most commonly used methodologies for analysing the status of the plant using conditional data. For this model, an analytical neural network (ANN) is usually created to simplify analysis as it can complete numerous interconnected non-linear calculations at the same time such as: prediction of an output value, classification, function approximation and pattern recognition (IAEA, 2008). ANNs can be used to recognise patterns and calculate non-linearity of fuzzy sets (Guo, et al., 2009).

Wavelets transform has become predominantly popular on fault diagnosis systems over the past 10 years (Yan, et al., 2013). Caprioli, et al. (2007) have looked into the possibility of using wavelet technique on processing condition monitoring signals on recent time-frequency. Ovanesova & Suarez (2004) discuss the application of wavelet transform structural-crack growth detection and processing. Tang, et al. (2014) have developed an innovative fault diagnosis system using a Shannon wavelet support vector.

3.4.5 Major Observations of Maintenance-related Analysis Tools and Systems

Criticality analysis concerning FMECA can create a quantitative analysis of the importance of failures of different components. This technique contains types of components, their failure types and probabilities, effects of their failures, consequences of their failures and mitigation methods for the failure modes. Fault tree analysis (FTA) represents a tree-like representation of major failure events with their derivative of failure events. Using FTA facilitates the demonstration of probability failures caused by minor components and their influence on the overall system. FTA is only used on constant failure rate systems and a dynamic gate should be added using Markov chains or other methods in order to allow the calculation of the probability of time-variant failure events.

The Bayesian Belief Network (BBN) undertakes a similar task to FTA except it uses nodes and neural networks to analyse the relationship between failures. BBN is slightly more complex than FTA but it can be more effective on systems with greater dependencies as it can create a connection from different nodes under two different major events. The dynamic feature can also be added to BBN just like FTA. Some studies have used both FTA and BBN and have created a connection between them. Weibull's distribution, using density function, can simplify the demonstration of continuous probability distributions on a model such as adding a dynamic gate on an FTA. Markov chains are statistical models that can create connection between different states of a system. Monte Carlo simulations are used when the exact result is rather difficult to achieve so it uses a scientific sampling technique in order to find the results. The Monte Carlo method can be useful in determining the statistical results and algorithms for Weibull's distribution and Markov Chains.

Fuzzy logic and fuzzy reasoning are useful when information is sparse, especially concerning decision-making processes. Fuzzy reasoning consists of different types such as fuzzy thresholding and BOCR. During the decision-making process it is crucial to rank different results, failures and decisions using a hierarchical process such as analytical hierarchy process (AHP). The whole AHP process can be included inside a larger decision-making process called multi-criteria decision-making (MCDM). MCDM includes various tools put together to simplify multi-attribute decision-making. Risk, like cost, is one of the major elements concerning maintenance strategy so risk analysis methodologies such as ALARP, HAZID, HAZOP and SWIFT are vital maintenance planning tools. ALARP is beneficial when creating a benchmark risk criteria for preventing disastrous failures. HAZID, HAZOP and SWIFT are useful in identifying risk elements and their consequences on the system. The large number of data obtained from condition monitoring systems can be overwhelming and it is essential to use different signal and data processing models such as AutoRegressive, FFT, ANN and wavelet transforms. The next section will introduce performance measurement techniques for evaluating the effectiveness of maintenance policies and tools described in previous sections.

3.5 Maintenance Performance Measurements

It is vital for companies to assess the effectiveness of their chosen maintenance policy throughout its life. This section will look into different methodologies used in industry for evaluating the performance of the selected maintenance system.

3.5.1 Maintenance Key Performance Indicators (KPIs)

Maintenance performance indicators (MPIs) are an important feature of maintenance performance measurement (MPM) in order to continuously improve the performance properties of an organisation. There are two types of indicator (Parida & Chattopadhyay, 2007): 1) Leading: a performance driver for early indication, which is non-financial and statistical. 2) Lagging: outcome measures that provide a foundation for the performance after activity completion such as cost of maintenance and time between breakdowns.

Every maintenance plan should be supported by its objectives. These objectives are strategically important in the eyes of low-level managers but are tactical in the eyes of high-level managers. Maintenance objectives can be linked into company objectives using KPIs and MPIs (Rosqvist, et al., 2009)**.** Using maintenance KPIs helps the organisation to evaluate its state, measure/compare performance, identify pros/cons, progress control, objective definition, strategy planning, communication, motivation, expenditure update and benchmarking. There are two major types of indicators: external and internal. These types themselves fall into the three categories: economic, technical and organisational. There are also three major importance levels for these indicators (BSI, 2007). A full list of MPIs used in the industry can be found in (BSI, 2007).

3.6.2 Maintenance Performance Reporting

Performance reporting systems developed in the past can be set into four groups: Indicators, reference numbers, graphs (pie charts, multi-index profile and radar graphs) and more elaborate models (Pintelon & Puyvelde, 1997). More elaborate maintenance performance reporting models include Hibi, luck and the maintenance management tool (MMT) (Kutucuoglu, et al., 2001).

3.6.3 Overall Equipment Effectiveness (OEE)

There are two main factors when evaluating the performance of a plant: Overall equipment effectiveness (OEE) and overall plant effectiveness (OPE). OEE can be calculated using the equation below (Pun, et al., 2002):

$$OEE = availability \times performance\ efficiency \times quality$$

Equation 1

Other factors such as response time are also important for maintenance performance. The effectiveness of ECM implementation can usually be measured by the two indices of overall system effectiveness (OSE) and individual system effectiveness (ISE) (Pun, et al., 2002). OEE is used as a measure for effectiveness and machinery performance. OEE is an important measure used in TPM methodology that identifies all the equipment losses (Kennedy, 2009). Availability, productivity and quality are usually represented together using OEE in TPM methodology. These three measures also require the calculation of the following maintenance losses: Breakdowns, set-up, minor stoppage, reduced speed, scrap rate and start-up losses (Labib, 1999). TPM can help OEE by creating an environment for assessing losses and prioritising maintenance schemes. OEE itself is calculated in three areas of production, maintenance and product quality (Tsarouhas, 2007).

3.6.4 Reliability, Availability, Maintainability and Supportability (RAMS)

Reliability, availability, maintainability and supportability (RAMS) can be used to observe all steps of product development and quality measurements (Lundteigen, et al., 2009). Zerwick (1996) has represented a review of integrity of critical equipment (RICE) program using RAMs for the maintenance pressure vessels. Martorella, et al. (1999) discuss the importance of RAMS within nuclear power plants. They have introduced a methodology that combines RAMs with RCM, on-line maintenance (OLM) and residual life management (RLM) systems. However, Martorell, et al. (2005) have added a criticality factor to RAMS in order to create a RAMS + C approach for nuclear power plants. Hwang (1996) has introduced the joint methodology of using RAMS and LCC for product performance evaluation.

3.6.5 Balanced Scorecard (BSC)

Tsang (1998) introduced a systematic maintenance performance management strategy using the balanced scorecard (BSC). There are three major performance categories for maintenance: Equipment performance measures (availability, reliability, OEE, etc.), cost performance measures (O&M labour, material cost, etc.), and process performance measures (planned and unplanned work ratio, schedule compliance, etc.) (Tsang, 1998). Wong, et al. (2009) have created an adapted BSC for evaluating various design parameters on different styles of buildings. Seyedhosseini, et al. (2011) used the BSC to analyse the performance of the production/service of auto part manufacturers.

3.6.6 Quality Function Deployment (QFD)

Quality function development (QFD) is a technique that can be used to create a performance measurement system (PMS) for maintenance (Parida & Chattopadhyay, 2007). Kutucuoglu, et al. (2001) gathered different types of maintenance performance reporting systems in order to create a customised QFD system. Benner, et al. (2003) looked into the application of QFD food product development. Kuo, et al. (2009) developed an eco-quality function deployment (Eco-QFD) environmental product design strategy using fuzzy grouping. A more widespread review of all the different QFD methodologies used in the past can be found in a paper by Chan & Wu, 2002. Schmidt (1997) has established an integrated concept development (ICoDe) aspect in order to enhance the performance of QFD results.

3.6.7 Benchmarking

Benchmarking works by comparing the performance of one of piece of equipment with the best in class. This can also introduce areas for improvement (Madu, 2000). Corporative benchmarking can be used in order to assess the effectiveness of maintenance strategies compared with the market (Tsang, 1998). This technique can be effective when improving the efficiency and performance of an organisation by comparing its process map with other leading and successful businesses. Benchmarking itself can be integrated as one of the indicators of the MPI system. The schematic diagram of the linkage between MPIs and benchmarking is illustrated by Ahren & Parida, (2009).

3.6.8 Major Observations on Maintenance Performance Measurements

KPIs and MPIs describe the major goals and incentives of an organisation, MPIs can be used in order to determine the progress of the organisation towards it main goals and objectives. Organisational goals should be determined on both internal and external bases. OEE is a measure of effectiveness of an operation that is usually implemented through the TPM technique. RAMS analysis can be performed on a product of a company in order to determine its maintenance cost and performance including the use of spares. RAMS can be an on-going process and can be integrated with the online maintenance system of the organisation. The BSC is a valuable tool for measuring the performance of actions such as maintenance from the design stage until decommissioning. QFD is similar to the BSC but it is three-dimensional and can include more analysis criteria. Benchmarking can be beneficial for comparing the performance of the company with similar organisations using other maintenance performance measurement techniques

3.6 Inspection and Monitoring Tools & Methodologies

This section will represent the inspection and monitoring tools used in industry for obtaining the data for maintenance policies and performance measurements or restoring equipment to design conditions.

3.7.1 Electromagnetic Testing

The oil and gas industry uses inspection techniques such as alternating current field measurement (ACFM), and time of flight and saturated low frequency eddy current (SLOFEC). These techniques would allow the company to identify any inner or outer cracks, defects and discontinuities within the materials. ACFM is a very cost effective technique and SLOFEC can work even with marine growth on the surface (Caldwell, 2012). Ming, et al. (2007) implemented alternating current field measurement (ACFM) for crack detection by analysing the reduction of magnetic flux. ACFM is also used in three different case studies by LeTessier, et al., 2002. Tehranchi, et al. (2011) used the magnetic flux inspection technique for detecting cracks using giant magneto-impedance (GMI).

Halleux, et al. (1996) used the eddy current technique to evaluate the thickness of circular non-magnetic conductive tubes. Yamada, et al. (2008) performed low frequency eddy current testing for flaw detection on multi-layered aluminium plates. Rekanos, et al. (1997) used a neural network for conductivity profiling issues of low frequency eddy current probes. He, et al. (2011) introduced pulsed eddy current (PEC) non-destructive testing for flaw detection using a C-Scan image format. Gros (1995) implemented eddy current non-destructive testing on evaluation of low-impact damage to carbon fibre reinforced plastic (CFRP) structures.

3.7.2 Wave and Vibration Frequency Monitoring

Recently, vibrational analysis equipment has become much cheaper than before due to advances in piezo-electric sensors, signal processing theory, and digital signal processors. There are two sets of well-known time-domain analysis signal processing equipment: auto-correlation and Cepstrum. There are also numerous types of bearing checker equipment for vibration monitoring of wind turbines. Some of the most commonly used bearing checkers include: Pruftechnick's VIBSCANNER, sock pulse method (SPM), SWANTECH and SKF's spectral emitted energy (SEE) method, (ICP) accelerometers (McGowin, 2006). CORPAC is an important corrosion monitoring system that uses acoustic signals. This equipment can purify corrosion product noises from the process and other field noises (Cole & Watson, 2005). Miettinen & Siekkinen (1995) used acoustic emissions to monitor the performance and sliding contact behaviour of seals.

Loutas, et al. (2009) discuss the use of acoustic emission monitoring for the conditional monitoring of gearbox components during operation. Ravindra, et al. (1997) implemented acoustic emission monitoring into evaluating the condition of metal cutting tools. Rabiei and Modarres (2013) selected acoustic emission monitoring as an appropriate technique for monitoring the crack growth on aluminium structures. Davies, et al. (1996) performed acoustic emission analysis on a cement-metal interface. Infrared thermography is a non-contact method that shows the heat changes within machinery. Spot radiometers are common thermography equipment used in industry. They are relatively cheap and easy to use but provide very diminutive measurements. They also only take measurements on circles, not dots as they only measure the average temperature from dots on an area and the size of the area is distance dependable (Salva, et al., 2004).

Jamalabadi (2013) implemented infrared cameras to evaluate thermal loading of thin carbon-steel plates. Classification societies and international regulations are forcing companies to use enhanced survey programs (ESP) and measurement equipment such as ultrasonic thickness measurements (UTM) for corrosion analysis (Jaramillo, 2006). Ultrasonic guided waves were used by Raisutis, et al. (2010) in order to identify flaws within carbon fibre reinforced plastic (CFRP) products. Impulse excitation technique (IET) was performed by Swarnakar, et al. (2009) to determine the performance of ceramic coatings. Kazantsev, et al. (2002) investigated the radiographic detection technique for weld performance evaluations.

3.7.3 Structural Surface and Material Property Analysers and Visual Inspection

Swain, et al. (2007) looked into the applications of the British Maritime Technology Hull Roughness Analyser (BAHRA) and barnacle adhesion strength measurements for testing performance of anti-fouling coatings on ship hulls. Ellipsometry is another type of surface analyser for analysing the film thickness of coatings (Keddie, 2001). Augmented reality (AR) can be used as an effective tool in order to display technical data easily to engineers and operators. AR is basically the overlapped real world with the virtual reality model. Due to the complexity of the pipe networks of FPSOs, it could be difficult for the engineer to simply use design information in order to carry out inspections and maintenance. Therefore, AR could facilitate the use of the design data as they are represented in virtual reality on the real images and videos of the site (Lee, et al., 2010). Lyu & Chen (2009) looked into the application of automated visual inspection in manufacturing plants. Shriwardhankar, et al. (2010) discuss the implementation of visual helium leak inspection techniques for checking the containment and sealing effectiveness of vertical shell and tube type heat exchangers.

3.7 Overall Observations

Both fault tree analysis (FTA) and Bayesian belief network (BBN) are useful tools for failure, reliability and probability analysis but not enough work has been done on comparing these two techniques in similar case studies. Time-dependency and dynamic parameters for both FTA and BBN are also not well-represented in the literature. Values estimated for these two maintenance analysis tools would create uncertainty factors. These uncertainties would have a serious effect on final decisions obtained from maintenance analysis. Moreover, both of the above tools should be able to face interdependencies between different failure systems. FMEA and SWIFT analysis tools are additional tools that can be used in conjunction with FTA and BBN but they are qualitative methods and turning their results into quantitative data and obtaining likelihood factors would create further uncertainty factors. Markov chains can also help in probabilistic analysis and can be used in partnership with other techniques but it could represent sequential dependencies. Dynamic gates on FTA and dynamic nodes structure on BBN would both require other methods such as Weibull's distribution or Monte Carlo simulations to obtain their results.

However, not much research has been directed toward the preference and comparison of these statistical techniques used within the maintenance and reliability tools. All fuzzy techniques can be helpful in dealing with the uncertainties arising from the maintenance decision making process, although it is not fully understood which fuzzy technique should be used and in what specific situation. If multiple failures occur at the same time, there are different techniques such as MCDM and AHP to classify and compare different decisions in order to achieve the final unified decision. However, a further sensitivity analysis would be required to determine the effectiveness of the technique used. The concept of maintenance measurement is a rather new concept and most of the well-known performance measurement techniques are not fully tried in industry. QFD, BSC and benchmarking are commonly used in other types of performance measurement situations in industry but not fully developed to be used in maintenance performance cases. The most well established maintenance performance techniques include MPIs, OEE and RAMS, though there remains space for further improvement in both techniques.

Even though maintenance has come a long way since the basic ‘fix it when it is broken’ methodology of the pre-world war era, it remains in need of improvement. This is due to the fact that manufacturing techniques and equipment used recently are becoming more complex; consequently, their maintenance and repairs are becoming more challenging. The main reasons behind these complexities include the progress of automation and computerised systems. However, both automation and computerised systems used for maintenance can also be considered a benefit concerning the simplification and efficiency of maintenance of these complex systems. In general, there remain some shortcomings that must be addressed. In this section, some of the future work required for resolving these issues will be discussed.

A thorough research is required to identify suitable predictive and preventive policies for small to medium sized companies. Prognostic systems should be developed for quicker prediction of future degradation patterns of equipment. These prognostic systems are also effective within the whole system on real-life remote monitoring rather than singular components. This requires an adoption of a generic system in different industries. An integration methodology of company KPIs and MPIs should be created to minimise the gap between the business side of maintenance policy and its technical aspects. RCM methodology is a well-known maintenance policy but still requires more research and modifications. For example, more comparison of case studies is needed to compare shortened versions of RCM with more effective and full versions. VDM is one of the most comprehensive RCM methodologies that require extensive research and application in industry. The main missing research area on VDM policy is burden to importance ratio (BIR).

Another type of well-represented maintenance policy is CBM. Condition monitoring systems in CBM do not have a unified software language and the adaption of a more comprehensive and common language for all monitoring systems would save valuable time and effort in decision-making. RBI is another important maintenance policy that requires more research especially on the addition of extra sections such as reliability analysis to increase its performance. For all of the above maintenance policies, business and management sides can be added using a TPM approach. This proves the importance of discussing the effects of using the combination of more than one maintenance policy together. Most maintenance tools also require more development. More research is required concerning the application of dynamic BBN instead of DFTA in maintenance. Solving the time-dependent variable of the DBBN itself would require further study, as there are numerous statistical methods that can analyse this variable. Finally, additional exploration of maintenance performance measurements is needed, as research on the use of QFD, BSC and benchmarking techniques in maintenance techniques is sparse.

3.8 Chapter Summary

In summary, this chapter discussed the difference between three major maintenance approaches: Corrective, preventive and predictive. It stated all the different policies used in these three approaches. It then described the different tools used to obtain data for these policies and various ways of measuring their effectiveness. Finally, it stated the different types of inspection and monitoring tools used in industry. This would help companies to select the most appropriate methodology for their needs. This paper is only a brief review of most of the maintenance methodologies available in the industry as further in-depth studies will be required in order to obtain more knowledge on the procedures, pros and cons of each methodology.

4 CHAPTER 4-BUSINESS-ORIENTED PROBABILITY-BASED MAINTENANCE (BOPM) MODEL

4.1 Chapter Introduction

This chapter will represent the overall business-oriented probability-based maintenance (BOPM) methodology and all the analysis models and data clients included as part of the methodology. It will also present the overall connection of different tools with each other and how they work together to achieve the final maintenance scheduling decisions and the goals of the aim and objectives of this PhD thesis.

4.2 Overall Business-oriented Probability-based Maintenance (BOPM) Structure

The maintenance platform created for this thesis uses both cost analysis data and probabilistic risk-related classification of the components and sub-systems together with overall continuous performance assessment of them per their condition monitoring data together in one unified central platform. This platform uses condition monitoring data recorded previously from an on-board data-gathering campaign from the sensors in addition to logged data by the vessel crew to determine the overall performance of machinery equipment and sub-systems. These performance-related data are evaluated against the manufacturers' requirement for the performance limits with additional input from the company side concerning the performance indicators. Subsequently, these evaluated data are further analysed by the main analysis unit of the platform, the probability analysis unit (PAU) to determine the overall performance of the sub-system and predict its future performance.

Consequently, cost data, in addition to criticality assessment of the components and sub-systems, are combined within the decision-analysis unit (DAU), as mentioned in section 4.10, to create suggestions for maintenance tasks for the analysed system. Past preventive maintenance reports and general maintenance scheduling of the vessel can also be used in decision-making in order to alter scheduling of coinciding and overlapping tasks. Figure 13 demonstrates the overall structure of the BOPM platform and the interaction between different data sources and analysis units. This chapter of the dissertation will discuss each part of the

BOPM platform in detail. As a result, the following subsections of this chapter will demonstrate the overall sections of the methodology as follows: Company goals with MPIs (explained fully in Section 4.3), component-specific performance measures (explained fully in Section 4.4), past PMS reports (explained fully in Section 4.5), observed sensorial data (explained fully in Section 4.6), cost data (explained fully in Section 4.7), component criticality classification (explained fully in Section 4.8), probability analysis unit (PAU) (explained fully in Section 4.9) and decision analysis unit (DAU) (explained fully in Section 4.10).

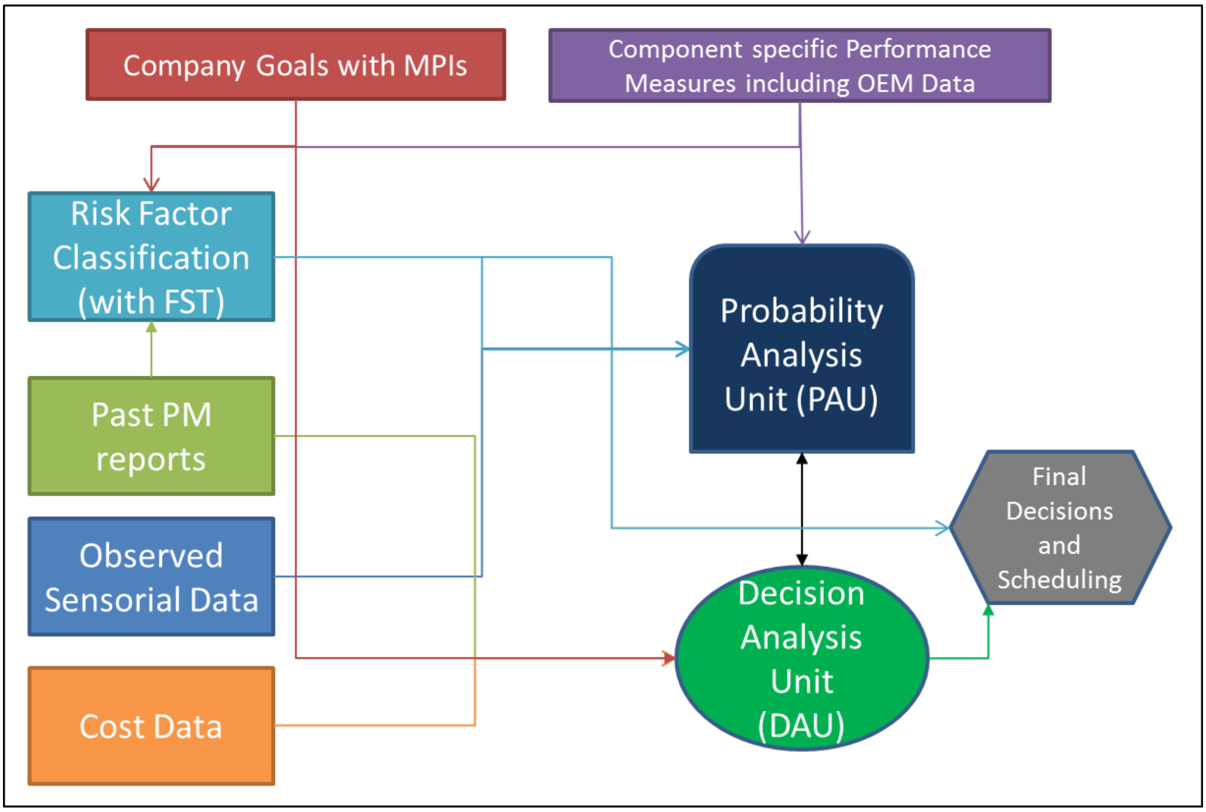

Figure 13 – Business-oriented Probability-based Maintenance (BOPM) Methodology

As Figure 14 represents the overall connection between analysis units (PAU and DAU) and data clients (OEM data, observed data, cost data and FST risk factors), the overall structure of the analysis models together can be represented as Figure 14. This figure shows how data treated for missing values are then turned into performance indicators using measurement limits modified by company MPIs to be used within the DBN tool. Subsequently, performance predictions generated from the DBN model are combined with utility and decision nodes to perform net cost analysis and produce maintenance decisions. Finally, overall prioritisation of intervening maintenance tasks using the relative risk factors produced from the FST tool from

MATLAB creates maintenance-scheduling decisions. The overall interactions between the analysis units and data clients are explained in more detail in sections 4.9 and 4.10.

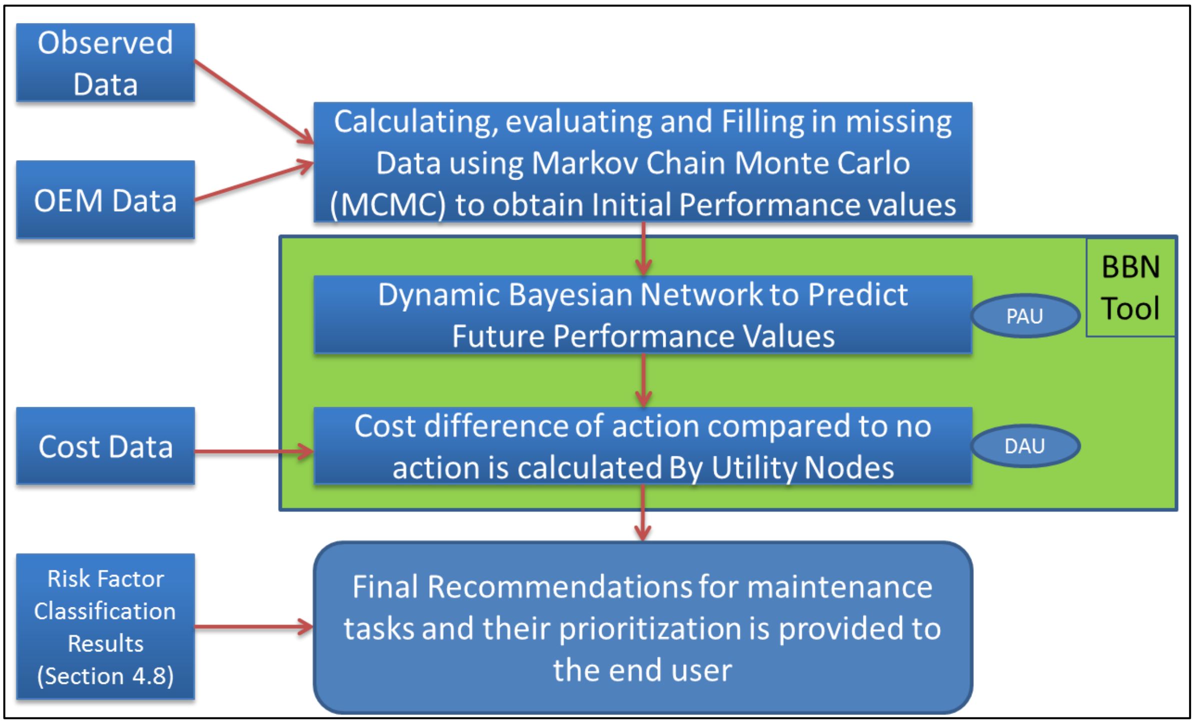

Figure 14 - Overall Analysis Flow of the BOPM Methodology

4.3 Company Goals with Maintenance Performance Indicators (MPIs)

In general, each major company, including ship operators, can have their own specific Maintenance Performance Indicators (MPIs) in order to help them achieve certain business, safety and reputational goals. For this methodology, company goals and their MPIs are adopted in two major sections. Firstly, overall cost data are altered based on company business aspects. This cost alteration has been performed mainly on cost of downtime per sub-system/system and repair prices. This is since business teams also measure the employee cost for both downtime and repairs on top of the actual vessel chartering costs and delaying penalties per journey.

This employee cost can be in three major groups: on board vessel crew, on-shore management personnel and repair/inspection crew costs (third party technicians). Downtime effects for the crew on-board the vessel is due to the fact that they still have to be paid while stationary. Onshore personnel cost is as a result of the time spent managing and finding the repair or replacement scenarios for the vessel. Finally, repair/inspection, specifically from a third party, must be measured according to where they are from and where the vessel is based. For this study an average cost of all cost aspects, mentioned previously, are adopted based on the average of Southeast Asia.

Secondly, component specific measurement limits on every piece of machinery based on pressure, temperature, vibration, etc., have been adopted based on company history of the specific component, their experts'/engineers' specific analyses on the identified limit from the manufacturer and, finally, on the operational performance and risk factor that has been set by the company-specific goals and MPIs. These MPIs are more specific KPIs targeting the technical aspects of the vessel lifecycle and its maintenance performance. These MPIs are shown on Table 1. The methodology and case studies of this thesis use these factors in addition to the recommended manufacturer limits to define the most optimum limits to be used for the probabilistic analysis section of the overall BOPM maintenance platform.

Table 1 - Maintenance Performance Indicators (MPIs)

Item	Maintenance Performance Indicator (MPI)	Measurement and Expectation	Weightage
1	Technical Condition Index (TCI) to be adopted for all major ship machinery parts	Minimum 80%	12%
2	Fuel Consumption based on TCI recommendation	> 80% TCI	12%
3	Environmental Pollution based on TCI recommendation	> 80% TCI	12%
4	First Alarm on Component degradation	> 80% TCI	12%
5	PMS Outstanding Task Percentage per month	<30%	12%
6	Defects-average time between issuance and Closing	Routine <30 Days, Critical <10 Days	7%
7	Spare parts-time between requisition and the delivery of the order	<60 days	6%
8	Spare parts-Percentage of the wriong delivery	<3%	6%
9	Difference between actual and budget drydock cost	<5%	7%
10	Uschduled stoppage due to equipment melfunction	1 day per year	8%
11	Condition of class impossed to vessel	<15%	6%

The main observation that can be taken from the MPIs of Table 2 is the Technical Condition Index (TCI) value which is the percentage of the change of the condition compared with the design condition. This value is 80% for all different measurable aspects of the vessels including component performance degradation, fuel consumption and environmental pollution. This 80% TCI value was adopted on evaluation of the performance limits for component performance analysis on the PAU section of this BOPM methodology.

Additionally, percentage difference of 3% for spare parts and 5% for the dry dock and repair costs were also adopted on top of the overall cost and was also imputed on the DAU section of the BOPM methodology. Finally, all MPI conditions were checked at the final decision stage together with evaluation of the effectiveness of the BOPM methodology to ensure that the methodology meets all MPI items. This means that the overall cost data and general risk indices are arranged in way to follow these MPIs. This is further explained in sections 4.7 and 4.8.

4.4 Component-specific Performance Measures

OEMs (original equipment manufacturers) and suppliers generally specify the normal working condition characteristics of the components and sub-systems inside machinery systems (which are lube-oil system, fuel-oil system and turbocharger for the case studies of this PhD thesis). In the case of ship machinery numerous data such as usual fuel consumption, oil consumption, heat generation, emission, power and other performance limits are defined overall. Then, more specific details such as recommended pressure, temperature and vibration limits of the equipment on different operational conditions such as engine RPM have also been recorded and presented to the ship owner.

In some special cases, the manufacturers have also determined degradation patterns for components and maximum working limits to meet classification society requirements. Generally, classification societies recommend certain safety limits and inspection/maintenance schedules per system or component for ship machinery. This also influences the overall manufacturer’s specified limits and determines the final performance limits to be used for this study. These limits are further modified using company MPIs and experts’ opinions in some cases to alter the limits in order to meet company-specific goals on reducing the possibility of failures and increasing the overall effectiveness of each system within the vessel. This study then uses these limits in conjunction with observed data to determine overall probabilistic performance of the component/sub-system to be used in analysis modules namely PAU and DAU.

4.5 Past Preventive Maintenance (PM) Reports

All past preventive maintenance schedules and reports, including any repairs or part exchanges done, would include any major overhauls and dry-docking activities. This would provide extra information on top of the recommendation made by probability analysis and decision-making units. Furthermore, any scheduled inspection, maintenance or repair activity logged on the PMS report from the manufacturer can clash timing-wise with the recommended maintenance time from the decision-making unit of the overall BOPM platform on other equipment within or in close proximity to the sub-system of the scheduled maintenance.

Therefore, component risk-related classification must also be performed on the component that has been scheduled for maintenance in order to prioritise the maintenance tasks for within the overall maintenance plan of the vessel including maintenance plan determined by the BOPM platform. Additionally, PM reports can also give more information about any unwanted failures or any further degradation patterns on any components that may not yet have had an effect on the overall performance analysis.

4.6 Observed Sensorial Data

This section of the BOPM platform includes all the sensorial records on temperature changes, pressure changes and vibration acceleration measurements obtained from different components/sub-systems. Other operational conditions such as voyage data, environmental conditions, fuel types and engine load/speed are also stamped on the measured data. This produces an overall conditional profile of all the observed machinery and equipment within the vessel and this thesis's case studies. Comparing these data with specified and adopted manufacturers' limits, overall probabilistic performance of the components and sub-systems are measured. This is done by finding, statistically, how many times recorded data for each component or sub-system has passed the recommended limit compared with all other recorded time. Using these sensorial data with the measurement limits that are modified according to company MPIs can help to obtain performance indicators for each component's/sub-system's measurements within a certain time-period. This can then be put into the probability analysis unit (PAU) of the BOPM to predict the future performance values of each component/sub-system.

4.7 Cost Data

This section of the methodology includes all the following cost data for the equipment adopted by the company recommended changes:

- Spare part prices
- Repair costs
- Capital loss from delays
- Docking costs
- Incident/failure costs (including loss of life, oil spill and any other types of harm to both crew, environment and major ship machinery)

These cost values are adjusted using company MPIs and experts' comments. These cost values can then be inserted into the decision-making unit (DMU) of the BOPM to implement net cost analysis and produce maintenance decisions.

4.8 Risk Factor Classification

This section of the methodology classifies all components and sub-systems on four major risk criteria. This is useful in the decision-making part of the methodology, when there are various clashing scheduled maintenance/repair activities on systems. The three major risk areas for component classifications are:

1. Human risk factor
2. Environmental risk factor
3. Operational loss

These factors are determined according to the failure causes they would have had if the system they are based upon failed completely due to the failure of those specific components or sub-systems. For this study, general risk criteria and matrices recommended by ABS (American

Bureau of Shipping) (ABS, 2000) (Verzbolovskis, 2004) have been used. This further follows the UK government health and safety standards for marine risk assessment developed by DNV (det Norske Veritas) (HSE, 2001). The specific types of vessels and their overall cost data used in the case studies then adopt these matrices. More specific tabulated definitions of each of the risk matrices are demonstrated in the results chapter of this thesis. Consequently, these risk factors are then compared with the probability of the failure of the observed equipment or sub-system to obtain overall risk factors for each risk criterion. This comparison and combination of overall risk factor for each criterion is completed using fuzzy logic theory.

Fuzzy set theory (FST) was first introduced by Zadeh (Zadeh, 1965) for observation of vague linguistic factors from a more objective perspective. This method can alter fuzzy linguistic terms and interaction between linguistic terms into more numerical values. Therefore, any expression of linguistic terms such as minor failure cost level with the occasional occurrence probability of failure can have medium failure-consequence risk criteria for the case study of this thesis.

There are various types of fuzzy membership functions that define the relationship between different linguistic statements used within the fuzzy logic created for the study. The main membership functions used in industry are: triangular, trapezoidal, Gaussian and Cauchy. After testing different membership functions and also due to having only two comparison axes from the fuzzy linguistic framework of the case studies for this thesis, triangular fuzzy membership function has been used. This triangular function is simpler to use and gives equally accurate results as other more complex membership functions. A general expression for the membership function can be presented as Equation 2 (Mentes & Helvacioglu, 2011):

$$\mu_A(x) = \left\{ \begin{matrix} 0 & x < a \\ \dfrac{x-a}{b-a} & a \leq x \leq b \\ \dfrac{C-x}{c-b} & b \leq x \leq c \\ 0 & x > c \end{matrix} \right\}$$

Equation 2

Where $\mu_A(x)$ is the membership function of fuzzified value x for the triplet min, medium and max values of (a,b,c). This can be further understood from Figure 15 (Mentes & Helvacioglu, 2011).

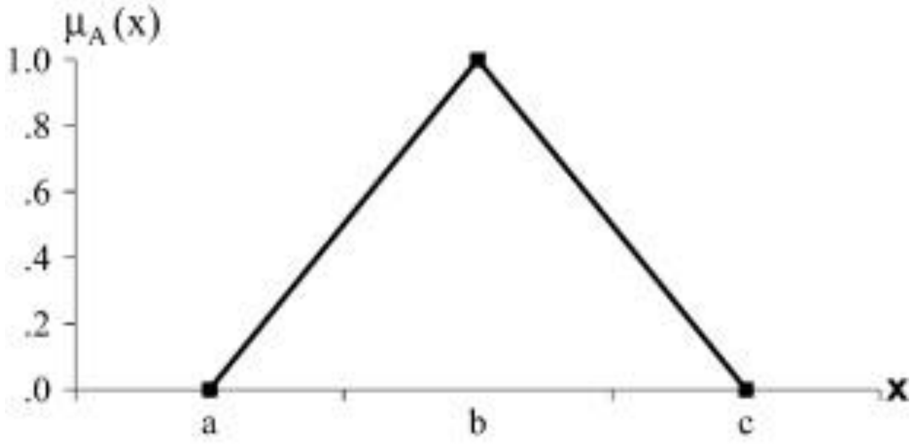

Figure 15 - Triangular Fuzzy Format

Fuzzy logic for the membership functions used between failure rate and risk factors are shown in Table 1. The overall combination of all risk factors is designed in a Simulink MATLAB environment using a fuzzy logic toolbox. Their overall design is shown in Figure 16. Final outcomes of fuzzy analysis will be shown in the results section of this thesis for all three vessel case studies and a sample of MATLAB outcomes are shown in Appendix D.

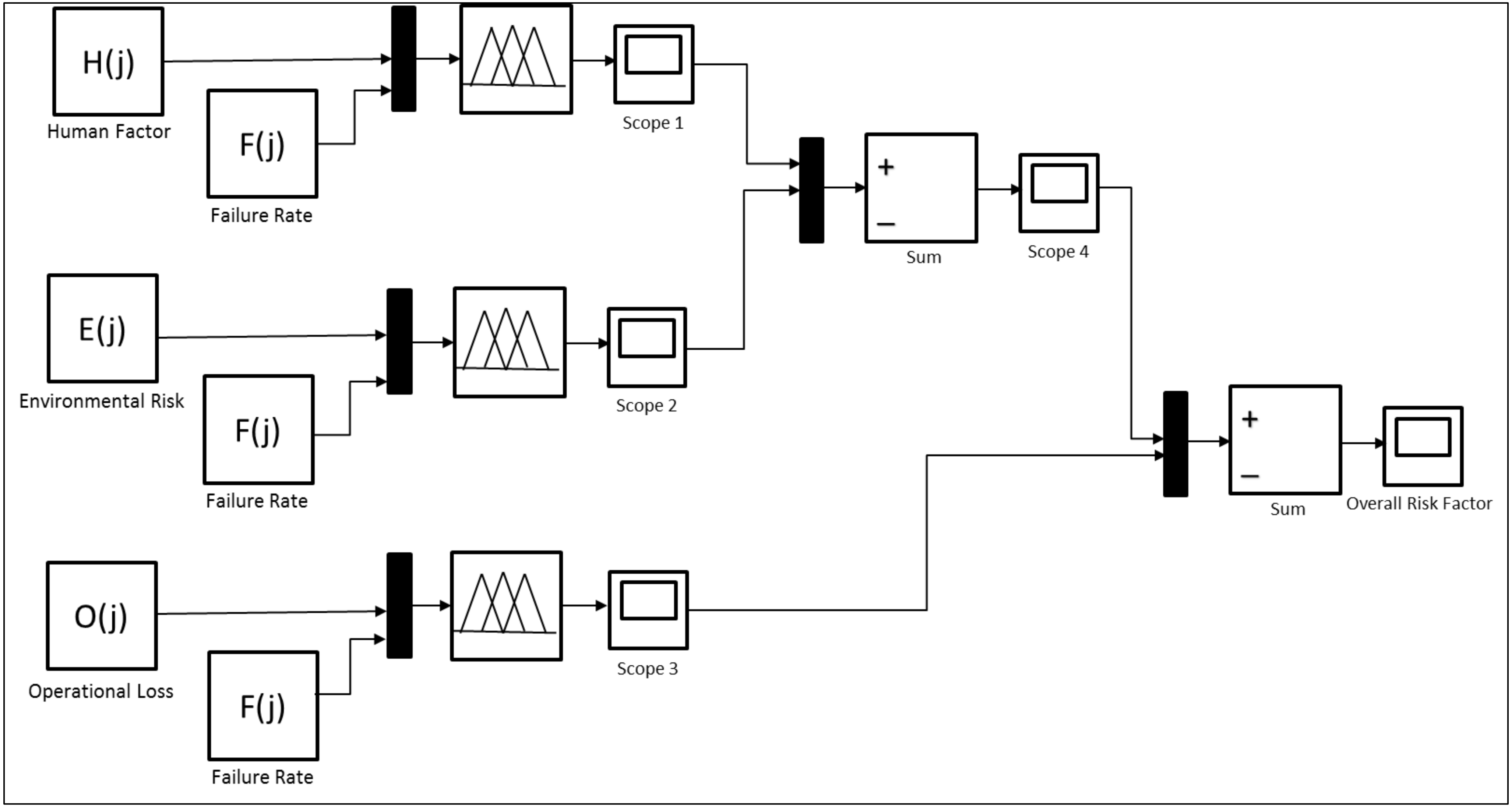

Figure 16 - Overall Model of Fuzzy Set Addition in a MATLAB Simulink Environment

4.9 Probability Analysis Unit (PAU)

This section of the BOPM methodology demonstrates the overall probabilistic analysis unit. This unit uses the analysed performance indicators produced combining observed sensorial data with component performance limits modified by company MPIs to implement probability analysis to predict future performance of each component/sub-system. Then, it smooths the results by filling in the missing data using Markov Chain Monte Carlo (MCMC) simulation. This increases the effectiveness of the data set by making sure they all have equal observation times. Next, the static part of the BBN, developed for the particular case study, creates a connection between the main systems and other sub-systems and components within the system. Subsequently, this BBN model analyses the overall probabilistic performance of the system at a given time.

Finally, by adding the first-order Markov chains to the Bayesian nodes and using data from one previous time slice and the current time slice, the resulting dynamic Bayesian network (DBN) model predicts the system performance for the next four future time slices. These time slices are determined by the amount of time in days, weeks or months that data have been gathered, divided by two in order to obtain two distinctive time slices. If the duration of the time slices is lower the general accuracy of the model would be higher as, in reality, the system can have some unpredictable behavioural changes where shorter time slices can capture that better. However, time slice duration can be shortened by some amount depending on how often data are gathered as the total amount of data gathered will also increase the accuracy of the probabilistic values and, in turn, the results of the BBN analysis. Additionally, over a very short duration of time, the overall system may not have any malfunctions or failures, which makes future analysis redundant as there would be no alteration between the past and present. Further, future study using more machinery systems and from more vessels can help to determine the minimum amount of data required for accurate analysis, but for the absolute minimum there should not be less than one data capture per week and overall analysis duration should not be more than one third of the year as the overall result of the first predicted time period would be past the one year mark where there could be various unwanted anomalies and irregularities in the machinery and overall vessel conditions may occur within this long period of study. Figure 17 illustrates the overall flow of the analysis units used for both the probability analysis unit (PAU) and decision analysis unit (DAU) of the BOPM platform.

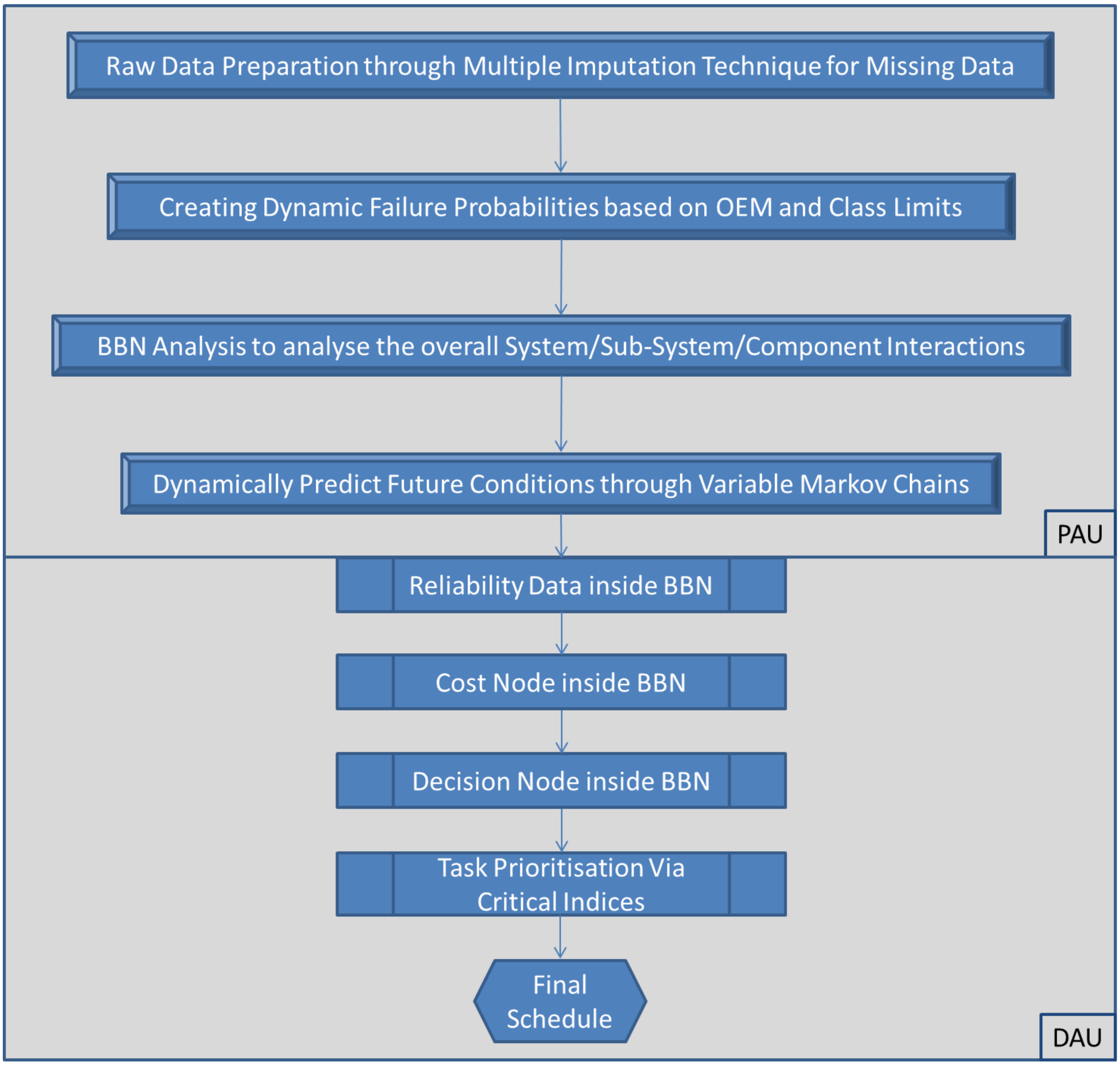

Figure 17 - BOPM Overall PAU and DAU Analysis Flow

4.9.1 Markov Chain Monte Carlo (MCMC) Multiple Imputation

For treatment of missing data, different methods, i.e., mean substitution (MS), expectation-maximisation (EM) of maximum likelihood (ML) and multiple imputations are used. The chosen model with the highest accuracy is called Markov Chain Monte Carlo (MCMC) multiple imputation technique. This was tried using SPSS software to observe which type gave the closest prediction of the values compared with the actual observed value. For the purpose of this, a full set of real-time data with no missing values was used. Then, randomly, some of the data were deleted from the dataset in order to mimic the missing data scenario. Subsequently, different types of missing data treatment methods were used within the SPSS software environment. Finally, plotting the graph of the calculated results with the real data was completed. The model with the closest values was chosen for the BOPM platform. This will be further explained with more graphical details in Section 2 of Chapter 6, the results chapter.

The chosen model with the highest accuracy is called MCMC multiple imputation technique. Further study was generated for different iteration numbers as shown in Section 6.2 of Chapter 6; it was observed that after five iterations there was no observable change in generated data. Therefore, it was decided that the MCMC multiple imputation missing data treatment model should have five iterations and then use the mean of the iterated data as the final data. This section will now briefly explain the mathematics behind the MCMC multiple imputation technique for the missing data treatment.

For the MCMC model, a Gibbs sampler was used in order to ease the calculation load and make it similar to the way SPSS does its calculation. Gibbs sampler has high-dimensional series of univariate conditional distributions with simpler joint distribution (Ni and Leonard, 2005). If Y is the state to be iterated with n subsectors of $Y=(Y_1,Y_2,\ldots,Y_n)$, then each iterative step of Y can be a time step of t. In this scenario for data augmentation purposes Y_{mis} can be denoted as the missing data and then the parameter of the interest for the Gibbs sampler can be called Θ. Then, data can be iterated between the two steps of imputation step (I-step) and posterior step (P-step) which updates the missing parameters of the probability distributions. These steps are shown below:

$$I - step:\ Y_{mis}^{(t+1)} = p\left(Y_{mis}\middle|\Theta^{(t)}, Y_{obs}, G\right)$$

Equation 3

$$P - step:\ \Theta^{(t+1)} = p\left(\Theta\middle|{Y_{mis}}^{(t+1)}, Y_{obs}, G\right)$$

Equation 4

Where G is Gibbs sampler. However, this model only assumes independent and identical distributions and does not take into account that data are missing randomly. Therefore, the autoregressive integrated moving average is added to the time series as Equation 5.

$$\Phi_p(B)\Delta^d y_t = \Omega_q(B)\varepsilon_t$$

Equation 5

Where p is the order of the autoregressive part, d is the order of the differencing, q is the order of the moving average process, t is the time indices and B is the backshift operator which can be defined by Equation 6 (Ni and Leonard, 2005).

$$By_t = y_{t-1}$$

Equation 6

Consequently, autoregressive (Φ) and moving average (**Ω**) operators can be represented as polynomial equations of the backshift operator as below:

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 \ldots - \phi_p B^p$$

Equation 7

$$\Omega(B) = 1 - \omega_1 B - \omega_2 B^2 \ldots - \omega_q B^q$$

Equation 8

From autoregressive integrated moving average equation, Δ is the differencing operator and ε is the white noise. These can be evaluated using Equations 9 and 10.

$$\Delta^d = (1 - B)^d$$

Equation 9

$$E = \varepsilon_t \sim N(0, \Sigma)$$

Equation 10

Where Σ is the variance. Putting all the above equations back inside the main parameters of interest (Θ = (Φ,**Ω**,Σ,E)) from P-step, and the Gibbs sampler together, the following five main equations will be obtained for the iteration of the missing data through MCMC multiple imputation technique (Ni and Leonard, 2005):

$$Y_{mis}^{(t+1)} = p(Y_{mis} | \Phi^{(t)}, \Omega^{(t)}, \Sigma^{(t)}, E^{(t)}, Y_{abs}, G)$$

Equation 11

$$\Phi^{(t+1)} = p(\Phi | Y_{mis}^{(t+1)}, \Omega^{(t)}, \Sigma^{(t)}, E^{(t)}, Y_{abs}, G)$$

Equation 12

$$\Omega^{(t+1)} = p(\Omega | Y_{mis}^{(t+1)}, \Phi^{(t+1)}, \Omega^{(t+1)}, E^{(t)}, Y_{abs}, G)$$

Equation 13

$$\Sigma^{(t+1)} = p(\Sigma | Y_{mis}^{(t+1)}, \Phi^{(t+1)}, \Omega^{(t+1)}, E^{(t)}, Y_{abs}, G)$$

Equation 14

$$E^{(t+1)} = p(\Sigma | Y_{mis}^{(t+1)}, \Phi^{(t+1)}, \Omega^{(t+1)}, \Sigma^{(t+1)}, Y_{abs}, G)$$

Equation 15

4.9.2 Bayesian Belief Network (BBN)

This section presents the overall static BBN probabilistic model used in the methodology. This model uses Bayes' theorem as a connection between different probabilities. These connections can be expressed as conditional probability tables (CPTs). Figure 18 demonstrates a simple child to parent node BBN connections for "k" number of child nodes "c" to parent node "p".

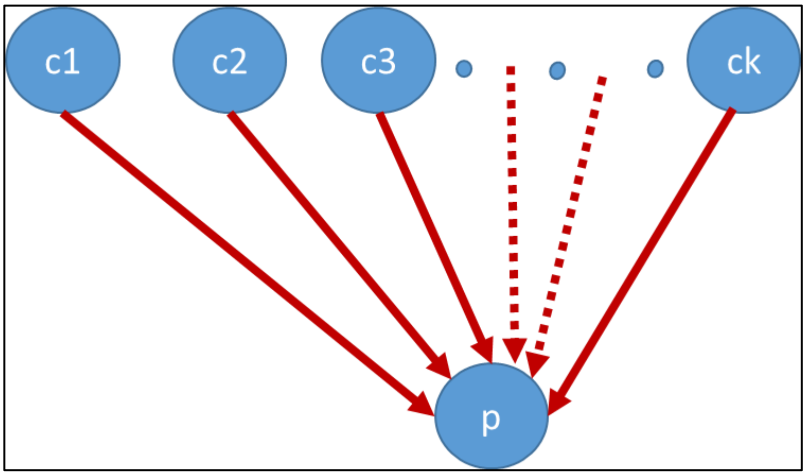

Figure 18 - Simple Parent to Child BBN Representation

Bayesian networks are formed as dynamic acyclic graphs (DAGs). Parent node "p" from Figure 19 can have "m" numbers of probabilities with its "k" numbers of child nodes, which follows the expression ($m = 2^k$). If "P" is probability value of each connection from parent node "p" to Child node "c", the overall conditional probability table (CPT) of the BBN from Figure 19 can be represented as an equation set on Table 2. In this table "w" presents working state probability and f states failing state probability. Summation of these probabilities using Bayes' theorem will result in the overall probability of the parent node "p". This is represented by Equation 16.

$$\boldsymbol{P(comp)} = \sum_{j=1}^{m} \left(\sum_{i=1}^{k} \boldsymbol{P}(\boldsymbol{ft}_{f(i)}, \boldsymbol{ft}_{f(j)}) \right)$$

Equation 16

Table 2 - Overall BBN Model Probability Table Equational Flow

$\boldsymbol{P_1} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100} \\ \boldsymbol{f}: \ \ \boldsymbol{0} \end{cases};$
$\boldsymbol{P_2} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - ft_{f1}} \\ \boldsymbol{f}: \quad \boldsymbol{ft_{f1}} \end{cases};$
$\boldsymbol{P_3} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - ft_{f2}} \\ \boldsymbol{f}: \quad \boldsymbol{ft_{f2}} \end{cases};$
$\boldsymbol{P_4} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - (ft_{f1} * ft_{f2})} \\ \boldsymbol{f}: \quad \boldsymbol{(ft_{f1} * ft_{f2})} \end{cases};$
$\boldsymbol{P_5} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - ft_{f4}} \\ \boldsymbol{f}: \quad \boldsymbol{ft_{f4}} \end{cases};$
$\boldsymbol{P_6} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - (ft_{f1} * ft_{f3})} \\ \boldsymbol{f}: \quad \boldsymbol{(ft_{f1} * ft_{f3})} \end{cases};$
$\boldsymbol{P_7} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - (ft_{f2} * ft_{f3})} \\ \boldsymbol{f}: \quad \boldsymbol{(ft_{f2} * ft_{f3})} \end{cases};$
$\boldsymbol{P_8} = \begin{cases} \boldsymbol{w}: \ \boldsymbol{100 - (ft_{f1} * ft_{f2} * ft_{f3})} \\ \boldsymbol{f}: \quad \boldsymbol{(ft_{f1} * ft_{f2} * ft_{f3})} \end{cases};$
.
.
.
$\boldsymbol{P_m} = \left\{ \begin{matrix} \boldsymbol{w}: \boldsymbol{100 - (ft_{f1} * ft_{f2} * ft_{f3} * \ldots * ft_{fk})} \\ \boldsymbol{f}: \quad \boldsymbol{(ft_{f1} * ft_{f2} * ft_{f3} * \ldots * ft_{fk})} \end{matrix} \right\}$

4.9.3 Dynamic Bayesian Network (DBN) Using Markov Chains

Using BBN equations from previous sub-sections, reliability and cost analysis results from only one point in time would be obtained as it is a static method rather than dynamic with variable timing. To gain results from multiple time points including future prediction, a Markov Chain model can be added to the BBN model. This will change the BBN into a dynamic Bayesian network (DBN). In the Markov chain, results from two consecutive previous moments or slices in time are used to predict the result for the next time slice or time-period. Equation 17 demonstrates the steps of achieving future prediction through Markov chains. This model for a single node can be adapted easily to a Bayesian network. Figure 19 illustrates the change for simple two-child nodes and one parent node BBN networks into DBN network.

$$P_{X(n-1),x(n)} = P\{X_{t_n} = X_n | X_{t_{n-1}} = X_{n-1}\}$$

Equation 17

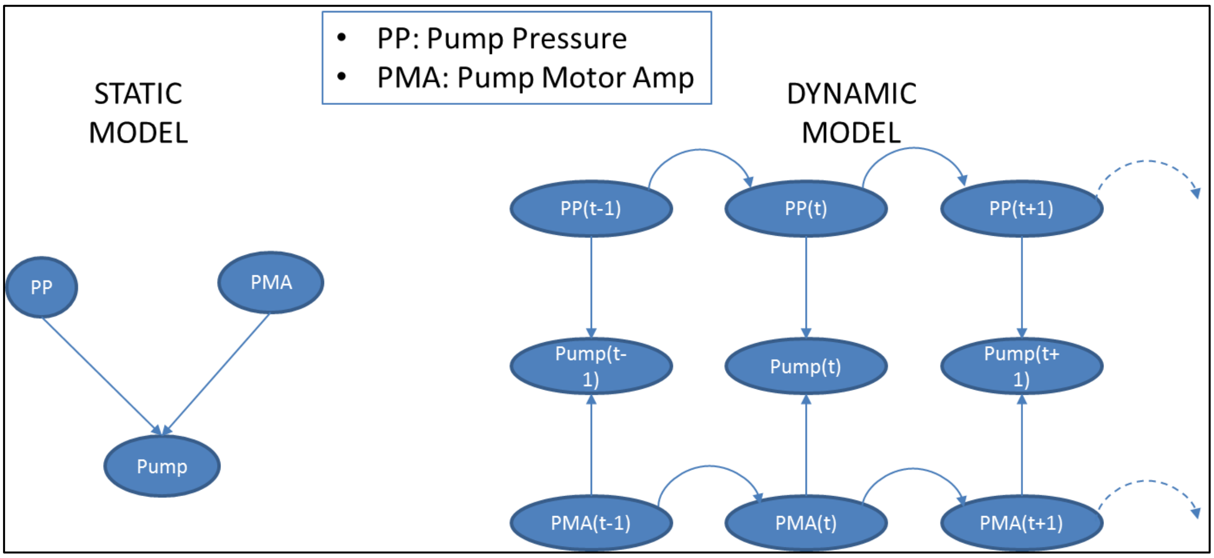

Figure 19 - Example of Static to Dynamic BBN Conversion

In simpler terms, the first transition from time "t" to "t+1" can be illustrated as Equation 18.

$$P(w_{t+1}) = P(w|w_t)P(w_t) + P(w|f_t)P(f_t)$$

Equation 18

In all the case studies in this thesis, failure probability for times "t" and "t+1" is known. However, transition matrix, which is represented by "$P(w|f_t)$" is not known at the beginning.

This can be calculated by Equation 19. On all equations, “w” represents the working condition and “f” represents the failing condition.

$$P(w|f_t) = \frac{P(w_{t+1}) - (P(w|w_t)P(w_t))}{P(f_t)}$$

Equation 19

The equation above can be represented in matrix format, where the transition matrix is shown more clearly. This matrix is shown in Equation 20.

$$P_{t+1} = \begin{bmatrix} P(w_t) & P(f_t) \\ P(w|w_{t+1}) & P(w|f_{t+1}) \end{bmatrix}$$

Equation 20

Further steps of these calculations for next available time slices can be represented by Equation set 21.

$$P(w_{t+2}) = P(w|w_{t+1})P(w_{t+1}) + P(w|f_{t+1})P(f_{t+1})$$
$$\mathrm{P}(\mathrm{w}_{t+3}) = \mathrm{P}(\mathrm{w}|(\mathrm{w}_{t+2}),(\mathrm{w}_{t+1}))\mathrm{P}(\mathrm{w}_{t+2})\mathrm{P}(\mathrm{w}_{t+1}) + \mathrm{P}(\mathrm{w}|(\mathrm{f}_{t+2}),(\mathrm{w}_{t+1}))\mathrm{P}(\mathrm{f}_{t+2})\mathrm{P}(\mathrm{w}_{t+1})$$
$$+ \mathrm{P}(\mathrm{w}|(\mathrm{w}_{t+2}),(\mathrm{f}_{t+1}))\mathrm{P}(\mathrm{w}_{t+2})\mathrm{P}(\mathrm{f}_{t+1}) + \mathrm{P}(\mathrm{w}|(\mathrm{f}_{t+2}),(\mathrm{f}_{t+1}))\mathrm{P}(\mathrm{f}_{t+2})\mathrm{P}(\mathrm{f}_{t+1})$$
$$\vdots$$

Equation 21

4.10 Decision-making Model

A decision node is a node that connects the decision of an action that can change the results of the model. Utility nodes that represent a matrix of different cost possibilities are needed in order to add quantitative value to decisions to decide if the action with current probabilities is feasible. In general, the final decision of a BBN model can be represented as expected utility "EU". In general, expected utility of decision node D can be calculated via Equation 22:

$$\mathrm{EU(D|e)} = \sum_{x_1}^{m} \boldsymbol{U_1}(\boldsymbol{X_1})\boldsymbol{P}(\boldsymbol{X_1}|\mathbf{D},\mathbf{e}) + \cdots + (\sum_{X_n} \boldsymbol{U_n}(\boldsymbol{X_n})\boldsymbol{P}(\boldsymbol{X_n}|\mathbf{D},\mathbf{e})))$$

Equation 22

Here, "X" is the predicted probability value matrices from DBN analysis and "U" are the relevant utility values for each X value. To add cost analysis and decision-making into the overall BBN created, utility and cost nodes can be created. In this thesis, due to limited information, the expected utility function is assumed without loss of generality to be linear. Utility nodes represent the monetary values associated with consequences and the cost of avoiding them. Decision nodes, on the other hand, facilitate the introduction of all types of scenarios for all different types of events. Utility and decision nodes together help the operator to analyse the effects of the different scenarios and decide upon the cheapest and most efficient option. Utility and decision nodes can be demonstrated inside a Bayesian network using Equation 15.

4.11 Calculation Sequence

This subsection will further clarify the data collection and analysis and overall methodology sequence of the BOPM. Initially, overall system/sub-system/components architecture for the systems studied for this thesis within the ships are created in order to identify which components and sub-systems require data to be collected from. Then, overall MPIs have to be determined using experts' knowledge from the company. These MPIs can then be used to update both cost data and risk factors. Subsequently, cost data are determined including cost of failure, downtime, repairs, parts and labour for each component and failure types. Next, company past PM reports are evaluated with cost data and using experts' knowledge on severity of each failure to determine risk factors.

Subsequently, using OEM data, company feedback and experts' comments, overall satisfactory working condition limits for each component and sub-system are determined to be used for probability analysis. These OEM data also include overall life expectancy of components which are also used as an input of frequency for risk factors. Afterwards, real time data are obtained and the missing data are treated using MCMC within the SPSS environment. Then, these values are fed into the designed Dynamic Bayesian Networks within the Bayesia lab environment. Later, utility and cost nodes are added to perform net cost analysis of performance probability degradation results within the Bayesia Lab.

Afterwards, using the cost benefit values, maintenance schedule estimates for the highly degraded sub-systems and components are determined. Finally, using risk factors maintenance tasks are prioritised especially in the case of the intersecting tasks. Overall flow of these analysis sequences are shown on Figure 20. Numbering on each box represents their sequences and arrows represent where each item of data or information flow or are given to other sections of the BOPM.

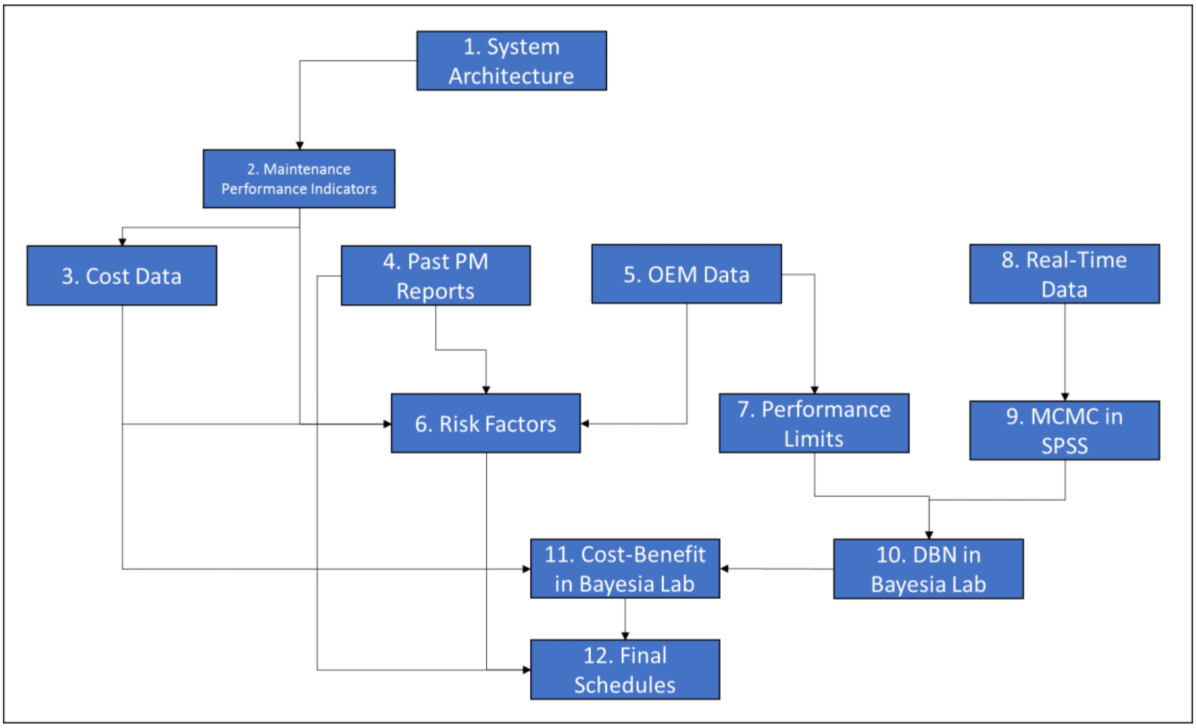

Figure 20 - Analysis Sequence of BOPM

4.12 Chapter Summary

This chapter demonstrated the main methodology of the thesis in detail. It started by introducing the main data clients to the analysis modules such as cost data, manufacturers' limits, company goals and past PMS reports. It also demonstrated that input from the company was used to modify some of the performance limits and cost data in order to meet their specific business related KPIs. Then, components and sub-systems were ranked according to their importance and criticality through risk indices and a fuzzy set theory (FST) addition where it identifies one unique risk value for each of the components or sub-systems.

Subsequently, observed data were treated for missing data using the MCMC multiple imputation technique and then their probabilistic performance degradation was evaluated from the modified manufacturers' limits. Next, DBN with first order Markov chains were used to evaluate the overall performance of the system, component, and sub-system interaction and predict their future performance. Subsequently, utility and decision nodes were used to perform cost analysis and suggest decisions for maintenance plans. Finally, all maintenance tasks were prioritised according to their calculated criticality values and other PMS reports. In general, this methodology incorporates both company MPIs and modified cost values as business aspects with overall condition monitoring data that are evaluated by their limits also modified according to the company MPIs as the technical aspect to produce maintenance decisions. In brief, this model analyses both the performance predictions of each system within DBN models and combines it with net cost analysis and evaluated risk factors according to company MPIs to produce best possible maintenance scheduling recommendations by combining both technical (performance indices and risk factors) and business (net cost analysis and company MPIs inputs) aspects in a single platform.

5 CHAPTER 5-SHIP CASE STUDIES WITH DIFFERENT SHIP MACHINERY SYSTEMS

5.1 Chapter Introduction

In this chapter, data has been gathered from three different vessels. Two of these vessels are sister ship chemical tankers. This creates an opportunity for comparison between vessels, which will be explored in the discussion chapter. The other vessel type is a multi-purpose cargo ship. Three major machinery systems consisting of the lube-oil system, fuel-oil system and turbochargers from the three vessels are analysed using the BOPM methodology and platform. More information on vessels and system characteristics will be discussed in later sections of this chapter. Due to the confidentiality agreement, exact vessel information, vessel name and owners are not shown for the case studies. All of the the operational flowcharts and overall Bayesian Networks in this thesis are created and assessed by the experts from the industry.

5.2 Ships 1 and 2 – Sister Chemical Tanker Vessels

The sister chemical tankers have total lengths of 144.22 meters and total widths of 23 meters. They have Dead Weight Tonnage (DWT) of 16500 tonnes and use two-stroke MAN B7W engines. Further information on their engine characteristics is shown in Table 3. Ship number one of the sister vessels (Ship 1) has been operating on the west coast of Canada in relatively harsher seas and environment. However, sister ship number two (Ship 2) has been operating in South-east Asia with a much milder climate than Ship 1 with only some occasional tropical storms. Both vessels were approximately nine years old at the time of the data gathering campaign.

Table 3 - Sister Chemical Tanker Engines Info

Manufacturer	MAN B&W
Engine Type	7S35MC
Number of Cylinders	7
Engine Max Power	5.180 KW
Engine Max Power RPM	173 RPM

5.3 Ship 3 – Multi-Purpose Cargo Vessel

This multi-purpose cargo vessel has an overall length of 141.60 meters and width of 32.20 meters. It has the overall capacity of 9500 DWT. Unlike the chemical tanker sister vessels, it uses an eight-cylinder two-stroke Wartsila engine where further information on the engine is illustrated in Table 4. This vessel has been operating on the Mediterranean Sea in a relatively mild environmental conditions and at the time of the data gathering campaign was 11 years old.

Table 4 - Multi-Purpose Cargo Vessel

Manufacturer	Wartsila
Engine Type	8L46D
Number of Cylinders	8
Engine Max Power	13.2 KW
Engine Max Power RPM	105 RPM

5.4 Data-gathering Campaign

Having three different vessels creates an opportunity for validating the methodology and ensuring that it works for various ship types. Additionally, having two sister ships that operate in different environmental conditions creates an opportunity to compare the reliability of each individual system from the same manufacturer and determine the influence of the environmental and operational conditions on each system. Finally, having numerous ships evaluated through the same platform makes it possible to save time by developing a central database and maintenance scheduling system for the operator.

The first four months of the data have been used as the datum point, so the next eight months predicted from the model can be compared with existing data. The data obtained also include operational conditions such as sea state, engine RPM, engine load, weather, ship's speed and total operational hours. Additionally, log books of any maintenance, inspection or repairs were obtained in order to validate any decision-making results made by the model. The next sections of this chapter will demonstrate overall flow diagram and BBN networks of three major ship machinery systems from these vessels.

5.5 Lube-oil System

The main engine lube-oil system for all three vessels has a very similar design outline. The structural flow diagram of the lube-oil system for the three vessels is demonstrated in Figure 21. On average the marine diesel engine lube-oil system, oil gathered in the oil sump at the bottom of the engine, is pumped out using screw type pumps. Then, it is passed through two oil filters and a purifier and fed back to the engine. Finally, lube-oil is gathered at the bottom of the engine to start the cycle again.

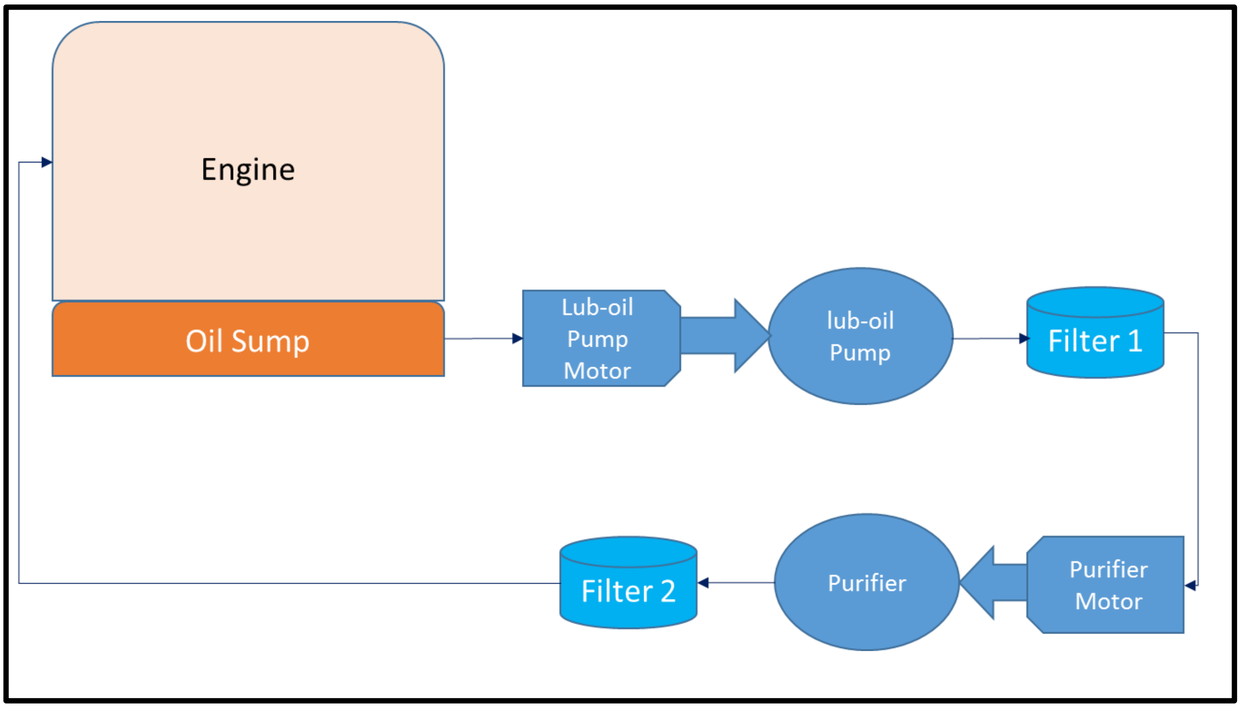

Figure 21- Lube-Oil System Structural Flow Diagram

The main conditional data obtained from this system for all vessels include oil sump level, lube-oil pump pressure, lube-oil pump motor amp, purifier flowrate, purifier motor amp, filter 1 and filter 2 flowrates. Using the manufacturers' limits with recommendations from the ship operator, the ideal working condition limits for each of the above readings were obtained for all three vessels. Tables 5 and 6 demonstrate the obtained limits for the sister ships and multi-purpose cargo vessel respectively to be used for calculating the probabilistic performance value that can be implemented on the BBN model within the PAU section of the BOPM platform in order to provide future performance predictions.

Table 5 - Ships 1 and 2 Lube-oil System Limits

Component/Sub-System	Measurement Type	Limits	Unit
Lube-oil Pump	Pressure	5.4 to 5.5	bar
Lube-oil Pump Motor	Current	5 to 5.5	Amp
Lube-oil Sump	Oil Consumption	18 to 22	Ltrs/day
Filter 1	Flowrate	Min 1.98	Kg/cm²
Purifier	Flowrate	Min 2	Kg/cm²
Purifier Motor	Current	5 to 5.5	Amp

Table 6 - Ship 3 Lube-oil System Limits

Component/Sub-System	Measurement Type	Limits	Unit
Lube-oil Pump	Pressure	5.6 to 5.8	bar
Lube-oil Pump Motor	Current	5 to 5.5	Amp
Lube-oil Sump	Oil Consumption	24 to 26	Ltrs/day
Filter 1	Flowrate	Min 2	Kg/cm²
Purifier	Flowrate	Min 2.1	Kg/cm²
Purifier Motor	Current	5 to 5.5	Amp

Using the flow diagram of Figure 21 and measurement types from Tables 6 and 7, the dynamic Bayesian network (DBN) of the lube-oil system for all three ship types can be generated. This was done on Genie BasiaLab software and the final DBN model of the lube-oil system without utility and decision nodes is shown in Figure 22, which are firstly used to predict the future probabilistic performance values. The design of the overall system has been checked both through the INCASS FP7 EU project and further validated by Jamal Ghotbazadeh, an expert from the Norbulk company.

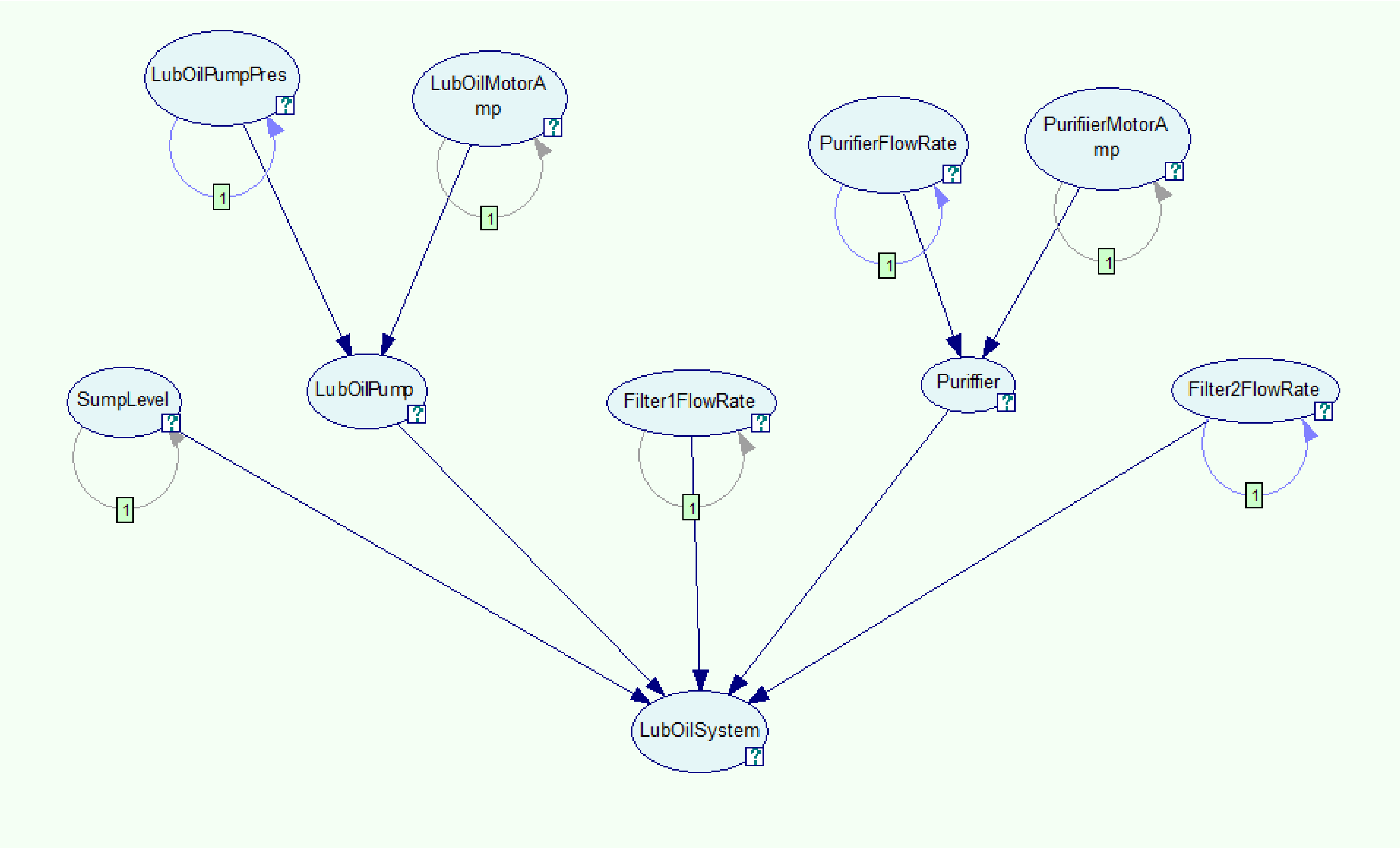

Figure 22 - Lube-oil System DBN Network without Utility and Decision Nodes

Subsequently, for the cost analysis and decision-making of the methodology for the lube-oil system all failure scenarios and repair jobs are evaluated for each component/sub-system. Then, their cost values are obtained from the operators' spare system and previous maintenance job logs. Tables 7 and 8 illustrate the costs of repair and if not repaired cost failures including downtime for sister ships and multi-purpose cargo vessel respectively by adding decision and utility nodes to the previous DBN structures. These repair costs are based on average repair rates of engineers from the Far East. Additionally, downtime costs are calculated by the average chartering cost of the vessel per day.

Table 7 - Ships 1 and 2 Lube-oil System Cost Data

Component/Sub-system	Failure Type	Repair Type	Repair Cost ($)	Failure Cost ($)
Lube-oil Pump	Pump Failure	Pump Overhaul	1800	8600
Lube-oil Pump Motor	Motor Failure	Motor Repair	800	3600
Lube-oil Sump	Leakage	Overhaul	1600	8000
Filter 1	Blockage	Filter Change	180	780
Purifier	Purifier Failure	Overhaul	3300	14000
Purifier Motor	Motor Failure	Motor Repair	2400	6400
Filter 2	Blockage	Filter Change	180	780

Table 8 - Ship 3 Lube-oil System Cost Data

Component/Sub-system	Failure Type	Repair Type	Repair Cost ($)	Failure Cost ($)
Lube-oil Pump	Pump Failure	Pump Overhaul	2200	8900
Lube-oil Pump Motor	Motor Failure	Motor Repair	800	3600
Lube-oil Sump	Leakage	Overhaul	2400	8400
Filter 1	Blockage	Filter Change	180	820
Purifier	Purifier Failure	Overhaul	3800	15200
Purifier Motor	Motor Failure	Motor Repair	2700	7000
Filter 2	Blockage	Filter Change	180	820

Using these two cost tables and the DBN network from Figure 22, the complete DBN of the Lube-oil systems for all three vessels including utility and decision nodes can be developed in Genie BiasiaLab environment as illustrated in Figure 23. In this system, each measured reading corresponds to only a single failure cause.

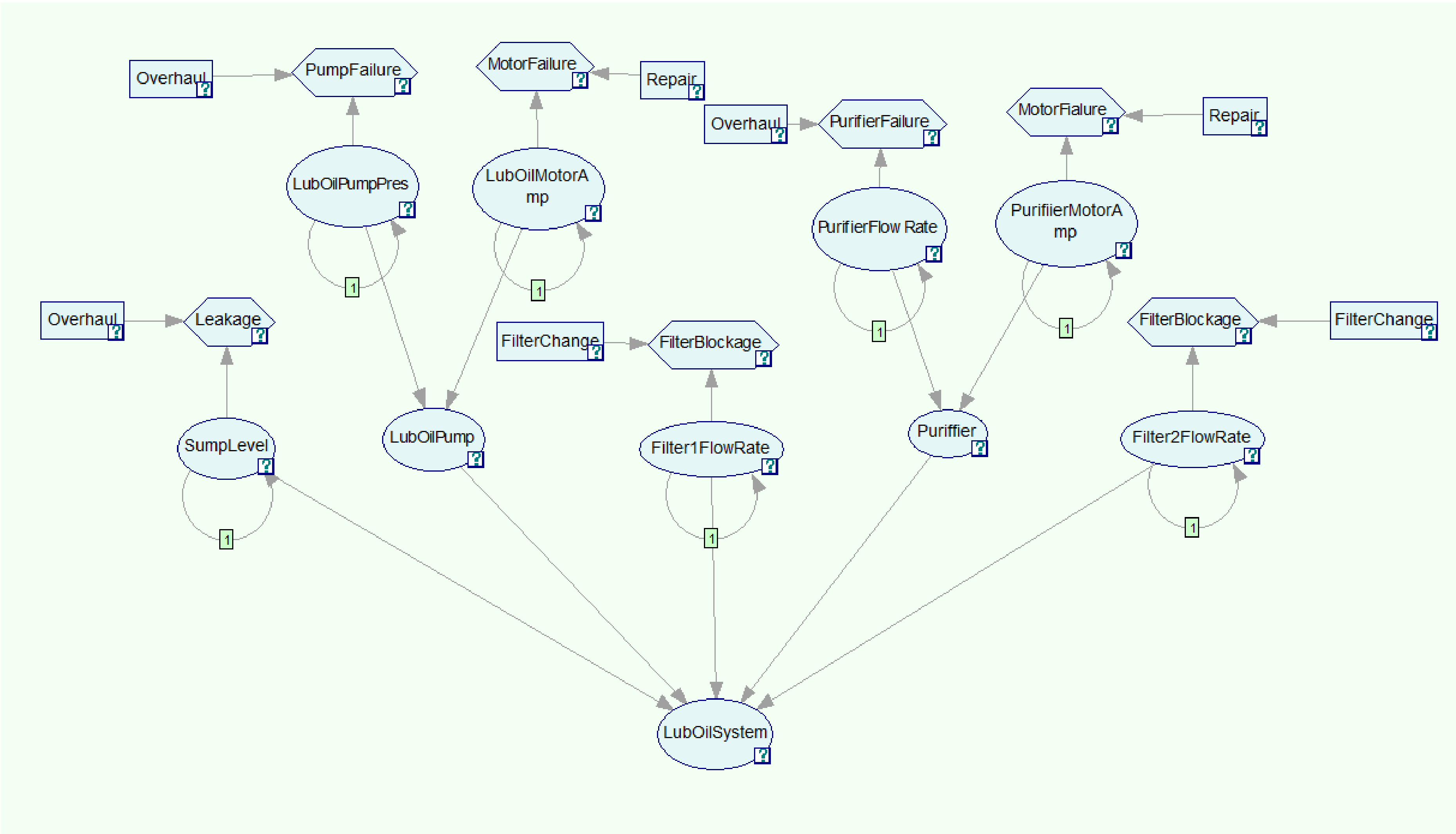

Figure 23 - Lube-oil System DBN Network with Utility and Decision Nodes

5.6 Fuel System

The main engine fuel-oil systems for all three vessels have very similar design outlines. However, the sister vessels use seven-cylinder engines whereas the multi-purpose cargo ship uses an eight-cylinder engine. The operational structure flow diagrams of the fuel-oil system for all three vessels are demonstrated in Figures 24 and 25 respectively. In general, the fuel-oil system operation of a two-stroke marine engine starts by pumping fuel from a heated storage tank using a transfer pump into a purifier and service tank. From this point, the amount of daily required fuel is taken from the service tank to a heated settling tank then to the auto-filter. Finally, fuel is pumped to each cylinder of the engine using cylinder fuel pumps.

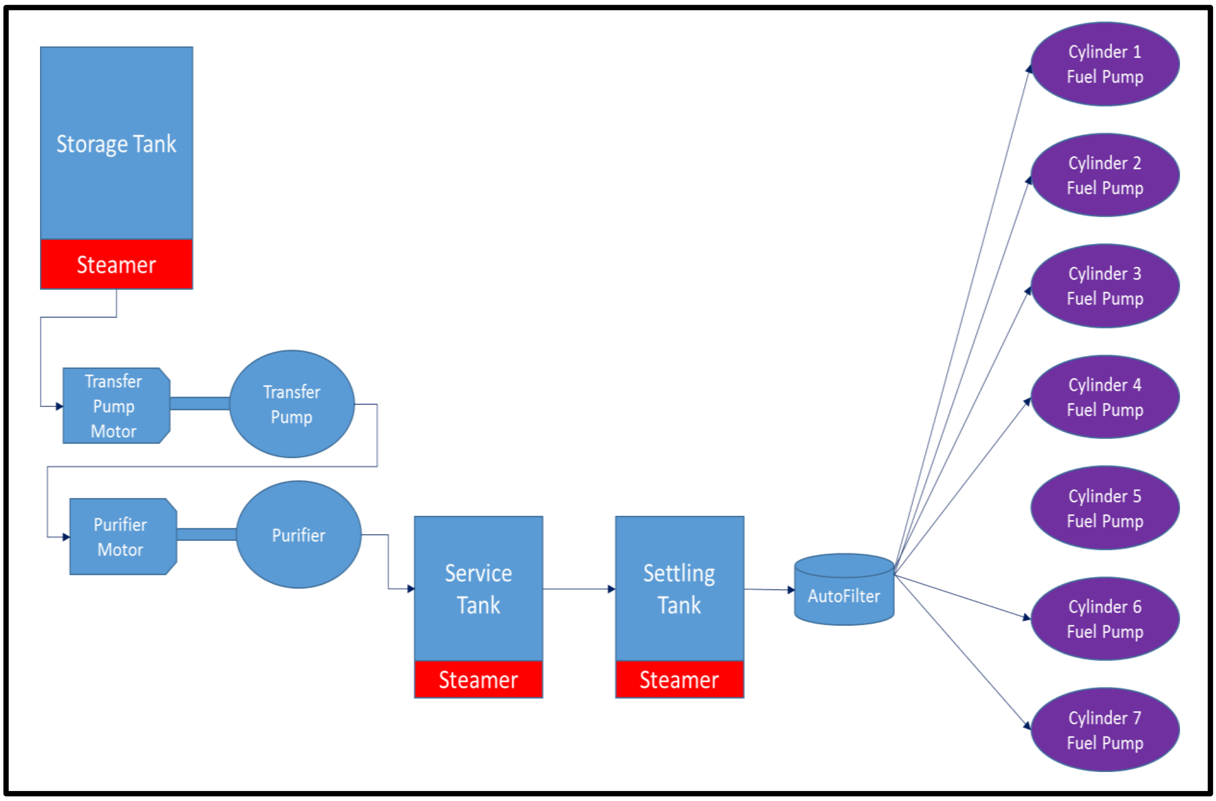

Figure 24 - Ships 1 and 2 Fuel-oil System Operational Structure Flow Diagram

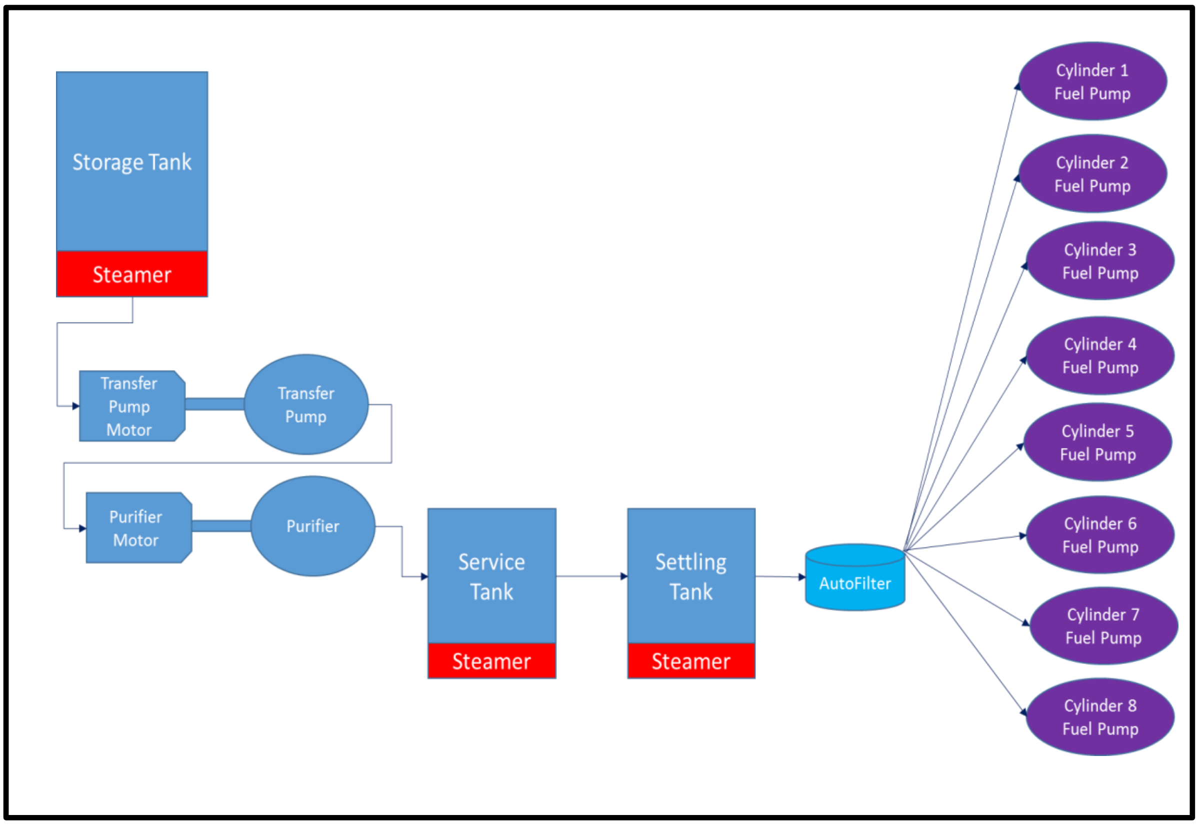

Figure 25 - Ship 3 Fuel-oil System Operational Structure Flow Diagram

The main conditional data obtained from this system for all three vessels include storage tank temperature, transfer pump pressure, transfer pump motor current, purifier flowrate, purifier motor current, service tank temperature, settling tank temperature, auto-filter flowrate and cylinder fuel pumps pressures. Using the manufacturers' limits with recommendations from the ship operator, the ideal working condition limits for each of the above readings was obtained for all vessels. Tables 9 and 10 demonstrate the overall obtained limits for the sister ships and the multi-purpose cargo vessel respectively to calculate probabilistic performance values that can be implemented on the BBN model within the PAU section of the BOPM platform.

Table 9 - Ships 1 and 2 Fuel-oil System Limits

Component/Sub-System	Measurement Type	Limits	Unit
Storage Tank	Temperature	90 to 95	°C
Transfer Pump	Pressure	5.5 to 6	bar
Transfer Pump Motor	Amp	5 to 5.5	Amp
Purifier	Flowrate	Min 7	Kg/cm²
Purifier Motor	Amp	5 to 5.5	Amp
Service Tank	Temperature	90 to 95	°C
Settling Tank	Temperature	90 to 95	°C
Auto-filter	Flowrate	Min 5	Kg/cm²
Cylinder Fuel Pumps	Pressure	168 to 180	bar

Table 10 - Ship 3 Fuel-oil System Limits

Component/Sub-System	Measurement Type	Limits	Unit
Storage Tank	Temperature	90 to 95	°C
Transfer Pump	Pressure	5.6 to 6	bar
Transfer Pump Motor	Amp	5 to 5.5	Amp
Purifier	Flowrate	Min 7.5	Kg/cm²
Purifier Motor	Amp	5 to 5.5	Amp
Service Tank	Temperature	90 to 95	°C
Settling Tank	Temperature	90 to 95	°C
Auto-filter	Flowrate	Min 6	Kg/cm²
Cylinder Fuel Pumps	Pressure	174 to 190	bar

Using the flow diagrams of Figures 24 and 25 with measurement types from Tables 10 and 11, the DBN of the lube-oil system for all three ship types can be generated. This was done on Genie BasiaLab software and the final DBN model of the lube-oil system without utility and decision nodes for the sister ships and multi-purpose cargo ship are shown in Figures 26 and 27 respectively.

Subsequently, for the cost analysis and decision-making of the methodology for the fuel-oil system, all failure scenarios and repair jobs were evaluated for each component/sub-system. Then, their cost values were obtained from the operators' spare system and previous maintenance job logs. Tables 11 and 12 illustrate the costs of repair and, if not repaired, cost failures including downtime for the sister ships and multi-purpose cargo vessel respectively by adding decision and utility nodes to the previous DBN structures. These repair costs are based on average repair rates of engineers from the Far East. Additionally, downtime costs were calculated by the average chartering cost of the vessel per day.

Table 11- Ships 1 and 2 Fuel-oil System Costs

Component/Sub-system	Failure Type	Repair Type	Repair Cost ($)	Failure Cost ($)
Storage Tank Steamer	Heater Failure	Steamer Repair	1900	26000
Fuel Transfer Pump	Pump Failure	Overhaul	8900	22000
Fuel Transfer Pump Motor	Motor Failure	Motor Repair	3000	18000
Purifier	Dirtiness	Cleaning	800	18000
Purifier Motor	Motor Failure	Motor Repair	6000	22000
Service Tank Steamer	Heater Failure	Steamer Repair	1400	16000
Settling Tank Steamer	Heater Failure	Steamer Repair	1400	16000
Auto-Filter	Blockage	Clean/Change	400	1200
Cylinder Fuel Pumps	Pump Failure	Overhaul	5000	20000

Table 12 - Ship 3 Fuel-oil System Costs

Component/Sub-system	Failure Type	Repair Type	Repair Cost ($)	Failure Cost ($)
Storage Tank Steamer	Heater Failure	Steamer Repair	1900	28000
Fuel Transfer Pump	Pump Failure	Overhaul	10000	24000
Fuel Transfer Pump Motor	Motor Failure	Motor Repair	4000	20000
Purifier	Dirtiness	Cleaning	800	20000
Purifier Motor	Motor Failure	Motor Repair	6000	24000
Service Tank Steamer	Heater Failure	Steamer Repair	1400	18000
Settling Tank Steamer	Heater Failure	Steamer Repair	1400	18000
Auto-Filter	Blockage	Clean/Change	400	1300
Cylinder Fuel Pumps	Pump Failure	Overhaul	6500	22000

Using these two cost tables and DBN networks from Figures 26 and 27, the complete DBN of Lube-oil systems for the sister ships and multi-purpose cargo ship, including utility and decision nodes, can be developed in Genie BiasiaLab environment as illustrated in Figures 28 and 29. In this system, as with the lube-oil system, each measured reading corresponds to only a single failure cause.

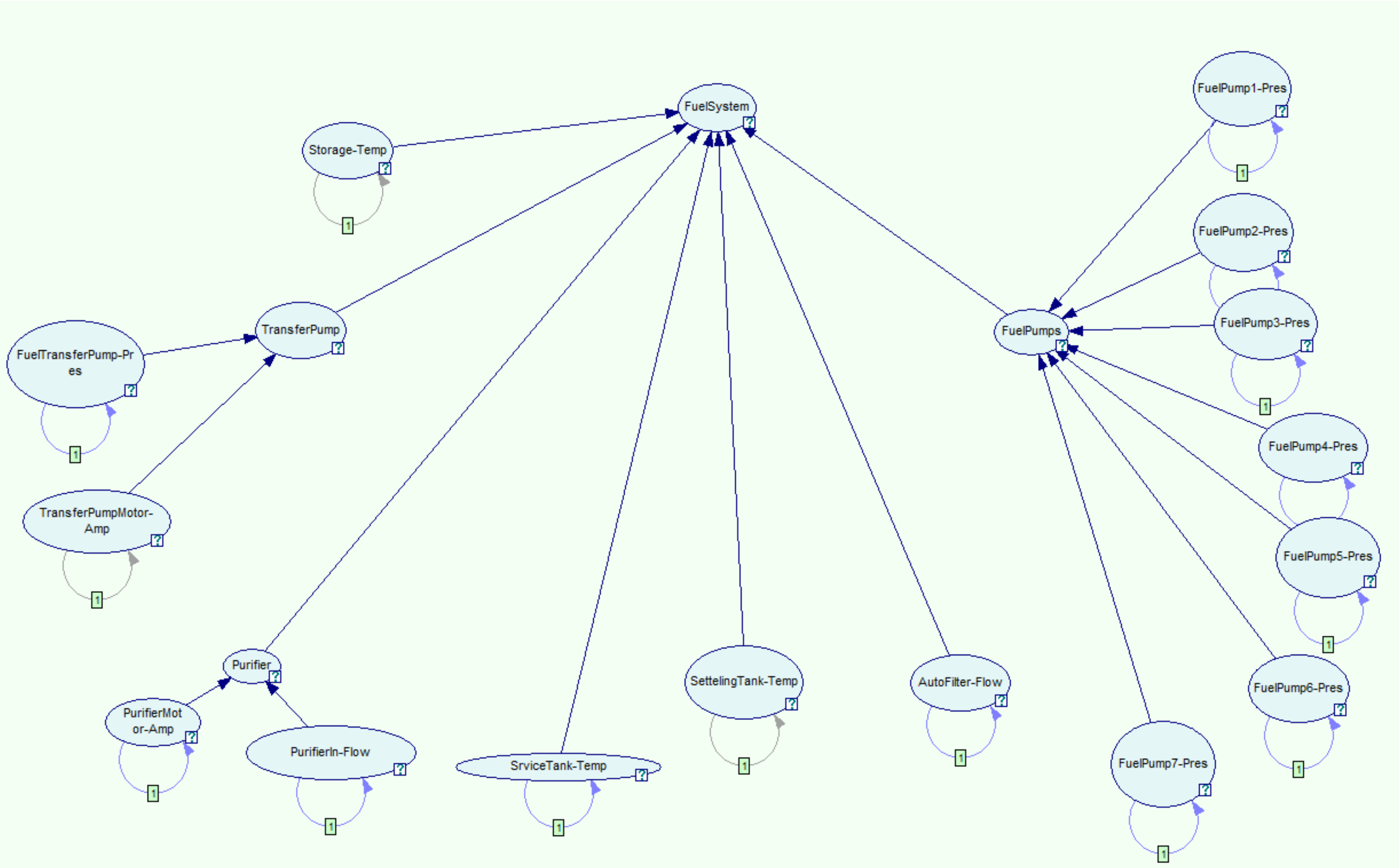

Figure 26 - Ships 1 and 2 Fuel-oil System DBN Network without Utility and Decision Nodes

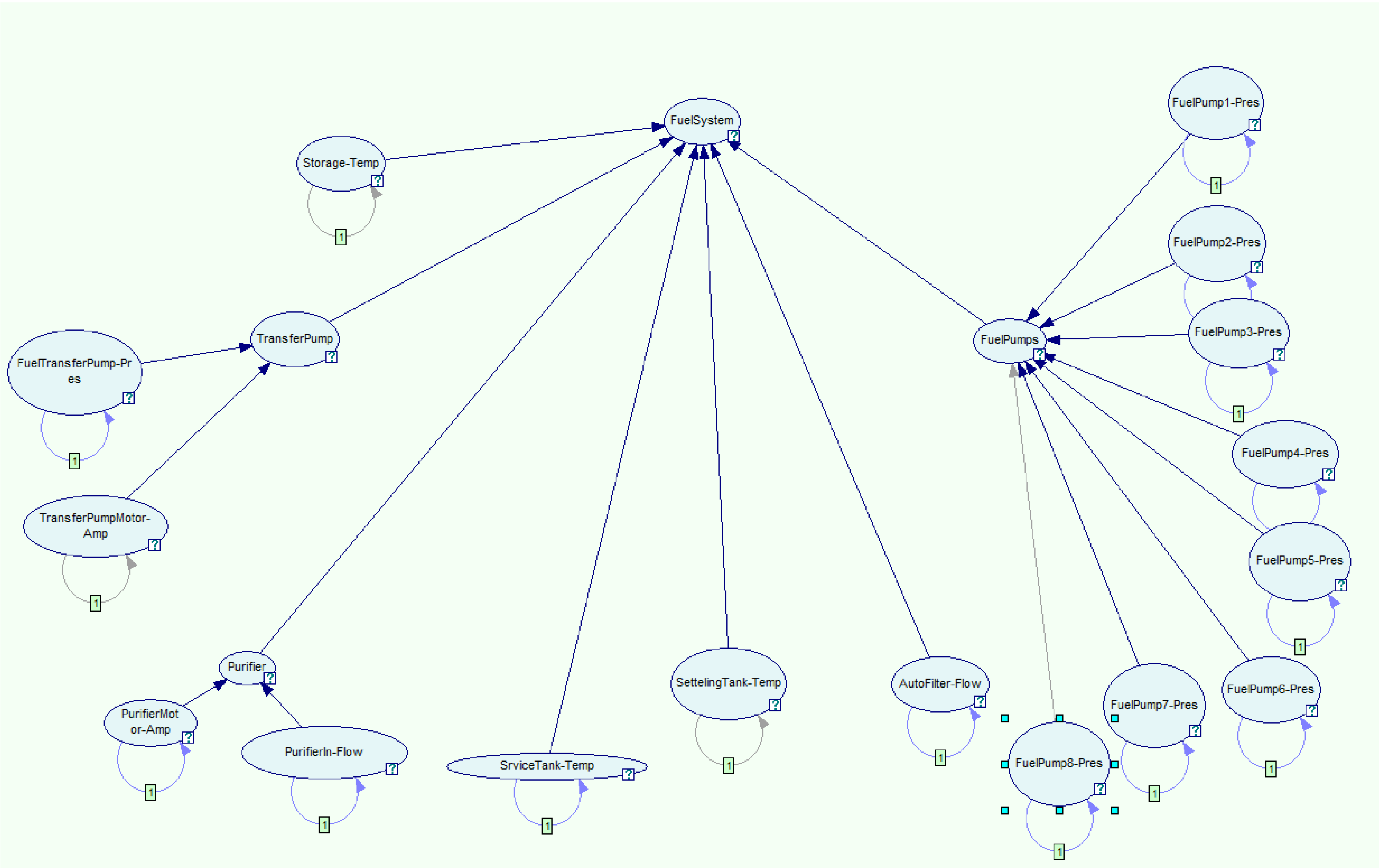

Figure 27 - Ship 3 Fuel-oil System DBN Network without Utility and Decision Nodes

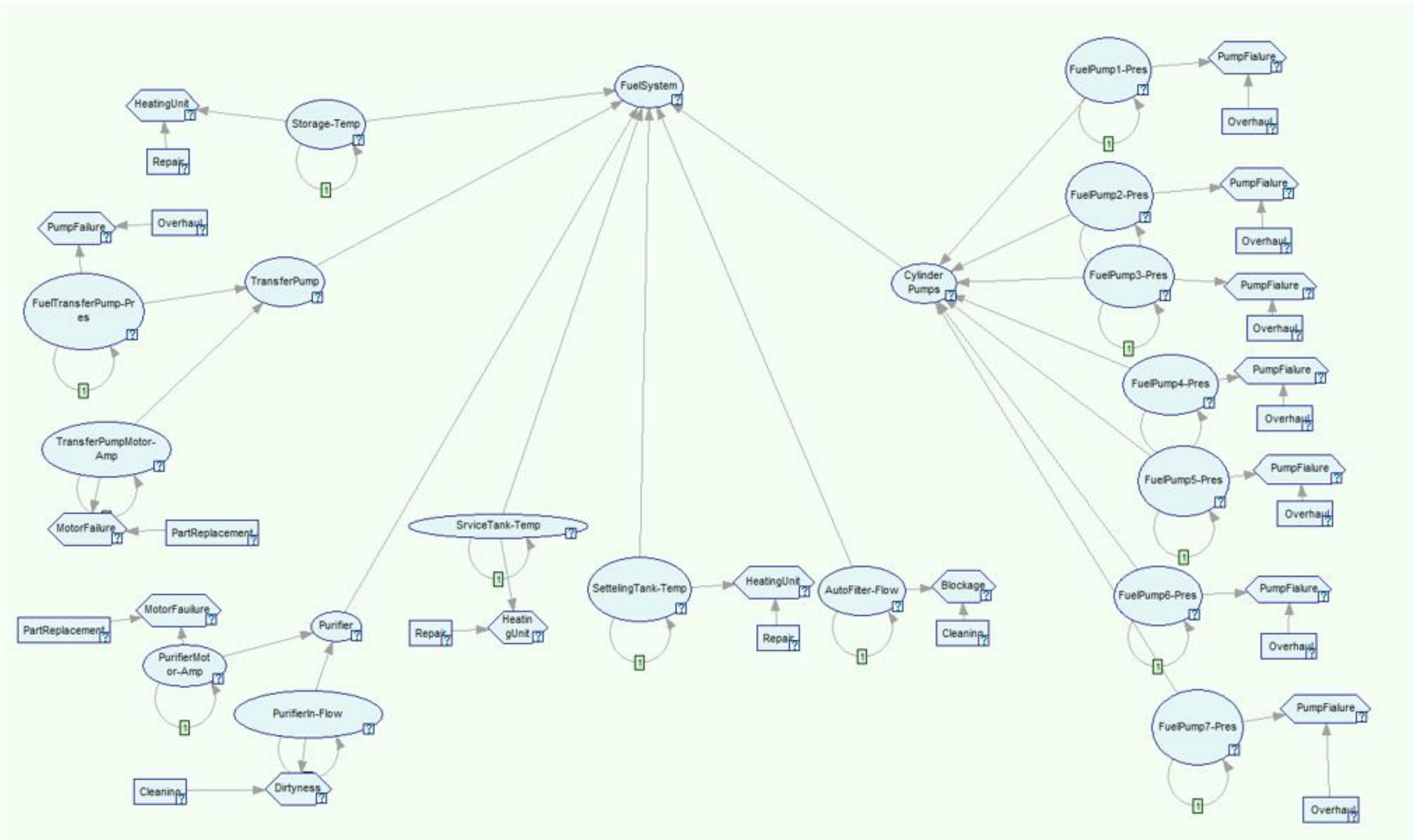

Figure 28 - Ships 1 and 2 Fuel-oil System DBN Network with Utility and Decision Nodes

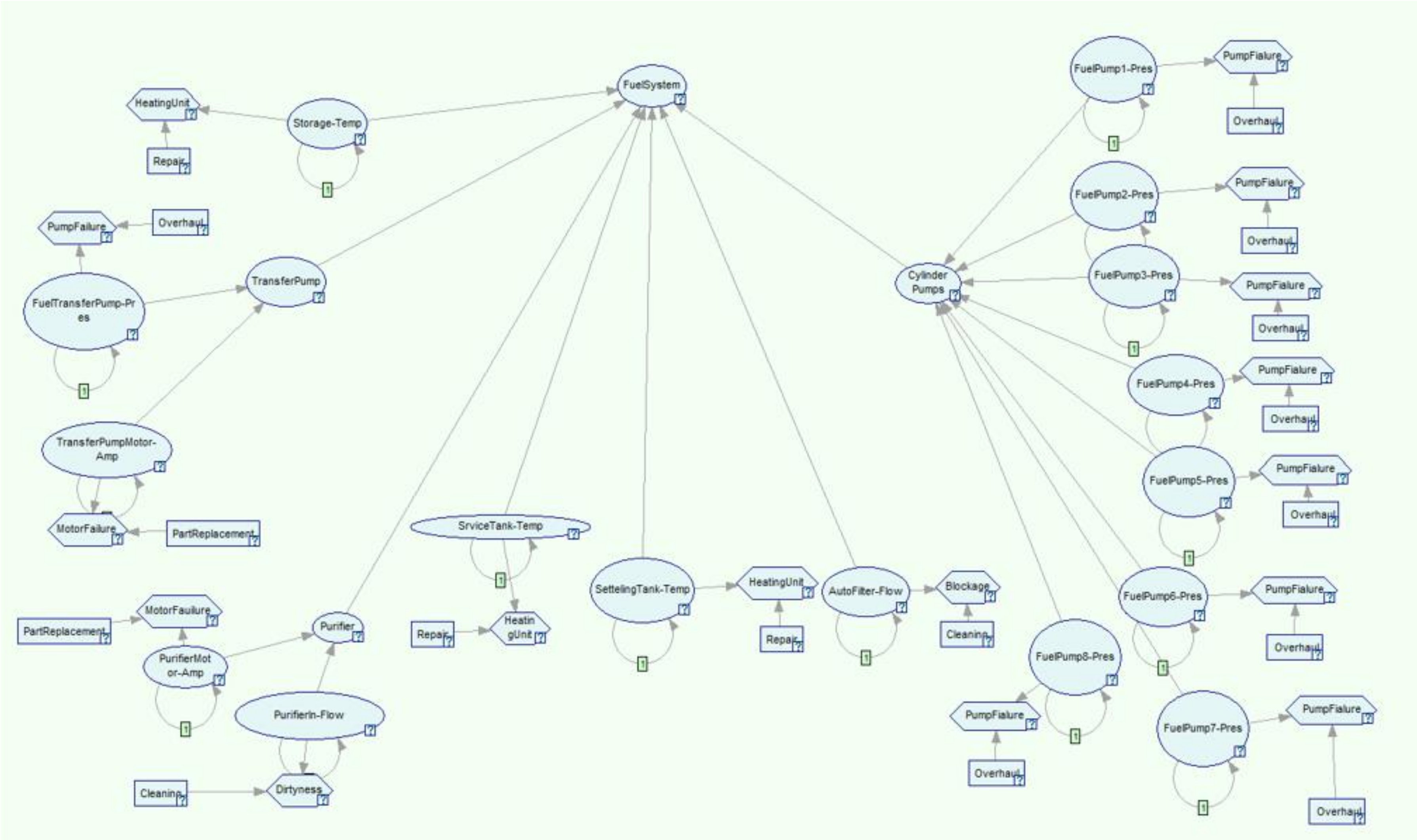

Figure 29 - Ship 3 Fuel-oil System DBN Network with Utility and Decision Nodes

5.7 Turbochargers

The main engine turbochargers for all three vessels have very similar design outlines. The structural flow diagram of the turbocharger for the sister vessels and multi-purpose cargo vessel are demonstrated in Figure 30. In brief, turbochargers consist of two major sections, the compressor and the turbine. The compressor side sucks charge air in and compresses it, then sends it to be mixed with fuel in a manifold after passing through the scavenge air cooling system. The turbine side of the turbocharger provides the rotational power for the compressor side using rotational energy provided by the cooled exhaust gasses from the engine.

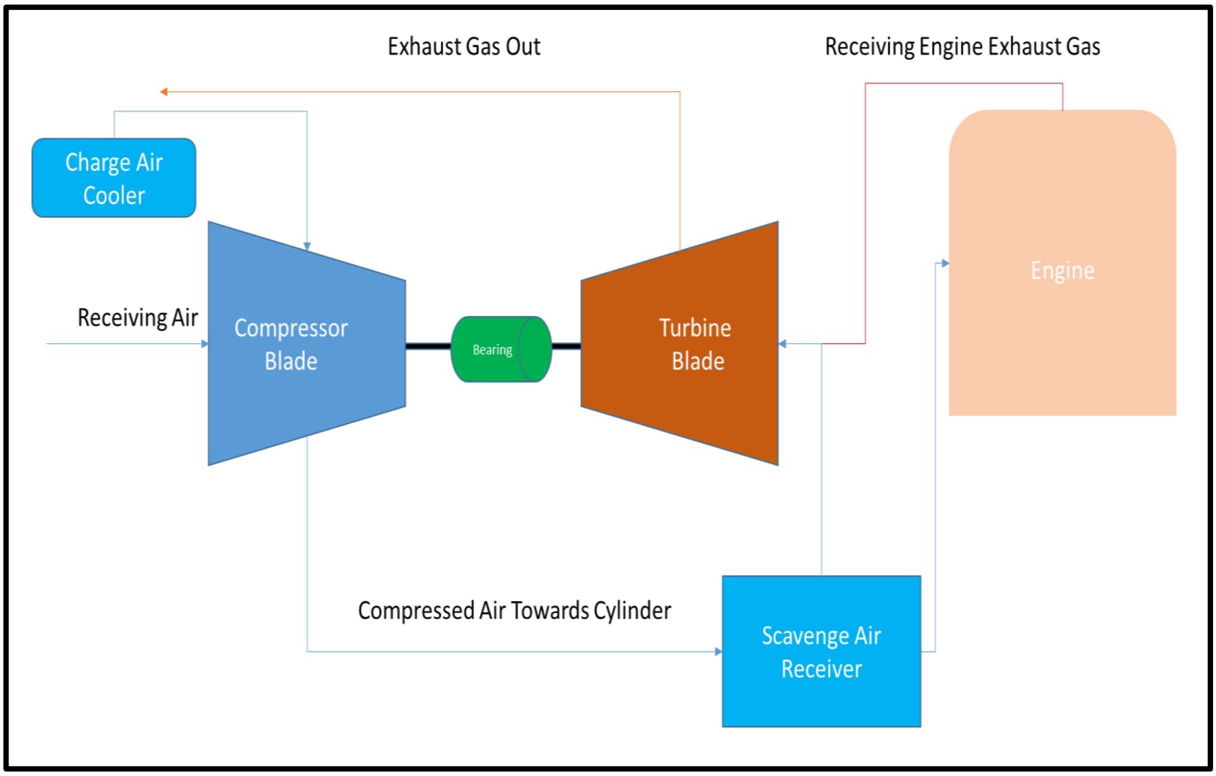

Figure 30 - Turbocharger Operational Structure Flow Diagram

Both turbine and compressor blades used in the turbocharger are attached to each other via connecting shaft and bearings. This system has a more complicated structure compared with the lube-oil and fuel-oil systems as it depends on several other inlet values for each failure type. This means that a single reading can correspond to various failure scenarios.

In order to make decisions on the possibility of best action from the available failure types and repair actions, the costs and consequences of having/not having a maintenance action on each failure mitigation technique should be evaluated. These are shown as positive and negative nodes inside the DBN networks respectively. Further explanation of the methodology and decision-making of this type of DBN analysis will be discussed in the results and discussion chapters of the dissertation.

The main conditional data obtained from this system for all vessels are the scavenge air in/out temperature, scavenge air in/out pressure, bearing vibration, air cooler in/out temperature, turbocharger exhaust out temperature, charge air pressure and exhaust back-pressure. Using the manufacturers' limits with recommendations from the ship operator, the ideal working condition limits for each of the above readings was obtained for all three vessels. Tables 13 and 14 demonstrate the overall obtained limits for the sister ships and multi-purpose cargo vessel respectively to be used for calculating probabilistic performance value that can be implemented on the BBN model within the PAU section of the BOPM platform.

Table 13 - Ships 1 and 2 Turbocharger Limits

Component/Sub-System	Measurement Type	Limits	Unit
Scavenge Air In	Pressure	Min 3.8	bar
Scavenge Air Out	Pressure	Min 3.5	bar
Scavenge Air In	Temperature	175 to 180	°C
Scavenge Air Out	Temperature	80 to 78	°C
Bearing	Vibration	Max 3	a(g)
Air Cooler In	Temperature	48 to 50	°C
Air Cooler Out	Temperature	73 to 75	°C
Exhaust Turbo Out	Temperature	430 to 450	°C
Charge Air	Pressure Low/High	5.3 to 5.5	bar
Exhaust Back-Pressure	Pressure	Max 115	mmWC

Table 14 - Ship 3 Turbocharger Limits

Component/Sub-System	Measurement Type	Limits	Unit
Scavenge Air In	Pressure	Min 3.9	bar
Scavenge Air Out	Pressure	Min 3.5	bar
Scavenge Air In	Temperature	190 to 200	°C
Scavenge Air Out	Temperature	85 to 80	°C
Bearing	Vibration	Max 3	a(g)
Air Cooler In	Temperature	50 to 53	°C
Air Cooler Out	Temperature	76 to 78	°C
Exhaust Turbo Out	Temperature	435 to 450	°C
Charge Air	Pressure Low/High	5.3 to 5.5	bar
Exhaust Back=Pressure	Pressure	Max 125	mmWC

Using the flow diagram of Figure 30 and measurement types from Tables 14 and 15, the DBN of turbochargers for all three ship types can be generated. This was done in Genie BasiaLab software and the final DBN model of the turbocharger without utility and decision nodes is shown in Figure 31. It can be noticed that, unlike previous systems, there are multiple coresponding failures for some of the readings.

Subsequently, for the cost analysis and decision-making of the methodology for the turbocharger all failure scenarios and repair jobs with cost of testing for the measured readings with more than one corresponding failure type was analysed. Then, their cost values were obtained from the operators' spare system and previous maintenance job logs. Tables 15 and 16 illustrate the costs of repair and, if not repaired, cost failures including downtime for the sister ships and multi-purpose cargo vessel respectively. These repair costs are based on average repair rates of engineers from the Far East. Additionally, downtime costs are calculated by the average chartering cost of the vessel per day.

Using these two cost tables and DBN network from Figure 31, the complete DBN of turbochargers for all three vessels including utility and decision nodes can be developed in the Genie BiasiaLab environment as illustrated in Figure 32. As mentioned earlier, some measured readings have multiple failure causes therefore test nodes had to be added to the overall network of turbochargers. This will be further explained in both the results and discussion chapters.

Table 15 - Ships 1 and 2 Turbocharger Costs

Failure Point	Test/Check	Cost in $	Repair	Cost in ($)	Total Fail Cost in ($)
T/C Contamination	Dismantle and Repair	3000	Cleaning with dismantle	3300	6000
Fuel Injector	Engine Performance Test	1100	Change	2500	17500
Exhaust Fouling	Dismantle	1500	Cleaning with dismantle	3000	22000
Air cooler	Pressure Test	100	Cleaning	1300	12000
Rotor blade	Dismantle	3000	Change	6000	26000
Air filter	N/A	N/A	Change	100	1100
Exhaust duct	Leak Test	100	Repair	2000	9000
bearing	N/A	N/A	Change	6000	26000
Scavenge air leak	N/A	N/A	Cleaning	1100	14000

Table 16 - Ship 3 Turbocharger Costs

Failure Point	Test/Check	Cost in ($)	Repair	Cost in ($)	Total Fail Cost in ($)
T/C Contamination	Dismantle	3000	Cleaning with dismantle	3300	7000
Fuel Injector	Engine Performance Test	1100	Change	2800	19000
Exhaust Fouling	Dismantle	1500	Cleaning with dismantle	3000	24000
Air cooler	Pressure Test	100	Cleaning	1300	13000
Rotor blade	Dismantle	3000	Change	7000	28000
Air filter	N/A	N/A	Change	100	1200
Exhaust duct	Leak Test	100	Repair	2000	10000
bearing	N/A	N/A	Change	7500	28000
Scavenge air leak	N/A	N/A	Cleaning	1100	15500

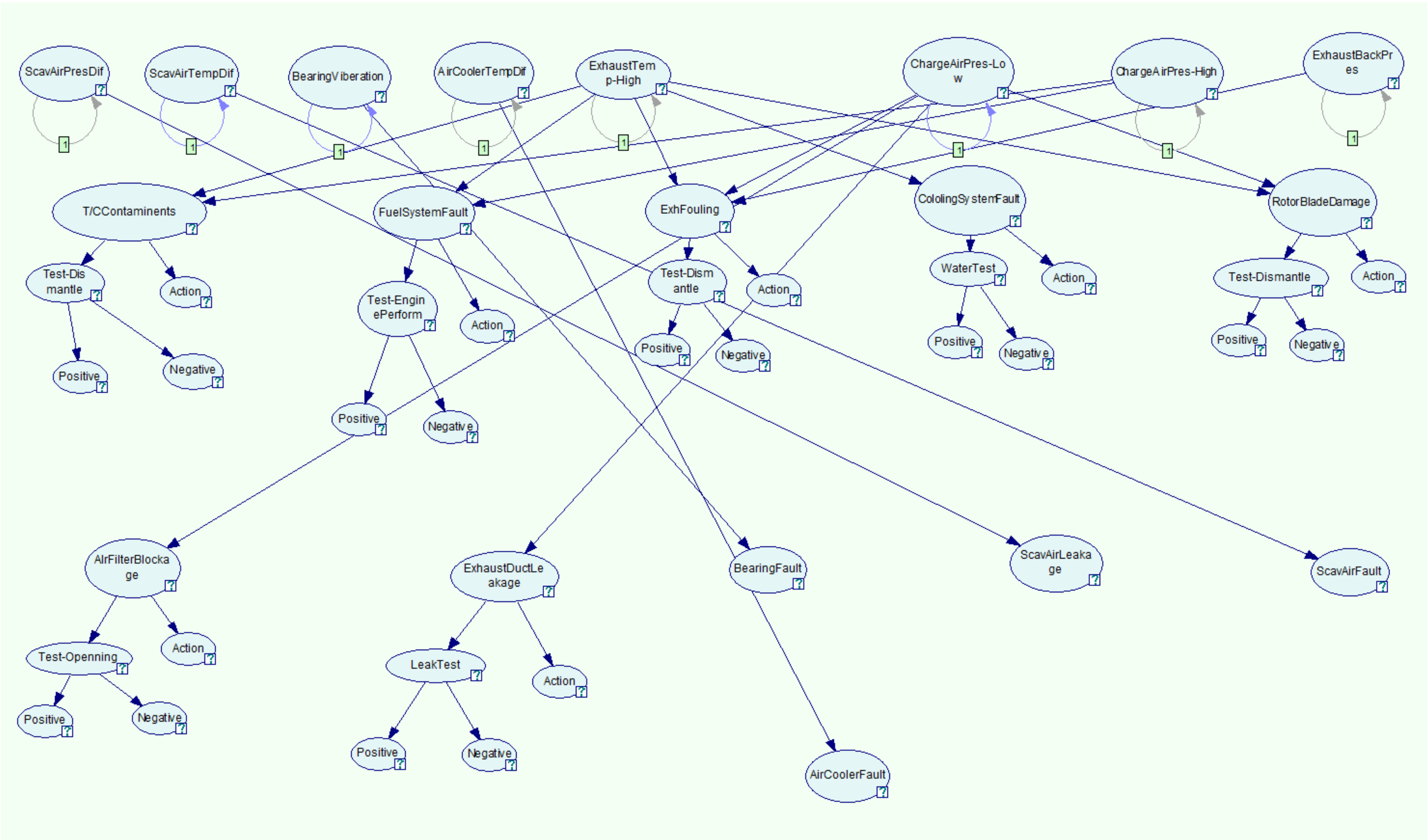

Figure 31 - Turbocharger DBN Network without Utility and Decision Nodes

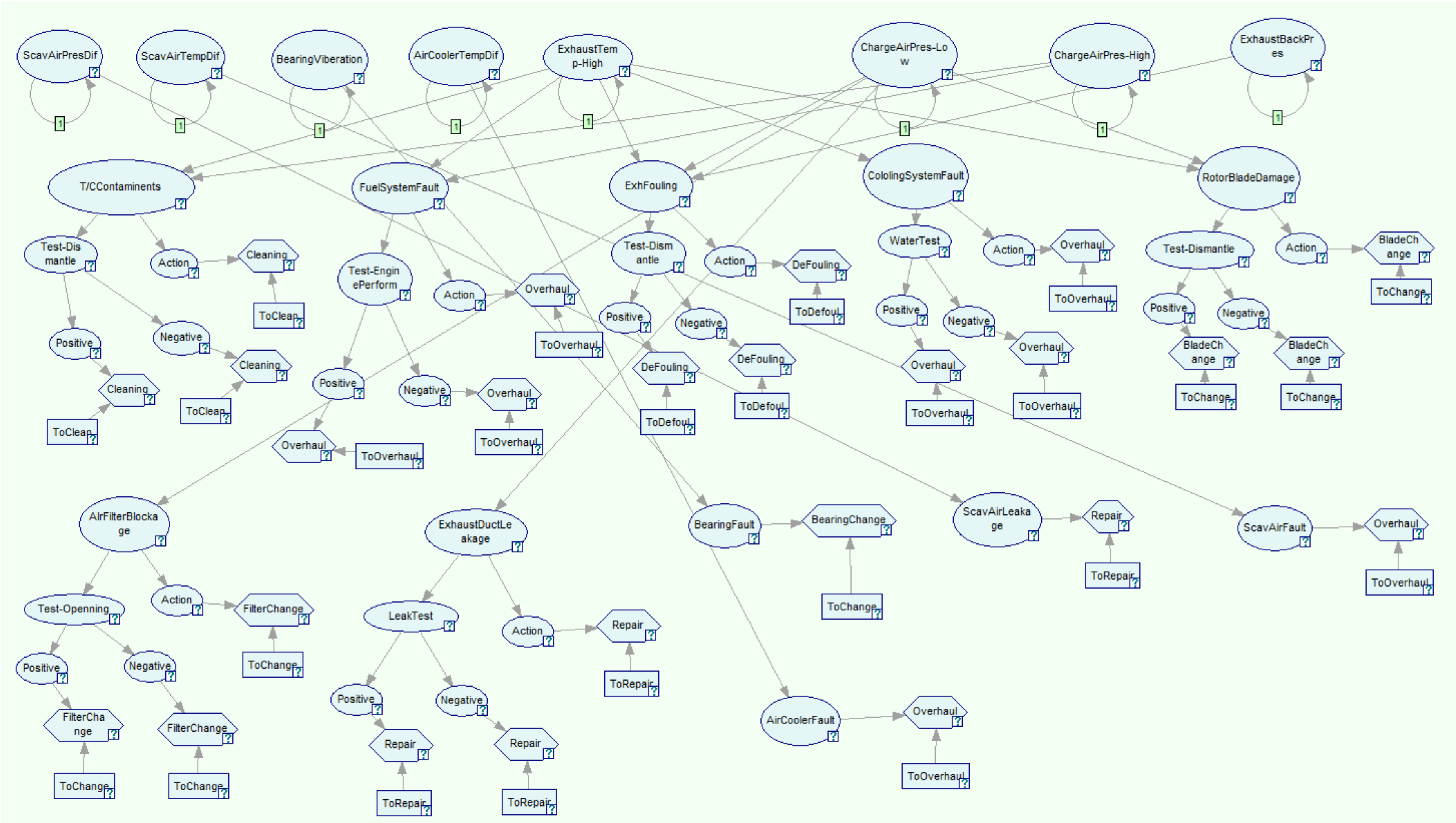

Figure 32 - Turbocharger DBN Network with Utility and Decision Nodes

5.8 Criticality Risk Matrices of the Vessels

All risk factors mentioned in the methodology chapter were obtained from the ABS (American Bureau of Shipping) (ABS, 2000) with the addition of rules from DNV created for the UK Maritime Health and Safety Executive (HSE) (HSE, 2001) has been adopted to be used with the current case studies. Factor number five, failure rate, has also been added using general recommended operator reliability data for each system for 15 years or approximately 10^5 hours of operation. This is usually close to half of the effective life of an average vessel. Other risk factors from the previous chapter are also adopted per average repair costs, downtime and average accidents from each ship obtained from both cost data and experts' judgments. Tables 18 and 19 demonstrate the risk consequence matrices for human risk, environmental risk and operational loss respectively. Table 20 demonstrates classification of the probability of failure level on 10^5 operational hours.

Table 17 – Health and Safety Consequence Matrix

Health and Safety Factor	**Definition**
A _ Safe	Will not result in injury
B _ Insignificant	Will not result in significant injury
C _ Minor Injury	May cause an average injury (less than a week in hospital with no further future treatment needed)
D _ Major Injury	May cause significant injury
E _ Fatalities	May cause death

Table 18 - Environmental Impact Consequence Matrix

Environmental Impact Factor	**Definition**
A _ Insignificant	No environmental consequences
B _ Minor	Intra system influence with no economic consequence
C _ Local	From system to equipment influence with slight economic consequence
D _ Major	Out of system and equipment influence with possibility of settling within enterprise
E _ Significant	Accident has to be settled with local government (with both financial consequences and possible incarceration)

Table 19 - Risk Consequence Matrix on Operational Loss

Operational Loss	**Definition**
A _ Insignificant	<= 2h operational loss
B _ Minor	<= 2h-8h operational loss
C _ Local	<= 8h-24h operational loss
D _ Major	<= 24h-48h operational loss
E _ Significant	> 48h operational loss

Table 20 - Probability of Failure Levels

Probability of Failure Level	**Probability of Failure per 100000 Hours of Operation**
5 _ Common Occurrence	>0.4
4 _ Occasional Occurrence	0.1 ~ 0.4
3 _ Chance	0.02 ~ 0.1
2 _ Infrequent	0.002 ~ 0.02
1 _ Rare	< 0.002

Risk factors and probability failure levels can be multiplied together using the triangular fuzzy function and overall fuzzy calculation network shown in Figure 15 of Chapter 4. However, the fuzzy multiplication function of this model follows the general definition from Table 21. The final results of fuzzy multiplications for all of the observed components and sub-systems will be shown in the next chapter of the dissertation. Environmental risks are based on possibility of oil pollution, air pollution, noise and other wastes, which are highlighted and ranked by experts.

In summary, these factors will then be used in the final decision-making process where two or more recommended maintenance actions through the PAU and DAU sections of analysis as part of the methodology are intersecting one another. Consequently, maintenance jobs with the highest risk factors will be prioritised relative to the other maintenance job recommendations and this will result in the final maintenance schedule for the vessel. Further, the calculation process using MATLAB is demonstrated with an example in Appendix D.

Table 21 - Overall Fuzzy Multiplication Definitions

Probability of Failure		**Consequence of Failure**				
5	>0.8	Medium	Medium	Medium	High	High
4	0.1 ~ 0.8	Low	Medium	Medium	Medium	High
3	0.02 ~ 0.1	Low	Low	Medium	Medium	Medium
2	0.002 ~ 0.02	Low	Low	Low	Medium	Medium
1	< 0.002	Low	Low	Low	Low	Medium
		A	B	C	D	E

5.9 Chapter Summary

This chapter demonstrated the data obtained from three vessels, two of which are sister chemical tanker ships and one multi-purpose cargo ship. Three types of machinery systems were implemented for the data gathering campaign from the case study vessels. Two of these systems, namely the lube-oil system and fuel-oil, have only one failure type per each corresponding measured reading. However, turbochargers can have multiple failure scenarios for each corresponding measurement. Moreover, adopted criticality matrices of different risk factors with the probability of failure levels have also been shown in this chapter. The next chapter of the thesis will illustrate the probability, cost analysis, decision-making and criticality value results obtained using the BOPM methodology on case studies from this chapter.

6 CHAPTER 6-RESULTS

6.1 Chapter Introduction

This chapter will demonstrate the results using data from the previous chapter and use the overall BOPM methodology. However, this chapter will initially discuss the reasons for selecting the missing data treatment methodology and overall data representation limits for the measured results using sensitivity analysis and comparison graphs and tables. Subsequently, the overall performance probabilistic analysis and predicted cost results of the lube-oil system, fuel-oil system and turbochargers from all three ship case studies will be represented. Finally, the overall calculated risk values for all of the calculated sub-systems, components or failure types from the observed three ship systems will be shown.

6.2 Missing Data Treatment

Three major missing data treatment methodologies have been compared using data available from the vessels. These missing data methodologies include: mean substitution (MS), expectation-maximisation (EM) of the maximum likelihood (ML) and Markov Chain Monte Carlo (MCMC) multiple imputation techniques. For comparison of the performance of these methodologies, three measured data types have been chosen with no missing data.

These three selected data types are: scavenge air inlet temperature from Ship 1, Turbocharger exhaust out temperature from Ship 2, and cylinder-eight fuel pump from Ship 3. These selected measurement types did not have any missing values for at least the first 200 days of recording. By observing the other obtained data types it has been found that the minimum number of missing data was 14 and the maximum was 48. Another important reason for selecting these three data types is that they are highly important for the general operation of the vessel, as also indicated by their criticality values.

As a result, the missing data treatment comparison of these selected data types was done on the three scenarios of 50 missing data, 30 missing data and 15 missing data points. For this, data was randomly removed from all three selected data types and then treated with data treatment options. Consequently, the results from missing data treatment options and the full set of real data have been compared based on their standard deviation and mean values. Furthermore, the overall data has been factorised into different sections based on the observed data and then, compared on bar charts, the number of data per missing data methodologies compared with the full data set. Tables 21, 22 and 23 demonstrate standard deviations, means and errors compared with the full data set for all three missing data treatment methodologies for all three of the selected data types in 50, 30 and 15 missing data scenarios. Subsequently, Figures 33 to 41 illustrate comparison bar charts of the treated data sets compared with the full data set within determined data factors.

In the tables the second column represents the standard deviation and mean values of full data without any missing values. Columns 3, 4 and 5 represent standard deviation, mean and errors compared with full data of using missing data treatment methodologies of MS, EM of the ML and MCMC multiple imputation respectively for 50 missing data. Columns 6, 7 and 8 do the same for the three types of missing data treatment methods for 30 missing data and columns 9, 10 and 11 do the same for 15 missing data. On the bar charts, the Y-axis represents the number data values found on data value categories represented on the X-axis of each bar inside the chart. This is due to the fact that data are divided into categories in order to simplify the visual comparison of the accuracy of the missing data treatment methodologies.

For scavenge air inlet temperature of ship 1, the standard deviation for full data was 1.6148. However, the standard deviation for 50 missing data case scenarios for MS, EM of the ML and MCMC multiple imputation data treatment techniques were 1.6888, 1.6450 and 1.6126 respectively. In the case of 15 missing data of the Table 22 case scenario standard deviation for the previous missing data treatment techniques were 1.6718, 1.5986 and 1.6044 respectively. In brief, the errors for 50 missing data for MS, EM of the ML MCMC multiple imputation data treatment techniques were 4.3863%, 1.8368% and 0.648% respectively, which proves that the MCMC multiple imputation technique has the lowest error. This error pattern was also repeated for the 15 missing data cases as the errors were 3.4127%, 1.01% and 0.1313% respectively. Comparing the above error values between the 50 missing data and 15 missing data scenarios, it can be concluded that the lower the number of missing data, the lower the error value from all three data treatment methodologies.

Table 22 - Missing Data Treatment Methodology Comparison for Scavenge Air-in Temperature for Ship 1

		50 Missing Data			30 missing data			15 Missing Data		
Data Distribution Information	**Full Data**	**MS**	**EM**	**MCMC**	**MS**	**EM**	**MCMC**	**MS**	**EM**	**MCMC**
Standard Deviation	1.6148	1.6888	1.6450	1.6126	1.6491	1.5907	1.6085	1.6718	1.5986	1.6044
Mean	177.66	177.89	177.74	177.68	177.79	177.68	177.66	177.85	177.67	177.67
Error STDEV (%)		4.3863	1.8368	0.1313	2.0820	1.5138	0.3877	3.4127	1.0100	-0.6480
Error Mean (%)		0.1293	0.0450	0.0113	0.0731	0.0113	0.0000	0.1040	0.0028	0.0056

Figures 33, 34 and 35 illustrate comparison bar charts of full data compared with three different missing data treatment techniques for the scavenge air inlet temperatures of Ship 1 in the cases of 50, 30 and 15 missing data respectively. It can be seen that the dotted bar representing the MS technique on all three bar charts has a relatively higher difference in the number of values compared with solid full data bar. On the other hand, the diamond pattern bar representing the MCMC multiple imputation technique has the lowest difference in number of values compared with solid full data bar. Additionally, EM of the ML technique represented by the horizontal lone patterned bar fits right in the middle of previous techniques on accuracy scale. Therefore, MCMC is the most accurate technique followed by EM with MS having the lowest accuracy. Comparing the three bar charts it can also be noticed that lower missing data numbers increase the accuracy of all of the missing data treatment methodologies.

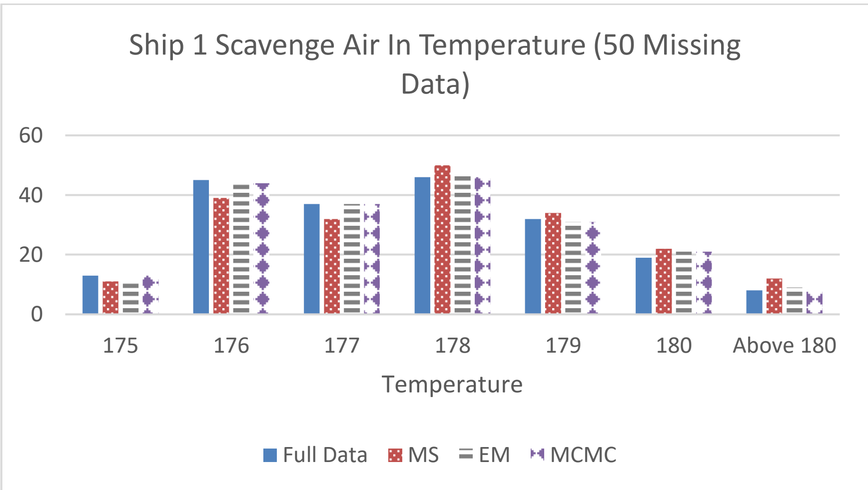

Figure 33 - Data Treatment Comparison for Ship 1 with 50 Missing Data

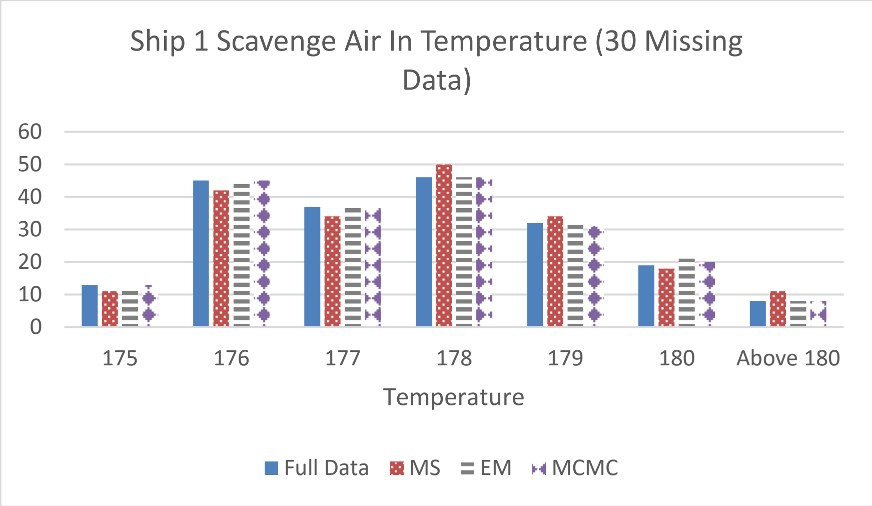

Figure 34 - Data Treatment Comparison for Ship 1 with 30 Missing Data

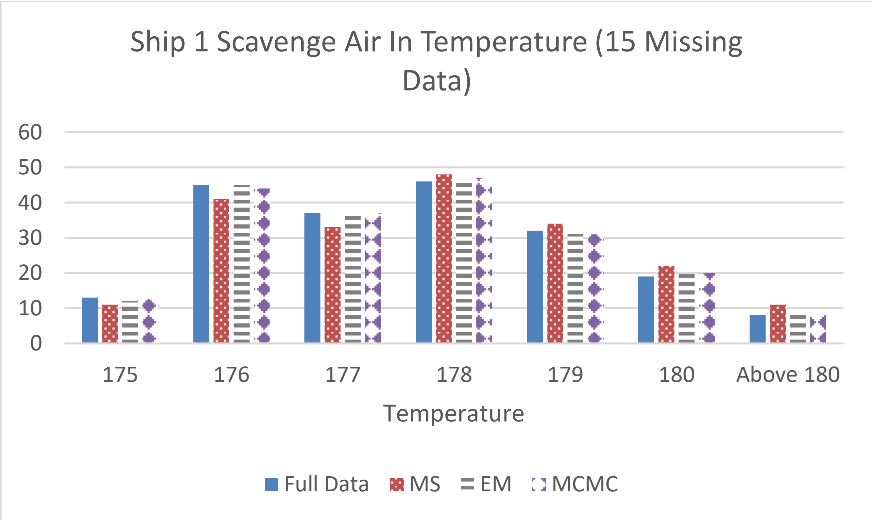

Figure 35 - Data Treatment Comparison for Ship 1 with 15 Missing Data

For turbocharger exhaust out temperature of Ship 2, the standard deviation for full data was 6.367. However, standard deviation for 50 missing data case scenarios for MS, EM of the ML and MCMC multiple imputation data treatment techniques were 6.2144, 6.3155 and 6.3712 respectively. In the case of 15 missing data, in Table 23, case scenario standard deviation for the previous missing data treatment techniques were 6.2889, 6.3602 and 6.3677 respectively. In brief, the errors for 50 missing data for MS, EM of the ML and MCMC multiple imputation data treatment techniques were 2.4553%, 0.8149% and 0.0658% respectively, which proves that the MCMC multiple imputation technique has the lowest error. This error pattern was also repeated for the 15 missing data case as the errors were 1.2412%, 0.1074% and 0.0106%

respectively. Comparing the above error values between 50 missing data and 15 missing data scenarios, it can be concluded that the lower the number of missing data, the lower the error value from all three data treatment methodologies.

Table 23 - Missing Data Treatment Methodology Comparison for Turbocharger Exhaust Out Temperature for Ship 2

		50 Missing Data			30 missing data			15 Missing Data		
Data Distribution Information	**Full Data**	**MS**	**EM**	**MCMC**	**MS**	**EM**	**MCMC**	**MS**	**EM**	**MCMC**
Standard Deviation	6.3670	6.2144	6.3155	6.3712	6.2670	6.3388	6.3707	6.2889	6.3602	6.3677
Mean	439.91	438.55	439.35	440.004	438.99	439.56	440	439.21	439.7	439.99
Error STDEV (%)		2.4553	0.8149	0.0658	1.5961	0.4454	0.0581	1.2412	0.1074	0.0106
Error Mean (%)		0.3094	0.1270	0.0225	0.2091	0.0792	0.0207	0.1578	0.0457	0.0198

Figures 36, 37 and 38 illustrate comparison bar charts of full data compared with three different missing data treatment techniques for the turbocharger exhaust out temperature of Ship 2 in cases of 50, 30 and 15 missing data respectively. It can be seen that the dotted bars representing the MS technique on all three bar charts have a relatively higher difference in the number of values compared with the blue solid coloured full data bar. On the other hand, the diamond pattern bar representing the MCMC multiple imputation technique has the lowest difference in the number of values compared with the solid coloured full data bar. Additionally, EM of the ML technique, represented by the horizontal lone patterned bar, fits right in the middle of previous two techniques on the accuracy scale. Therefore, MCMC is the most accurate technique followed by EM with MS having the lowest accuracy. Comparing the three bar charts it can also be noticed that lower missing data numbers increase the accuracy of all the missing data treatment methodologies.

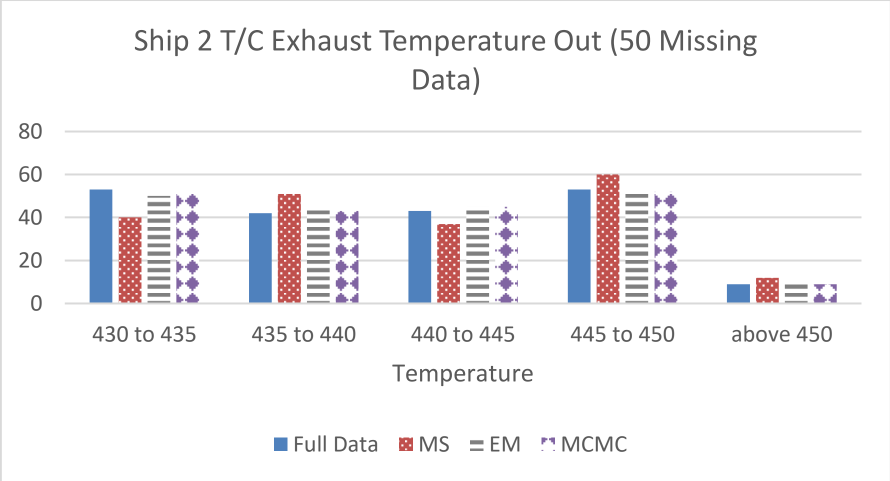

Figure 36 - Data Treatment Comparison for Ship 2 with 50 Missing Data

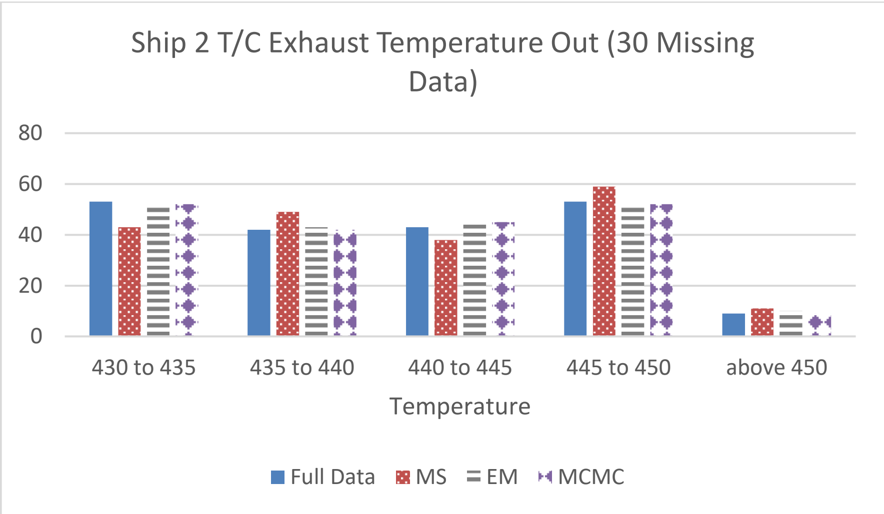

Figure 37 - Data Treatment Comparison for Ship 2 with 30 Missing Data

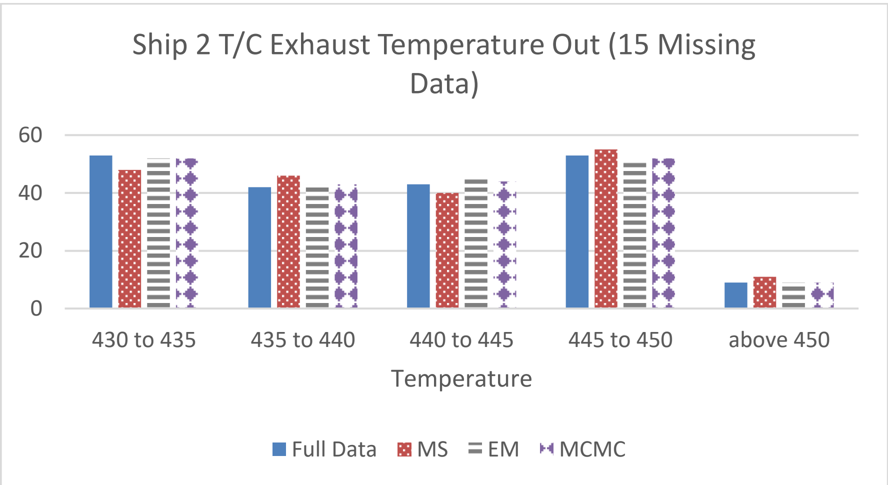

Figure 38 - Data Treatment Comparison for Ship 2 with 15 Missing Data

For cylinder-eight fuel pump pressure of Ship 3, the standard deviation for full data was 6.367. However, standard deviation for 50 missing data case scenarios for MS, EM of the ML and MCMC multiple imputation data treatment techniques were 4.5243, 4.6321 and 4.5754 respectively. In the case of 15 missing data of Table 24 the standard deviation for the previous missing data treatment techniques were 4.5947, 4.5316 and 4.5213 respectively. In brief, the errors for 50 missing data for MS, EM of the ML and MCMC multiple imputation data treatment techniques were 2.3277%, 1.1178% and 0.3199% respectively, which proves that MCMC multiple imputation technique has the lowest error. This error pattern was also repeated for the 15 missing data case as the errors were 1.5334%, 0.1607% and 0.0670% respectively. Comparing the above error values between 50 and 15 missing data scenarios, it can be concluded that the lower the number of missing data, the lower the error value from all three data treatment methodologies.

Table 24 - Missing Data Treatment Methodology Comparison for Cylinder-8 Fuel Pump Pressure for Ship 3

		50 Missing Data			**30 missing data**			**15 Missing Data**		
Data Distribution Information	**Full Data**	**MS**	**EM**	**MCMC**	**MS**	**EM**	**MCMC**	**MS**	**EM**	**MCMC**
Standard Deviation	4.5243	4.6321	4.5754	4.5099	4.6137	4.5538	4.5148	4.5947	4.5316	4.5213
Mean	179.87	179.53	179.8	179.913	179.62	179.81	179.89	179.68	179.83	179.87
Error STDEV (%)		2.3277	1.1178	0.3199	1.9390	0.6474	0.2109	1.5334	0.1607	0.0670
Error Mean (%)		0.1866	0.0378	0.0267	0.1353	0.0306	0.0156	0.1007	0.0178	0.0039

Figures 39, 40 and 41 illustrate comparison bar charts of full data compared with three different missing data treatment techniques for the cylinder-eight fuel pump pressure of Ship 3 in cases of 50, 30 and 15 missing data respectively. It can be seen that the dotted bar representing the MS technique on all three bar charts have relatively higher difference in the number of values compared with the solid coloured full data bar. On the other hand, the diamond pattern bar representing the MCMC multiple imputation technique has the lowest difference in the number of values compared with solid coloured full data bar. Additionally, EM of the ML technique represented by the horizontal lone patterned bar fits right in the middle of the previous two techniques on accuracy scale. Therefore, MCMC is the most accurate technique followed by EM with MS having the lowest accuracy. Comparing the three bar charts it can also be noticed that lower missing data numbers increase the accuracy of all the missing data treatment methodologies.

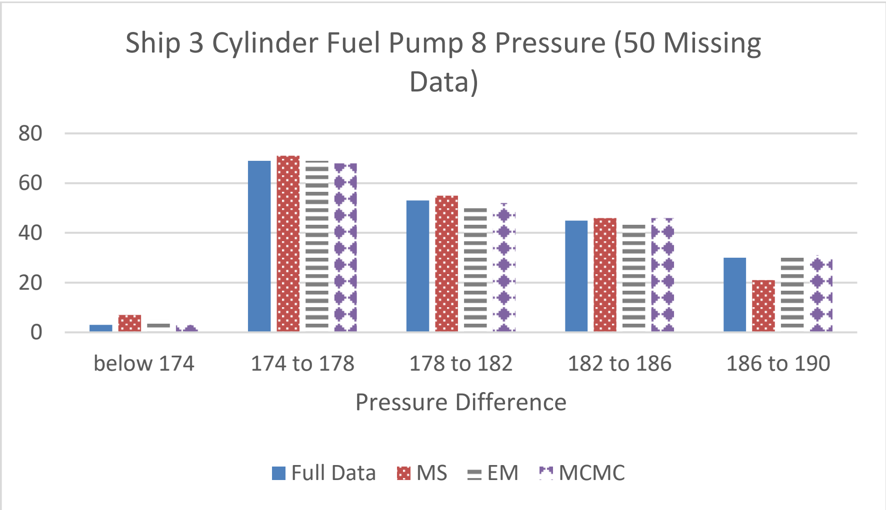

Figure 39 - Data Treatment Comparison for Ship 3 with 50 Missing Data

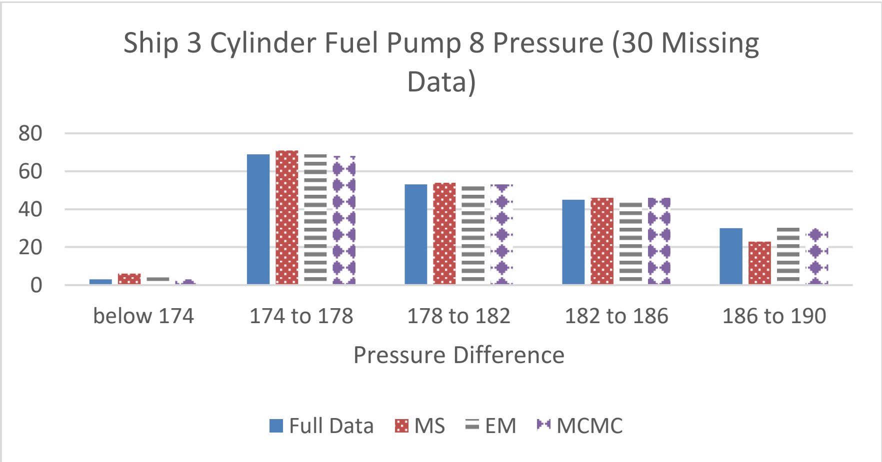

Figure 40 - Data Treatment Comparison for Ship 3 with 30 Missing Data

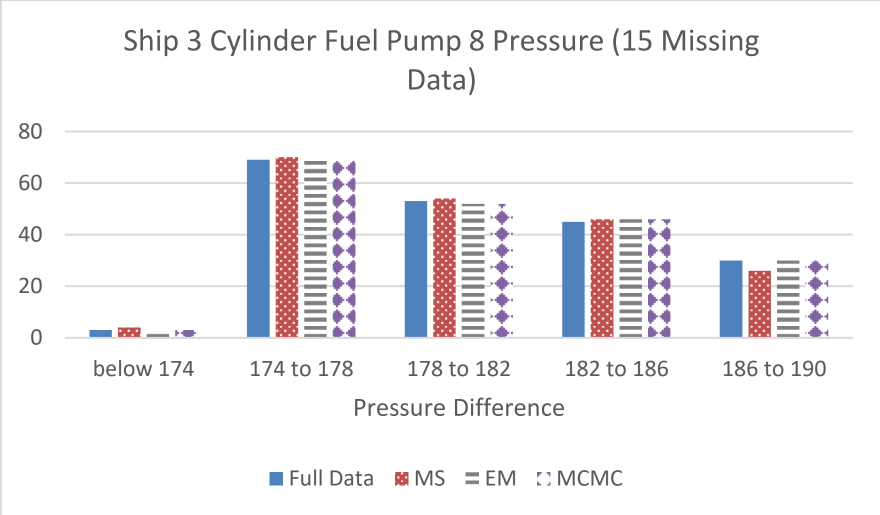

Figure 41 - Data Treatment Comparison for Ship 3 with 15 Missing Data

Finally, for the selected MCMC multiple imputation technique, the difference in accuracy of the data treatment was compared for three, four, five, six and seven iterations. Results of these comparisons are highlighted in Table 26 and Figures 42, 43 and 44. In Table 26 Column 3 represents standard deviation and the mean for full data whereas from Columns 4 - 8 standard deviations and mean values of the MCMC method with three to seven iterations are illustrated. On all figures, the x-axis represents the specific factorised data value categories and the y-axis represents the number of data available on each factorised data category.

It can be determined from these figures and the table generally that the accuracy change after five iterations does not change much. For example, from Table 25 it can be observed that standard deviation of the scavenge air in temperature data after three iterations is 1.60896, after four iterations is 1.61167, after five iterations is 1.61276 and after six iterations is 1.61276. It can be noticed that the difference between five and six iterations is much smaller than it is with three and four iterations. Standard deviation five and six iterations are also closer to full data value of 1.6147. This is also the case for the other two examples. A similar conclusion can be determined from Figures 42, 43 and 44, where five iteration results shown with the amber bar chart colour is relatively close to full data points shown by the blue bar chart colour. Therefore, it was decided to use five iterations for all of the data missing data treatments in order to minimise calculation efforts.

Table 25 - Comparison of Number of Iterations of MCMC Multiple Imputation Technique for 50 Missing Data

Measurement Reading Type	Data Distribution Information	Full Data	3 Iterations	4 Iterations	5 Iterations	6 Iterations	7 Iterations
Ship 1 Scavenge Air In Temp.	Standard Deviation	1.6147	1.60896	1.61167	1.61263	1.61276	1.62778
	Mean	177.66	177.71	177.69	177.68	177.68	177.68
Ship 2 T/C Exhaust Out Temp.	Standard Deviation	6.367	6.3758484	6.3731145	6.3711898	6.3711799	6.3711788
	Mean	439.905	440.534	440.21	440.004	440.004	440.003
Ship 3 Cylinder Fuel Pump Pres.	Standard Deviation	4.52428	4.501574	4.505738	4.509856	4.509867	4.509869
	Mean	179.865	180.048	179.972	179.913	179.911	179.911

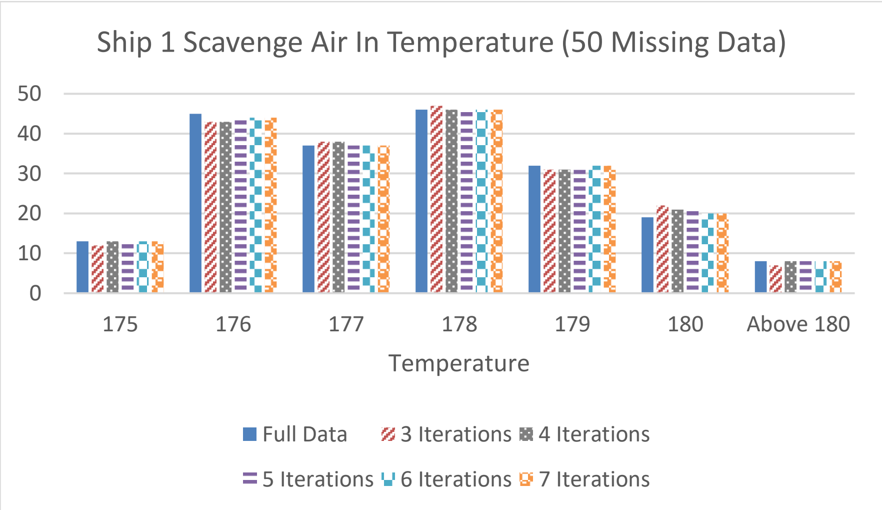

Figure 42 - Comparison of Number of Iterations of MCMC Multiple Imputation Technique for 50 Missing Data for Ship 1

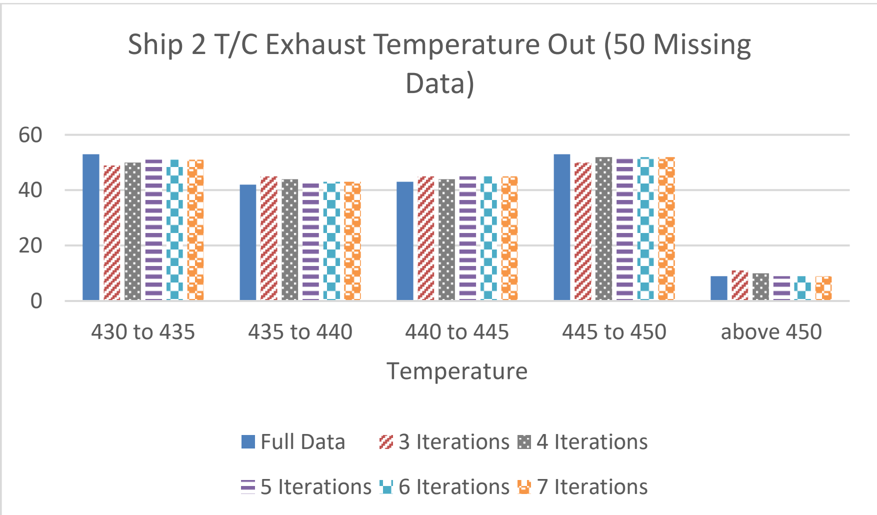

Figure 43 - Comparison of Number of Iterations of MCMC Multiple Imputation Technique for 50 Missing Data for Ship 2

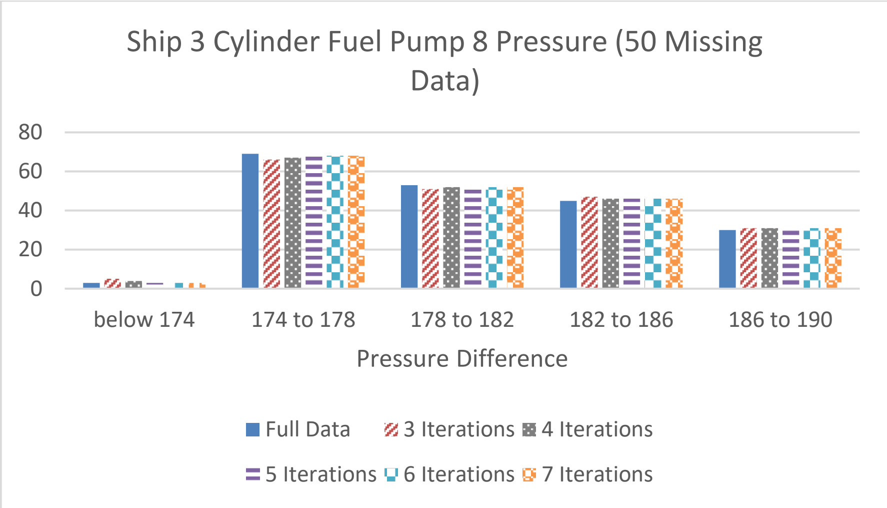

Figure 44 - Comparison of Number of Iterations of MCMC Multiple Imputation Technique for 50 Missing Data for Ship 3

In summary, MCMC missing data treatment method with five iterations was the chosen method of dealing with missing data points for each reading used within the PAU model to predict the future condition of each sub-system/component within the chosen machinery systems. The next section will demonstrate the full PAU and DAU analysis results in more detail.

6.3 Overall Analysed Performance and Cost Probability Results

This section will illustrate the overall calculated performance index prediction and cost predictions for the component and sub-systems for all three ship case studies for the three observed systems of lube-oil system, fuel-oil system and turbochargers. All data analysed follow the overall data treatment and analysis rules mentioned in the previous section. Time-periods indicated by periods 1,2,3,4,5, and 6 are representative of Jan-Apr 2015, May-Aug 2015, Sep-Dec 2015, Jan-Apr 2016, May-Aug 2016 and Sep-Dec 2016 three month observed time-periods respectively. These time-periods are all dependent upon the first month that the measurement started and can change accordingly. Some of the analysed results of the performance index values for the systems with negligible performance degradations are demonstrated in Appendices B and C.

All the cost values shown on the graphs are actually net cost values where they represent the cost difference between maintenance and no maintenance. This represents whether undertaking maintenance will be beneficial or not. Therefore, a positive cost benefit value would mean it would cost the company extra if they undertake maintenance. However, a negative value would mean that the benefit of undertaking maintenance is high and it would potentially save the company money (due to increase in performance of the overall system and/or elimination of a possible failure). Additionally, due to the relatively low observation time of less than two years, the overall effect of possible interest rates is assumed to be minimal and no discount factor has been used within the cost calculations.

6.3.1 Lube-oil System

The lube-oil system of Ship 1 only had two major sub-systems/components with major degradation in their overall performance. Lube-oil Filter 2 of Ship 1, as seen from Figure 45, observed performance index degradation from 91% to 76%. This means that, on average, during 76% of the observed period, Filter 2 was operating under satisfactory conditions determined by OEM reports and company MPIs. Using the DBN tool of the BOPM methodology, general degradation of the performance index was calculated for the next four time-periods. Comparing the predicted results with actual observed data, it was determined that the general error is relatively low.

Using the utility and decision nodes of the DBN tool and monetary values determined from the company MPIs, cost data and experts' opinions, the overall cost difference between the cost of having action compared with cost of failure was calculated for all the performance index values and plotted on the graph shown on Figure 46. It can be noticed that cost difference value after time-period three becomes negative. This means that, from a cost point of view, cost of possibility of failure is higher than the cost of maintenance or repair. This means that maintenance, or in this case replacement of filter, is recommended. Observed performance index cost values also results in similar determined outcomes as predicted values. This recommended result was compared with ship maintenance logs, and it was found that lube-oil filter 2 was replaced in February 2016. This proves the accuracy of the decision provided by the analysis. Similar analysis and prediction of performance index and cost data with comparison to observed values and maintenance logs was performed for all sub-systems/components from all three vessels and three major machinery systems.

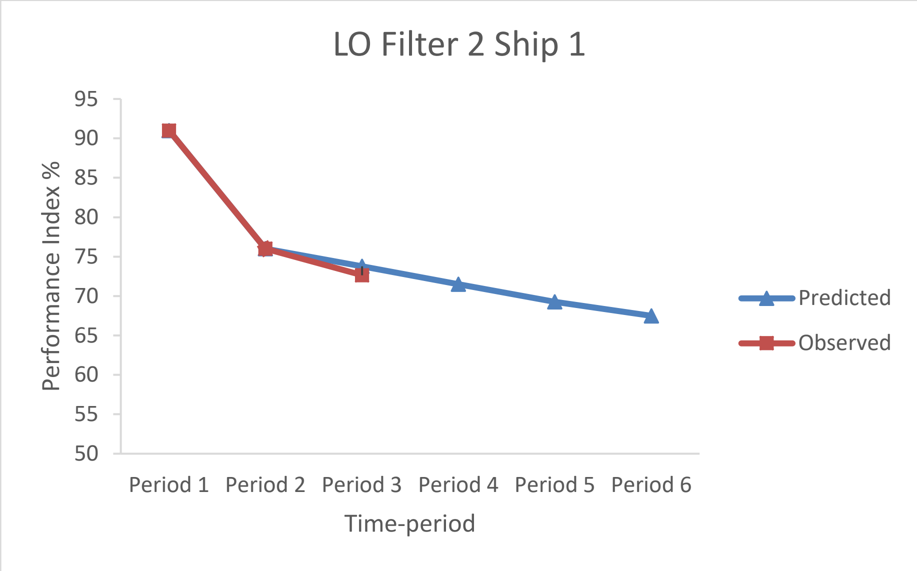

Figure 45 - Lube-oil Filter 2 Probabilistic Performance Prediction for Ship 1

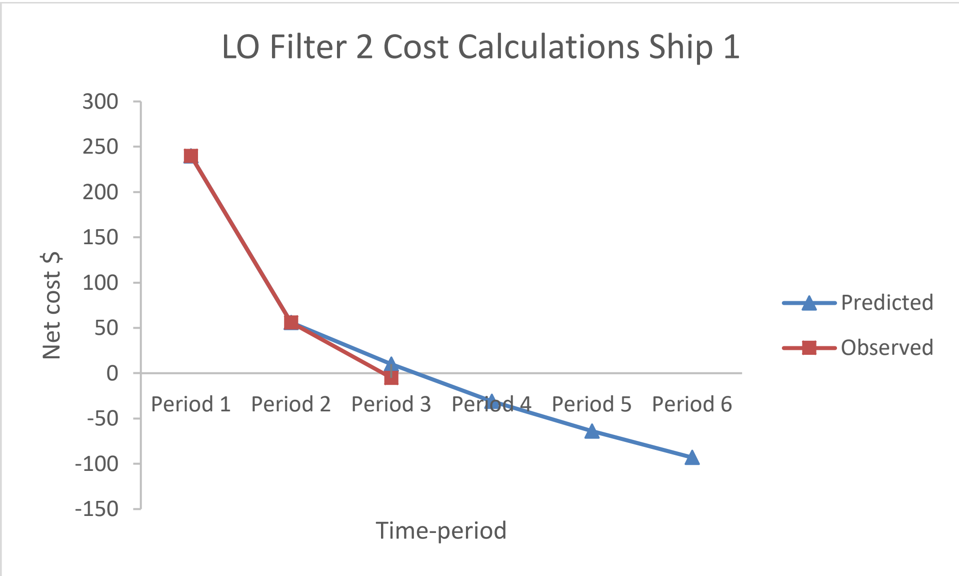

Figure 46 - Lube-oil Filter 2 Net cost Difference Prediction for Ship 1

The lube-oil pump of Ship 1 had an observed degradation of its performance index from 92% to 76% (Figure 47). It was then determined that overall performance index at the end of the fourth predicted time-period will be 73.2%, which is relatively close to the 72.3% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 48. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $710, which is very close to the observed value of $670. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

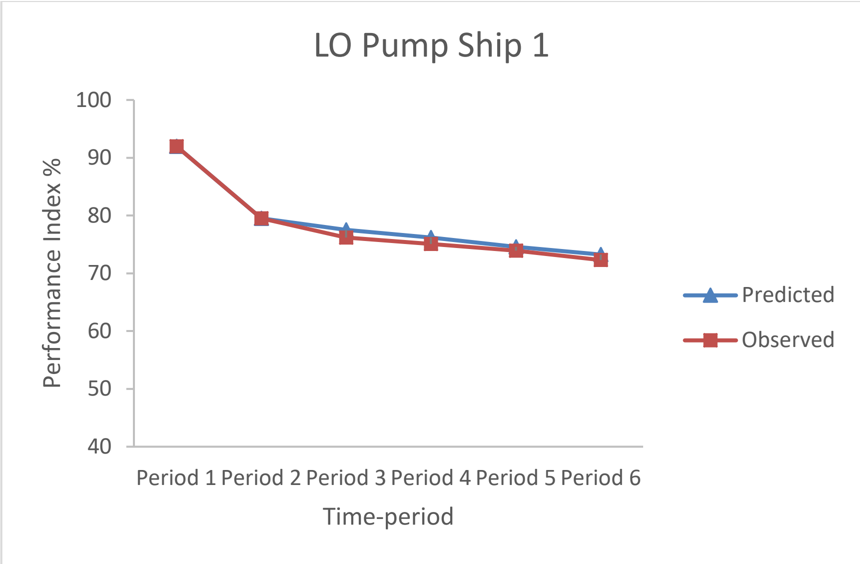

Figure 47 - Lube-oil Transfer Pump Probabilistic Performance Prediction for Ship 1

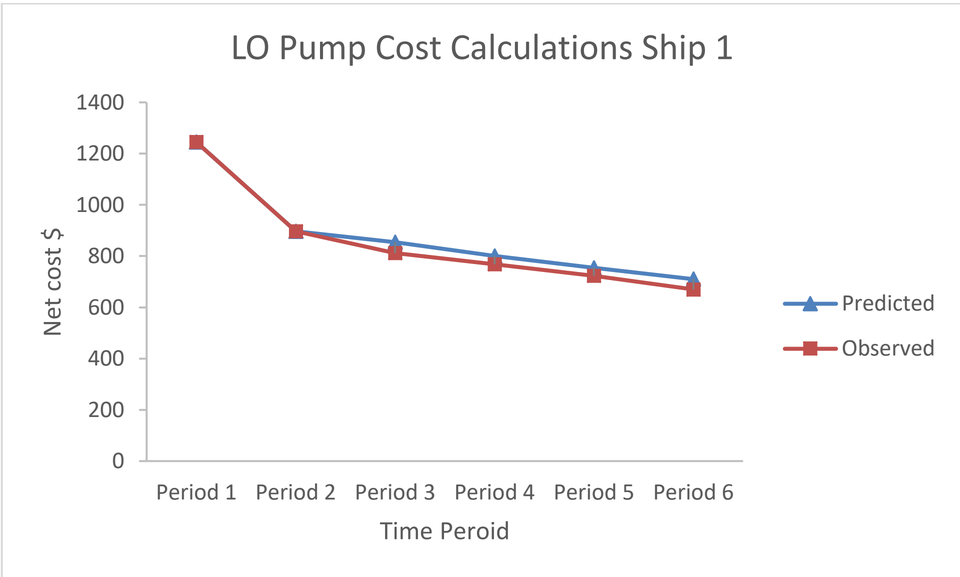

Figure 48 - Lube-oil Transfer Pump Net cost Prediction for Ship 1

The lube-oil system of Ship 2 also had only two sub-systems/components with major performance deterioration. Firstly, lube-oil filter 1 of Ship 2 had an observed degradation of its performance index from 94.5% to 87.2% (Figure 49). It was then determined that overall performance index at the end of the fourth predicted time-period will be approximately 79%, which is relatively close to the 79.5% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 50. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $15, which is very close to the observed value of $22.

Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. However, these values are very close to zero and overall angle of deterioration is high, which means that there is high possibility of maintenance replacement being required after December 2016. This was later proved correct as on the PMS schedule of the ship, a replacement of lube-oil filter 1 was scheduled for late January 2017.

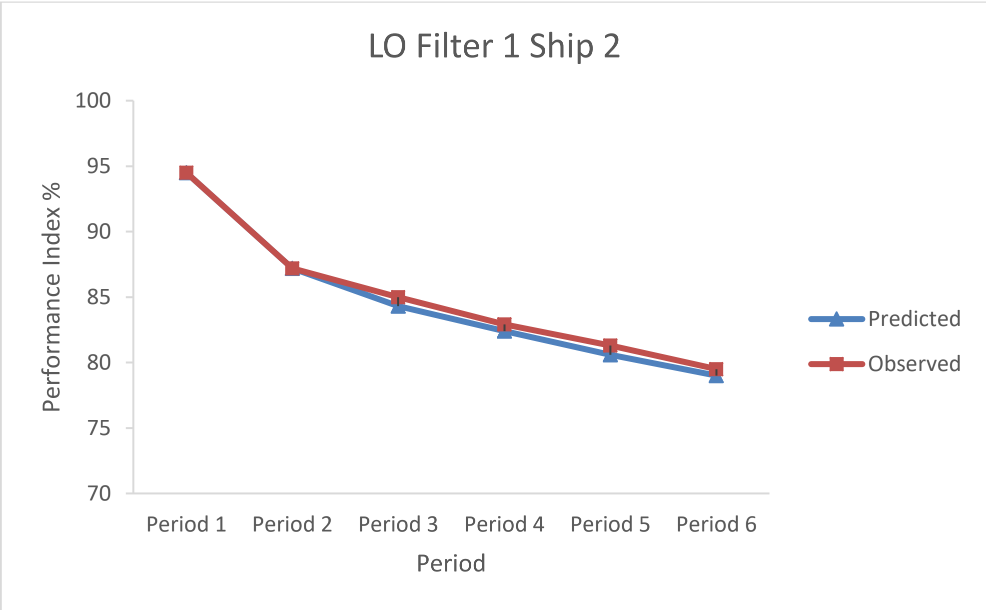

Figure 49 - Lube-oil Filter 1 Probabilistic Performance Prediction for Ship 2

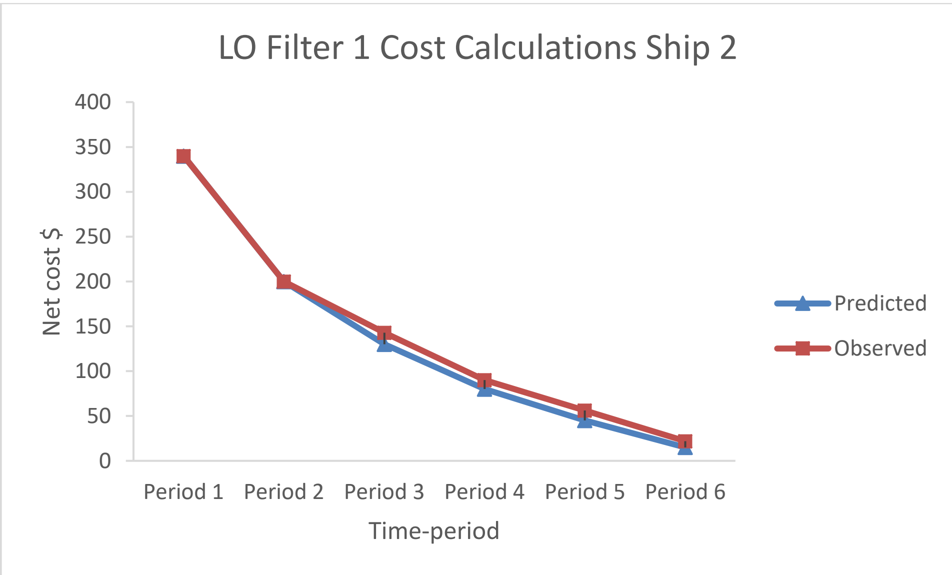

Figure 50 - Lube-oil Filter 1 Net cost Prediction for Ship 2

Secondly, the lube-oil purifier of Ship 2 had an observed degradation of its performance index from 99.4% to 98.7%, which is relatively low (Figure 51). It was then determined that the overall performance index at the end of fourth predicted time-period will be approximately 97.6%, which is the same as the observed performance index value. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 52. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $4110. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. The predicted and observed values have the same outcome values at the end of the fourth predicted time-period, which shows the accuracy of the tool. However, in between, especially at the first and second time-periods, there is a higher gap. This could be because of other deteriorations within the system or general operational conditions may have been slightly different than those predicted.

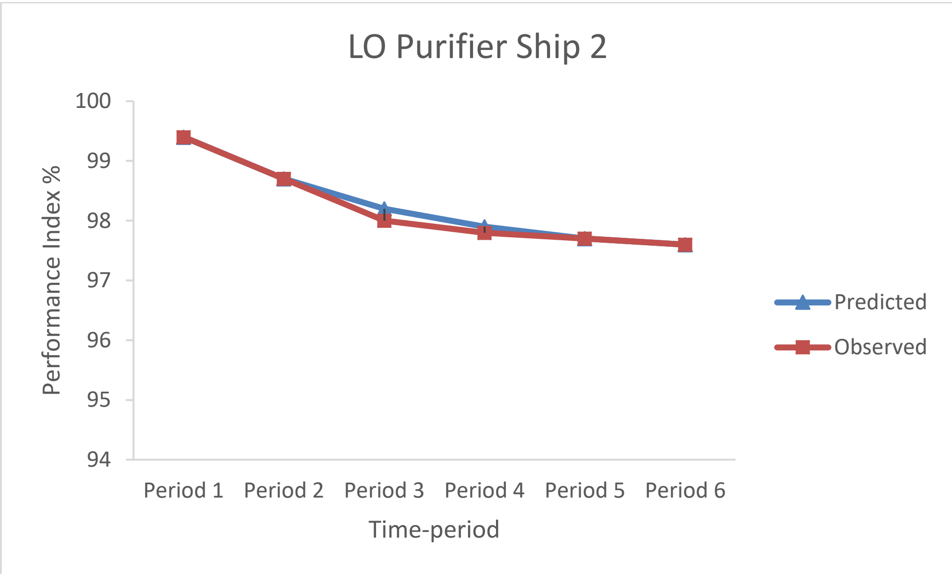

Figure 51 - Lube-oil Purifier Probabilistic Performance Prediction for Ship 2

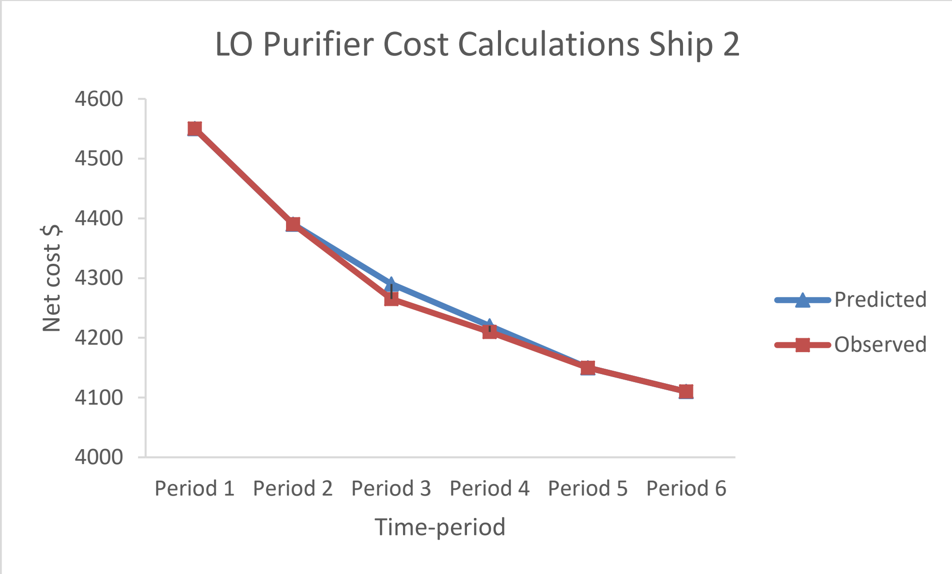

Figure 52 - Lube-oil Purifier Net cost Prediction for Ship 2

The lube-oil system of Ship 3 had three sub-systems/components with major performance deterioration. Firstly, lube-oil filter 1 of Ship 3 had an observed degradation of its performance index from 96.7% to 91% (Figure 53). It was then determined that overall performance index at the end of the fourth predicted time-period will be approximately 83.3%, which is relatively close to the 82.2% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined on Figure 54. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $175, which is very close to the observed value of $162. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. Predicted values are slightly lower at the beginning of the prediction period and then go slightly higher than the observed values but overall have very close values. This can again be due to some further errors in the system that have affected the linearity of its deterioration.

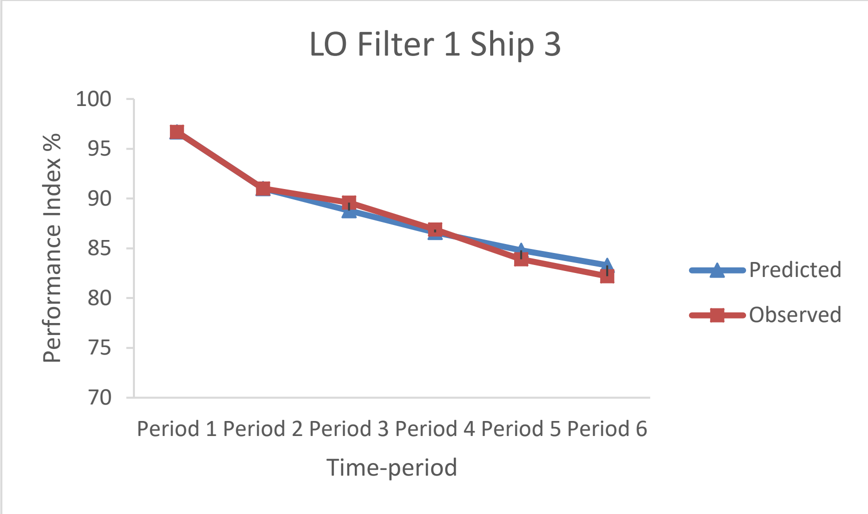

Figure 53 - Lube-oil Filter 1 Probabilistic Performance Prediction for Ship 3

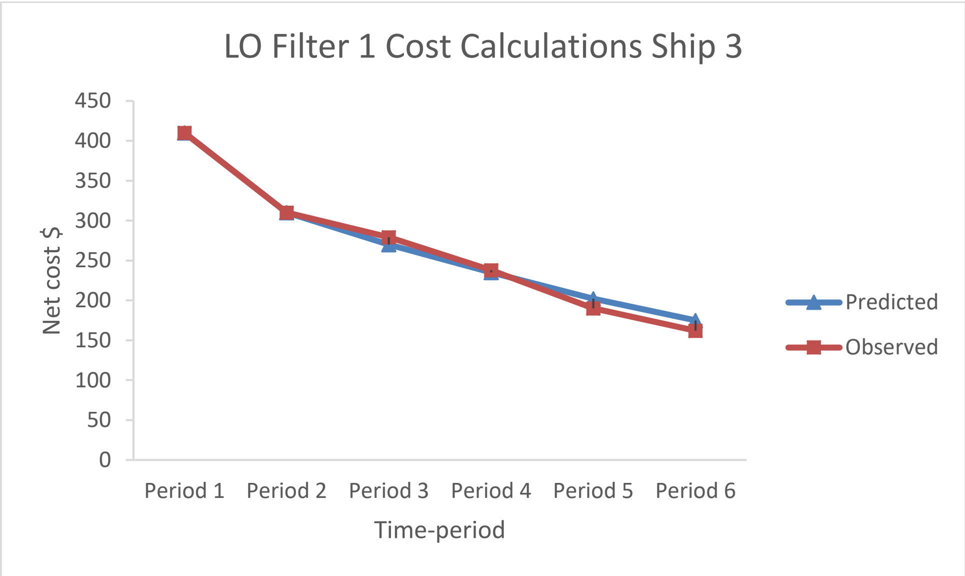

Figure 54 - Lube-oil Filter 1 Net cost Prediction for Ship 3

Secondly, lube-oil filter 2 of Ship 3 had an observed degradation of its performance index from 98.8% to 95.1% (Figure 55). It was then determined that the overall performance index at the end of the fourth predicted time-period will be approximately 89.8%, which is very close to 89.7% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined on Figure 56. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $275, which is very close to the observed value of $271. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

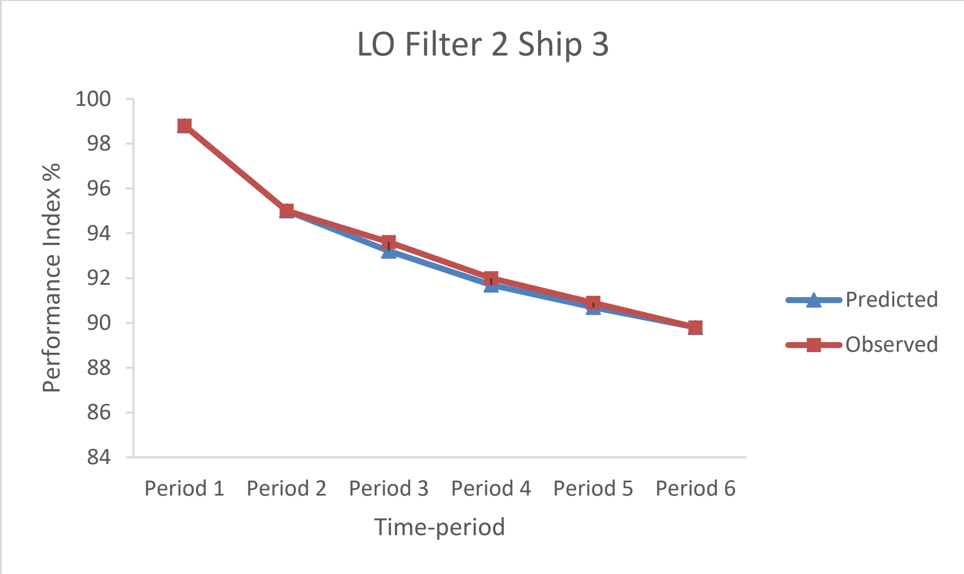

Figure 55 - Lube-oil Filter 3 Probabilistic Performance Prediction for Ship 3

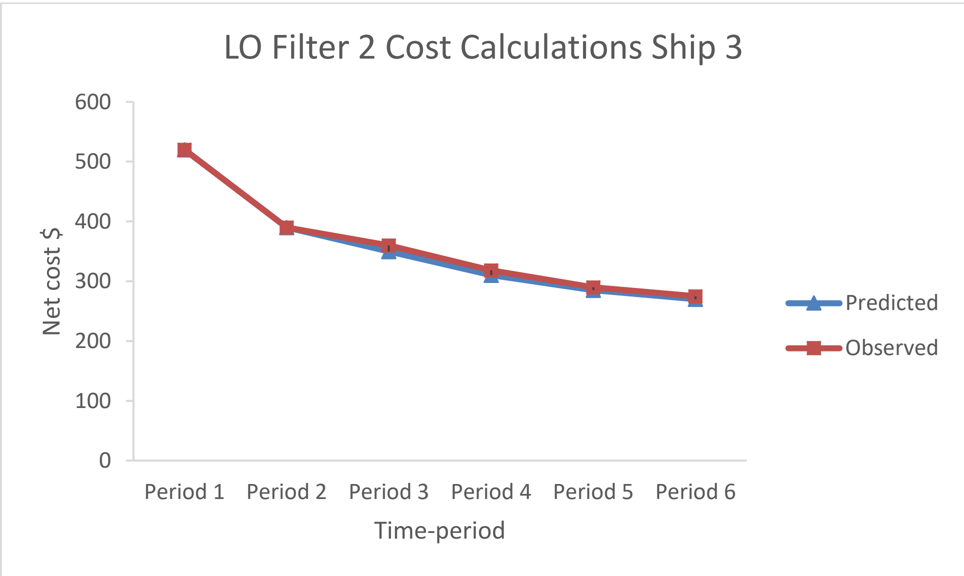

Figure 56 - Lube-oil Filter 2 Net cost Prediction for Ship 3

Thirdly, the lube-oil pump of Ship 3 had an observed degradation of its performance index from 98.7% to 93.6% (Figure 57). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 85.6%, which is decidedly close to the 85% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 58. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $880, which is highly close to the observed value of $848. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

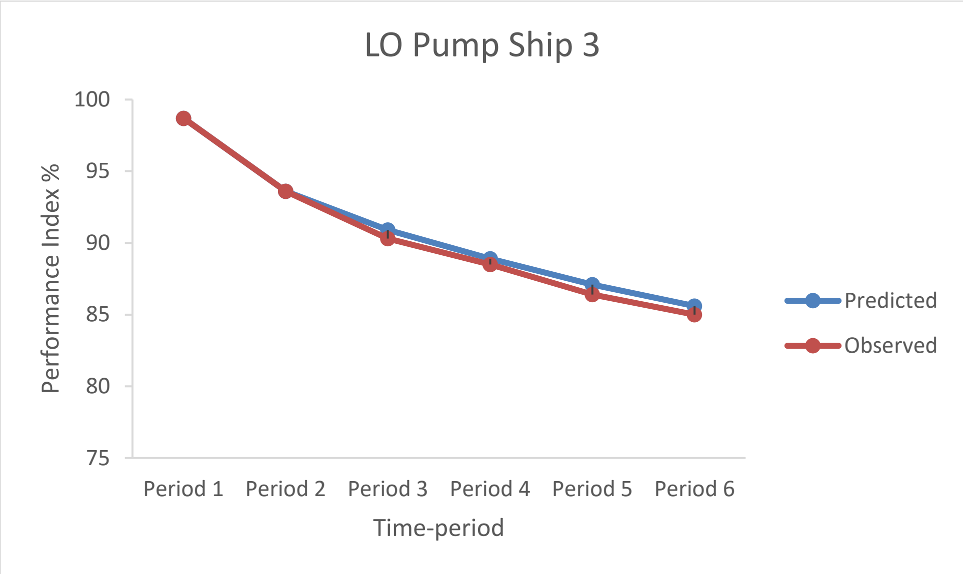

Figure 57 - Lube-oil Transfer Pump Probabilistic Performance Prediction for Ship 3

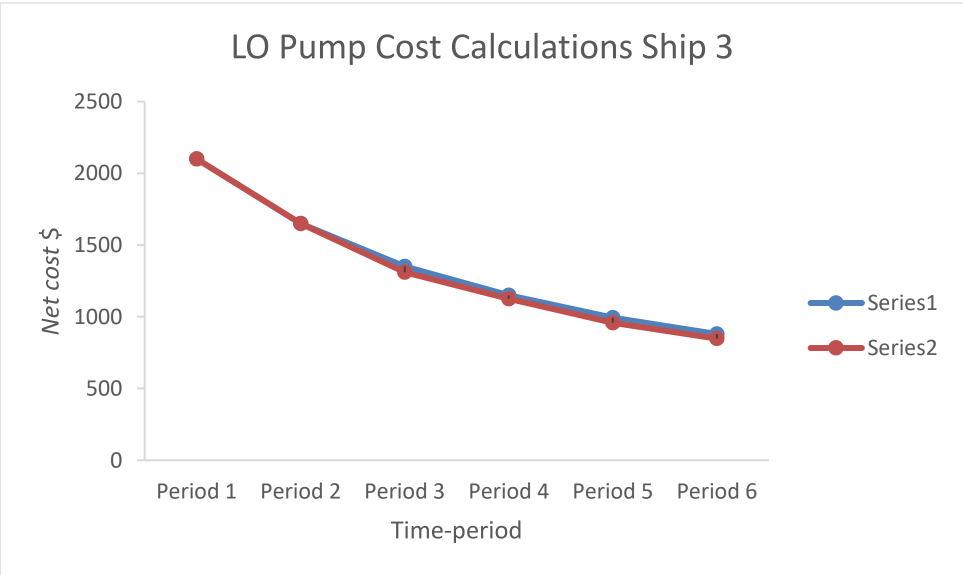

Figure 58 - Lube-oil Transfer Pump Net cost Prediction for Ship 3

6.3.2 Fuel-oil System

The fuel-oil system of Ship 1 had five sub-systems/components with major performance deterioration. Firstly, the fuel-oil purifier of Ship 1 had an observed degradation of its performance index from 83% to 66.9% (Figure 59). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 60.1%, which is very close to 59.9% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 60. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $294, which is very close to observed value of $289. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

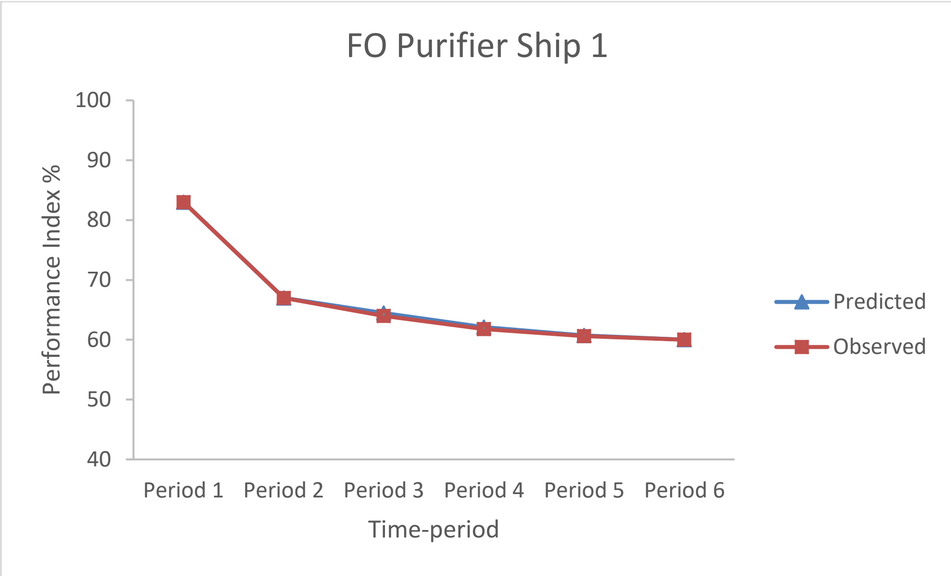

Figure 59 - Fuel-oil Purifier Probabilistic Performance Prediction for Ship 1

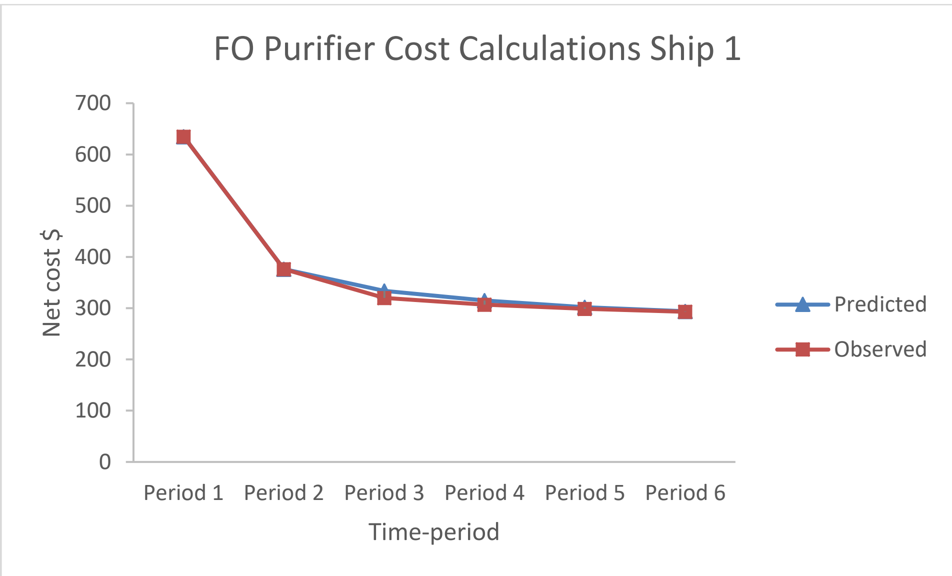

Figure 60 - Fuel-oil Purifier Net cost Prediction for Ship 1

Secondly, the fuel-oil transfer pump of Ship 1 had an observed degradation of its performance index from 91.6% to 83% (Figure 61). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 80.8%, which is very close to 81.2% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 62. It was observed that overall cost at the end of the fourth predicted time-period is still positive with a value of $823, which is relatively close to observed value of $862. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

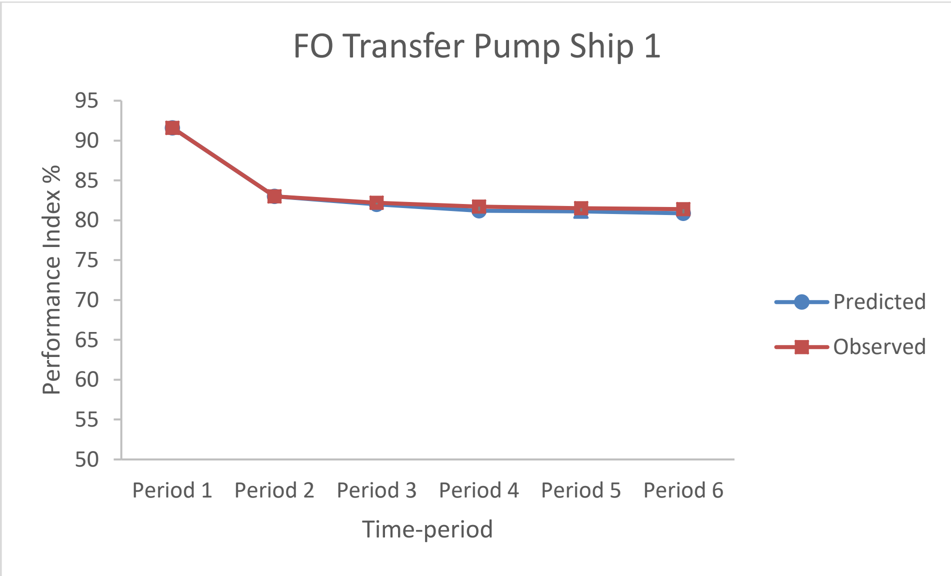

Figure 61 - Fuel-oil Transfer Pump Probabilistic Performance Prediction for Ship 1

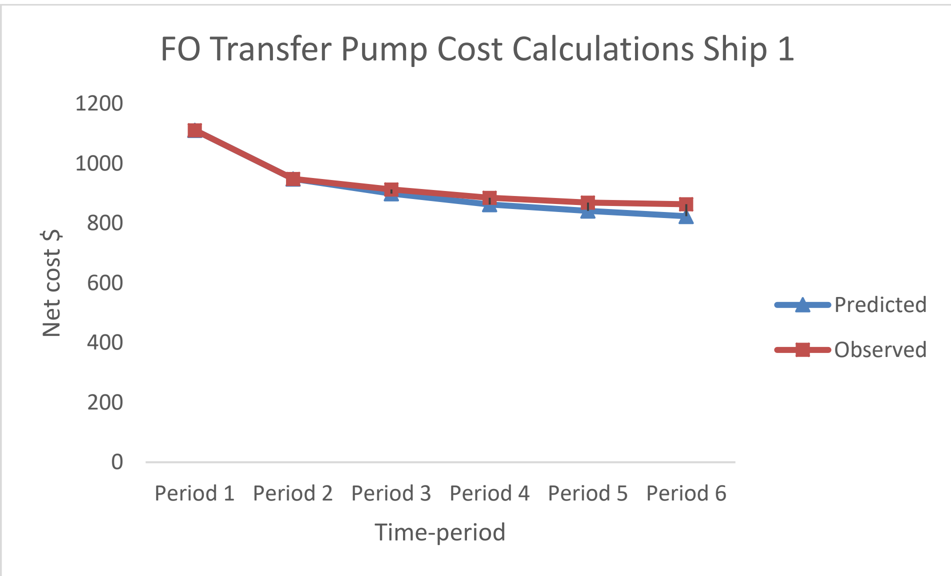

Figure 62 - Fuel-oil Transfer Pump Net cost Prediction for Ship 1

Thirdly, cylinder-1 fuel-oil pump of Ship 1 had an observed degradation of its performance index from 92.9% to 91.1% (Figure 63). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 90.3%, which is relatively close to the 90.6% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 64. It was observed that overall cost at the end of the fourth predicted time-period is positive with a value of $2112, which is very close to the observed value of $2089. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

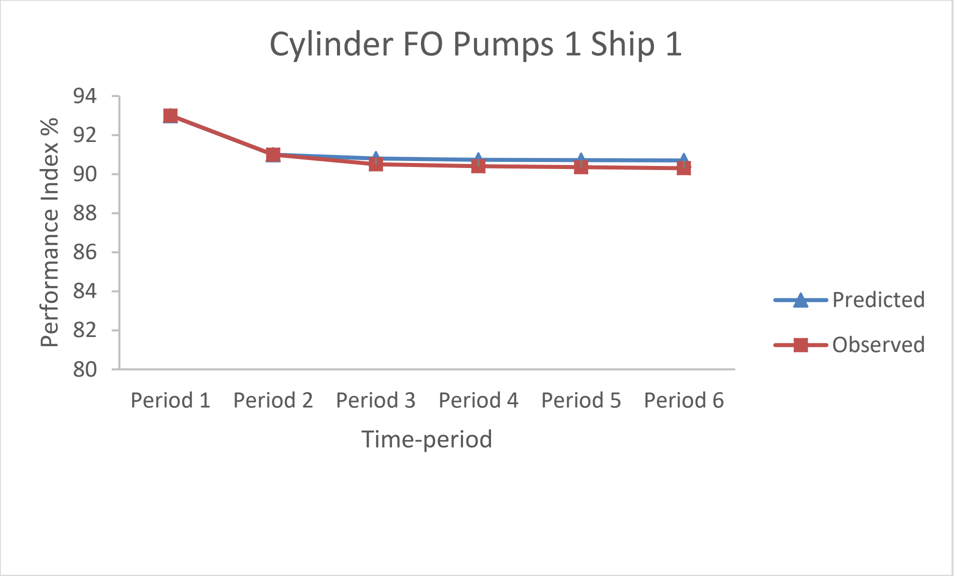

Figure 63 - Cylinder 1 Fuel-oil Pump Probabilistic Performance Prediction for Ship 1

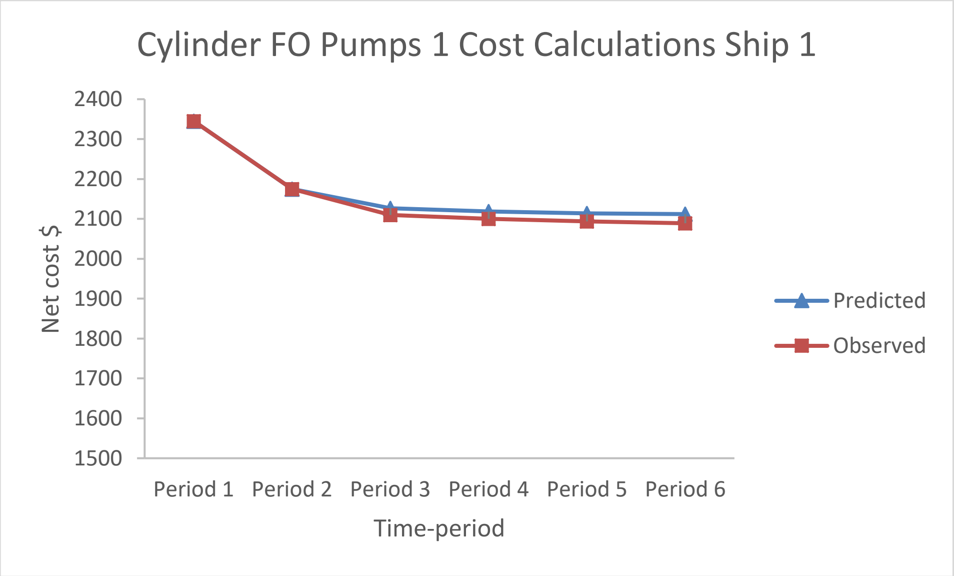

Figure 64 - Cylinder 1 Fuel-oil Pump Net cost Prediction for Ship 1

Fourthly, cylinder-4 fuel-oil pump of Ship 1 had an observed degradation of its performance index from 84.5% to 70% (Figure 65). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 62.15%. Using monetary values and calculated performance index values, overall cost difference predictions were determined on Figure 66. It was determined that from second period predicted time-period overall cost difference will be negative on both predicted and observed cost values. However, this negative value is relatively small at -$12. Therefore, if the time is not right, the maintenance of the system can be delayed as close to the third time-period as possible. This was the case as the maintenance log of the vessel proved that repair and overhaul of the cylinder-4 fuel-oil pump was carried out in June 2016.

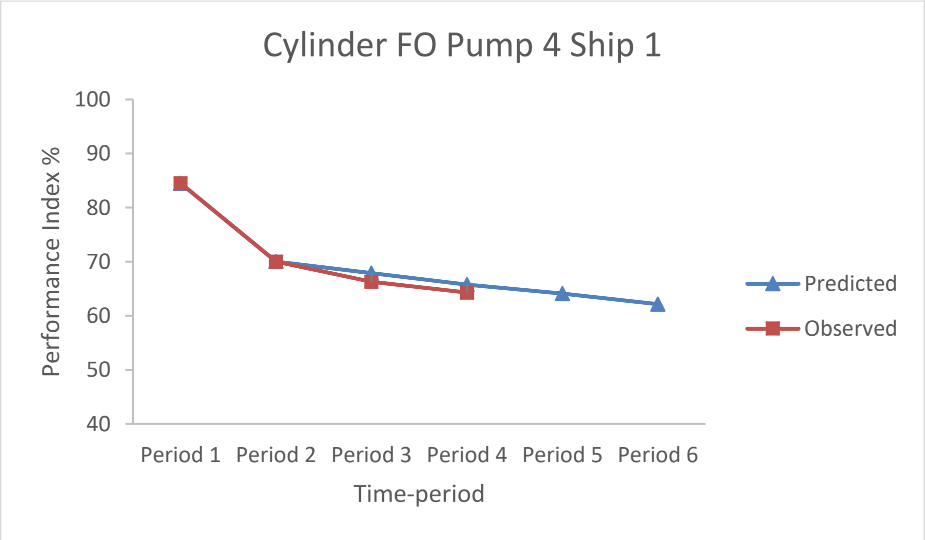

Figure 65 - Cylinder 4 Fuel-oil Pump Probabilistic Performance Prediction for Ship 1

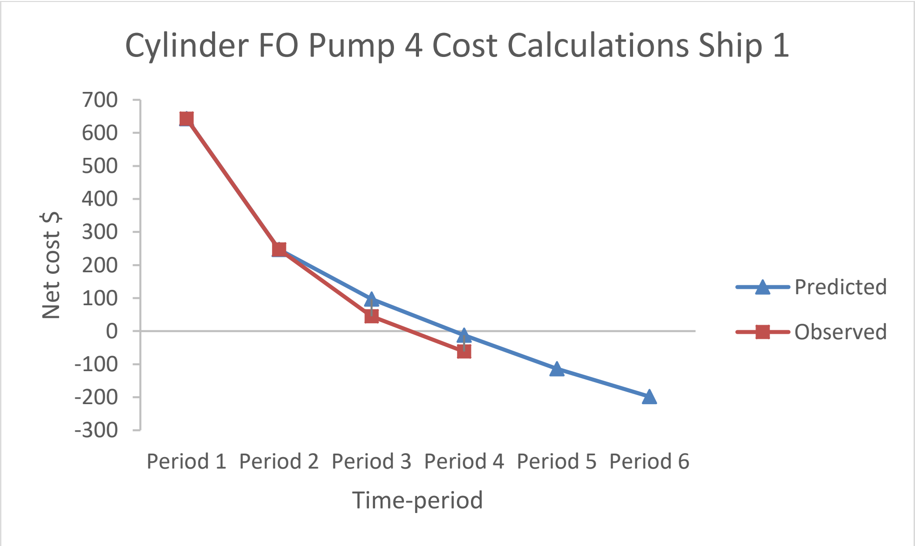

Figure 66 - Cylinder 4 Fuel-oil Pump Net cost Prediction for Ship 1

Fifthly, cylinder-1 fuel-oil pump of Ship 1 had an observed degradation of its performance index from 92% to 90.8% (Figure 67). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 89.7%, which is the same as the observed performance index value. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 68. It was observed that overall cost at the end of the fourth predicted time-period is positive with a value of $606. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. The predicted and observed values have the same outcome values at the end of the fourth predicted time-period, which shows the accuracy of the tool. However, in between, especially at the first and second time-periods, there is a larger gap. This could be due to the fact that other deteriorations within the system or general operational conditions may have been slightly different than those predicated.

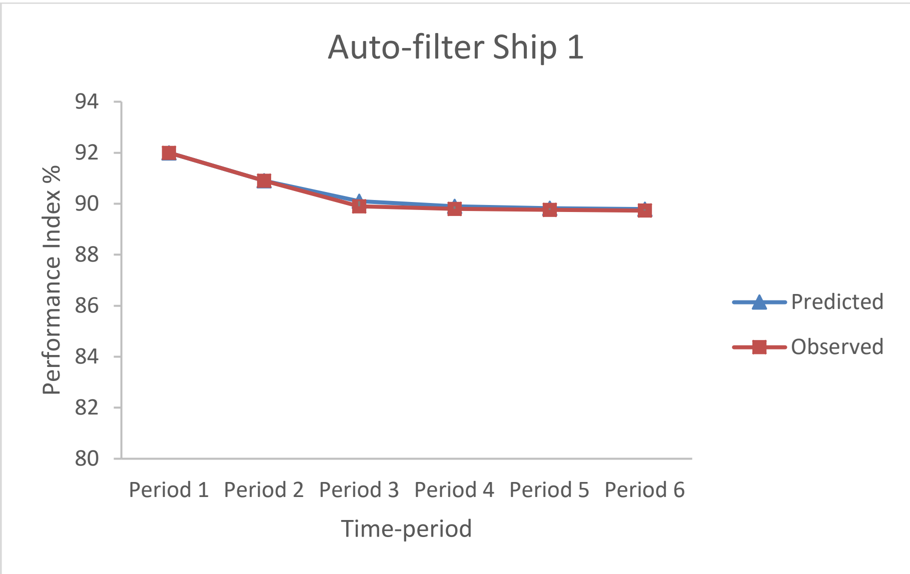

Figure 67 - Auto-filter Probabilistic Performance Prediction for Ship 1

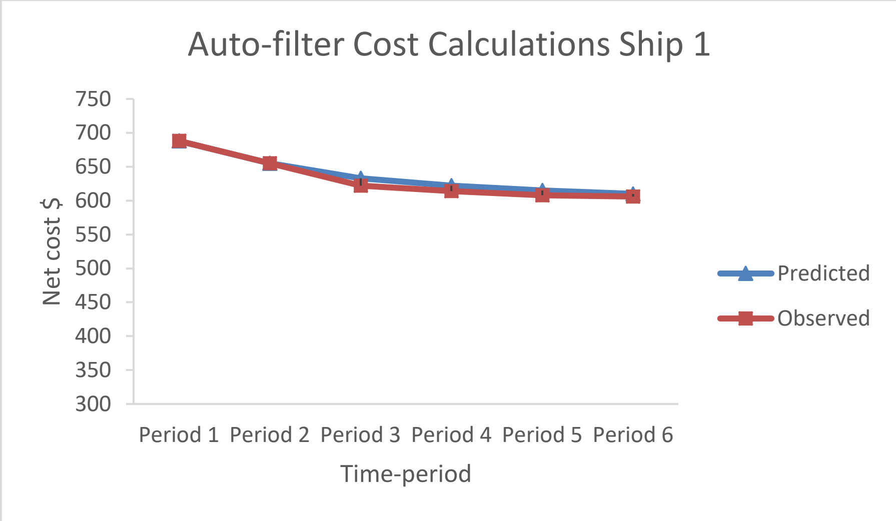

Figure 68 - Auto-filter Net cost Prediction for Ship 1

The fuel-oil system of Ship 2 also had five sub-systems/components with major performance deterioration. Firstly, cylinder-3 fuel-oil pump of Ship 2 had an observed degradation of its performance index from 98.3% to 95.4% (Figure 69). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 90.9%, which is very close to 90.7% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 70. It was observed that overall cost at the end of the fourth predicted time-period is positive with a value of $1710, which is very close to the observed value of $1695. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

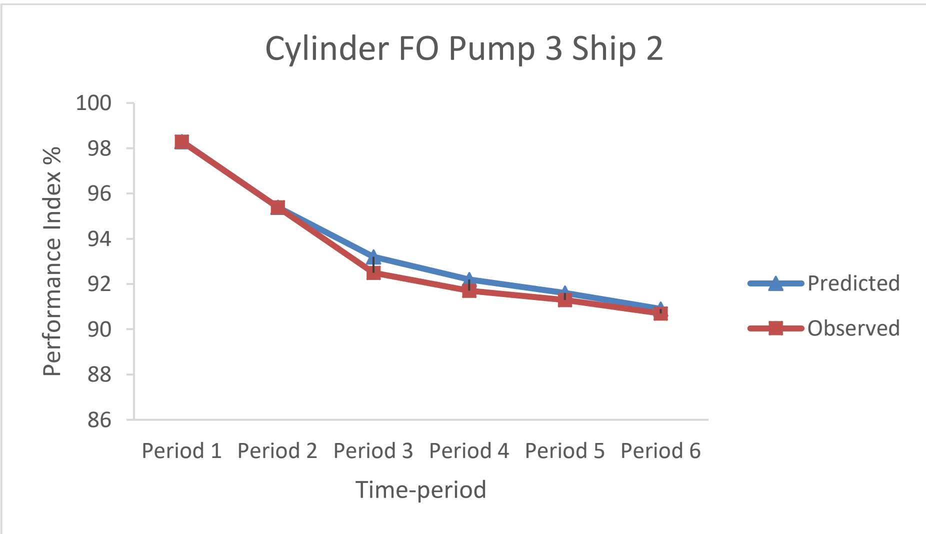

Figure 69 - Cylinder 3 Fuel-oil Pump Probabilistic Performance Prediction for Ship 2

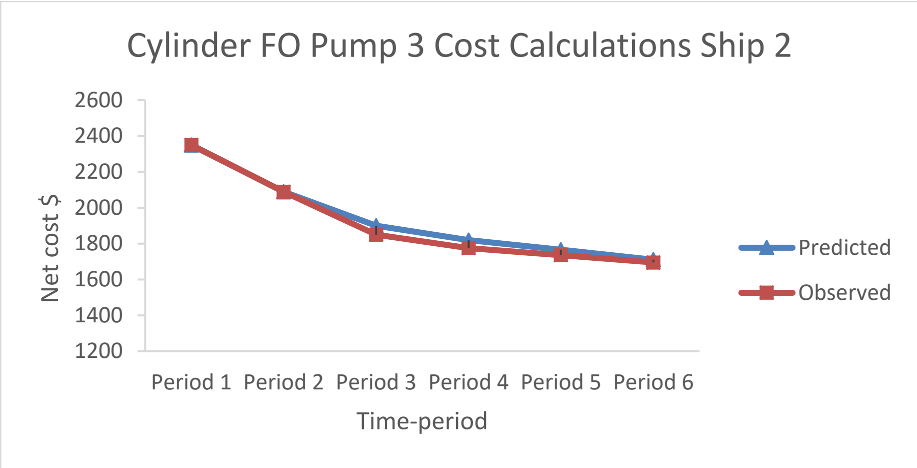

Figure 70 - Cylinder 3 Fuel-oil Pump Net cost Prediction for Ship 2

Secondly, cylinder-5 fuel-oil pump of Ship 2 had an observed degradation of its performance index from 94.7% to 88.4% (Figure 71). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 90.9%, which is very close to 90.7% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 72. It was observed that overall cost at the end of the fourth predicted time-period remains positive with a value of $655, which is relatively close to the observed value of $717. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. Predicted values are slightly higher at the beginning of the prediction period and then go slightly lower than the observed values but, overall, have very close values. This can, again, be due to some further errors in the system that have affected the linearity of its deterioration.

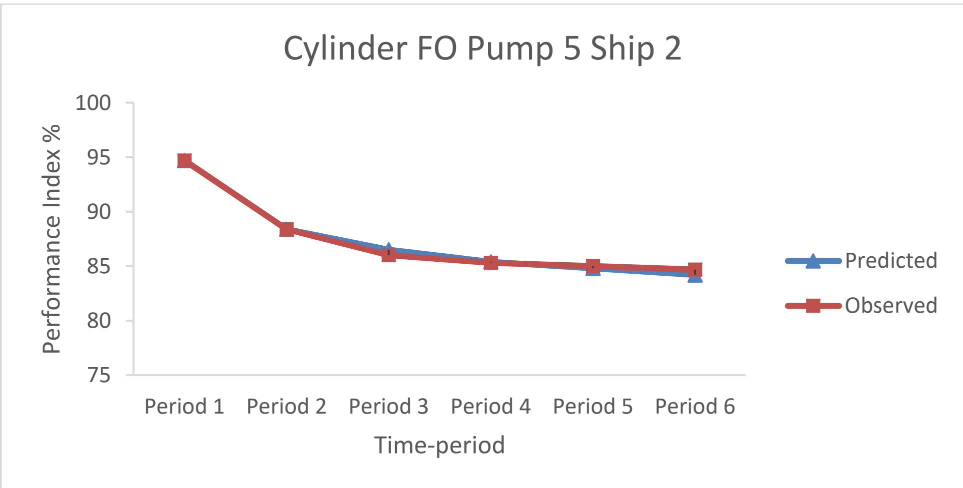

Figure 71 - Cylinder 5 Fuel-oil Pump Probabilistic Performance Prediction for Ship 2

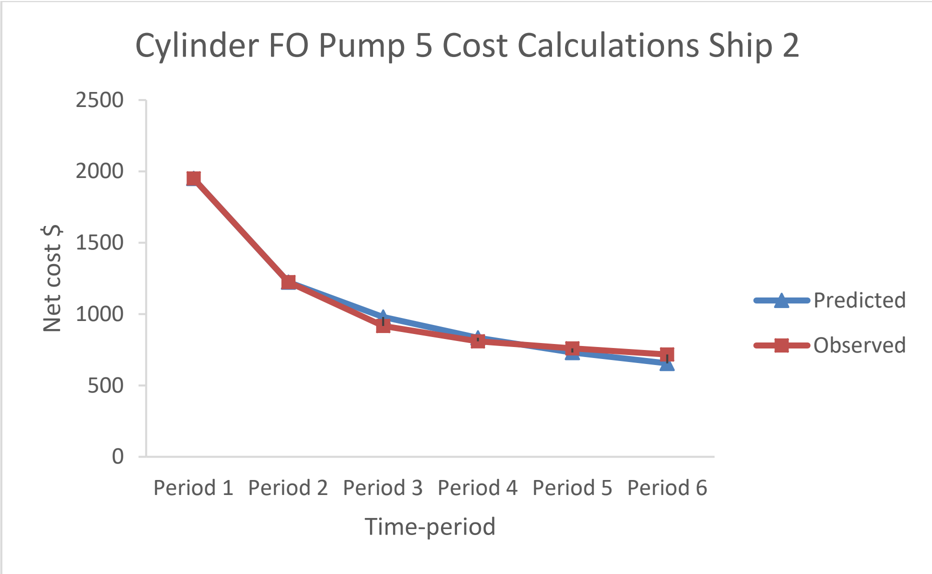

Figure 72 - Cylinder 5 Fuel-oil Pump Net cost Prediction for Ship 2

Thirdly, cylinder-6 fuel-oil pump of Ship 2 had an observed degradation of its performance index from 97.3% to 94.4% (Figure 73). It was then determined that the overall performance index at the end of fourth predicted time-period will be approximately 90.3%, which is fairly close to 90.8% observed performance index but with a slightly higher error than usual, which could be due to performance degradation on other relevant components that may have affected the overall degradation. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 74. It was observed that overall cost at the end of the fourth predicted time-period remained positive with a value of $1640, which is relatively close to the observed value of $1690. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

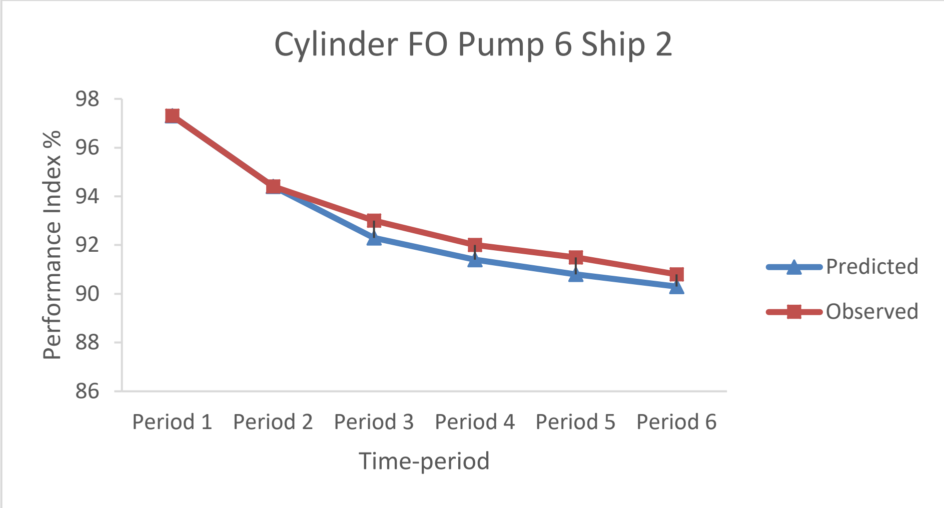

Figure 73 - Cylinder 6 Fuel-oil Pump Performance Prediction for Ship 2

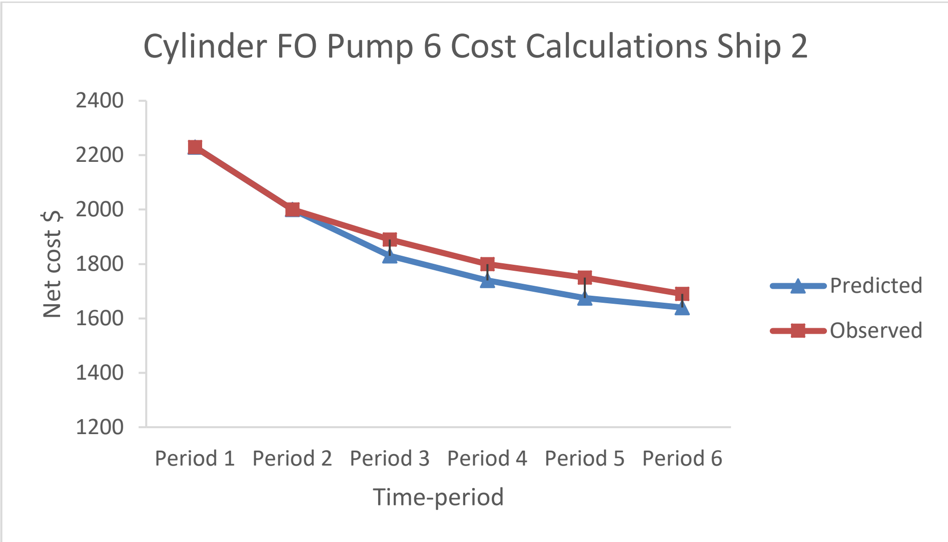

Figure 74 - Cylinder 6 Fuel-oil Pump Net cost Prediction for Ship 2

Fourthly, cylinder-5 fuel-oil pump of Ship 2 had an observed degradation of its performance index from 99.7% to 99.1% (Figure 75). It was then determined that overall performance index at the end of fourth predicted time-period will be approximately 98.1%, which is the same as the observed performance index value. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 68. It was observed that overall cost at the end of the fourth predicted time-period is still positive with a value of $950. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. The predicted and observed values have the same outcome values at the end of the fourth predicted time-period, which shows the accuracy of the tool. However, in between, especially at the first and second time-periods there is a larger gap. This could be because other deteriorations within the system or general operational conditions may have been slightly different than the predicated ones. In general, this system had a performance index with a relatively small degradation angle.

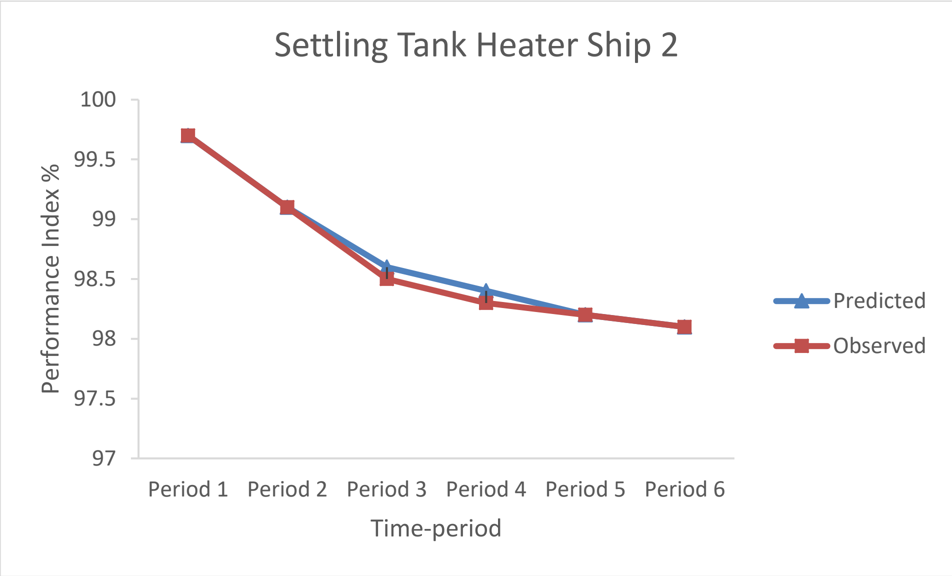

Figure 75 - Settling Tank Heater Probabilistic Performance Prediction for Ship 2

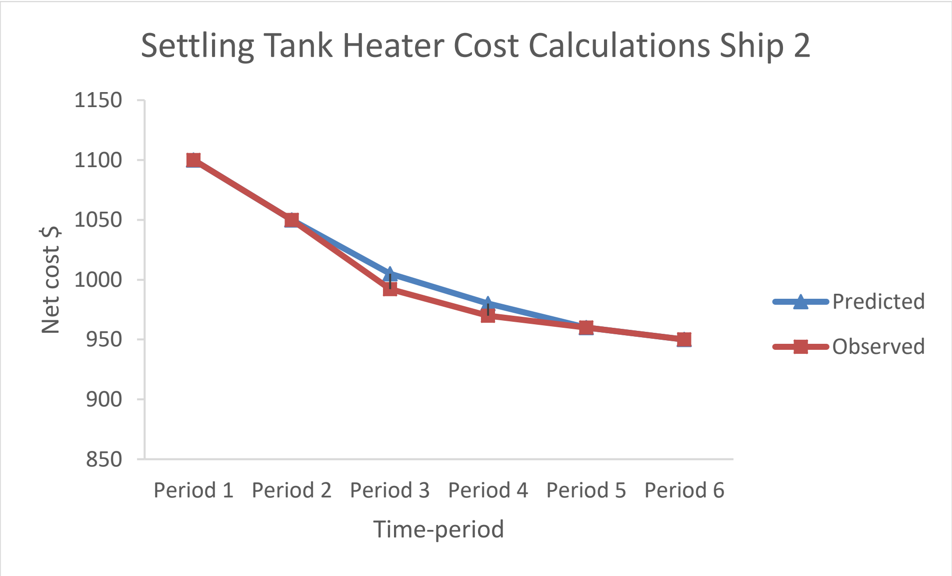

Figure 76 - Settling Tank Heater Net cost Prediction for Ship 2

Fifthly, the auto-filter pump of Ship 2 had an observed degradation of its performance index from 88.4% to 82.1% (Figure 77). It was then determined that the overall performance index at the end of fourth predicted time-period will be approximately 71.5. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 78. It was determined that from the third period the predicted time-period overall cost difference will be negative on both predicted and observed cost values. However, this negative value is relatively small at -$10. Therefore, if the time is not right, the maintenance of the system can be delayed as close to the third time period as possible. This was the case as the maintenance log of the vessel proved that replacement of the auto-filter was carried out in August 2016.

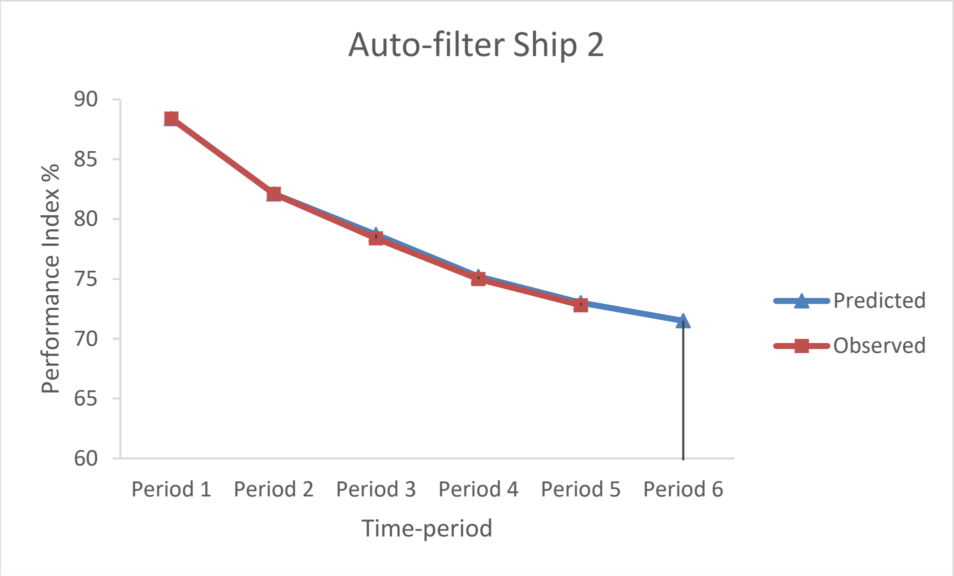

Figure 77 - Auto-filter Probabilistic Performance Prediction for Ship 2

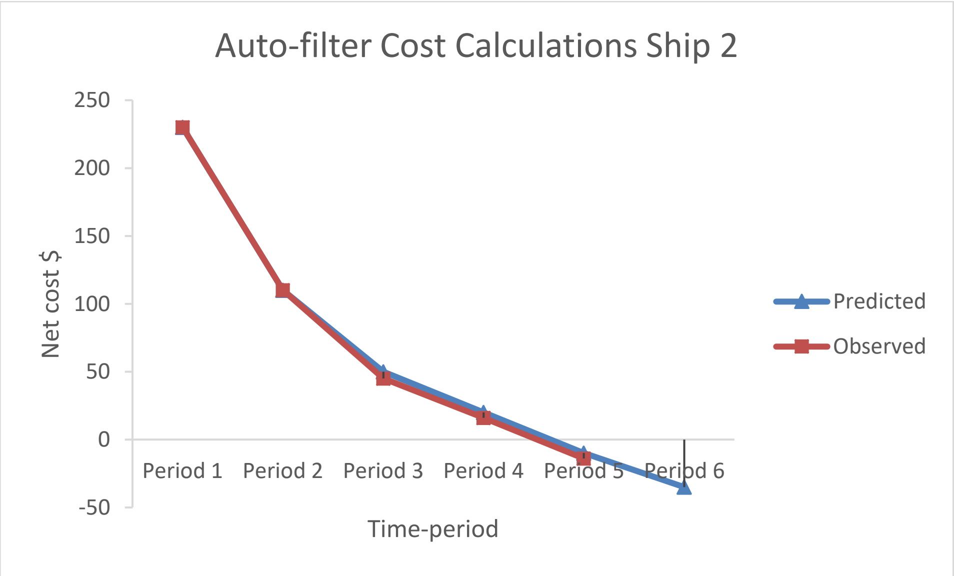

Figure 78 - Auto-filter Net cost Prediction for Ship 2

The fuel-oil system of Ship 3 had four sub-systems/components with major performance deterioration. Firstly, cylinder-2 fuel-oil pump of Ship 3 had an observed degradation of its performance index from 98.2% to 96.5% (Figure 79). It was then determined that overall performance index at the end of the fourth predicted time-period will be approximately 93.5%, which is relatively close to 93% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 80. It was observed that overall cost at the end of the fourth predicted time-period remains positive with a value of $1710, which is very close to the observed value of $1650. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. Predicted values are slightly higher at the beginning of the prediction period and then go slightly lower than the observed values but, overall, have very close values. This can again be due to some further errors in the systems that have affected the linearity of its deterioration.

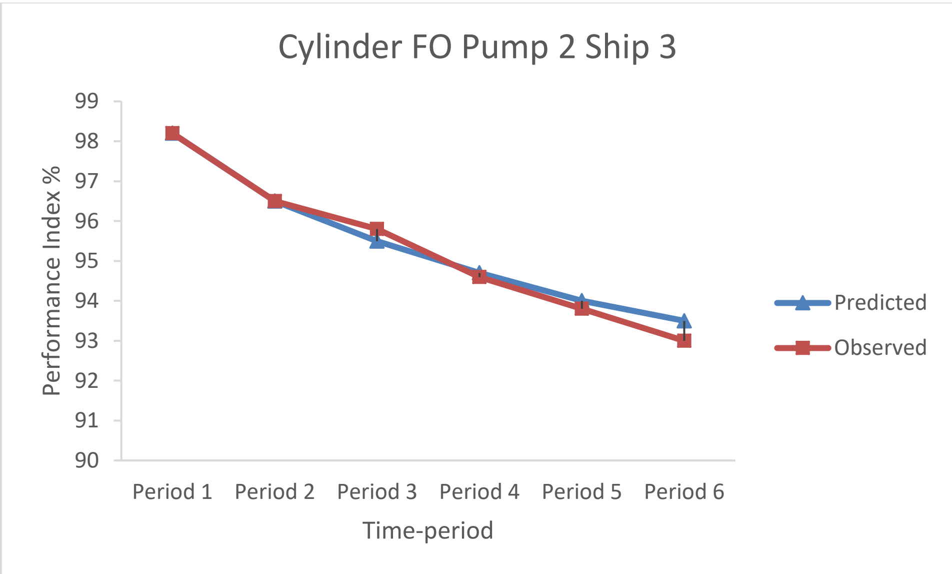

Figure 79 - Cylinder 2 Fuel-oil Pump Probabilistic Performance Prediction for Ship 3

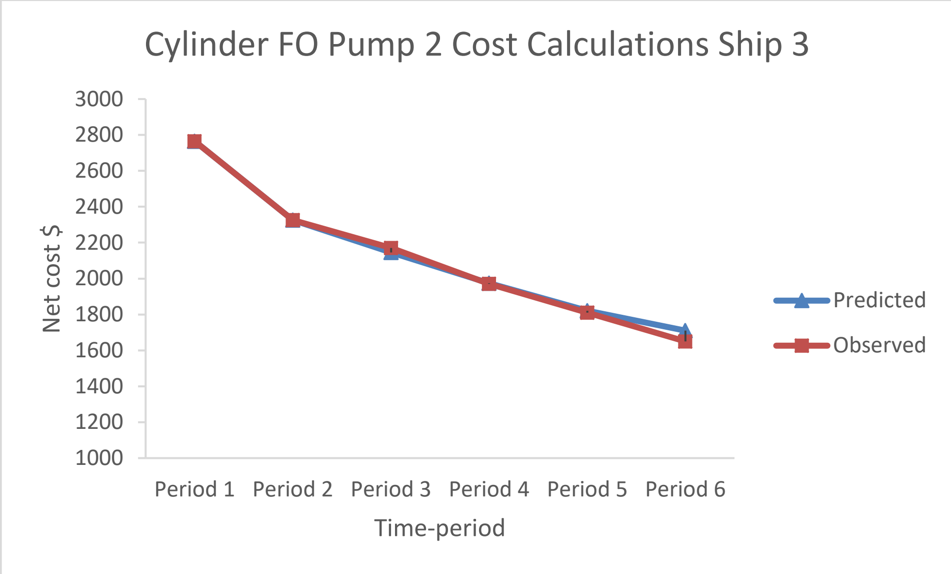

Figure 80 - Cylinder 2 Fuel-oil Pump Net cost Prediction for Ship 3

Secondly, cylinder-8 fuel-oil pump of Ship 3 had an observed degradation of its performance index from 95.4% to 91.4% (Figure 81). It was then determined that overall performance index at the end of fourth predicted time period will be approximately 84.6%, which is very close to the 84.9% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 82. It was observed that overall cost at the end of the fourth predicted time-period is still positive with a value of $1075, which is very close to the observed value of $1105. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

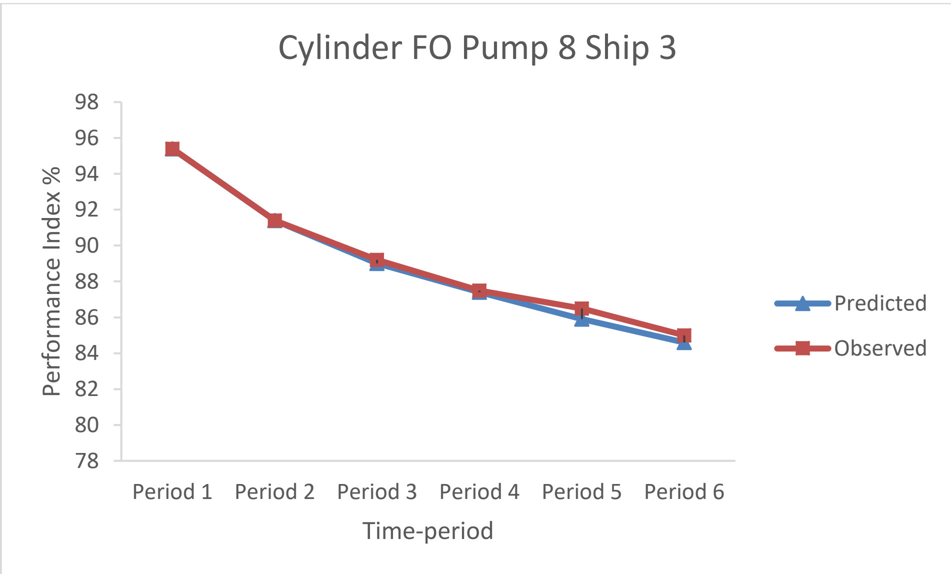

Figure 81 - Cylinder 8 Fuel-oil Pump Probabilistic Performance Prediction for Ship 3

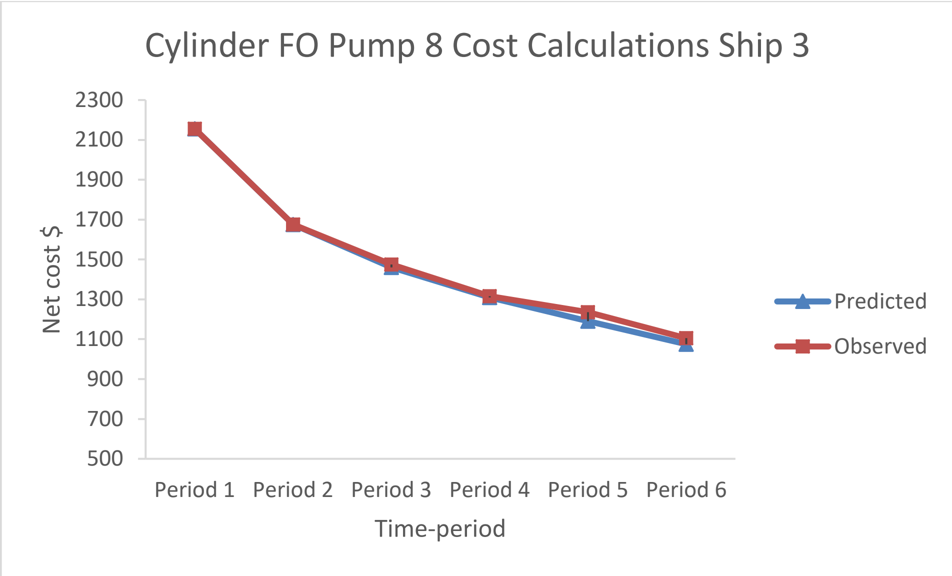

Figure 82 - Cylinder 8 Fuel-oil Pump Net cost Prediction for Ship 3

Thirdly, the auto-filter of Ship 3 had an observed degradation of its performance index from 96.6% to 92.2% (Figure 81). It was then determined that the overall performance index at the end of the fourth predicted time-period will be approximately 85.5%, which is the same as the observed performance index value. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 82. It was observed that overall cost at the end of the fourth predicted time period is still positive with a value of $195. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern. The predicted and observed values have the same outcome values at the end of fourth predicted time period, which shows the accuracy of the tool. However, in between, especially at first and second time-periods, there is a larger gap. This could be because other deteriorations within the system or general operational conditions may have been slightly different than the predicated ones. In general, this system had a relative performance index with a small degradation angle.

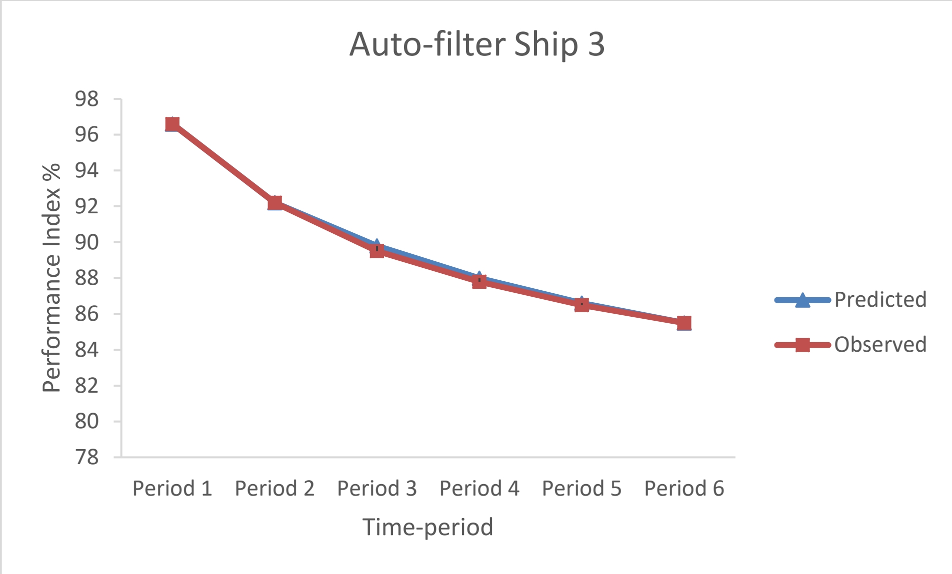

Figure 83 - Auto-filter Probabilistic Performance Prediction for Ship 3

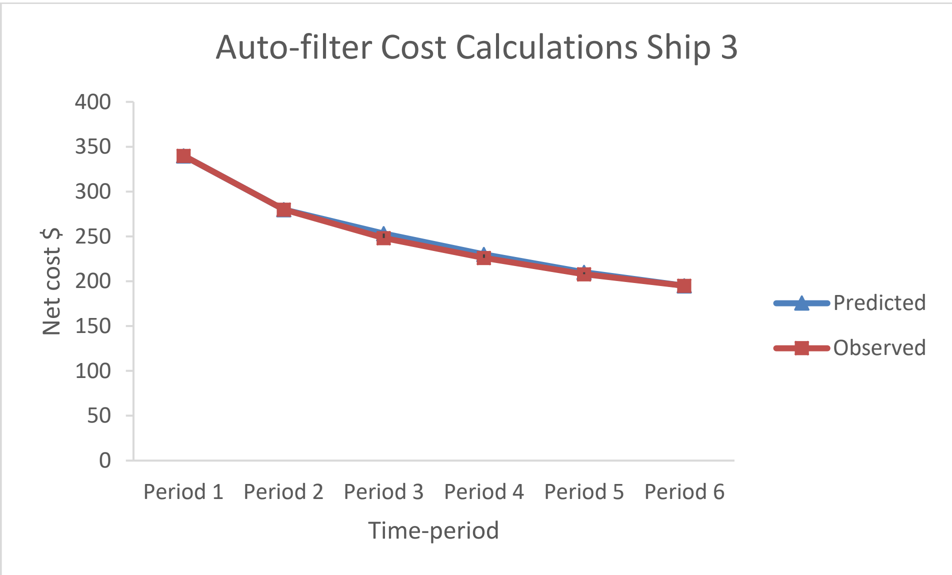

Figure 84 - Auto-filter Net cost Prediction for Ship 3

Fourthly, the fuel-oil transfer pump of Ship 3 had an observed degradation of its performance index from 99.1% to 98.2% (Figure 85). It was then determined that overall performance index at the end of the fourth predicted time period will be approximately 96.2%, which is very close to the 96.5% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 86. It was observed that overall cost at the end of the fourth predicted time period is still positive with a value of $890, which is very close to the observed value of $910. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

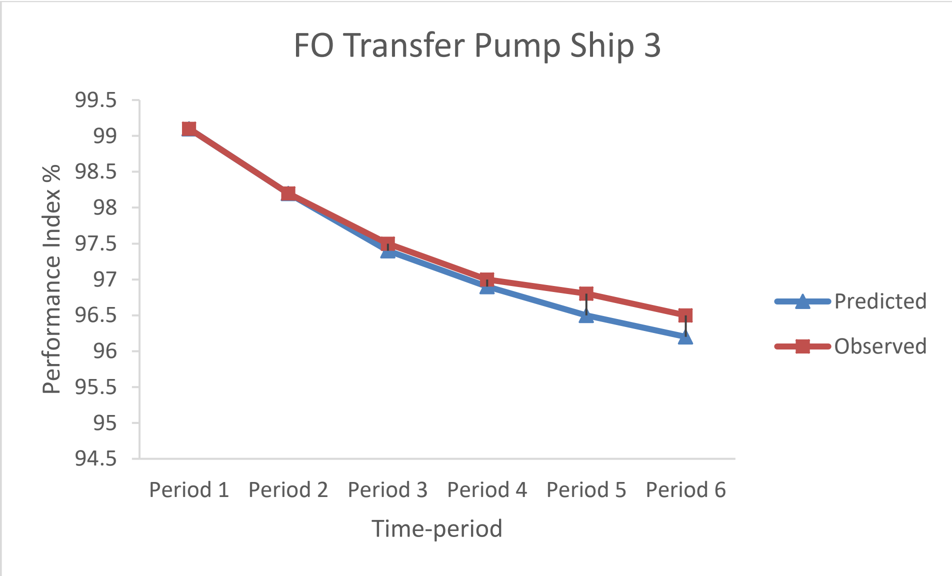

Figure 85 - Fuel-oil Transfer Pump Probabilistic Performance Prediction for Ship 3

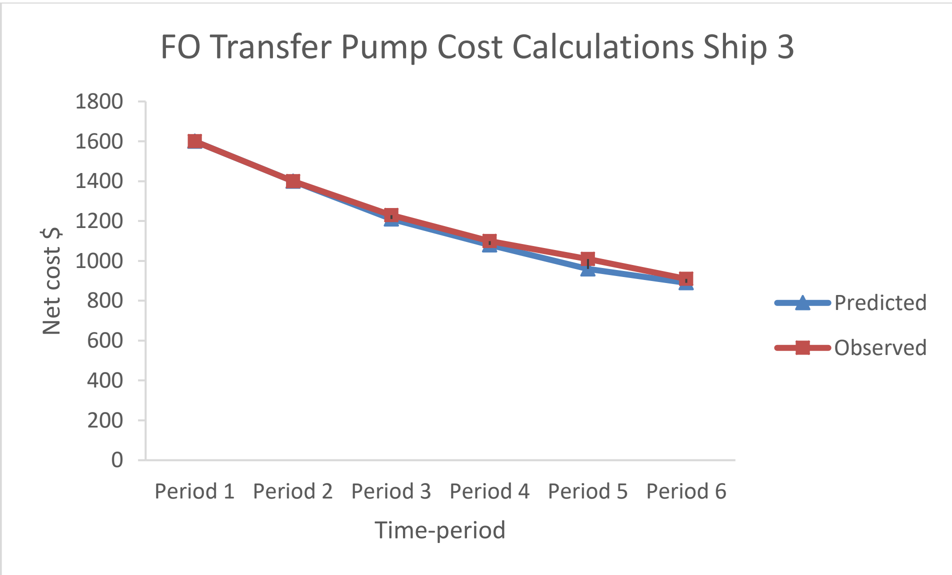

Figure 86 - Fuel-oil Transfer Pump Net cost Prediction for Ship 3

6.3.3 Turbochargers

Unlike the lube-oil and fuel-oil systems, where each performance reading had only one failure outcome, in the turbochargers some of the performance readings have more than one outcome, as also discussed in the previous chapter. This makes the decision-making process more complex. Therefore, some test nodes are added with their cost benefit analysis. Before doing each test for failure type, the cost of the most probable failure can be detected. So, this failure type must be tested first. In general, this method creates an overall prioritisation system and ranking of different failure scenarios and their test procedures. Thus, the utility and decision nodes of this system may also include test costs on top of the cost of failure and cost of repair/replacement.

Using the above strategy and DBN networks presented in the case studies and methodology chapters, performance and cost predictions of each vessel is done in this sub-section. Initially, for Ship 1 it has been detected that there are three performance readings with major deterioration. The first two only have one possibility of failure for degradation, whereas the third has two failure possibilities from single performance deterioration.

Firstly, deterioration on bearing vibration reading can only have one outcome - that of bearing replacement. Subsequently, the turbocharger bearing of Ship 1 had an observed degradation of its performance index from 98.3% to 95.7% (Figure 87). It was then determined that the overall performance index at the end of the fourth predicted time period will be approximately 94.2%, which is close to the 94.1% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 88. It was observed that overall cost at the end of the fourth predicted time period remained positive with a value of $6040, which is relatively close to the observed value of $6015. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

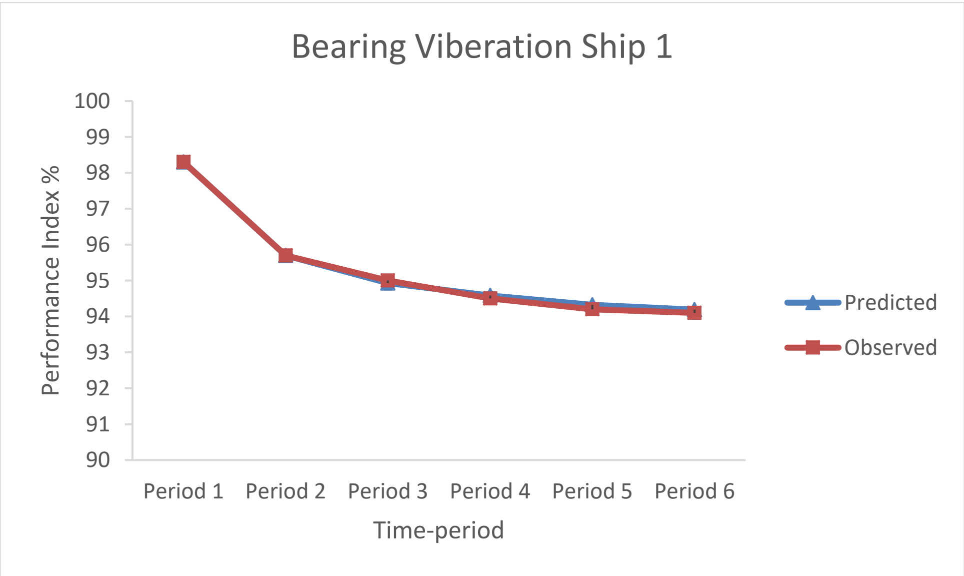

Figure 87 - Turbocharger Bearing Vibration Probabilistic Performance Prediction for Ship 1

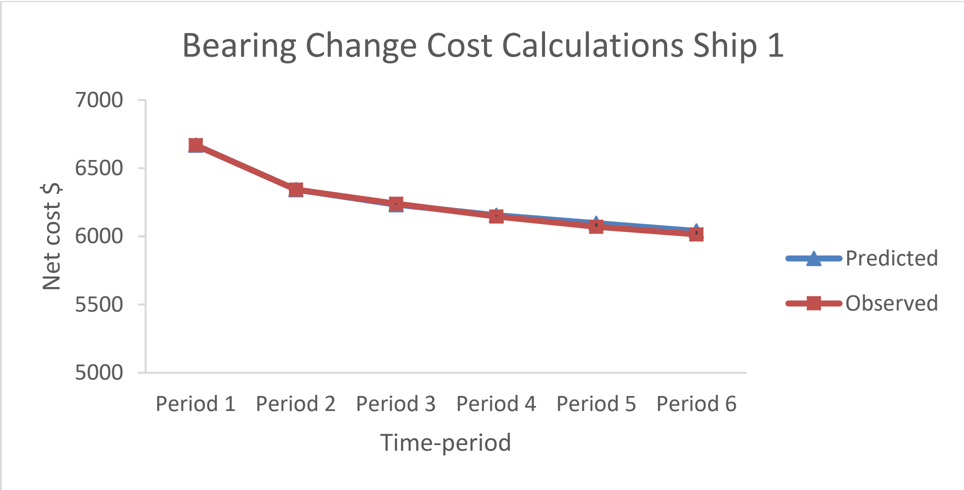

Figure 88 - Turbocharger Bearing Change Net cost Prediction for Ship 1

Secondly, the reduction in and out temperature difference of the scavenge air cooler, similar to the bearing, can only have one outcome - that of air cooler repair. Subsequently, the scavenge air temperature difference of Ship 1 had an observed degradation of its performance index from 100% to 97.9% (Figure 89). It was then determined that, overall, the performance index at the end of the fourth predicted time period will be approximately 97.14%, which is very close to 97.2% observed performance index. Using monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 90. It was observed that overall cost at the end of the fourth predicted time period is still positive with a value of $4061, which is very close to the observed value of $4070. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

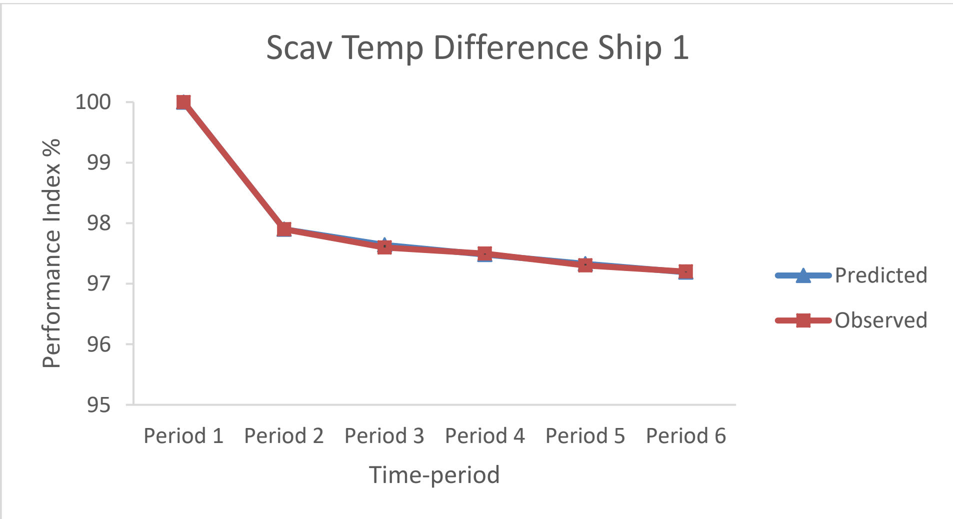

Figure 89 - Scavenge Air Temperature Difference Probabilistic Performance Prediction for Ship 1

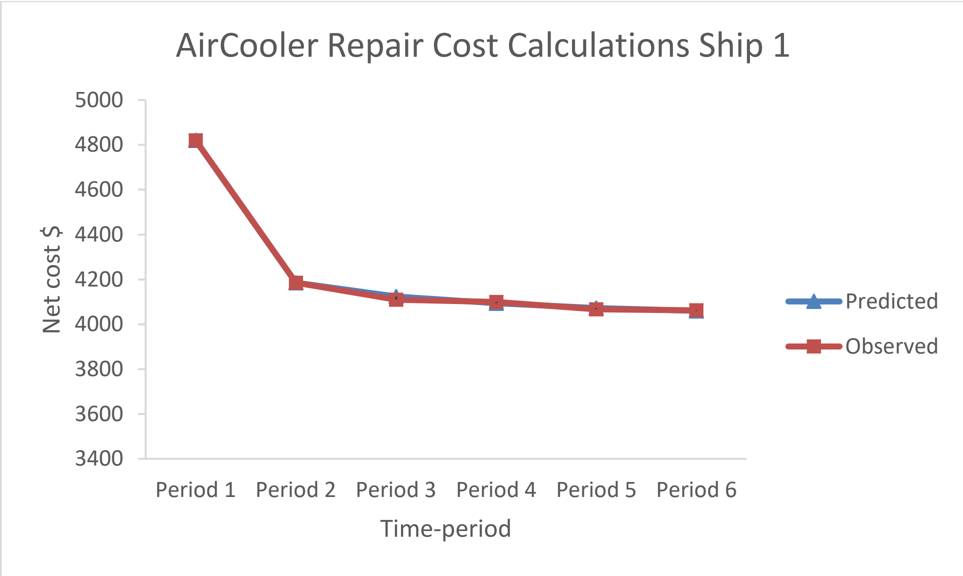

Figure 90 - Air Cooler Repair Net cost Prediction for Ship 1

Thirdly, reduction in the charge air pressure for the turbocharger can have two major possibilities, those of exhaust duct leak and air filter blockage. Overall observed performance reduction for the charge air pressure of Ship 1 was from 80.2% to 68.9% (Figure 91). It was then determined that the overall performance index at the end of the fourth predicted time period will be approximately 92.37%, which is relatively close to the 92.5% observed performance index. Subsequently, the cost difference of failure compared with test was analysed for both failure possibilities. The cost difference for testing the exhaust duct leak compared with the cost of failure at the end of the fourth predicted time period was positive at $557 which is similar to the observed cost of $569 (Figure 92). However, cost difference for the air filter was negative after the third time period and at the end of the fourth period was negative at $72, which is close to the observed negative value of $66 (Figure 93). Thus, it would be cost-effective to first schedule a check of the air filter for blockage; if everything is acceptable then a check of the exhaust duct for leakage should be scheduled. After checking the maintenance schedule and the maintenance log of the vessel it was noticed that the air filter was changed at 8th January 2017.

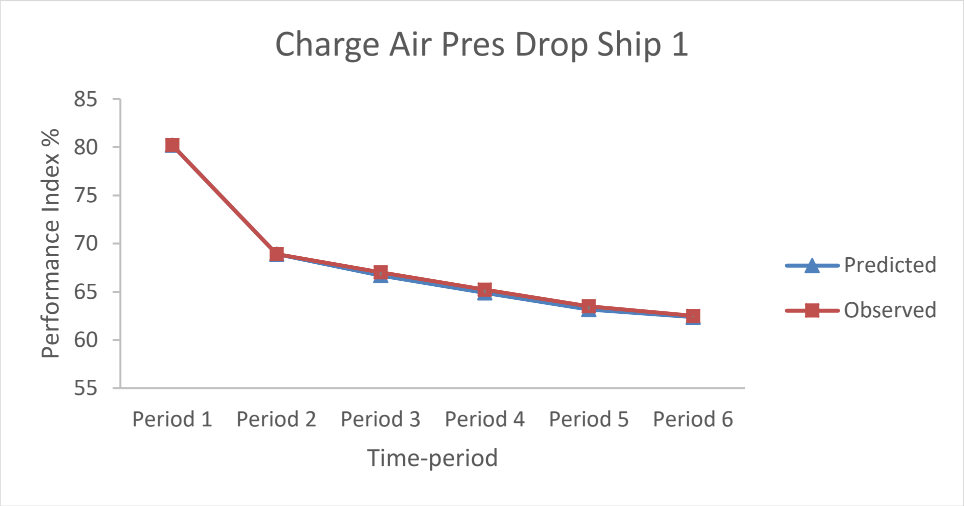

Figure 91 - Turbocharger Charge Air Pressure Drop Probabilistic Performance Prediction for Ship 1

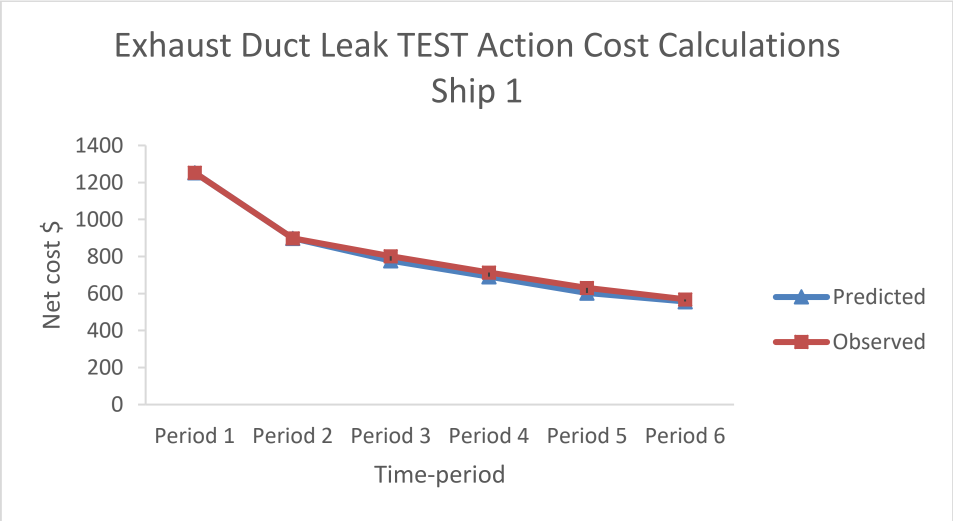

Figure 92 - Exhaust Duct Leak Check Action Test Net cost Prediction for Ship 1

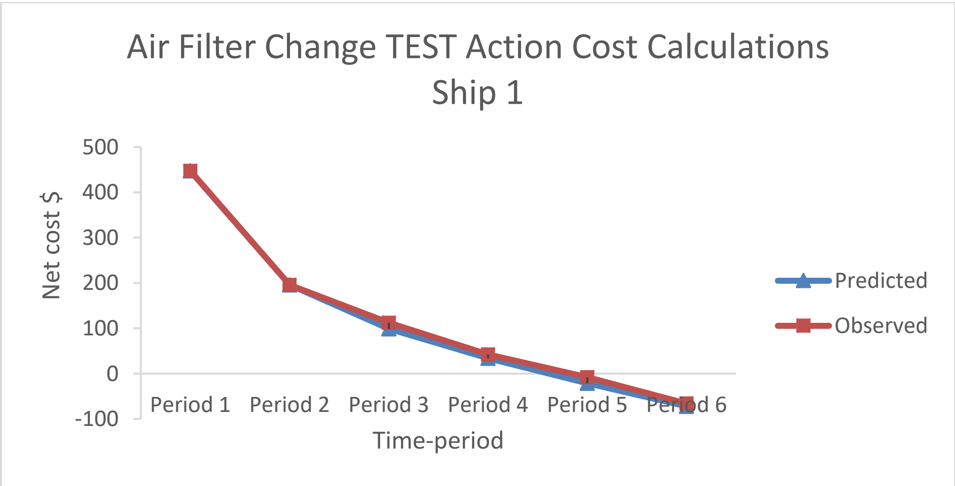

Figure 93 - Air Filter Change Action Test Net cost Prediction for Ship 1

Unlike Ship 1, Ship 2 had three performance degradations that resulted in a single failure cause. However, it also had a performance degradation that resulted in one single separate failure cause. This performance reading was the scavenged air pressure drop which had an observed degradation from 98.3% to 96.4% (Figure 94). It was then determined that the overall performance index at the end of the fourth predicted time period will be approximately 94.1%, which is very close to the 94.3% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 95. It was observed that the overall cost at the end of the fourth predicted time period remained positive with a value of $659, which is very close to the observed value of $667. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

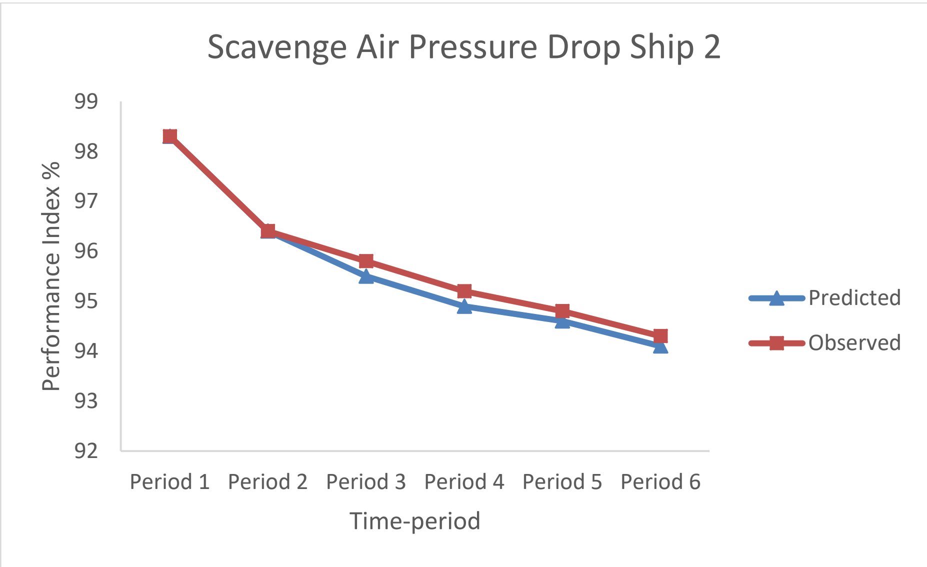

Figure 94 - Scavenge Air Pressure Drop Probabilistic Performance Prediction for Ship 2

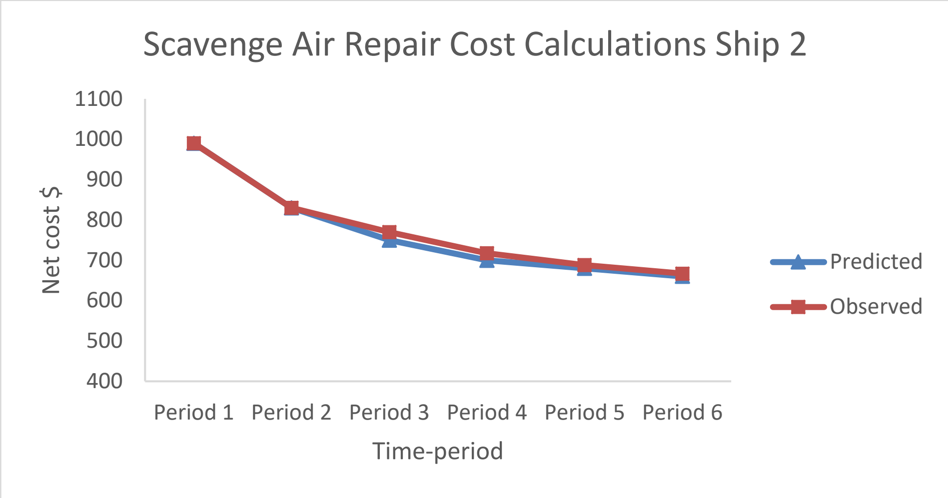

Figure 95 - Scavenge Air Receiver Repair Net cost Prediction for Ship 2

Subsequently, the three performance readings that resulted in one single failure cause are due to low exhaust temperature, low charge air pressure and exhaust back-pressure. These performance readings determine the single failure cause of exhaust fouling. From Figure 96 the observed performance degradation for low exhaust temperature went from 89.1% to 86.5%. Similarly, for low charge air pressure and exhaust back-pressure from Figures 97 and 98, the observed performance degradations went from 93.5% to 90.9% and 90.5% to 87.2% respectively. Using utility and decision nodes, the overall cost difference for exhaust dismantling and cleaning due to fouling was calculated to be negative after the predicted time period. At the end of the fourth time period it was observed to be negative at $195 (Figure 99). Therefore, exhaust cleaning is needed after the first predicted time period. The maintenance logs of the vessel, where exhaust duct overhaul for defouling was done in February 2016, proved this.

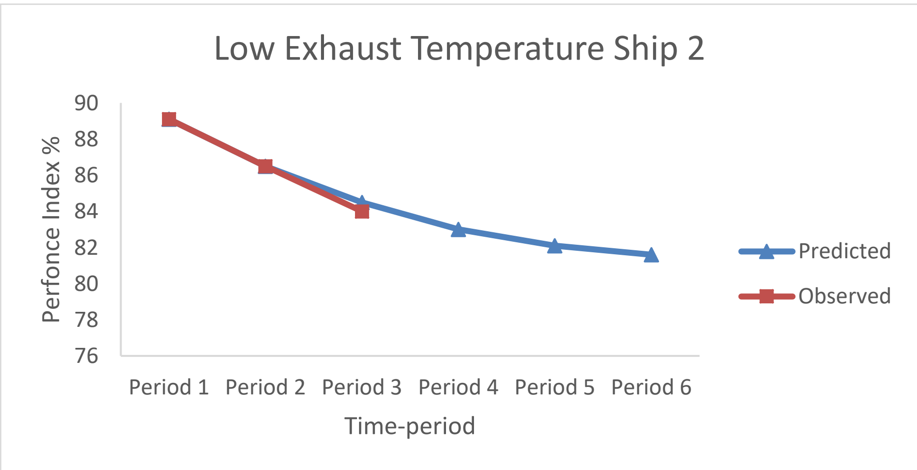

Figure 96 - Turbocharger Low Exhaust Gas Temperature Probabilistic Performance Prediction for Ship 2

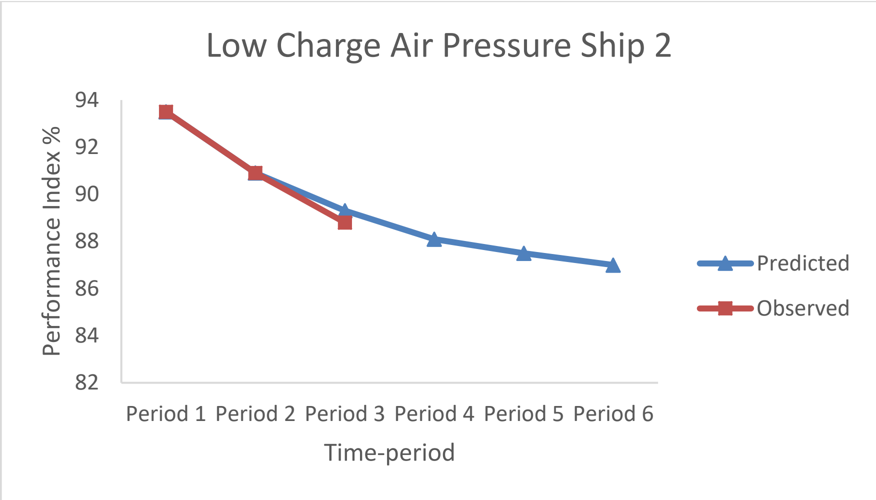

Figure 97 - Turbocharger Low Charge Air Pressure Probabilistic Performance Prediction for Ship 2

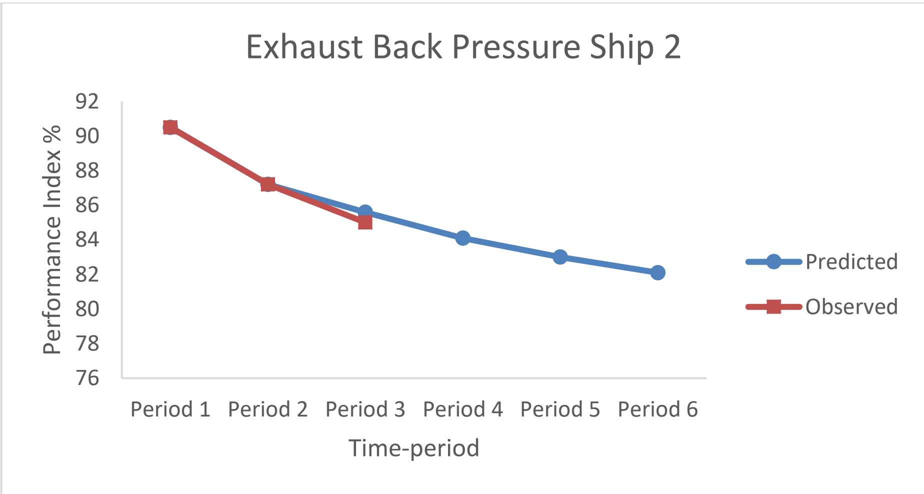

Figure 98 - Turbocharger Exhaust Back-pressure Probabilistic Performance Prediction for Ship 2

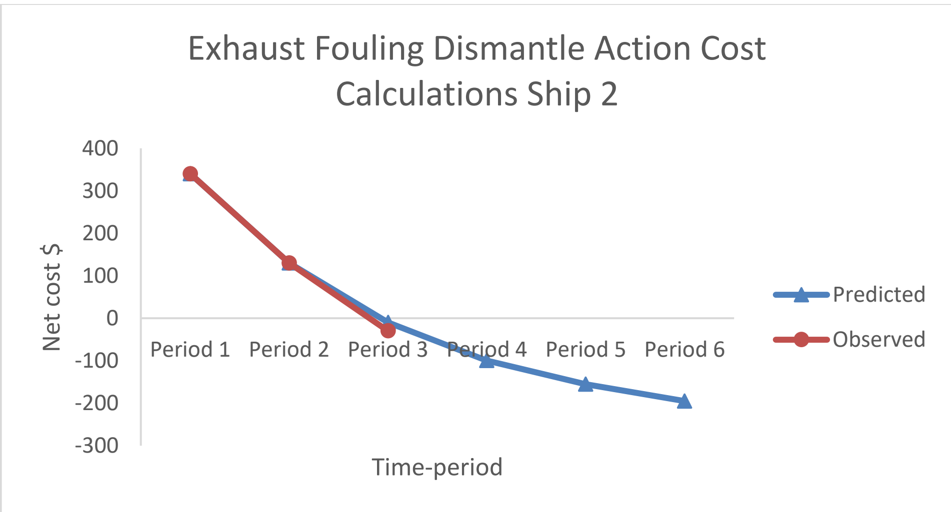

Figure 99 - Exhaust Fouling with Dismantle Action Net cost Prediction for Ship 2

Ship 3 had two performance readings each of which caused a single separate failure scenario. However, two other performance readings each had two relevant failure causes attached . The first performance degradation reading with a single failure cause was bearing vibration, which had an observed degradation from 99.1% to 97.2% (Figure 100). It was then determined that the overall performance index at the end of the fourth predicted time period will be approximately 95.8%, which is highly close to the 96% observed performance index. Using monetary values and calculated performance index values, the overall cost difference predictions were determined in Figure 101. It was observed that the overall cost at the end of the fourth predicted time period remained positive with a value of $7460, which is very close to the observed value of $7465. Therefore, no maintenance is needed for the next four time-periods or 16 months with the current degradation pattern.

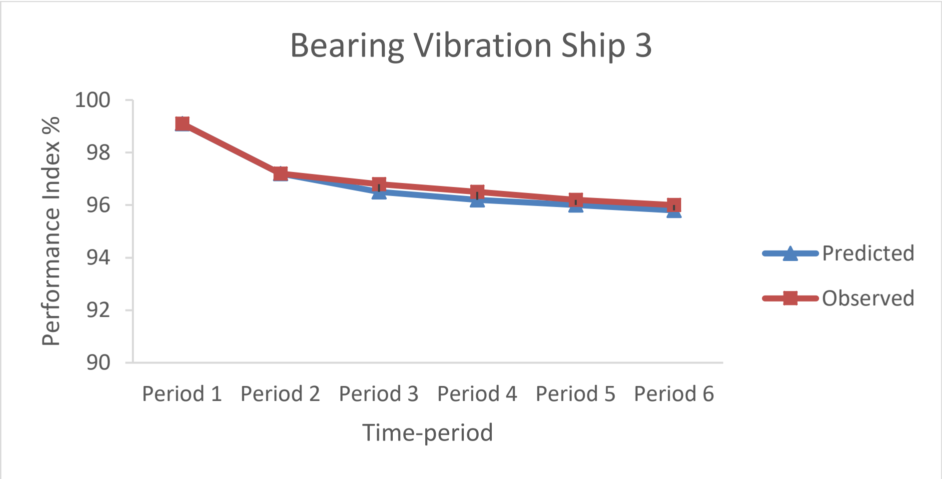

Figure 100 - Turbocharger Bearing Vibration Performance Prediction for Ship 3

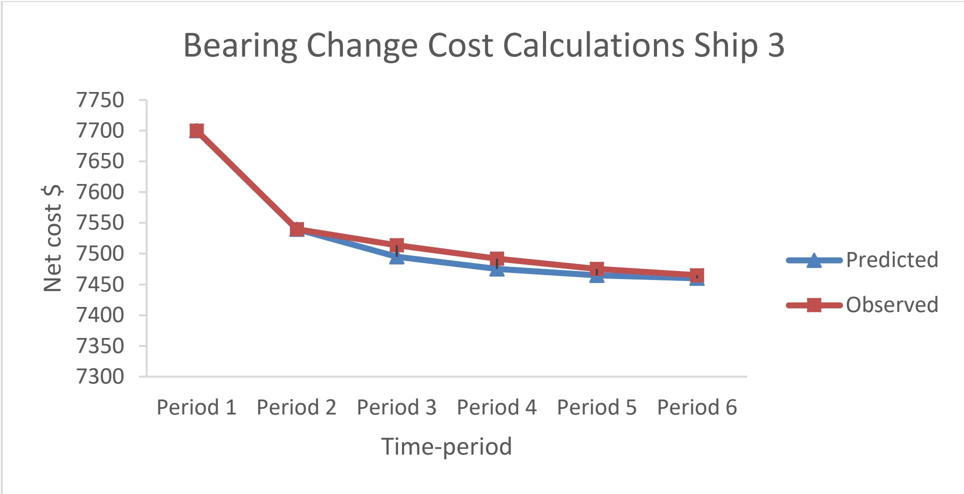

Figure 101 - Turbocharger Bearing Change Net cost Prediction for Ship 3

The second performance degradation reading with a single failure cause was the scavenge air pressure drop, which had an observed degradation from 98.8% to 96.9% (Figure 102). It was then determined that the overall performance index at the end of the fourth predicted time period will be approximately 93.3%, which is relatively close to the 93.7% observed performance index. Using the monetary values and calculated performance index values, overall cost difference predictions were determined in Figure 103. It was observed that the overall cost at the end of the fourth predicted time period is still positive with a value of $1976, which is highly close to the observed value of $1997. Therefore, no maintenance is needed for the next four time periods or 16 months with the current degradation pattern. Predicted values are slightly higher at the beginning of the prediction period and then go slightly lower than the observed values but, overall, have very close values. This can again be due to some further errors in the system that have affected the linearity of its deterioration.

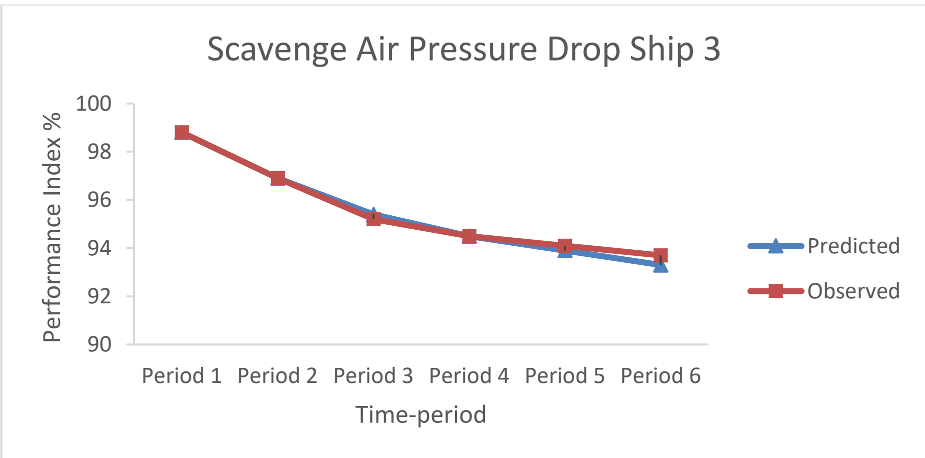

Figure 102 - Scavenge Air Pressure Drop Probabilistic Performance Prediction for Ship 3

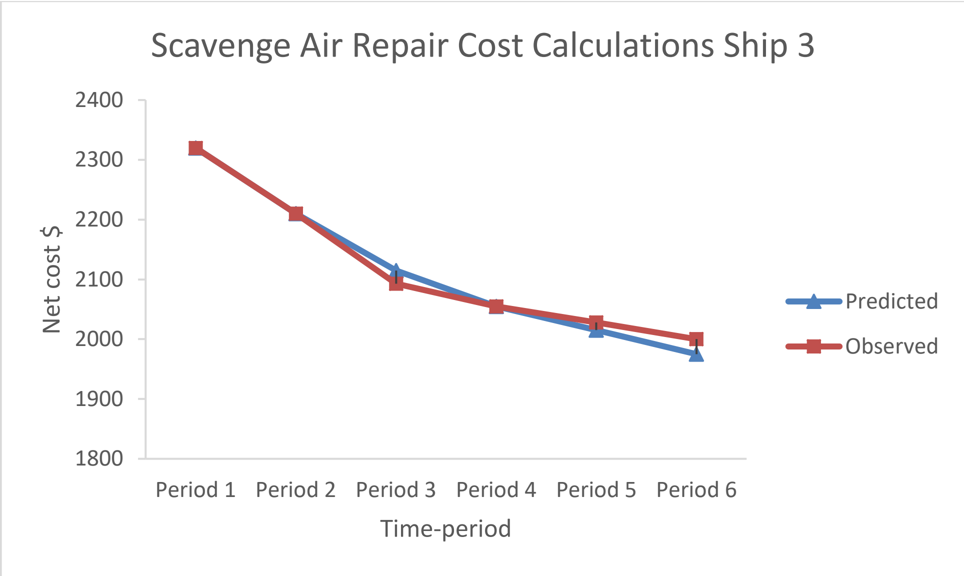

Figure 103 - Scavenge Air Receiver Repair Net cost Prediction for Ship 3

Unlike the previous two performance readings, high exhaust temperature and high charge air pressure readings, together, had two simultaneous failure causes. This requires both failure causes to be tested in order of the most critical with the negative cost value first. From Figures 104 and 105, high exhaust temperature had an observed degradation from 89.3% to 85.4% and high charge air pressure had an observed degradation from 91.3% to 88.4% respectively. The cost difference to dismantle the turbocharger for contaminant cleaning was positive at $135 and $130 for the predicted and observed values respectively (Figure 106). However, the cost difference for engine performance test due to injection faults was negative from the third time period. This would mean that it is recommended to perform an engine test by the fourth time period first and if no fault is found then check for contaminants inside the turbocharger. However, on checking the maintenance log, it was found that an engine injection fault was detected later and it was scheduled for repair by the end of December 2016. This is slightly outside the recommended time by the BOPM methodology but still had a correct prediction as cost differences for predicted and observed performance values by the fourth time period were negative at $49 and $52 respectively, which are highly similar.

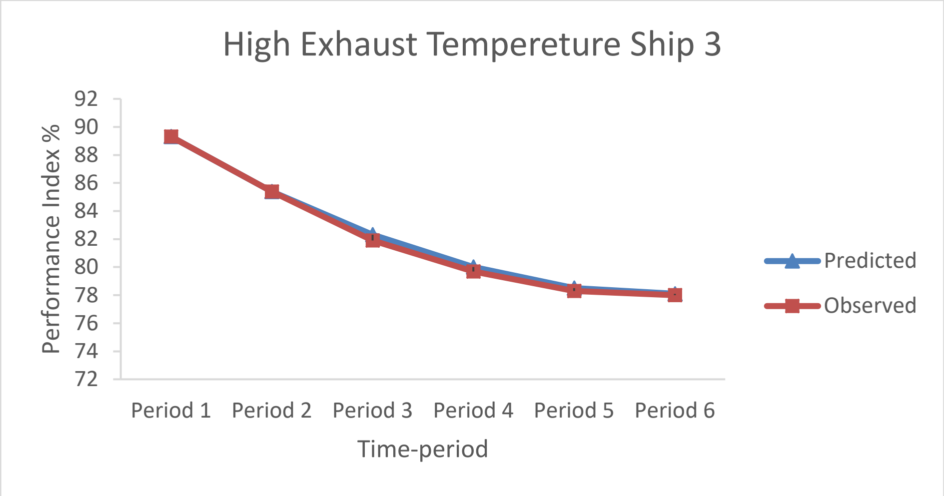

Figure 104 - Turbocharger High Exhaust Gas Temperature Probabilistic Performance Prediction for Ship 3

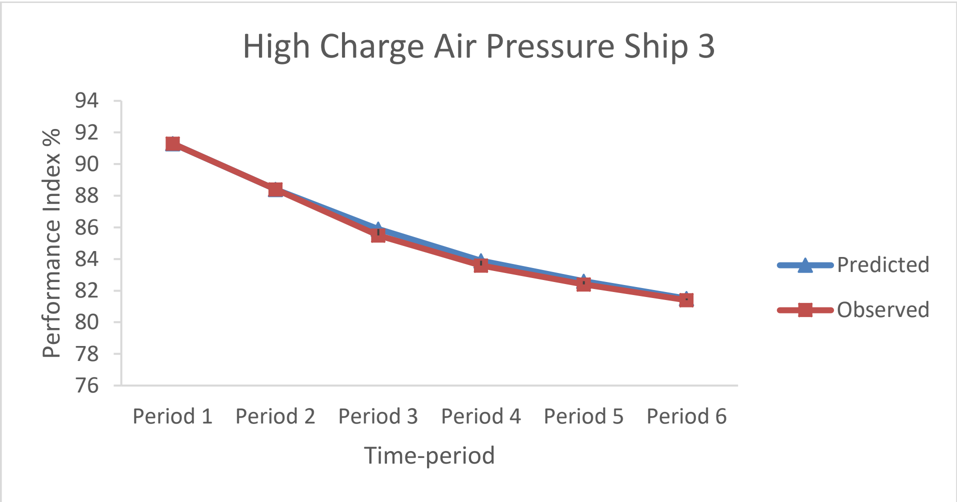

Figure 105 - Turbocharger High Charge Air Pressure Probabilistic Performance Prediction for Ship 3

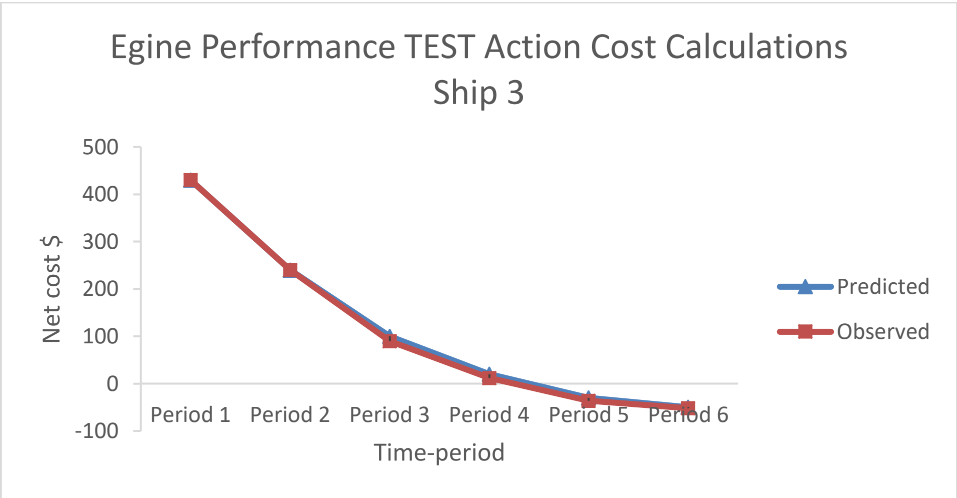

Figure 106 - Engine Injection System Performance-test Action Test Net cost Prediction for Ship 3

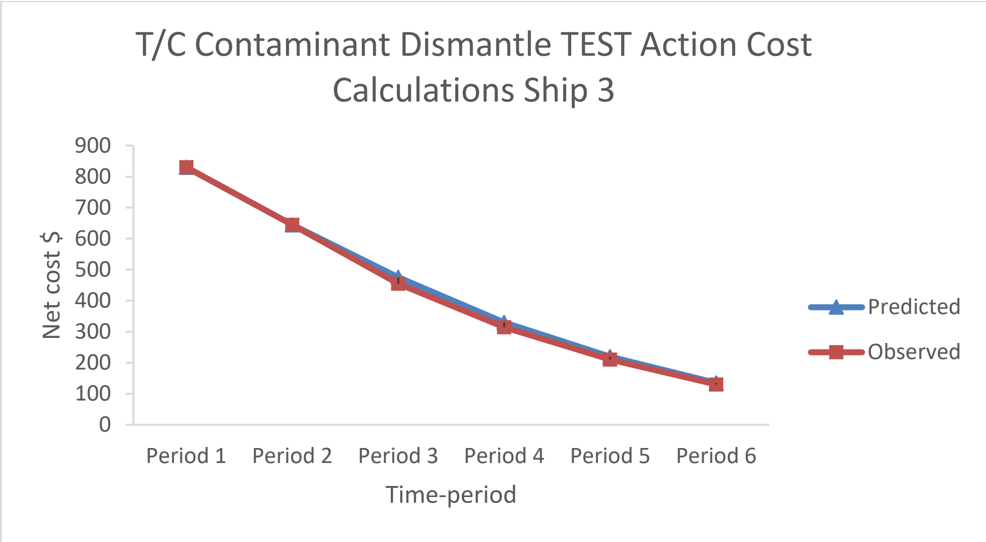

Figure 107 - Turbocharger Dismantle due to Contaminants Action Test Net cost Prediction for Ship 3

6.4 Results Comparison

In this section, comparison of different performance readings from all three ships is shown. This can help operators to identify the most problematic components and sub-systems as the machinery systems are similar, specifically between ships 1 and 2. Consequently, it can also highlight the systems that have higher degradation and separate them for closer monitoring. Finally, this comparison will also recognise the effect of differing environmental conditions on different machinery components/sub-systems of sister ships 1 and 2.

The first main machinery system compared in this section is the lube-oil (LO) system. In this system the LO filters on all three vessels should be monitored carefully (Figures 108 and 109). This is specifically the case for the sister ships, where both required a filter change. As those ships use similar LO filters, this can also highlight the possibility that their filter performance is worse than the different filter type used on the multi-purpose cargo vessel.

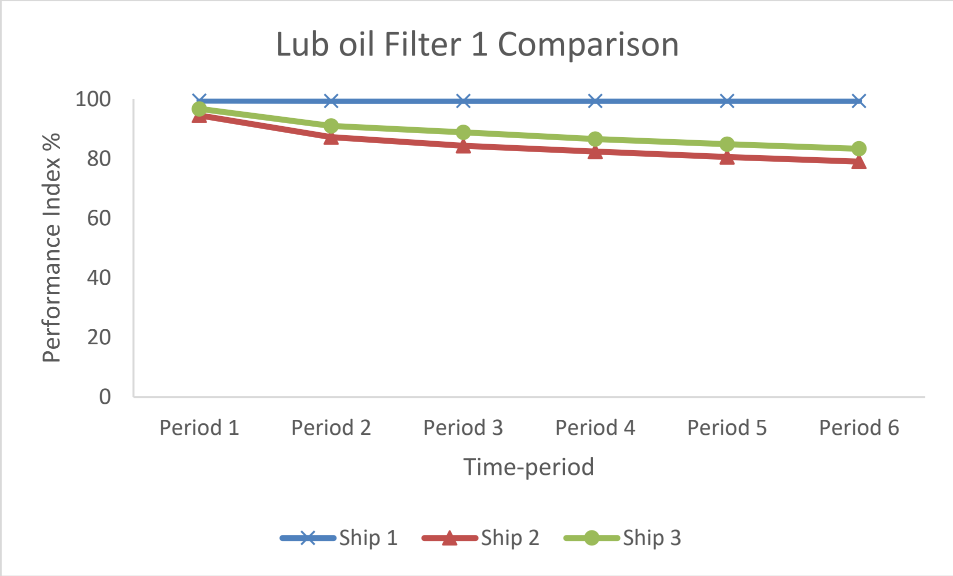

Figure 108 – Lube-oil Filter 1 Performance Comparison

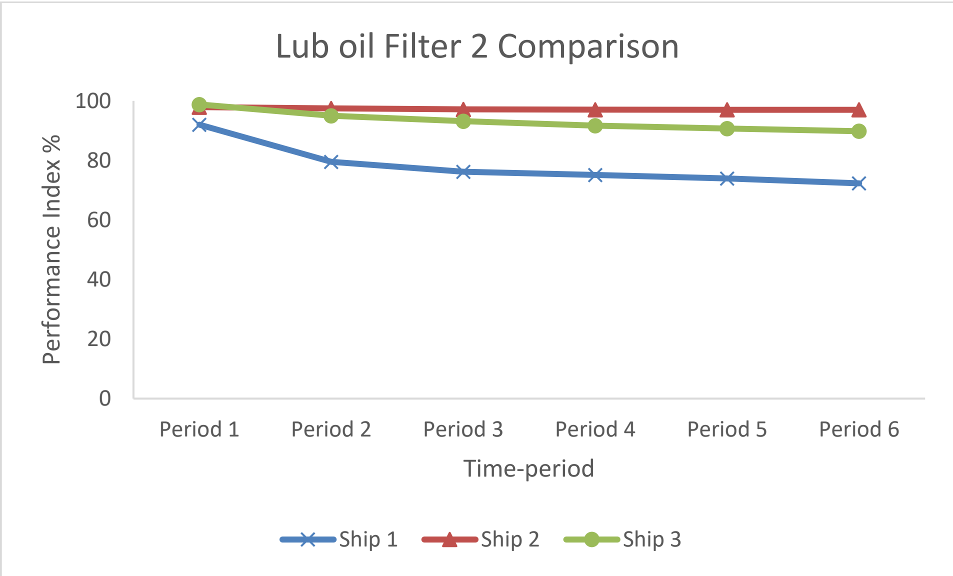

Figure 109 – Lube-oil Filter 2 Performance Comparison

The lube-oil pumps on all three vessels had some observable performance degradation. However, Ship 1 from the sister ships, which was operating in much harsher environments, had much higher degradation as seen in Figure 110. This further highlights the effect of the environmental and sea state conditions on the reliability of ship machinery systems.

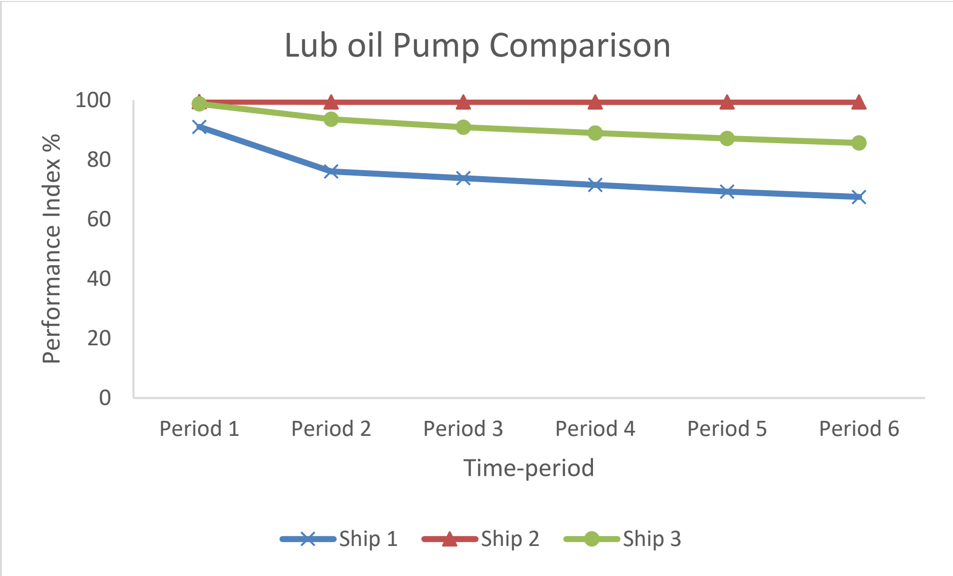

Figure 110 – Lube-oil Pump Performance Comparison

Other systems such as the lube-oil purifier (Figure 111) and lube-oil pump motor (figure 112) had much lower performance degradation observed on all three vessels. This is also the case for the lube-oil purifier motor and oil sump level observations.

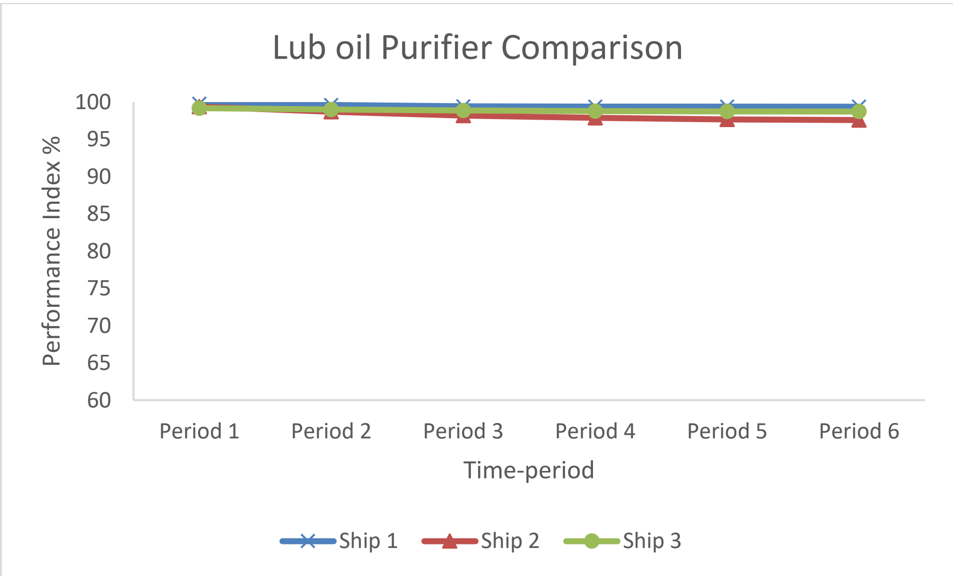

Figure 111 – Lube-oil Purifier Performance Comparison

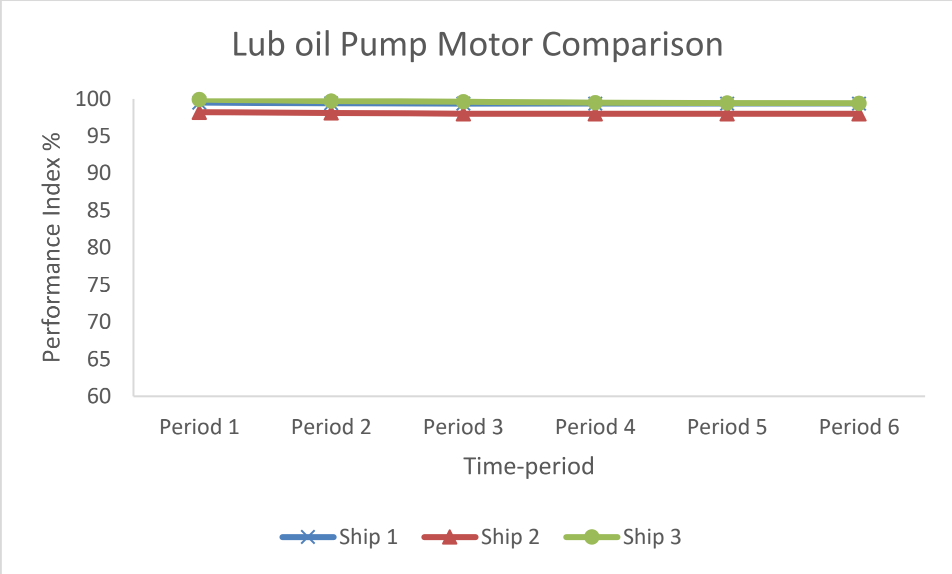

Figure 112 – Lube-oil Pump Motor Performance Comparison

The second main machinery system compared in this section is the fuel-oil (FO) system. In this system, even though there is no connection between different cylinder FO pumps within the system, looking at a comparison of results from a few chosen cylinder pumps such as cylinder FO pump 1 (Figure 113), cylinder FO pump 3 (Figure 114) and cylinder FO pump 4 (Figure 115) it can be noticed that Ship 1 has the highest average degradation of cylinder FO pumps' performance. This can again be due to the harsher environmental conditions that Ship 1 should deal with, especially compared with its sister ship 2.

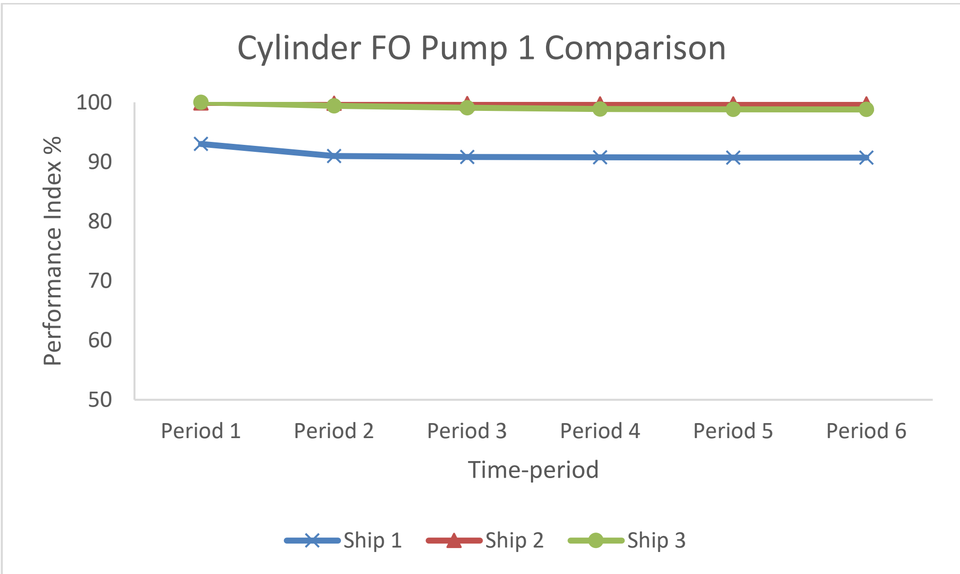

Figure 113 - Cylinder FO Pump 1 Performance Comparison

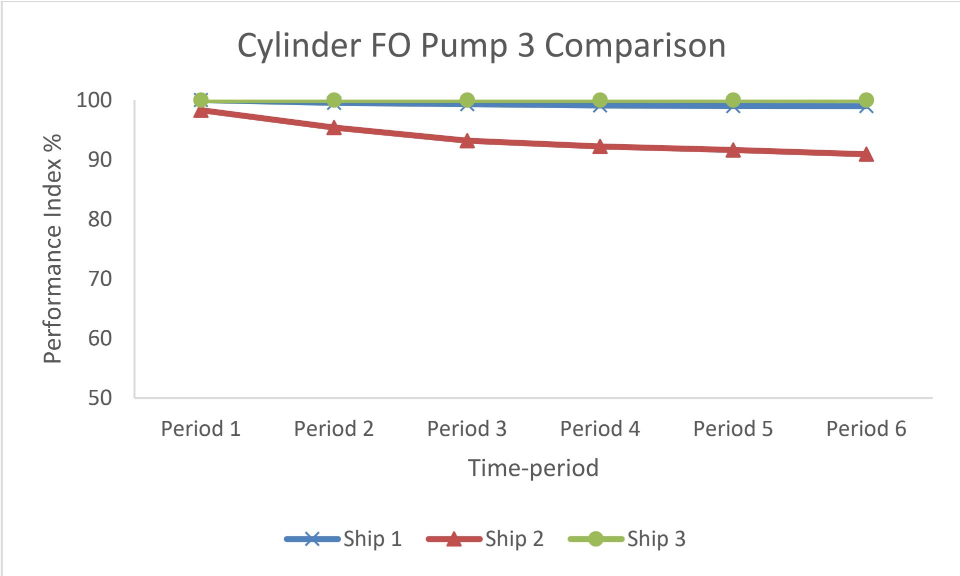

Figure 114 - Cylinder FO Pump 3 Performance Comparison

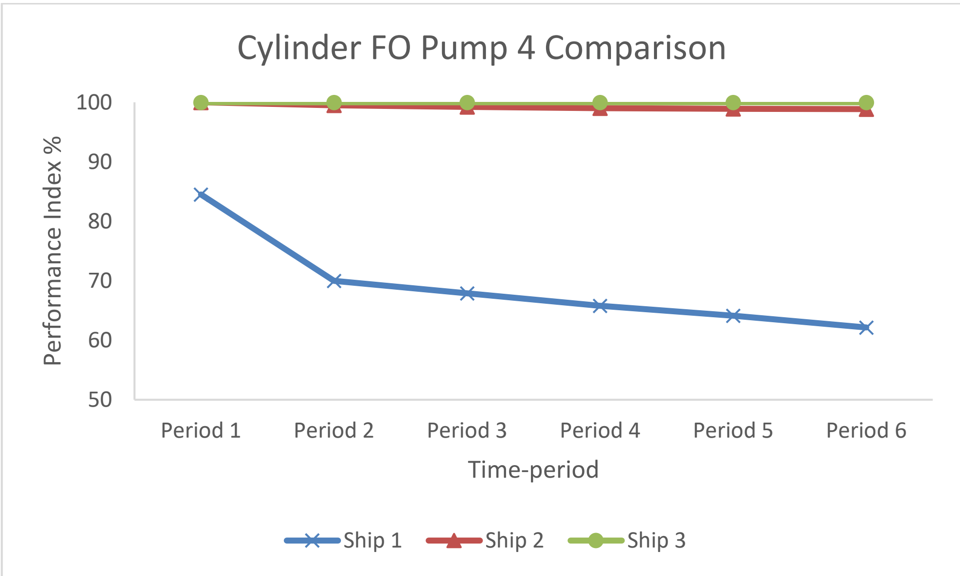

Figure 115 - Cylinder FO Pump 4 Performance Comparison

This higher performance degradation pattern for Ship 1 compared with the other ships can also be observed on FO purifier performance comparison, FO transfer pump performance comparison and service tank heater performance comparison graphs shown in Figures 116, 117 and 118 respectively.

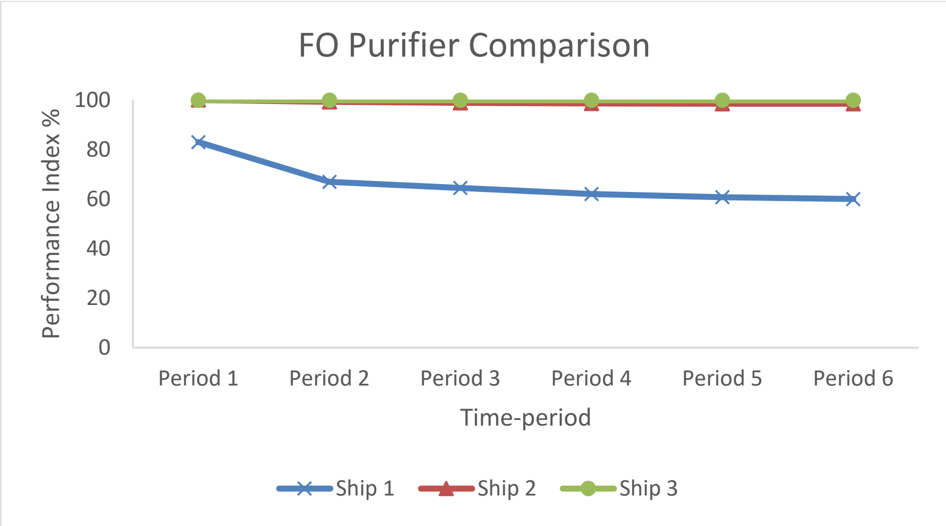

Figure 116 - FO Purifier Performance Comparison

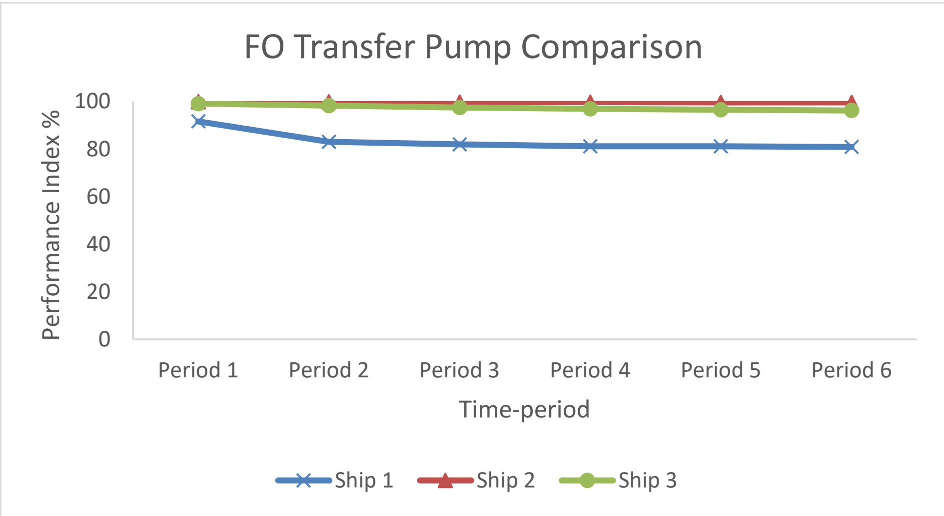

Figure 117 - FO Transfer Pump Performance Comparison

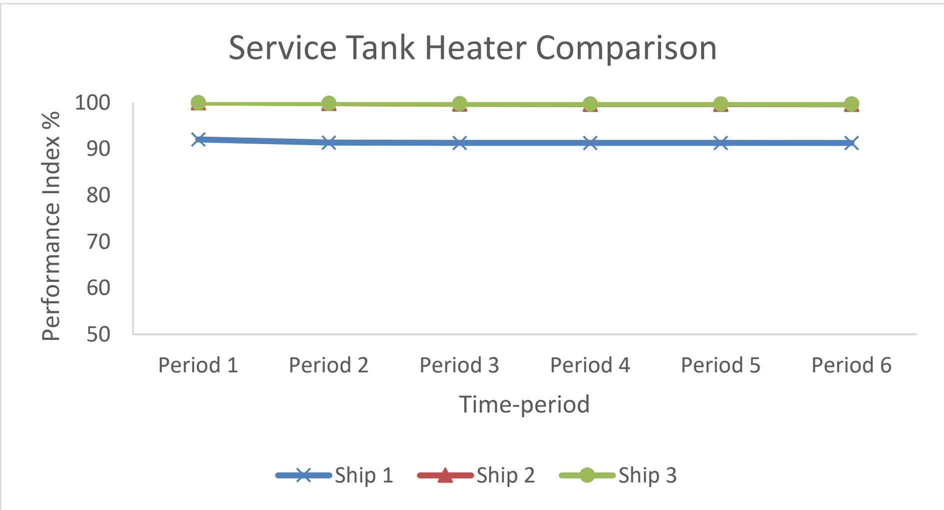

Figure 118 - Service Tank Heater Performance Comparison

Conversely, auto-filter performance degradation is an exception from the previously observed scenarios. In this sub-system, Ship 2 had the highest degradation observed and Ship 1 had the lowest (almost non-existence) as demonstrated in Figure 119. This proves that, sometimes,unexpected degradations can still occur unrelated to the environmental conditions.

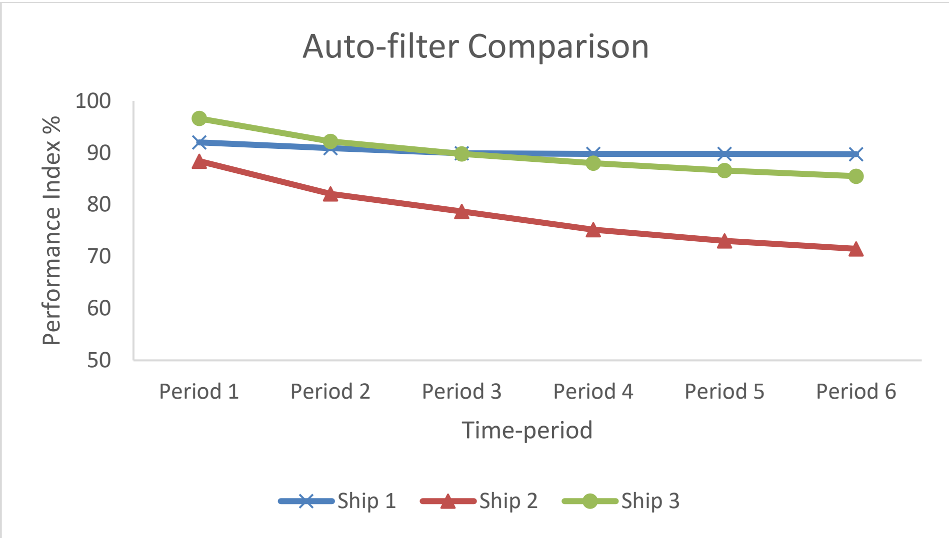

Figure 119 – Auto-filter Performance Comparison

As with the lube-oil system, the fuel-oil system also had several sub-system/components with minimal or non-existing performance degradations observed. A selected few of these types of systems are illustrated in Figures 120, 121 and 122 for the sub-systems/components of settling tank heater, storage tank heater and FO transfer pump motor respectively.

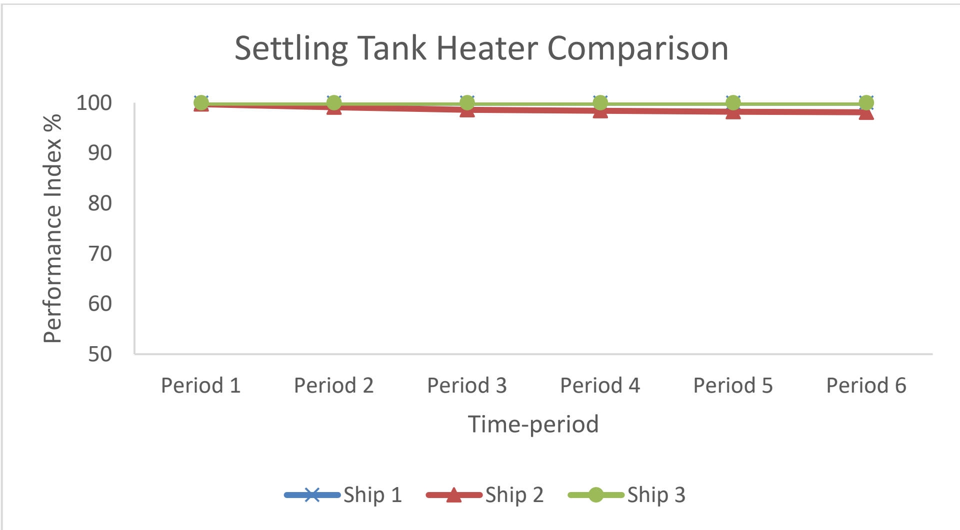

Figure 120 - Settling Tank Heater Performance Comparison

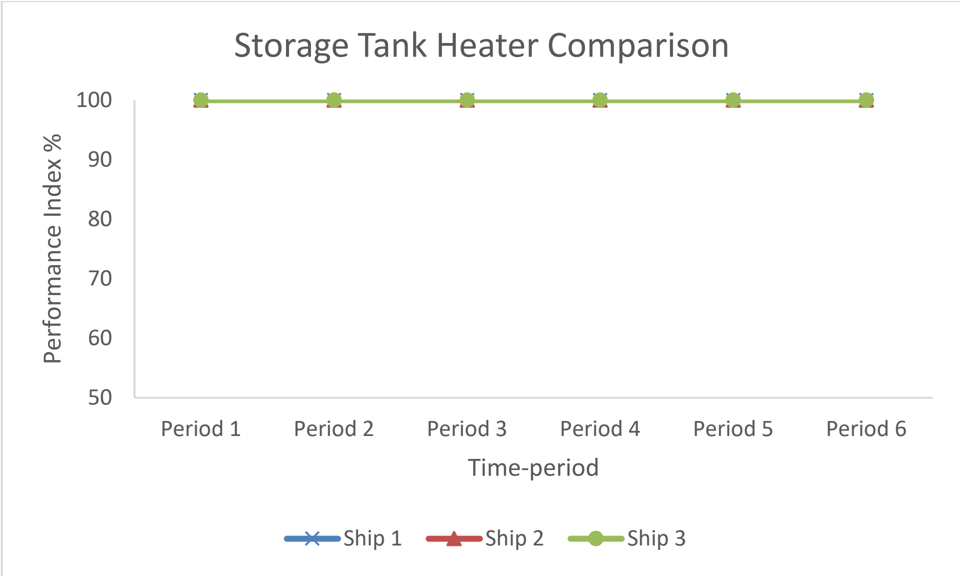

Figure 121 - Storage Tank Heater Performance Comparison

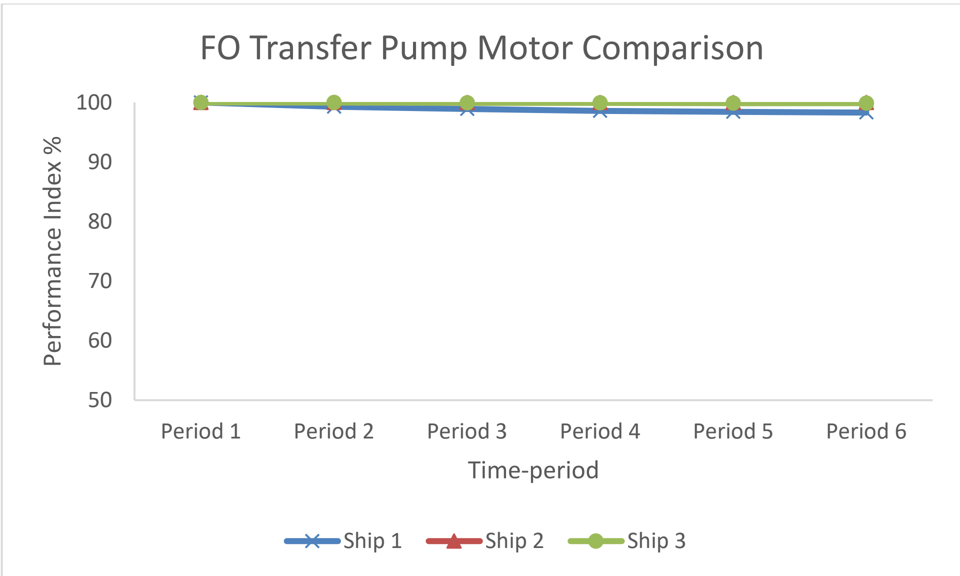

Figure 122 - FO Transfer Pump Motor Performance Comparison

The third and the final system compared between the three vessels is the turbocharger. In this system where there can be multiple possibilities for each degradation reading, only the deprivation of the observed readings in respect to the satisfactory limits is compared. In general, by comparing Figures 123, 124 and 125 for the comparison of low charge air pressure, scavenge air temperature difference and low exhaust temperature respectively, it is noticed that Ship 1, in two positions, had the highest degradation observed whereas Ship 2 had only one.

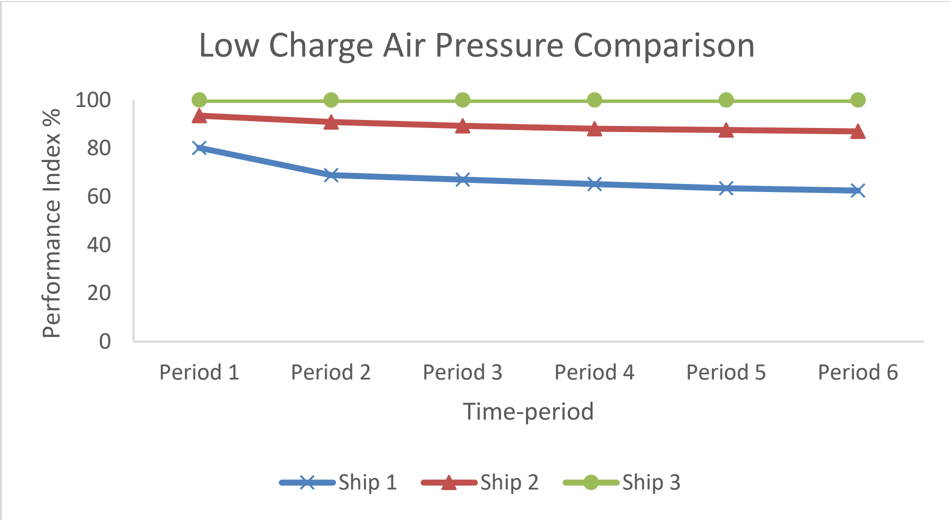

Figure 123 - Low Charge Air Pressure Performance Comparison

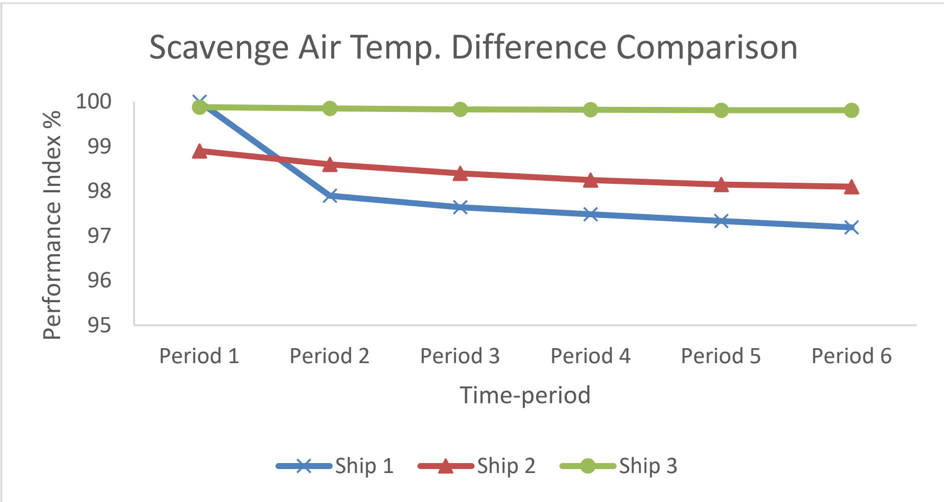

Figure 124 - Scavenge Air Temperature Difference Performance Comparison

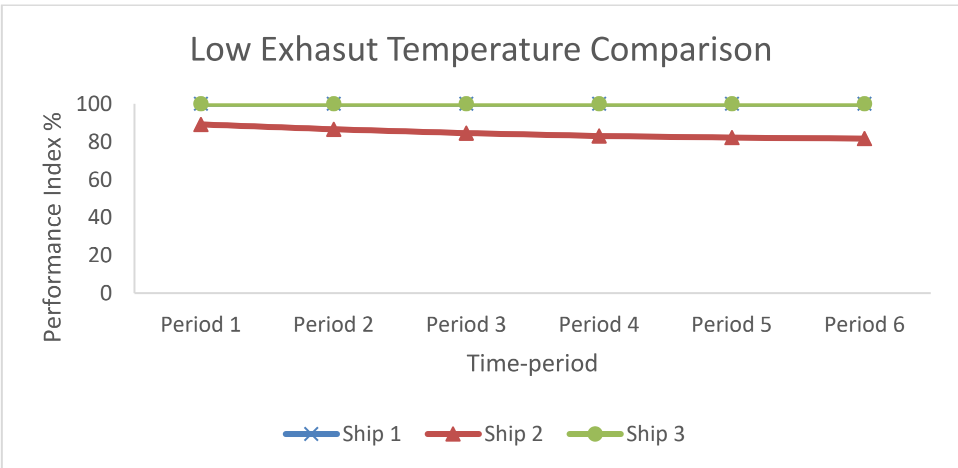

Figure 125 - Low Exhaust Temperature Performance Comparison

A relatively high bearing vibration (Figure 126) was observed on all three vessels; however, Ship 1 again had the highest unwanted bearing vibration. This also proves that environmental conditions have played an important role on general reliability of the system.

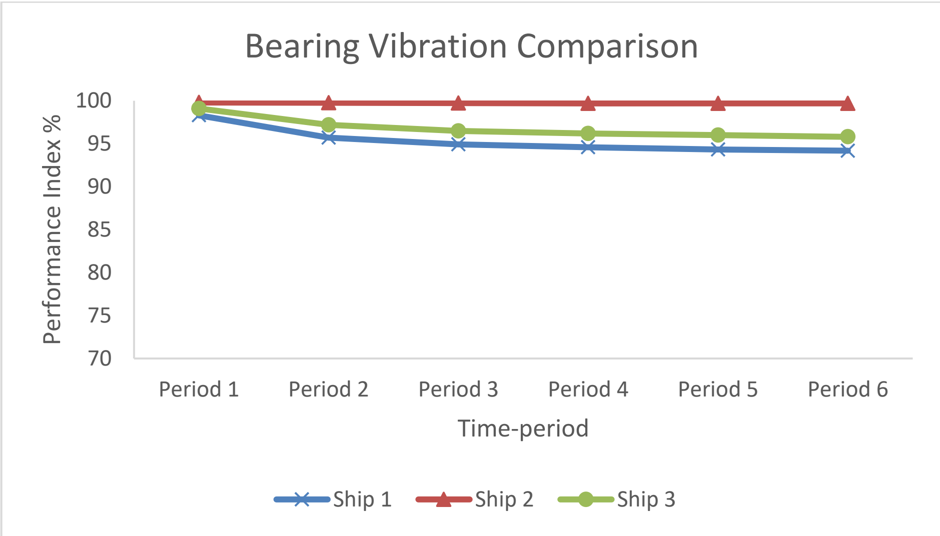

Figure 126 - Bearing Vibration Performance Comparison

Finally, exhaust temperature and high charge air pressure was only observed on Ship 3 (Figures 127 and 128 respectively). This ship does not share engine type with the two sister vessels. Therefore, this type of degradation pattern that was caused by a problem in the ignition system is only specific to this engine type used in the Ship 3 multi-purpose cargo vessel.

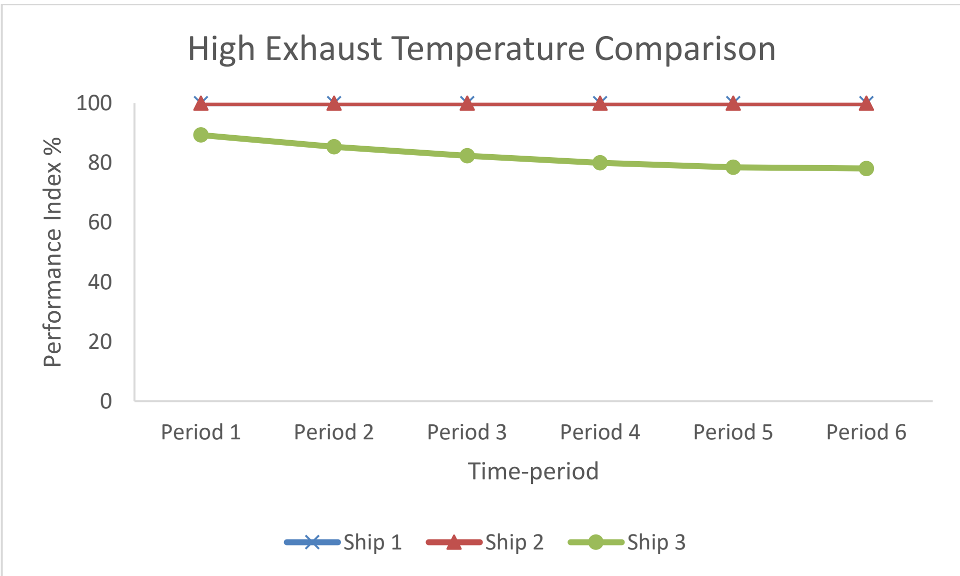

Figure 127 - High Exhaust Temperature Performance Comparison

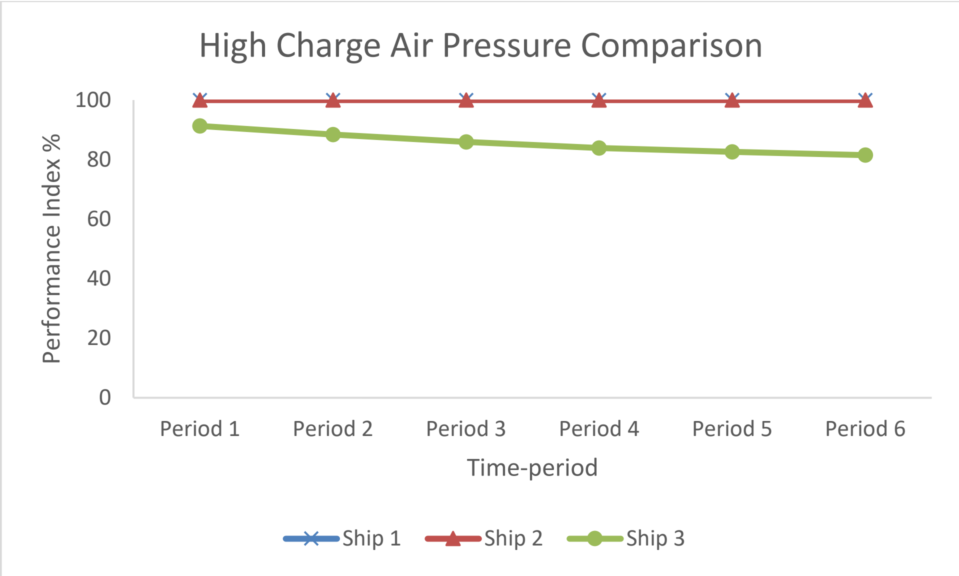

Figure 128 - High Charge Air Pressure Performance Comparison

In summary, comparison of performance degradation of different component/sub-system types from all three vessels proved that environmental and sea-state conditions faced by vessels in the operational areas can have noticeable effects on the reliability of these systems. However, this does not mean that some vessels may not have their own unique, unwanted failures.

6.5 Different Time Intervals

For this section, two-month intervals instead of four-month intervals were used. This would help to compare the result using different intervals in order to determine the best time intervals to be used. In this case, the overall results were plotted; they were very similar to predictions from four-month interval results in most cases. This can be seen from the comparison of results between Figures 129 and 130. These two graphs follow a similar degradation pattern.

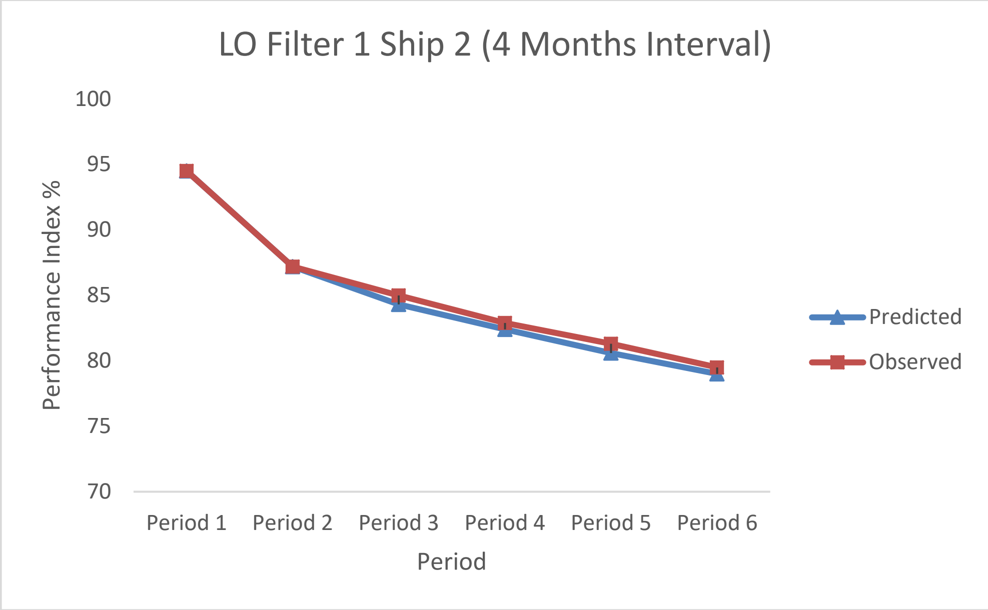

Figure 129 - LO Filter 1 Ship 2 Four-Month Intervals)

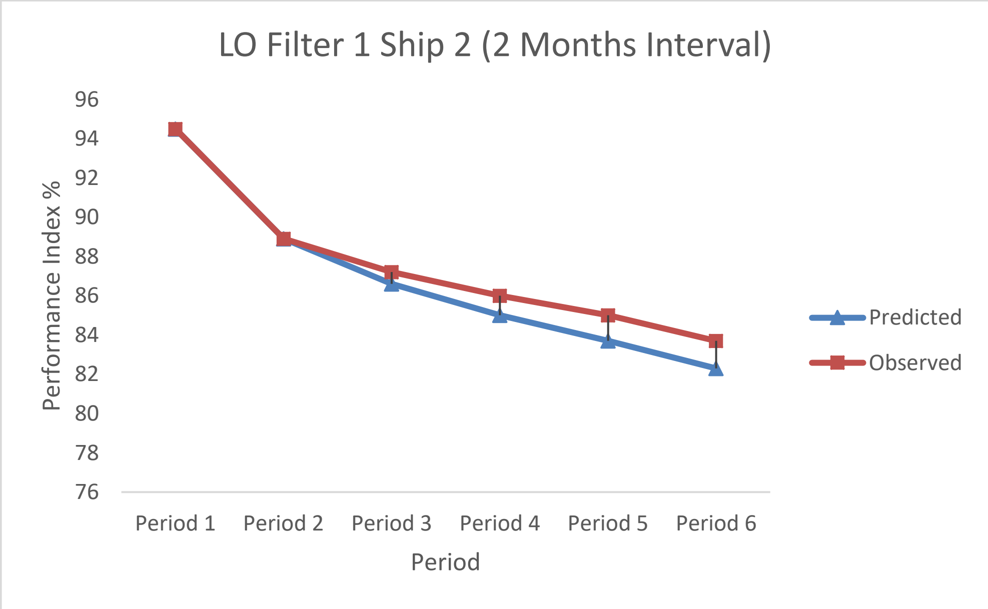

Figure 130 - LO Filter 1 Ship 2 (Two-month Intervals)

In some cases, the pattern was slightly different but overall prediction accuracy was almost as good. This is the case for figures 131 and 132. These two have different patterns of degradation but overall results obtained at the end of each analysis are still very similar and have high accuracy compared with the observed values. However, four-month intervals still have higher accuracy compared with two-month intervals due to the fact that there are more data points available.

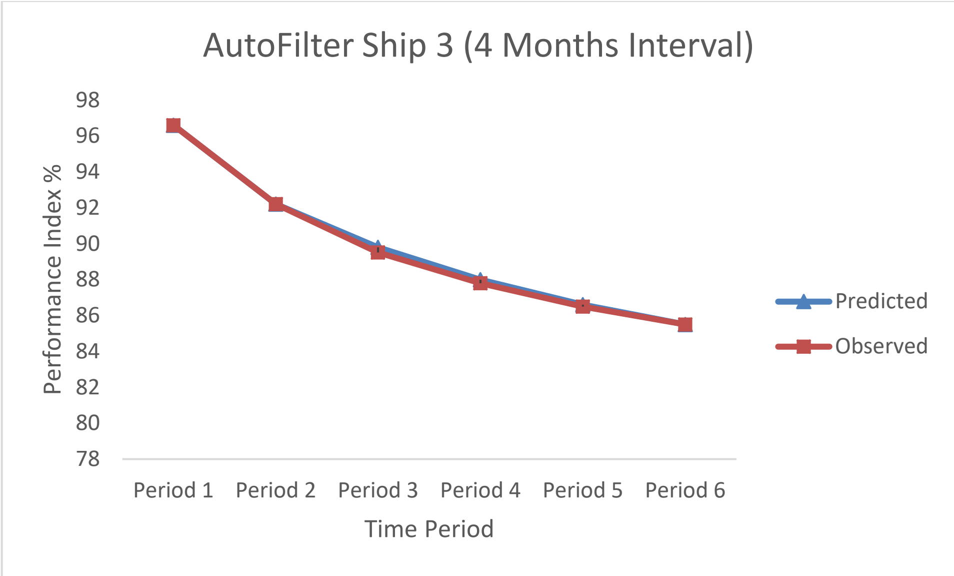

Figure 131 - AutoFilter Ship 3 (Four-month Intervals)

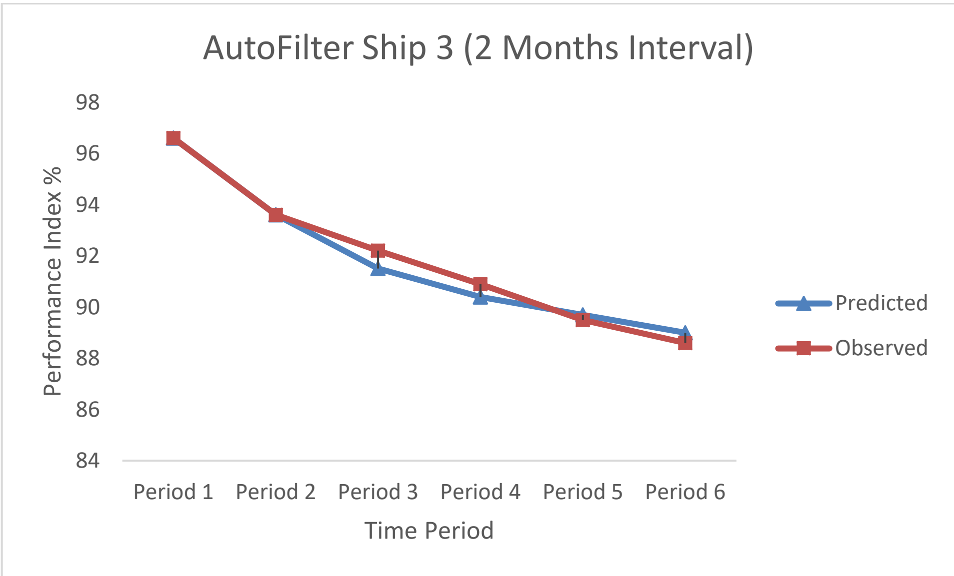

Figure 132 - AutoFilter Ship 3 Two-month Intervals)

In some other cases where cost data became negative in the middle of intervals, this was moved to the time intervals when two-month intervals were used. This is more obvious when comparing the results of Figures 133 and 134. In case of the two-month intervals, the decision of planning the maintenance will have more accurate data as the intervals are shorter. But, overall, the accuracy of results compared with observed values are slightly lower than the four-month period results.

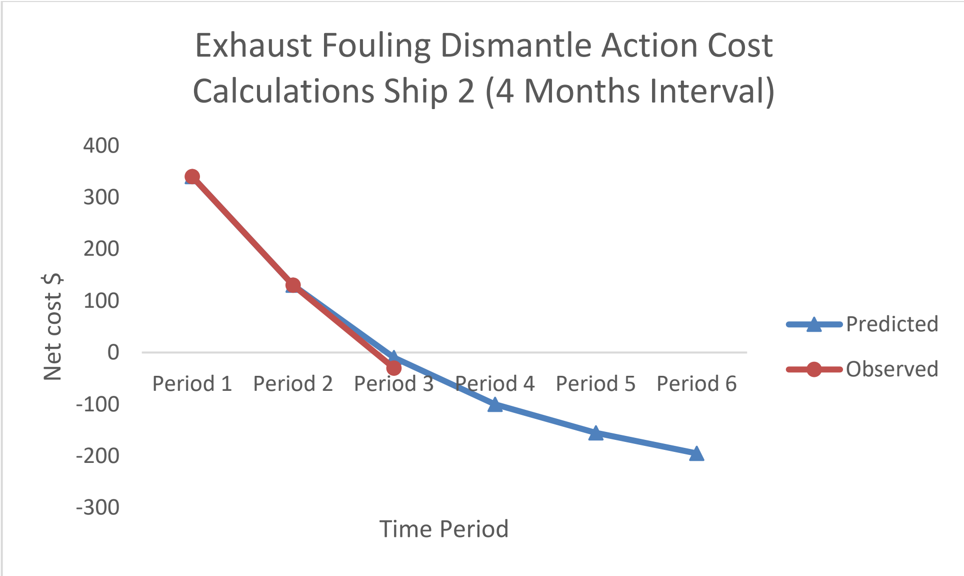

Figure 133 - Exhaust Fouling Dismantle Action Net cost Ship 2 (Four-month Intervals)

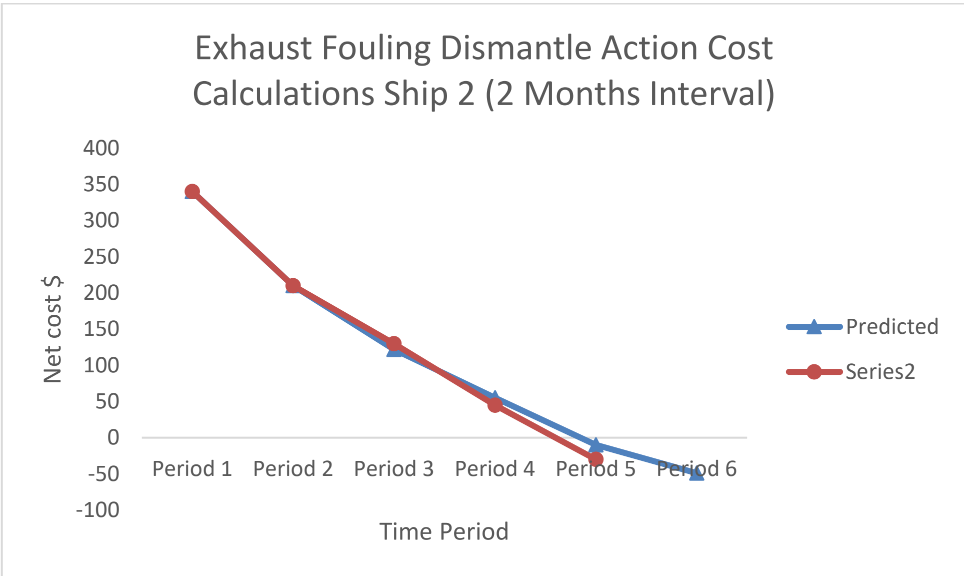

Figure 134 - Exhaust Fouling Dismantle Action Net cost Ship 2 (Two-month Intervals)

Finally, in some cases where, within two months, the overall probabilities were 100% but after that the probability values degraded, they would have a different graph type than the four-month intervals where those degradations where considered. Figures 135 and 136 show an example where, in two months, there was no degradation observed and the overall probabilities were 100%. However, in these cases where there is a slight change in degradation from the 100% starting point, the general degradation slope is very small and overall effect on maintenance planning of the system is negligible.

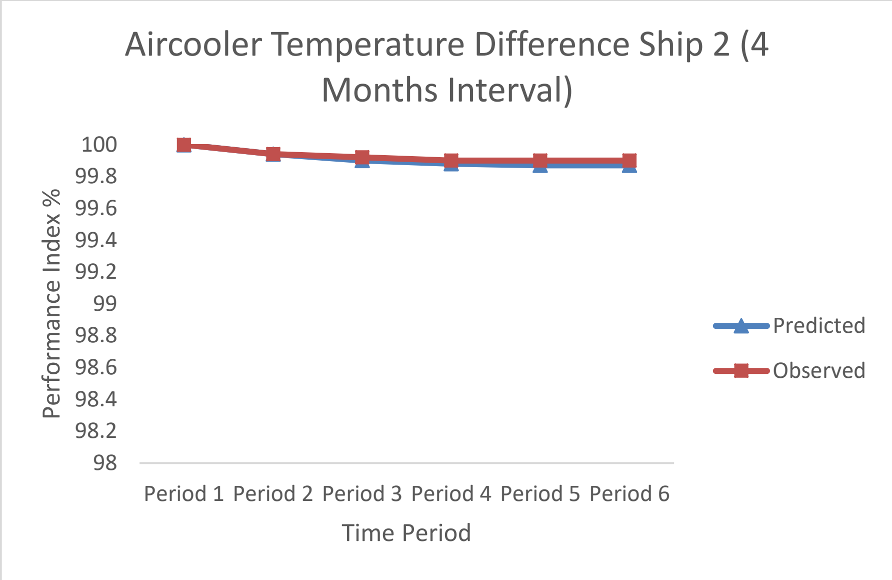

Figure 135 – Air Cooler Temperature Difference Ship 2 (Four-nonth Intervals)

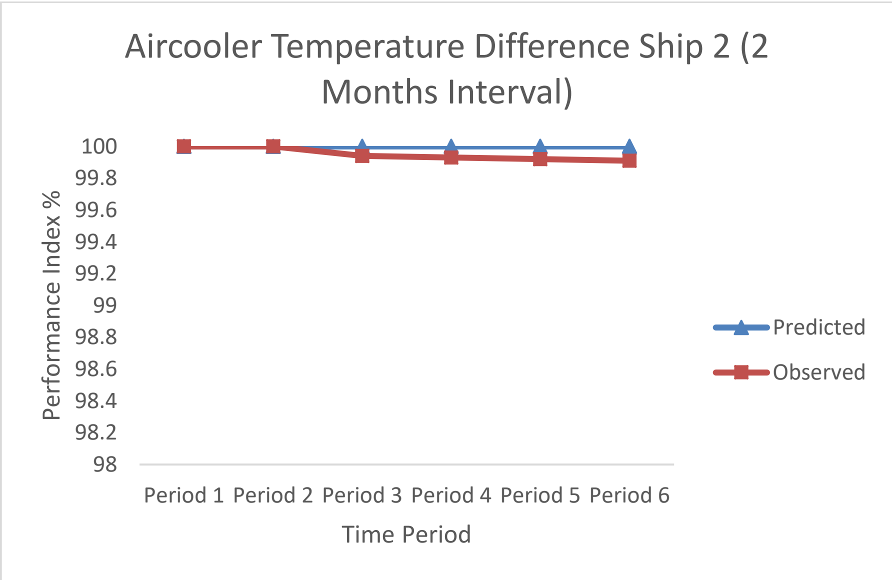

Figure 136 – Air Cooler Temperature Difference Ship 2 (Two-month Intervals)

In brief, the overall accuracy of four-month intervals on calculating values is higher than two-month intervals. However, in some cases it would be better to use the two-month intervals as it would give a better estimation of the period where maintenance is required. As a result, the best case scenario would be to use both types in order to both understand further future behaviour of the overall machinery using four-month intervals and, in case of some machinery with higher degradation and possible failures, to use smaller time intervals to observe their behaviour more closely and define the maintenance period more accurately. More results for two-months interval are shown in Appendix C.

6.6 Overall Analysed Risk Values

After using the risk matrices from Tables 17, 18, 19 and 20 from Section 5.8 and general fuzzy multiplication technique represented in Section 4.7, the overall risk consequences value of all the studied sub-systems, components and failure types were determined. The results of this calculation are shown in Table 26. The next section of this chapter will demonstrate how these values can be used within the overall BOPM methodology to help with decision-making.

Table 26 – Consequences of Different Risk for All Studied Sub-systems, Components and Failure Types

Components/Sub-systems/Failures	Human Risk Consequence	Environmental Risk Consequence	Operational Loss Consequence	Probability of Failure
Lube-oil Sump	C	C	C	1
Lube-oil Pump	B	B	C	3
Lube-oil Pump Motor	B	B	C	3
Lube-oil Filter 1	A	C	A	5
Lube-oil Filter 2	A	C	A	5
Lube-oil Purifier	B	D	D	2
Lube-oil Purifier Motor	B	D	D	2
Fuel-oil Storage Tank	C	C	B	1
Fuel-oil Transfer Pump	B	B	C	3
Fuel-oil Transfer Pump Motor	B	B	C	3
Fuel-oil Purifier	B	C	D	2
Fuel-oil Purifier Motor	B	C	D	2
Fuel-Oil Service Tank	B	C	A	1
Fuel-oil Settling Tank	B	C	A	1
Auto Filter	A	C	A	4
Cylinder Fuel Pumps	B	B	B	3
Fuel System Injection	B	C	D	1
T/C Contamination	B	C	C	3
T/C Rotor Blade	C	C	D	2
T/C Main Bearing	C	C	D	2
Air Cooler	D	C	E	3
Scavenge Air Receiver	D	C	D	3
T/C Cooling Pipework	C	C	B	3
Exhaust Fouling	B	D	B	4
T/C Air Filter	A	B	A	5

It can be noticed that the lube-oil sump has human and environmental risk values. This is since any major oil leak from the engine oil sump can create a hazardous atmosphere for both people involved within the engine room and pollution of the surrounding environment. Operational loss is also rather high as it would force the operator to stop the engine in the middle of the sea. However, it is relatively cheap to fix even though actual failure resulting in cleaning is high. Therefore, the overall cost of failure is medium. Probability of failure for this incident is extremely low as it is very easy to detect and observe plus the general conditions causing damage to the lube-oil sump body are rare and its overall structural rigidity is high. Hence, it had a failure probability value of approximately $0.8x10^{-3}$ per 100000 hours of operation.

Conversely, the fuel-oil transfer pump has medium to low human and environmental risk values in case of failure as no hazardous chemical can leak because there are preventive systems in place and, generally, the pump is very well sealed with only some operational loss due to change to the secondary pump which may occur. However, the overall operational loss can be higher if the secondary pump was already out of order. Therefore, the overall operational loss risk value is higher than average. In contrast, cost of failure is high as it is expensive and time-consuming to detect the actual fault within the pump and can cause longer man-hours. Additionally, the overall cost of both repair and replacement of parts or the overall transfer pump on its own is somewhat high. Its probability of failure is medium as the transfer pump requires more service than most other components within the engine fuel-oil system. Consequently, if the servicing is not properly followed it can have a high failure probability of approximately 0.01 per 100000 hours of operation.

Lube-oil filters have very low human risk factors as no apparent dangerous content can be exposed by their malfunction or blockage. They also have low operational loss and failure cost risk values as the general cost of change of filter is low and the speed of the replacement process and its parts availability within the ship is high. Although, environmental risk is medium as it can cause both small leakages within the overall lube-oil system and increase the overall engine emissions, probability of failure is the highest as they are blocked more frequently and require replacements more regularly with the probability of failure of approximately 0.5 per 100000 hours of operation.

Another type of example with a different pattern of risk values can be the turbocharger rotor blade. Human and environmental risk values for this component are above medium as it can cause blowout of the turbocharger. This can send both metal pieces to the surrounding areas and emit poisonous exhaust gases. Operational and failure cost risk values are even higher as it will cause major loss of power of the main engine. The turbocharger itself is expensive to dismantle or repair/replace. Additionally, the particles from the blowout can cause damage to other parts and could further increase the cost factors. However, its overall probability of failure is rather low, which is approximately 0.015 per 100000 hours of operation. Table 27, below, represents the final calculated risk factors using the fuzzy set MATLAB model presented in Chapter 4 of this thesis.

Table 27 - Calculated Overall Relative Risk Factors for All Components/Sub-systems/Failures

Components/Sub-systems/Failures	Expected Consequence of Human Risk	Expected Consequence of Environmental Risk	Expected Consequence of Operational Cost	Final Relative Risk Factor
Lube-oil Sump	2	2	2	6
Lube-oil Pump	3	3	3	9
Lube-oil Pump Motor	3	3	3	9
Lube-oil Filter 1	2.5	2.5	2.5	7.5
Lube-oil Filter 2	2.5	2.5	2.5	7.5
Lube-oil Purifier	2	3	3	8
Lube-oil Purifier Motor	2	3	3	8
Fuel-oil Storage Tank	2	3	1	6
Fuel-oil Transfer Pump	3	3	3	9
Fuel-oil Transfer Pump Motor	3	3	3	9
Fuel-oil Purifier	2	3	3	8
Fuel-oil Purifier Motor	2	3	3	8
Fuel-oil Service Tank	1	2	1	4
Fuel-oil Settling Tank	1	2	1	4
Auto Filter	2	3	2	7
Cylinder Fuel Pumps	3	3	3	9
Fuel System Injection	1	2	2	5
T/C Contamination	3	3	3	9
T/C Rotor Blade	3	3	3	9
T/C Main Bearing	3	3	3	9
Air Cooler	4	4	2.5	10.5
Scavenge Air Receiver	4	4	4	12
T/C Cooling Pipework	3	3	3	9
Exhaust Fouling	3	4	3	10
T/C Air Filter	2.5	2.5	2.5	7.5

From Table 27 it can be observed that the air cooler and scavenge air receiver have the highest calculated human and environmental risk probability to the probability of failure values of 4. This is because their human and risk values from Table 25 are high and their probability failure is above medium. The scavenge air receiver also has a very high operational loss probabilistic risk value. Thus, it has the highest overall relative risk factor of 12. The fuel-oil transfer pump has a high overall relative risk factor of 9 due to the high probabilistic risk values on all three risk factor types. Lube-oil filters have exactly average probabilistic risk values, which resulted in the average final relative risk factor of 7.5. Fuel-oil service and settling tanks have the lowest values on all the probabilistic risk values, which resulted in the lowest overall calculated relative risk factor of only 4. This is because of very low probability of failure values combined with below average risk values that resulted in low calculated probabilistic risk values.

6.7 Overall Maintenance Schedules

Using the results and recommendations determined using DBN models and their cost analysis outcomes from Section 6.4, the overall maintenance plan required for each vessel for the observed main systems can be determined. For Ship 1 cylinder four fuel-oil pump and lube-oil filter two require maintenance at the January to March 2016 time period. However, looking at table 27, it can be noticed that the cylinder fuel-oil pump has a relative criticality risk factor value of 9 whereas lube-oil filter two has a relative criticality risk factor of 7.5. This is due to the higher overall risk and cost factors related to the fuel pump. Therefore, the cylinder fuel-oil pump has priority compared with the lube-oil filter when considering maintenance task scheduling. The turbocharger in Ship 1 also requires the air filter to be checked by the October to December 2016 time period. If no blockage in the filter was detected, then within a month the exhaust duct leakage test should be scheduled.

For Ship 2, the exhaust was due to be checked for fouling between October and December 2015. If excessive fouling was detected, the whole exhaust should be dismantled and cleaned within a month. It was also found that the auto-filter for the fuel-oil system should be scheduled for maintenance. Finally, it was recommended to observe the performance readings for lube-oil filter two of Ship 2 as the overall cost analysis predicted that there may be a filter change required around January to March 2017.

For Ship 3, the first engine performance test should be carried between October and December 2016. If any fault with the engine injection system was found it should be repaired within a month. If no fault was detected, then the turbocharger should be scheduled within two months for dismantlement and cleaning due to the presence of contaminants that cause high exhaust temperatures and high charge air pressure. In summary, the results presented here predict overall maintenance tasks well before the company's own predictions and the routine maintenance tasks. It also helps them save money.

6.8 Chapter Summary

This chapter started with an explanation and analysis of different missing data treatment techniques to justify the selection of the MCMC multiple imputation technique as the most suitable technique for this work. Then, performance degradation results from the BOPM methodology DBN tool for the components/sub-systems of three main systems from all three vessels were shown. Additionally, using utility and cost nodes, the cost difference between maintenance action and total failure were plotted to make possible maintenance action decisions.

It was proven that the lube-oil and fuel-oil main systems only had performance readings that corresponded to single failure causes. However, the turbocharger main system had some performance readings that resulted in multiple failure scenarios and, in some cases, multiple performance readings corresponded to single or multiple related causes of failure. Therefore, cost analysis test scenarios were used in order to determine the maintenance scheduling for the turbocharger.

Subsequently, the relative risk factors for all the observed sub-systems/components were determined based on their human risk, environmental risk, operational loss and cost of failure factors. These factors, combined with results obtained from DBN tools, can help prioritise the maintenance tasks that must be scheduled at a similar time period. In brief, since maintenance task requirements are predicted efficiently well before companies' own predictions and routine PMs, BOPM methodology helps them both save money and not simply meet their MPI and KPI targets but also exceed them. The next chapter of the thesis will discuss, further, the results obtained from this chapter in addition to an overall discussion of all the previous chapters.

7 CHAPTER 7-DISCUSSION

7.1 Chapter Introduction

This chapter will discuss the outcomes of the four major chapters of this dissertation namely literature review, methodology, case studies and results and compare them with the general aim and objectives of the PhD title. This chapter will also clarify and summarise the general achievements of each chapter and how they interact with each other.

7.2 Maintenance Critical Literature Review

The major maintenance task classifications have shown to be those of the corrective, preventive and predictive styles. Corrective is an old methodology type of 'fix it when it is broken' and it does not fit with the overall aim of this thesis on preventing all unwanted breakdowns. Preventive fits some parts of the thesis objectives where scheduled maintenance prevents failures. However, it does not support the overall prediction of failure patterns and consideration of the monetary-related effects on overall maintenance task planning. Therefore, predictive maintenance task type is the most appropriate style, which allows alteration of maintenance task scheduling depending on performance and cost predictions of the system, sub-systems and components. This is directly in line with the aim and objectives of the business-oriented probability-based maintenance (BOPM) methodology of this PhD thesis.
The main maintenance management systems and methodologies covered in the literature review of this dissertation include reliability-centred maintenance (RCM), condition-based monitoring (CBM), asset management, risk-based maintenance (RBM) and business-centred maintenance (BCM). The BOPM introduced in this PhD thesis follows the advantages of most of these methodologies without their shortcomings. Reliability and probabilistic analysis of the RCM method has been used in order to analyse and predict the overall performance of the system. However, RCM does not include business aspects in its methodology. This is more obvious in the 12 RCM methodology steps highlighted by Rausand (1998).

The BS EN 60300-3-11:2009 standard has also introduced five standardised RCM steps, which still do not tackle this issue (BSI, 2009). Therefore, net cost analysis was added to the RCM methodology within the BOPM platform in order to cover the business aspects on the final decision-making process. This is similar to the net cost analysis used on the BCM methods. In a similar work, but not to the full extent, Mkandawire, et al. (2015) use KPIs to evaluate the performance of their RCM methodology. However, they do not create a specific MPI checklist already integrated within their methodology. Therefore, they can only check the effectiveness of their methodology after maintenance planning and action has been concluded. However, BOPM incorporates the MPIs from the beginning within the methodology in order to improve the overall effectiveness of the maintenance scheduling.

On the other hand, BCM only focusses on the cost and performance probabilistic aspects, which is also highlighted in a study by Peters (2015). The BOPM method goes further by adding risk matrices to the prioritisation of intertwining maintenance tasks on the same scheduled day/week in a similar way to RBM without its main drawback or gap of not including the business aspects as found from critical review of the available literature. The overall BOPM uses data obtained from on-board measurement systems and therefore it follows the main logics of the CBM technique. However, it also adds company business aspects and goals on top of the CBM condition monitoring analogies based on the on-board continuous measurement and readings (including pressure measurements and temperature readings). Consequently, BOPM follows all the advantages of the RCM, BCM, RBM and CBM methods together in one generalised package. Parts of the RCM methodology are used on the basis of previous reliability data for determining the probability of failure factors within the risk matrices. Probabilistic analysis units of BOPM also follow the performance degradation-related analysis required by RCM.

BOPM uses company related goals and business aspects in a similar way to BCM to modify inputs within different sections of the methodology including modifications to net cost analysis data, OEM measurement limits and some of the risk factors. Finally, risk matrices and overall risk analysis are used as part of the RBM method with probabilistic analysis similar to the study by Dong & Frangopol (2015) used within the risk related task prioritisation section of the BOPM platform. Using all the advantageous parts of these separate maintenance policies helps BOPM to eliminate their disadvantages and achieve the main aim of this PhD thesis by considering both technical and business aspects on predicting a maintenance schedule for the overall system.

The literature review chapter of this dissertation highlights the main maintenance tools and systems used within other maintenance policies. The literature review chapter also covers all the pros and cons of each tool used in the industry. In order to achieve the main aim and objectives, the BOPM platform uses different types of maintenance-related tools available in the literature. After reviewing the relevant literature, BOPM has selected the Bayesian belief network (BBN) tool with first order Markov chain dynamic prediction pattern to predict the performance of the system. Cost and business aspects of decision-making of the performance prediction have been developed by the addition of cost and utility nodes to the finalised dynamic Bayesian network (DBN) tool. DBN allows interconnectivities between different components/sub-systems within the same system or even larger overall system to be identified in a much easier way than the traditionally used fault tree analysis (FTA) tools (Weber, et al., 2012). In different studies, Liang, et al. (2017) highlight the fact that DBN is a very effective tool for defining an accurate reliability and performance profile of complex structures.

Having utility and decision nodes added to the DBN eliminates requirements for a separate net cost analysis and decision-making tool which, in turn, reduces calculation efforts and increases overall accuracy (Poropudas & Virtanen, 2011). In order to obtain more unified and smooth data, the missing data treatment method was implemented to the methodology. Finally, risk analysis was performed using risk matrices and fuzzy logic in order to obtain overall risk values and help the final decision-making process with prioritisation of tasks. Prioritising tasks with the higher overall relative risk factors compared with others if they are scheduled for similar time periods did this.

7.3 Business-oriented Probability-based Maintenance (BOPM)

BOPM methodology uses inputs and data from different sources and combines it with its analysis tools to obtain final decisions and maintenance schedules. Raw data sources for this methodology include company goals in the form of company MPIs, past PMS reports, OEM component specific data, observed condition monitoring data from sensors and cost data. Company MPIs are used to modify both OEM related component/sub-system limits and cost analysis data regarding risk matrices' creation. Expertise from engineers inside the company has been used to finalise these two types of data inputs. Finalised OEM related component/sub-system limits were then used as the main limits for obtaining performance indices within the probability analysis tool.

Subsequently, company MPIs, past PMS reports and some of the cost data has been used in order to determine limits for the four main risk matrix criteria used for the analysis. These risk matrices are: human risk, environmental risk and operational loss. A fourth criterion, probability of failure, has been created in order to connect previous failure types together and calculate the final overall risk factor per failure type. The overall risk factor for each risk matrix relevant to the probability of failure is then calculated using triangular fuzzy logic. A triangular fuzzy membership function is the most useful function in this case as there are only two axes with a linear linguistic reasoning pattern. Therefore, it is simpler and more calculation-friendly with similar accuracy to more advanced membership functions for this case (Mentes & Helvacioglu, 2011).

Afterward, condition-monitoring data obtained from the sensors need to be considered for missing data. It was observed that some sensorial readings had up to 25% missing data. Therefore, different missing data treatment methodologies were analysed to select the most accurate option. This missing data treatment allows smoother and more unified data for the performance index analysis. Then, the performance index value for each type of sensorial reading was put into the probability analysis and prediction tool, which uses the Bayesian belief network (BBN) tool with first order Markov chain dynamic prediction pattern (Vhanmane & Patra, 2010). One of the main advantages of using BBN is the ease of representation of interconnectivity and inter-relational pattern among different components and sub-systems within the system. The DBN tool also makes it easier to create different types of relationship between different components, sub-systems and readings without a need to create more complex and/or gate types used in fault tree analysis (FTA) that has been used traditionally in the industry.

Additionally, the DBN tool can have both decision and utility nodes, which helps to perform a net cost analysis and decision-making. Therefore, cost data obtained can be used for final cost analysis and maintenance scheduling inside the BOPM platform. In brief, using the DBN tool with utility and decision nodes helps to achieve the major objectives of the thesis by combining both technical and business aspects inside a single platform to obtain maintenance scheduling. This includes adding company goals and MPIs within an innovative probabilistic analysis that can then use the MPI-modified cost results to create decisions. Finally, in cases of intersecting maintenance, task overall risk values are combined with concluded decisions from the DBN tool in order to prioritise the tasks and achieve the final maintenance scheduling decisions. In general, the overall methodology of BOPM has been created using the literature and gaps found with a comparison of different techniques. Data obtained from vessels and knowledge obtained working within the INCASS EU FP7 project, helped to refine and validate the methodology specifically concerning the development of the dynamic connections using first order Markov chains (Taheri, et al., 2014). Experts from the project also helped to develop the overall network patterns by adding their opinion of how each system and its relevant network should be designed.

In summary, BOPM helps ship operators to have full power by adding their inputs from business aspects and their expert opinion onto the overall performance analysis and decision-making of the maintenance programme of their vessels. The DBN tool used in this platform can almost fully mimic the real machinery systems within the ship with added practicality of fast forwarding the engine performance to future time-periods and discover the problems that could occur. Therefore, engineers and maintenance managers can then predict and prevent failures from occurring. The net cost analysis part of the methodology can also help with overall decision-making so no maintenance has to be undertaken prematurely, which can reduce the overall costs of some unwanted inspection and repair tasks.

7.4 Ship Case Studies with Different Ship Machinery Systems Overview

Three vessels were chosen for these case studies. Two were chemical tankers that sailed in different environments as one sailed in the cold and choppy waters of the North Atlantic and the other worked within the more subdued tropical Pacific, experiencing occasional tropical storms. As the vessels were very similar it gives an opportunity to compare the effectiveness of different systems in different environmental conditions within a specific time period. The third vessel was a multi-purpose cargo vessel which proves that this methodology can work in any other ship and variety of sea-worthy vessel. Three different systems that were chosen for this thesis, all of which have similar general outlines with small differences such as the multi-cargo vessel has an eight-cylinder engine whereas the sister chemical tanker vessels have seven cylinder engines.

The first two machinery systems chosen are the lube-oil and fuel-oil systems, where both have only one possibility of failure for each reading type. These two systems are essential for the sea-worthiness and overall health and safety of the vessels as no ship engine can work without fuel and consistent lubrication. Another important factor in selecting these two systems is their relatively simple operational profile, which makes it easier to verify the results obtained from the methodology. The third machinery system is the turbocharger. Turbochargers, unlike the other two systems, may have some readings that would result in multiple failures (as seen on Ship 1's charge air pressure drop example in Section 6.4.3) or multiple readings into a single failure (as seen on Ship 2's exhaust fouling example in Section 6.4.3). It could also have a scenario that multiple readings result in multiple, related failure patterns (as seen on Ship 3's high charge air pressure example in Section 6.4.3). Therefore, extra test nodes with relevant utility and decisions have been added in order to compensate for those extra scenarios. The structures of the chosen machinery systems are represented in Figures 21, 24, 25 and 30 in Chapter 5 of this dissertation. These are designed using OEM reports and consulting with experts and knowledge learned by being involved in the INCASS EU FP7 project.

Subsequently, all the failure scenarios in connection with the two condition monitoring readings were put into tables in order to create the overall DBN structures. Finally, cost values were added with the decision nodes in order to develop the finalised DBN models with net cost analysis and decision-making inside the BiasiaLab environment as shown in Figures 23, 28, 29 and 32. The limits of the working conditions for each reading type were shown after adjustment with the company MPIs and experts' input. These inputs were then considered using the risk matrix creation criteria and were combined with the ABS 2012 risk matrix criteria rules and recommendations.

Each risk matrix criteria has five calculating factors with "a" showing the lowest risk and "e" showing the highest. These risk matrices were then combined in a fuzzy environment with the probability of failure levels in order to create their overall two-dimensional risk factors. Probability of failure itself is determined using the manufacturers' estimation of failure and past PMS reports. They are factorised in five levels with "5" being the common occurrence and "1" being rare occurrence. At the end, a table was created demonstrating the connections between different risk factors and their probability of occurrence in order to help the development of fuzzy wording. This can be used inside the triangular fuzzy model developed in Chapter 4 to determine the overall risk factors for each component/sub-system.

7.5 Results Overview

In the results section of Chapter 6, missing data treatment methods that were explained in Chapter 4 were put to the test using the data acquired from Chapter 5. Three different sets of readings that had full data with no missing data were used. These reading sets were chosen as they also represented a crucial role in their relevant machinery system. These readings were from different machinery systems and each from a different vessel in order to ensure the results obtained covered all involved aspects. Then, randomly, 15, 30 and 50 data were eliminated from each system to create mock missing data scenarios. These numbers were chosen as the lowest number of missing data from other systems with missing data was 14 and the highest was 48.

The three most commonly used missing data treatment methodologies of Mean Substitution (MS), Expectation-Maximisation (EM) of the Maximum Likelihood (ML) and Markov Chain Monte Carlo (MCMC) multiple imputation were compared with the full data set and it was found that the latter technique has the closest data variation and pattern to the full data. Then, for the MCMC multiple imputation technique itself different scenarios of 3, 4, 5, 6 and 7 iterations were compared with the full data, which found that after five iterations there is no significant change in accuracy. Zhu & Collette (2015) have also determined that for small reading data to be used in conjunction with a DBN tool, the MCMC technique has the highest accuracy. As a result, for all the missing data treatment of the results obtained from all the vessels, the MCMC multiple imputation technique with five iterations was used inside the SPSS environment.

Using the DBN models with the utility and decision nodes designed in Chapter 5 and results obtained from missing data treatment, overall probabilistic performance and cost predictions were evaluated for all sub-systems and components involved. Some of these sub-systems and components did not have a significant reduction in their overall performance so were not shown within the main body of Chapter 6 but are demonstrated in the Appendices. In order to ensure the predictions were accurate the actual observed values were also plotted along the predicted values. In general, few different types of graphical patterns and their accuracy with relevance to the observed data were detected.

In some graphs, as in Figure 47 probabilistic performance predictions of Ship 1 lube-oil pump, there was a sudden reduction in the decreasing pattern and the angle of the graph. This would mean that the overall system has had its first bathtub curve reduction and overall speed of degradation is slowing down. Some graphs, however, only showed a uniform reduction in the speed of degradation such as those seen in Figures 51 (probabilistic performance predictions of Ship 2 lube-oil purifier) and 77 (probabilistic performance predictions of Ship 2 auto-filter). This either means that it has already passed the optimum degradation of the component or it is degrading fast towards a more settled step of degradation and, eventually, failure.

There is also the possibility that the speed of degradation of the component is not high enough to be problematic and may settle into a single degraded state where it still works well for an extended time period. Finally, some graphs, e.g., Figure 79 (probabilistic performance predictions of Ship 3 cylinder-2 fuel-oil pump) demonstrated an increasing pattern of degradation which could mean that the component/sub-system is degrading fast towards a failure and there is a constant malfunctioning factor within the component/sub-system that stops the reduction in performance to be settled.

In a relation between predicted and observed data, different graphical pattern types for data have been detected. In some cases, as in Figure 83 (probabilistic performance predictions of Ship 3 auto-filter), the difference between the values and reduction pattern of the predicted and observed graphs is very low which means there is a very low error on prediction. In some cases, predicted values are slightly lower (Figure 73 probabilistic performance predictions of Ship 2 cylinder-6 fuel-oil pump) or higher (Figure 63 probabilistic performance predictions of Ship 1 cylinder-1 fuel-oil pump) than the observed values but overall reduction follows a similar pattern. In some other cases, such as that in Figure 69 (probabilistic performance predictions of Ship3 cylinder-3 fuel-oil pump), prediction is slightly separated from the observed values, then merged together at the end. Finally, in some cases, the line representing the predicted values in the probabilistic performance graph would cross the line representing the probabilistic performance graph of observed values as seen in Figure 53 (probabilistic performance predictions of Ship 3 lube-oil filter 1).

All three scenarios, with a slightly higher error in the pattern, can be due to the presence of other concurring and relevant failures within or around the observed component/sub-system. However, by observing new values for the next time period and updating the predictions these errors can be significantly minimised.

Using the cost prediction results for decision-making, the first two machinery systems had only one possibility of failure per reading. This can be seen in both Figures 46 (cost difference predictions of Ship 1 lube-oil filter 2) and 78 (cost difference predictions of Ship 2 auto-filter) for two separate machinery system components/sub-systems for two separate vessels. In both cases, a negative cost value was predicted after a certain time period where it would be beneficial to have maintenance scheduled for that time period. However, in the case of Figure 78, the negative cost value is so low that the maintenance can be also scheduled for the following time period, if at all possible.

In the case of the turbocharger, there were more complicated scenarios to be determined from some of the readings. In the case of the charge air pressure drop reading shown in Figure 91, there were the two failure possibilities of exhaust duct leakage and air filter blockage. After plotting a test cost difference to failure cost difference, it was found that the cost of air filter test becomes negative at a certain time period. Therefore, it is viable to test the air filter for blockages at that time and if no blockage is detected, then an exhaust duct leak test could be scheduled. In the case of the three different readings on Figures 96 (probabilistic performance predictions of Ship 2 turbocharger low exhaust gas temperature scenario), 97 (probabilistic performance predictions of Ship 2 turbocharger low charge air pressure scenario) and 98 (probabilistic performance predictions of Ship 2 turbocharger exhaust back pressure scenario), there was only one possibility of failure, which was caused by the same failure scenario of exhaust fouling. This fouling was determined to be affecting the turbocharger more as its cost difference became negative after a certain time-period; as a result defouling of the exhaust duct is recommended (Figure 99 cost difference predictions of Ship 2 exhaust defouling).

In the case of Figures 104 (probabilistic performance predictions of Ship 3 turbocharger high exhaust gas temperature scenario) and 105 (probabilistic performance predictions of Ship 3 turbocharger high charge air pressure scenario), two failure possibilities have to be tested; those of the engine injection fault and turbocharger contaminants. After the cost analysis of the test was compared with failure, it was determined after a certain time period that the injection fault had a negative cost compared with its test cost of performing an engine performance test. Therefore, it would be beneficial to implement an engine performance test within that time-period and if nothing was found to be wrong then observation of the overall turbocharger performance and turbocharger dismantlement for contaminant cleaning should be scheduled.

Finally, the risk factors and probability of failure for each component/sub-system was determined using the limits driven from the MPIs, past PMS reports, experts and ABS 2012 document described in Chapter 5. In brief, ABS 2012 provides the overall platform on how different risk matrices for ships should be determined which, in the case of this study, include human risk, environmental risk, operational loss and cost of failure with the addition of probability of failure. Then, past PMS reports are used to determine the probability of failures and their categories within a risk matrix. Finally, other risk levels within each risk category are determined using the company's MPIs and their expert input.

Subsequently, fuzzy logic, shown in Chapter 4, was used to calculate the overall two-dimensional risk factors and, eventually, final relative risk factor for each component. Consequently, the final relative risk factors were combined with the maintenance decisions made from the DBN net cost analysis in the case of Ship 1 where there were two components/sub-systems requiring maintenance at the same time. Therefore, the component/sub-system with the highest risk value was prioritised for maintenance. This is especially helpful if we consider all of the ship machinery systems and, also, in older ships where there can be multiple maintenance tasks required per time period. At the end, it was also noticed that Ship 1 had more general degradations compared with its sister, Ship 2. This could be due to the fact Ship 1 is operating in a much harsher environment in the North Atlantic region.

In conclusion, it has been observed that BOPM has given probabilistic performance predictions with accuracies of 97.9%, 98.1% and 97.4% on average for the lube-oil system, fuel-oil system and turbocharger, respectively, from all three case study vessels. This results in an overall average accuracy of 97.8%, which is a relatively high accuracy for any predictive probabilistic model. Net cost analysis and decision-making parts of the methodology have also provided accurate results that matched the overall maintenance decisions of the company. However, there were two cases where the company had performed a scheduled maintenance task, as part of the manufacturer's requirement that BOPM had identified that would not require maintenance for some time. Both of the tasks were from Ship 3, one being the auto-filter change and the other was lube-oil filter-2. The company would have saved $212 and $253 respectively by cancelling those two replacement jobs. In conclusion, this methodology not only meets the overall requirements of the company goals based on their KPIs and MPIs but also surpasses their expectations by saving them more capita.

7.6 Summary of Findings

This section shows how all the points within the aim and using BOPM on three different machinery systems from three different sea-worthy vessels, meets the objectives of the PhD using the achievements:

- In the literature review section of this dissertation, both historical and recent definitions of the maintenance subject were described first. Subsequently, the overall maintenance subject was studied in five major sections of maintenance classifications, maintenance management systems and policies, maintenance related analysis tools and systems, maintenance performance measurements, and inspection and monitoring tools and methodologies.
- The maintenance management systems and methodologies section looked into all different types of maintenance policies developed in the industry including reliability-centred maintenance, condition-based monitoring, risk-based maintenance and business-centred maintenance. This section also compared the pros and cons of each methodology with comparisons from the literature and presented a summary of major observations and overall gaps in these maintenance policies to be addressed by the BOPM platform. The main overall gap found was that none of the methodologies combined both the technical side of the maintenance with business aspects of the company in equal manner.
- The maintenance-related analysis tools and systems section critically reviewed all reliability and probability analysis techniques such as failure mode, effect and criticality analysis, fault tree analysis, Bayesian Belief network and Monte Carlo simulations, with the summary of the major observations which are made at the end of this section. This helped to notify that some techniques such as BBN are better than FTA as they can represent interconnectivities between different components/sub-systems. BBN also

allows adoption of net cost analysis using utility and decision nodes without the need for an external tool, which minimises calculation efforts and decreases possibilities of decision-making errors.

- The methodology chapter of this thesis demonstrated the overall BOPM platform including a description of each section of the methodology and the connections to each other for producing the final maintenance schedule.
- This section started with a presentation of the company maintenance performance indicators (MPIs) used to adjust overall sensorial data limits and cost data with representation of the network models. Then, data clients, including component specific performance limits from OEM reports, were demonstrated to be used within the performance index evaluations inside the probability model. Afterwards, past PMS reports with cost data were used for both risk factor classifications and net cost analysis for decision-making.
- The methodology chapter then used observed sensorial data such as dynamic inputs relevant to their MPI adjusted OEM limits to obtain performance index values to be used inside the probability model. Component and sub-system risk classification criteria were also explained, based on the four major areas of human risk, environmental risk, operational loss and cost of failure. A second dimension was added for these factors on the basis of the probability of failure using fuzzy logic and reasoning with a triangular membership function, so the overall relative risk factor for each component/sub-system can be defined.
- At the end of the methodology chapter, the main analysis units were explained in the two major sections of probability analysis unit and decision analysis unit. PAU is based on the Bayesian belief network with first order Markov chain dynamic prediction.
- The decision-making model used the utility and decision nodes added to the overall dynamic Bayesian network model, where it made it possible to perform net cost analysis to obtain maintenance scheduling decisions. This model was then complemented with relative risk factors for task prioritisation and producing final decisions.
- The BOPM platform with the combination of its analysis units (i.e., risk analysis unit, PAU and DAU) and data clients (company MPIs, observed sensorial data, component specific OEM limits) has made it possible to analyse the overall condition of the machinery systems within the ship and then combine it with company business factors

to predict its future performance and schedule maintenance tasks to both minimise risk and reduce cost.

- ❖ For the case studies to be used to validate methodology by producing results, three main vessels, used as case studies, were introduced. The first two vessels were chemical tanker sister vessels that operated in different sea conditions and environments. The third vessel was a multi-purpose cargo ship with 11 years of operational history. Three major systems consisting of the lube-oil system, fuel-oil system and turbocharger were used from all vessels for the data gathering campaign. Adjusted OEM limits, based on company MPIs and overall operational flow, of each system were demonstrated in this chapter.
- ❖ Having two sister ships made it possible to compare the reliance of similar components operating in different environmental conditions. Having a third different ship also proved that the methodology can work for any ship type.
- ❖ The Bayesian network models of each system were developed using their operational flow charts. Subsequently, MPI-adjusted cost values of possible failures for each component/sub-system inside the selected machinery systems were tabulated to be used for net cost analysis and decision-making purposes. Finally, levels and factor limits within the risk criteria were finalised using the ABS (2012) report, cost limits, past PMS reports, company MPIs and information from experts.
- ❖ The results chapter started with analysis of different missing data treatment methods using real full data obtained from the case study vessels. These missing data methodologies included mean substitution, expectation-maximisation of the maximum likelihood and Markov Chain Monte Carlo multiple imputation techniques. It was determined that the Markov Chain Monte Carlo multiple imputation technique with five iterations is the most suitable missing data treatment methodology.
- ❖ The results chapter then illustrated both probabilistic analysis and net cost analysis results obtained from all vessels for each of the three machinery systems. It was shown that for the lube-oil and fuel-oil systems there is only one failure possibility arising from each degradation reading. However, in the turbocharger there some readings could correspond to multiple failure types or multiple readings resulting in single or multiple related failure types.
- ❖ Subsequently, test cost values were compared with the cost of failure on these scenarios for performing the decision-making process. Afterward, using the net cost results, initial maintenance scheduling decisions were made for each system.

- Then, the final relative risk values were determined for each component/sub-system used within the chosen machinery systems. These were determined based on the limits calculated in the case study chapter and overall fuzzy logic methodology developed in the methodology chapter. Finally, the risk factors were combined with the decisions made from the DBN model with utility and decision nodes from the previous paragraph to achieve the final maintenance-scheduling programme, thus answering the research question.
- These risk factors were used in the ordering of intersecting tasks scheduled because of the DBN decision-making model. It was proved that the methodology has 97.8% accuracy when predicting probabilistic performance values. It was also identified that in the case of Ship 3 two manufacturer-required scheduled maintenance tasks could have been avoided, saving the operator $467 overall.
- Overall methodology meets company-approved KPIs and MPIs.

7.7 Possible Limitations

There are several limitations when using the BOPM within the marine industry. One of the major limitations for this methodology is the requirement of a decent understanding and generation of system flow and network within the Bayesian statistical environment with representation of all interdependencies within components/sub-systems. This would require consultation with various marine experts.

Furthermore, BOPM has numerous data clients and requires stringently-obtained and established data sources and classification. Even though the MCMC algorithm helps minimise missing data, there would still be some data to be present in order to commence the analysis processes. Some of the most important data that BOPM cannot work without include: major cost data, OEM data/reports, PMS reports and company MPIs.

Subsequently, some learning algorithms can be used to more accurately find the relationship between different components within the system and find which order type of Markov chains they would follow as some systems may follow higher orders of Markov chains than first order. Finally, more automation of calculations using a uniquely developed program (possibly in the JAVA environment) can increase the overall speed of calculations and save valuable time on defining maintenance schedules for overall machinery systems of a vessel.

7.8 Chapter Summary

This chapter discussed the overall findings of the literature review and how they were related to the overall aim and objectives and, eventually, to the development of the BOPM methodology. It then explained the reason behind each section of the methodology and why each tool was used for a certain part of the analysis within the methodology compared with the overall aim and objectives of this PhD. Subsequently, it described the major motives for the selection of each case study and how their represented data were used for the results chapter and validation of the BOPM methodology. Finally, the results obtained from each of the case studies were discussed. This discussion of results also included the relationship between risk factors and DBN maintenance decisions to obtain the final maintenance-scheduling plan. This section also included the comparison of graphical representations and differences between some of the outcomes. Additionally, the reason behind the selection of the determined missing data treatment method was illustrated.

8 CHAPTER 8-CONCLUSION AND FUTURE RESEARCH

8.1 Chapter Introduction

This chapter will show the overall summary of major points made in all previous chapters of this dissertation including the literature review, methodology, ship case studies and discussion in order to demonstrate the effectiveness of the business-oriented probability-based maintenance (BOPM) and how it addresses the aim and objectives of this PhD. Finally, a brief list of future work and research recommendations will be discussed.

8.2 Overall Conclusion

This section will give a summary of all the points made within the thesis on showing the advantages of using BOPM in the maritime industry based on existing gaps identified from the research. The overall aim of BOPM is to integrate business and technical aspects of maintaining a seaworthy vessel in the most optimum way possible considering both cost and risk of failure elements. This was achieved by developing the BOPM, which is explained in detail throughout this thesis and using eight major objectives. Next, bullet points will highlight a brief recap of the points made within the thesis to address these eight PhD objectives:

- ✓ Using critical literature review, all the gaps from previous maintenance methodologies were identified and used to strengthen the overall BOPM methodology.
- ✓ This critical review also helped to identify the most appropriate tools needed to create the different sections of the methodology. The overall BOPM platform has nine sub-sections of which six fit with the data client criteria. These six data clients include company goals with MPIs, component-specific performance measurements including OEM data, risk factor classification, past PM reports, and cost data. The remaining three sub-sections are those of the analysis units, which consist of probability analysis unit, decision analysis unit, and final decisions and scheduling.

- ✓ All the above data clients, apart from risk factor classification, were gathered using the three main ship case studies and using experts' knowledge from the industry. However, risk factors were determined by classification of the three major risk factors of human risk, environmental risk and operational risk based on both available numerical data and further input from industrial experts. Then, they were added together using probability failure per each failure type and triangular fuzzy functions. This resulted in the final risk factor per failure type. This would be later used in the final decision-making and scheduling sub-section of the methodology.
- ✓ Having both risk factors that incorporate company goals and company specific MPIs helps to integrate company business aspects with the overall maintenance and decision-making process. This is further enhanced by modifying the OEM performance values and cost values in accordance with company goals, which are then used inside the two main analysis units of the BOPM, namely PAU and DAU.
- ✓ Based on research, a dynamic Bayesian network was chosen for the overall probabilistic analysis as it can easily integrate complex interactions between different components/sub-systems within a system. Its dynamic abilities also allow the analysis of past and current performances of the system and predict its future.
- ✓ Dynamic connections of the methodology were completed using first order Markov chains, which helps achieve distinctive time slices within each continuous performance value of each component/sub-system.
- ✓ The DAU module of the BOPM was developed using utility and decision nodes within the already developed DBN model. This is due to the fact that research proves that having an integrated decision-making system with the probabilistic analysis in one single unit enhances the overall accuracy and decreases calculation efforts because it will eliminate any further assumptions, and external adoption algorithms would be required between the two different analysis tools.
- ✓ The final decision and scheduling sub-section of the BOPM uses the final maintenance decisions made by the DAU sub-section and, in the case of intersecting maintenance schedules, to prioritise the more critical jobs with respect to those less critical using risk factors from the risk factor classification sub-section. This will result in the final fully organised maintenance schedule for the vessel.

- ✓ Validity and general performance of the BOPM platform was initially completed using experts and knowledge from the INCASS EU FP7 project. Then it was further proven using three different ship case studies containing two sister chemical tankers and one multi-purpose general cargo vessel.
- ✓ Three major machinery systems from these three vessels were used for the study: Lube-oil system, fuel-oil system and turbocharger. These three systems are vital for the survival of the engine which, in turn, is vital for the general operation, and navigation of the vessels on the open sea.
- ✓ There were also major differences between the lube-oil system and fuel-oil system compared with the turbocharger. Both lube-oil and fuel-oil systems have only one failure possibility per performance or conditional reading. However, the turbocharger is more complex and can have four different possibilities for performance readings. In some cases one reading can result in one type of failure, in other cases one reading can result in multiple failures, or multiple performance readings can result in one failure type. Additionally, multiple but identical batches of performance readings may cause multiple but identical batches of failure types.
- ✓ This methodology has proven able to tackle the probabilistic analysis and decision-making process for all types of complex scenarios of failure to performance reading relations.
- ✓ Comparing the predicted results with the observed values, it has been calculated that the BOPM had an overall accuracy of approximately 97.8%, which is much higher than more conventional techniques using FTA with an average accuracy of below 90%. Additionally, it was evaluated that the company would have saved $467 by simply delaying some of their maintenance jobs according to the recommendations from the BOPM.
- ✓ Therefore, BOPM was successful when integrating the business and technical aspects of maintenance within the company and saved money in the long run. This is in accordance with the main aim and objectives of this PhD thesis. Additionally, it meets company-relevant KPI and MPI targets.

8.3 Future Research

This section will represent recommendations made for future research based on the outcomes of this PhD thesis in bullet points:

- One of the shortcomings of this PhD was the lack of enough data from other machinery systems, which would have helped to simulate the overall machinery systems of each ship to observe the wider scenario and create interconnections between different components within different systems. For example, gas inlet of the turbocharger used in the case study is directly connected to the injection system of the cylinders. Therefore, it would be beneficial to have the DBN of the overall engine so each failure can be identified more clearly and rapidly.
- All analysed machinery systems can be put together as one major system called ship machinery where everything about the performance and degradation patterns can be observed in one single platform. This would also increase the efficiency of the overall system observation and create a possibility of defining a relationship between system degradation and fuel consumption.
- Learning algorithms such as naive Bayes algorithm, Bayes net inference, Bayes net structure learning and Maximum A-posteriori (MAP) estimation techniques can be added to the DBN model in order to learn the overall behaviour of components/sub-systems compared with their main system and identify interconnectivities between different components/sub-systems within the system. This would help to model the overall system in the most perfect way; furthermore, adding all systems inside a single platform will make it possible to find interconnections of components/sub-systems from different major systems in the vessel.
- Additionally, learning algorithms can identify any special pattern in the dynamic pattern of the BBN analysis for each component/sub-system and determine if higher order Markov chains can be adopted. Some systems may follow higher order Markov chains than first order as their dynamic dependency may correlate to longer time periods than t=1.
- Using programming languages such as JAVA, a more specialised platform can be created that would not require application of different software packages and create a

more automatic and rapid analysis system as used in the BOPM. This would even further enhance the accuracy of the methodology.

- Creation of a broad automatic database system with online data gathering and imputation system can be beneficial in lowering the operational time required by inputting data manually.
- Having an automatic database connected to the fully automatic analysis system for the BOPM can accelerate the overall maintenance management system specifically in the case of large companies with numerous vessels and machinery systems.

8.4 Chapter Summary

In conclusion, this chapter explained a summary of all the points and outcomes made within different chapters of this thesis and their connection with each other and overall aim and objectives of the PhD. It also recommended the possible future research and work that can improve the performance of the business-oriented probability-based maintenance platform.

9 References

Abdul-Nour, G., Beaudoin, H., Ouellet, P., Rochette, R. & Lambert, S., 1998. A reliability based maintenance policy; a case study. *Computers & Industrial Engineering,* 35(3-4), pp. 591-594.

Ablitt, C. & Speck, J., 2005. *Experiances in implementing Risk-Based Inspection.* Manama, Bahrain, Middle East Nondestructive Testing Conference & Exhibition.

ABS, 2000. *Guidance Notes On Risk Assessment Applications for the Marine and Offshore Oil and Gas Industries,* Houston, TX, USA: ABS (American Bureau of Shipping).

ABS, 2016. *Rules for Conditions of Classification* , Houston, TX, USA: American Bureau of Shipping (ABS).

Agrell, P. J., 1997. On redundancy in multi criteria decision making. *European Journal of Operational Research,* 98(3), pp. 571-586.

Ahmad, R., Kamaruddin, S., Azid, I. A. & Almanar, I. P., 2012. Failure analysis of machinery component by considering external factors and multiple failure modes – A case study in the processing industry. *Engineering Failure Analysis,* 25(1), pp. 182-192.

Ahren, T. & Parida, A., 2009. Maintenance Performance Indicators (MPIs) for benchmarking the railway infrastructure. *Benchmarking: An International Journal,* 16(2), pp. 247-258.

Albonico, A., Kalyvitis, S. & Pappa, E., 2014. Capital maintenance and depreciation over the business cycle. *Journal of Economic Dynamics and Control,* 39(1), pp. 273-286.

Al-Najjar, B., 2006. *Cost-effective & continuous improvement of production process and company's business when using total quality maintenance (TQMain).* ChengDu, China, International Conference on Maintenance Engineering.

Arunraj, N. & Maiti, J., 2007. Risk-based maintenance—Techniques and applications. *Journal of Hazardous Materials,* 142(3), pp. 653-661.

Aslan, B., Stevenson, M. & Hendry, L. C., 2012. Enterprise Resource Planning systems: An assessment of applicability to Make-To-Order companies. *Computers in Industry,* 63(7), pp. 692-705.

Baserba, M. G., Reif, R., Hernandez, F. & poch, M., 2012. Implementation of a knowledge-based methodology in a decision support system for the design of suitable wastewater treatment process flow diagrams. *Journal of Environmental Management,* 112(1), pp. 384-391.

Ben-Daya, M., 2000. You may need RCM to enhance TPM implementation. *Journal of Quality in Maintenance Engineering,* 6(2), pp. 82-85.

Benner, M., Linnemann, A. R., Jongen, W. F. & Folstar, P., 2003. Quality Function Deployment (QFD)—can it be used to develop food products?. *Food Quality and Preference,* 14(4), pp. 327-339.

Bleakie, A. & Djudjanovic, D., 2013. Feature extraction, condition monitoring, and fault modeling in semiconductor manufacturing systems. *Computers in Industry,* 64(3), pp. 203-213.

BSI, 2006. *Application of Markov technique.* United Kingdom (UK), Patent No. BS EN 61165:2006.

BSI, 2007. *Maintenance- Maintenance Key Performance Indicators.* United Kingdom (UK), Patent No. BS EN 15341:2007.

BSI, 2008. *Asset management- Part 1: Specification for the optimized management of physical assets.* United Kingdom (UK), Patent No. PAS 55-1:2008.

BSI, 2009. *Dependability Management - Reliabilty Centred Maintenance.* United Kingdom (UK), Patent No. BS EN 60300-3-11:2009.

Cagno, E., Caron, F. & Mancini, M., 2002. Risk analysis in plant commissioning: the Multilevel Hazop. *Reliability Engineering & System Safety,* 77(3), pp. 309-323.

Cai, B., Liu, Y., Zhang, Y., Fan, Q., Liu, Z. & Tian, X., 2013. A dynamic Bayesian networks modeling of human factors on offshore blowouts. *Journal of Loss Prevention in the Process Industries,* 26(4), pp. 639-649.

Caldwell, R., 2012. *Hull Inspection Techniques & Strategy.* London, UK, Royal Institute of Naval Architecture (RINA) Conference.

Caprioli, A., Cigada, A. & Raveglia, D., 2007. Rail inspection in track maintenance: A benchmark between the wavelet approach and the more conventional Fourier analysis. *Mechanical Systems and Signal Processing,* 21(2), pp. 631-652.

Chang, H. H. & Huang, W. C., 2006. Application of a quantification SWOT analytical method. *Mathematical and Computer Modelling,* 43(1-2), pp. 158-169.

Chan, L. K. & Wu, M. L., 2002. Quality function deployment: A literature review. *European Journal of Operational Research,* 143(3), pp. 463-497.

Chen, J., Zhang, C., Zhang, Z., Zi, Y., He, S. & Yang, Z., 2014. Planetary gearbox condition monitoring of ship-based satellite communication antennas using ensemble multiwavelet analysis method. *Mechanical Systems and Signal Processing.*

Chen, T., Li, J., Jin, P. & Cai, G., 2013. Reusable rocket engine preventive maintenance scheduling using genetic algorithm. *Reliability Engineering & System Safety,* 114(1), pp. 52-60.

Cole, P. & Watson, J., 2005. *Acoustic Emission For Corrosion Detection.* Manama, Bahrain, Middle East Nondestructive Testing Conference & Exhibition.

Contini, S., 1995. A new hybrid method for fault tree analysis. *Reliability Engineering & System Safety,* 49(1), pp. 13-21.

Crocker, J. & Kumar, U. D., 2000. Age-related maintenance versus reliability centred maintenance: a case study on aero-engines. *Reliability Engineering and System Safety,* 67(2), pp. 113-118.

Cross, P. & Ma, X., 2014. Nonlinear system identification for model-based condition monitoring of wind turbines. *Renewable Energy,* 71(1), pp. 166-175.

Davies, J. P., Tse, M. K. & Harris, W. H., 1996. Monitoring the integrity of the cement—metal interface of total joint components in vitro using acoustic emission and ultrasound. *The Journal of Arthroplasty,* 11(5), pp. 594-601.

Dhouib, D., 2014. An extension of MACBETH method for a fuzzy environment to analyze alternatives in reverse logistics for automobile tire wastes. *Omega*, 42(1), pp. 25-32.

Dikis, K., Lazakis, I., Taheri, A. & Theotokatos, G., 2015. *Risk and Reliability Analysis Tool Development for Ship Machinery Maintenance.* Athens, Greece, 5th International Symposium on Ship Operations, Management and Economics (SOME).

DNV, 2001. *Marine risk assessment,* London, UK: Det Norsk Veritas.

Dong, Y. & Frangopol, D. M., 2015. Risk-informed life-cycle optimum inspection and maintenance of ship structures considering corrosion and fatigue. *Ocean Engineering*, 101(1), pp. pp. 161-171.

ECSA, 2013. *European Community of Shipowners' Association (ECSA).* [Online] Available at: http://www.ecsa.eu/9-latest-news/126-co2-emissions-from-ships-a-call-to-reason [Accessed 14 05 2016].

EFNMS, 2014. *European Federation of National Maintenance Societies.* [Online] Available at: http://www.efnms.org/ [Accessed 10 10 2014].

Eisinger, S. & Rakowsky, U. K., 2001. Modeling of uncertainties in reliability centered maintenance — a probabilistic approach. *Reliability Engineering & System Safety*, 2(2001), p. 71.

Emmanouilidis, C., Jantunen, E. & MacIntyre, J., 2006. Flexible software for condition monitoring, incorporating novelty detection and diagnostics. *Computers in Industry*, 57(6), pp. 516-527.

EPRI, 1998. *Electric Power Research Institute (EPRI).* [Online] Available at: http://www.epri.com/Pages/Default.aspx [Accessed 2013].

Eti, M. C., Ogaji, S. O. & Probert, S. D., 2006. Reducing the cost of preventive maintenance (PM) through adopting a proactive reliability-focused culture. *Applied Energy*, 83(11), pp. 1235-1248.

Faber, M. H., 2002. Risk-Based Inspection: The Framework. *Structural Engineering International,* 12(3), pp. 186-195.

Fernandez, O., Labib, A. W., Walmsley, R. & Petty, D. J., 2003. A decision support maintenance managemetn system- Development and implementation. *International Journal of Quality & Reliability Management*, 20(8), pp. 965-979.

Fitouhi, M. C. & Nourelfath, M., 2013. *Integrating noncyclical preventive maintenance scheduling and production planning for multi-state systems.* [Online] Available at: http://www.sciencedirect.com/science/article/pii/S0951832013002196 [Accessed 2013].

Fonseca, D. J. & Knapp, G. M., 2000. An expert system for reliability centered maintenance in the chemical industry. *Expert Systems with Applications*, 19(1), pp. 45-57.

Gabbar, H. A., Yamashita, H., Suzuki, K. & Shimada, Y., 2003. Computer-aided RCM-based plant maintenance management system. *Robotics and Computer-Integrated Manufacturing,* 19(5), pp. 449-468.

Gao, C. Y. & Peng, D. H., 2011. Consolidating SWOT analysis with nonhomogeneous uncertain preference information. *Knowledge-Based Systems,* 24(6), pp. 796-808.

Garbatov, Y. & Soares, C. G., 2001. Cost and reliability based strategies for fatigue maintenance planning of floating structures. *Reliability Engineering & System Safety,* 73(3), pp. 293-301.

Gento, A. M., 2004. Decision rules for a maintenance daatabase. *Journal of Quality in Maintenance Engineering,* 10(3), pp. 210-220.

Gorener, A., Toker, K. & Ulucay, K., 2012. Application of Combined SWOT and AHP: A Case Study for a Manufacturing Firm. *Procedia - Social and Behavioral Sciences,* 58(1), pp. 1525-1534.

Goyet, J., Straub, D. & Faber, M. H., 2002. Risk-Based Inspection Planning of Offshore Installations. *Structural Engineering International,* 12(3), pp. 200-208.

Gros, X. E., 1995. An eddy current approach to the detection of damage caused by low-energy impacts on carbon fibre reinforced materials. *Materials & Design*, 16(3), pp. 167-173.

Guo, H., Watson, S., Tavner, P. & Xiang, J., 2009. Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation. *Reliability Engineering & System Safety,* 94(6), pp. 1057-1063.

Guo, L., Gao, J., Yang, J. & Kang, J., 2009. Criticality evaluation of petrochemical equipment based on fuzzy comprehensive evaluation and a BP neural network. *Journal of Loss Prevention in the Process Industries*, 22(4), pp. 469-476.

Gupta, M. & Kohli, A., 2006. Enterprise resource planning systems and its implications for operations function. *Technovation*, 26(5-6), pp. 687-696.

Halleux, B. D., Stirum, B. L. & I'tchelintsev, A., 1996. Eddy current measurement of the wall thickness and conductivity of circular non-magnetic conductive tubes. *NDT & E International,* 29(2), pp. 103-109.

Hamada, K., Fujimoto, Y. & Shintaku, E., 2002. Ship inspection support system using a product model. *Marine Science and Technology,* 6(1), pp. 205-215.

Hamalainen, R. P., 2002. *Value tree analysis,* Helsinki, Finland: Systems Analysis Laboratory, Aalto University.

Hameed, Z., Ahn, S. H. & Cho, Y. M., 2010. Practical aspects of a condition monitoring system for a wind turbine with emphasis on its design, system architecture, testing and installation. *Renewable Energy,* 35(5), pp. 879-894.

Han, T. & Yang, B. S., 2006. Development of an e-maintenance system integrating advanced techniques. *Computers in Industry,* 57(6), pp. 569-580.

Hauser, D. & Tadikamalla, P., 1996. The Analytic Hierarchy Process in an uncertain environment: A simulation approach. *European Journal of Operational Research,* 91(1), pp. 27-37.

Heo, E., Kim, J. & Cho, S., 2012. Selecting hydrogen production methods using fuzzy analytic hierarchy process with opportunities, costs, and risks. *International Journal of Hydrogen Energy,* 37(23), pp. 17-655-17662.

Heo, J. H., Kim, M. K. & Lyu, J. K., 2014. Implementation of Reliability-Centered Maintenance for transmission components using Particle Swarm Optimization. *International Journal of Electrical Power & Energy Systems,* 55(1), pp. 238-245.

He, Y., Pan, M., Luo, F. & Tian, G., 2011. Pulsed eddy current imaging and frequency spectrum analysis for hidden defect nondestructive testing and evaluation. *NDT & E International,* 44(4), pp. 344-352.

Hifi, N. & Barltrop, N. P., 2012. *Improving Techniques for Ship Inspection and Maintenance Planning.* London, UK, Royal Institute of Naval Architecture (RINA) Conference.

Hipkin, I. B. & De Cock, C., 2000. TQM and BPR: lessons for maintenance management. *Omega,* 28(3), pp. 277-292.

Hoch, J. E. & Dulebohn, J. H., 2013. Shared leadership in enterprise resource planning and human resource management system implementation. *Human Resource Management Review,* 23(1), pp. 114-125.

Holland, C. P., Shaw, D. R. & Kawalek, P., 2005. BP's multi-enterprise asset management system. *Information and Software Technology,* 47(15), pp. 999-1007.

Hontelez, J. A. M., Burger, H. H. & Wijnmalen, D. J. D., 1996. Optimum condition-based maintenance policies for deteriorating systems with partial information. *Reliability Engineering & System Safety,* 51(3), pp. 267-274.

HSE, 2001. *Marine Risk Assessment for Health and Safety Executive (HSE),* London, U.K.: DNV (Det Norske Veritas).

Hughes, B., 2001. *Business Centred Maintenance.* [Online] Available at: http://www.maintenanceresources.com/referencelibrary/ezine/busscm.html [Accessed 2013].

Huin, S. F., Luong, L. S. & Abhary, K., 2003. Knowledge-based tool for planning of enterprise resources in ASEAN SMEs. *Robotics and Computer-Integrated Manufacturing,* 19(5), pp. 409-414.

Hu, J. Q., Zhang, L. B., Liang, W. & Wang, Z. H., 2009. Quantitative HAZOP Analysis for Gas Turbine Compressor based on Fuzzy Information Fusion. *Systems Engineering - Theory & Practice,* 29(8), pp. 153-159.

Hu, J. & Zhang, L., 2014. Risk based opportunistic maintenance model for complex mechanical systems. *Expert Systems with Applications,* 41(6), pp. 3105-3115.

Hwang, H. S., 1996. A performance evaluation model for FMS based on RAM and LCC using FACTOR/AIM. *Computers & Industrial Engineering,* 31(3-4), pp. 593-598.

IACS, 2017. *International Association of Classification Societies.* [Online] Available at: http://www.iacs.org.uk/default.aspx [Accessed 28 01 2017].

IAEA, I. A. E. A., 2008. *Online monitoring for improving performance of nuclear power plants- part 2: Process and component condition monitoring and diagnostics,* Vienna, Austria: IAEA.

ICS Shipping., 2015. *ICS Shipping REpresenting the Global Shipping Industry.* [Online] Available at: http://www.ics-shipping.org/shipping-facts/shipping-and-world-trade/predicted-increases-in-world-seaborne-trade-gdp-and-population [Accessed 12 06 2016].

Igba, J., Alemzadeh, K., Anyanwu-Ebo, I., Gibbons, P. & Friis J., 2013. A Systems Approach towards Reliability-Centred Maintenance (RCM) of Wind Turbines. *Procedia Computer Science,* 16(1), pp. 814-823.

IMO, 2016. *International Convention for the Prevention of Pollution from Ships (MARPOL).* [Online] Available at: http://www.imo.org/en/about/conventions/listofconventions/pages/international-convention-for-the-prevention-of-pollution-from-ships-(marpol).aspx [Accessed 01 06 2016].

Ingwald, A. & Al-Najjar, B., 2006. *System for monitoring machines financial and technical effectiveness.* Lulea, Sweden, 9th international congress Condition monitoring and diagnostic engineering managemen (COMADEM06), pp. 219-230.

Ishizaka, A. & Labib, A., 2011. Selection of new production facilities with the Group Analytic Hierarchy Process Ordering method. *Expert Systems with Applications,* 38(6), pp. 7317-7325.

Jamalabadi, M. A., 2013. *Experimental investigation of thermal loading of a horizontal thin plate using infrared camera.* [Online] Available at: http://www.sciencedirect.com/science/article/pii/S101836391300010X [Accessed 2013].

Jaramillo, d., 2006. *Extracting NAPA Steel Data for Hull Condition Monitoring,* Helsinki,Finland: NAPA Ltd..

Jardine, A. K., Banjevic, D. & Makis, V., 1997. Optimal replacement policy and the structure of software for condition-based maintenance. *Journal of Quality in Maintenance Engineering,* 3(2), pp. 109-119.

Jhang, J. P. & Sheu, S. H., 1999. Opportunity-based age replacement policy with minimal repair. *Reliability Engineering & System Safety,* 64(3), pp. 339-344.

Jones, W., Kubenka, J. & Ledet, W., 2008. *Business Driven Reliability at Mobil's Beaumont Refinery.* [Online] Available at: http://www.marshallinstitute.com/inc/eng/resources/Areas/articles/Body/articles/tmg3.pdf [Accessed 23 04 2013].

Kans, M. & Ingwald, A., 2008. Common database for cost-effective improvement of maintenance performanc. *International Journal of Production Economics*, 113(2), pp. 734-747.

Kauer, R., Jovanovic, A., Angelsen, S. & Vahe, G., 2004. *PLANT ASSET MANAGEME NT RIMAP (RISK-BASED INSPECTION AND MAINTENANCE FOR EUROPEAN INDUSTRIES)† THE EUROPEAN APPROAC H.* San Diego, California, USA, American Society of Mechanical Engineers (ASME).

Kawamura, Y. & Sumi, Y., 2005. *Information system for structural integrity of ships.* Southhampton, UK, Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment.

Kazantsev, I. G., Lemahieu, I., Salov, G. I. & Denys, R., 2002. Statistical detection of defects in radiographic images in nondestructive testing. *Signal Processing,* 82(5), pp. 791-801.

Keddie, J. L., 2001. Structural analysis of organic interfacial layers by ellipsometry. *Current Opinion in Colloid & Interface Science,* 6(2), pp. 102-110.

Kennedy, R., 2009. *Plant-Maintenance.* [Online] Available at: http://www.plant-maintenance.com/articles/RCMvTPM.shtml [Accessed 16 04 2013].

Khan, F. I., Sadiq, R. & Haddara, M. M., 2004. Risk-Based Inspection and Maintenance (RBIM): Multi-Attribute Decision making with Aggregative Risk Analysis. *Process Safety and Environmental Protection,* 82(6), pp. 398-411.

Kolios, S. J., Collu, M. & Brennan, F. P., 2010. *Reliability of Floating Foundation Concepts for Vertical Axis Wind Turbines.* Rio de Janeiro, Brazil, PRADS Conference.

Ku, A. P., Spong R. E., Serratella, C., Wu, X. S., Basu, R. & Wang, G., 2005. *Structural Reliability Applications in Risk-Based Inspection Plans and Their Sensitivities to Different Environmental Conditions.* Houston, TX, USA, Offshore Technology Conference.

Kuo, T. C., Wu, H. H. & Shieh, J. I., 2009. Integration of environmental considerations in quality function deployment by using fuzzy logic. *Expert Systems with Applications*, 36(3), pp. 7148-7156.

Kutucuoglu, K. Y., Hamali, J., Irani, Z. & Sharp, J. M., 2001. A framework for managing maintenance using performance measurement systems. *International Journal of Operations & Production Management,* 21(1), pp. 173-194.

Labib, A. W., 1998. World-class maintenance using a computerised maintenance management system. *Quality in Maintenance Engineering,* 4(1), pp. 66-75.

Labib, A. W., 1999. A framework for benchmarking appropriate productive maintenance. *Management Decision,* 37(10), pp. 792-799.

Labib, A. W., 2004. A decision analysis model for maintenance policy selection using a CMMS. *Journal of Quality in Maintenance Engineering,* 10(3), pp. 191-202.

Labib, A. W., O'Connor, R. F. & Williams, G. B., 1998. An effective maintenance system using the analytic hierarchy process. *Integrated Manufacturing*, 9(2), pp. 87-98.

Lampis, M. & Andrews, J. D., 2008. Bayesian BeliefNetworks for system fault diagnostics. *International Journal of Quality and Reliability Engineering,* 25(4), pp. 409-426.

Lazakis, I., 2011. *Establishing an innovative and integrated reliability and criticality based maintenance strategy for the maritime industry.* Glasgow, UK: University of Strathclyde, Department of Naval Architecture & Marine Engineering.

Lazakis, I., Dikis, K., Michala, A. L. & Theotokatos, G., 2016. Advanced ship systems condition monitoring for enhanced inspection, maintenance and decision making in ship operations. *Transportation Research Procedia,* 14(1), pp. pp. 1679-1688.

Lazakis, I. & Olcer, A., 2015. Selection of the best maintenance approach in the maritime industry under fuzzy multiple attributive group decision making environment. *Journal of Engineering for the Maritime Environment,* pp. pp. 1-13.

Lee, C., Lee, H., Seol, H. & Park, Y., 2012. Evaluation of new service concepts using rough set theory and group analytic hierarchy process. *Expert Systems with Applications,* 39(3), pp. 34034-3412.

Lee, J., Ghaffari, M. & Elmeligy, S., 2011. Self-maintenance and engineering immune systems: Towards smarter machines and manufacturing systems. *Annual Reviews in Control,* 35(1), pp. 111-122.

Lee, J. M., Lee, K. H., Kim, K. S. & Kim, J. H., 2010. *AR Based-Ship Design Information Supporting System for Pipe Maintenance.* Rio de Jeneiro, PRADS Conference.

Lee, J., Ni, J., Djurdjanovic, D., Qiu, H. & Liao, H., 2006. Intelligent prognostics tools and e-maintenance. *Computers in Industry,* 57(6), pp. 476-489.

Lee, J. & Wang, H., 2008. New Technologies for Maintenance. In: K. H. Kobbacy, D. P. Murthy & H. Pham, eds. *Complex System Maintenance Handbook.* London, UK: Springer, pp. 49-78.

Lee, S. S., Lee, J. K., Park, B.J., Lee, D. K., Kim, S. Y. & Lee, K. H., 2006. Development of internet-based ship technical information management system. *Ocean Engineering,* 33(13), pp. 1814-1828.

Leger, J. B., Iung, B., Ferro De Beca, A. & Pinoteau, J., 1999. An innovative approach for new distributed maintenance system: application to hydro power plants of the REMAFEX project. *Computers in Industry,* 38(2), pp. 131-148.

LeTessier, R., Coade, R. W. & Geneve, B., 2002. Sizing of cracks using the alternating current field measurement technique. *International Journal of Pressure Vessels and Piping,* 79(8-10), pp. 549-554.

Lewin, D. R., 1995. Predictive maintenance using PCA. *Control Engineering Practice,* 3(3), pp. 415-421.

Liang, X. F., Wang, H. D., Yi, H. & Li, D., 2017. Warship reliability evaluation based on dynamic bayesian networks and numerical simulation. *Ocean Engineering,* 135(1), pp. pp. 129-140.

Liang, Y. H., 2008. Combining neural networks and genetic algorithms for predicting the reliability of repairable systems. *International Journal of Quality & Reliability Management*, 25(2), pp. 201-210.

Lihovd, E., Johannessen, T. I., Steinebach, C. & Rasmussen, M., 1998. Intelligent diagnosis and maintenance management. *Journal of Intelligent Manufacturing,* 9(6), pp. 523-537.

Li, Y. G. & Nilkitsaranont, P., 2009. Gas turbine performance prognostic for condition-based maintenance. *Applied Energy,* 86(10), pp. 2152-2161.

Li, H., Parikh, D., He, Q., Qian, B., Li, Z., Fang, D. & Hampapur, A., 2014. Improving rail network velocity: A machine learning approach to predictive maintenance. *Transportation Research Part C: Emerging Technologies,* 45(1), pp. 17-26.

Liu, B., Xu, Z., Xie, M. & Kuo, W., 2014. A value-based preventive maintenance policy for multi-component system with continuously degrading components. *Reliability Engineering & System Safety,* 132(1), pp. 83-89.

Liu, L., Yu, M., Ma, Y. & Tu, Y., 2013. Economic and economic-statistical designs of an X control chart for two-unit series systems with condition-based maintenance. *European Journal of Operational Research*, 226(3), pp. 491-499.

Liu, Q., Zhang, Y., Kong, Y. & Wu, Q., 2012. Improving VRSS-based vulnerability prioritization using analytic hierarchy process. *Journal of Systems and Software,* 85(8), pp. 1699-1708.

Liu, S. & McDemid, J. A., 1996. A model-oriented approach to safety analysis using fault trees and a support system. *Journal of Systems and Software,* 35(2), pp. 151-164.

Loures, E. R., Busetti de Paula, M. A. & Pascal, J. C., 2006. *Maintenance integration in a control-monitoring architecture based on Petri net with objects. Application to a flexible manufacturing system.* Prague, Czech Republic, Emerging Technologies and Factory Automation, 2006. ETFA '06., pp. 929-936.

Loutas, T. H., Sotiriades, G., Kalaitzoglou, I. & Kostopoulos, V., 2009. Condition monitoring of a single-stage gearbox with artificially induced gear cracks utilizing on-line vibration and acoustic emission measurements. *Applied Acoustics,* 70(9), pp. 1148-1159.

Lundteigen, M. A., Rausand, M. & Utne, I. B., 2009. Integrating RAMS engineering and management with the safety life cycle of IEC 61508. *Reliability Engineering & System Safety,* 94(12), pp. 1894-1903.

Lynch, P., Adendorff, K., Yadavalli, V. S. & Adetunji, O., 2013. Optimal spares and preventive maintenance frequencies for constrained industrial systems. *Computers & Industrial Engineering,* 65(3), pp. 378-387.

Lyu, J. J. & Chen, M. N., 2009. Automated visual inspection expert system for multivariate statistical process control chart. *Expert Systems with Applications,* 36(3), pp. 5113-5118.

Madu, C. N., 2000. Competing through maintenance strategies. *International Journal of Quality & Reliability Management,* 17(9), pp. 937-949.

Magro, M. C. & Pinceti, P., 2009. A confirmation technique for predictive maintenance using the Rough Set Theory. *Computers & Industrial Engineering,* 56(4), pp. 1319-1327.

Manno, G., Chiacchio, F., Compagno, L., D'Urso, D. & Trapani, N., 2014. Conception of Repairable Dynamic Fault Trees and resolution by the use of RAATSS, a MATLAB® toolbox based on the ATS formalism. *Reliability Engineering & System Safety,* 121(1), pp. 250-262.

Maragakis, I. et al., 2009. *Safety Management System and Safety Culture Working Group,* s.l.: European Strategic Safety Initiative.

Marin, M. P. & Toral, M. R., 2013. HAZOP – Local approach in the Mexican oil & gas industry. *Journal of Loss Prevention in the Process Industries*, 26(5), pp. 936-940.

Maritime-Executive, 2014. *Towing Industry Safety Statistics.* [Online] Available at: http://www.maritime-executive.com/article/2014-towing-industry-safety-statistics
[Accessed 02 07 2016].

MARPOL, 2011. *Prevention of Air Pollutions from Ships.* [Online] Available at: http://www.imo.org/en/OurWork/environment/pollutionprevention/airpollution/pages/air-pollution.aspx
[Accessed 01 07 2016].

Marquez, A. C. & Iung, B., 2007.), A structured approach for the assessment of system availability and reliability using Monte Carlo simulation. *Journal of Quality in Maintenance Engineering,* 13(2), pp. 125-136.

Martorella, S. et al., 1999. The use of maintenance indicators to evaluate the effects of maintenance programs on NPP performance and safety. *Reliability Engineering and System Safety,* 65(2), pp. 85-94.

Martorell, S. et al., 2005. RAMS þ C informed decision making with application to multi-objective optimization of technical specifications and maintenance using genetic algorithms. *Reliability Engineering and System Safety,* 87(1), pp. 65-75.

Mathew, A. D., Zhang, S., Ma, L., Earle, T. & Hargreaves, D. J., 2006. Reducing maintenance cost through effective prediction analysis and process integration. *Advances in Vibration Engineering,* 5(2), pp. 87-96.

Mazza, A., Chicco, G. & Russo, A., 2014. Optimal multi-objective distribution system reconfiguration with multi criteria decision making-based solution ranking and enhanced genetic operators. *International Journal of Electrical Power & Energy Systems,* 54(1), pp. 255-267.

McCoy, S. A. et al., 2000. HAZID, A COMPUTER AID FOR HAZARD IDENTIFICATION: Learning Set, Main Study System, Output Quality and Validation Trials. *Institution of Chemical Engineers,* 78(B), pp. 91-119.

McGowin, C., 2006. *Condition Monitoring of Wind Turbines Technology Overview, Seeded-Fault Testing, and Net cost Analysis*, Palo Alto, CA, USA: Electric Power Research Institute.

Meller, R. D. & Kim, D. S., 1996. The impact of preventive maintenance on system cost and buffer size. *European Journal of Operational Research,* 95(3), pp. 577-591.

Mentes, A. & Helvacioglu, I. H., 2011. An application of fuzzy fault tree analysis for spread mooring systems. *Ocean Engineering,* 38(1), pp. pp. 285-294.

Miettinen, J. & Siekkinen, V., 1995. Acoustic emission in monitoring sliding contact behaviour. *Wear,* 181-183(2), pp. 897-900.

Ming, C. G., Wei, L. & Xin, W. Z., 2007. Structural optimization of 2-D array probe for alternating current field measurement. *NDT & E International,* 40(6), pp. 455-461.

Mitropoulou, C. C., Lagaros, N. D. & Papadrakakis, M., 2011. Life-cycle cost assessment of optimally designed reinforced concrete buildings under seismic actions. *Reliability Engineering & System Safety,* 96(10), pp. 1311-1331.

Mkandawire, B. O., Ljumba, N. & Saha, A., 2015. Transformer risk modelling by stochastic augmentation of reliability-centred maintenance. *Electric Power Systems Research,* 119(1), pp. pp. 471-477.

Mohammadfam, I., Mahmoudi, S. & Kianfar, A., 2012. Comparative Safety Assessment of Chlorination Unit in Tehran Treatment Plants with HAZOP & ETBA Techniques. *Procedia Engineering,* 45(1), pp. 27-30.

Mohammadpur, M. & Tabriz, A. A., 2012. SWOT Analysis using of Modified Fuzzy QFD – A Case Study for Strategy Formulation in Petrokaran Film Factory. *Procedia - Social and Behavioral Sciences,* 41(1), pp. 322-333.

Mokashi, A. J., Wang, J. & Vermar, A. K., 2002. A study of reliability-centred maintenance in maritime operations. *Marine Policy,* 26(5), pp. pp 325-335.

Montewka, J., Ehlers, S. & Tabri, K., 2012. Modelling risk of collision between a LNG tanker and a harbour tug. *Marine Systems & Ocean Technology,* 7(1), pp. 3-13.

Moore, W. J. & Starr, A. G., 2006. An intelligent maintenance system for continuous cost-based prioritisation of maintenance activities. *Computers in Industry,* 57(6), pp. 595-606.

Moubray, J., 2001. *Is Streamlined RCM Worth the Risk.* [Online] Available at: http://www.mt-online.com/january2001/is-streamlined-rcm-worth-the-risk [Accessed 2013].

Muller, J., 2012. *Chair of Process Control Engineering.* [Online] Available at: http://www.plt.rwth-aachen.de/fileadmin/plt/events/2012/Winterkolloquium/Plant_Asset_Management_RWTH_Aachen.pdf
[Accessed 2013].

Murphy, K. P., 2000. *MathWorks.* [Online] Available at: https://code.google.com/p/bnt/ [Accessed 10 07 2013].

New, C., 2012. – *Developing a Risk Based Policy for Integrating Safety and Maintenance Management.* London, UK, Royal Institute of Naval Architecture (RINA) Conference.

NPD-Solutions, 2017. *Failure Modes and Effects Analysis (FMEA).* [Online] Available at: http://www.npd-solutions.com/fmea.html [Accessed 20 01 2017].

Onoufriou, T. & Frangopol, D. M., 2002. Reliability-based inspection optimization of complex structures: a brief retrospective. *Computers & Structures,* 80(12), pp. 1133-1144.

Ovanesova, A. V. & Suarez, L. E., 2004. Applications of wavelet transforms to damage detection in frame structures. *Engineering Structures,* 26(1), pp. 39-49.

Paltrinieri, N., Tungoli, A., Buston, J., Wardman, M. & Cozzani, V., 2013. Dynamic Procedure for Atypical Scenarios Identification (DyPASI): A new systematic HAZID tool. *Journal of Loss Prevention in the Process Industries*, 26(4), pp. 683-695.

Pan, H. S. & Yun, W. Y., 1997. Fault tree analysis with fuzzy gates. *Computers & Industrial Engineering,* 33(3-4), pp. 569-572.

Parida, A. & Chattopadhyay, G., 2007. Development of a multi-criteria hierarchical framework for maintenance performance measurement (MPM). *Journal of Quality in Maintenance Engineering,* 13(3), pp. 241-258.

Patel, R. J., 2005. *Risk Based Inspection.* Manama, Bahrain, East Nondestructive Testing Conference & Exhibition.

Paulson, D. & Zahir, S., 1995. Consequences of uncertainty in the analytic hierarchy process: A simulation approach. *European Journal of Operational Research,* 87(1), pp. 45-56.

Percy, D. F., Kobbacy, K. A. H. & Fawzi, B. B., 1997. Setting preventive maintenance schedules when data are sparse. *International Journal of Production Economics,* 51(3), pp. 223-234.

Peres, F. et al., 2007. Anticipating aging failure using feedback data and expert judgment. *Reliability Engineering and System Safety,* 92(2), pp. 200-210.

Peters, R. W., 2015. *Profit and Customer-Centered Benefits of Planning and Scheduling.* ISBN: 978-0-12-397042-8 ed. Waltham, MA, USA: Gulf Professional Publishing (GPP).

Pillay, A., Wang, J., Wall, A. D. & Ruxton, T., 2001. A maintenance study of fishing vessel equipment using delay-time analysis. *Journal of Quality in Maintenance Engineering,* 7(2), pp. 118-128.

Pintelon, L. & Herz, A. P., 2008. Maintenance: An Evolutionary Perspective. In: K. H. Kobbacy, D. P. Murphy & H. Pham, eds. *Complex System Maintenance Handbook.* London, UK: Springer, pp. 21-48.

Pintelon, L. & Puyvelde, F. V., 1997. Maintenance performance reporting systems: some experiences. *Journal of Quality in Maintenance Engineering,* 3(1), pp. 4-15.

Poropudas, J. & Virtanen, K., 2011. Simulation metamodeling with dynamic Bayesian networks. *European Journal of Operational Research,* 214(3), pp. 644-655.

Pujadas, W. & Chen, F. F., 1996. A reliability centered maintenance strategy for a discrete part manufacturing facility. *Computers & Industrial Engineering,* 31(1-2), pp. 241-244.

Pun, K. F., Chin, K. S., Chow, M. F. & Lau, H. W., 2002. An effectiveness-centred approach to maintenance management: A case study. *Journal of Quality in Maintenance Engineering,* 8(4), pp. 346-368.

Rabiei, M. & Modarres, M., 2013. Quantitative methods for structural health management using in situ acoustic emission monitoring. *International Journal of Fatigue*, 49(1), pp. 81-89.

Raisutis, R. et al., 2010. Application of ultrasonic guided waves for non-destructive testing of defective CFRP rods with multiple delaminations. *NDT & E International,* 43(5), pp. 416-424.

Rao, J. S., Zubair, M. & Rao, C., 2003. condition monitoring of power plants through the internet. *Integrated Manufacturing Systems,* 14(6), pp. 508-517.

Rausand, M., 1998. Reliability Centered Maintenance. *Reliability Engineering and System Safety,* 60(1), pp. 121-132.

Ravindra, H. V., Srinivasa, Y. G. & Krishnamurthy, R., 1997. Acoustic emission for tool condition monitoring in metal cutting. *Wear,* 212(1), pp. 78-84.

Reithofer, W. & Naeger, G., 1997. Bottom-up planning approaches in enterprise modelling—the need and the state of the art. *Computers in Industry,* 33(2-3), pp. 223-235.

Rekanos, I. T., Theodoulidis, T. p., Panas, S. M. & Tsiboukis, T. D., 1997. Impedance inversion in eddy current testing of layered planar structures via neural networks. *NDT & E International,* 30(2), pp. 69-74.

Ribeiro, I., Pacas, P. & Henriques, E., 2013. Incorporating tool design into a comprehensive life cycle cost framework using the case of injection molding. *Journal of Cleaner Production,* 53(1), pp. 297-309.

Richet, D., Cotaina, N., Gabriel, M. & O'Reilly, K., 1995. Application of reliability centred maintenance in the foundry sector. *Control Engineering Practice,* 3(7), pp. 1029-1034.

Rodrigues, M. & Hatakeyama, K., 2006. Analysis of the fall of TPM in companies. *Journal of Materials Processing Technology*, 179(1-3), pp. 276-279.

Rodseth, O. j., Steineberg, C. & Mo, B., 2007. *The use of technical condition indices in ship maintenance planning and the monitoring of the ship's safety condition (Maritime Transport Systems "MARINTEK").* Athens, Greece, International Symposium on maritime Safety, securiy and environmental protection.

Rosqvist, T., Laasko, K. & Reunanen, M., 2009. Value-driven maintenance planning for a production plant. *Reliability Engineering & System Safety*, 94(1), pp. 97-110.

Rouhan, A., Goyet, J. & Faber, M. H., 2004. *Industrial Implementation Of Risk Based Inspection Planning Lessons Learned From Experience (2) The Case Of Steel Offshore Structures.*

Vancouver, Canada, International Conference on Offshore Mechanics and Arctic Engineering, OMAE.

Salva, M., Hernandez, R. & Sanz, C., 2004. Proposal of a Method for Implementing Infrared Scanning Inspection Programs in Merchant Vessels. *Marine Technology,* 41(1), pp. 1-6.

Samhouri, M. S., 2009. *An intelligent opportunistic maintenance (OM) system: A genetic algorithm approach.* Toronto, Canada, Science and Technology for Humanity, pp. 60-65.

Schea, M., Matha, D., Hofmann, M. & Muskulus, M., 2012.), Maintenance strategies for large offshore wind farms. *Energy Procedia,* 24(1), pp. 281-288.

Schmidt, R., 1997. The implementation of simultaneous engineering in the stage of product concept development: A process orientated improvement of quality function deployment. *European Journal of Operational Research,* 100(2), pp. 293-314.

Schroder, H. C. & Kauer, R., 2004. Regulatory requirements related to risk-based inspection and maintenance. *International Journal of Pressure Vessels and Pipping,* 81(1), pp. 847-854.

Seker, S. & Ozgurler, M., 2012. Analysis of the Turkish Consumer Electronics Firm using SWOT-AHP Method. *Procedia - Social and Behavioral Sciences,* 58(1), pp. 1544-1554.

Selvik, J. T. & Aven, T., 2011. A framework for reliability and risk centered maintenance. *Reliability Engineering and System Safety,* 96(2), pp. 324-331.

Seyedhosseini, S. M., Taleghani, A. E., Bakhsha, A. & Patrovi, S., 2011. Extracting leanness criteria by employing the concept of Balanced Scorecard. *Expert Systems with Applications,* 38(8), pp. 10454-10461.

Shalev, D. M. & Tiran, J., 2007. Condition-based fault tree analysis (CBFTA): A new method for improved fault tree analysis (FTA), reliability and safety calculations. *Reliability Engineering and System Safety,* 92(9), pp. 1231-1241.

Sharma, R. K., Kumar, D. & Kumar, P., 2006. Manufacturing excellence through TPM implementation: a practical analysis. *International Management & Data Systems,* 106(2), pp. 256-278.

Shriwardhankar, R. M., Patil, P. B. & Mahesh, L., 2010. Development of Helium Leak Testing System and Procedure for testing Welds of Steam Generator. *Energy Procedia,* 7(1), pp. 638-644.

Sia, C. L. & Ho, Y. S., 1997. Predictive capacity planning: a proactive approach. *Information and Software Technology,* 39(3), pp. 195-204.

Singh, R., Gohli, A. M., Shah, D. B. & Desai, S., 2013. Total Productive Maintenance (TPM) Implementation in a Machine Shop: A Case Study. *Procedia Engineering,* 51(1), pp. 592-599.

Sitton, R., 2005. *Integration of RBI with an Inspection Data Management System.* Manama,Bahrain, 3rd Middle Eastern Nondestructive Testing Conference & Exhibition.

Srinivasan, R. & Parlikad, A. K., 2013. *Value of condition monitoring in infrastructure maintenance.* [Online]
Available at: http://www.sciencedirect.com/science/article/pii/S0360835213001848 [Accessed 2013].

Straub, D., 2004. *Generic Approaches to RBI Planning for Steel Structures.* 1 ed. Zurich, Switzerland: Gedruckt auf Saurefreiem Papier.

Straub, D., Goyet, J., Sorensen, J. D. & Faber, M. H., 2006. *Benefits of risk based inspection planning for offshore structures.* Hamburg, Germany, 25th International Conference on Offshore Mechanics and Arctic Engineering (OMAE).

Sun, H. & Soares, G., 2006. Reliability-Based Inspection of Corroded Ship-Type FPSO Hulls. *Journal of Ship Research,* 50(2), pp. 171-180.

Suresh, P. V., Babar, A. K. & Raj, V. V., 1996. Uncertainty in fault tree analysis: A fuzzy approach. *Fuzzy Sets and Systems,* 83(2), pp. 135-141.

Swain, G. W. et al., 2007. Measuring the Performance of Today's Antifouling Coatings. *Journal of Ship Production,* 23(3), pp. 164-170.

Swanson, L., 2001. Linking maintenance strategies to performance. *International Journal of Production Economics,* 70(3), pp. 237-244.

Swarnakar, A. K., Donzel, L., Vleugelas, J. & Biest, O. V., 2009. High temperature properties of ZnO ceramics studied by the impulse excitation technique. *Journal of the European Ceramic Society,* 29(14), pp. 2991-2998.

Taheri, A., Lazakis, I. & Ghotbzadeh, J., 2016. *Cost Based Dynamic Bayesian Network Reliability Analysis and Decision Making for Lub-oil System of a Suezmax Vessel.* Glasgow, U.K., International Conference in Maritime Safety and Operations (MSO).

Taheri, A., Lazakis, I. & Koch , T., 2015. *Catalogue Data Model Based Innovative DAtabase System for Ship Structural and Machinery Condition Monitoring (MCM) Data Exchange Protocol.* Glasgow, U.K., Ship in Changing Climate (SCC).

Taheri, A., Lazakis, I. & Koch, T., 2015. *An Innovative MAchinery DAta MAnagement System for Ships using a Catalogue Data Model.* Pula, Croatia, International MAritime Association of Mediterranean (IMAM).

Taheri, A., Lazakis, I. & Turan, O., 2014. *Integration of Business and Technical Aspects of REliability and Maintenance.* GLasgow, U.K., Intenrational Conference on Maritime Technology (ICMT).

Tang, B., Song, T., Li, F. & Deng, L., 2014. Fault diagnosis for a wind turbine transmission system based on manifold learning and Shannon wavelet support vector machine. *Renewable Energy,* 62(1), pp. 1-9.

Tang, Y., Liu, Q., Jing, J., Yang, Y. & Zou, Z., 2017. A framework for identification of maintenance significant items in reliability centered maintenance. *Energy Journal,* 118(1), pp. pp. 1295-1303.

Tehranchi, M. M., Ranjbaran, M. & Eftekhari, H., 2011. Double core giant magneto-impedance sensors for the inspection of magnetic flux leakage from metal surface cracks. *Sensors and Actuators A: Physical,* 170(1-2), pp. 55-61.

Tetrault, P. J., 2012. *The Future of Marine Engine Remote Monitoring in Marine Applications.* London, UK, ROyal Institute Of Naval Architecture (RINA) Conference.

Tian, Z., Jin, T., Wu, B. & Ding, F., 2011. Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy,* 36(5), pp. 1502-1509.

Transport-Scotland, 2016. *Chapter 2: Historical Emission Analysis.* [Online] Available at: https://www.transport.gov.scot/publications/ [Accessed 01 07 2016].

Trucco, A., Cango, E., Ruggeri, F. & Grande, O., 2008. A Bayesian Belief Network modelling of organisational factors in risk analysis: A case study in maritime transportation. *Reliability Engineering and System Safety,* 93(1), pp. 823-834.

Tsang, A. H., 1998. A strategic approach to managing maintenance performance. *Journal of Quality in Maintenance Engineering,* 4(2), pp. 87-94.

Tsang, A. H., Yeung, W. K., Jardine, A. K. & Leung, B. P., 2006. Data management for CBM Optimization. *Journal of Quality in Maintenance Engineering,* 12(1), pp. 37-51.

Tsarouhas, P., 2007. Implementation of total productive maintenance in food industry: a case study. *Journal of Quality in Maintenance Engineering,* 13(1), pp. 5-18.

Turan, O., Lazakis, I., Judah, S. & Incecik, A., 2011. Investigating the Reliability and Criticality of the Maintenance Characteristics of a Diving Support Vessel. *Quality and Reliability Engineering International,* 27(7), pp. 931-946.

Turan, O., Olcer, A. I. & Martin, P. L., 2003. Risk assessment of loss of life for fishing vessels in fuzzy environment. *Safety and Reliability,* 23(2), pp. 19-38.

UNCTAD, 2014. *World Seaborne Trade.* [Online] Available at: http://www.ics-shipping.org/shipping-facts/shipping-and-world-trade/world-seaborne-trade
[Accessed 12 05 2016].

Utne, I. B., 2010. METHODOLOGY AND THEORY Maintenance strategies for deep-sea offshore wind turbines. *Journal of Quality in Maintenance Engineering,* 16(4), pp. 367-381.

Verzbolovskis, M., 2004. *ABS Approach to Classification using Risk Analyses.* Barcelona, Spain, 2nd International ASRANet Colloquium.

Vhanmane, S. c. & Patra, P. K., 2010. *Assessment of the Uncertainty in Ship Hull Girder Reliability Index based on Ultimate Limit States.* Rio de Janeiro, Brazil, PRADS Conference.

Waeyenbergh, G. & Pintelon, L., 2006. CIBOCOF: A framework for industrial maintenance concept development. *International Journal of Production Economics,* 121(2), pp. 633-640.

Wang, J., 2001. the Current Status and Future Aspects in Formal Ship Safety Assessment. *Safety Science,* 38(1), pp. 19-30.

Wang, Y., Deng, C., Wu, J., Wang, Y. & Xiong, Y., 2014. A corrective maintenance scheme for engineering equipment. *Engineering Failure Analysis,* 36(1), pp. 269-283.

Weber, P., Medina-Oliva, G., Simon, C. & Iung, B., 2012. Overview on Bayesian networks applications for dependability, risk analysis. *Engineering Applications of Artificial Intelligence,* 25(4), pp. 671-682.

Williams, G. B. & Hirani, R. S., 1997. A delay time multi-level on-condition preventive maintenance inspection model based on constant base interval risk—when inspection detects pending failure. *International Journal of Machine Tools and Manufacture,* 37(6), pp. 823-836.

Wong, F. H., Lam, P. I. & Chan, E. W., 2009. Optimising design objectives using the Balanced Scorecard approach. *Design Studies,* 30(4), pp. 369-392.

Wu, W. F. & Syau, J. J., 1995. A study of risk-based non-destructive in-service inspection. *Nuclear Engineering and Design,* 158(2-3), pp. 409-415.

Yamada, H. et al., 2008. Difference in the detection limits of flaws in the depths of multi-layered and continuous aluminum plates using low-frequency eddy current testing. *NDT & E International,* 41(2), pp. 108-111.

Yan, R., Gao, R. X. & Chen, X., 2013. *Wavelets for fault diagnosis of rotary machines: A review with applications.* [Online] Available at: http://www.sciencedirect.com/science/article/pii/S0165168413001588 [Accessed 2013].

Yeh, C. H. & Xu, Y., 2013. Managing critical success strategies for an enterprise resource planning project. *European Journal of Operational Research,* 230(3), pp. 604-614.

Yuksel, I. & Dagdeviren, M., 2007. Using the analytic network process (ANP) in a SWOT analysis – A case study for a textile firm. *Information Sciences,* 177(16), pp. 3364-3382.

Zadeh, L. A., 1965. Fuzzy Set. *Information and Control,* 8(3), pp. pp. 338-353.

Zhang, Z. & Dong, F., 2014. Fault detection and diagnosis for missing data systems with a three time-slice dynamic Bayesian network approach. *Chemometrics and Intelligent Laboratory Systems,* 138(1), pp. 30-40.

Zhou, Z. D., Chen, Y. P., Fuh, J. H. & Nee, A. C., 2000. Integrated Condition Monitoring and Fault Diagnosis for Modern Manufacturing Systems. *CIRP Annals - Manufacturing Technology,* 49(1), pp. 387-390.

Zhu, J. & Collette, M., 2015. A dynamic discretization method for reliability inference in Dynamic Bayesian Networks. *Reliability Engineering & System Safety,* 138(1), pp. pp. 242-252.

APPENDIX A - EXAMPLE OF DBN CALCULATIONS USING BIASIALAB

This appendix represents a sample calculation and methodology using purifier sub-system, part of the Lube-oil system from Ship 2. The figure below represents the DBN of this subsystem with its cost and decision nodes.

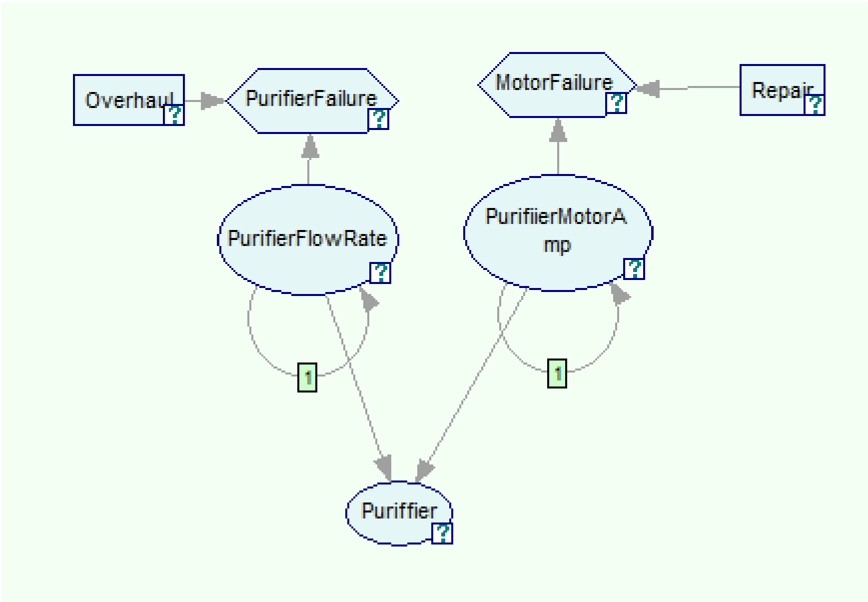

Figure 137 - DBN of the Purifier Sub-system of the Lube-Oil System, Ship 2

First observed value for the purifier flowrate probability of accepted values was 99.4%. This was then used as the input inside the Biasialab software as shown in the figure below as the condition t=0.

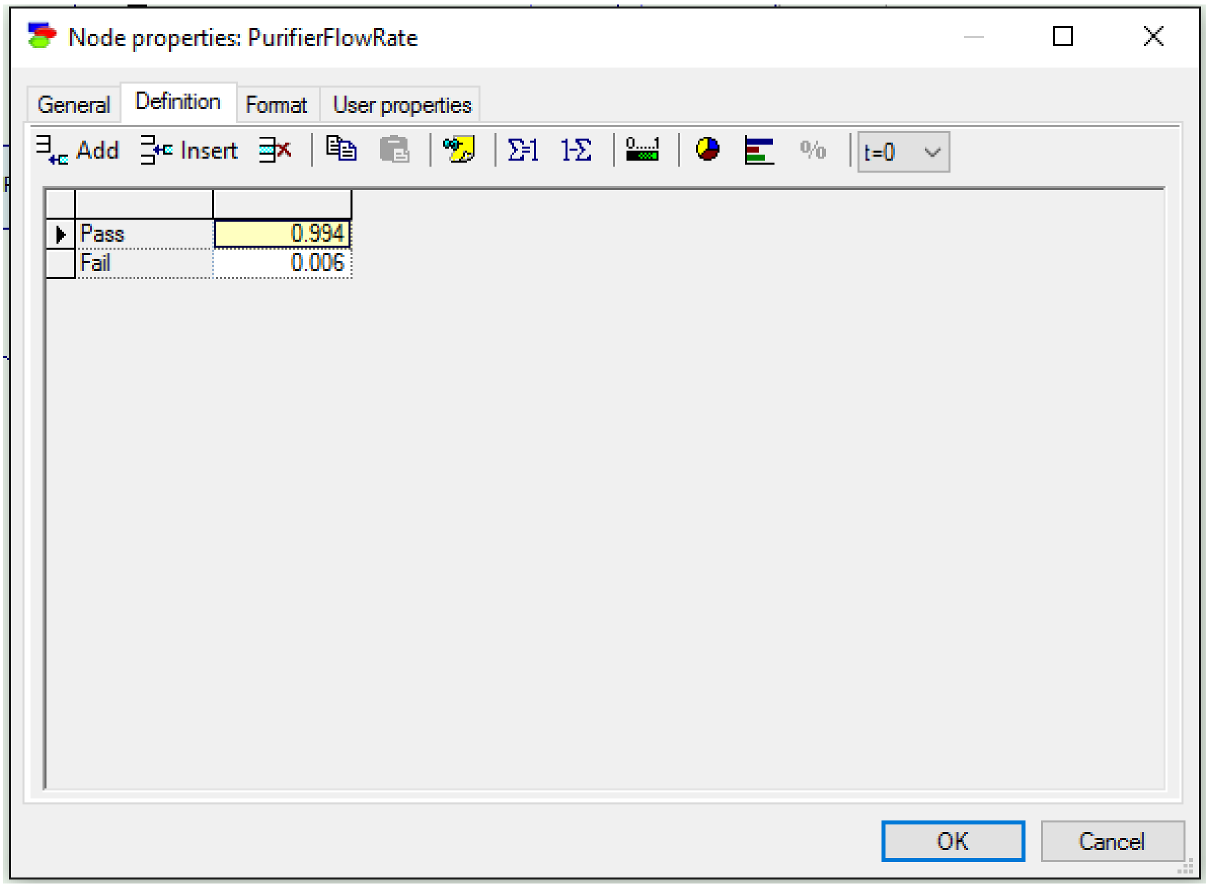

Figure 138 - Bayesia Lab Purifier Flow Rate t=0 Probability Input

The second observed probability of accepted values for the purifier was 98.8%. This value should then be used within the equation 19:($P(w|f_t) = \frac{P(w_{t+1})-(P(W|W_t)P(w_t))}{P(f_t)}$). This would give the matrix probability value of achieving 98.8% from 99.4% for this sub-system. This value was calculated to be 0.0356 or 3.56%. These were then put inside condition t=1, which represents the transition matrix inside the Biasialab as shown in the figure 139.

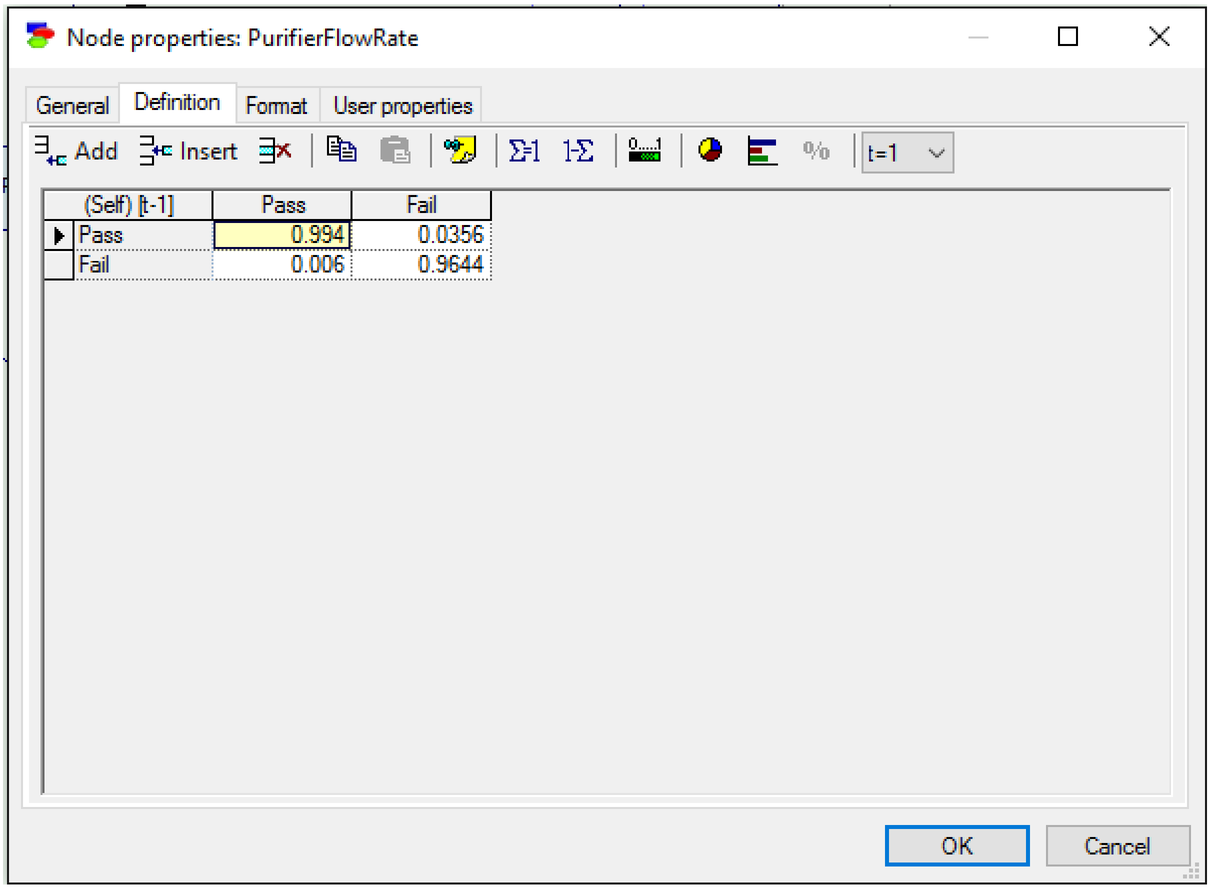

Figure 139 - Bayesia Lab Purifier Flow Rate t=1 Probability Input

Subsequently, other probability values can be calculated within the Biasialab for this sub-system as shown in the figure below. Asimilar procedure can be done for the Purifier Motor Amp as shown on Figures 140 to 143.

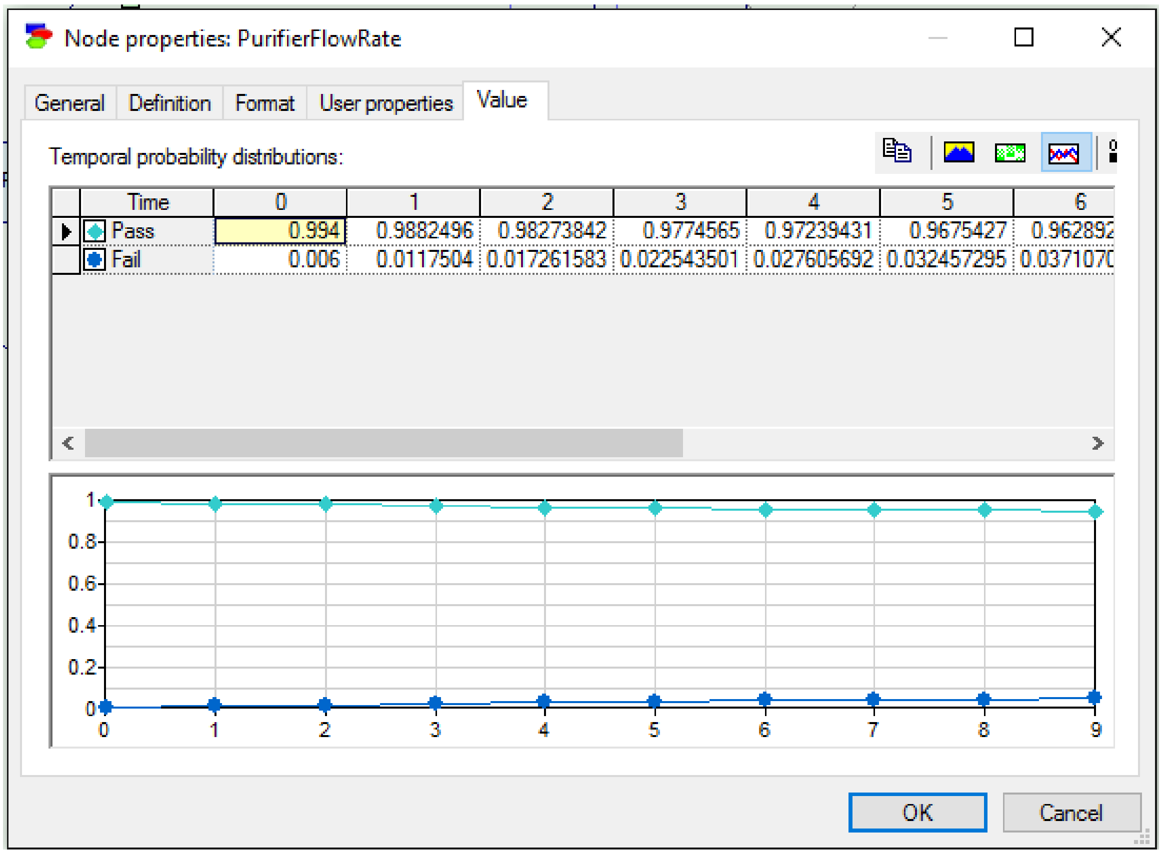

Figure 140 - Bayesia Lab Purifier Flow Rate Predicted Probability Results

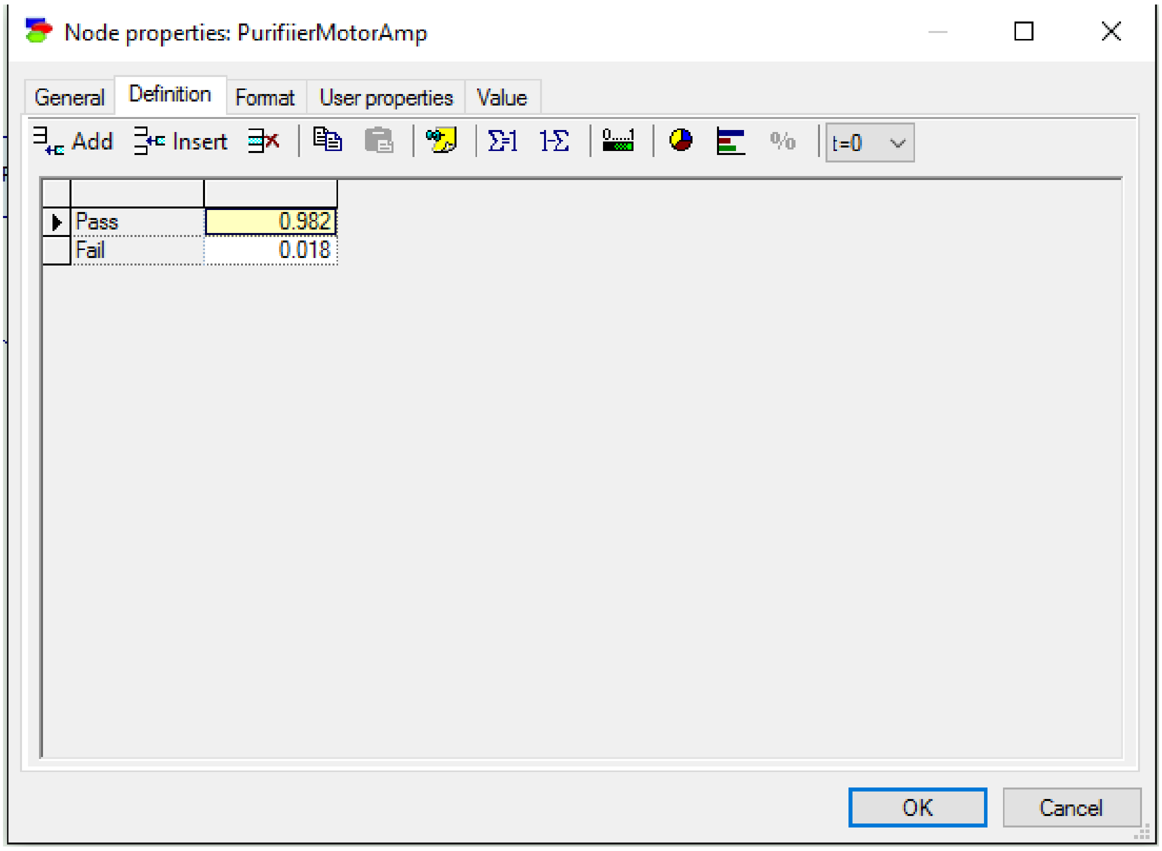

Figure 141 - Bayesia Lab Purifier Motor Amp t=0 Probability Input

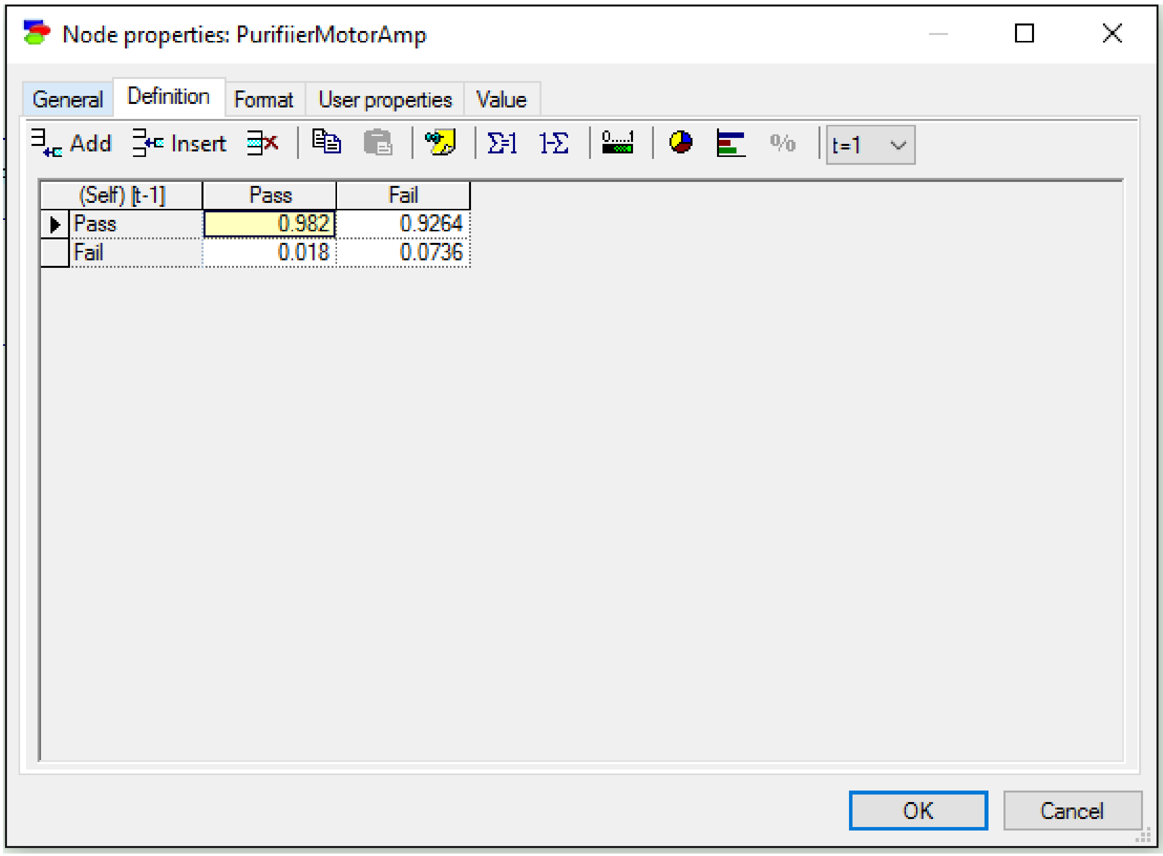

Figure 142 - Bayesia Lab Purifier Motor Amp t=1 Probability Input

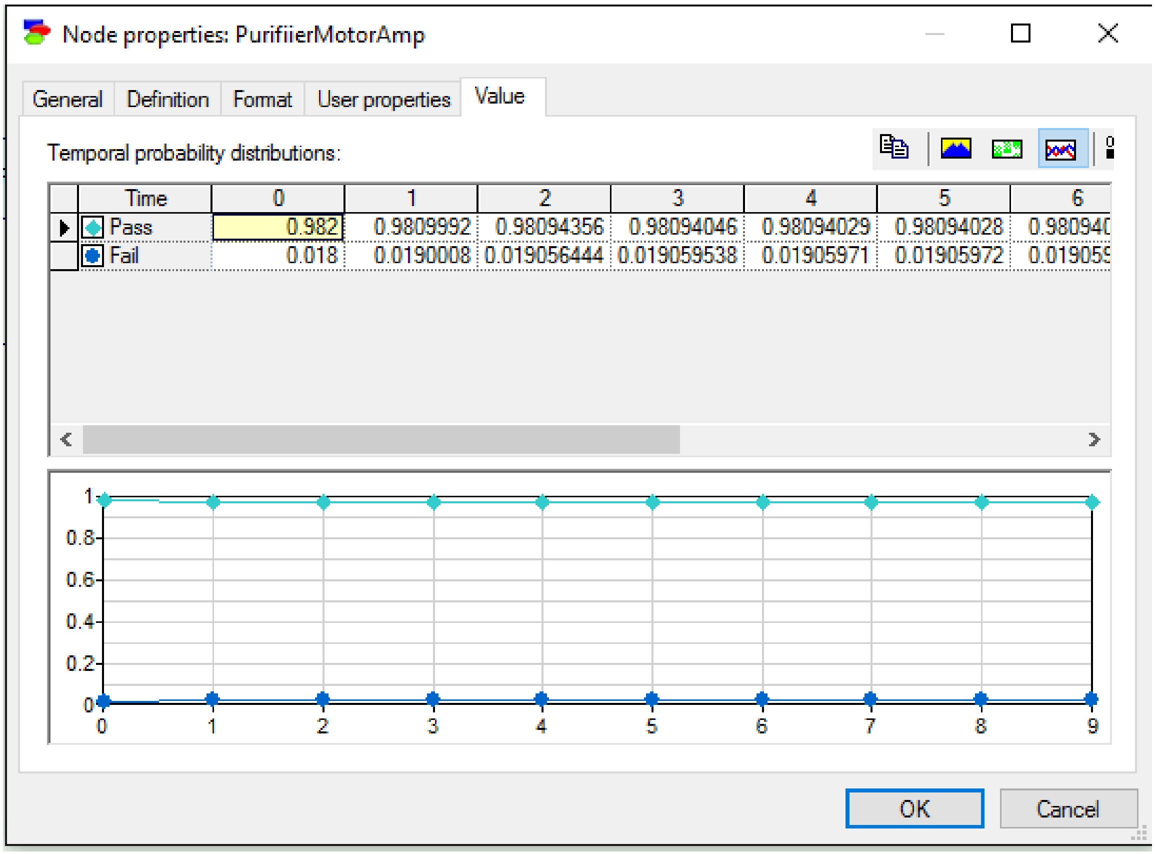

Figure 143 - Bayesia Lab Predictied Probabilities of Purifier Motor Amp

Finally, overall conditional probabilities for overall Purifier sub-systems can be determined within Biasialab by creating connections between the previous nodes and determining their Conditional Probability Tables (CPT) of the previous nodes to the final sub-system as shown in the Figure below. In this case we assume the influence of each child node in respect to the parent purifier sub-system node is equal. Therefore, the probability of the purifier having acceptable values due to one failing and the other working will be 50%. Another assumption in this case is that these two child nodes are the only reasons for the failure of the main sub-system. Therefore, if both fail, the main sub-system will also fail.

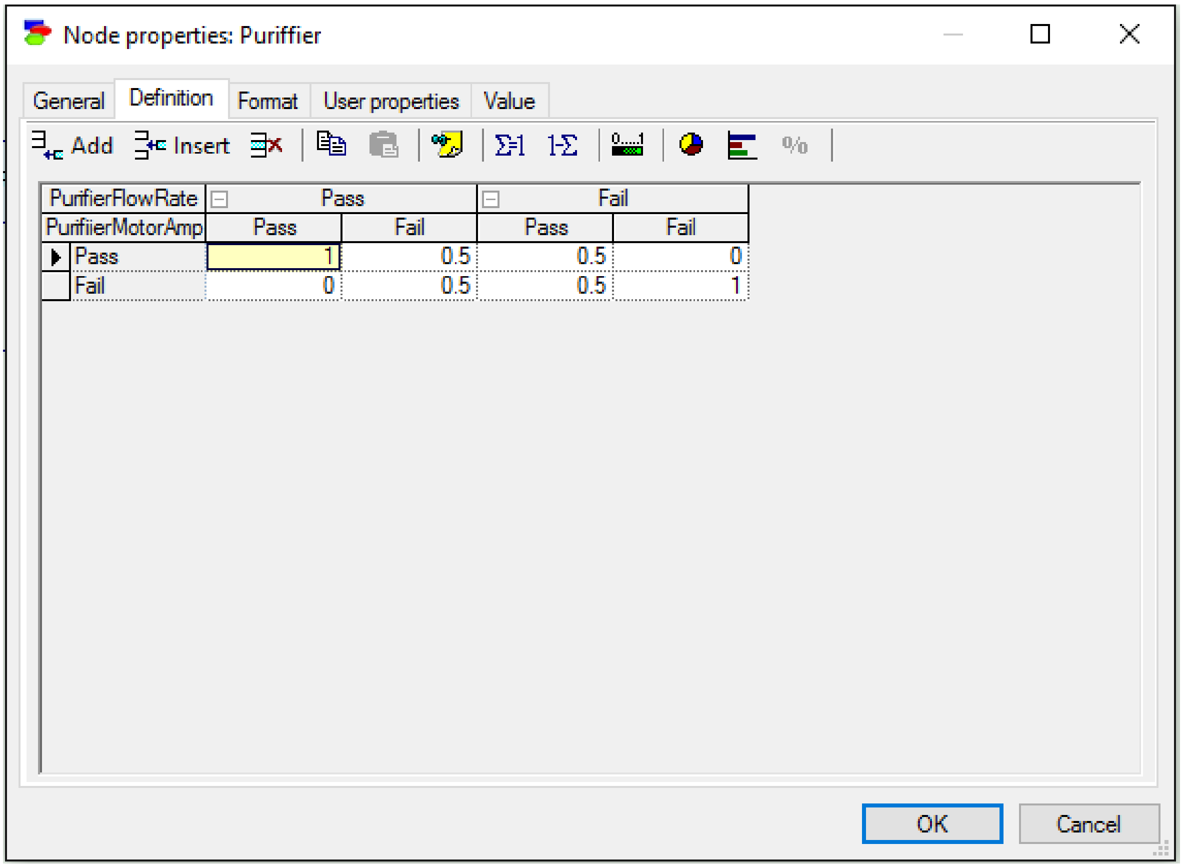

Figure 144 - Bayesia Lab Purifier Sum of Conditional Probability Table

Afterward, the overall probabilities of the sub-system in different time intervals are calculated as in the Figure 145.

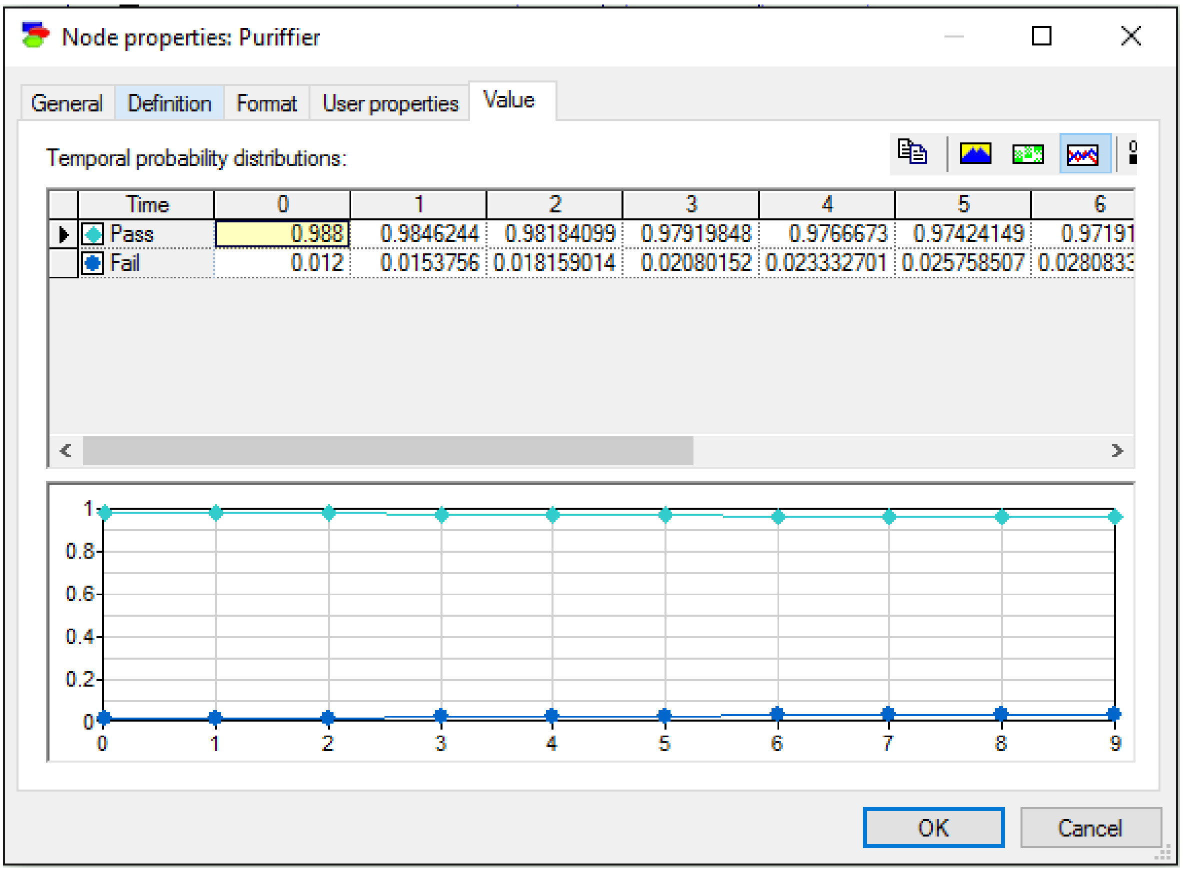

Figure 145 - Bayesia Lab Purifier Predicted Probabilities

The overall calculated results in respect to their actual observed values are then plotted in the Figure 146.

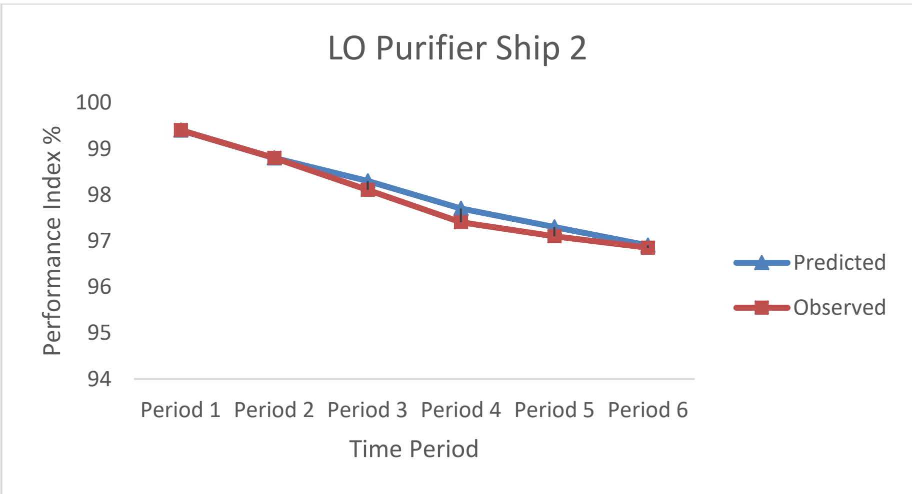

Figure 146 - LO Purifier Predicted Probabilities (Performance indices)

At the end, cost values were input inside the cost nodes according to failure possibilities mentioned within their decision nodes. In this case, if the overall system does not have a failure and a system overhaul has been done, the overall cost will be the expenditure of the overhauling. If the system does not have a failure and no overhaul has been commenced, then the overall cost will be zero. Subsequently, if failure has occurred and overhaul was in its correct time, its overall cost will be the cost of the failure. However, if failure has occurred and no overhaul has been done on-time the overall final cost will also include the cost of another overhaul plus the failure cost. For both of the sub-systems, overall cost inputs are shown in Figures 147 and 148. Figure 149 below represents the graph of all calculated and observed values for overall costs for the main sub-system of purifier.

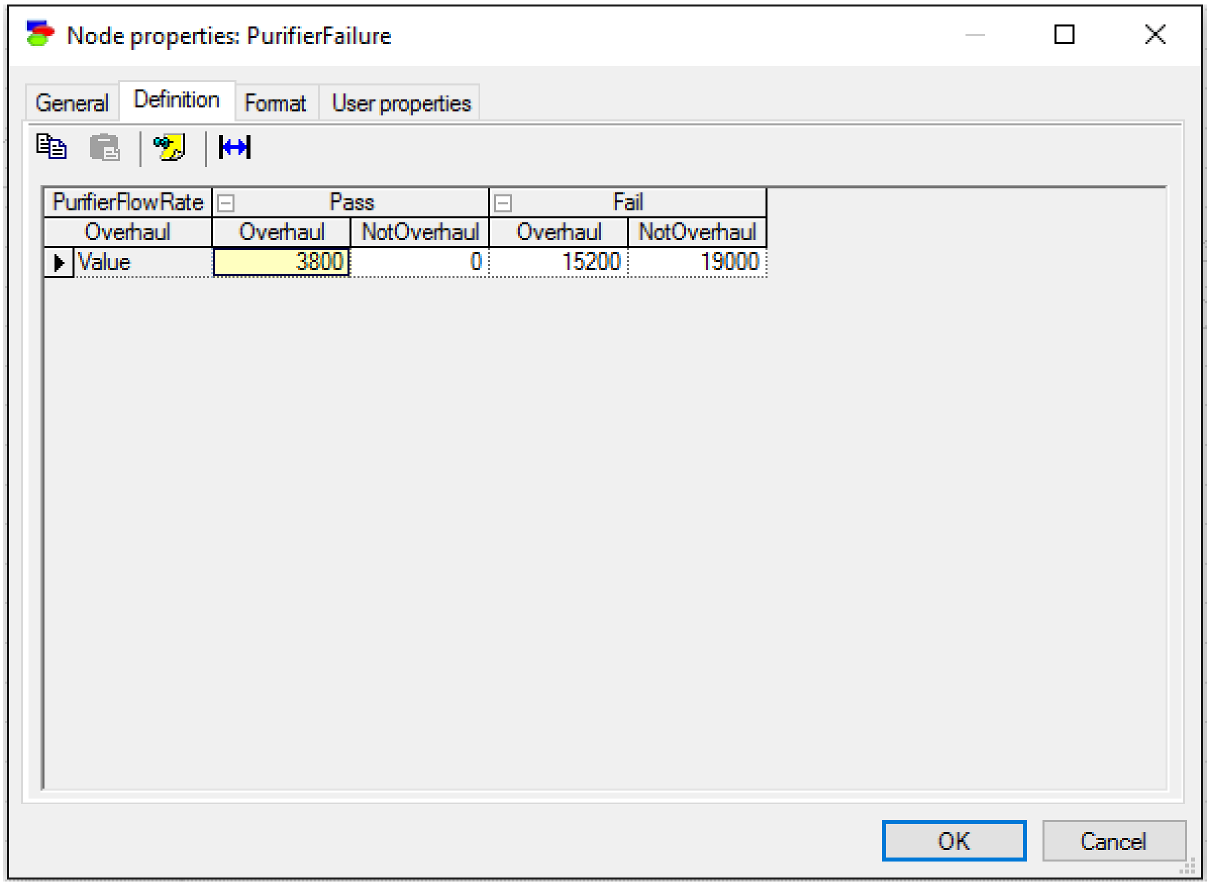

Figure 147 - Bayesia Lab Purifier Flowrate Cost Input

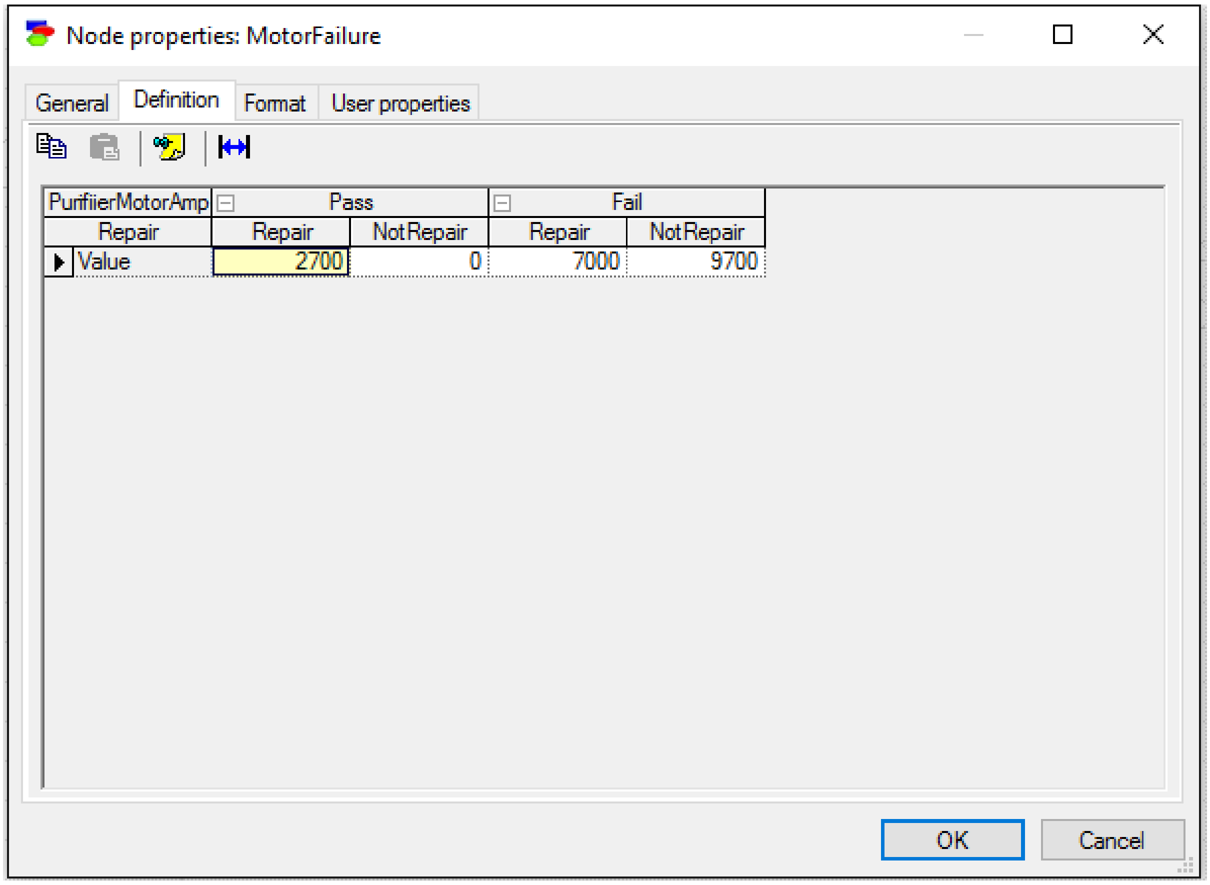

Figure 148 - Bayesia Lab Purifier Motor Cost Input

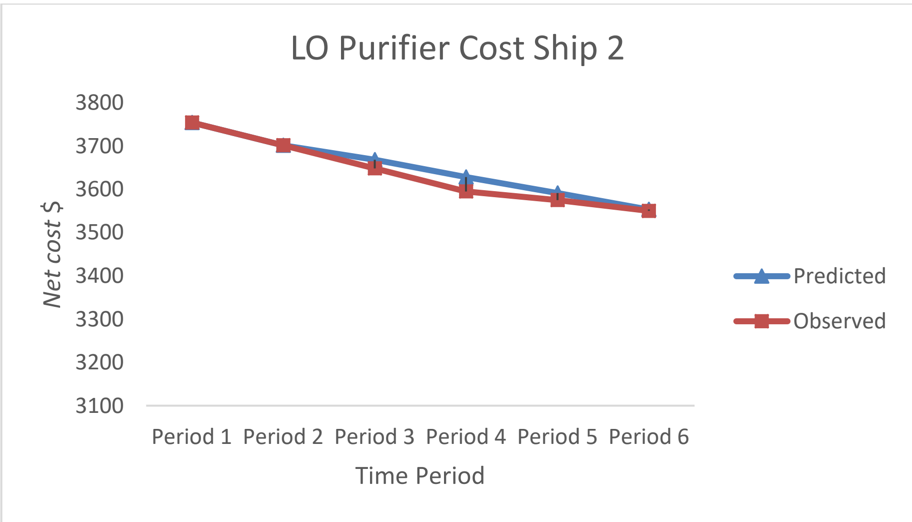

Figure 149 - Overall Purifier Net cost Results

APPENDIX B1-COMPONENT/SUB-SYSTEM PREDICTED AND OBSERVED PERFORMANCE INDEX VALUES FOR SHIP 1 SISTER CHEMICAL TANKER OPERATING IN WEST COAST CANADA

Appendix B1.1 Lube-oil System of Ship 1

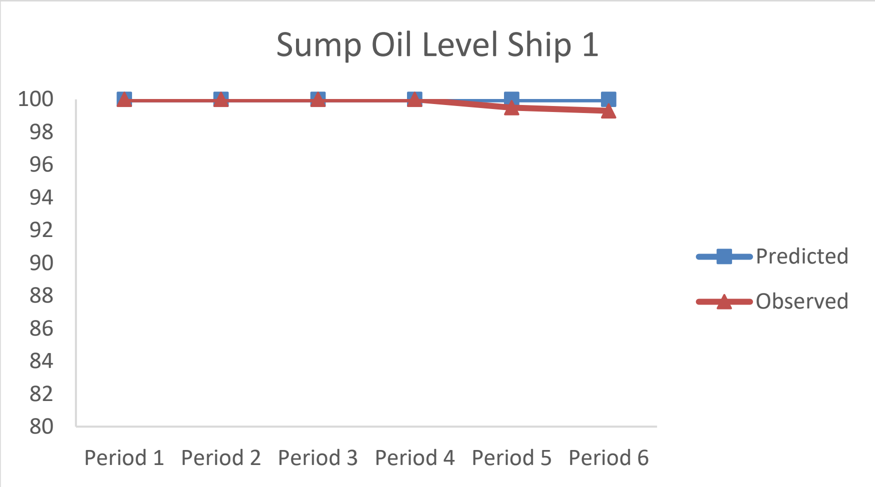

Figure 150 - Sump Oil Level Probabilistic Performance Prediction for Ship 1

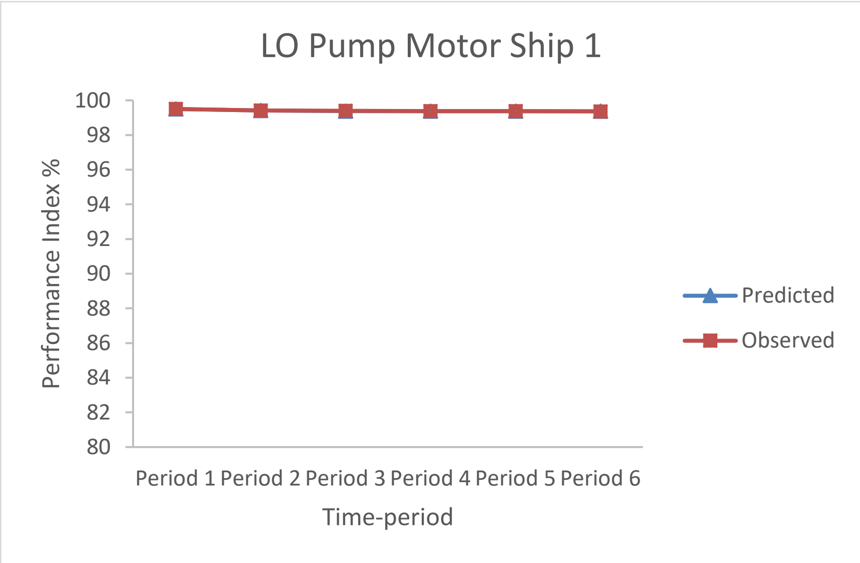

Figure 151 - Lube-oil Pump Motor Probabilistic Performance Prediction for Ship 1

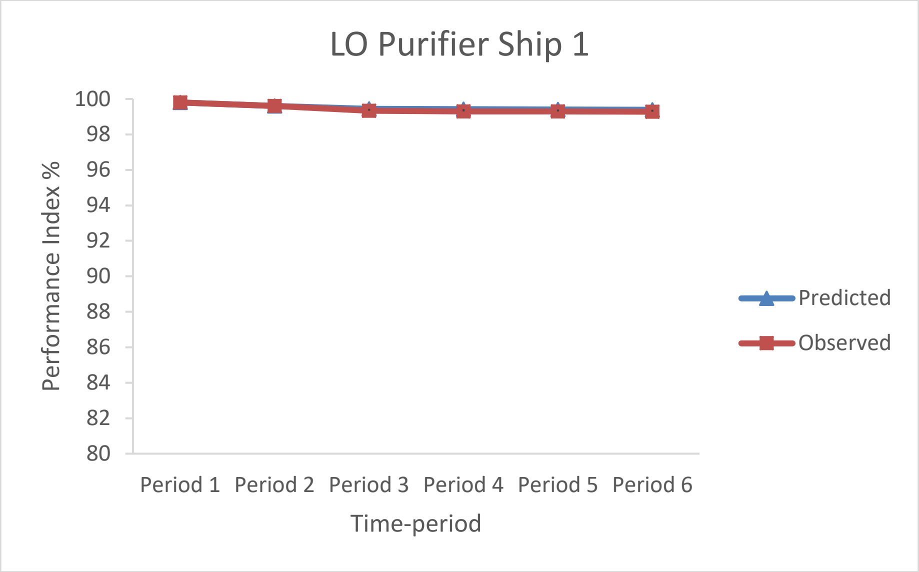

Figure 152 - Lube-oil Purifier Probabilistic Performance Prediction for Ship 1

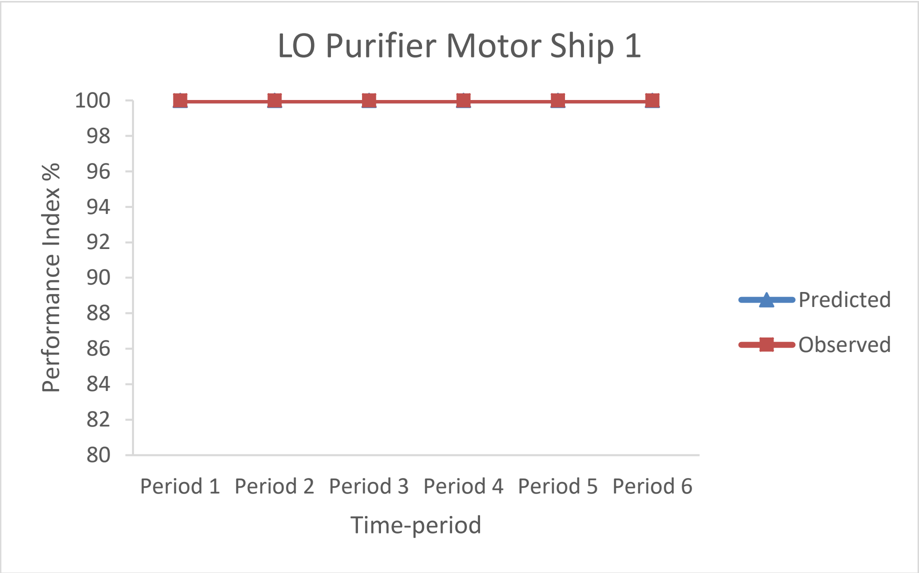

Figure 153 - Lube-oil Purifier Motor Probabilistic Performance Prediction for Ship 1

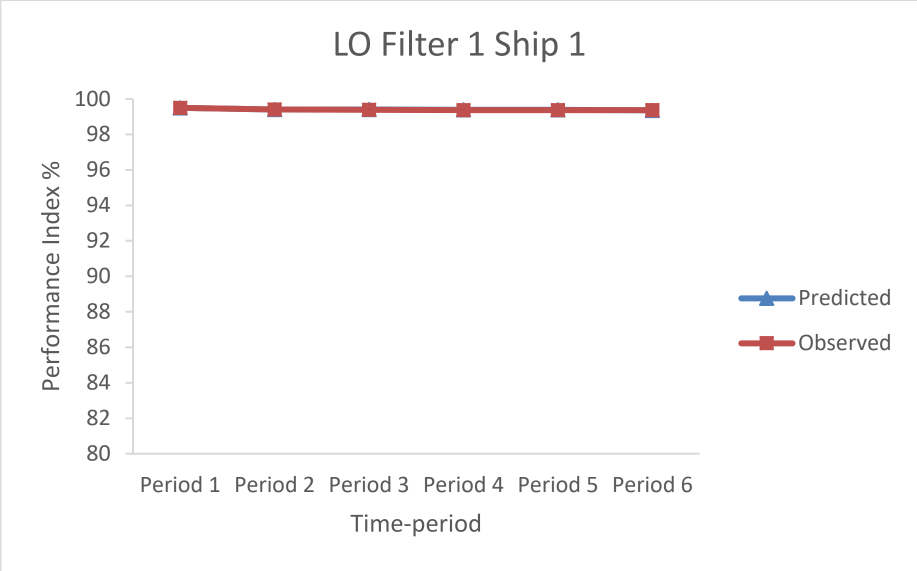

Figure 154 - Lube-oil Filter 1 Probabilistic Performance Prediction for Ship 1

Appendix B1.2 Fuel-oil System of Ship 1

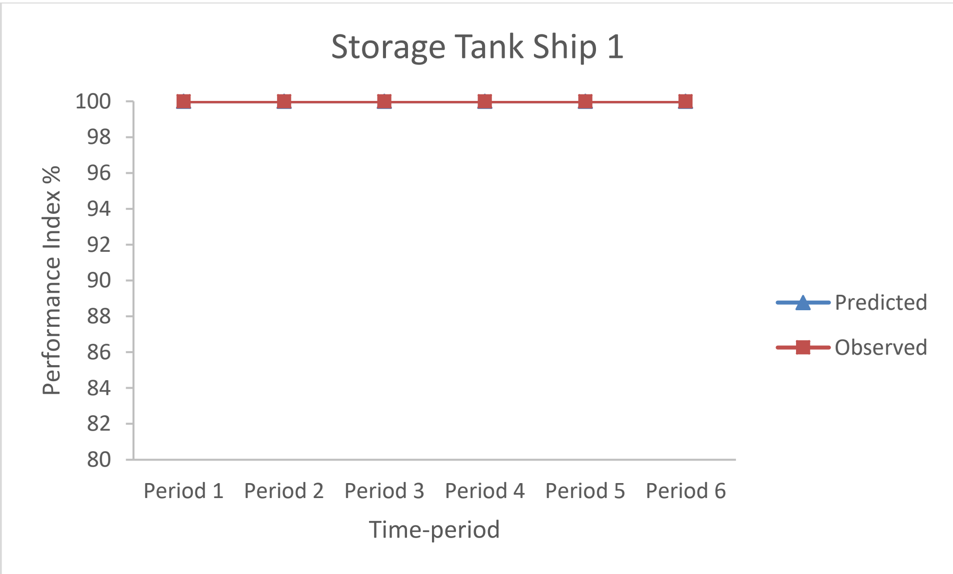

Figure 155 – Storage Tank Probabilistic Performance Prediction for Ship 1

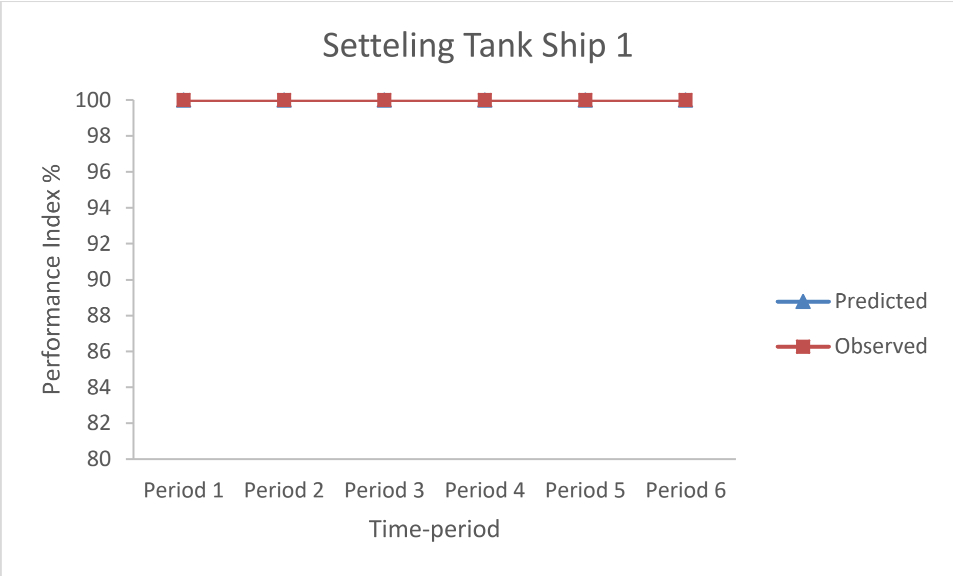

Figure 156 – Settling Tank Probabilistic Performance Prediction for Ship 1

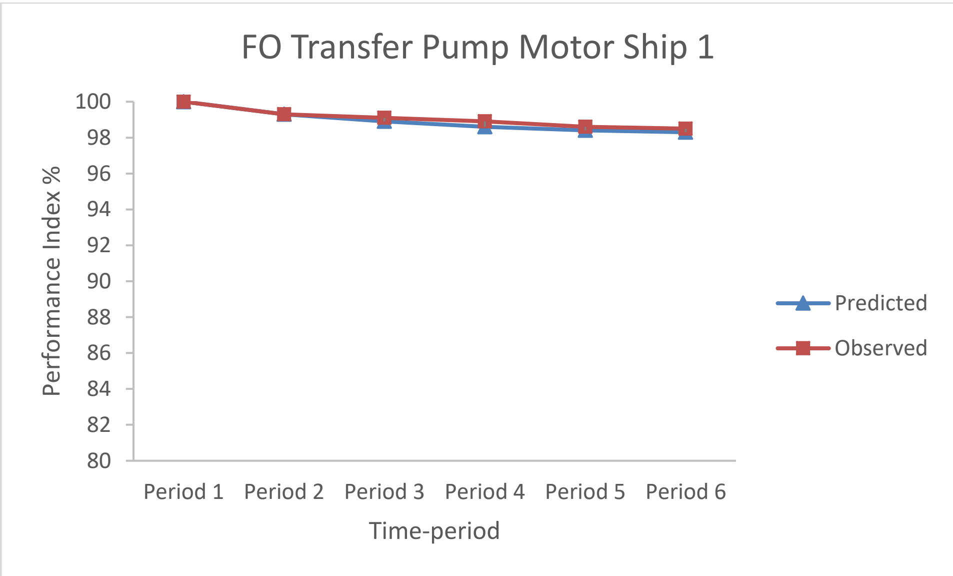

Figure 157 - Fuel-oil Transfer Pump Motor Probabilistic Performance Prediction for Ship 1

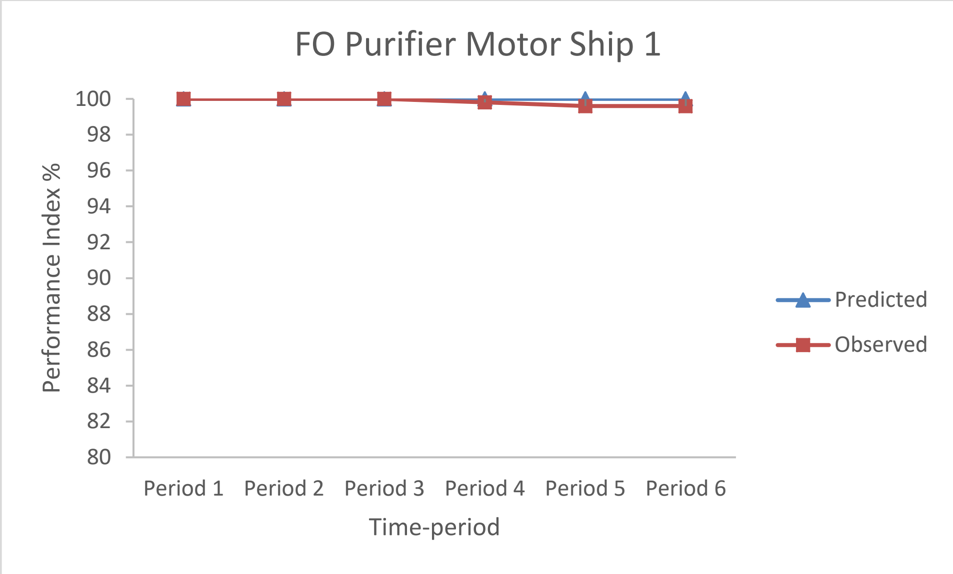

Figure 158 - Fuel-oil Purifier Motor Probabilistic Performance Prediction for Ship 1

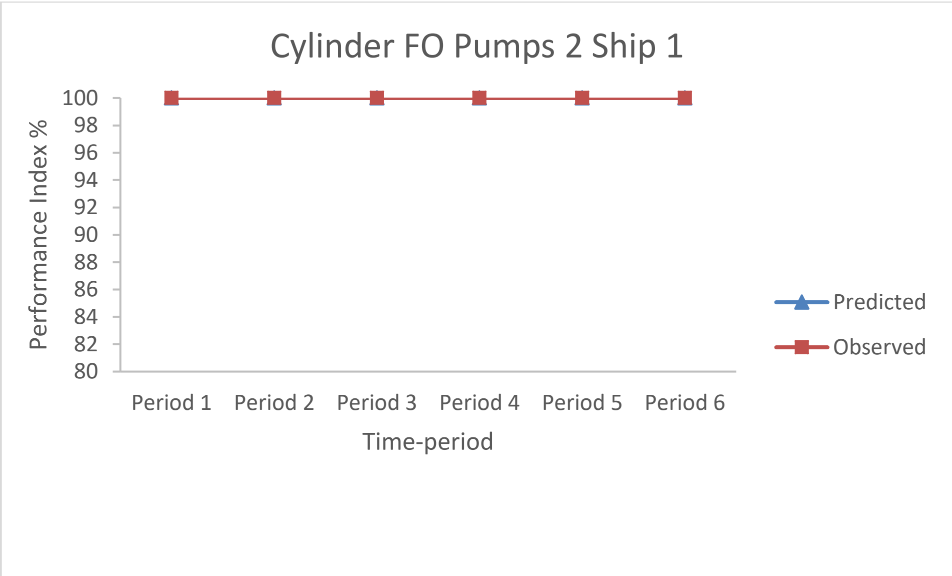

Figure 159 - Cylinder Fuel-oil Pump 2 Probabilistic Performance Prediction for Ship 1

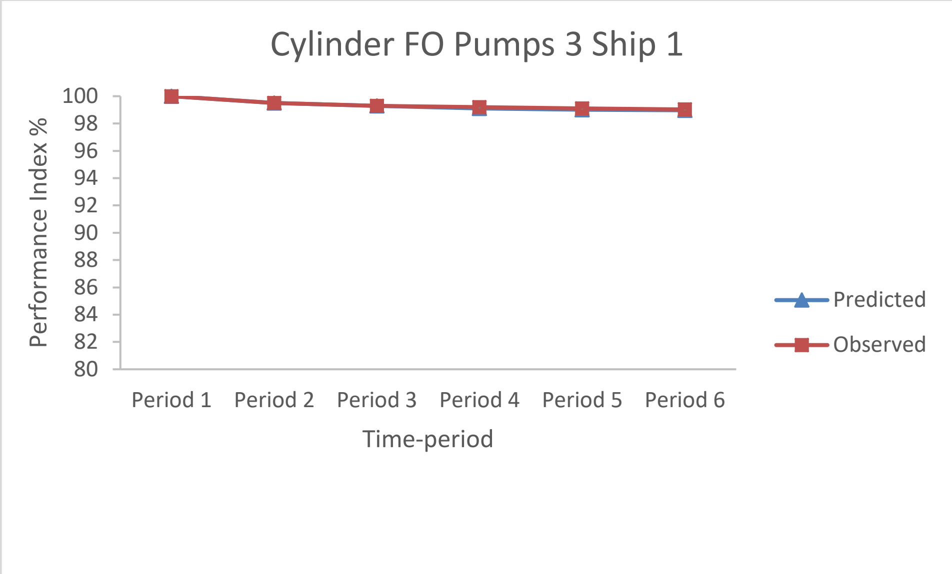

Figure 160 - Cylinder Fuel-oil Pump 3 Probabilistic Performance Prediction for Ship 1

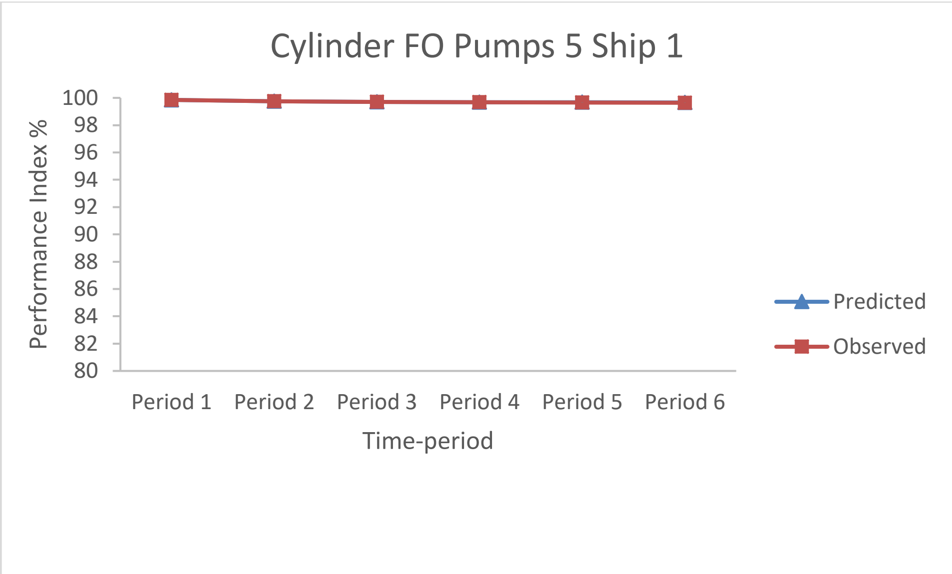

Figure 161 - Cylinder Fuel-oil Pump 5 Probabilistic Performance Prediction for Ship 1

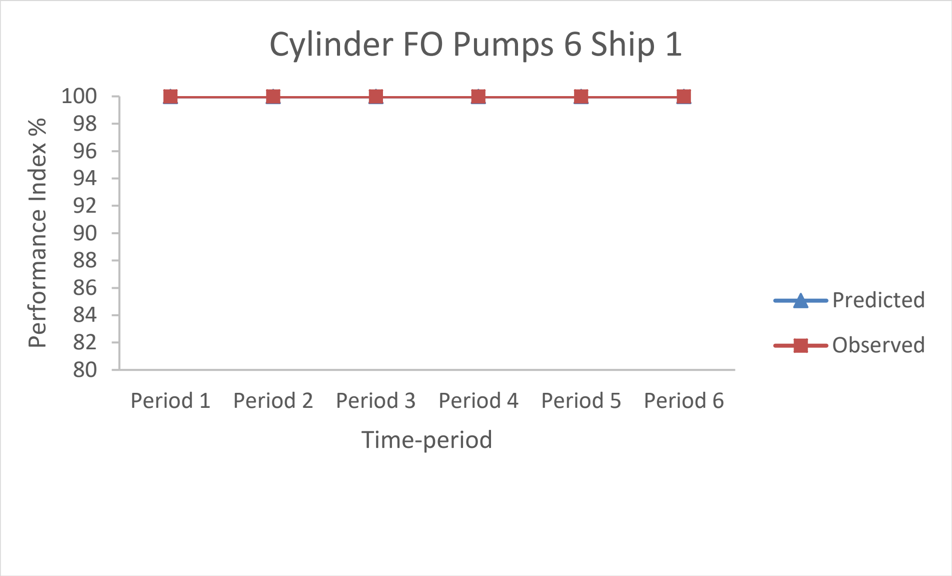

Figure 162 - Cylinder Fuel-oil Pump 6 Probabilistic Performance Prediction for Ship 1

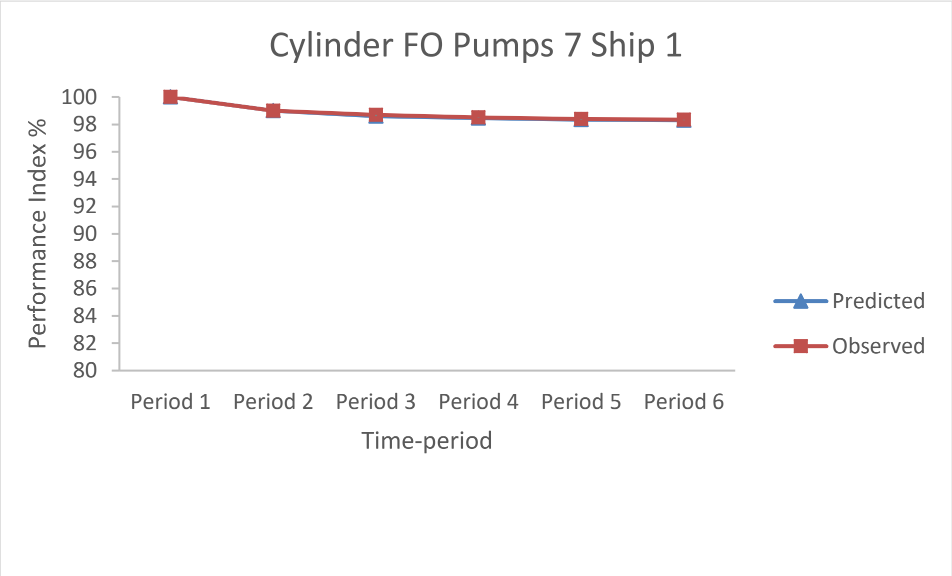

Figure 163 - Cylinder Fuel-oil Pump 7 Probabilistic Performance Prediction for Ship 1

Appendix B1.3 Turbocharger System of Ship 1

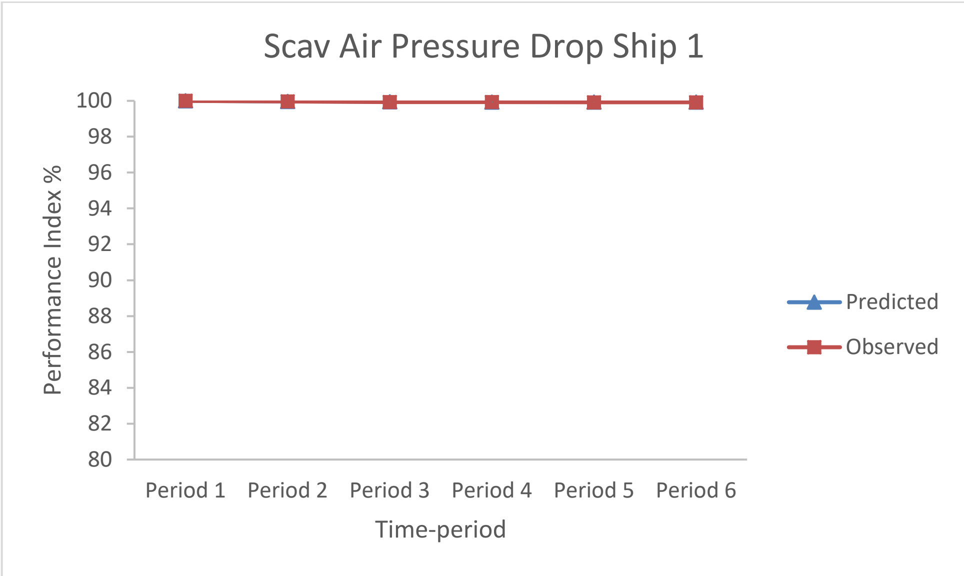

Figure 164 – Scavenge Air Pressure Difference Probabilistic Performance Prediction for Ship 1

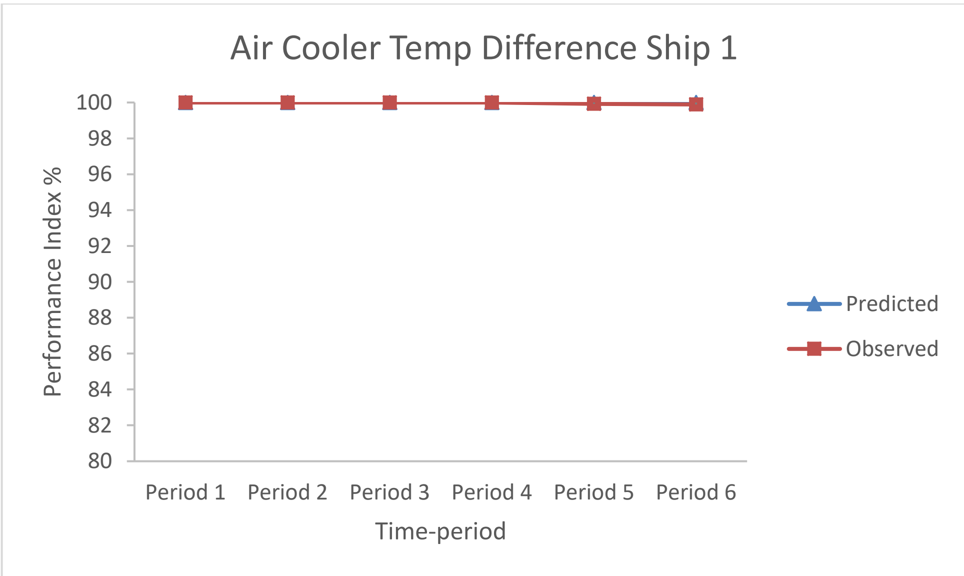

Figure 165 - Air Cooler Temperature Difference Probabilistic Performance Prediction for Ship 1

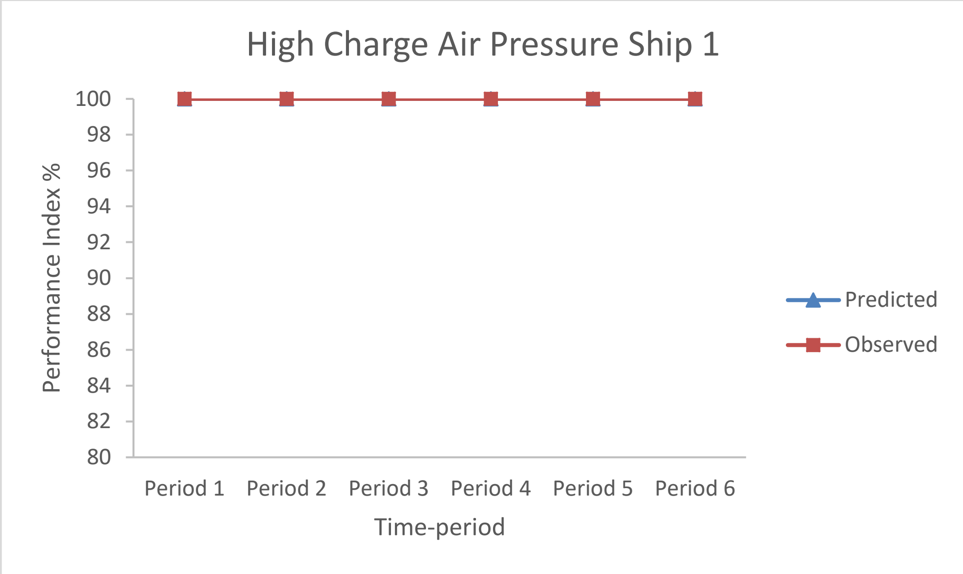

Figure 166 – High Charge Air Pressure Probabilistic Performance Prediction for Ship 1

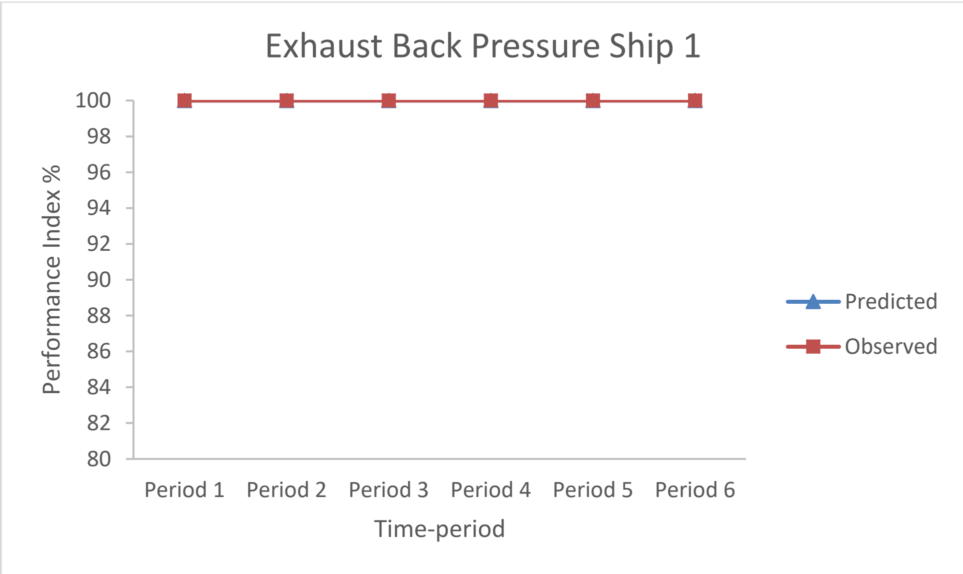

Figure 167 – Exhaust Back-pressure Probabilistic Performance Prediction for Ship 1

APPENDIX B2-COMPONENT/SUB-SYSTEM PREDICTED AND OBSERVED PERFORMANCE INDEX VALUES FOR SHIP 2 SISTER CHEMICAL TANKER OPERATING IN SOUTH-EAST ASIA

Appendix B2.1 Lube-oil System of Ship 2

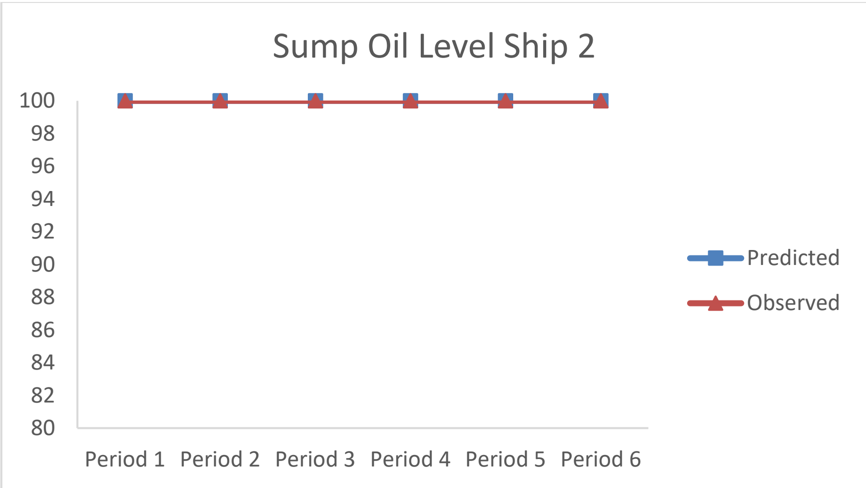

Figure 168 – Sump Oil Level Probabilistic Performance Prediction for Ship 2

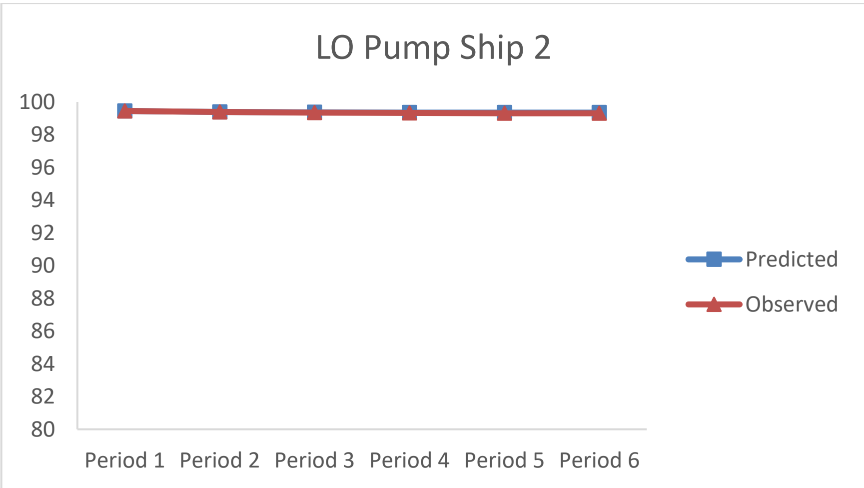

Figure 169 – Lube-oil Pump Probabilistic Performance Prediction for Ship 2

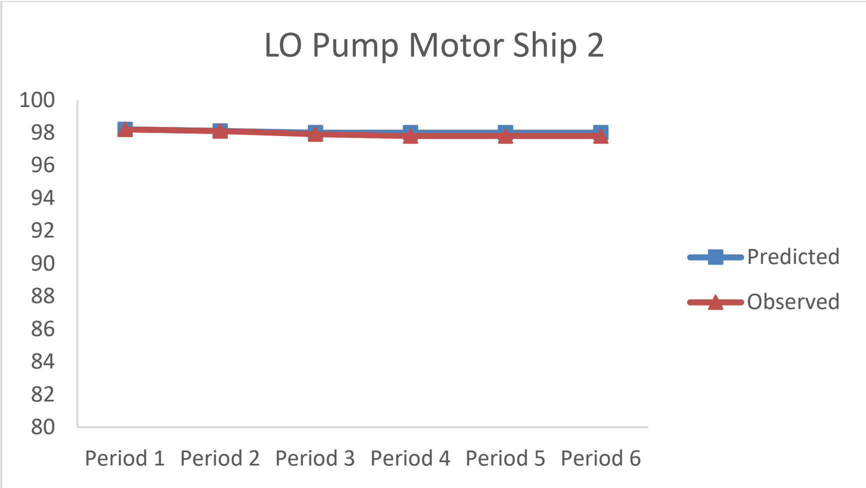

Figure 170 - Lube-oil Pump Motor Probabilistic Performance Prediction for Ship 2

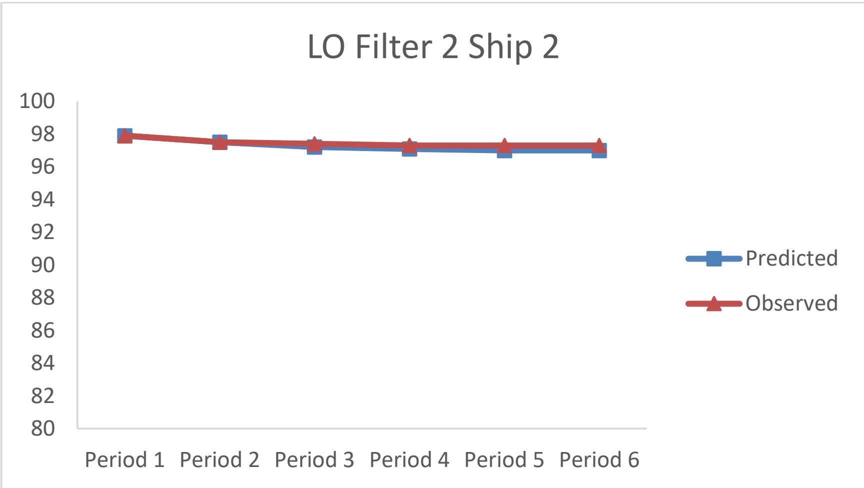

Figure 171 - Lube-oil Filter 2 Probabilistic Performance Prediction for Ship 2

Appendix B2.2 Fuel-oil System of Ship 2

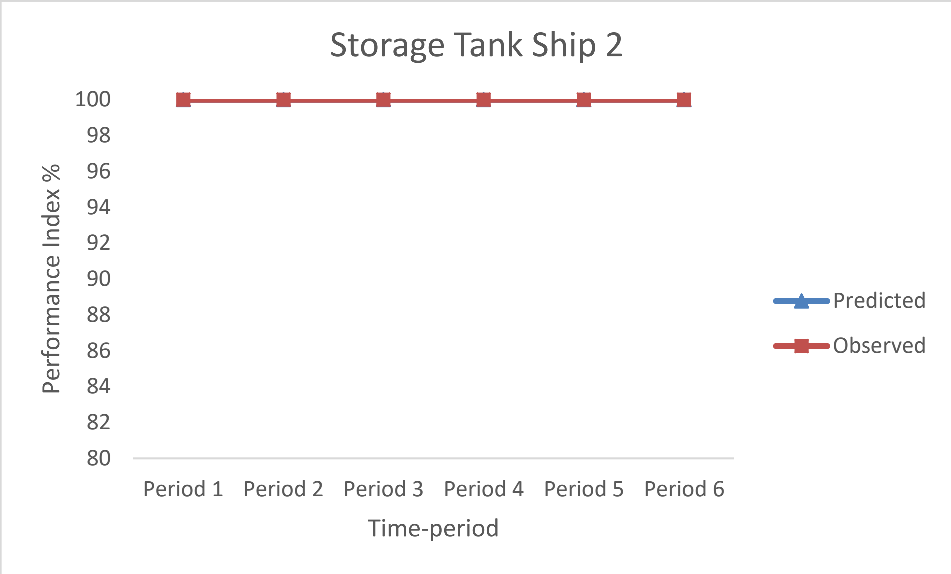

Figure 172 – Storage Tank Probabilistic Performance Prediction for Ship 2

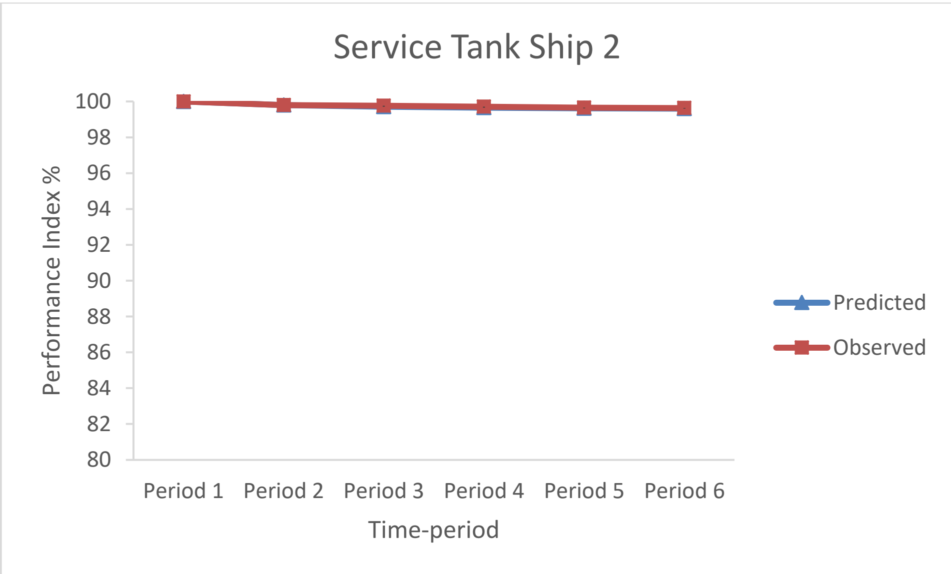

Figure 173 – Service Tank Probabilistic Performance Prediction for Ship 2

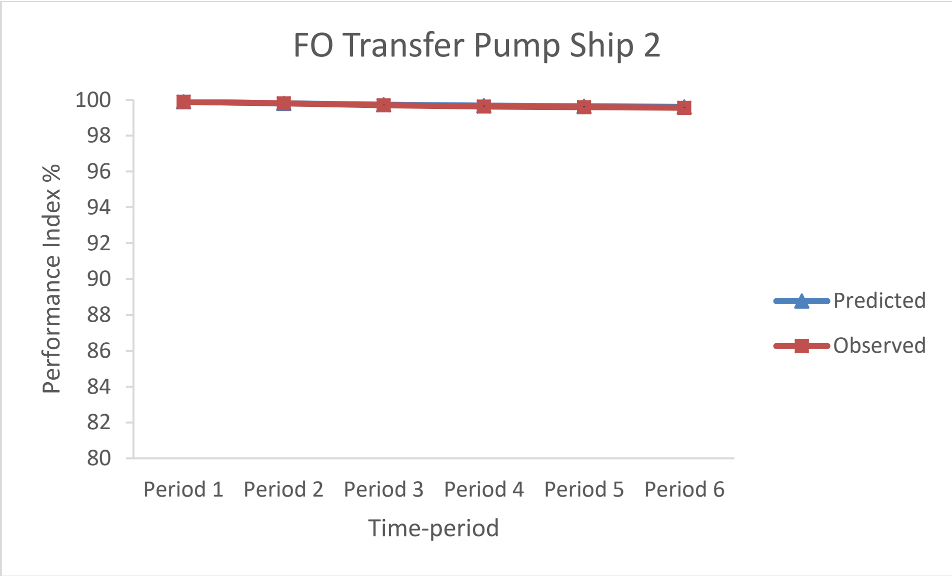

Figure 174 - Fuel-oil Transfer Pump Probabilistic Performance Prediction for Ship 2

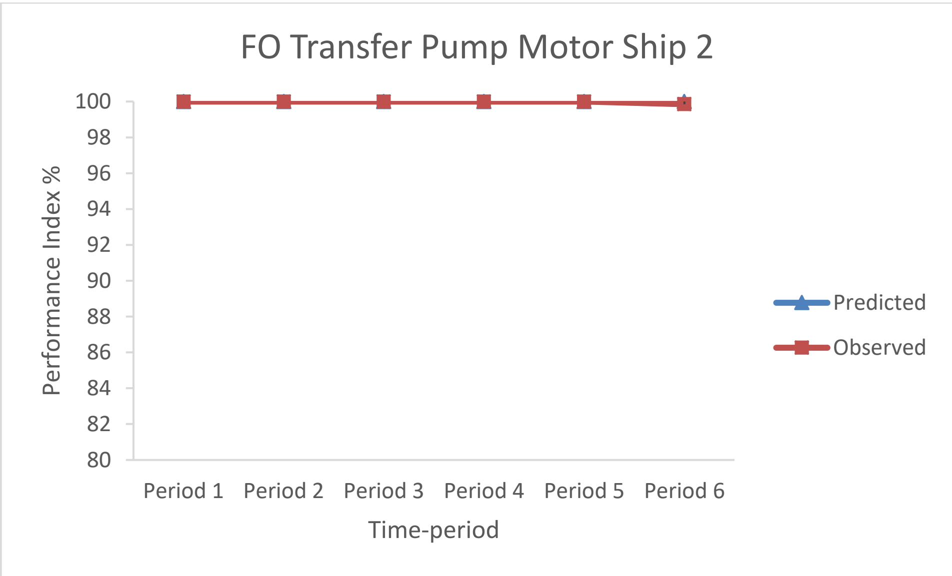

Figure 175 - Fuel-oil Transfer Pump Motor Probabilistic Performance Prediction for Ship 2

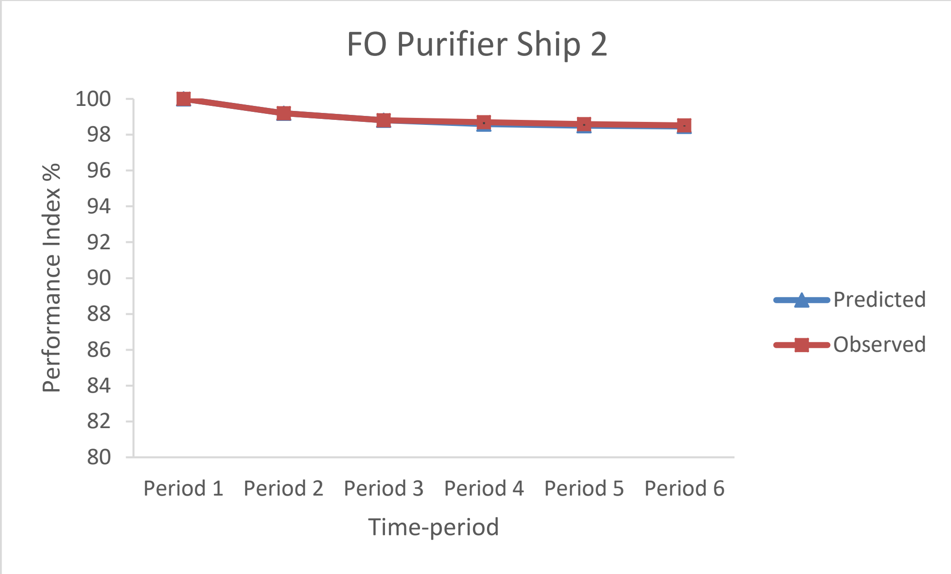

Figure 176 - Fuel-oil Purifier Probabilistic Performance Prediction for Ship 2

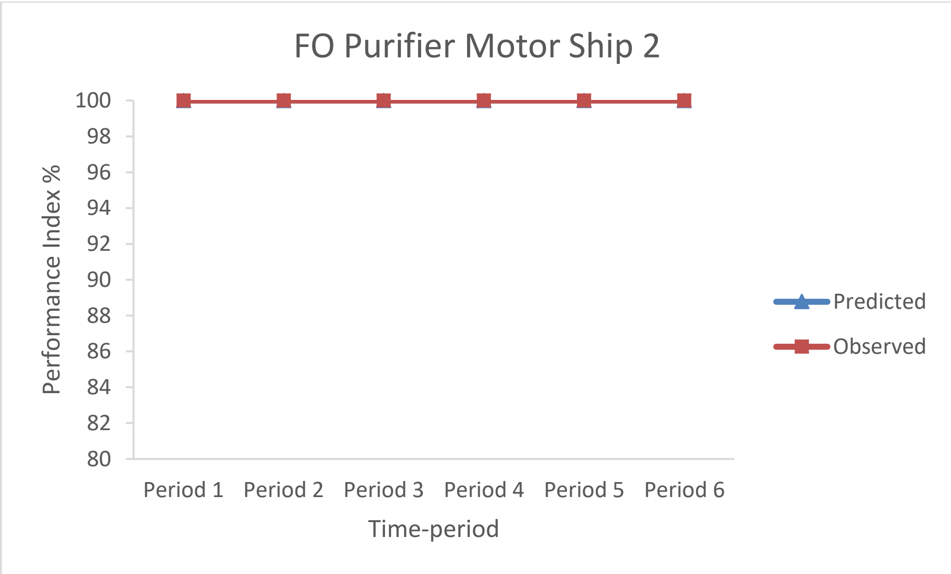

Figure 177 - Fuel-oil Purifier Motor Probabilistic Performance Prediction for Ship 2

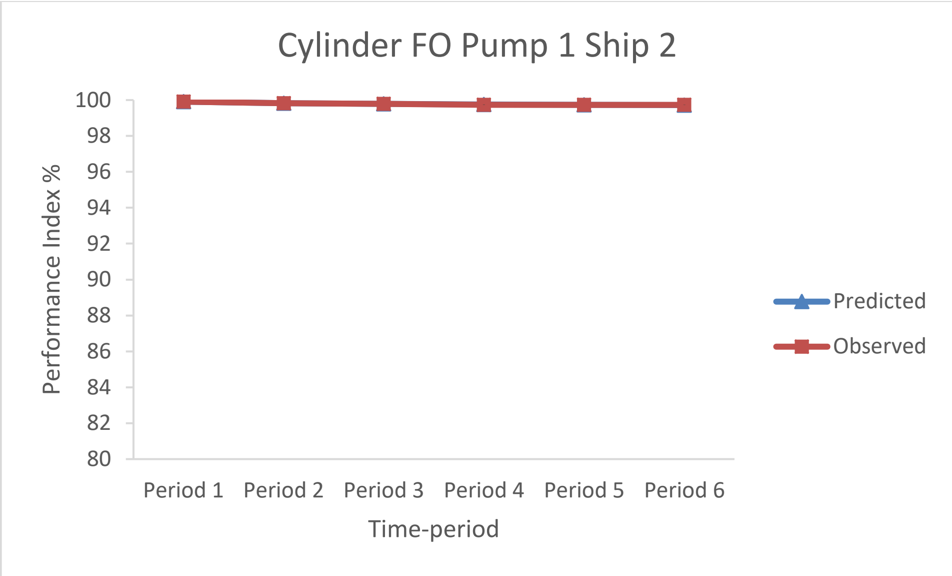

Figure 178 – Cylinder Fuel-oil Pump 1 Probabilistic Performance Prediction for Ship 2

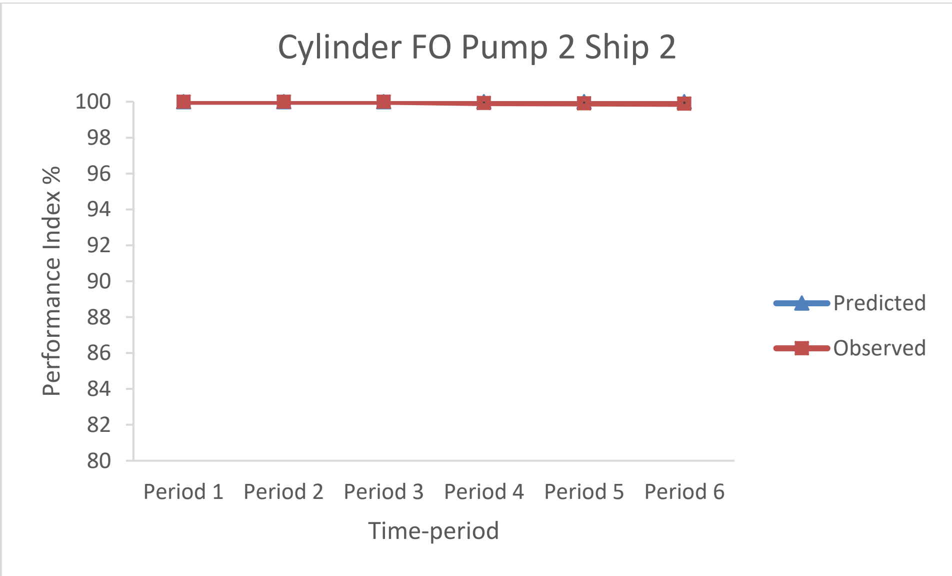

Figure 179 - Cylinder Fuel-oil Pump 2 Probabilistic Performance Prediction for Ship 2

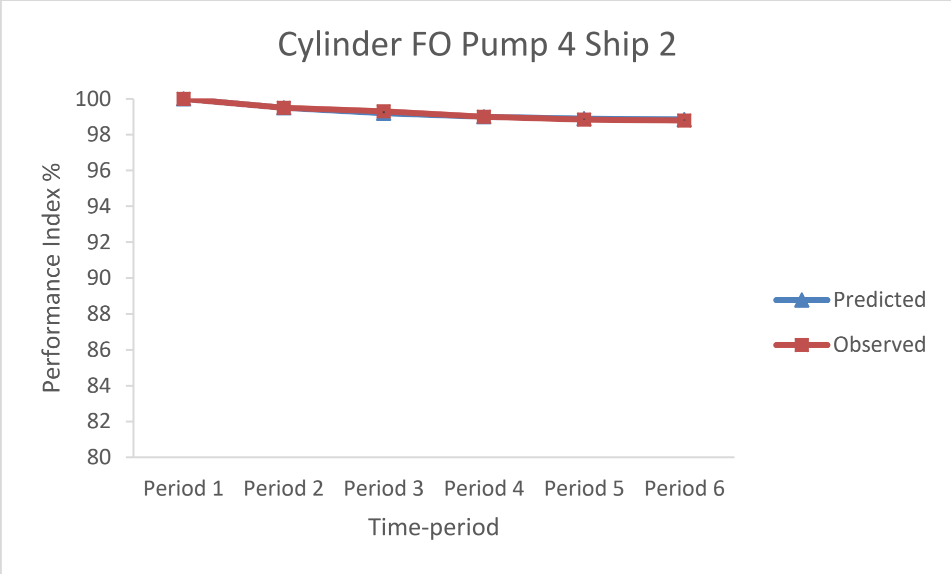

Figure 180 - Cylinder Fuel-oil Pump 4 Probabilistic Performance Prediction for Ship 2

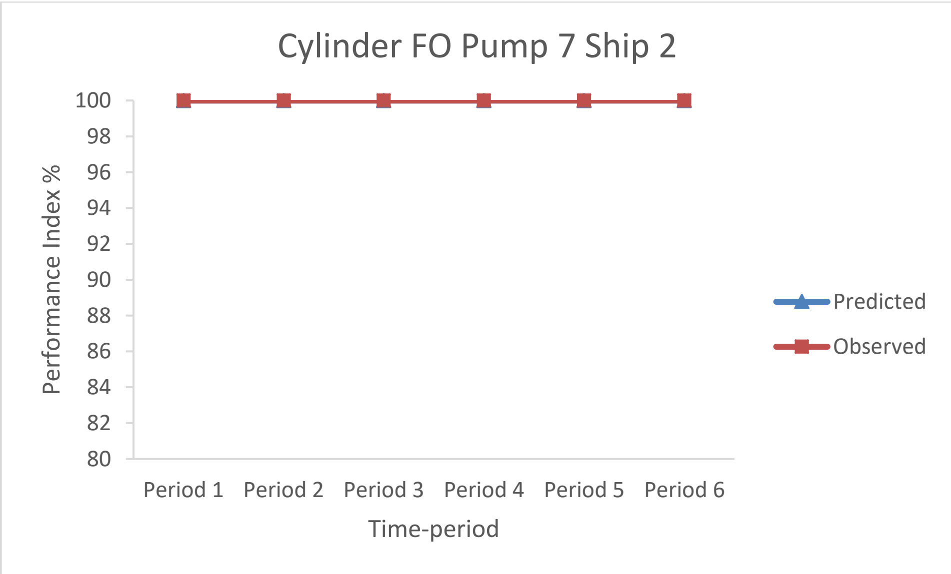

Figure 181 - Cylinder Fuel-oil Pump 7 Probabilistic Performance Prediction for Ship 2

Appendix B2.3 Turbocharger System of Ship 2

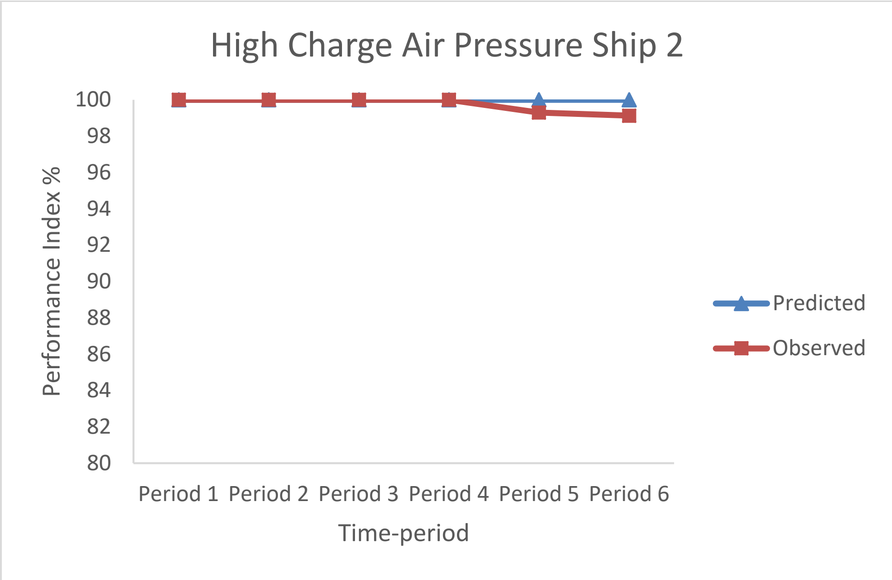

Figure 182 – High Charge Air Pressure Probabilistic Performance Prediction for Ship 2

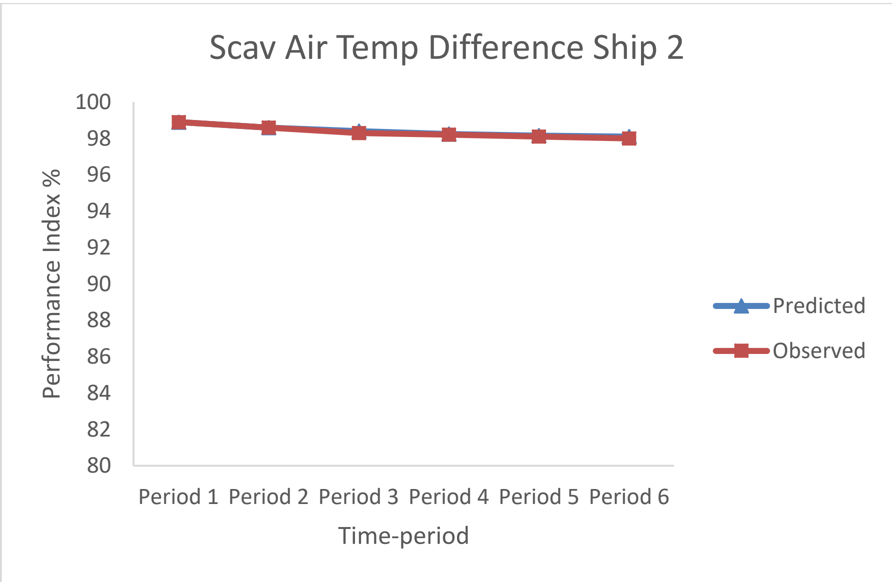

Figure 183 – Scavenge Air Temperature Difference Probabilistic Performance Prediction for Ship 2

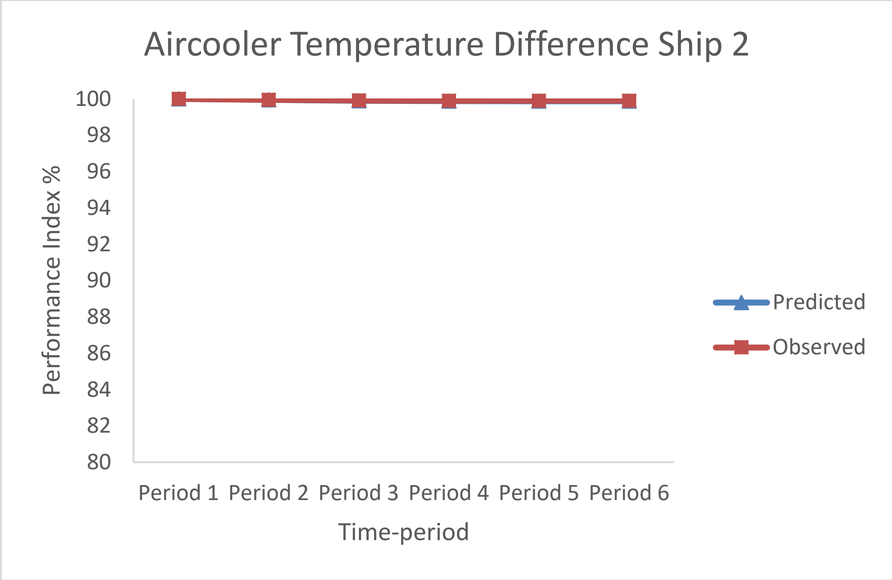

Figure 184 - Air Cooler Temperature Difference Probabilistic Performance Prediction for Ship 2

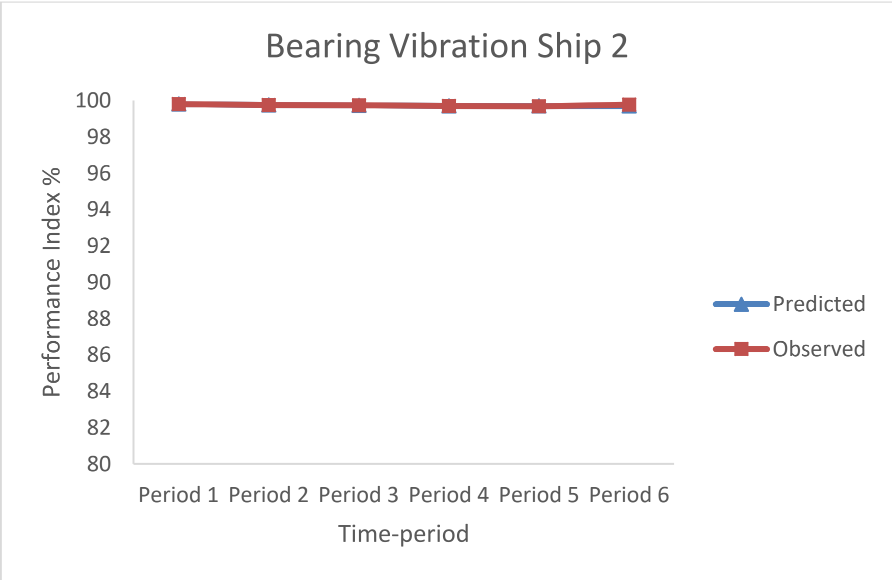

Figure 185 – Bearing Vibration Probabilistic Performance Prediction for Ship 2

APPENDIX B3-COMPONENT/SUB-SYSTEM PREDICTED AND OBSERVED PERFORMANCE INDEX VALUES FOR SHIP 3 MULTI-PURPOSE CARGO VESSEL

Appendix B3.1 Lube-oil System of Ship 3

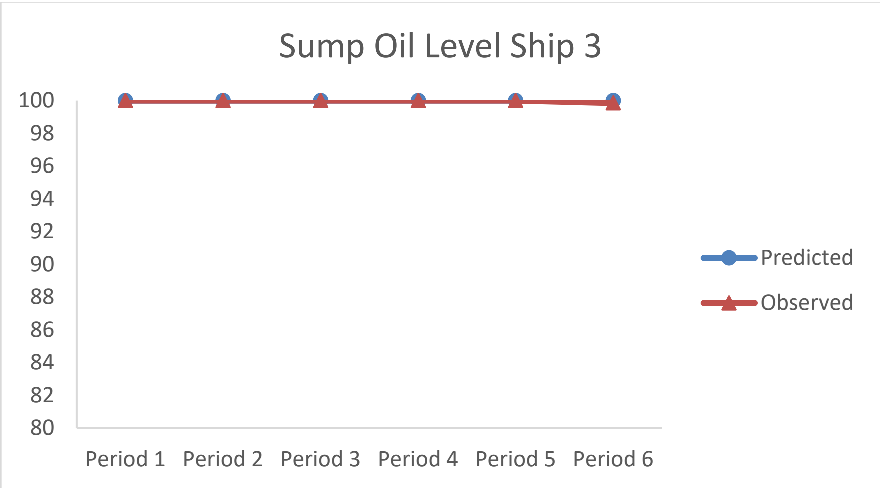

Figure 186 – Sump Oil Level Probabilistic Performance Prediction for Ship 3

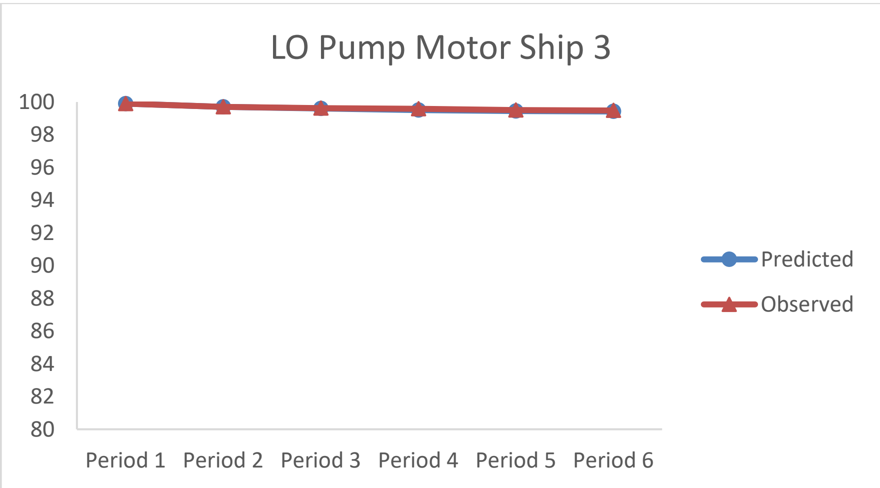

Figure 187 – Lube-oil Pump Motor Probabilistic Performance Prediction for Ship 3

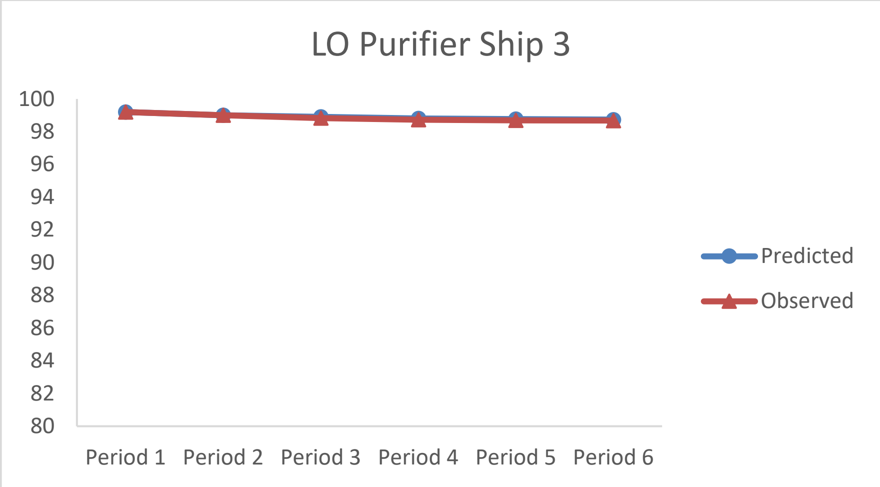

Figure 188 - Lube-oil Purifier Probabilistic Performance Prediction for Ship 3

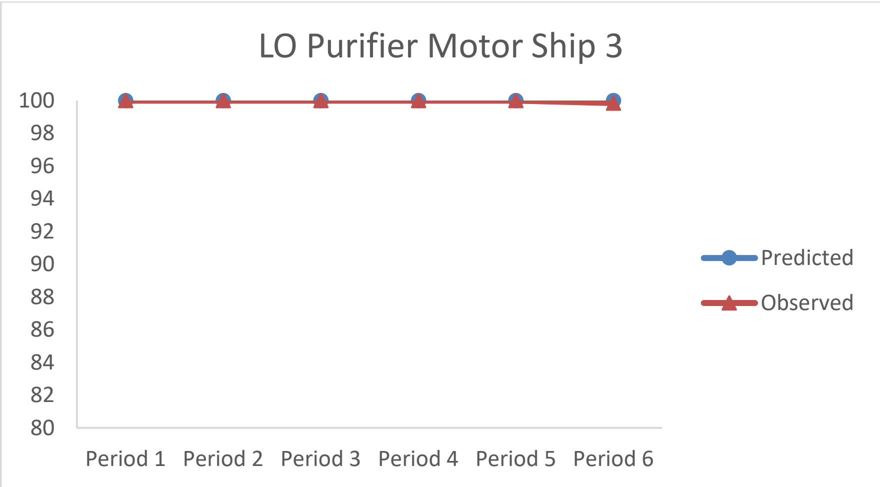

Figure 189 - Lube-oil Purifier Motor Probabilistic Performance Prediction for Ship 3

Appendix B3.2 Fuel-oil System of Ship 3

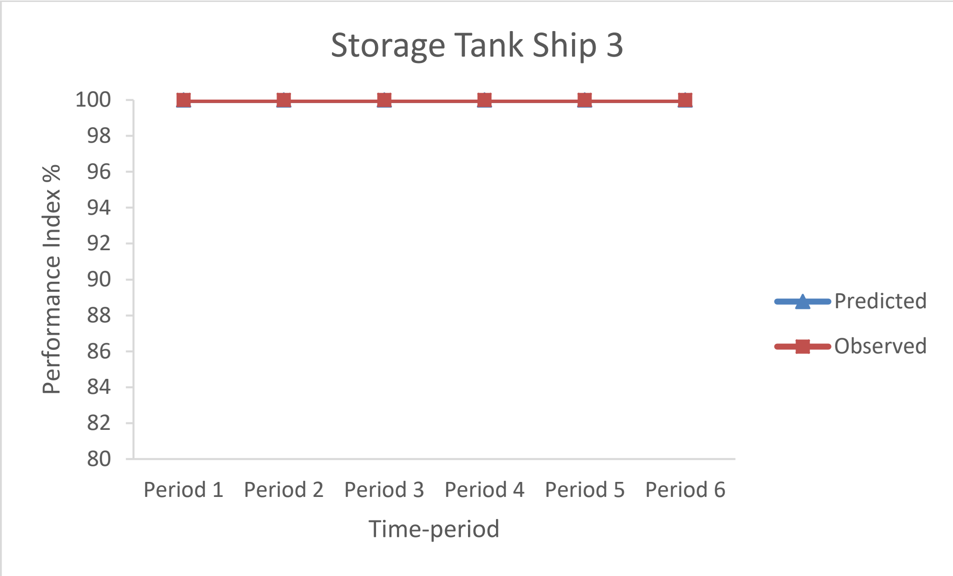

Figure 190 – Storage Tank Probabilistic Performance Prediction for Ship 3

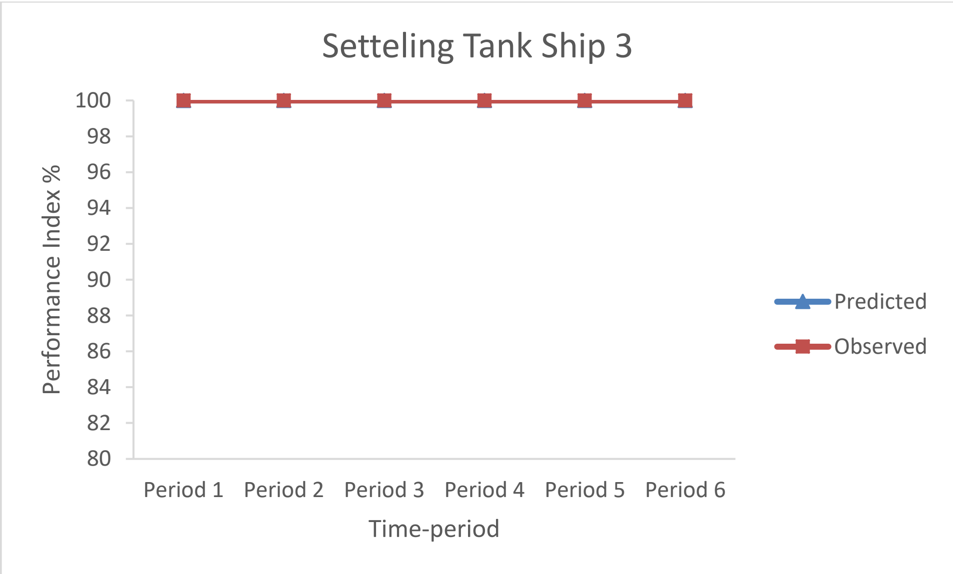

Figure 191 – Settling Tank Probabilistic Performance Prediction for Ship 3

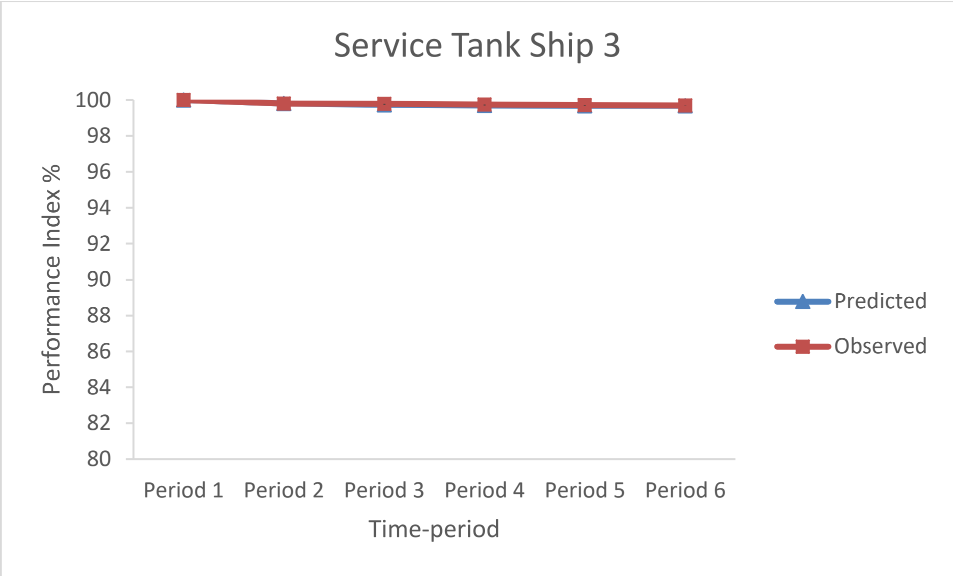

Figure 192 - Service Tank Probabilistic Performance Prediction for Ship 3

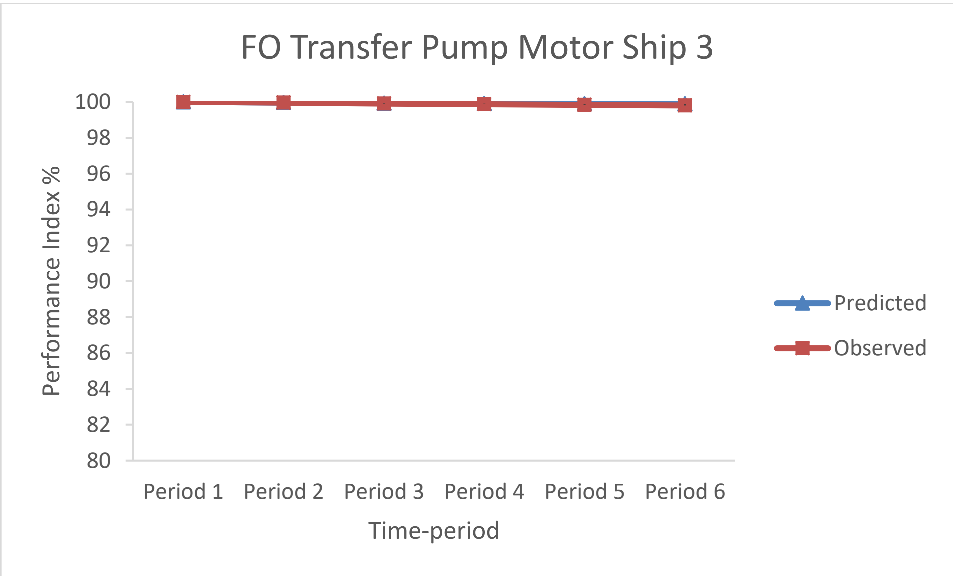

Figure 193 – Fuel-oil Transfer Pump Motor Probabilistic Performance Prediction for Ship 3

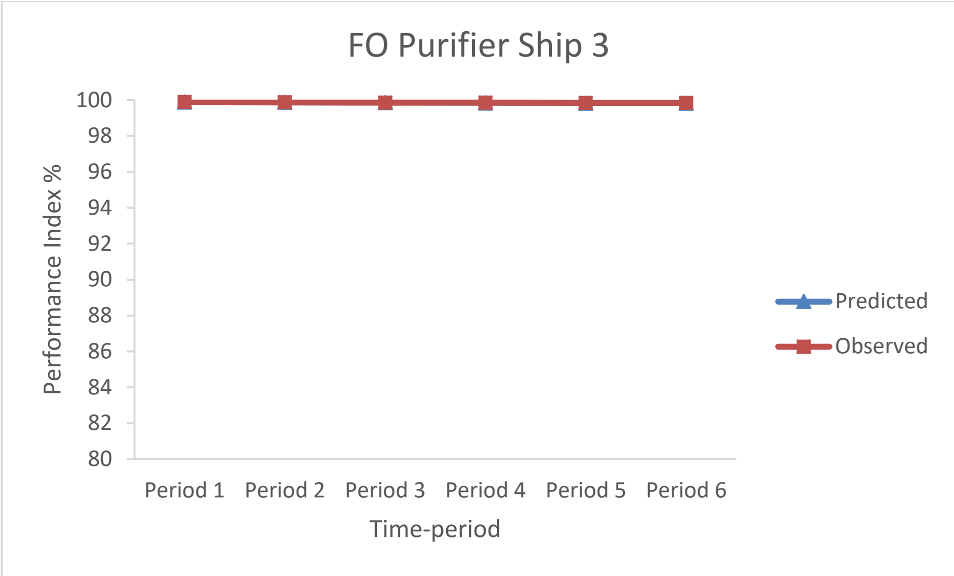

Figure 194 - Fuel-oil Purifier Probabilistic Performance Prediction for Ship 3

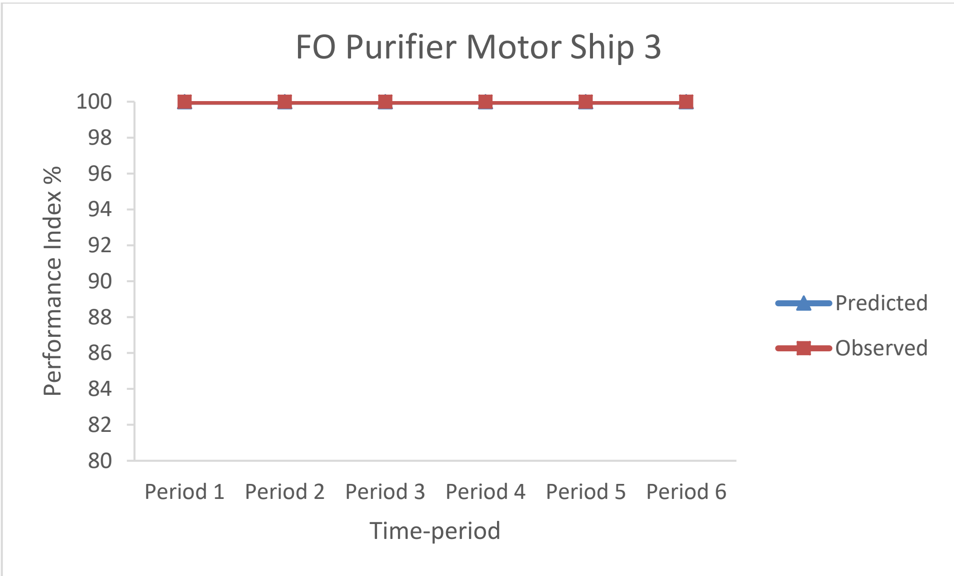

Figure 195 - Fuel-oil Purifier Motor Probabilistic Performance Prediction for Ship 3

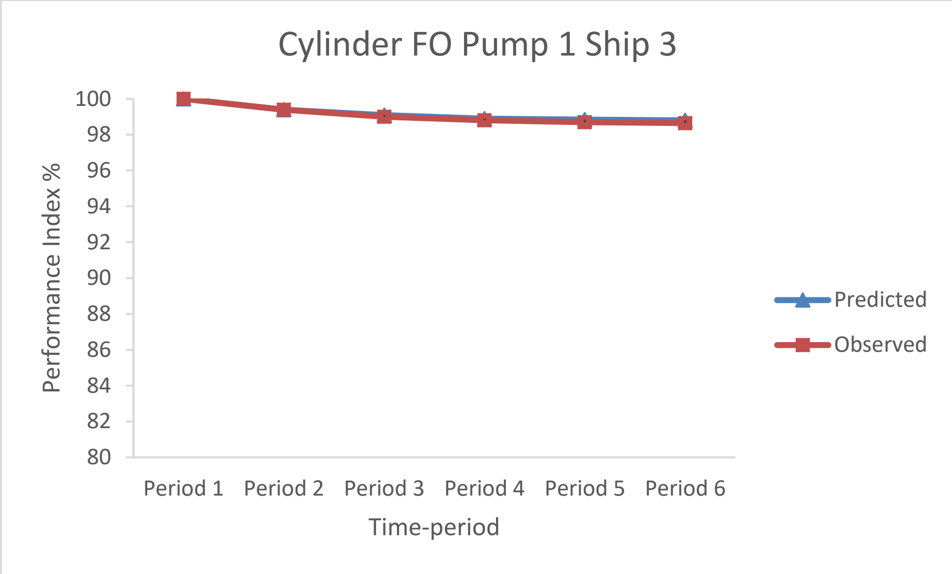

Figure 196 – Cylinder Fuel-oil Pump 1 Probabilistic Performance Prediction for Ship 3

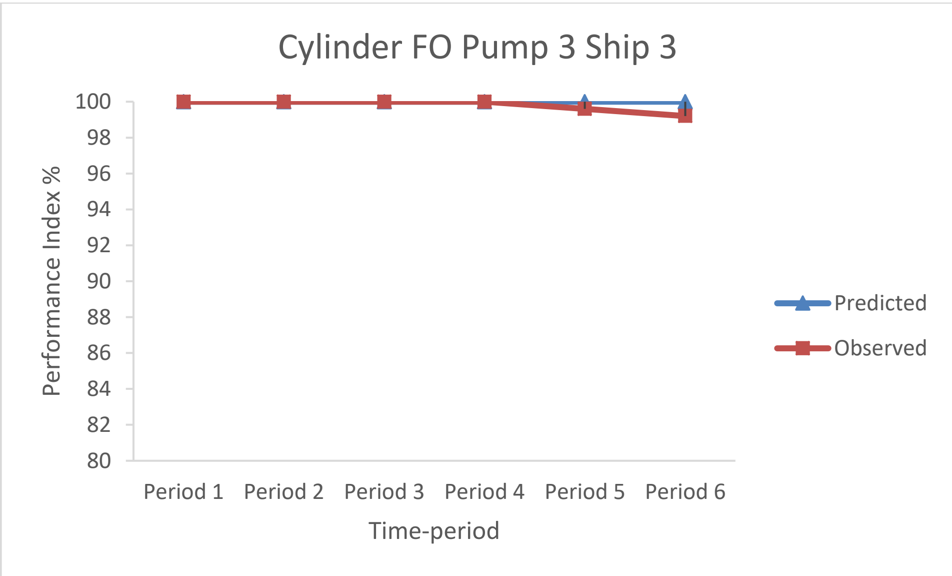

Figure 197 - Cylinder Fuel-oil Pump 3 Probabilistic Performance Prediction for Ship 3

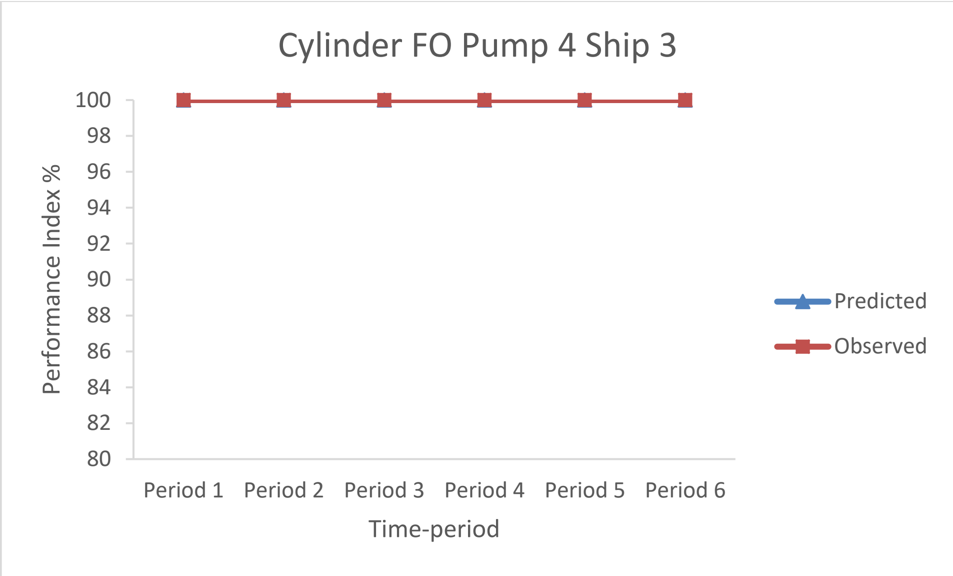

Figure 198 - Cylinder Fuel-oil Pump 4 Probabilistic Performance Prediction for Ship 3

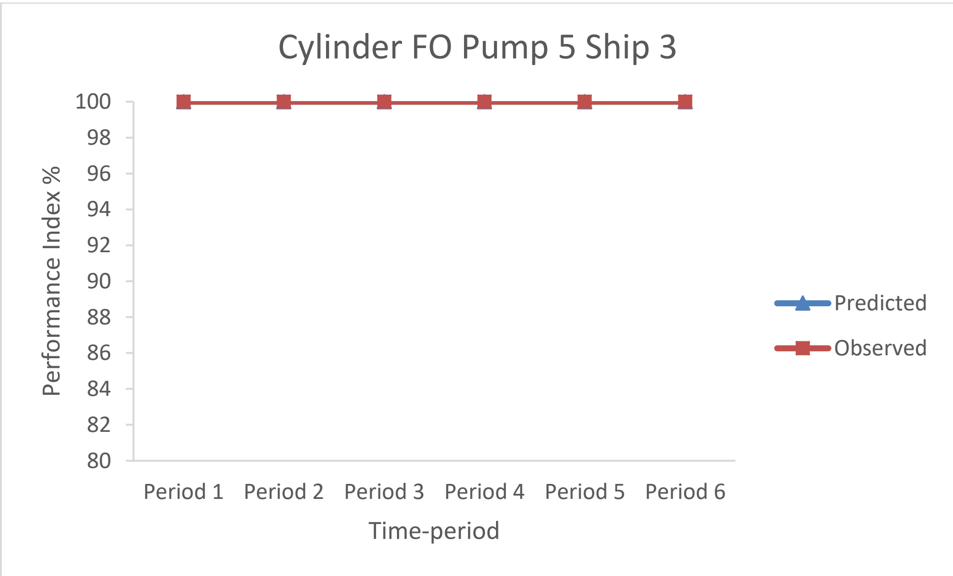

Figure 199 - Cylinder Fuel-oil Pump 5 Probabilistic Performance Prediction for Ship 3

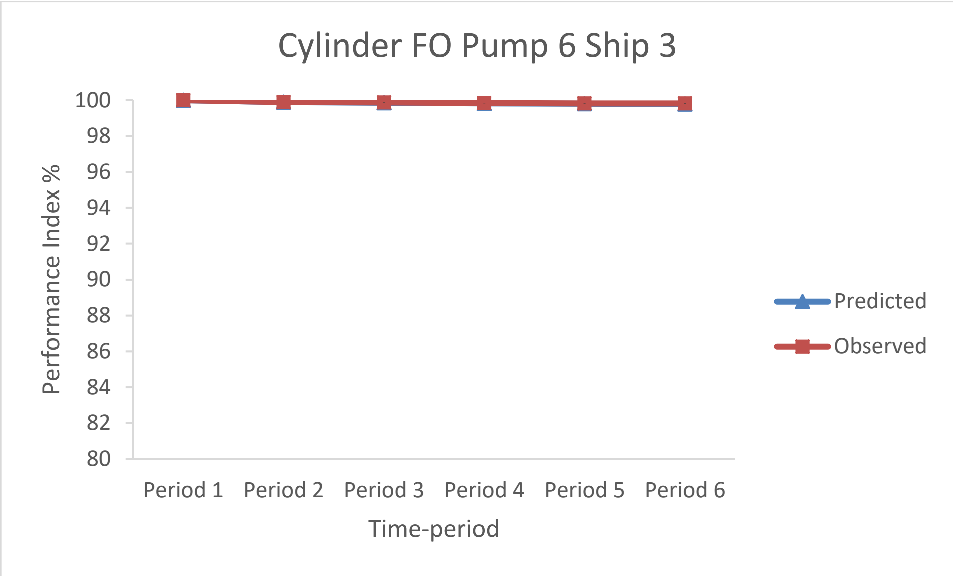

Figure 200 - Cylinder Fuel-oil Pump 6 Probabilistic Performance Prediction for Ship 3

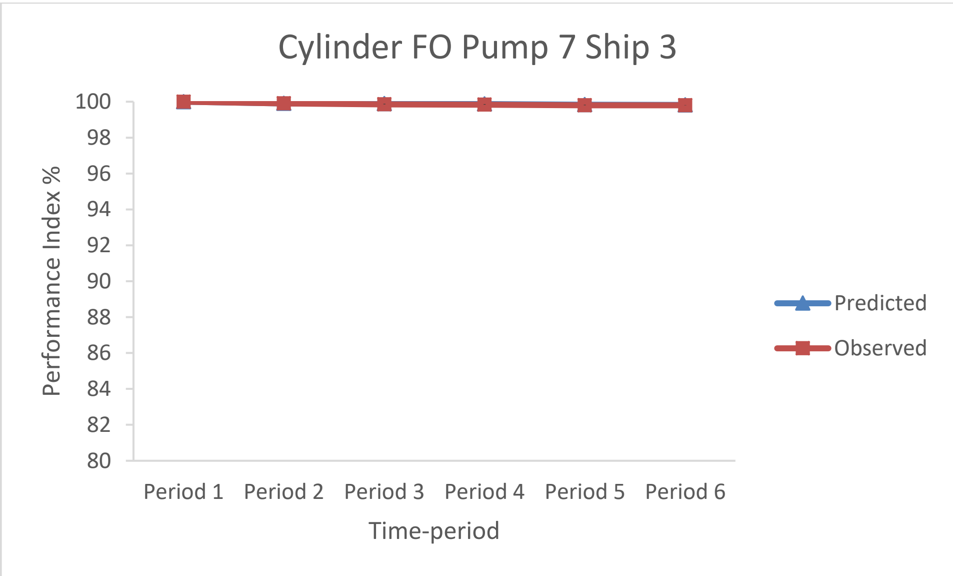

Figure 201 - Cylinder Fuel-oil Pump 7 Probabilistic Performance Prediction for Ship 3

Appendix B3.3 Turbocharger System of Ship 3

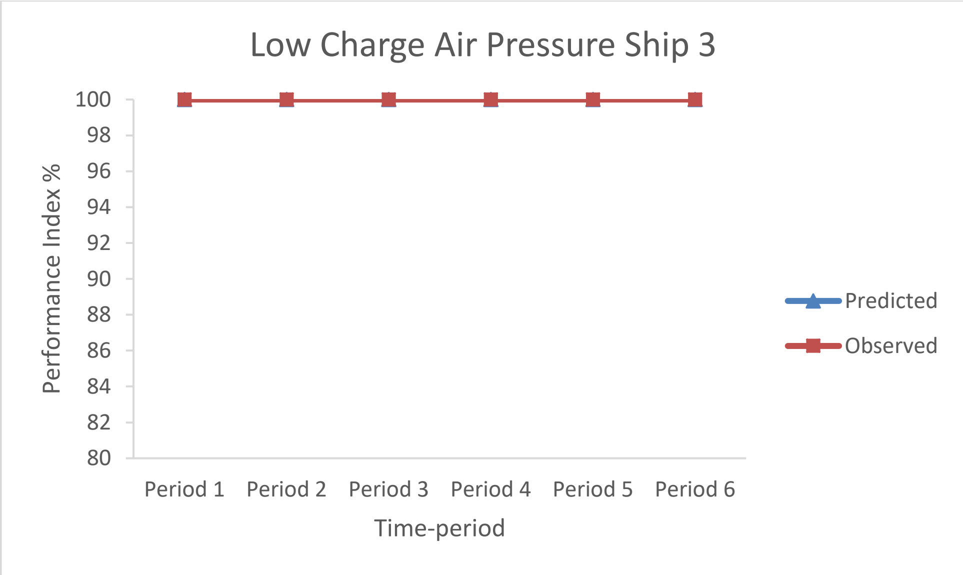

Figure 202 – Low Charge Air Pressure Probabilistic Performance Prediction for Ship 3

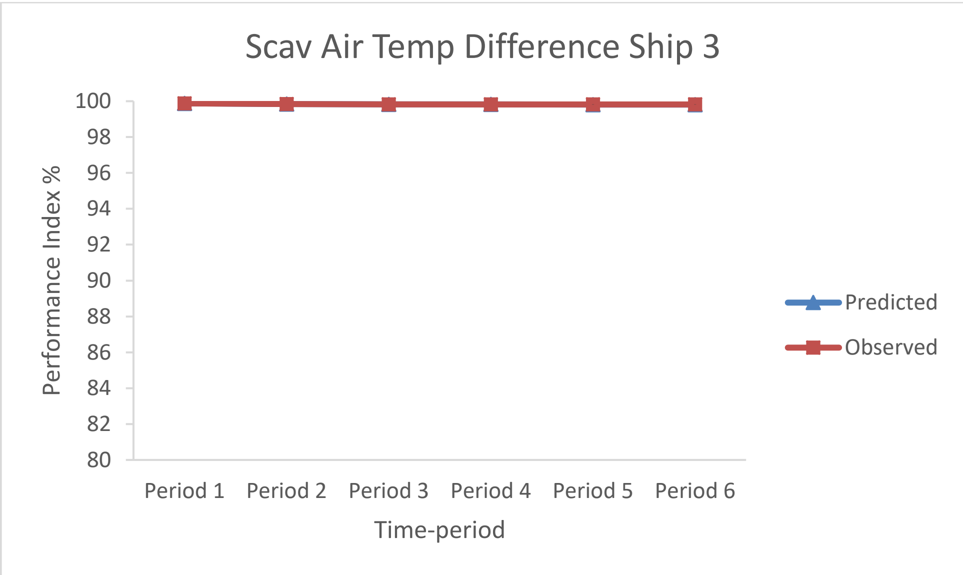

Figure 203 – Scavenge Air Temperature Difference Probabilistic Performance Prediction for Ship 3

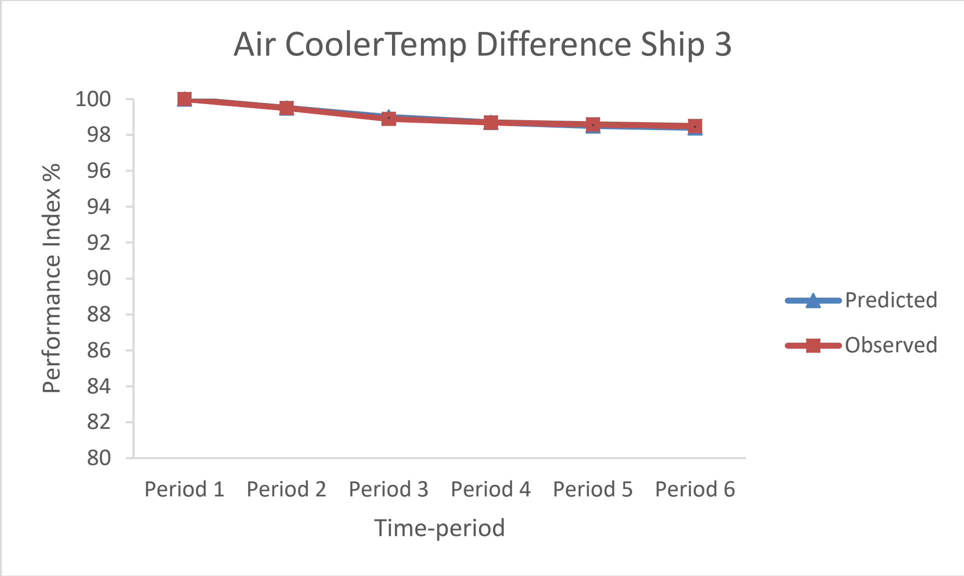

Figure 204 – Air Cooler Temperature Difference Probabilistic Performance Prediction for Ship 3

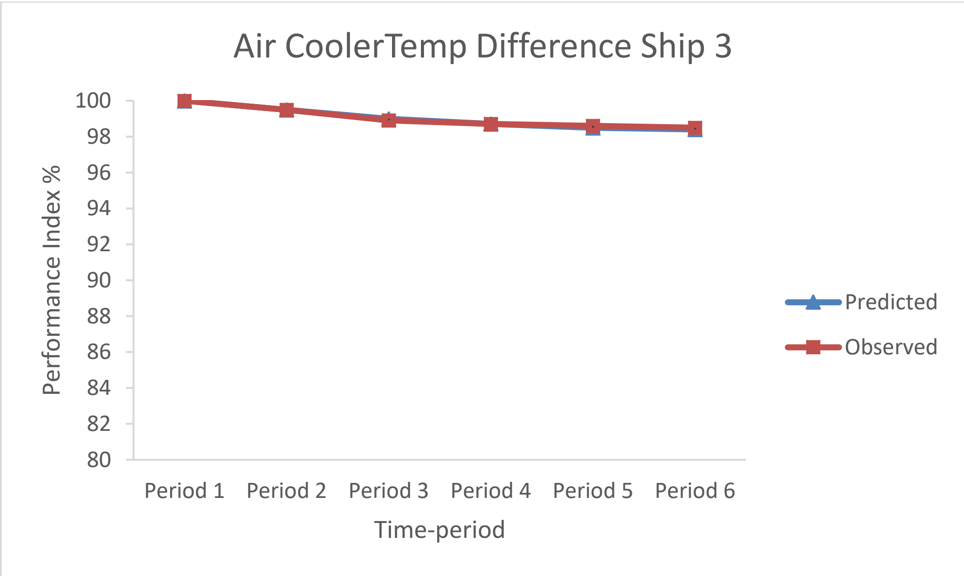

Figure 205 – Exhaust Back-pressure Probabilistic Performance Prediction for Ship 3

APPENDIX C1-COMPONENT/SUB-SYSTEM PREDICTED AND OBSERVED PERFORMANCE INDEX VALUES FOR SHIP 1 SISTER CHEMICAL TANKER OPERATING IN WEST COAST CANADA

Appendix C1.1 Lube-oil System of Ship 1

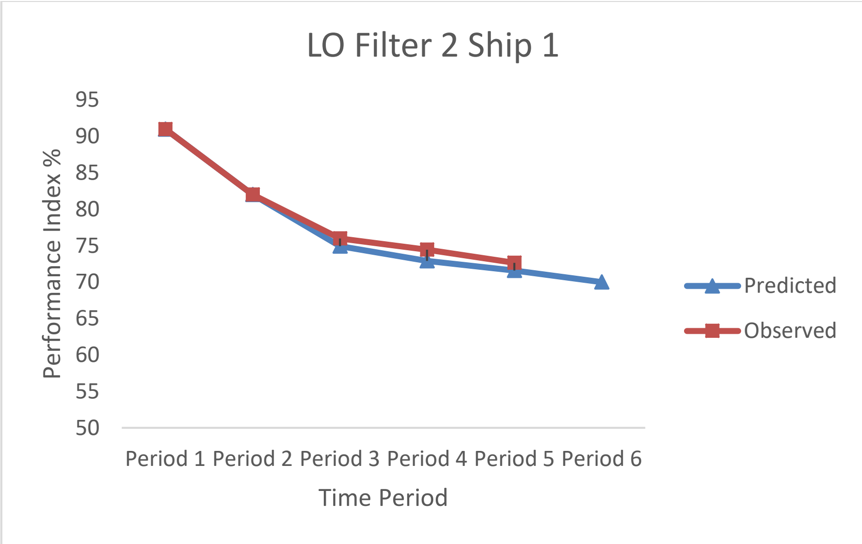

Figure 206 - LO Filter 2 Ship 1 Performance Indices

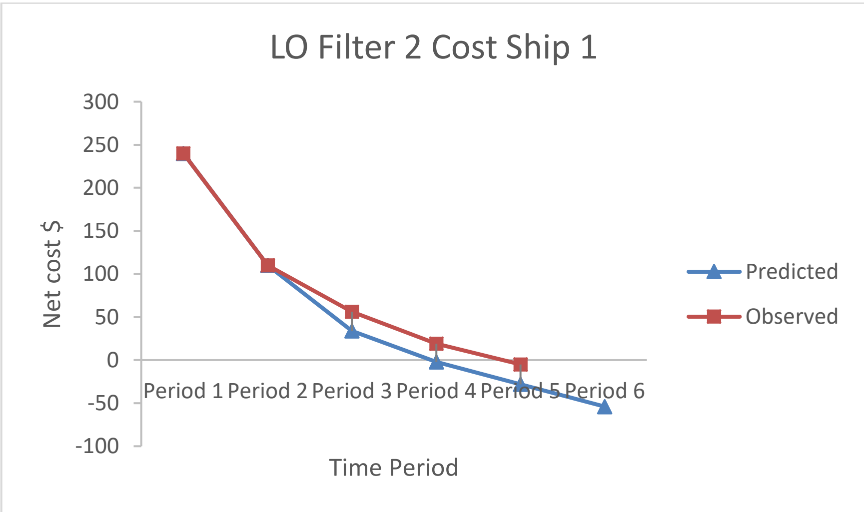

Figure 207 - LO Filter 2 Ship 1 Net cost

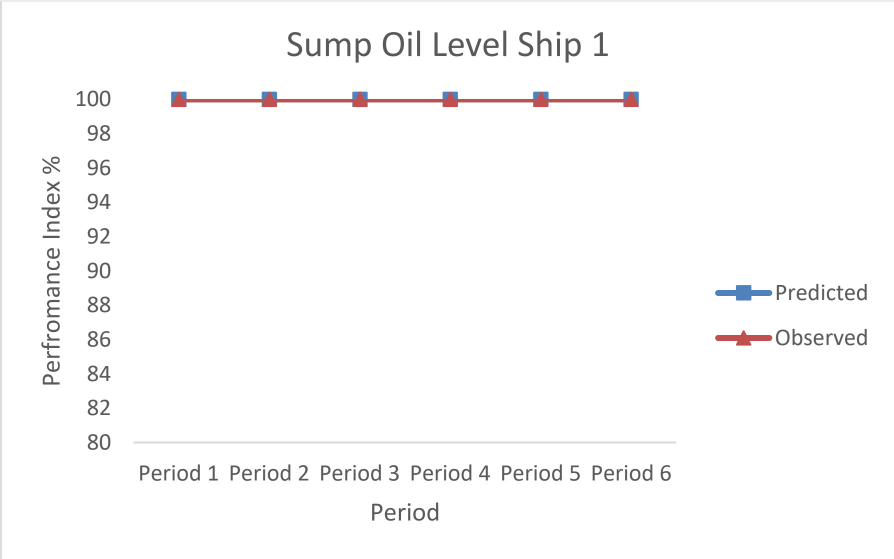

Figure 208 - Sump Oil Level Ship Performance Indices

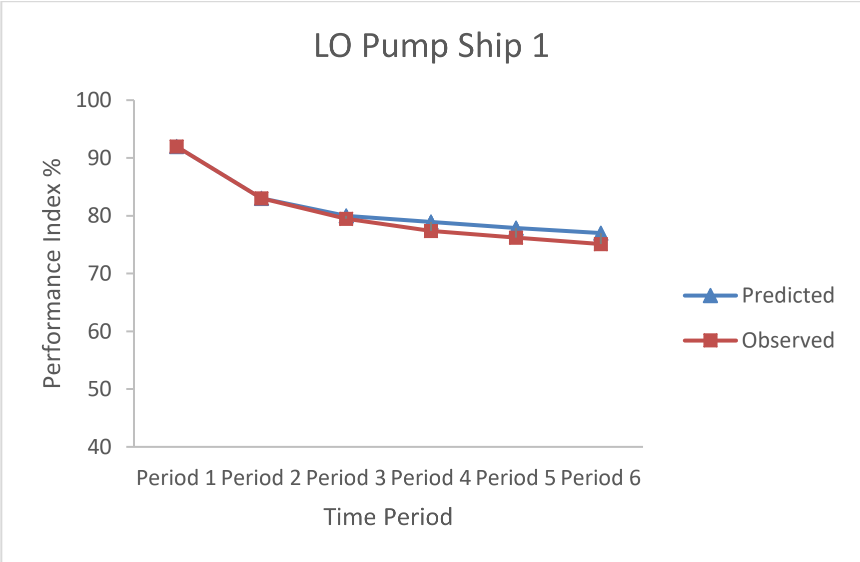

Figure 209 - LO Pump Ship 1 Performance Indices

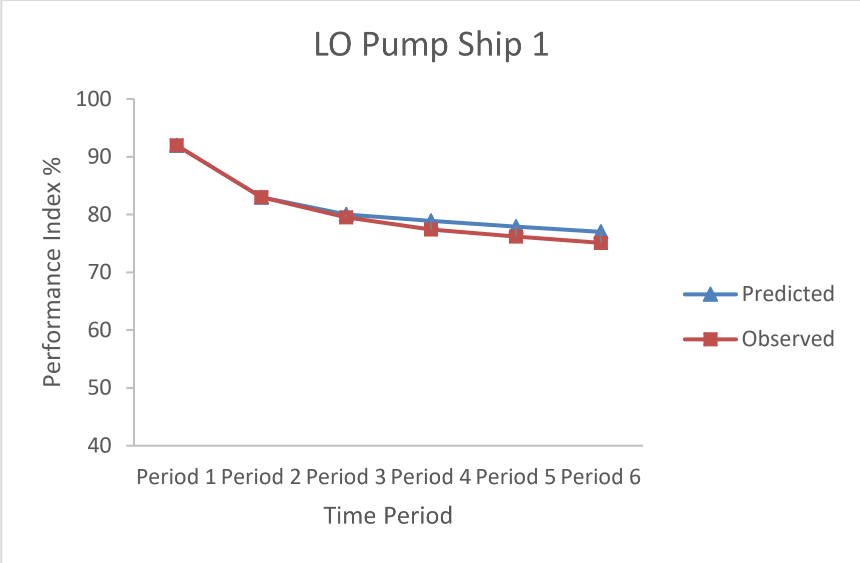

Figure 210 - LO Pump Ship 1 Performance Indices

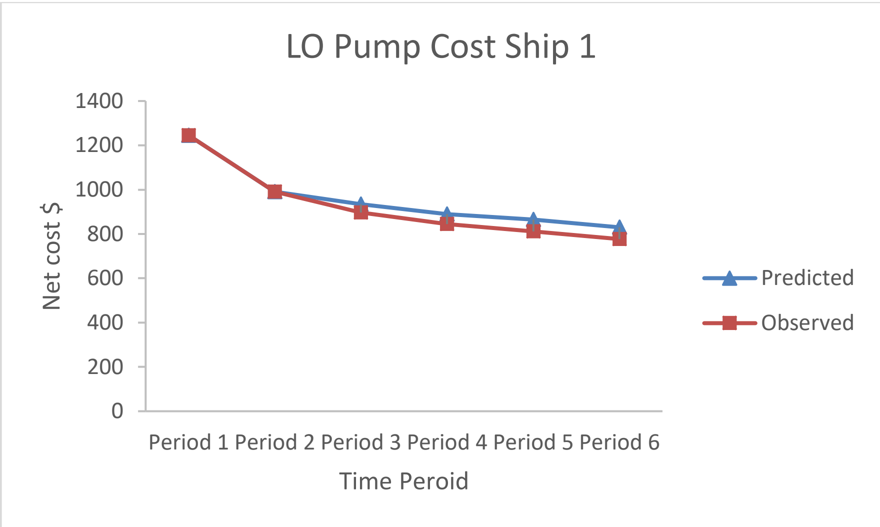

Figure 211 - LO Pump Ship 1 Net cost

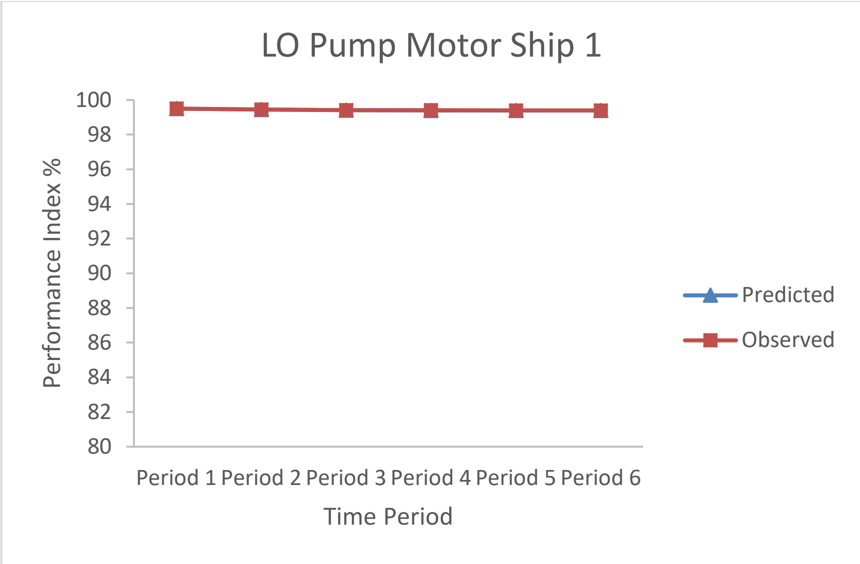

Figure 212 - LO Motor Ship 1 Performance Indices

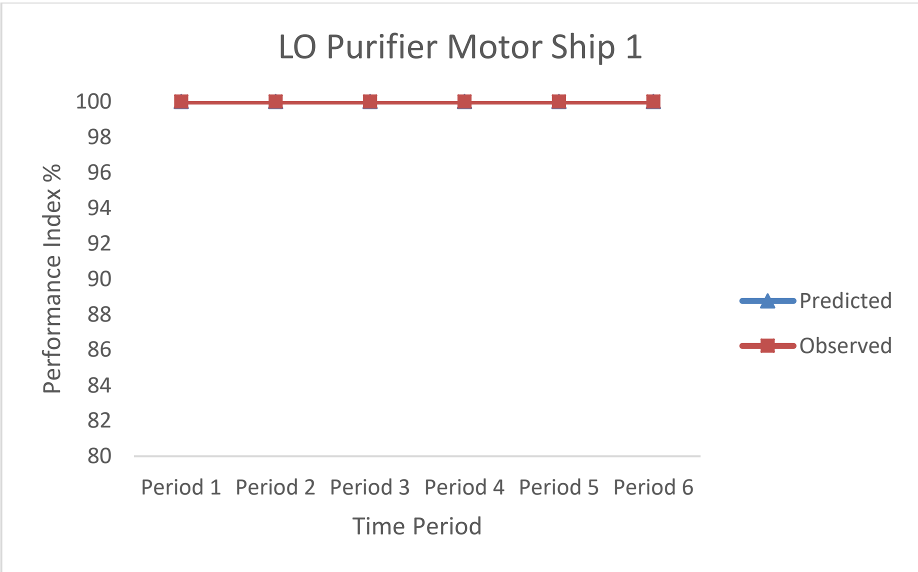

Figure 213 - LO Purifier Motor Ship 1 Performance Indices

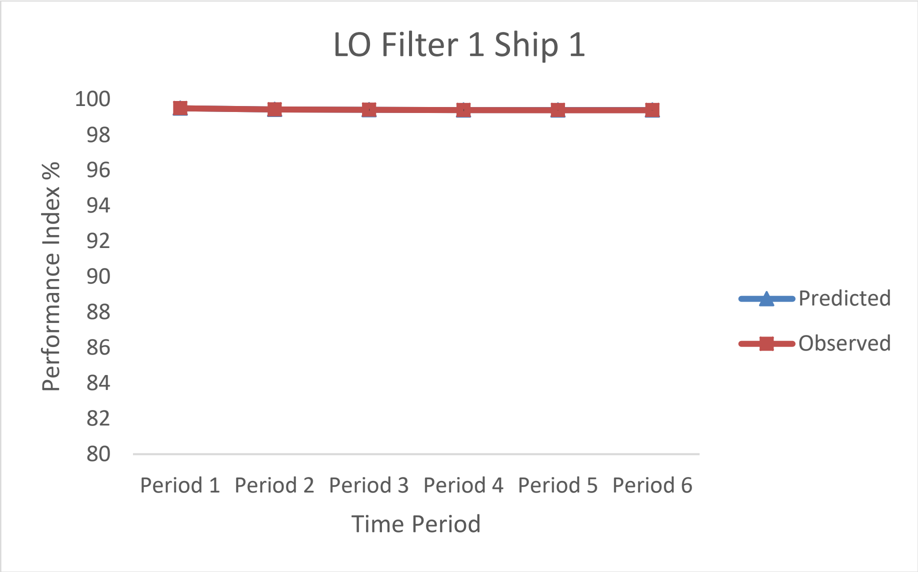

Figure 214 - LO Filter Ship 1 Performance Indices

Appendix C1.2 Fuel-oil System of Ship 1

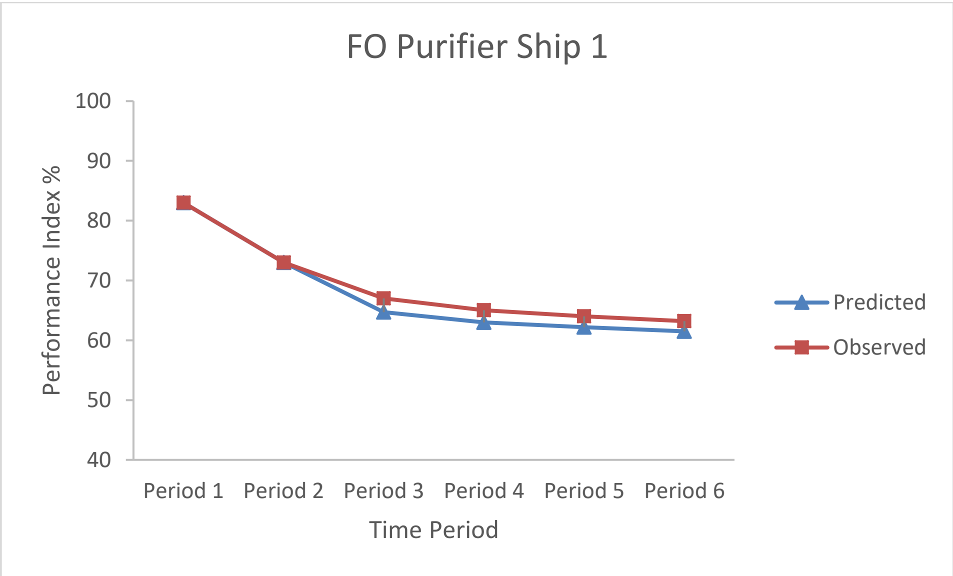

Figure 215 - FO Purifier Ship 1 Performance Indices

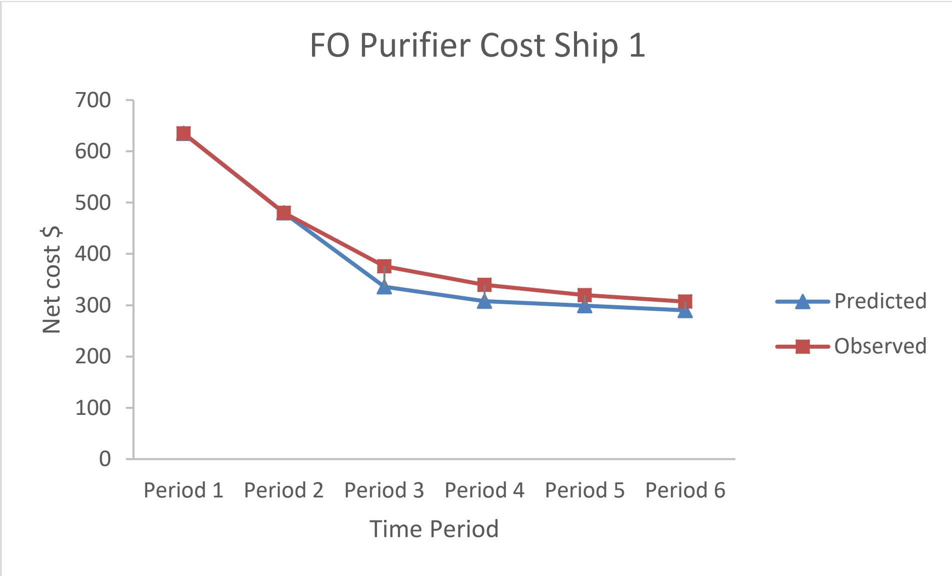

Figure 216 - FO Purifier Ship 1 Net cost

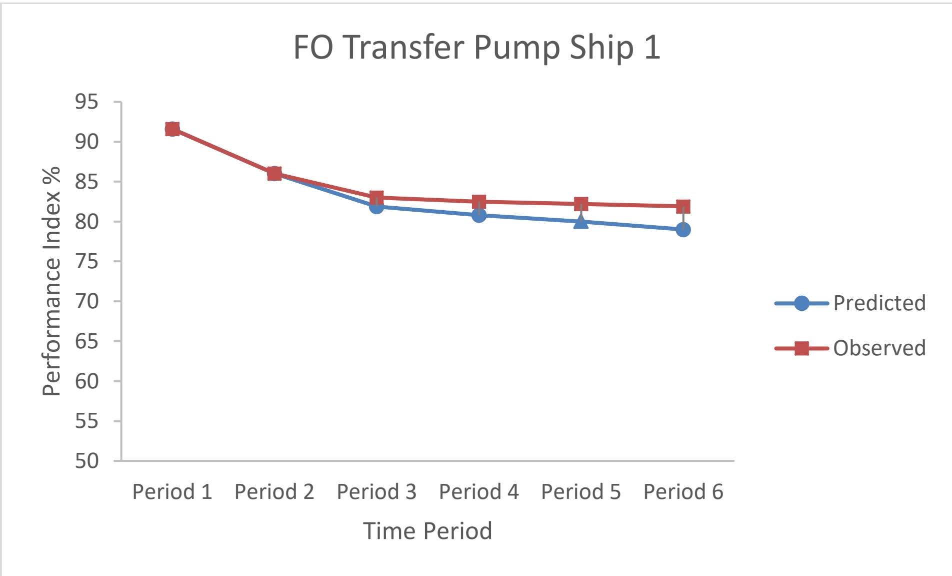

Figure 217 - FO Transfer Pump Ship 1 Performance Indices

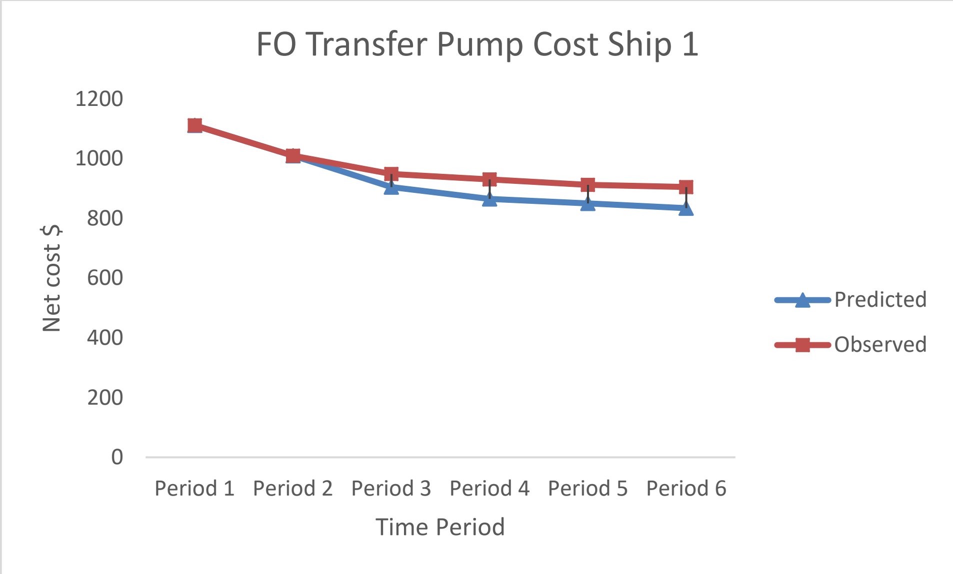

Figure 218 - FO Transfer Pump Ship 1 Net cost

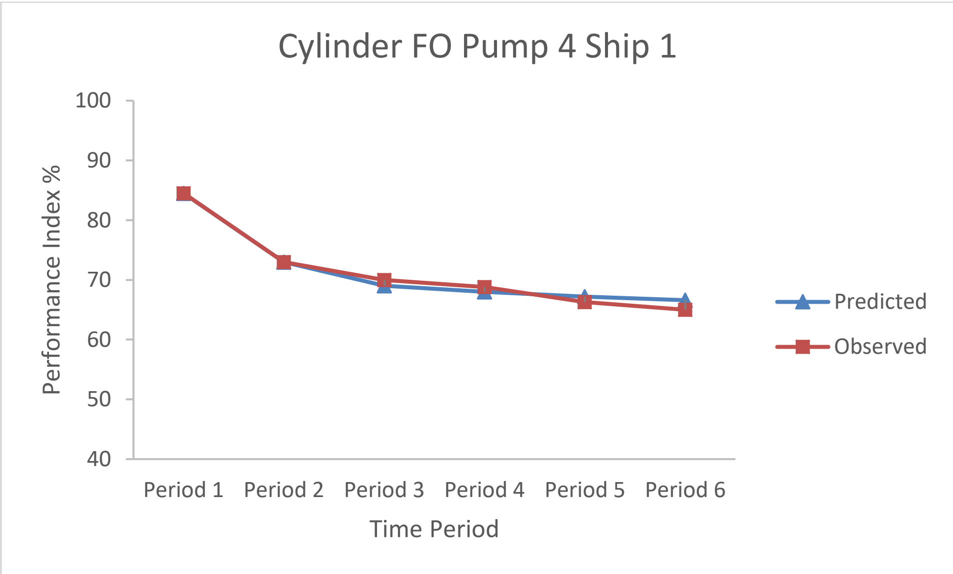

Figure 219 - Cylinder FO Pump 4 Ship 1 Performance Indices

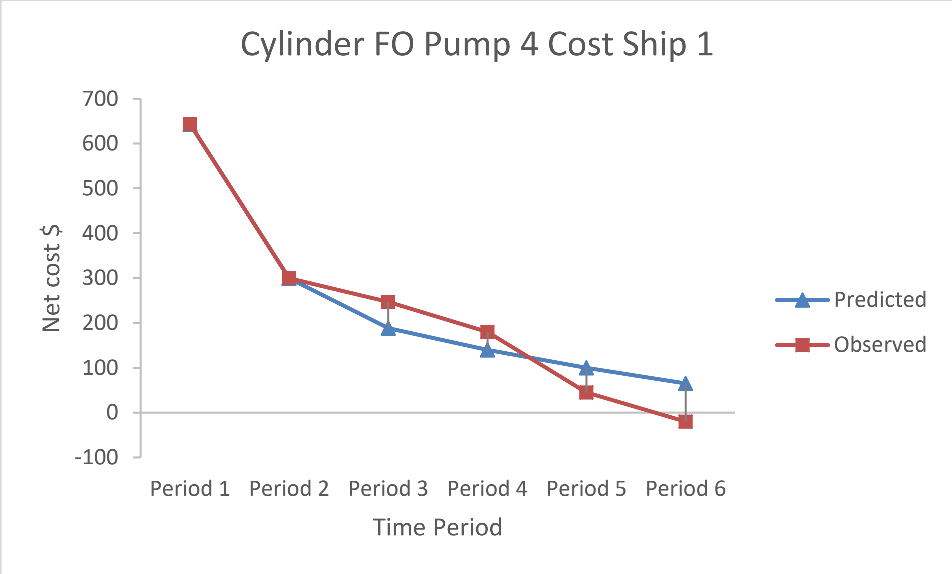

Figure 220 - Cylinder FO Pump 4 Ship 1 Net cost

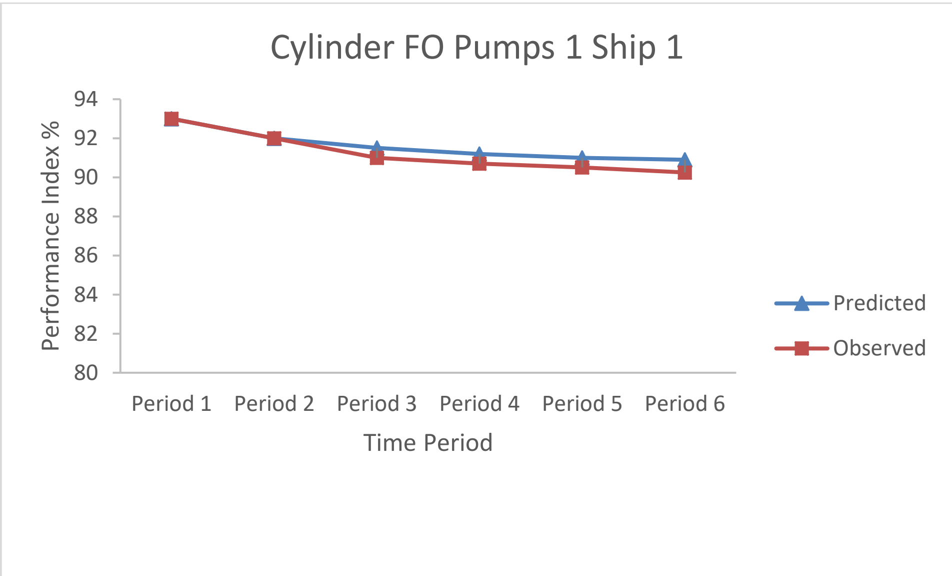

Figure 221 - Cylinder FO Pump 1 Ship 1 Performance Indices

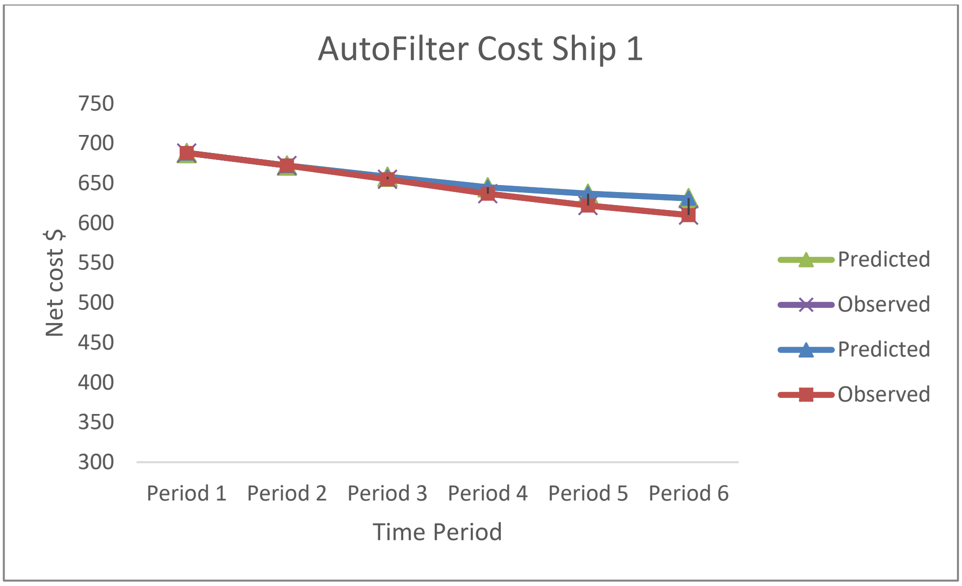

Figure 222 - AutoFilter Net cost

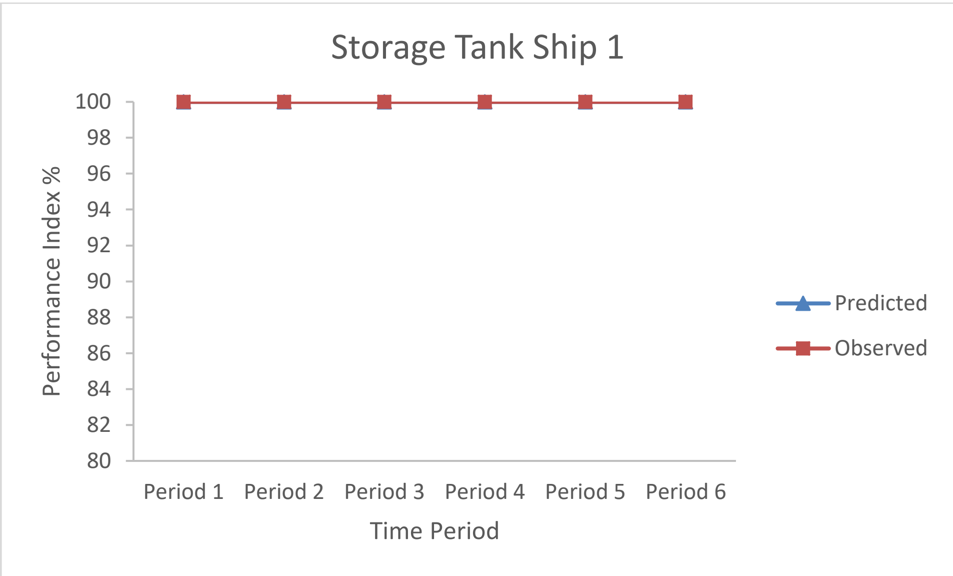

Figure 223 - Storage Tank Ship 1 Performance Indices

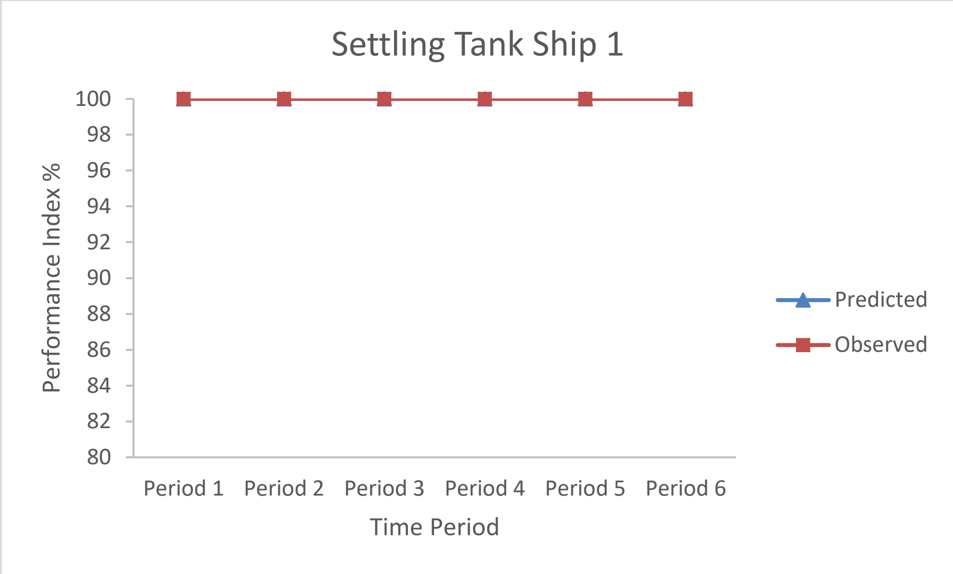

Figure 224 - Settling Tank Ship 1 Performance Indices

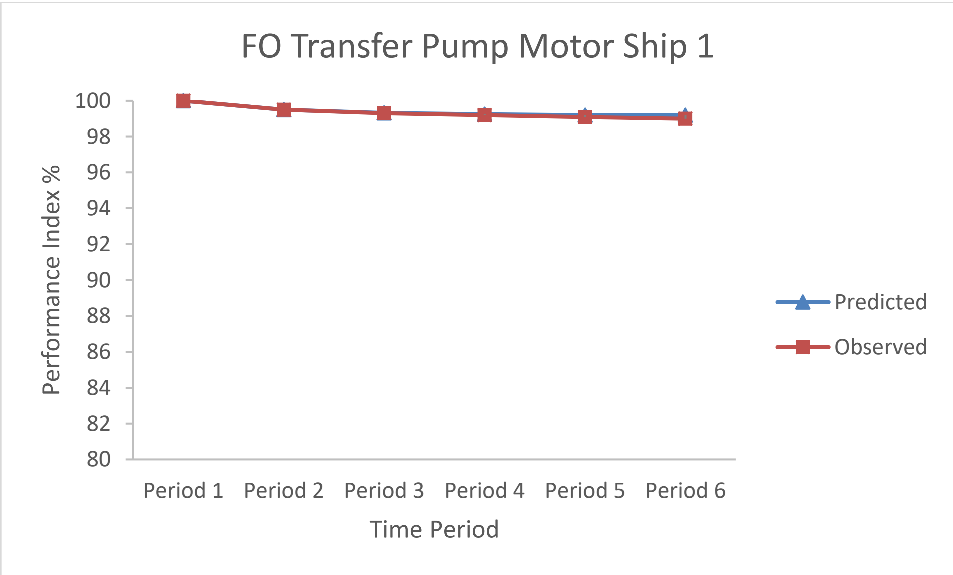

Figure 225 - FO Transfer Pump Motor Ship 1 Performance Indices

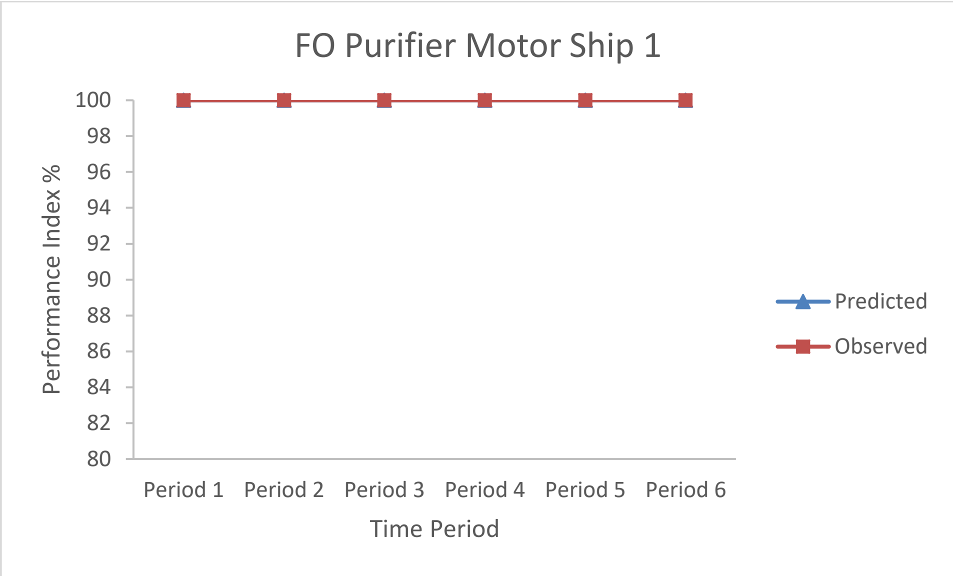

Figure 226 - FO Purifier Motor Ship 1 Performance Indices

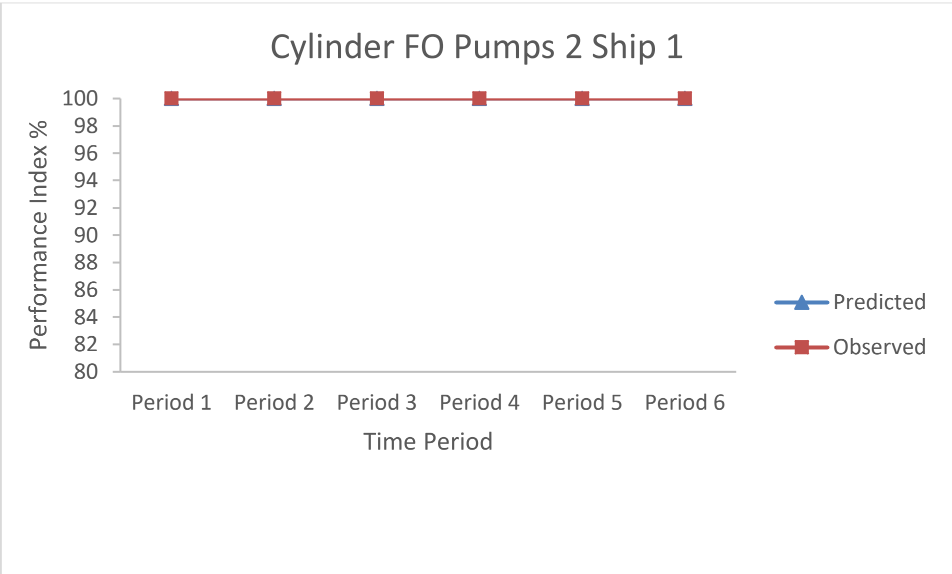

Figure 227 - Cylinder FO Pump 2 Ship 1 Performance Indices

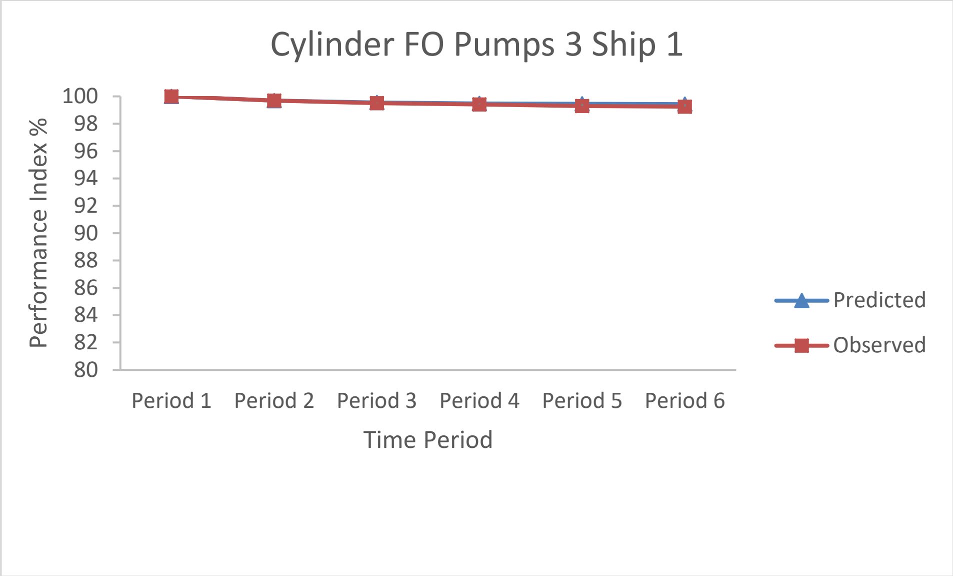

Figure 228 - Cylinder FO Pump 3 Ship 1 Performance Indices

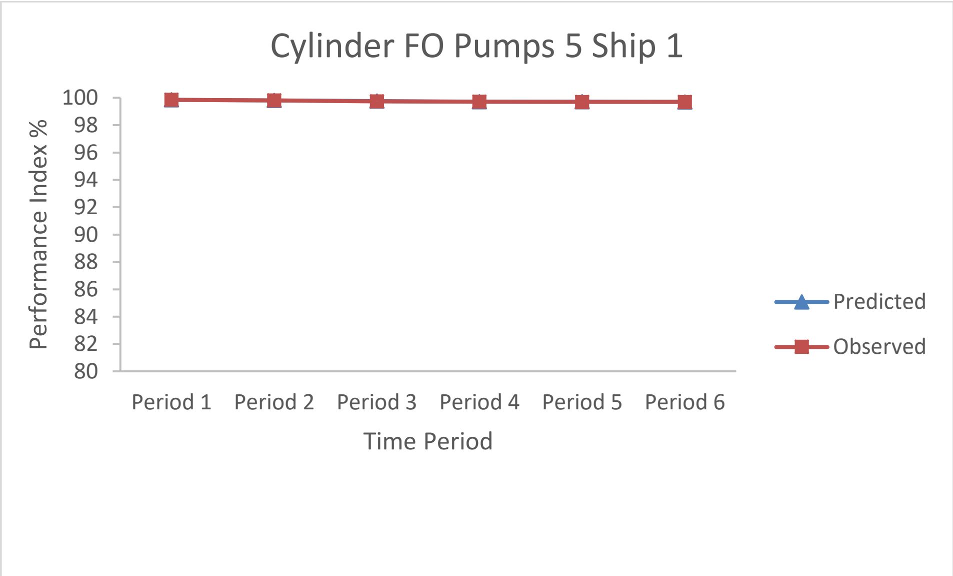

Figure 229 - Cylinder FO Pump 5 Ship 1 Performance Indices

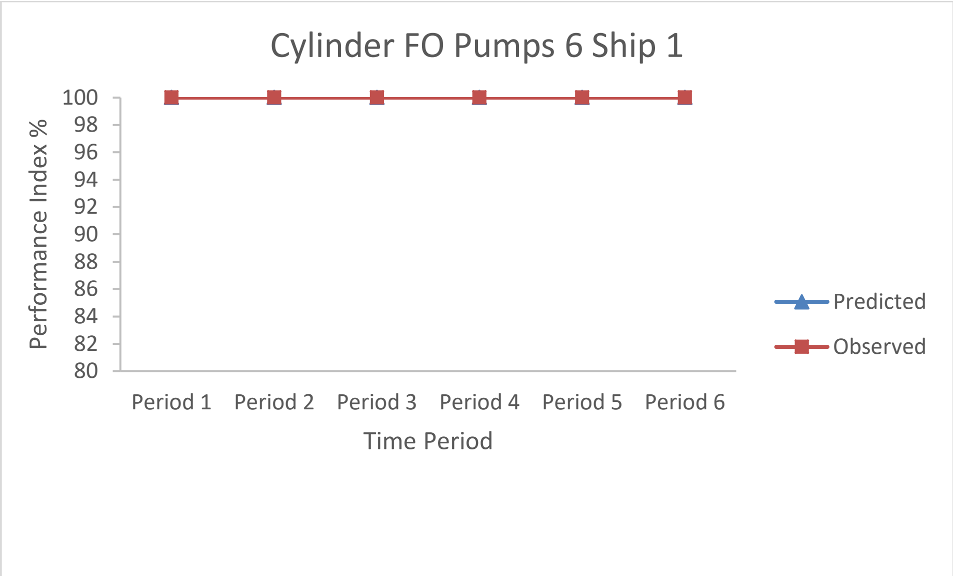

Figure 230 - Cylinder FO Pump 6 Ship 1 Performance Indices

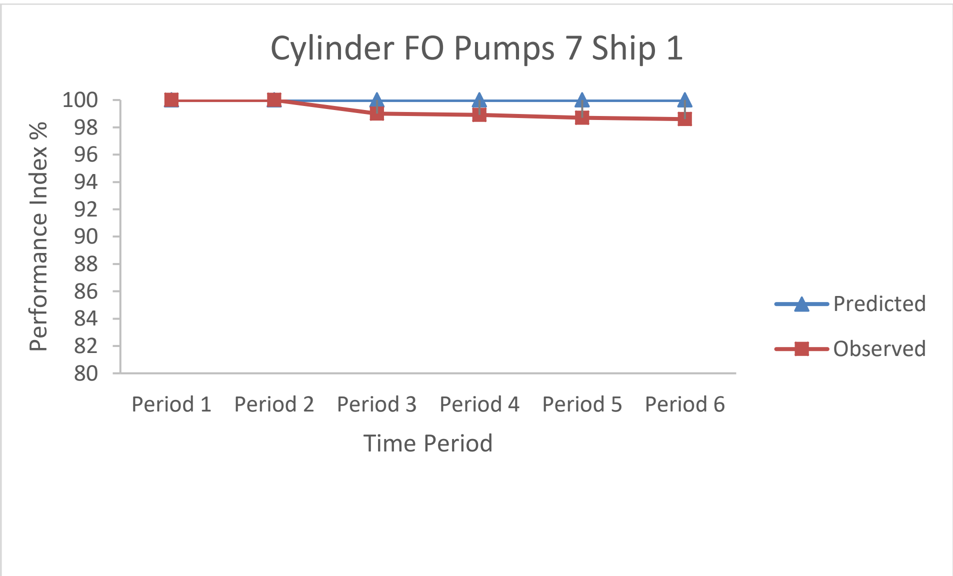

Figure 231 - Cylinder FO Pump 7 Ship 1 Performance Indices

Appendix C1.3 Turbocharger System of Ship 1

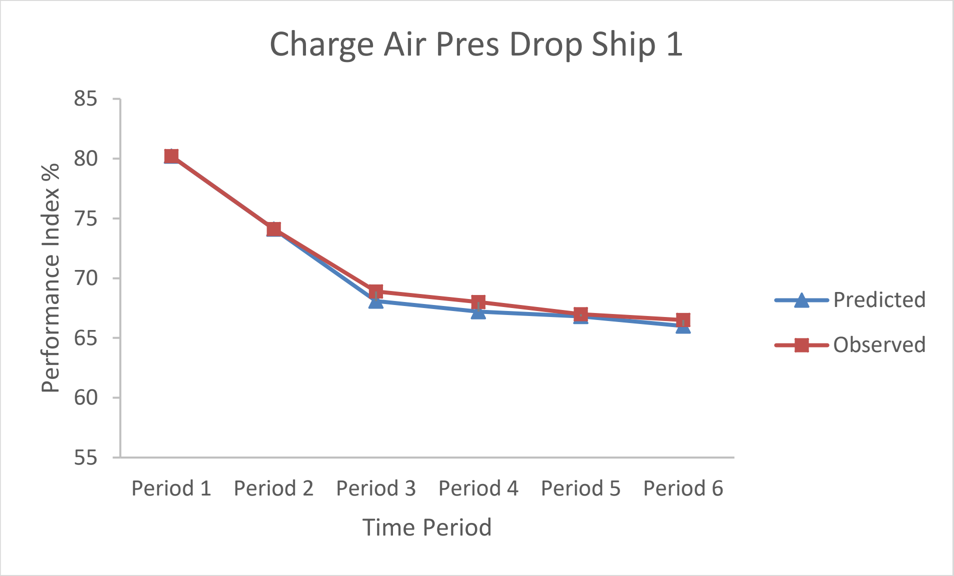

Figure 232 - Charge Air Pressure Drop Ship 1 Performance Indices

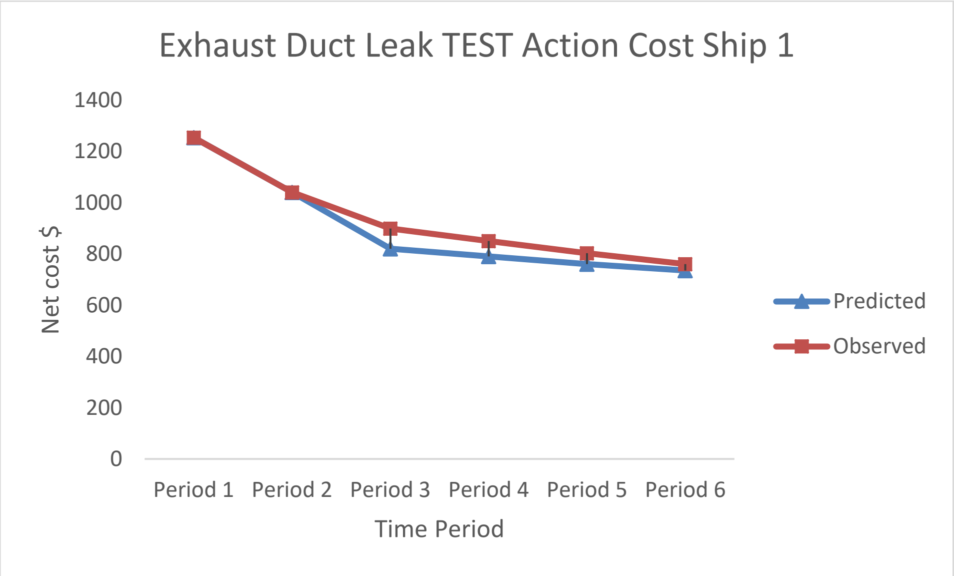

Figure 233 - Exhaust Duct Leak Test Ship 1 Net cost

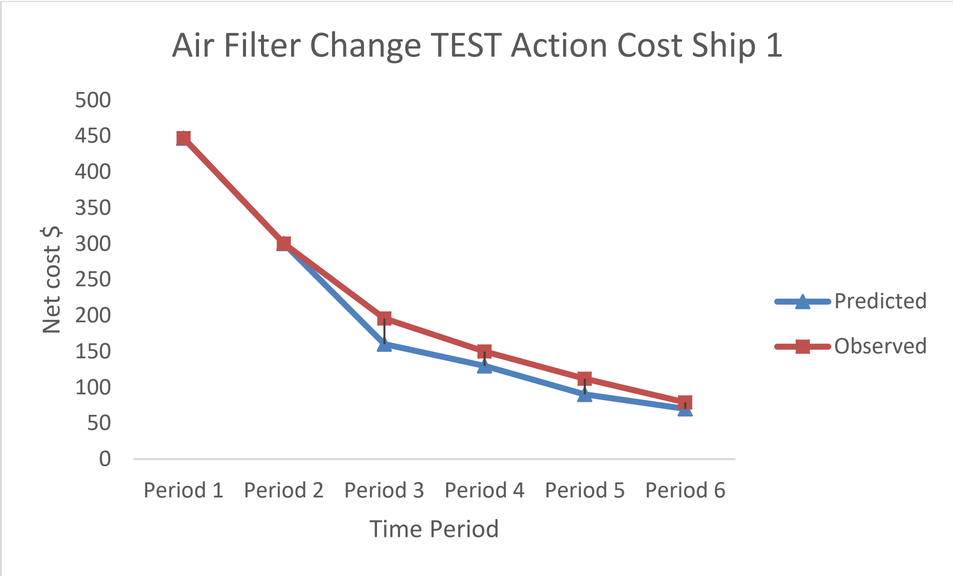

Figure 234 - Air Filter Change Test Action Ship 1 Cost Benefit

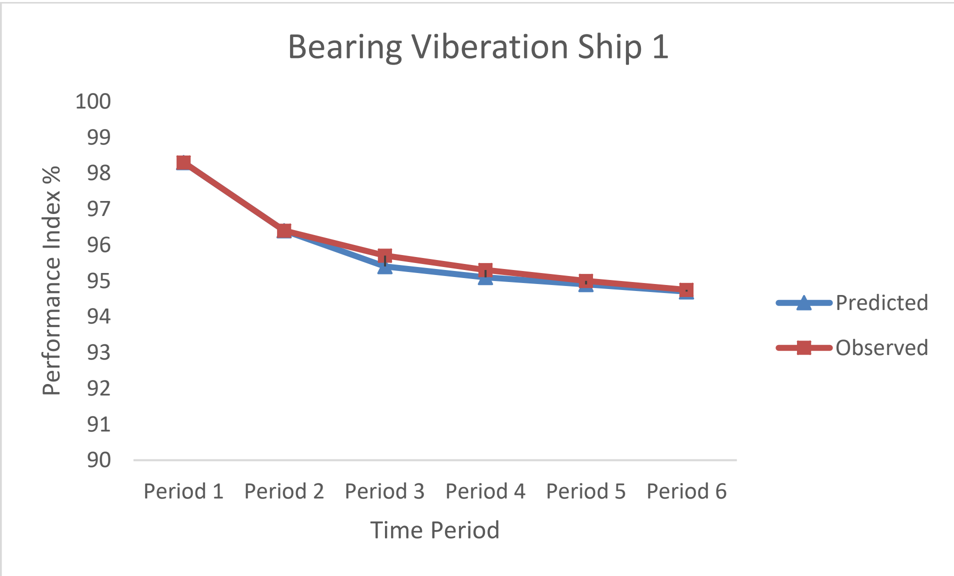

Figure 235 - Bearing Vibration Ship 1 Performance Indices

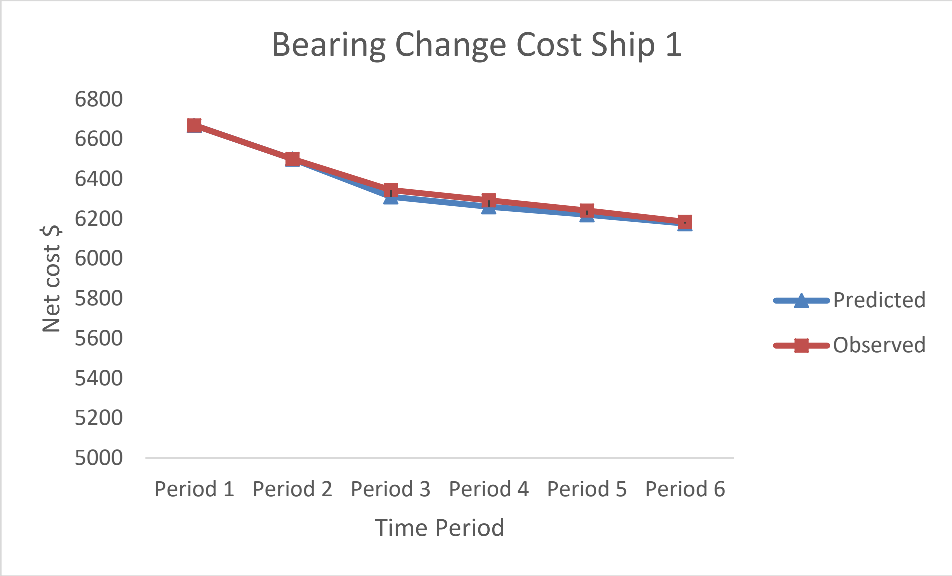

Figure 236 - Bearing Change Ship 1 Net cost

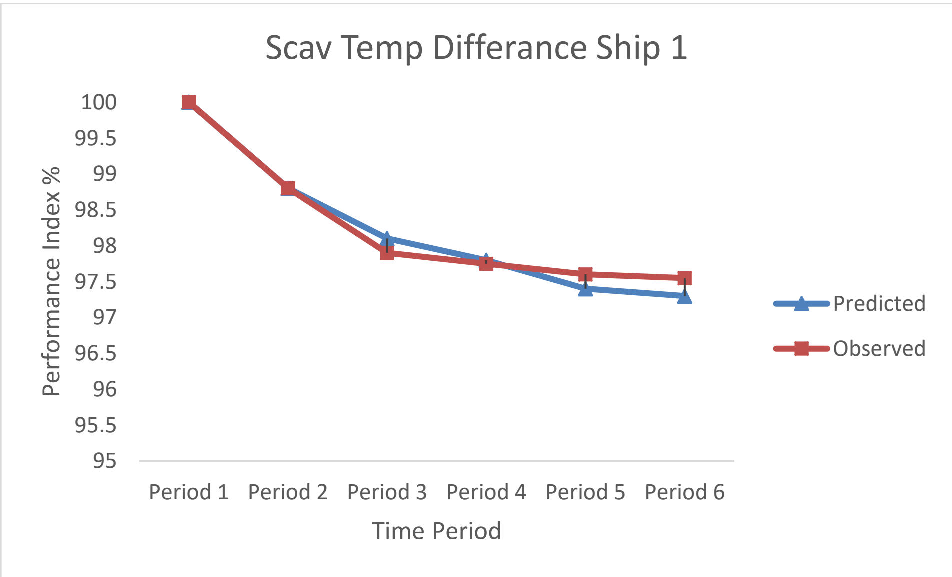

Figure 237 - Scavenger Temperature Difference Ship 1 Performance Indices

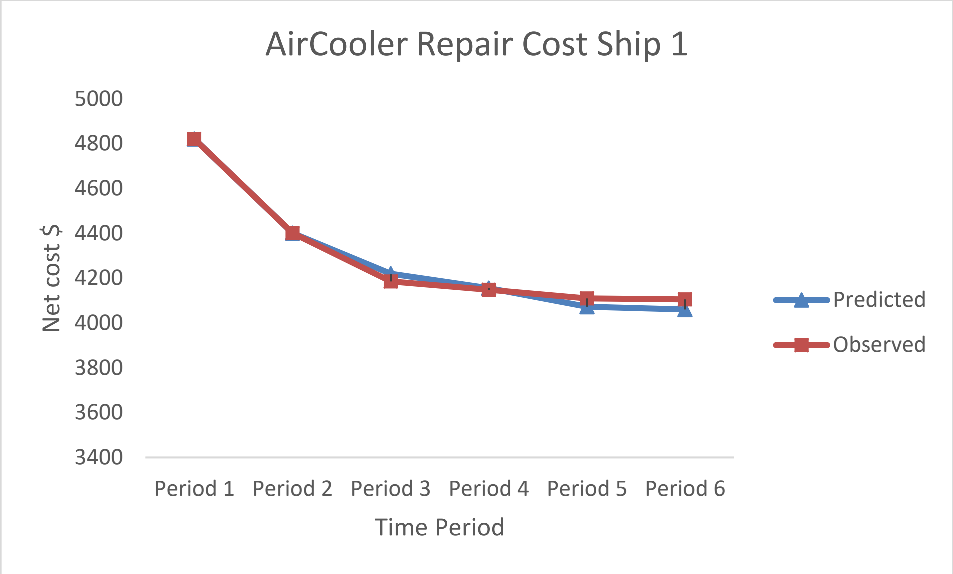

Figure 238 – Air Cooler Repair Ship 1 Net cost

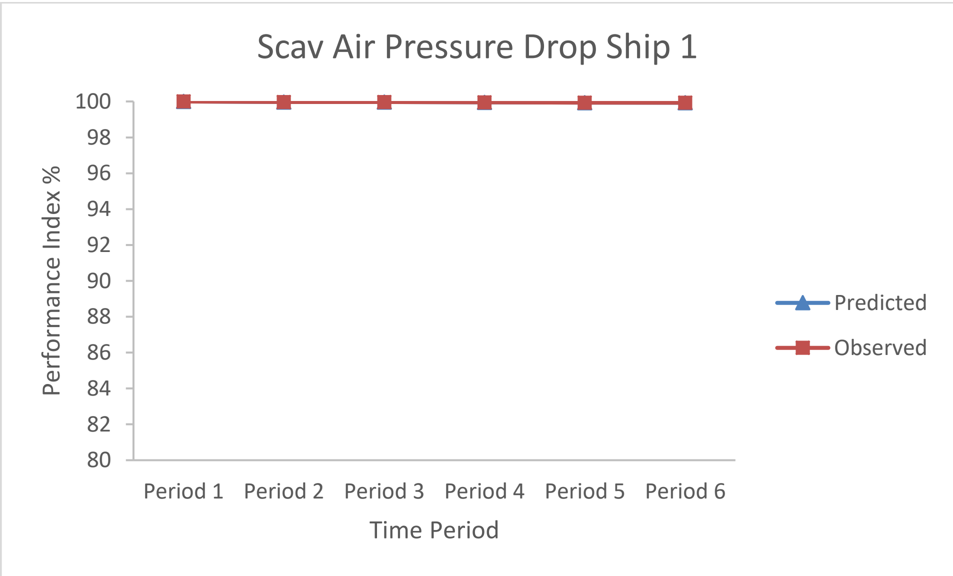

Figure 239 - Scavenge Air Pressure Drop Ship 1 Performance Indices

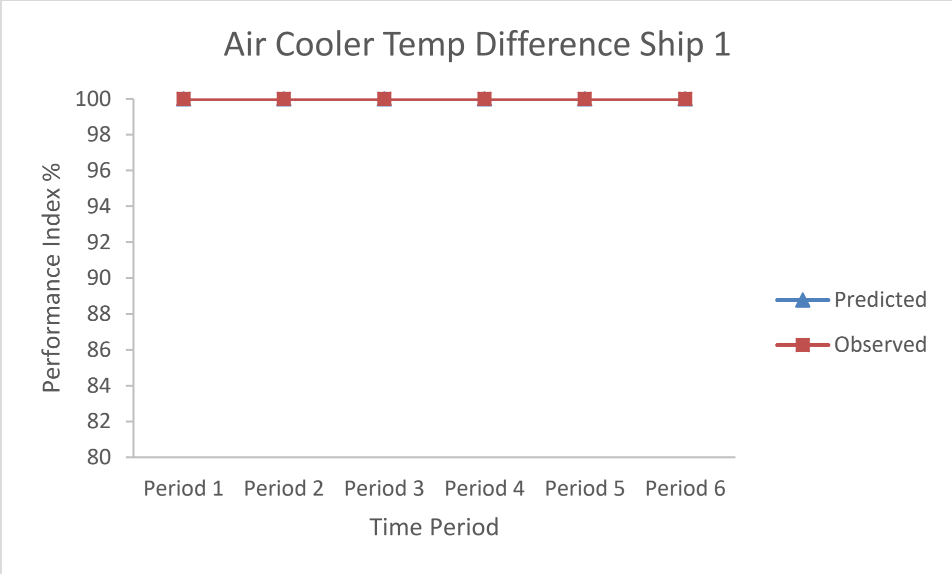

Figure 240 – Air Cooler Temperature Difference Ship 1 Performance Indices

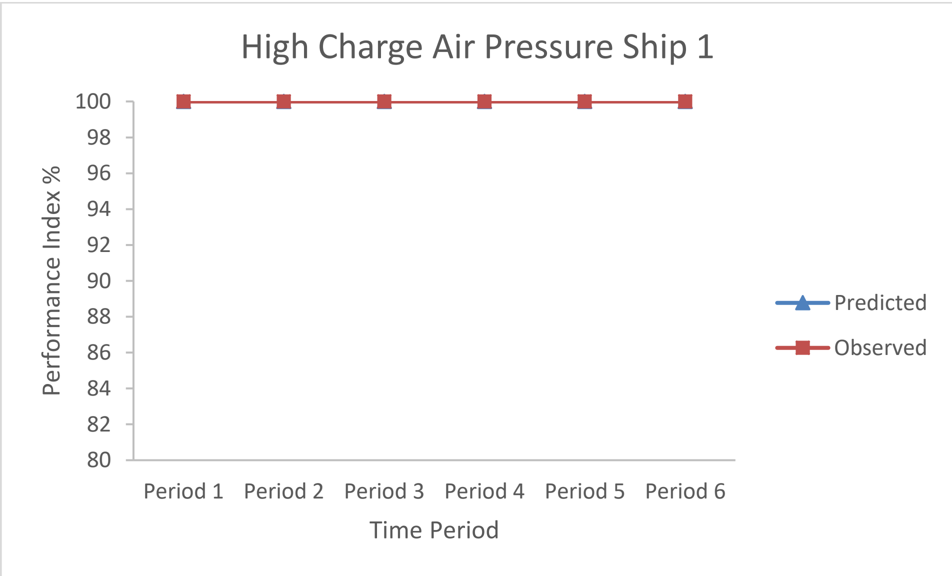

Figure 241 - High Charge Air Pressure Ship 1 Performance Indices

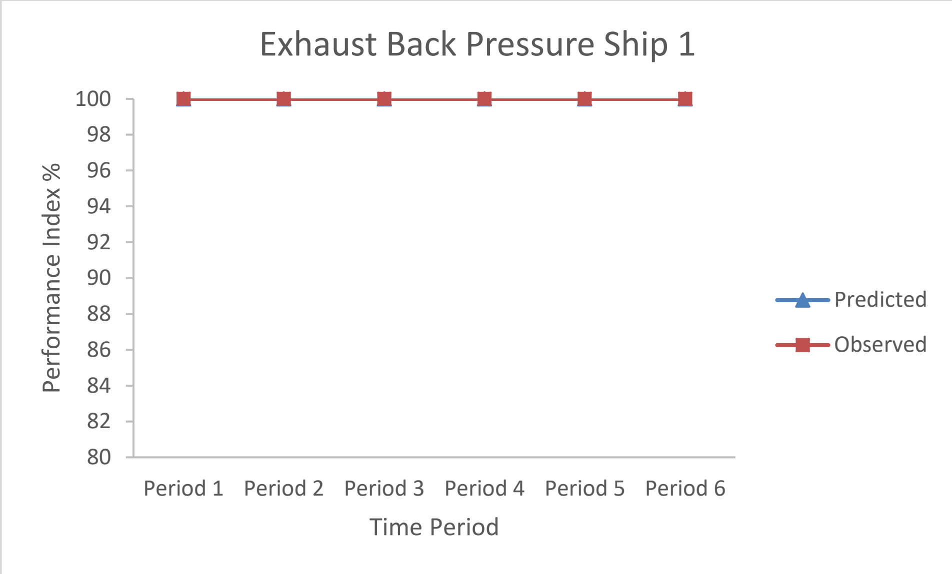

Figure 242 - Exhaust Back-pressure Ship 1 Performance Indices

APPENDIX C2-COMPONENT/SUB-SYSTEM PREDICTED AND OBSERVED PERFORMANCE INDEX VALUES FOR SHIP 2 SISTER CHEMICAL TANKER OPERATING IN SOUTH-EAST ASIA

Appendix C2.1 Lube-oil System of Ship 2

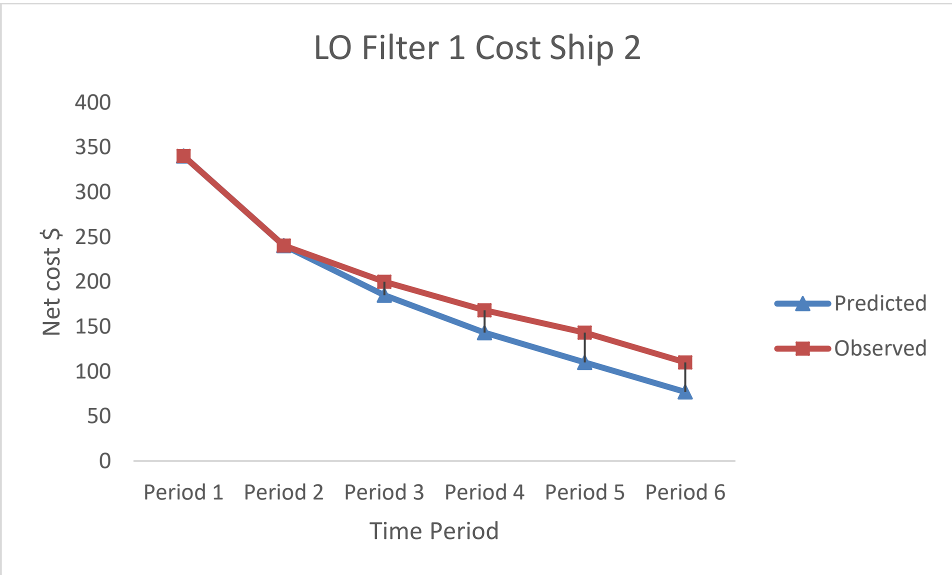

Figure 243 - LO Filter 1 Ship 2 Net cost

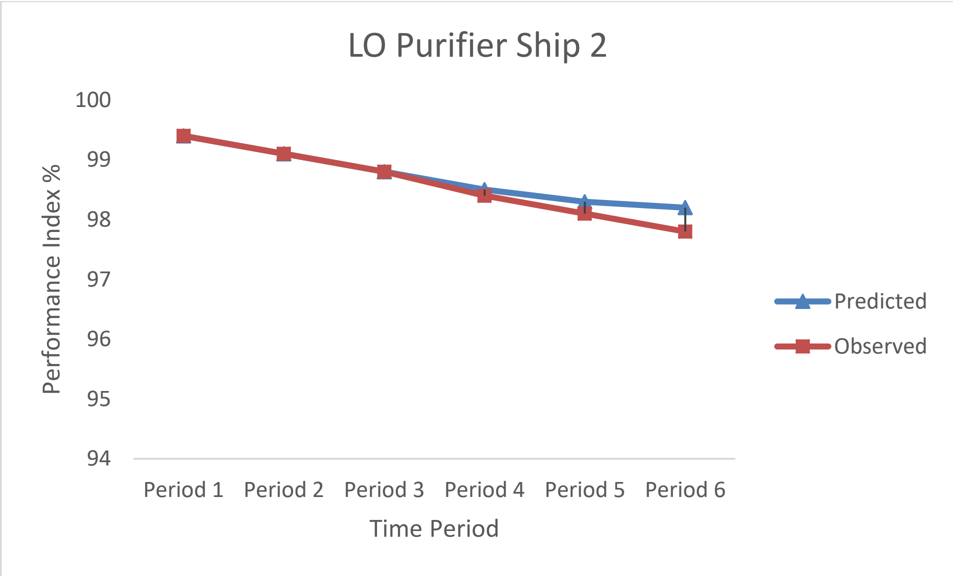

Figure 244 - LO Purifier Ship 2 Performance Indices

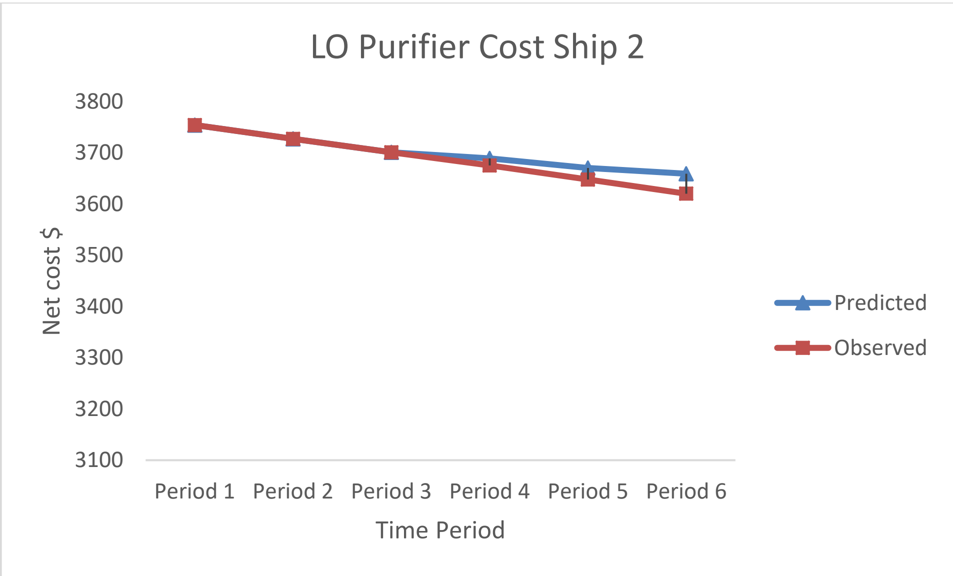

Figure 245 - LO Purifier Ship 2 Net cost

Appendix C2.2 Fuel-oil System of Ship 2

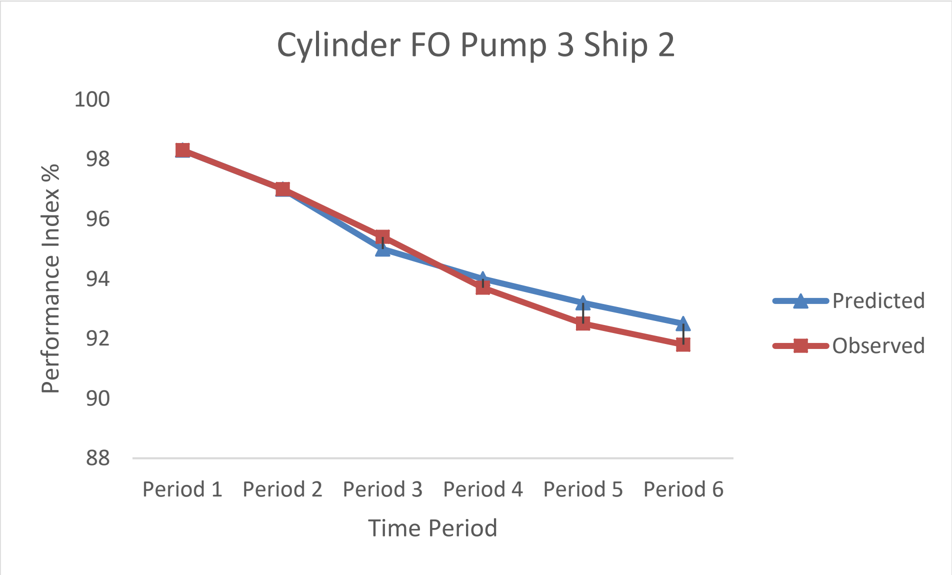

Figure 246 - Cylinder FO Pump 3 Ship 2 Performance Indices

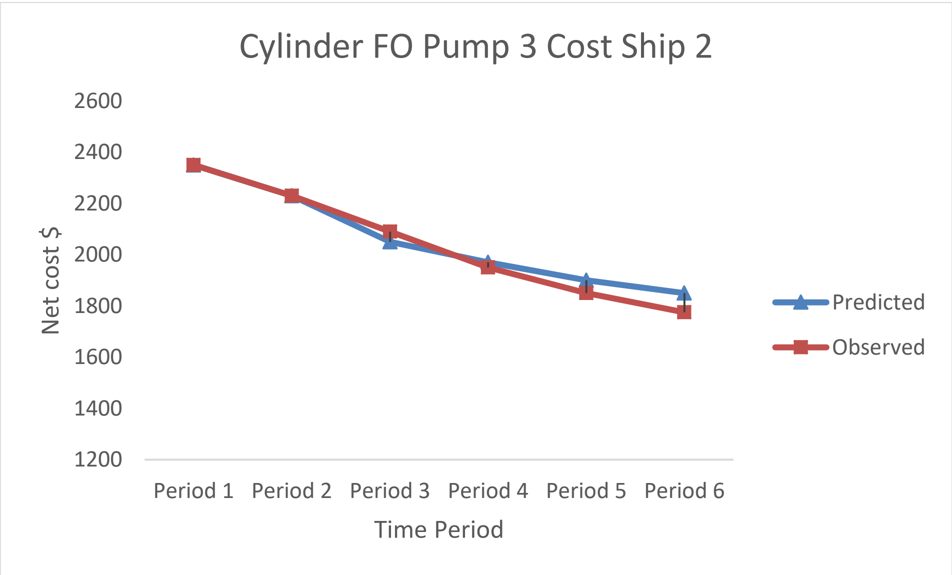

Figure 247 - Cylinder FO Pump 3 Net cost

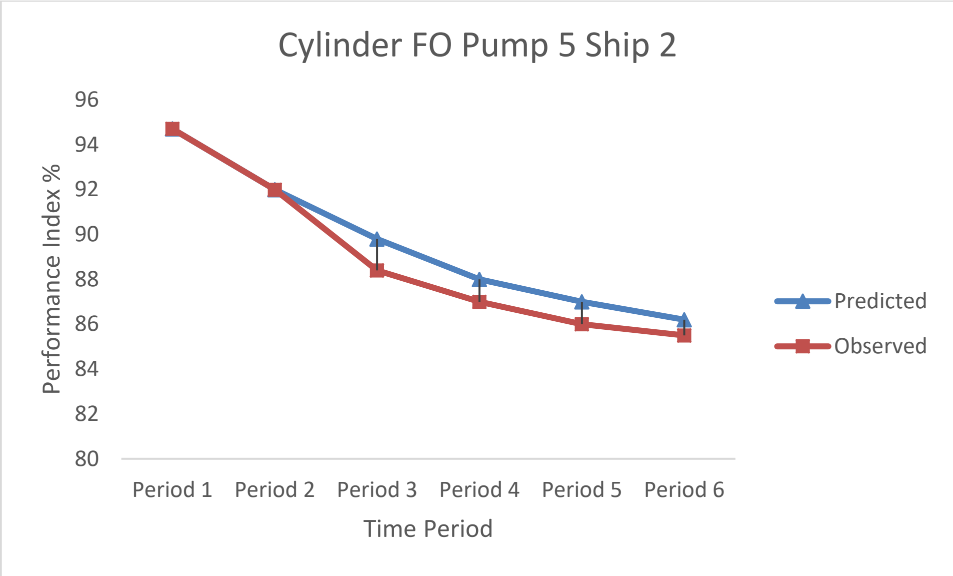

Figure 248 - Cylinder FO Pump 5 Ship 2 Performance Indices

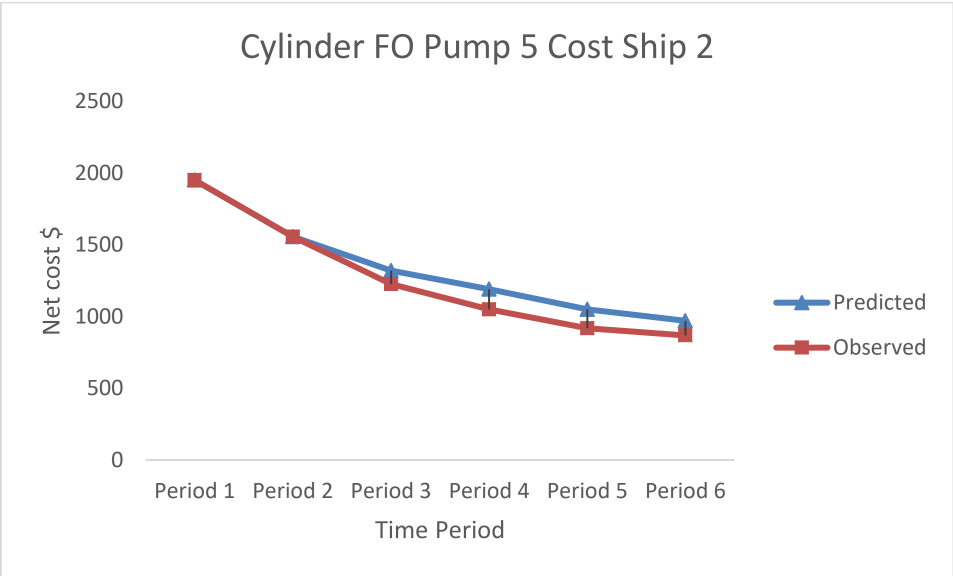

Figure 249 - Cylinder FO Pump 5 Ship 2 Net cost

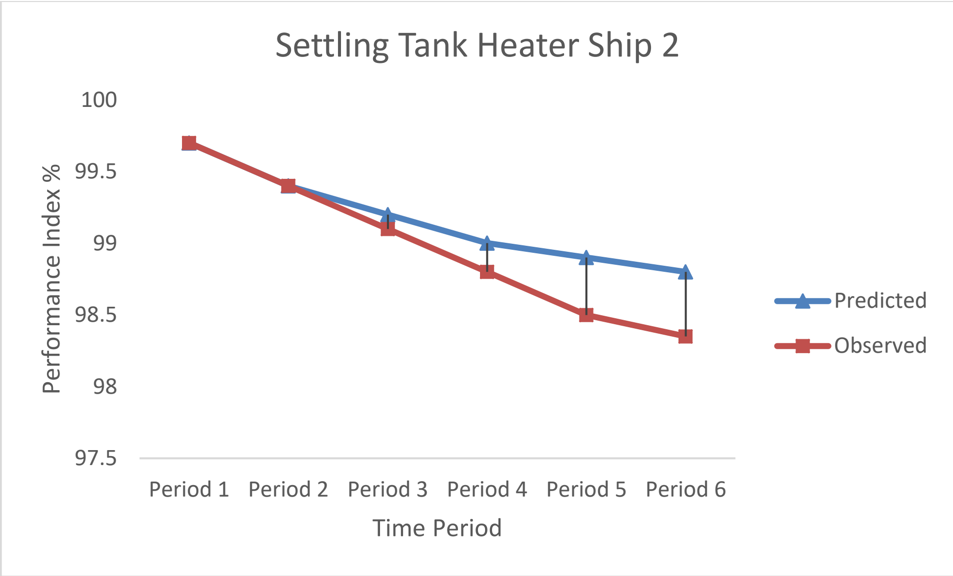

Figure 250 - Settling Tank Heater Ship 2 Performance Indices

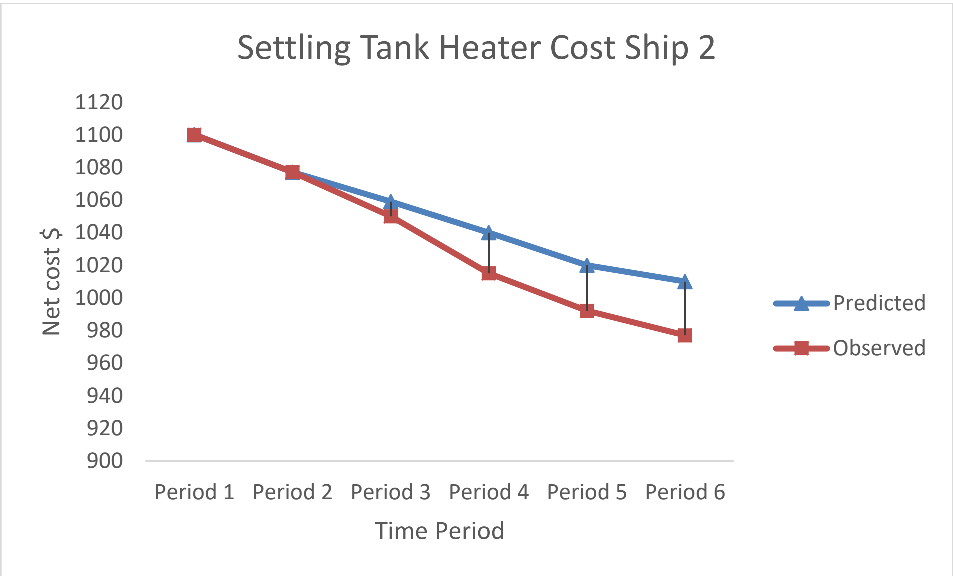

Figure 251 - Settling Tank Heater Ship 2 Net cost

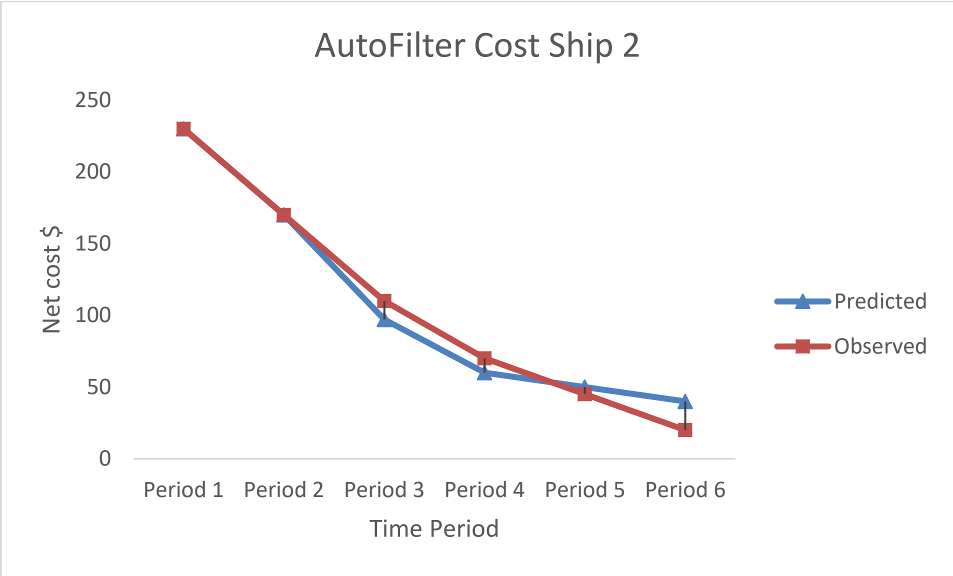

Figure 252 – Auto-filter Ship 2 Net cost

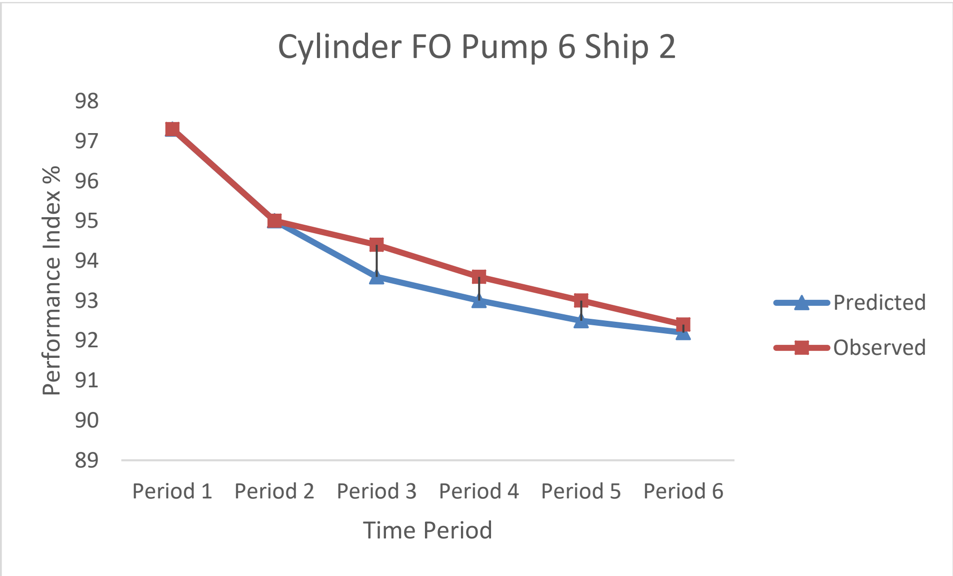

Figure 253 - Cylinder FO Pump 6 Ship 2 Performance Indices

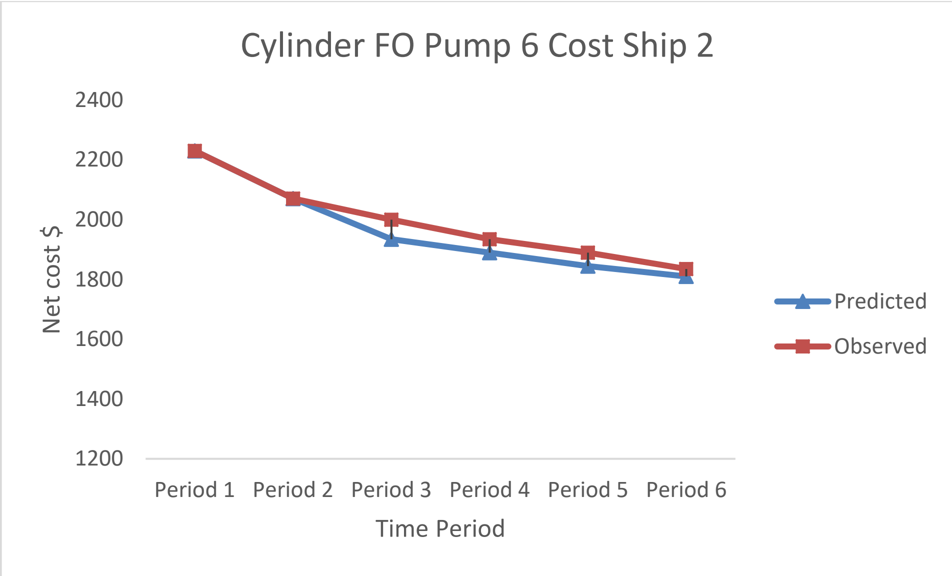

Figure 254 - Cylinder FO Pump 6 Ship 2 Net cost

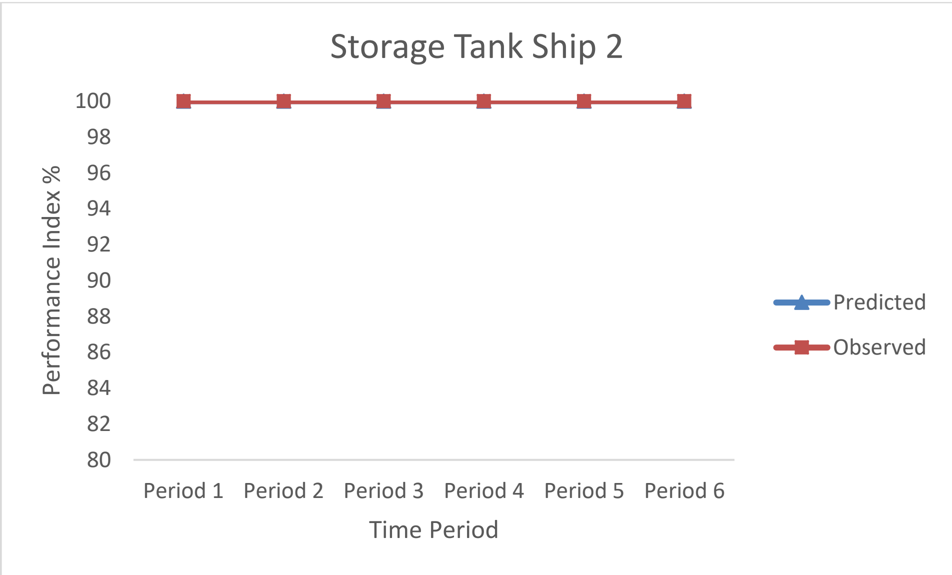

Figure 255 - Storage Tank Ship 2 Performance Indices

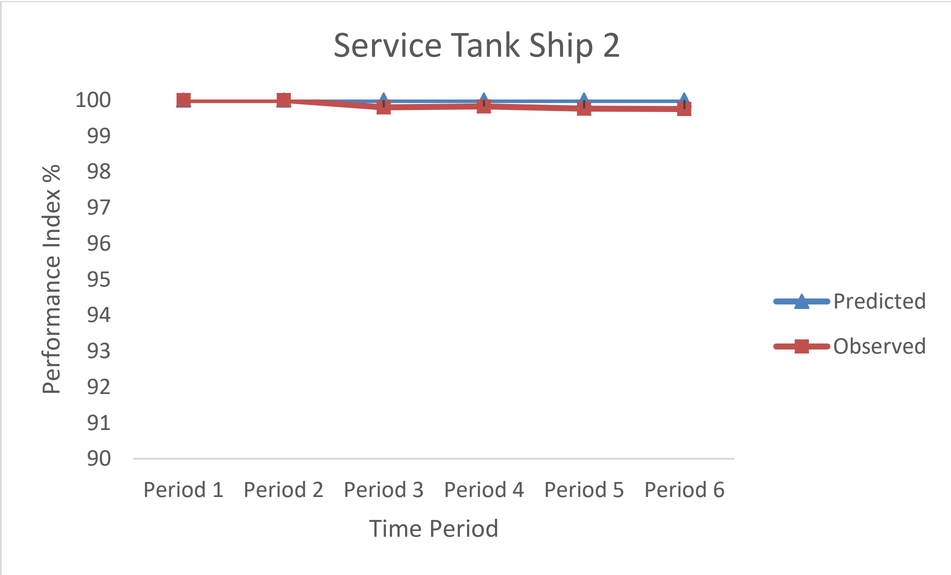

Figure 256 - Service Tank Ship 2 Performance Indices

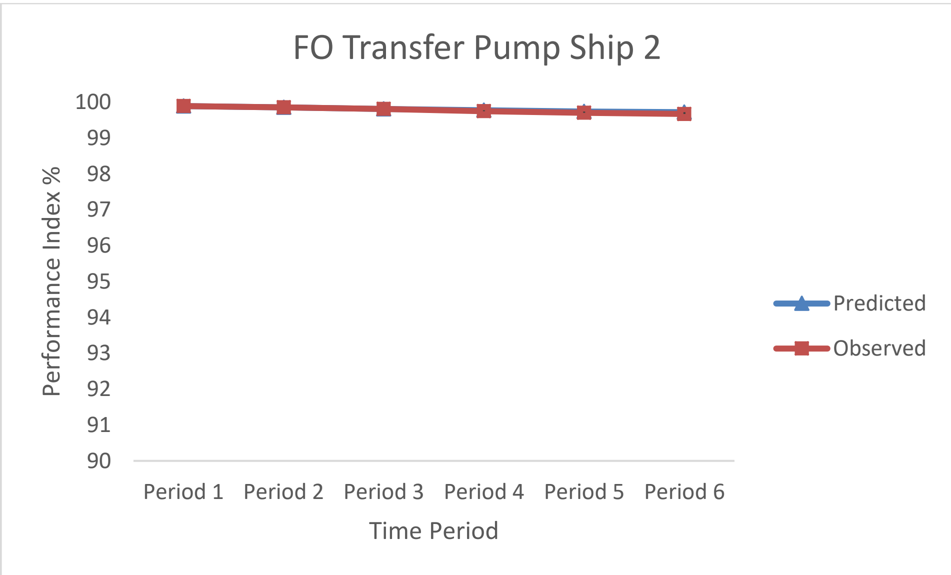

Figure 257 - FO Transfer Pump Ship 2 Performance Indices

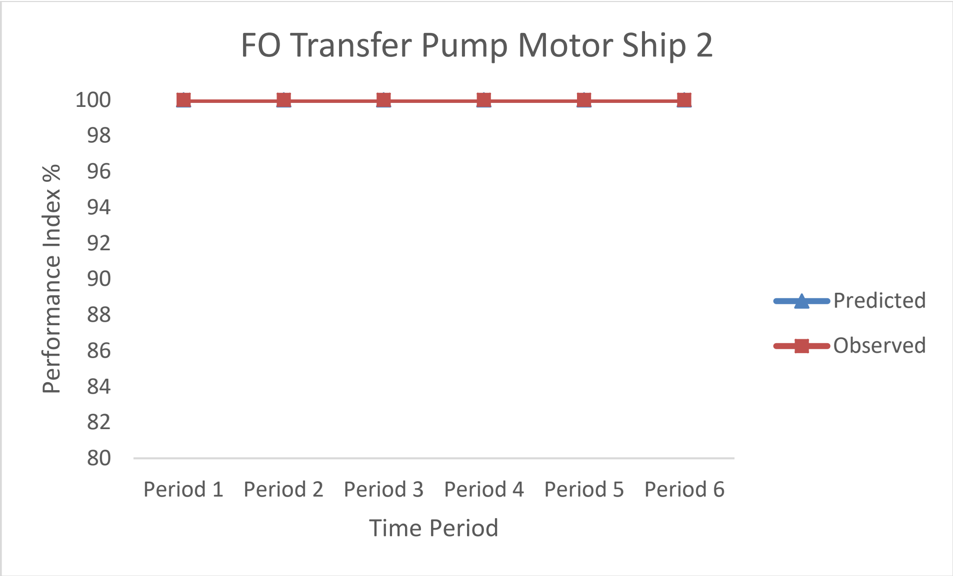

Figure 258 - FO Transfer Pump Motor Ship 2 Performance Indices

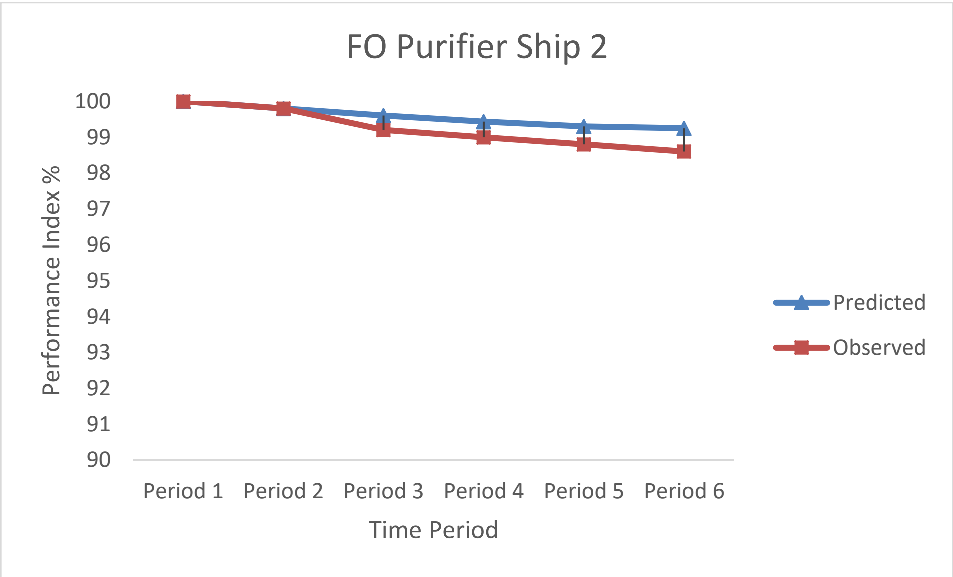

Figure 259 - FO Purifier Ship 2 Performance Indices

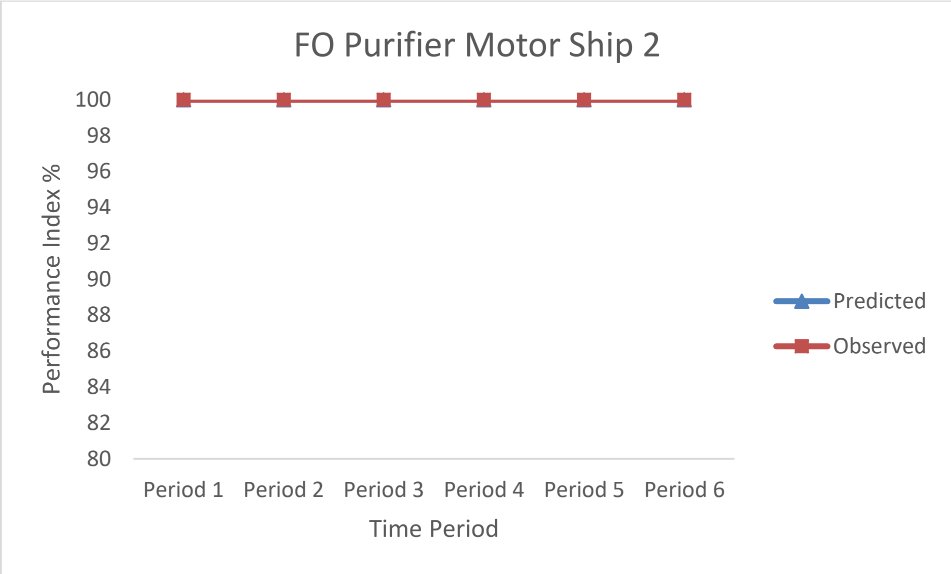

Figure 260 - FO Purifier Motor Ship 2 Performance Indices

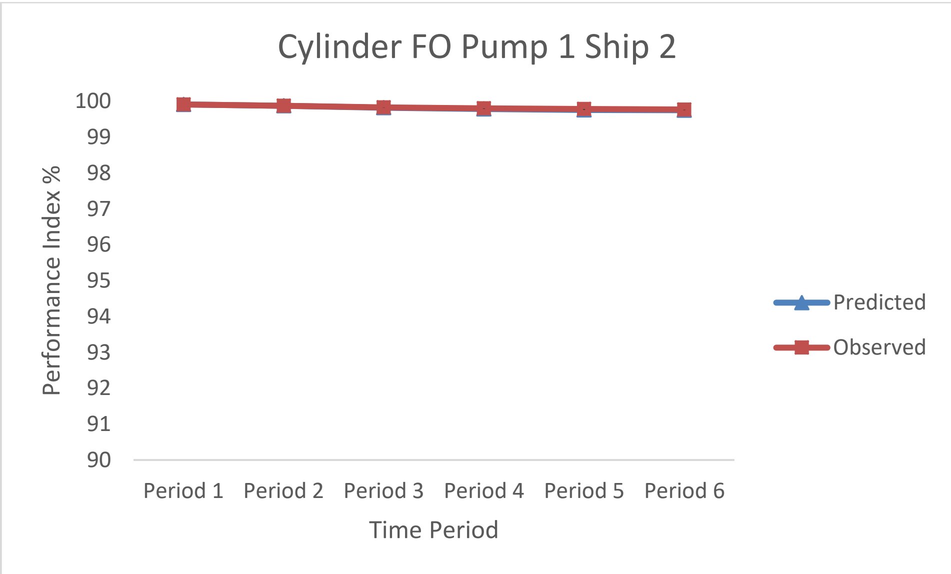

Figure 261 - Cylinder FO Pump 1 Ship 2 Performance Indices

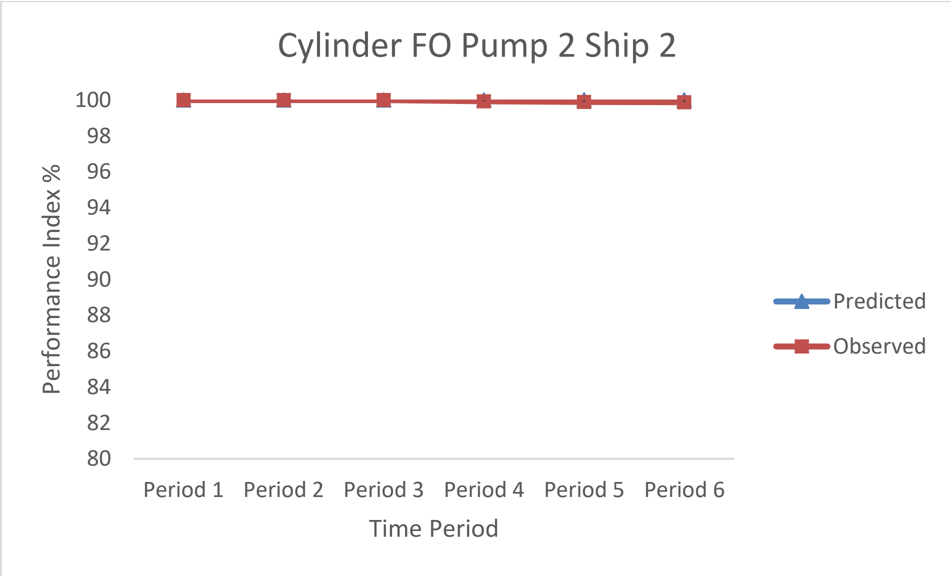

Figure 262 - Cylinder FO Pump 2 Ship 2 Performance Indices

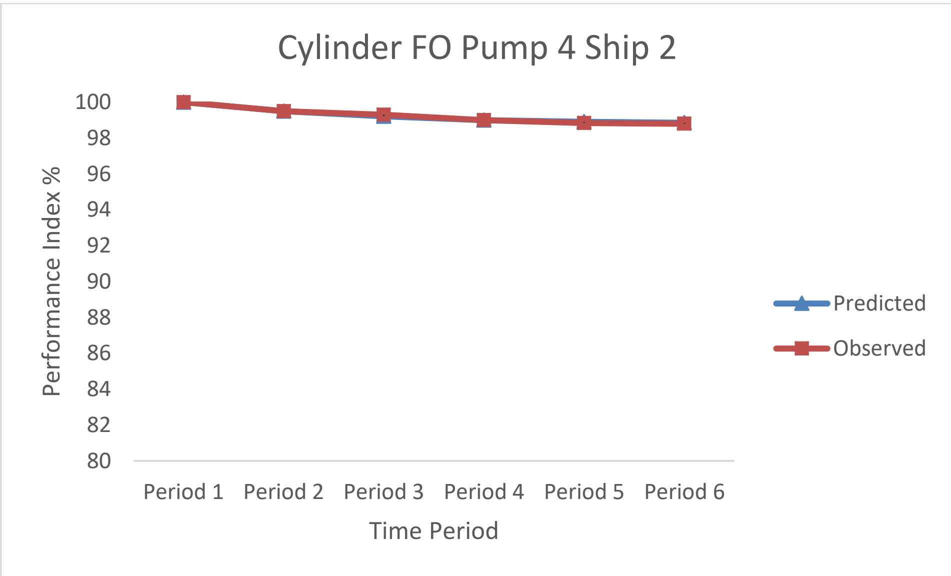

Figure 263 - Cylinder FO Pump 4 Ship 2 Performance Indices

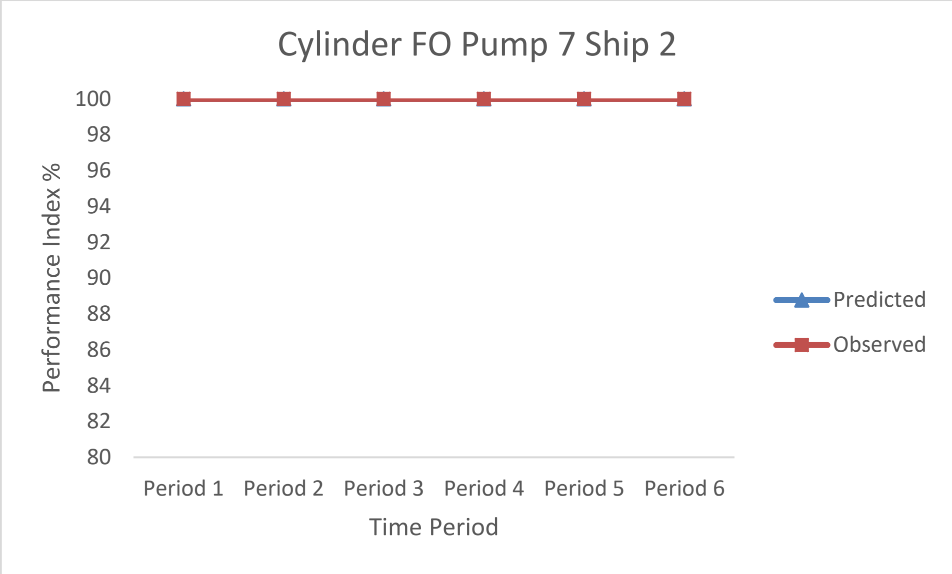

Figure 264 - Cylinder FO Pump 7 Ship 2 Performance Indices

Appendix C2.3 Turbocharger System of Ship 2

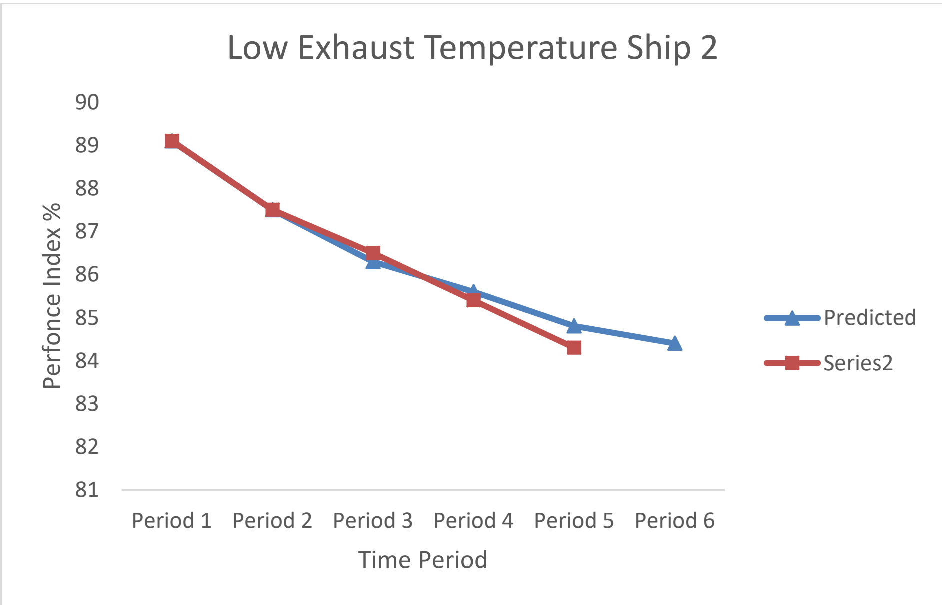

Figure 265 - Low Exhaust Temperature Ship 2 Performance Indices

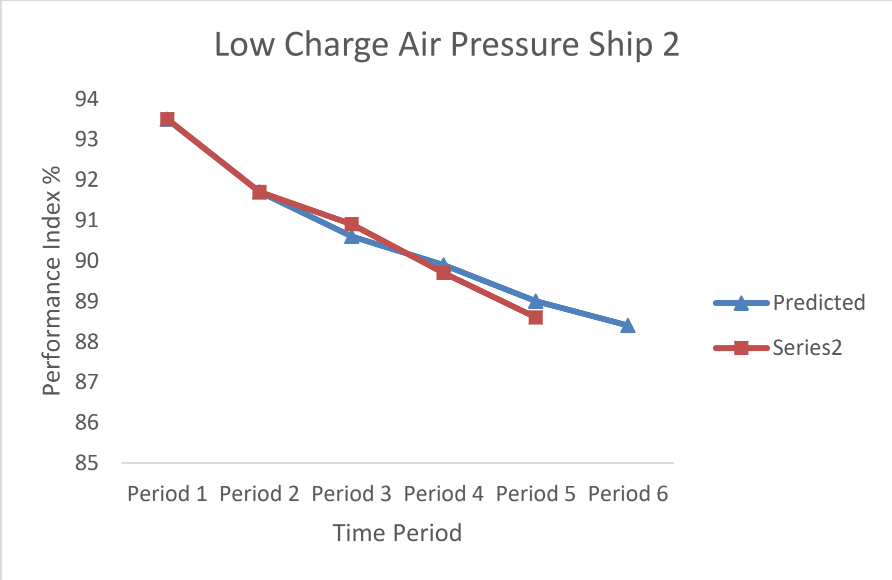

Figure 266 - Low Charge Air Pressure Ship 2 Performance Indices

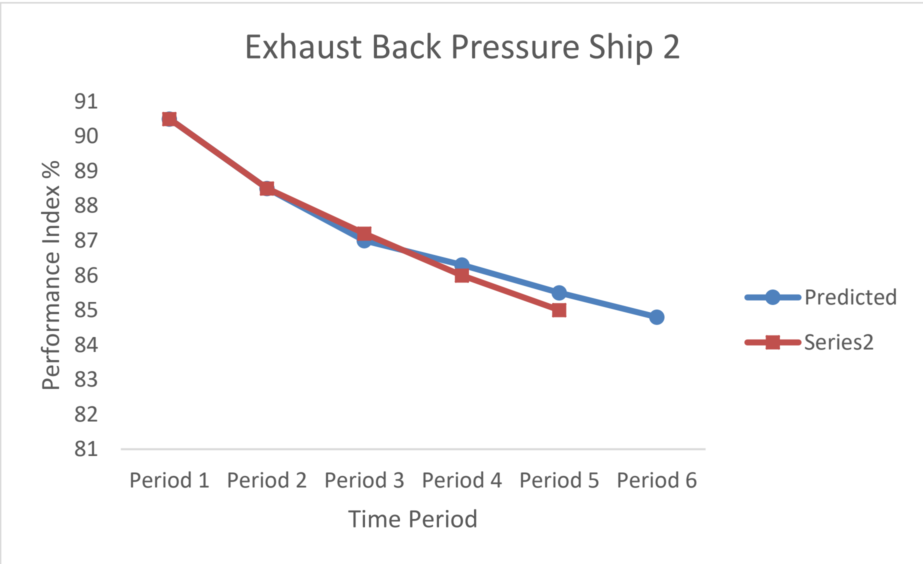

Figure 267 - Exhaust Back-pressure Ship 2 Performance Indices

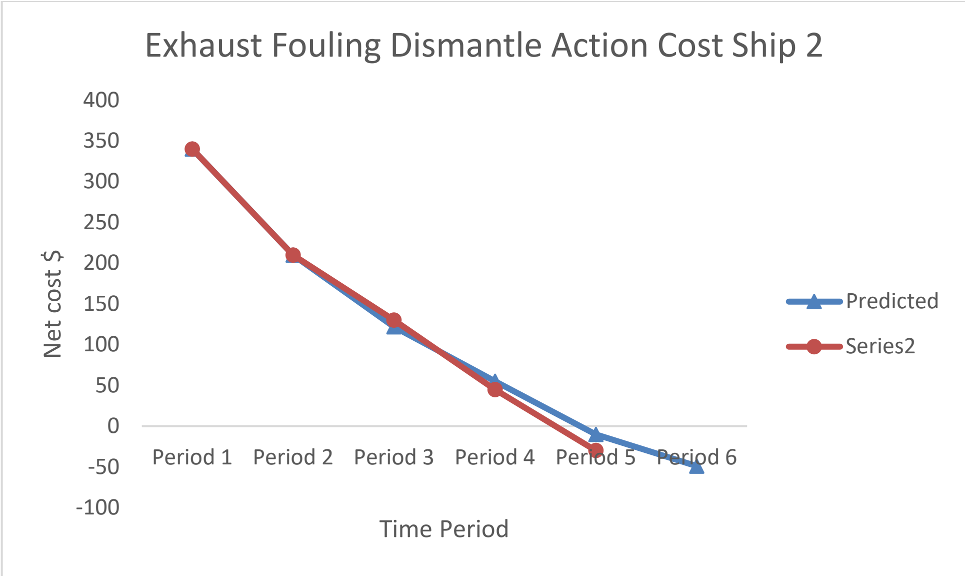

Figure 268 - Exhaust Fouling Dismantle Action Ship 2 Net cost

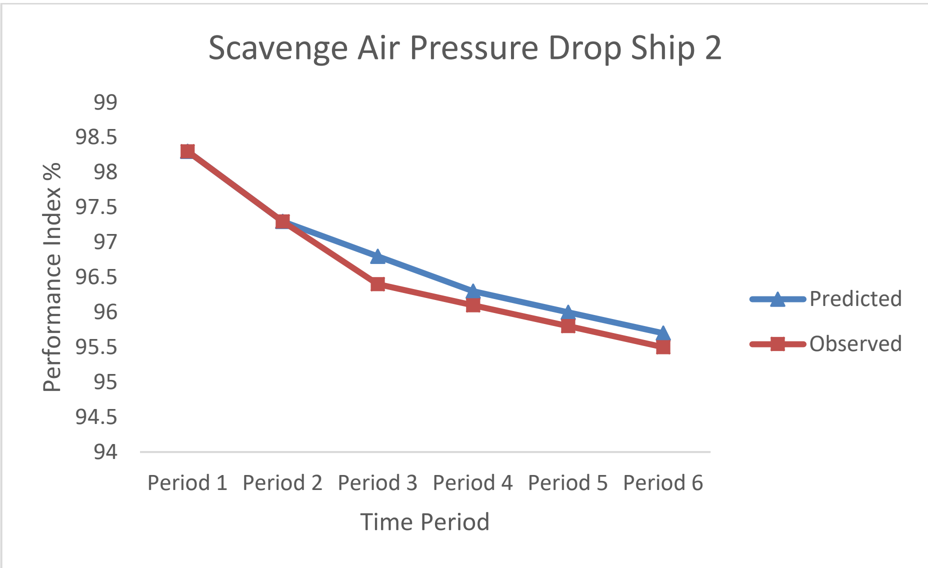

Figure 269 - Scavenge Air Pressure Drop Ship 2 Performance Indices

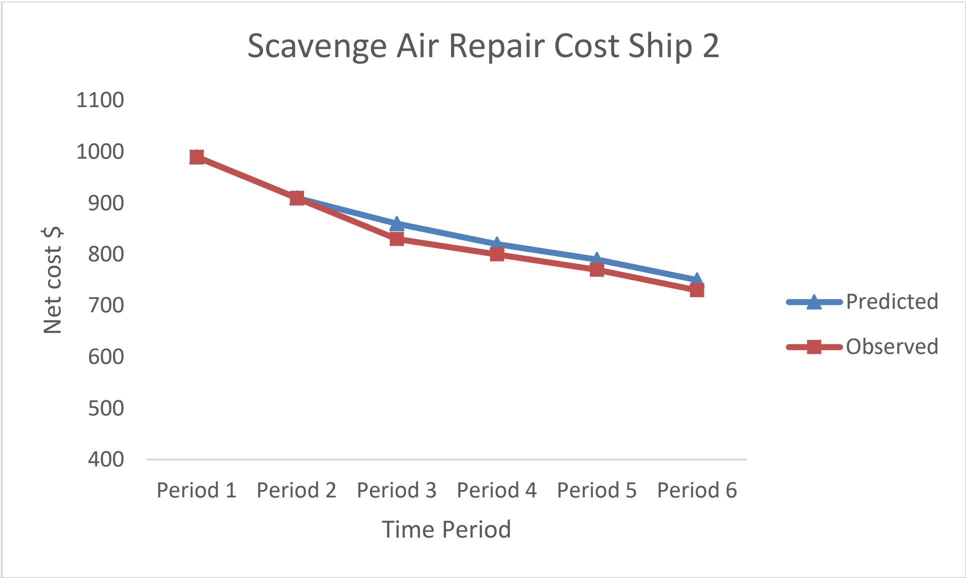

Figure 270 - Scavenge Air Repair Ship 2 Net cost

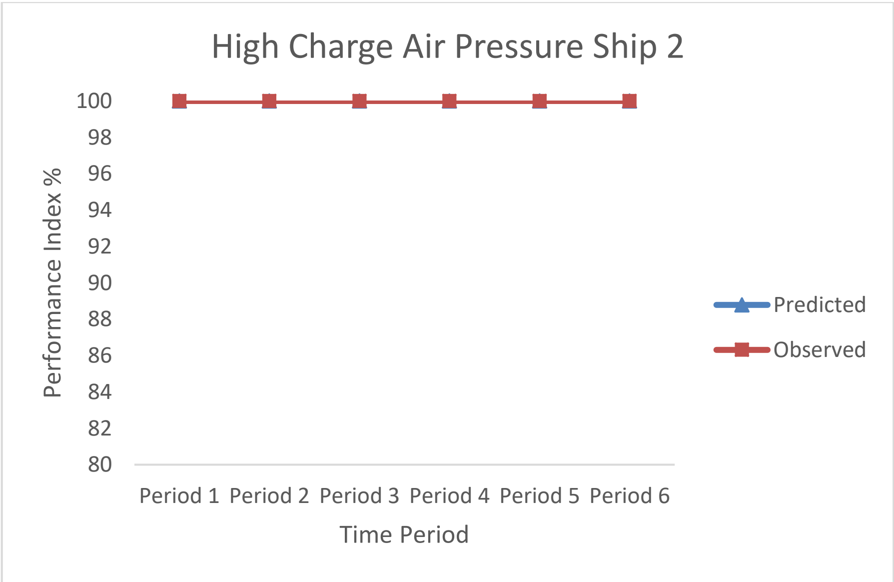

Figure 271 - High Charge Air Pressure Ship 2 Performance Indices

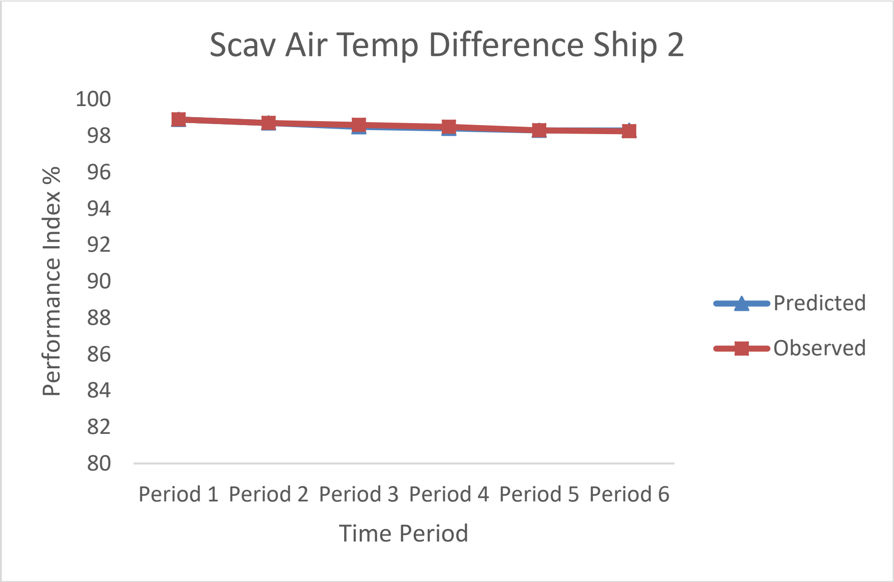

Figure 272 - Scavenge Air Temperature Ship 2 Performance Indices

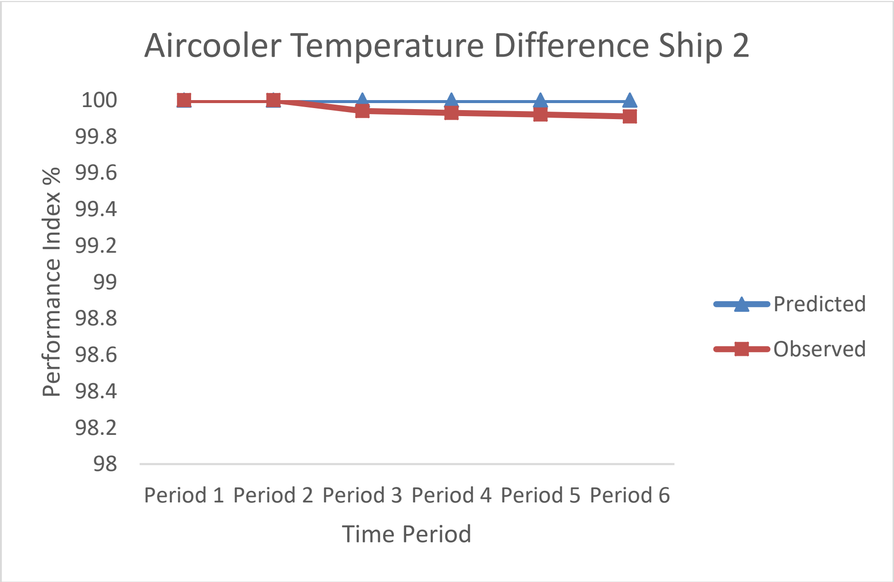

Figure 273 – Air Cooler Temperature Difference Ship 2 Performance Indices

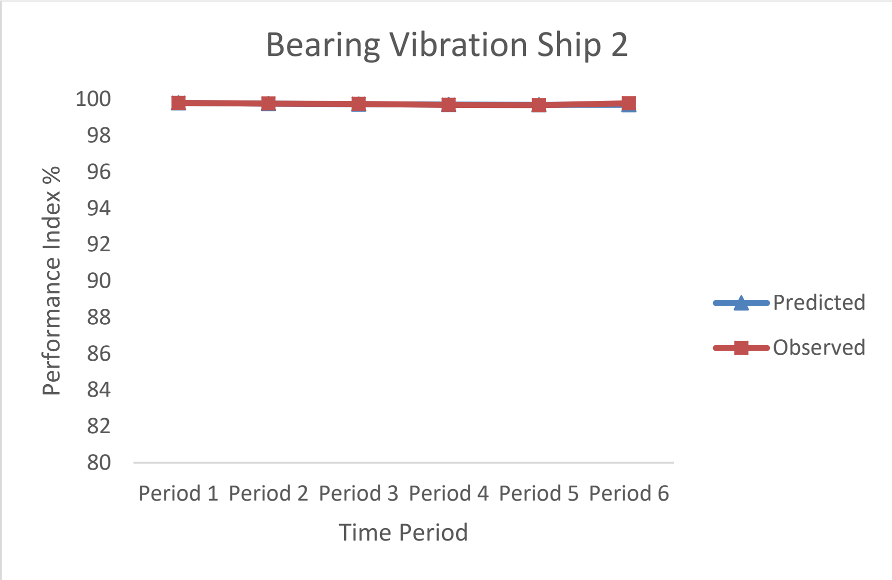

Figure 274 - Bearing Vibration Ship 2 Performance Indices

APPENDIX C3-COMPONENT/SUB-SYSTEM PREDICTED AND OBSERVED PERFORMANCE INDEX VALUES FOR SHIP 3 MULTI-PURPOSE CARGO VESSEL

Appendix C3.1 Lube-oil System of Ship 3

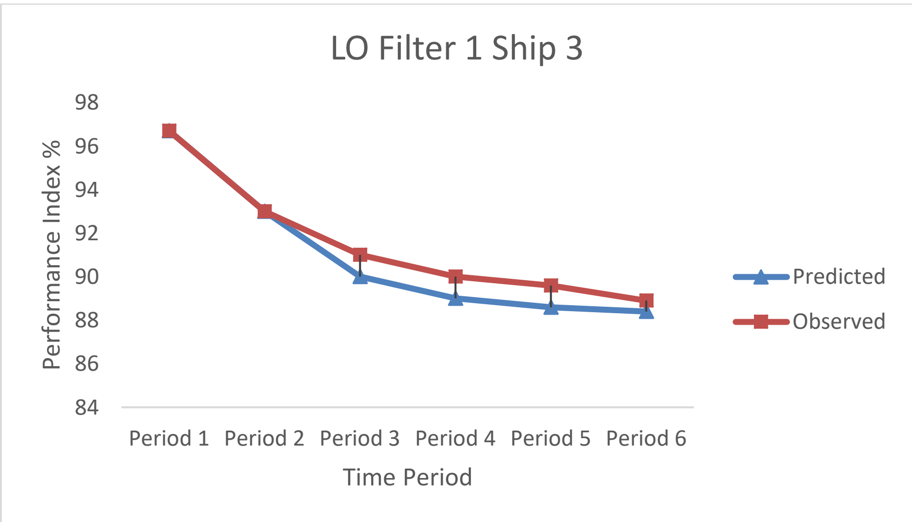

Figure 275 - LO Filter 1 Ship 3 Performance Indices

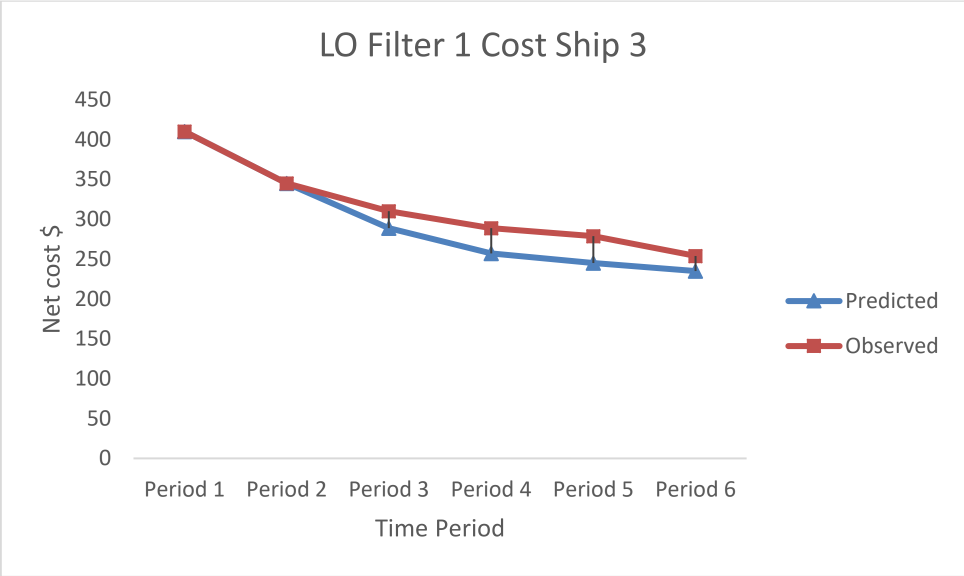

Figure 276 - LO Filter 1 Ship 3 Net cost

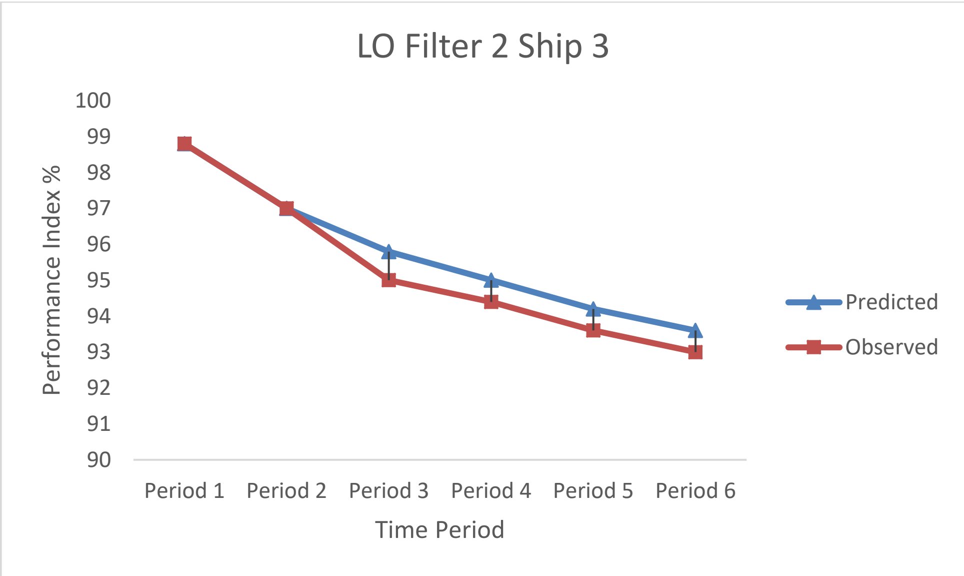

Figure 277 - LO Filter 2 Ship 3 Performance Indices

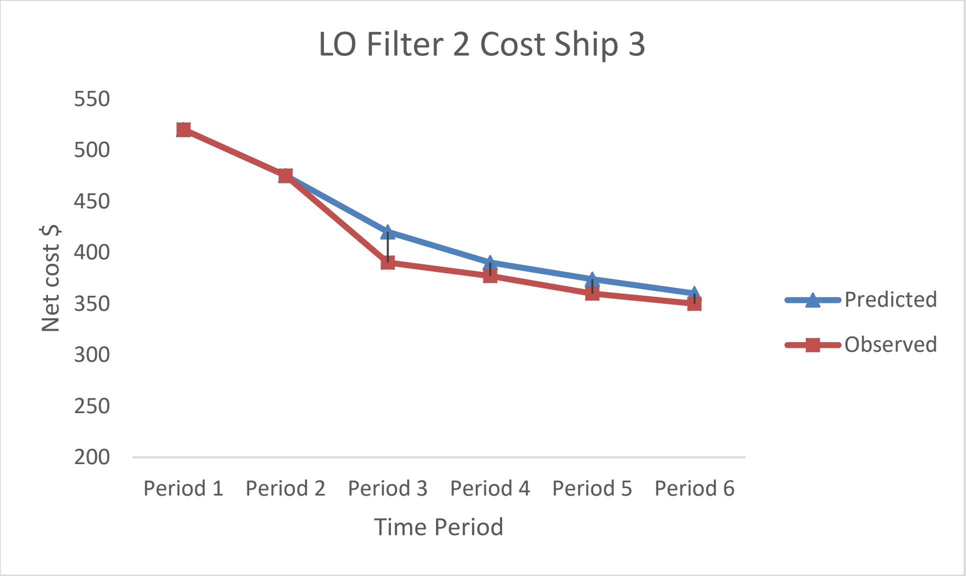

Figure 278 - LO Filter 2 Ship 3 Net cost

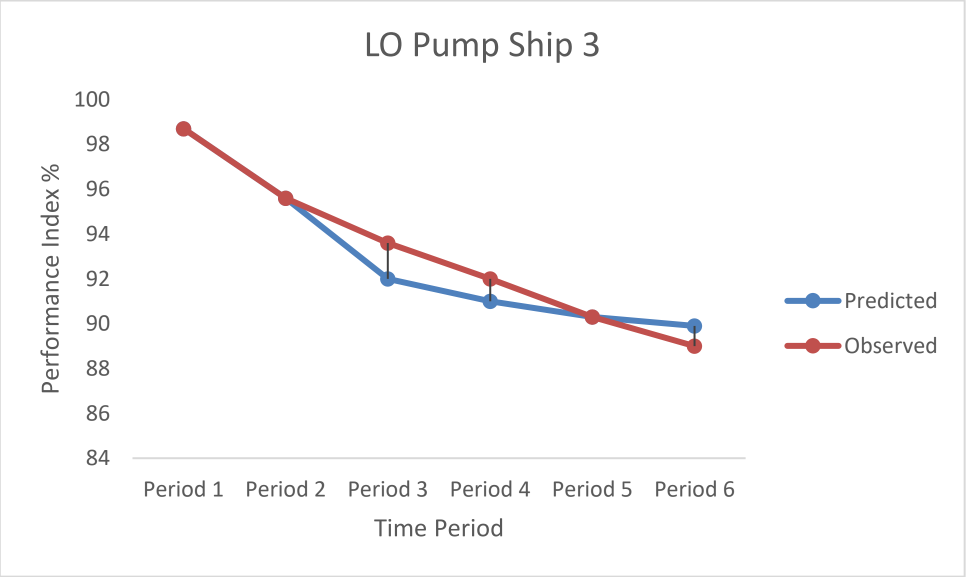

Figure 279 - LO Pump Ship 3 Performance Indices

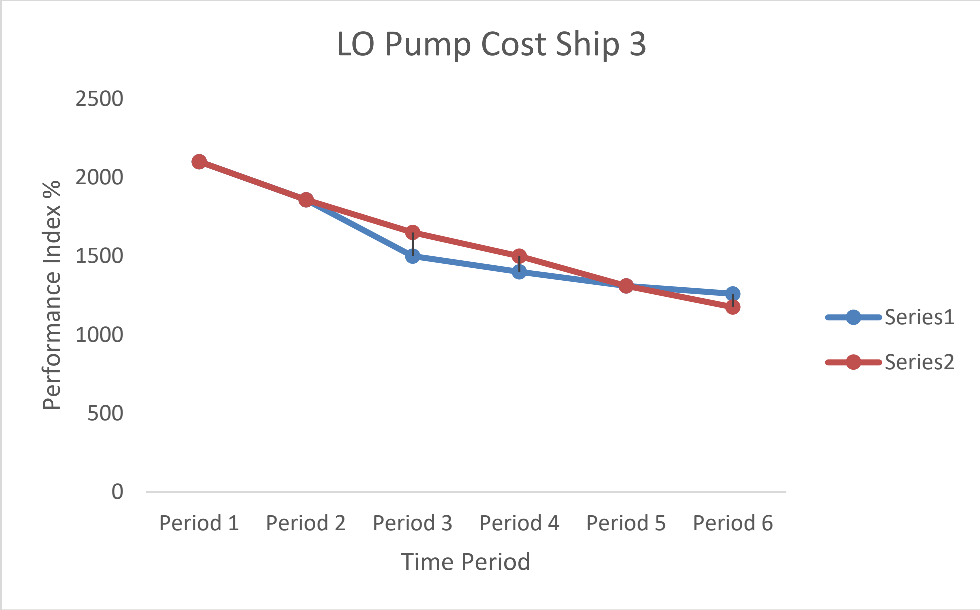

Figure 280 - LO Pump Ship 3 Net cost

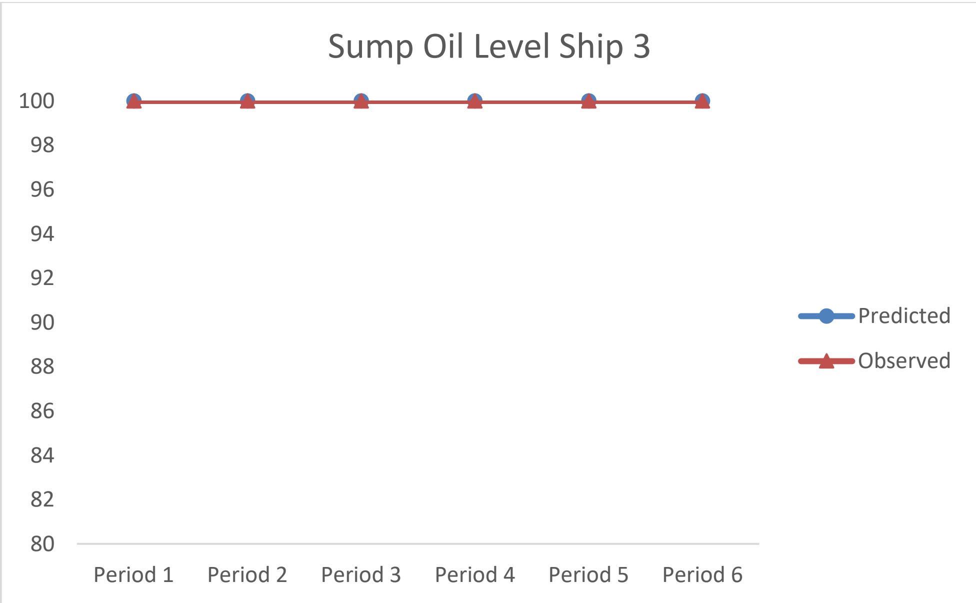

Figure 281 - Sump Oil Level Ship 3 Performance Indices

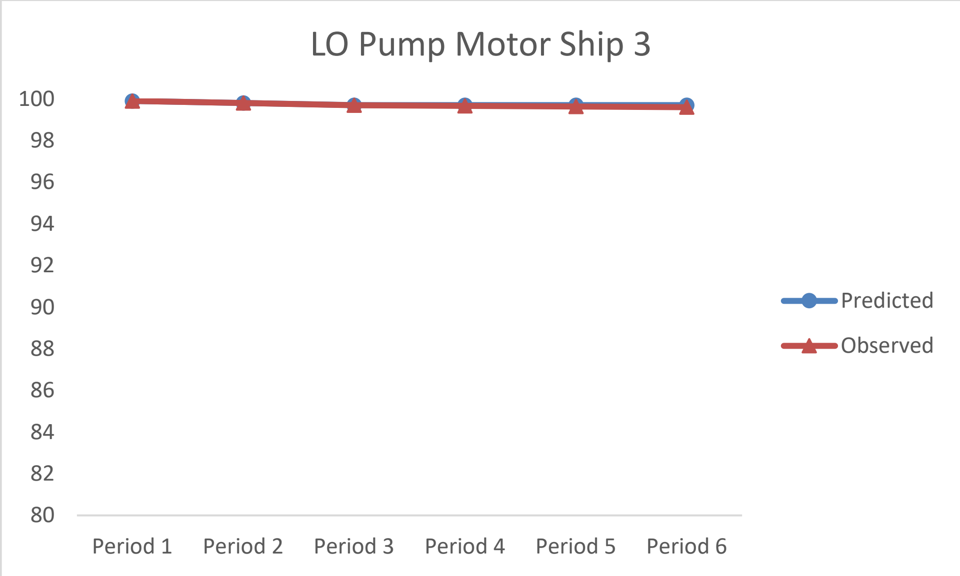

Figure 282 - LO Pump Motor Ship 3 Performance Indices

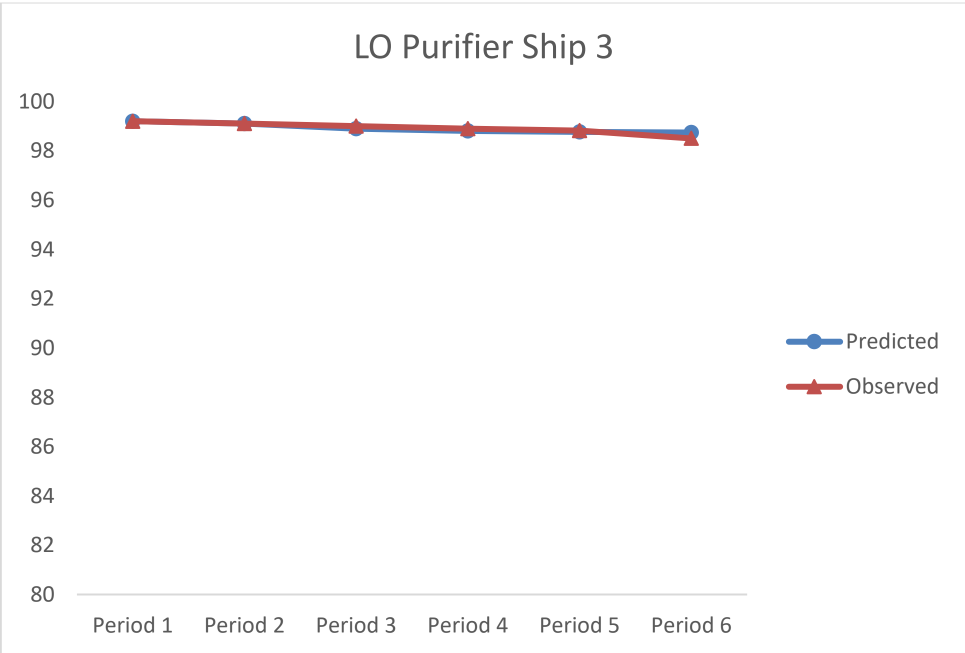

Figure 283 - LO Purifier Ship 3 Performance Indices

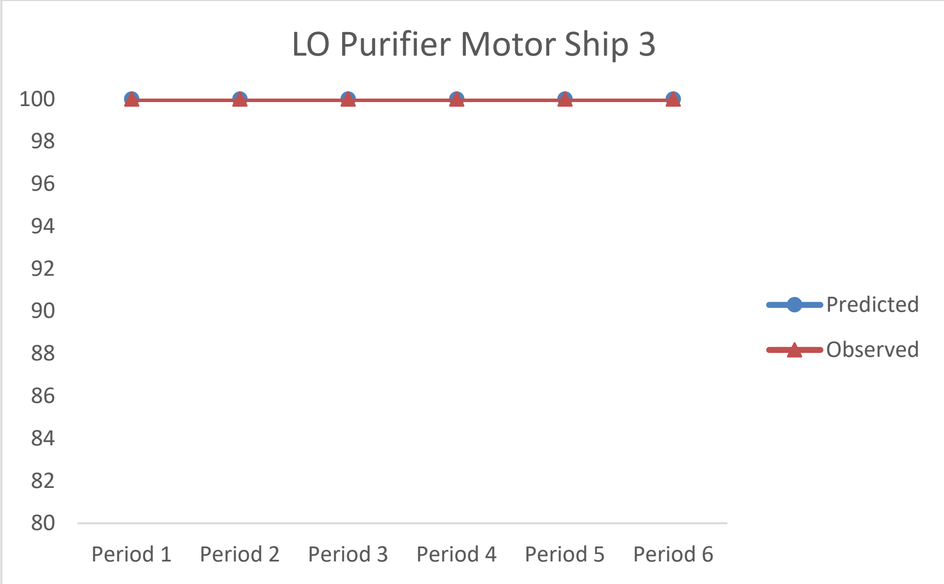

Figure 284 - LO Purifier Motor Ship 3 Performance Indices

Appendix C3.2 Fuel-oil System of Ship 3

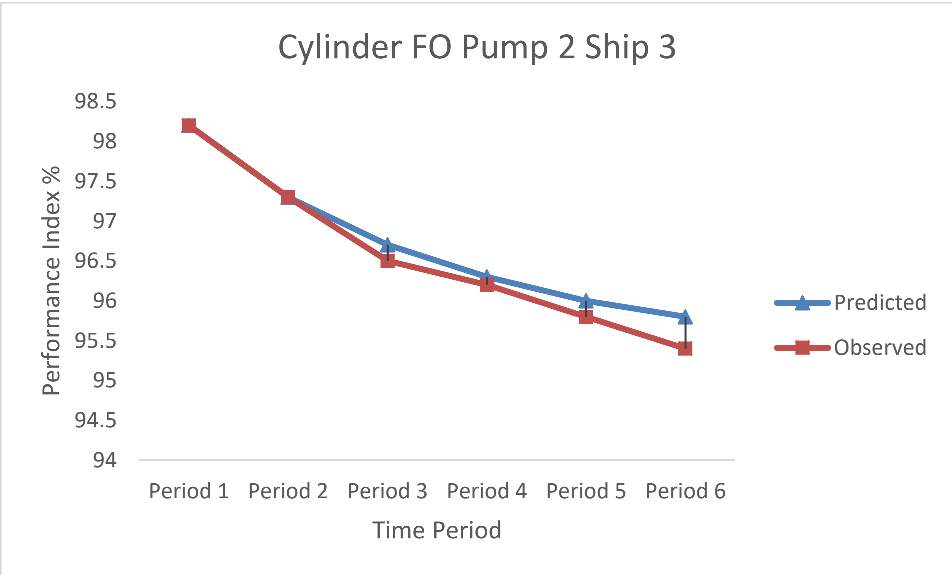

Figure 285 - Cylinder FO Pump 2 Ship 3 Performance Indices

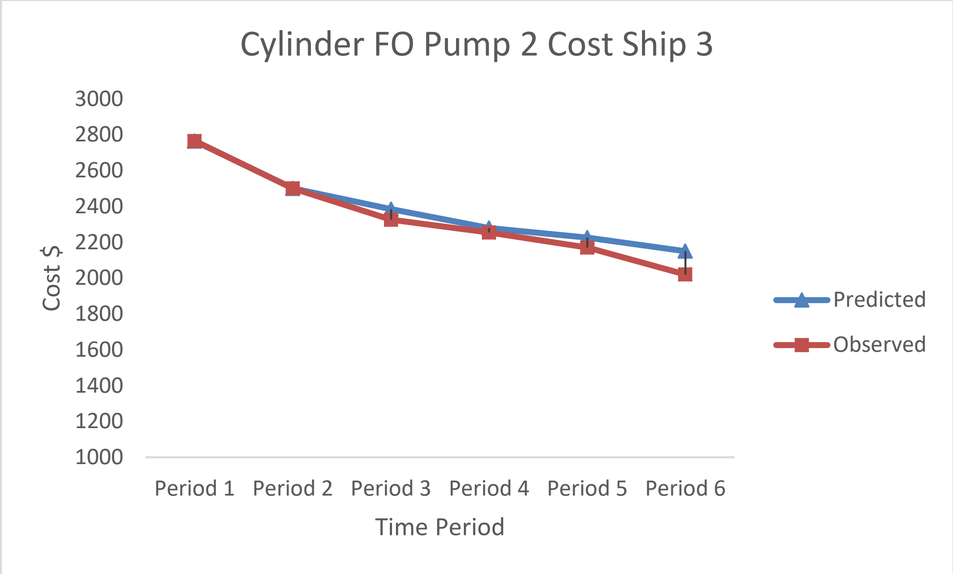

Figure 286 - Cylinder FO Pump 2 Ship 3 Net cost

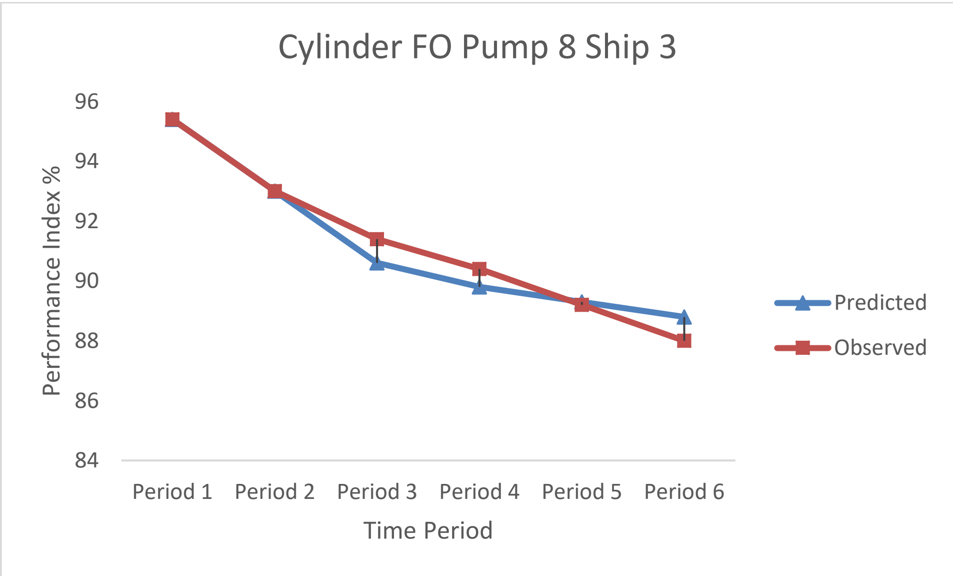

Figure 287 - Cylinder FO Pump 8 Ship 3 Performance Indices

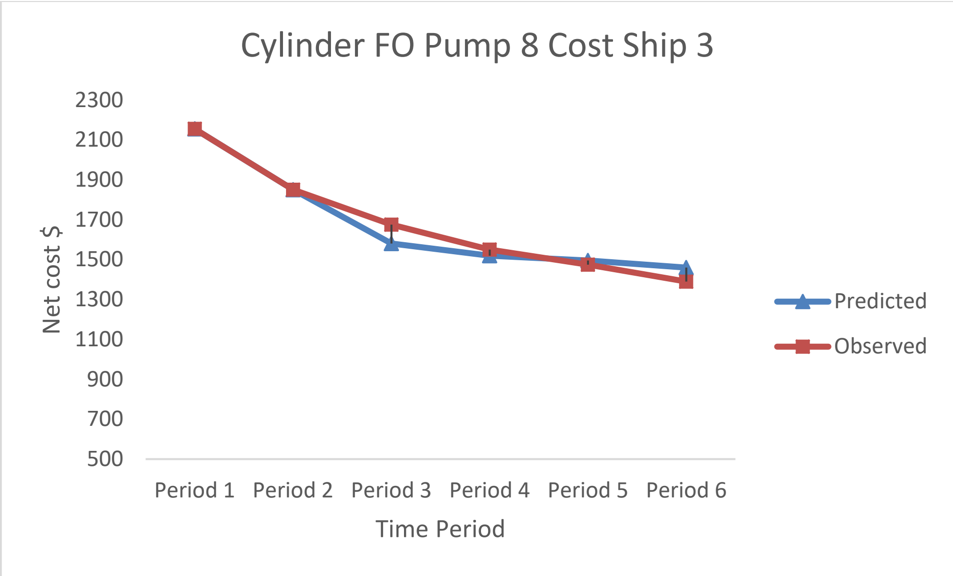

Figure 288 - Cylinder FO Pump 8 Ship 3 Net cost

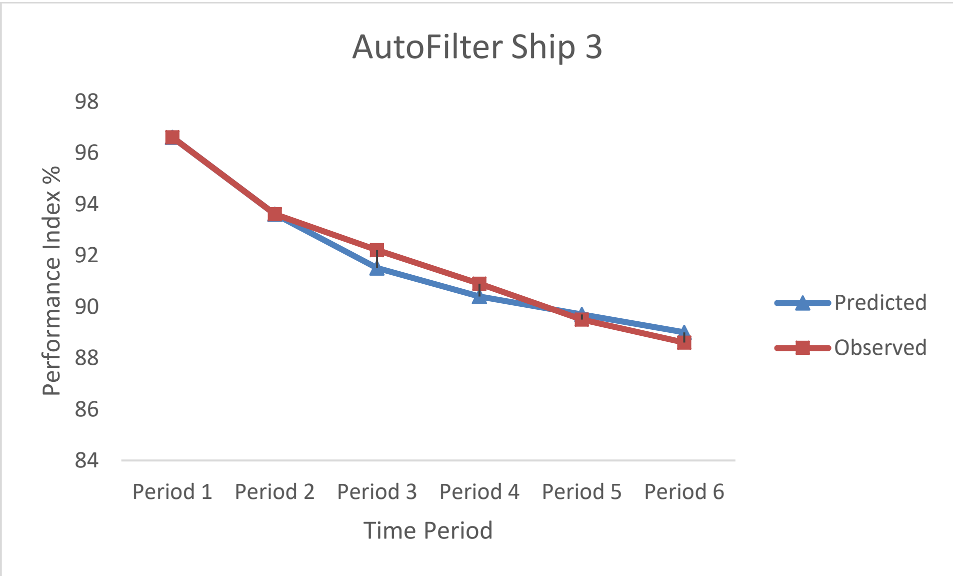

Figure 289 - AutoFilter Ship 3 Performance Indices

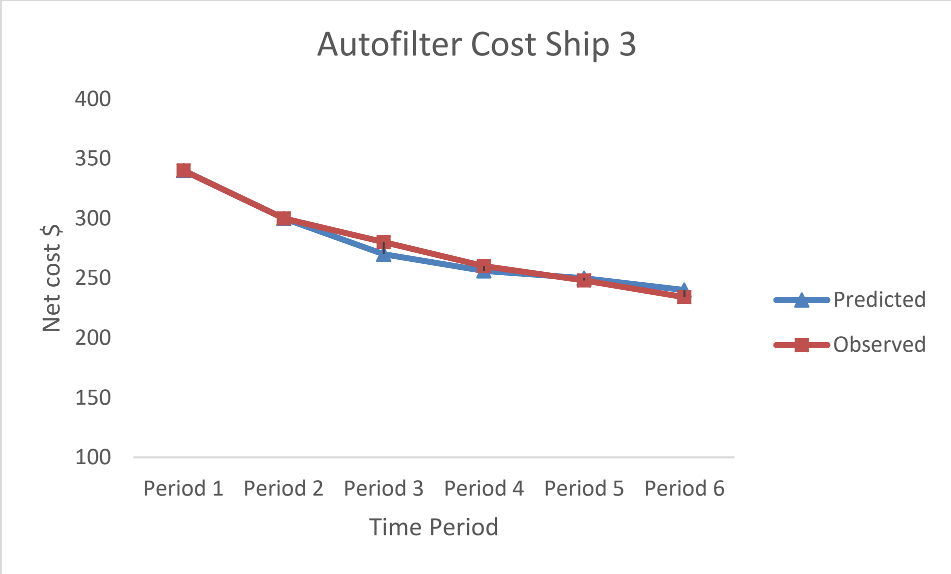

Figure 290 - AutoFilter Ship 3 Net cost

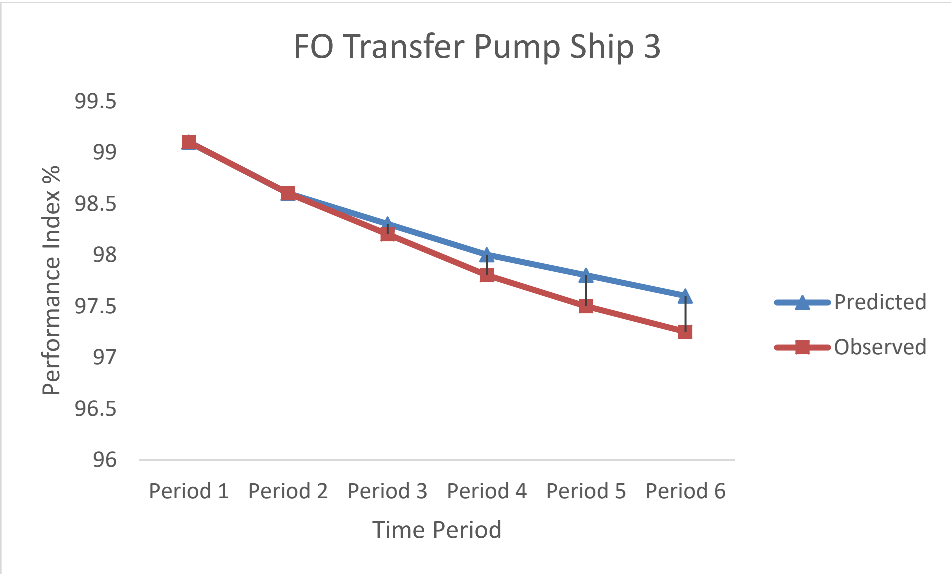

Figure 291 - FO Transfer Pump Ship 3 Performance Indices

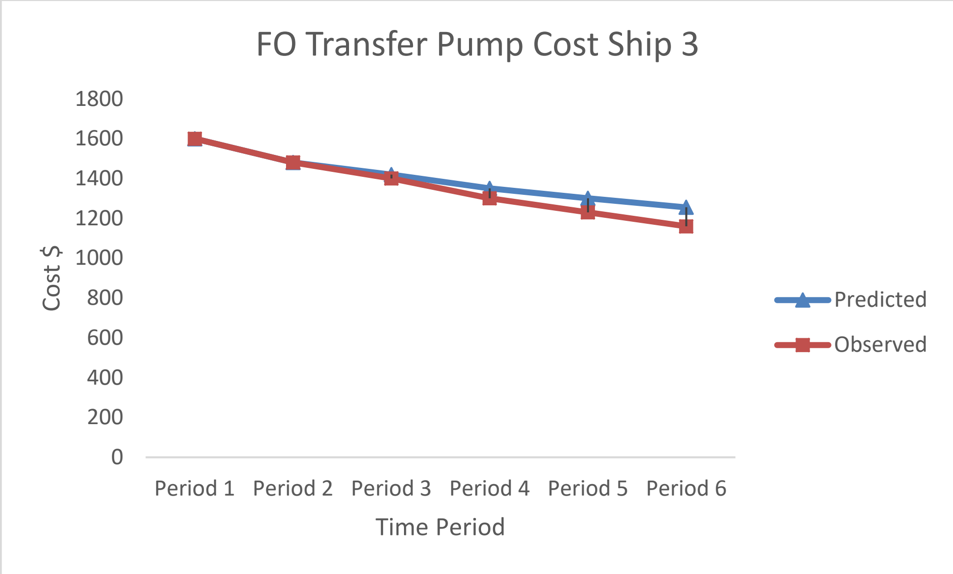

Figure 292 - FO Transfer Pump Ship 3 Net cost

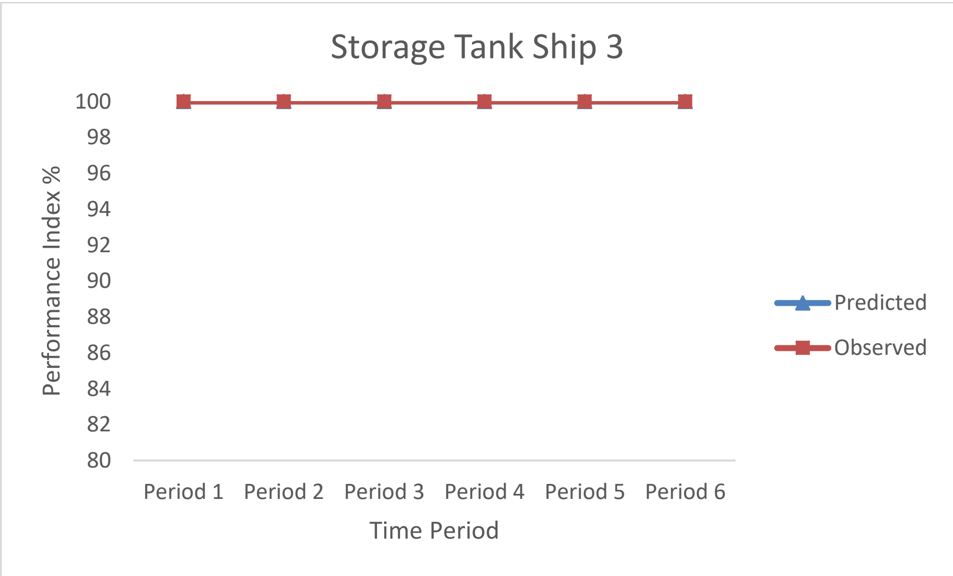

Figure 293 - Storage Tank Ship 3 Performance Indices

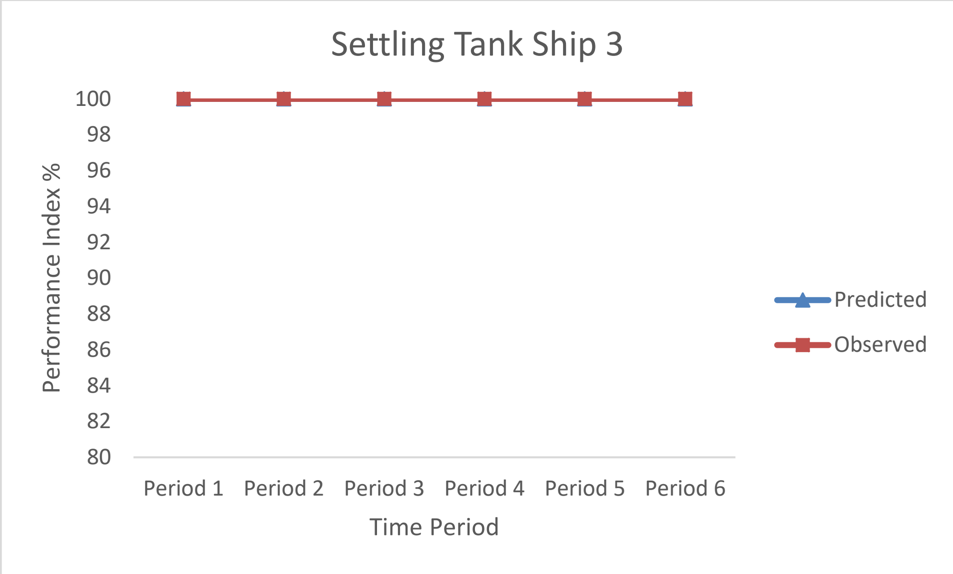

Figure 294 - Settling Tank Ship 3 Performance Indices

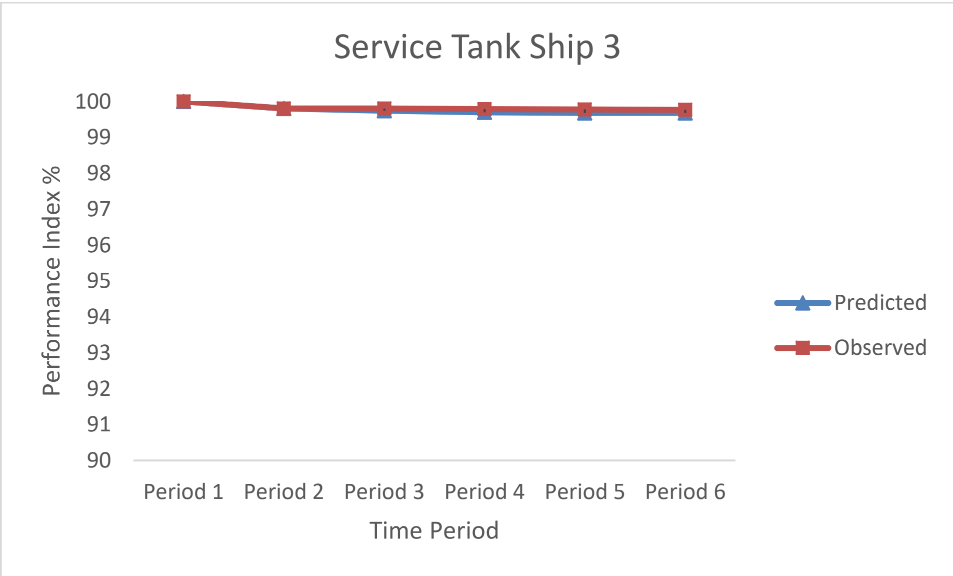

Figure 295 - Service Tank Ship 3 Performance Indices

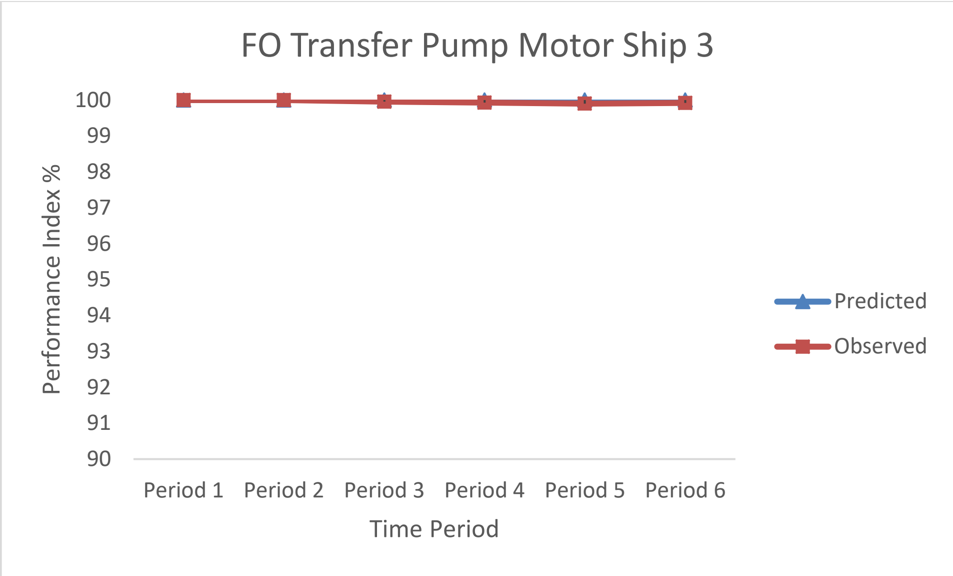

Figure 296 - FO Transfer Pump Motor Ship 3 Performance Indices

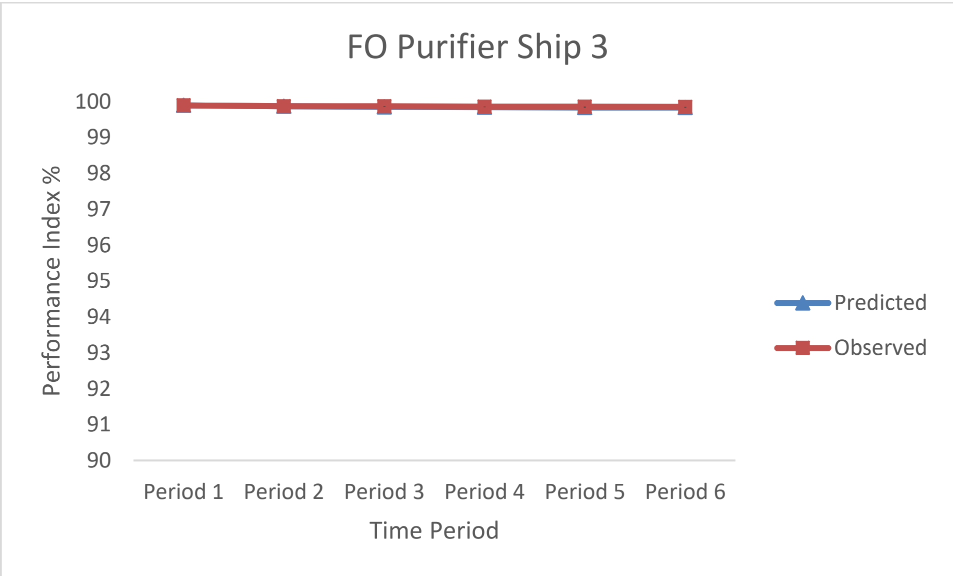

Figure 297 - FO Purifier Ship 3 Performance Indices

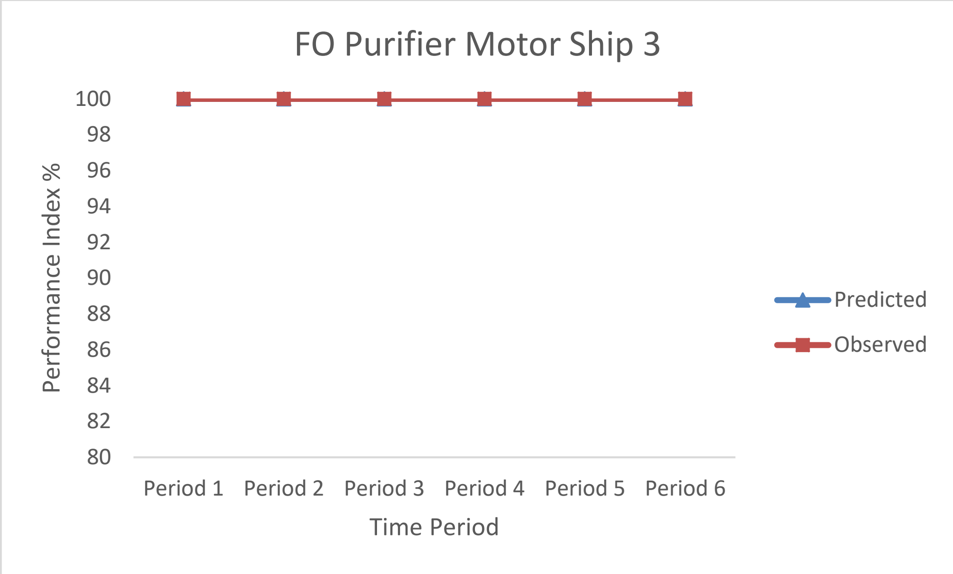

Figure 298 - FO Purifier Motor Ship 3 Performance Indices

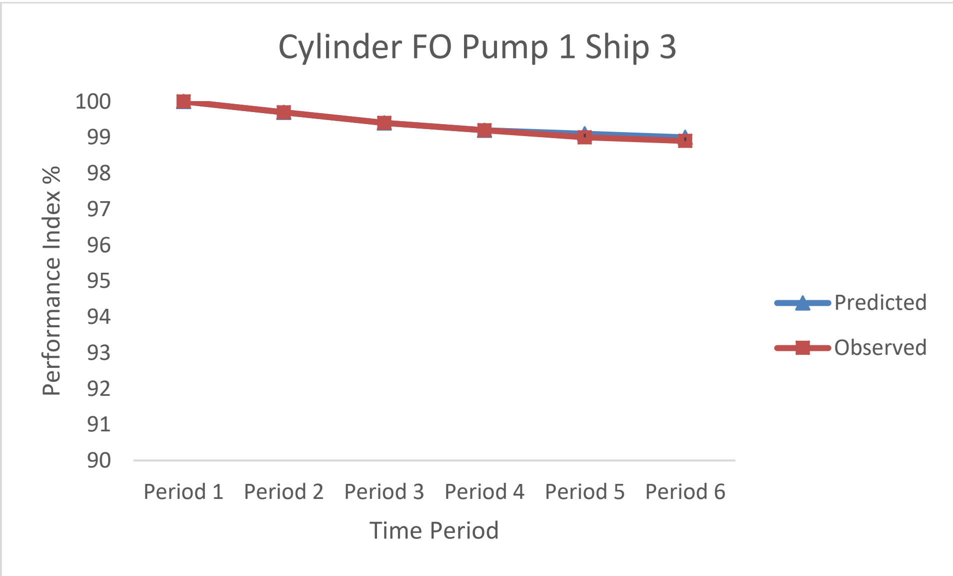

Figure 299 - Cylinder FO Pump 1 Ship 3 Performance Indices

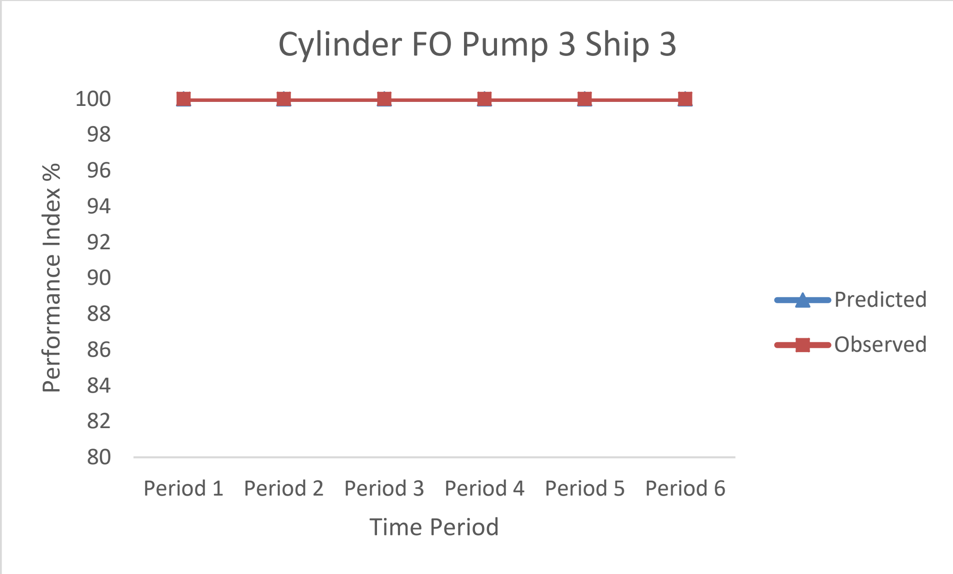

Figure 300 - Cylinder FO Pump 3 Ship 3 Performance Indices

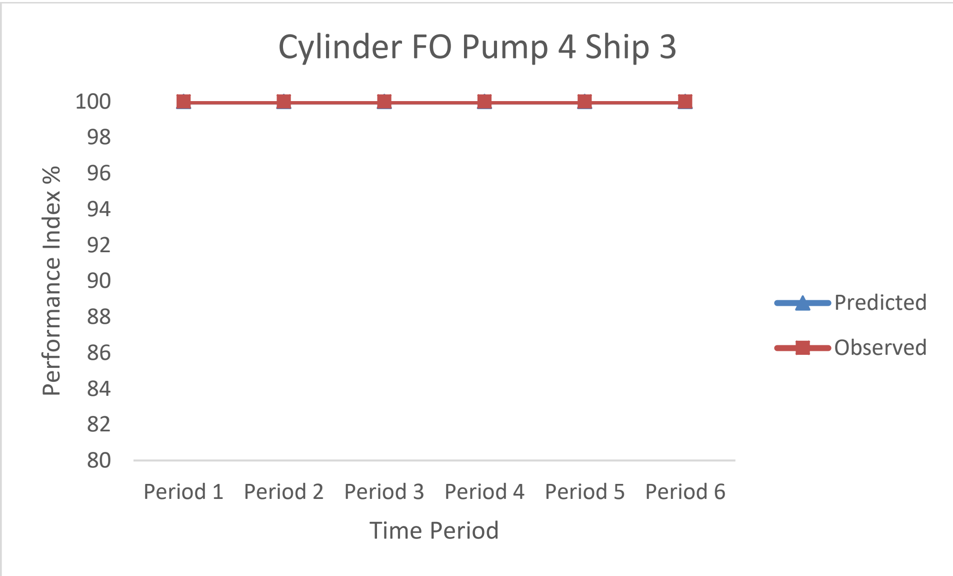

Figure 301 - Cylinder FO Pump 4 Ship 3 Performance Indices

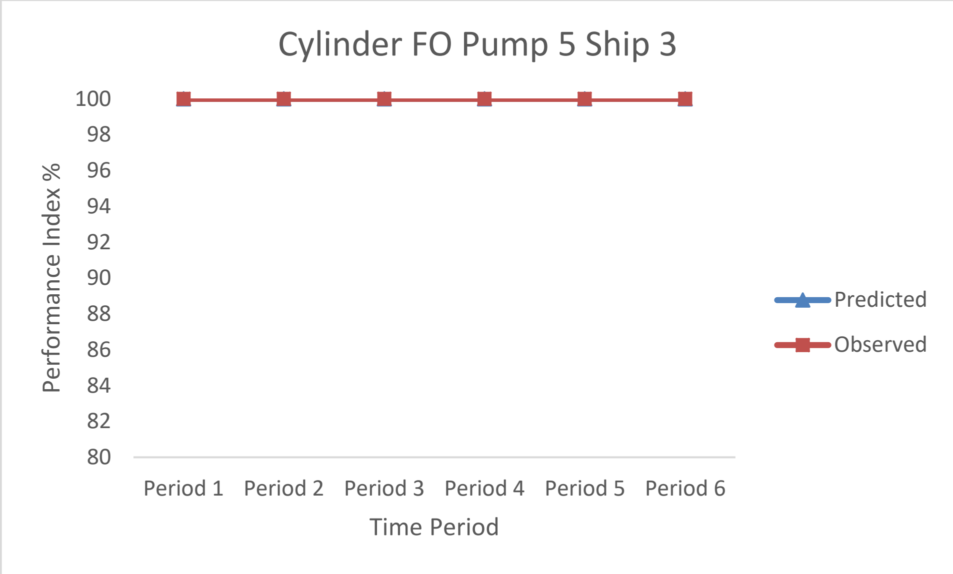

Figure 302 - Cylinder FO Pump 5 Ship 3 Performance Indices

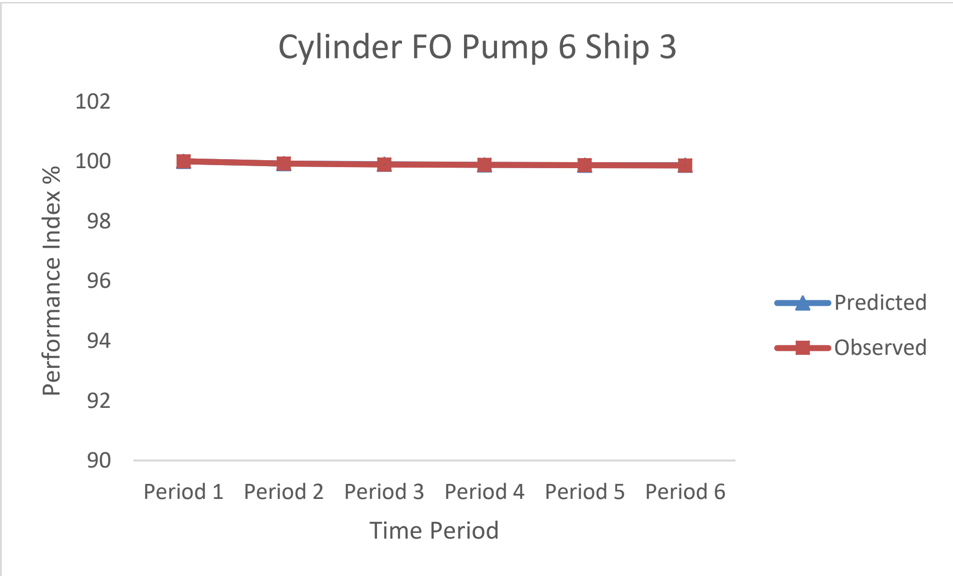

Figure 303 - Cylinder FO Pump 6 Ship 3 Performance Indices

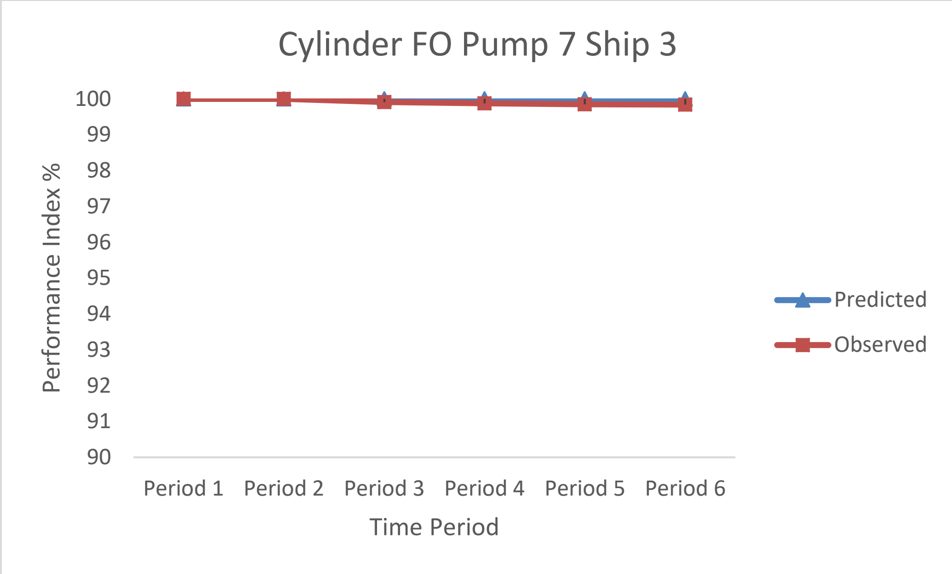

Figure 304 - Cylinder FO Pump 7 Ship 3 Performance Indices

Appendix C3.3 Turbocharger System of Ship 3

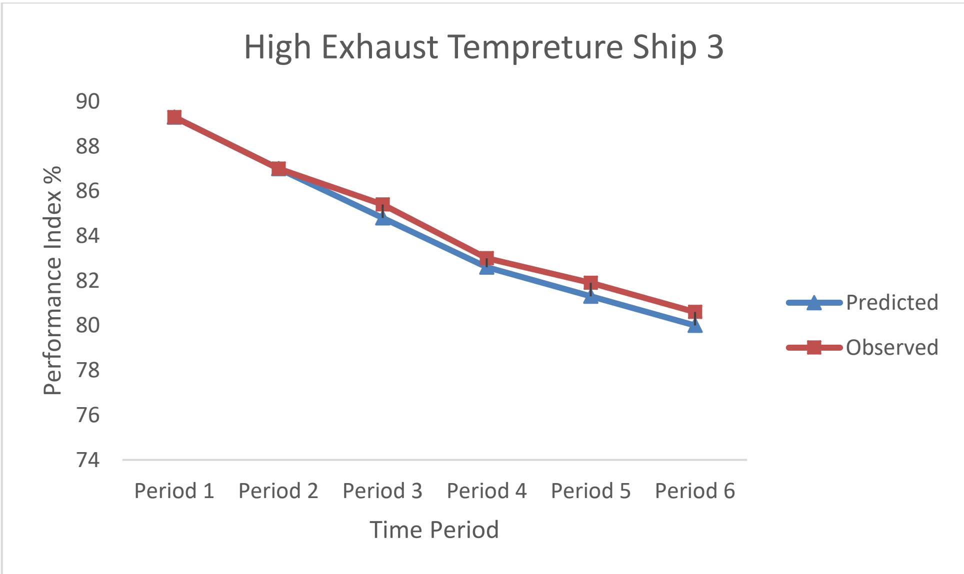

Figure 305 - High Exhaust Temperature Ship 3 Performance Indices

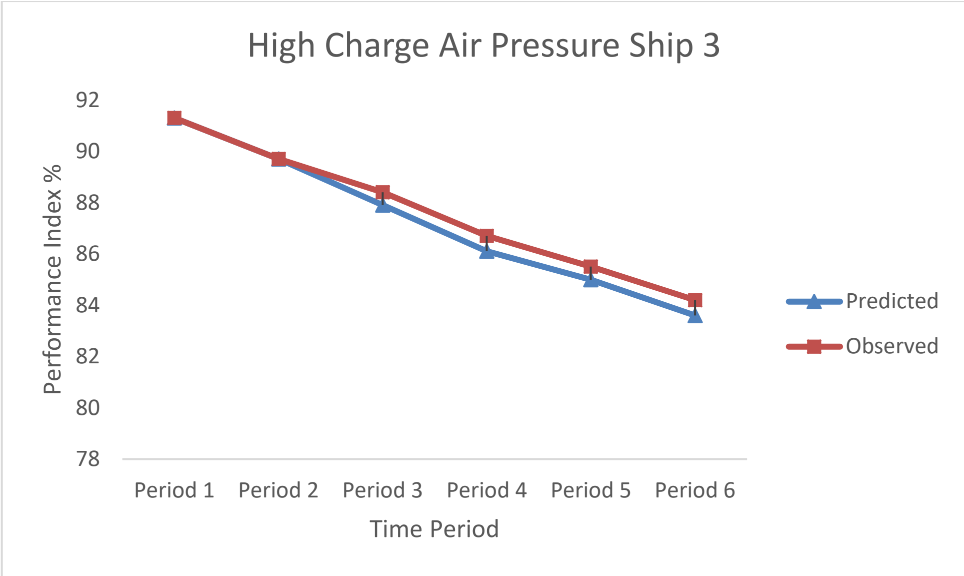

Figure 306 - High Charge Air Pressure Ship 3 Performance Indices

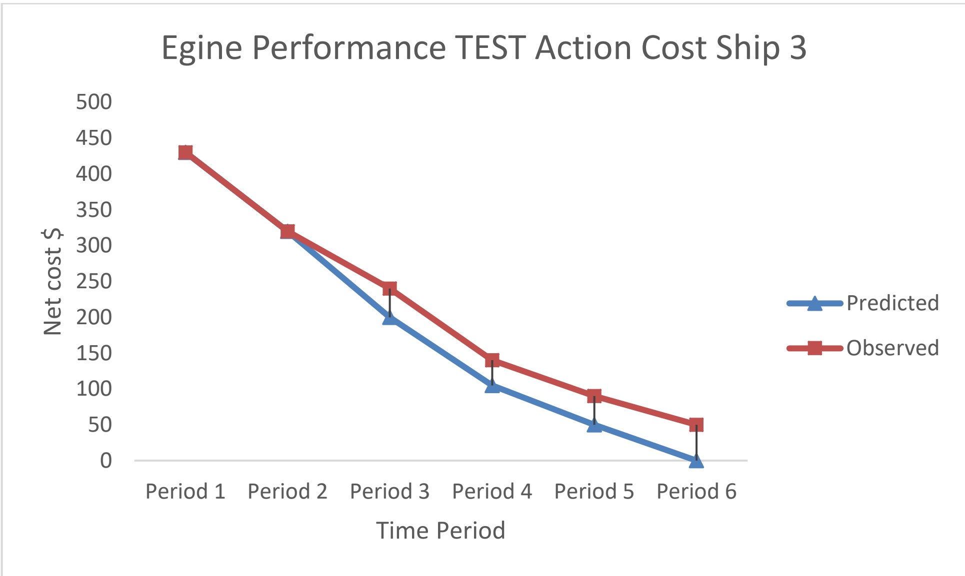

Figure 307 - Engine Performance Test Action Ship 3 Net cost

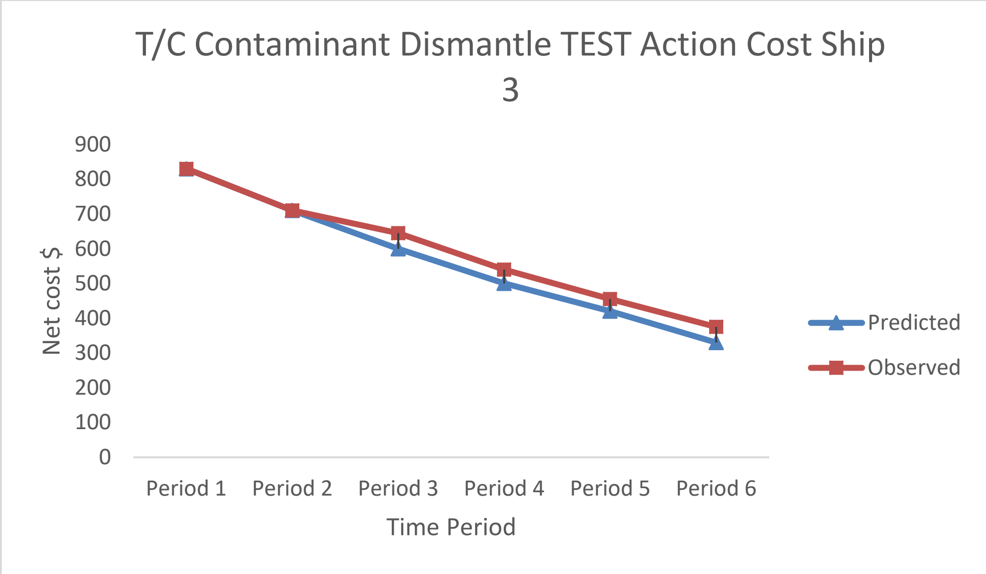

Figure 308 - T/C Contaminant Dismantle Test Action Ship 3 Net cost

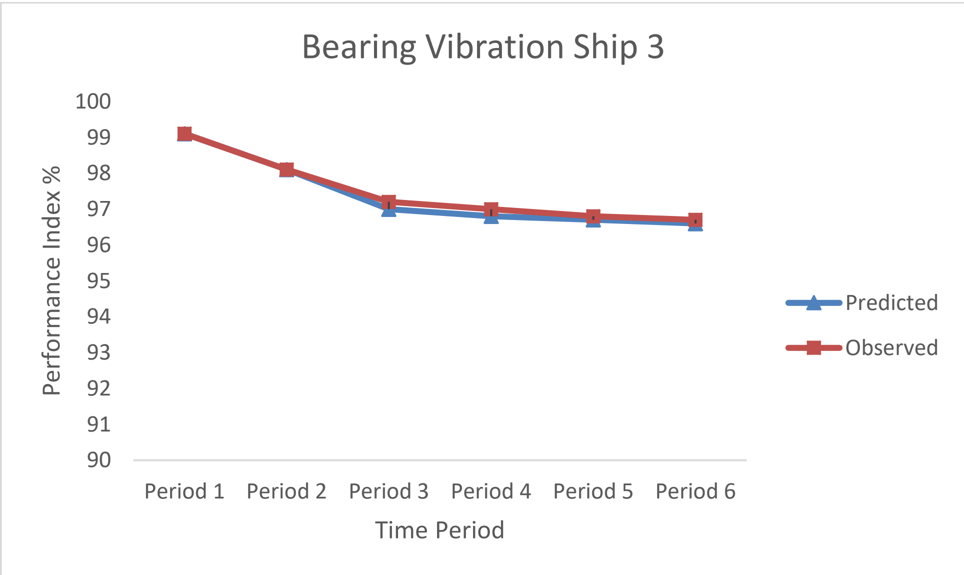

Figure 309 - Bearing Vibration Ship 3 Performance Indices

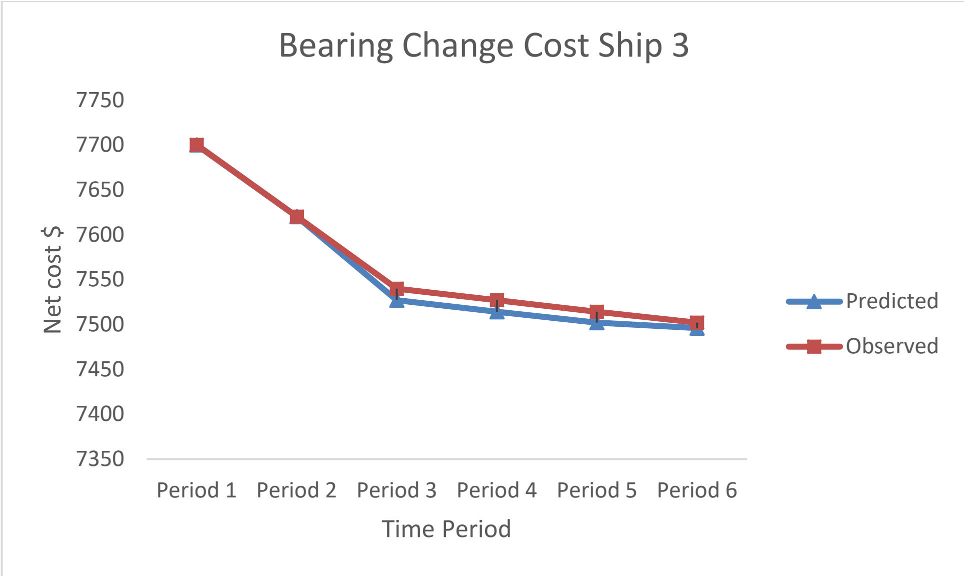

Figure 310 - Bearing Change Ship 3 Net cost

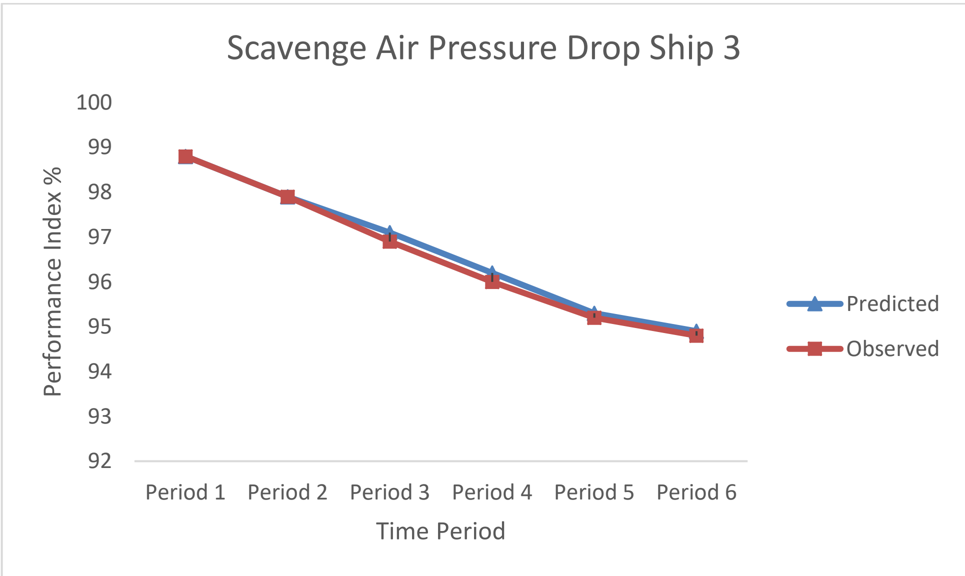

Figure 311 - Scavenge Air Pressure Drop Ship 3 Performance Indices

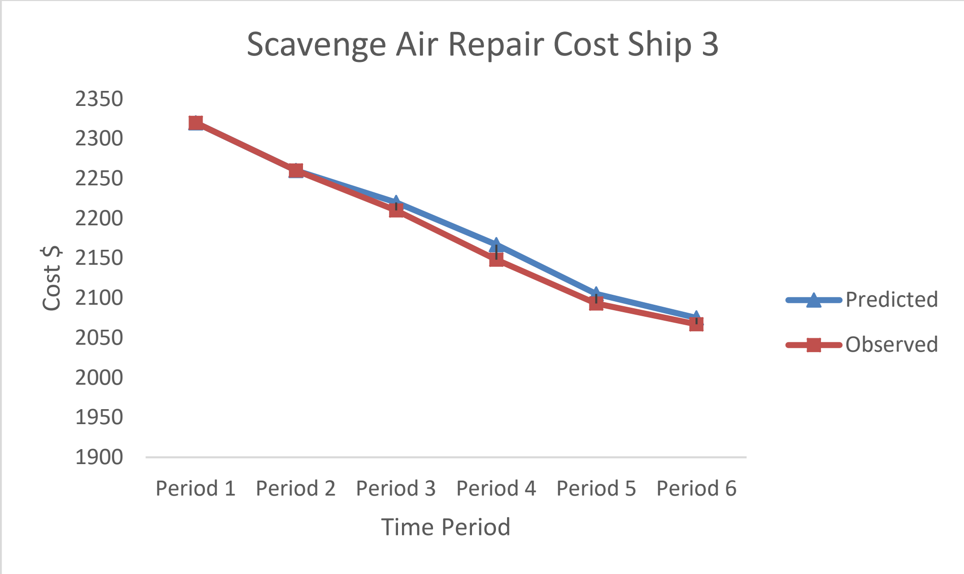

Figure 312 - Scavenge Air Repair Ship 3 Net cost

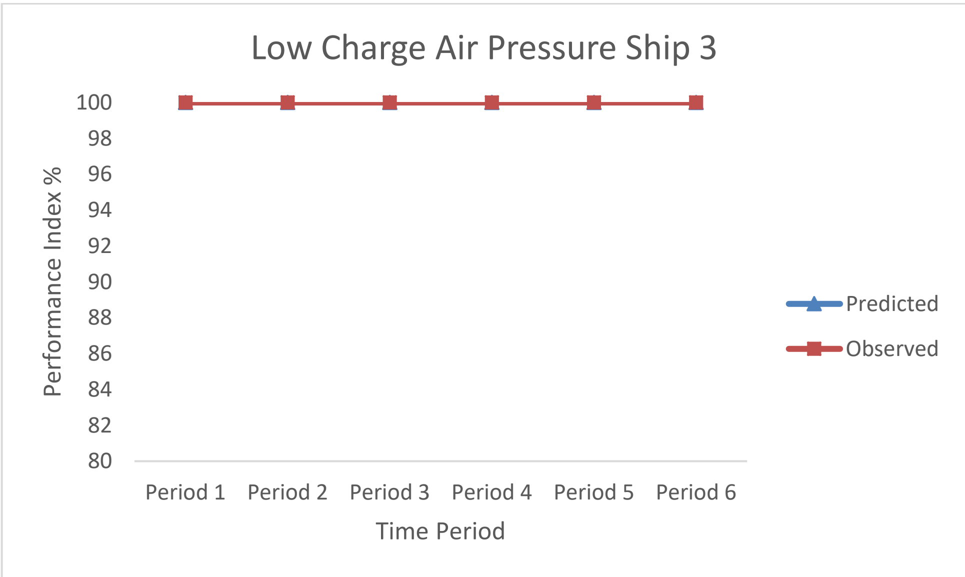

Figure 313 - Low Charge Air Pressure Ship 3 Performance Indices

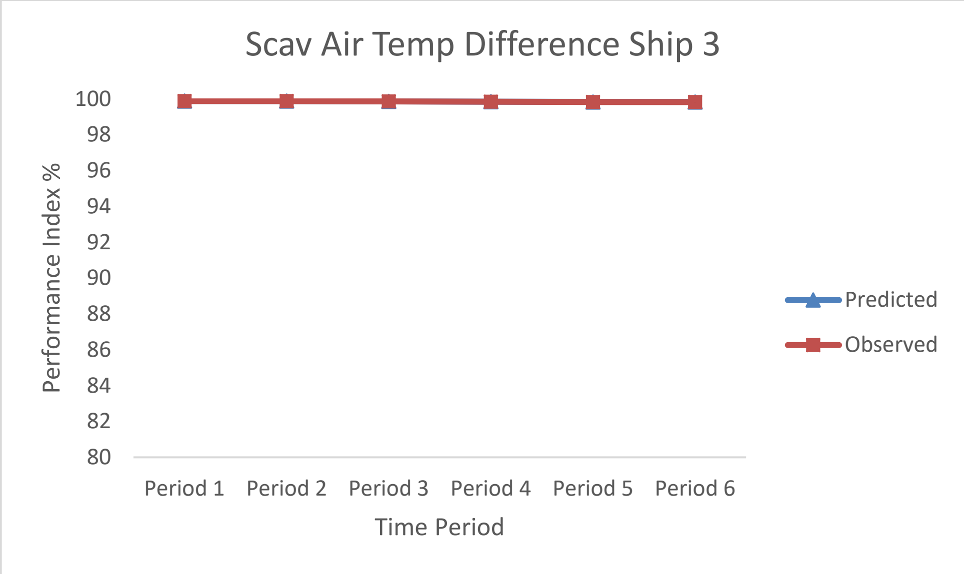

Figure 314 - Scavenger Air Temperature Difference Ship 3 Performance Indices

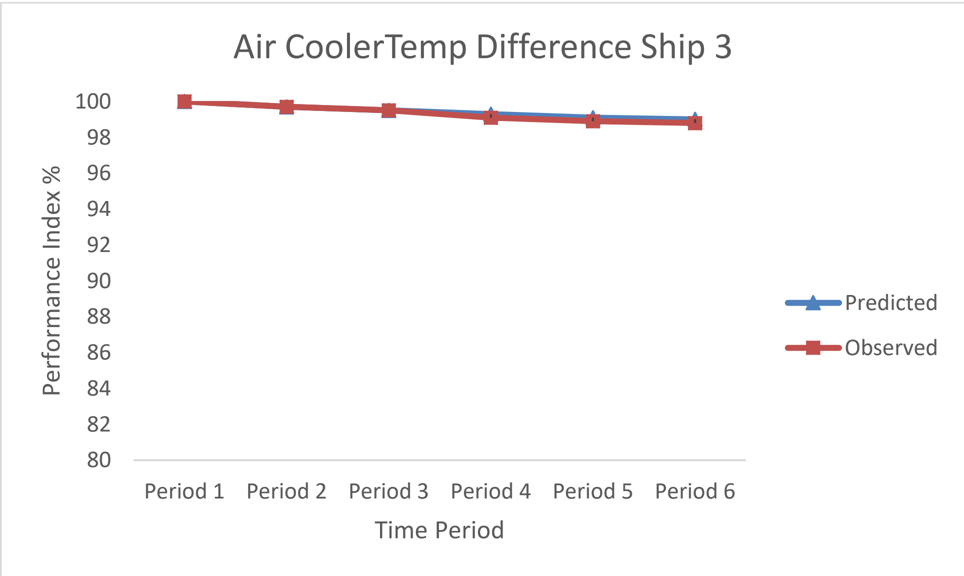

Figure 315 - Air Cooler Temperature Difference Ship 3 Performance Indices

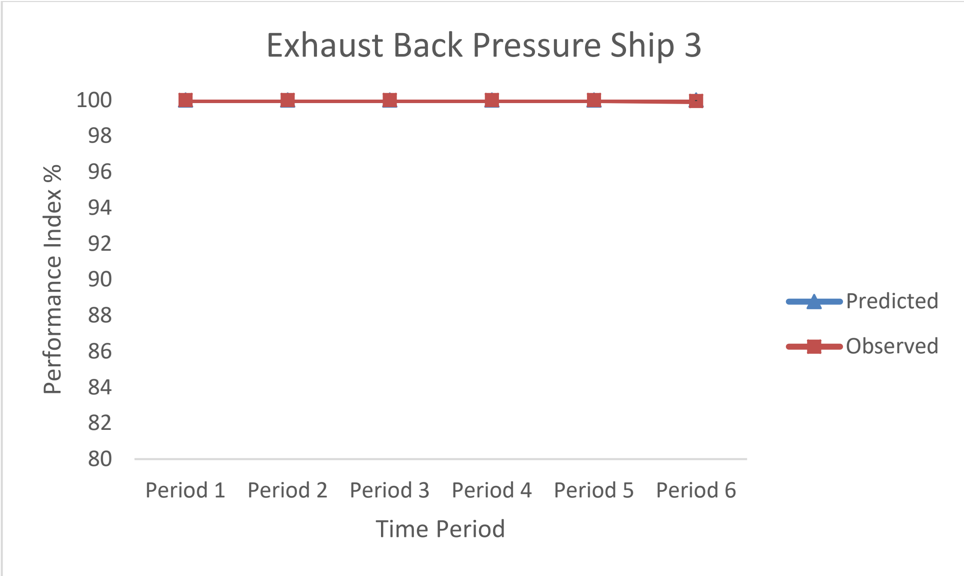

Figure 316 - Exhaust Back-pressure Ship 3 Performance Indices

APPENDIX D – ANALYSIS OF RISK FACTORS USING MATLAB SIMULINK FUZZY LOGIC TOOLBOX

Using Matlab Fuzzy Logic tool box and membership function editor, connection between human risk factor and probability of failure has been created. Figure 317 demonstrates the membership function using the statements from Table 17. In this form, expressions A to E are represented by values 0 to 5.

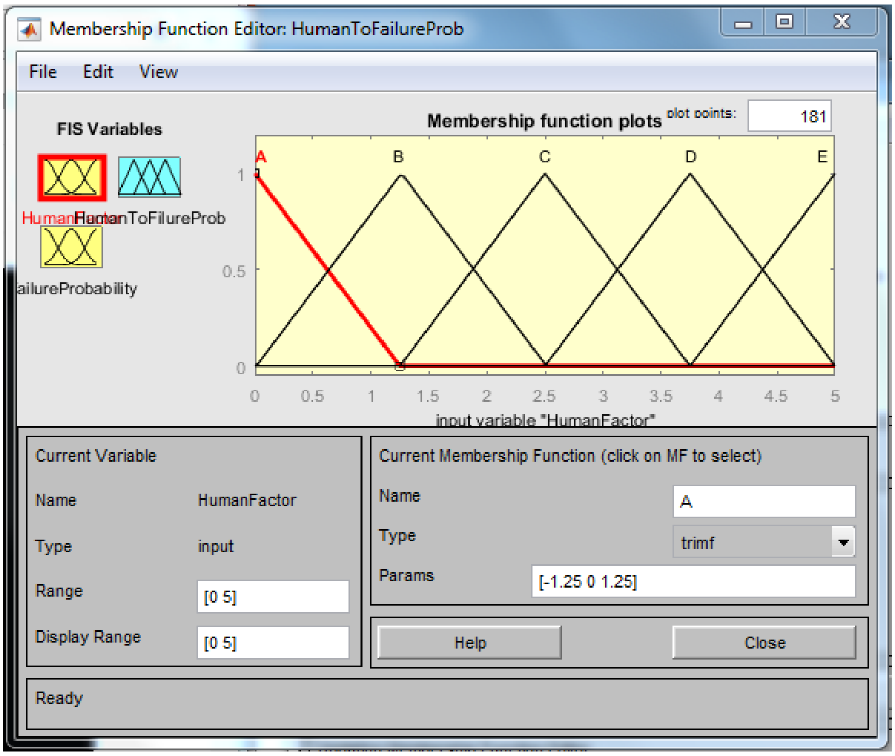

Figure 317 - Human Factor Membership Function Based on Table 17

Similarly, using Table 20, membership function failure probabilities are generated (Figure 318). In this membership function, statements 1 to 5 are represented by ranks of 0 to 5.

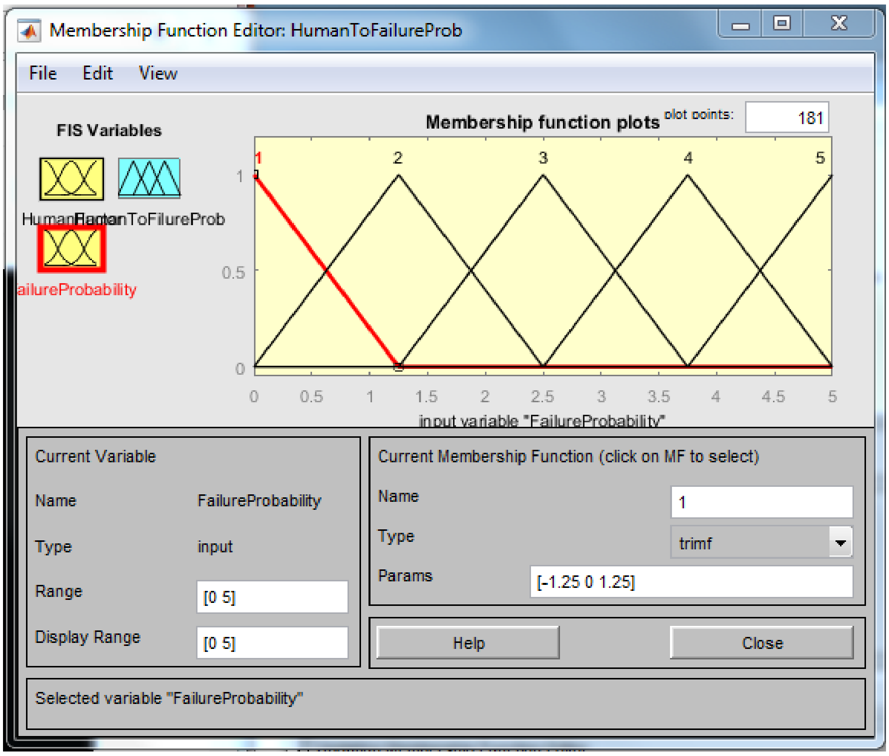

Figure 318 - Failure Probability Membership Function Based on Table 20

Subsequently, using Table 21 where it shows the relationship between risk factor and failure probability, the membership function overall risk factor is represented as Figure 319. In this membership function, statements Very Low (VL), Low (L), Medium (M), High (h) and Very High (VH) are ranked from 0 to 5.

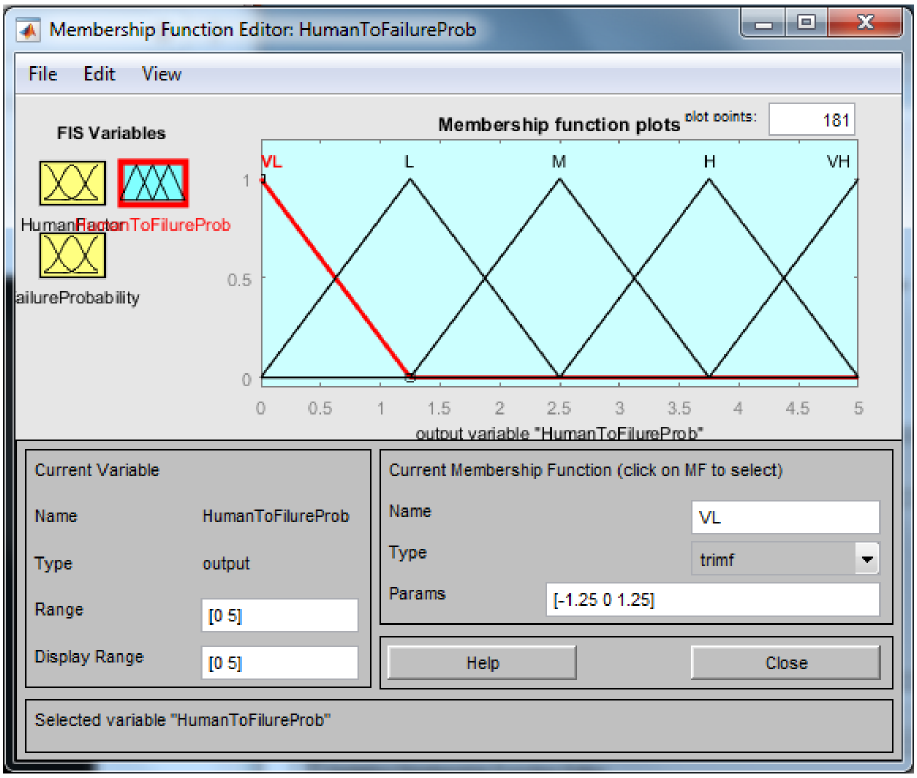

Figure 319 - Overall Membership Function Based on Table 21

Finally, overall results were analysed by the fuzzy logic tool box. A represented result of human factor of C and failure probability of 2 with final score of 2.5 is shown in Figure 320.

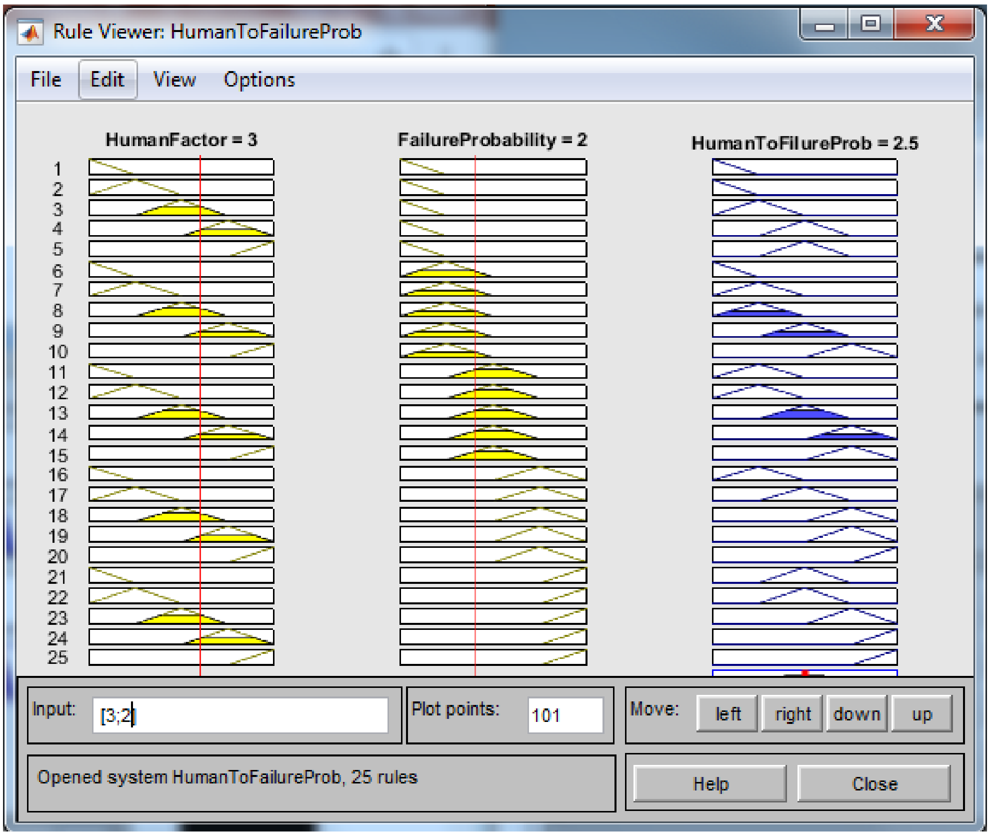

Figure 320 - Human to Failure Rate Risk Probabilities Results